



Journal of
***Risk and Financial
Management***

Special Issue Reprint

Financial Markets, Financial Volatility and Beyond, 3rd Edition

Edited by
Ruipeng Liu

mdpi.com/journal/jrfm



Financial Markets, Financial Volatility and Beyond, 3rd Edition

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Guest Editor

Ruipeng Liu



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This is a reprint of the Special Issue, published open access by the journal *Journal of Risk and Financial Management* (ISSN 1911-8074), freely accessible at: https://www.mdpi.com/journal/jrfm/special_issues/4W9GL69WP1.

For citation purposes, cite each article independently as indicated on the article page online and as indicated below:

Lastname, Firstname, Firstname Lastname, and Firstname Lastname. Article Title. <i>Journal Name</i> Year , Volume Number, Page Range.

ISBN 978-3-7258-5493-6 (Hbk)

ISBN 978-3-7258-5494-3 (PDF)

<https://doi.org/10.3390/books978-3-7258-5494-3>

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Editorial

Editorial: Financial Markets, Financial Volatility and Beyond, 3rd Edition

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This Special Issue of the *Journal of Risk and Financial Management* brings together 17 original research articles that offer timely and impactful insights into the evolving landscape of finance and risk management. The contributions span a wide geographical scope—from small island economies to major global markets—and address critical themes such as market volatility, financial contagion, banking sector dynamics, portfolio optimization, behavioral finance, and the intersection of finance with environmental and geopolitical risks.

1. Revisiting Market Volatility and Risk Measurement

Several contributions reimagine conventional approaches to volatility and uncertainty. Jha et al. introduce a revised volatility index grounded in a heavy-tailed Levy process to better capture uncertainty shocks in financial markets. Boudri and El Bouhadi compare econometric and deep learning models, finding that simpler GARCH models remain surprisingly effective in forecasting volatility in pre-emerging markets. Metelski and Sobieraj explore trading volume concentration across S&P 500 constituents, revealing its predictive power for portfolio performance, while Dumitrescu and Grecu assess the impact of financial shocks on economic cycles across European economies, finding divergent sensitivities between developed and emerging markets.

2. Banking, Lending, and Financial Institutions

Banking sector performance is examined in multiple contexts. Hanif assesses Islamic banking efficiency across the GCC, identifying key internal performance drivers. Kumar et al. and Chun and Ardaaragchaa explore determinants of bank profitability and loan growth, respectively, in small island economies such as Fiji and Mongolia—highlighting the nuanced role of non-performing loans, liquidity, globalization, and economic shocks. A complementary study by Chand et al. revisits Fiji's NPL trends, revealing heightened post-COVID vulnerabilities, especially among non-bank institutions.

3. Portfolio Optimization and Investment Behavior

In the realm of asset allocation, Kumar et al. apply the robust maximum diversified (RMD) portfolio to Fiji's stock market, proposing refined investment strategies for low-liquidity environments. Song et al. investigate how stock overvaluation in China incentivizes managerial myopia, with implications for long-term performance. Lee delves into behavioral finance, showing how psychological traits and prior outcomes shape risk–payoff decisions—providing valuable insight for financial literacy and decision framing.

4. Financial Integration, Contagion, and Globalization

This Special Issue also features cross-market integration and contagion analysis. Niyitegeka and Habiyaemye apply wavelet techniques to detect post-crisis financial con-

tagion between Germany and BRICS markets, while Izaguirre et al. document enhanced financial integration in Latin America following trade agreements with the US. Meanwhile, Truong et al. evaluate how geopolitical risks influence FDI in Vietnam, showing both short-term gains and long-term deterrents. Plastun et al. analyze the Ukrainian stock market's structural resilience over decades of geopolitical turmoil, identifying persistent inefficiencies amid reform attempts.

5. Sustainability and Macroeconomic Development

Lastly, Rastogi et al. examine how environmental efficiency influences GDP per capita globally. Their results suggest that environmental improvements may hinder growth in low-income countries, while high-income democracies can absorb or reverse this trade-off—offering critical guidance for global climate financing frameworks.

6. Conclusions

From novel volatility measures and portfolio strategies to behavioral insights and macro-financial linkages, the papers in this Special Issue reflect the richness and diversity of contemporary financial research. By combining rigorous empirical methods with practical policy relevance, the authors collectively contribute to a deeper understanding of financial markets, financial risk, and global economic resilience. We hope that this collection stimulates further inquiry and informs the decisions of researchers, practitioners, and policymakers navigating today's complex financial environment.

Conflicts of Interest: The author declares no conflict of interest.

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Article

Credit Card Default Prediction: An Empirical Analysis on Predictive Performance Using Statistical and Machine Learning Methods

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Abstract: This article compares the predictive capabilities of six models, namely, linear discriminant analysis (LDA), logistic regression (LR), support vector machine (SVM), XGBoost, random forest (RF), and deep neural network (DNN), to predict the default behavior of credit card holders in Taiwan using data from the UCI machine learning database. The Python programming language was used for data analysis. Statistical methods were compared with machine learning algorithms using the confusion matrix measured in metric terms of prediction accuracy, sensitivity, specificity, precision, G-mean, F1 score, ROC, and AUC. The dataset contained 30,000 credit card users' information, with 6636 default observations and 23,364 nondefault cases. The study results found that modern machine learning methods outperformed traditional statistical methods in terms of predictive performance measured by the F1 score, G-mean, and AUC. Traditional methods like logistic regression were marginally better than linear discriminant analysis and support vector machines in terms of the predictive performance measured by the area under the receiver operating characteristic curve. In the modern machine learning methods, deep neural network was better in the predictive performance metrics when compared with XGBoost and random forest methods.

Keywords: credit card default; confusion matrix; deep neural network; default prediction; linear discriminant analysis; logistic regression; machine learning; random forest; support vector machine; XGBoost

JEL Classification: C44; C45; C52; C55; C63

1. Introduction

Consumer credit in the U.S. rose by USD 8.93 billion in June 2024, following an upwardly revised USD 13.94 billion increase in the prior month and below market expectations of a USD 10 billion gain (Saraiva, 2024). Also, revolving credit, including credit cards, fell by nearly USD 1.7 billion, marking the largest drop since early 2021. Meanwhile, nonrevolving credit, such as loans for cars and education, climbed by USD 10.6 billion, the highest in 2024 (Saraiva, 2024). Americans have reduced their credit card debt and even reduced their credit card spending mainly because banks are carefully selecting the customers to whom they extend credit (Dicon, 2024). The credit card debt default crisis took place in several countries like South Korea in 2001 and Hong Kong in 2002, followed by Taiwan in the year 2005 (Chang, 2022). The same study highlighted adverse borrower selection and information asymmetry as the main reasons for default. The Taiwan cards

and payments market size was USD 139.5 billion in 2023, and the market is expected to grow at 8% until 2027 as per the Globaldata (2023) report. Taiwan has 58.12 million credit cards in circulation as of 2023, with 37.64 million active credit cards as per the 2024 press report released by the Financial Supervisory Commission of Republic of China (Taiwan).

Loan default prediction has always been a risk management strategy for financial institutions because a minor increase in the prediction accuracy results in better risk management strategies (Hubbard, 2020). Traditionally, statistical and econometric models have been used in prediction and decision-making processes. These prediction methods are not just for the purpose of assessing credit risk and scoring the individuals; they also have wider scope, from risk management strategies to optimizing the capital reserve requirements, forecasting the nonperforming assets and losses, and better recovery management strategies (Gauthier et al., 2012). Better customer profiling has always been the primary objective of banks to differentiate clients as prompt or irregular payers. Also, a minor improvement in the prediction accuracy of loan default will result in an increased profitability of the institution. In addition, early identification of the default potential of customers will help lending organizations prevent slippage into bad loans and encourage clients to repay by enforcing recovery management strategies.

Risk profiling of customers is an important aspect of credit risk management, and it is done based on the assessment of creditworthiness of the borrower that is measured in terms of the customers' ability and willingness to repay the loan (Bhandary et al., 2023a). Ability can be evaluated by income, age, number of dependents, marital status, and expenses, whereas willingness can be evaluated by attitudinal and psychological factors including the credit track record. The disadvantage associated with traditional credit scoring models in risk profiling is their inability to capture the details of people without a credit history (DeVaney, 1999). The past track record of the borrower is an important predictor of future payments to be made by the potential borrower (Schreiner, 2000). Hence, an analysis of the customers' probability of default based on the input parameters, model selection, and validation, with an objective to predict the default, will not only help the financial institutions with better risk management strategies and decision making but also help them to plan their loan portfolio and diversify accordingly.

The International Financial Reporting Standards (IFRS) 9 prescribes a structure to predict the expected credit loss (ECL) measured by the probability of default (PD), exposure at default (EAD), and loss given default (LGD). The PD is the major determinant of the ECL. It is measured by credit ratings based on historical repayment track records with default statistics (Bandyopadhyay, 2023). The LGD is defined as the estimated amount that is impossible to recover from an asset in the event of a default, equationally represented as one minus the recovery rate. Increased prediction accuracy of loss given default helps the banks accurately calculate the economic capital requirement of the bank (Bastos, 2010). EAD is the loan outstanding amount on which PD and LGD are applied. IFRS 9 classifies assets into three categories based on credit risk assessment. The three classes are assets with low credit risk, assets with high credit risk, and credit-impaired assets (IASB, 2014).

The biggest challenge in loan default prediction is the calculation of probability of default of the borrower (Baesens et al., 2003; Coşer et al., 2019; Hand & Henley, 1997; Yeh & Lien, 2009). To overcome this problem, there is a need to evaluate models on the pretext of loan default prediction with an increased predictive performance for better approximation of the probability of default. The aim of this study was to analyze credit card users' data from the University of California Irvine (UCI) machine learning platform, which contained details of credit card clients with default and nondefault data. The study evaluated a series of statistical and machine learning algorithms using six predictive models that could explain the studied event through classifiers, such as linear discriminant analysis (LDA),

logistic regression (LR), support vector machines (SVMs), XGboost, random forest (RF), and deep neural networks (DNNs).

2. Literature Review

A study on predicting credit defaults among microfinance institution borrowers found age, income, marital status, gender, number of dependents, residential status, tenure, and the amount of loan borrowed as the significant determinants of loan repayment (Ofori et al., 2014). Loan repayment depends on ability and willingness of the borrower to repay. Salary determines the ability of the borrower, and it affects the repayment behavior of the borrower (Bhandary et al., 2023b). Willingness is measured by attitude toward repayment that influences repayment behavior (Bhandary et al., 2023a). Also, the attained level of education increases loan repayment performance (Acquah & Addo, 2011; Addisu, 2006). To summarize, age, income, expenses, education attainment level, marital status, gender, number of dependents, psychological factors, attitude, and credit history are the factors that affect loan repayment.

Traditionally, lenders would use their human intuition to judge the repayment behavior of the applicant. Statistical methods use input variables from the customers' loan application forms and other sources that correlate with the output variable (default case) to calculate the probability of default (Hand & Henley, 1997). The statistical models used include the Bayes classifier, linear discriminant analysis, logistic regression technique, and k-nearest neighbor-based prediction models. Linear discriminant analysis is a very common technique for classification problems and dimensionality reduction (Tharwat et al., 2017). In addition, the performance of linear discriminant analysis is usually compared with a logistic regression model, which is another most widely used method in binary data classification problems (Maalouf, 2011). The advantage of using the discriminant analysis and logistic regression technique is its simplicity in application for classification problems, but the disadvantage is that it cannot capture the interaction effect of input variables, and neither can it be applied for nonlinear relations (Yeh & Lien, 2009).

Support vector machines is another solution for default prediction problems that is an extremely robust and powerful method in classification and regression applications (Cervantes et al., 2020). Also, the gradient boosting algorithm was developed for high predictive performance but with a compromised speed of execution. Hence, extreme gradient boosting was introduced with a high speed of execution and good predictive ability for classification problems (Ramraj et al., 2016). The random forest classifier is an ensemble approach that combines several classifiers. This combination provides high accuracy and is a superior technique for class-imbalanced datasets (More & Rana, 2017). The interaction effect is confirmed when the combined effect of two or more independent variables/features produces a significantly higher effect on the dependent variable when compared with the addition of their individual contributions. Neural network models have the unique ability to capture the presence of interactions in nonlinear relationships as mentioned in the findings of Shao et al. (2023). In addition, the deep neural network is a fast-growing machine learning method because of its superior performance (Sze et al., 2017).

The logistic regression credit scoring model was compared with the neural network model for predicting credit defaults in the Indian microfinance industry; the results showed that the neural network model outperformed the logistic regression model in calculating the prediction accuracy, and the major determinants of probability of default for the model included the income of the borrower, the quantum of the requested loan amount, the total expense, age, family size, and the length of stay at current residence (Viswanathan & Shanthi, 2017). A text mining technique from the loan application forms of an online crowdfunding platform in the U.S. was analyzed using machine learning to predict po-

tential loan defaults, and the findings of the study included patterns of words written by defaulting borrowers indicative of their personality traits and personality states, which seem to disclose their true nature, grounded in human behavior (Netzer et al., 2019).

Hamdi et al. (2024) compared the predictive performance of six models, namely, linear discriminant analysis, logistic regression, decision trees, support vector machines, random forest, and deep neural networks, for the bankruptcy prediction of Tunisian companies and found that the deep neural network performed with better accuracy, F1 score, and area under the curve in comparison with conventional models. A study on predicting the banking crisis in India using statistical methods like logistic regression; artificial intelligence; and machine learning methods like random forest, naïve Bayes, gradient boosting, support vector machines, neural networks, K-nearest neighbors, and decision trees found that neural networks and random forest models were effective models in banking crisis prediction (Puli et al., 2024).

A study on financial risk assessment using big data analysis and ten algorithms found that ensemble models using boosting algorithms outperformed traditional models like logistic regression and decision trees in terms of prediction accuracy (Suhadolnik et al., 2023). The study on predicting financial inclusion in Peru using machine learning methods like decision trees, random forests, artificial neural networks, XGBoost, and support vector machines found that these methods could be a valuable complement to standard models like generalized linear models and logistic regression models for assessing financial inclusion in Peru (Maehara et al., 2024). The study also found that neural network was the most effective method to predict account access. For account usage prediction, the random forest method and support vector machines employing the radial basis function were the most effective prediction methods.

Traditional methods like discriminant analysis and logistic regressions can capture linear relationships only, and this is a major limitation for big data analysis, whereas machine learning models can measure the interaction effect among explanatory variables, as well as predicting complex linear and nonlinear relationships (Chiang et al., 2006). Decision trees, support vector machines, and deep neural networks are more effective to capture complex nonlinear relationships than simple linear models (Varian, 2014). Also, relying exclusively on statistical models for decision making may lead to questionable findings. Hence, it is recommended to use a wide range of tools for reaching conclusions on data (Breiman, 2001b).

Machine learning models have emerged as a significant tool in default prediction methods mainly because they are scalable and agile. These models are widely used in decision making for classification, regression, and clustering problems. The predictive performances of these models are analyzed using the confusion matrix and the receiver operating characteristic curve (ROC). A confusion matrix classifies the actual values with the values predicted by the model (Luque et al., 2019). The ROC graphically characterizes the positive and negative events exploring the trade-offs between competing losses at different threshold levels (Brown & Davis, 2006). It is free from parametric assumptions and the value is independent from the ratio of positive and negative events. The area under the ROC (AUC) is also independent of the decision thresholds and hence suitable for classification problems in addition to confusion matrix analysis in machine learning applications. Machine learning models have been applied in a variety of fields like predicting asset pricing (S. Gu et al., 2020), option return predictions (Bali et al., 2023), stock market asset pricing (Drobetz & Otto, 2021), bankruptcy prediction (Hamdi et al., 2024), predicting banking crises (Puli et al., 2024), credit risk assessment (Suhadolnik et al., 2023), and predicting financial inclusion (Maehara et al., 2024).

Credit default prediction is not just for calculating the credit score; it has a wide range of applications in terms of devising credit risk management strategies, calculating the capital reserve requirements, loss forecasting, and provisioning purposes. Recent studies highlight a broad range of machine learning applications including credit risk assessment, and this study aimed to predict the credit card default risk with the following research questions:

- RQ1. Which model has the best predictive performance as per the confusion matrix?
- RQ2. Which model has the best area under the receiver operating characteristics?
- RQ3. How can the default score be calculated?

3. Materials and Methods

3.1. Linear Discriminant Analysis

Linear discriminant analysis (LDA) is a statistical technique to find a linear combination of features that best separates two or more classes of events. The primary goal of LDA is to project the data onto a lower-dimensional space with good class separability. The equation for linear discriminant analysis (LDA) introduced by Ronald Fisher is central to dimensionality reduction and classification tasks (Fisher, 1936). The equation is given below as

$$Z = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_n x_n \quad (1)$$

where β_n is the weight associated with the input variable x_n .

3.2. Logistic Regression

Logistic regression (LR) is a tool for classifying binary data and making predictions between zero and one. Logistic regression is used to explain the relationship between a binary dependent variable and independent variables. Logistic regression is used to obtain the odds ratio in the presence of more than one explanatory variable (Sperandei, 2014). It generates the coefficients and standard errors for the significance levels of the formula used to predict the probability of event occurrence. It is represented by the equation

$$P = \frac{1}{1 + e^{-(a+bx)}} \quad (2)$$

where P is the probability, and a and b are the parameters of the model.

3.3. Support Vector Machine

Support vector machine (SVM) is a supervised learning model used for classification problems developed by Vapnik (1998). This technique determines the best separating hyperplane between two classes of a dataset. The mathematical formulation is expressed in terms of optimization problem and decision function (Hearst et al., 1998). The optimization problem is written as

$$\text{minimize } \frac{1}{n} \sum_{i=1}^n \zeta_i + \lambda \|w\|^2 \quad (3)$$

Subject to $y_i(w^t x_i - b) \geq 1 - \zeta_i$ and $\zeta_i \geq 0$ for all i , where w^t is the normal vector to a hyperplane, where the y_i values are either 1 or -1 , each indicating the class to which the point x_i belongs. Each x_i is a p -dimensional real vector. The final classifier is given as

$$f(x) = \text{sgn}(w^t x - b) \quad (4)$$

where sgn is the sign function.

3.4. XGBoost

XGBoost is a highly scalable tree boosting machine learning algorithm. It can be scaled for big data with far fewer resources compared with the existing systems (Chen & Guestrin, 2016). In extreme gradient boosting (XGBoost), the objective function (loss function and regularization) $\mathcal{L}^t$ at iteration t that we need to minimize is given by the following equation:

$$\mathcal{L}^t = \sum_{i=1}^n l(y_i, \hat{y}_i^{(t-1)} + f_t(x_i)) + \Omega(f_t) \quad (5)$$

where y_i is the real label from the training dataset, and l is the function of the sum of current and previous additive trees.

3.5. Random Forest Classifier

Random forests are a combination of tree predictors proposed by Breiman (2001a). When performing random forest (RF) based on classification data, we can use the Gini index or entropy to decide how the nodes on a decision tree branch. The Gini formula is given by

$$Gini = 1 - \sum_{i=1}^c (p_i)^2 \quad (6)$$

This formula uses the class and probability to determine the Gini of each branch on a node, determining which of the branches is more likely to occur. Here, p_i represents the relative frequency of the class that is observed in the dataset, and c represents the number of classes.

The formula for entropy is given by

$$Entropy = \sum_{i=1}^c -p_i * \log_2(p_i) \quad (7)$$

Entropy uses the probability of a certain outcome to decide on how the node should branch. Unlike the Gini index, it is mathematically intensive due to the logarithmic function used in the calculation.

3.6. Deep Neural Network

Deep Neural Network Architecture

A deep neural network (DNN), as shown in Figure 1, is a type of artificial neural network (ANN) that has multiple hidden layers (usually more than one) between the input and output layers. Artificial neural networks (ANN), first proposed by McCulloch and Pitts (1943), are broadly classified into two types based on the direction of information flow between the input and output layers. The two types are feedforward neural network (uni-directional flow of information between the layers from input to output) and backpropagation neural network (bi-directional flow of information between the layers) (Krenker et al., 2011). Feedforward neural networks are simpler to design and test, and multilayer perceptron and radial basis functions are the most popular feedforward neural networks. Multilayer perceptrons (MLPs) are limited to performing linear functions only. Hence, neurons are used for nonlinear transformations. Backpropagation models are advanced, complex, and accurate for increased prediction accuracies since they iterate based on the given criteria and adjust the weights and bias accordingly (Krenker et al., 2011). The weight and bias adjustment with activation function is displayed in Figure 2. The activation functions used are tangent function, logistic function, hyperbolic tangent, rectifier function, softplus function, radial basis function, rectified linear unit (ReLU), and leaky ReLU. ReLU is usually used in the hidden layers as activation functions in deep learning (DL) models

to address the vanishing gradient problem. The network learns through an optimization algorithm known as the gradient descent. This algorithm compares the predicted output with the actual output and tunes the parameters (weights and bias) of the network through an optimization technique known as the learning rate (Hochreiter et al., 2001). Other learning functions include stochastic gradient descent and conjugate gradient descent, among many others.

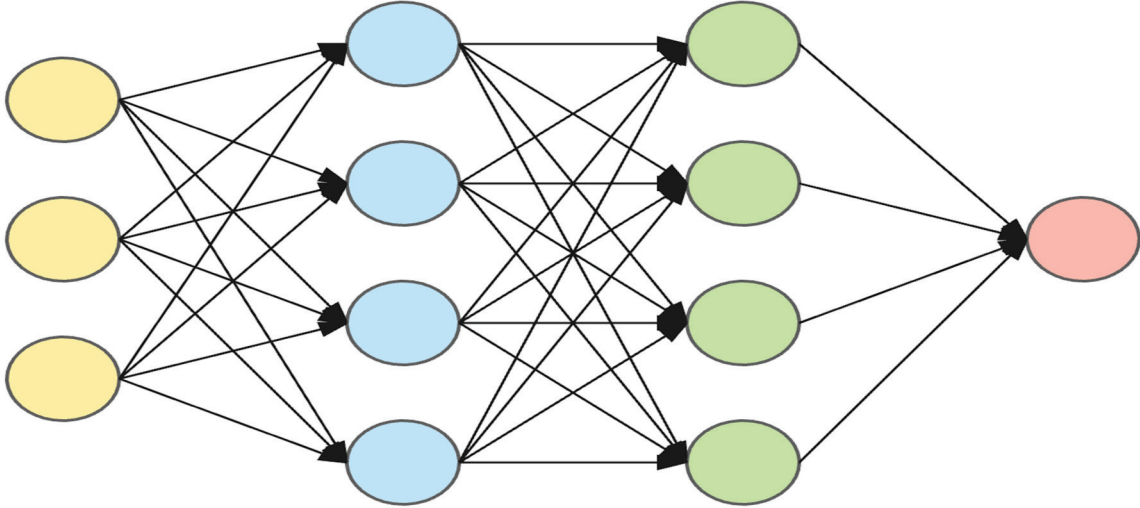


Figure 1. The deep neural network architecture. Source: Authors' own.

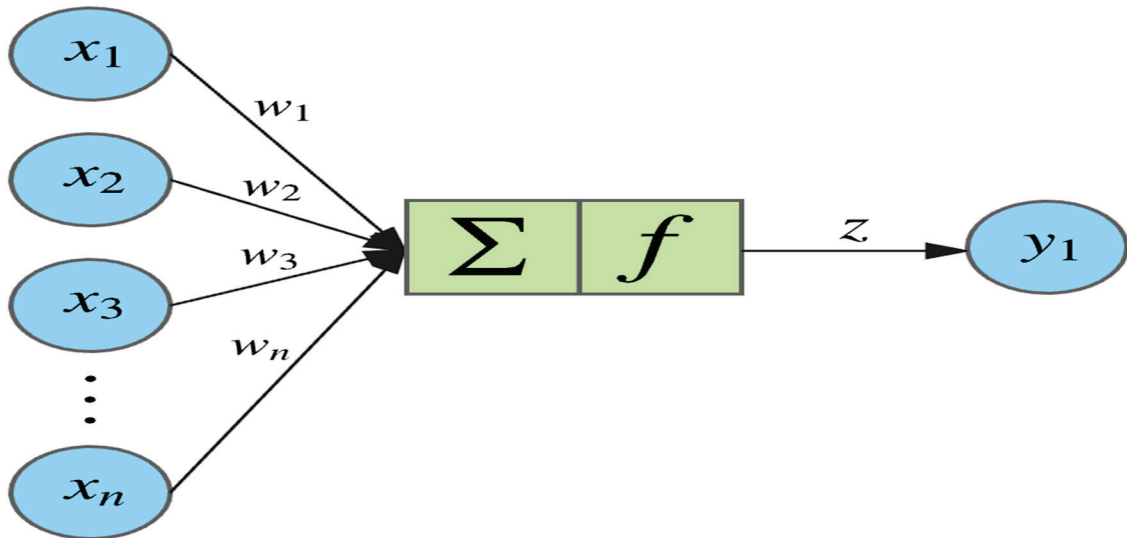


Figure 2. Weight and bias adjustment with activation function. Source: Authors' own.

The z value is calculated as given below:

$$z = f(b + x \cdot w) = f\left(b + \sum_{i=1}^n x_i w_i\right) \quad (8)$$

$$x \in d_{1 \times n}, w \in d_{n \times 1}, b \in d_{1 \times 1}, z \in d_{1 \times 1} \quad (9)$$

where b is the bias, w is the weight corresponding to input x , and n is the number of neurons.

3.7. Methodology

The dataset contains the following attributes as displayed in Table 1. The ID column was removed as it would not add value to analyze the data. Each of the input variables selected was correlated with an output variable (Default_status) and shortlisted if the values were greater than 0.2. The input variables shortlisted include the following: the sanctioned credit limit, coded as Limit_bal; the gender of the borrower, coded as Sex; the schooling of the borrower, coded as Education; the marital status and age of the borrower, coded as the same; and the repayment status, coded as Def_pay. The monthly billed amount was coded as Bill_amt1 for the month of April, Bill_amt2 for the month of May, Bill_amt3 for the month of June, Bill_amt4 for the month of July, Bill_amt5 for the month of August, and Bill_amt6 for the month of September. The completed monthly payment was coded as Pay_amt1 for the month of April, Pay_amt2 for the month of May, Pay_amt3 for the month of June, Pay_amt4 for the month of July, Pay_amt5 for the month of August, and Pay_amt6 for the month of September. The output variable was coded as Default_status (0 for no default and 1 for the presence of default). The income of the borrower was approximated by the credit limit provided by the issuer of the card since high-income customers are provided with a higher credit limit than low-income customers, who are provided with lower credit limits.

Table 1. Attributes of the dataset with feature code and description.

Feature ID	Feature Code	Description
X1	Limit_bal	The amount of credit that the card holder is entitled to avail. It includes individual and family credit.
X2	Sex	(Gender) 1 = male, 2 = female
X3	Education	1 = graduate, 2 = university, 3 = high school, 4 = others
X4	Marital status	1 = married, 2 = single, 3 = others
X5	Age	21 years to 79 years
X6 to X11	Repayment status codes – 1 = paid duly 1 = payment delay for one month 2 = payment delay for two months ... 9 = payment delay for 9 months and above	History of past payment month-wise X6 = repayment status for the month of September 2005 X7 = repayment status for the month of August 2005 X8 = repayment status for the month of July 2005 X9 = repayment status for the month of June 2005 X10 = repayment status for the month of May 2005 X11 = repayment status for the month of April 2005
X12 to X17	Amount of bill statement	X12 = amount of bill statement for September 2005 X13 = amount of bill statement for August 2005 X14 = amount of bill statement for July 2005 X15 = amount of bill statement for June 2005 X16 = amount of bill statement for May 2005 X17 = amount of bill statement for April 2005
X18 to X23	Amount of previous payment	X18 = amount paid in September 2005 X19 = amount paid in August 2005 X20 = amount paid in July 2005 X21 = amount paid in June 2005 X22 = amount paid in May 2005 X23 = amount paid in April 2005

Source: (Yeh, 2016).

The dataset was taken from the UCI machine learning repository that contained the credit card customers' payment details with default details in Taiwan released for public usage and analysis by Yeh (2016). The dataset contained 30,000 credit card users'

information with 6636 default observations and 23,364 nondefault cases. This dataset contained only numeric features with no duplicates and missing values. The dataset was imbalanced since the default and nondefault cases were not exactly equal. Hence, the efficiency levels of all the models were lower compared with balanced datasets (Karatas et al., 2020). Since the practical cases were always imbalanced, the dataset was not balanced using undersampling or oversampling techniques.

The data preprocessing was performed to clean the data (García et al., 2015). Feature scaling is a crucial data pre-processing technique, and it was performed to ensure that none of the variables (features) dominated the model because of their magnitude, in addition to reducing the impact of outliers, if any, present in the dataset (Zheng & Casari, 2018). The input variables were rescaled to normalize the training data. Feature scaling was performed using the standard scaler in Python. The dataset was split in the ratio of 80:20 for training and testing, correspondingly. Later, correlation among the explanatory variables was visualized using the heat map analysis (Gu, 2022).

The various models were benchmarked with confusion matrix analysis and receiver operating characteristic curves. Confusion matrix classifies the actual values with the predicted values of the model (Luque et al., 2019). The predictive performance was evaluated using the confusion matrix as established by the literary work of Kuhn and Johnson (2013). The data were analyzed as per the confusion matrix in Table 2 and the metrics mentioned in Table 3. The ROC curve characterized the positive and negative events, exploring the trade-offs between competing losses at different threshold levels (Brown & Davis, 2006). It was free from parametric assumptions, and the values were independent from the ratio of positive and negative events. The area under the ROC (AUC) was also independent of the decision thresholds and hence suitable for classification problems in addition to confusion matrix analysis.

Table 2. Confusion matrix.

Actual	Prediction	
	0 (Negative)	1 (Positive)
0 (negative)	True negative (TN)	False positive (FP)
1 (positive)	False negative (FN)	True positive (TP)

Source: (Bekkar et al., 2013).

Table 3. Metric used to assess the model's performance.

Metric	Formula
Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$
Error rate = 1 – accuracy	$\frac{FP+FN}{TP+TN+FP+FN}$
Sensitivity (or recall, accuracy of positive examples)	$\frac{TP}{TP+FN}$
Specificity (accuracy of negative examples)	$\frac{TN}{TN+FP}$
Precision	$\frac{TP}{TP+FP}$
F1 score	$2 \times \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}$
G-mean	$G = \sqrt{\text{Sensitivity} * \text{Specificity}}$

Source: (Bekkar et al., 2013).

The dataset was analyzed with the most widely used metric for classifier evaluation, i.e., accuracy. In addition to accuracy, the study used the model assessment method over imbalanced datasets as mentioned by Bekkar et al. (2013). Practical cases were mostly imbalanced in nature, and hence, the models' accuracy might decrease because of

imbalance in the default and nondefault cases (Karatas et al., 2020). Furthermore, the feature importance was calculated for the best performing model to highlight the importance of the input variables. Also, the default score formula was derived based on the F-score values of the feature importance graph of the best performing model.

The study was analyzed using the Python programming language. The packages Numpy and pandas were used for data analysis and interpretation. LDA, LR, SVM with radial basis function as the kernel, and RF were performed using the scikit learn package (Géron, 2022). Extreme gradient boosting was performed using the XGBoost package. The study used the Keras deep learning framework for deep neural network processing, which is a high-level API on top of Tensorflow (Géron, 2022). The best accuracy of the DNN model in this study was achieved using 4 hidden layers with rectified linear units as activation functions and repetitions of 25 epochs. Increasing the hidden layers above 4 and decreasing below 4 reduced the accuracy, and the case was similar with 25 epochs also. Hence, the model was optimized using 4 hidden layers and running 25 epochs. Furthermore, cross-validation was conducted, which was a resampling procedure to prevent overfitting and to check the model's ability to perform well on new and unseen data. K-fold cross-validation was performed to prevent overfitting of the model and to avoid normalizing the outliers. It was performed 10-fold as it is the most widely used method for validating the results (Nti et al., 2021). The various models were validated using the k-fold cross-validation technique to minimize the effects of outliers and therefore to prevent overfitting.

4. Results

4.1. Descriptives

The dataset was skewed for limit balance and age, as shown in Figure 3. The dataset had a greater number of clients having a limiting balance between 0 and 200,000 currencies as the limit balance and a greater number of clients in the age bracket of 20 to 40, i.e., clients from mostly young to middle-aged groups.

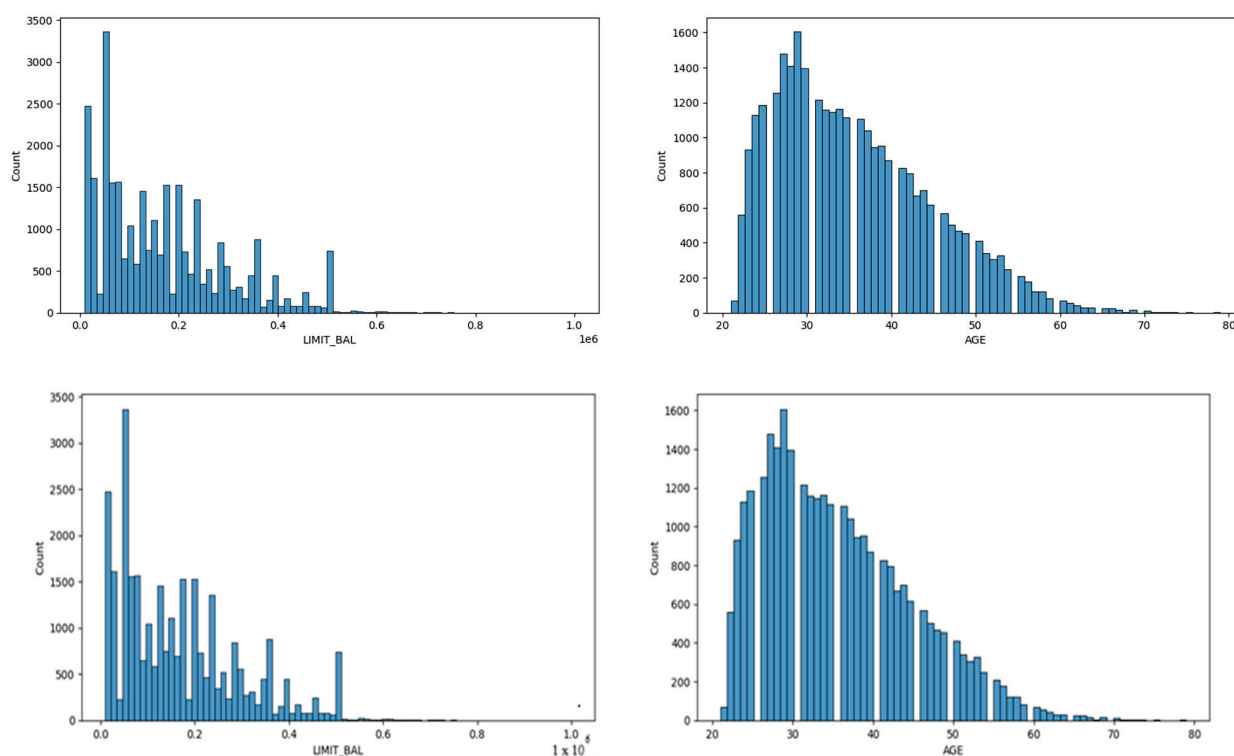


Figure 3. Skewed data for limit balance and age. Source: Authors' own.

4.2. Heat Map

Heat maps revealed complex patterns and correlations in the dataset (Gu et al., 2016). The heat map for the explanatory variables is represented in Figure 4. A high correlation can be seen between the bill amounts (month-wise) and the payment amounts (month-wise). It was not an issue since it was expected to be high. It could be inferred that a card holder spending a certain amount in the month of April was highly likely to spend a similar amount in the next month (May) also. Similarly, the card holder who made a certain bill payment in the month of April would make the repayment in the next months also, and there were fewer chances of default. A high correlation was found between the generated bill amount and the payment made in the corresponding month. The pair-wise correlation values in Figure 4 indicate that the explanatory variables were range-bound, and they did not display strong interdependence. It was an indication that the explanatory variables were independent of each other and displayed sufficient divergence to be treated as separate variables for further analysis.

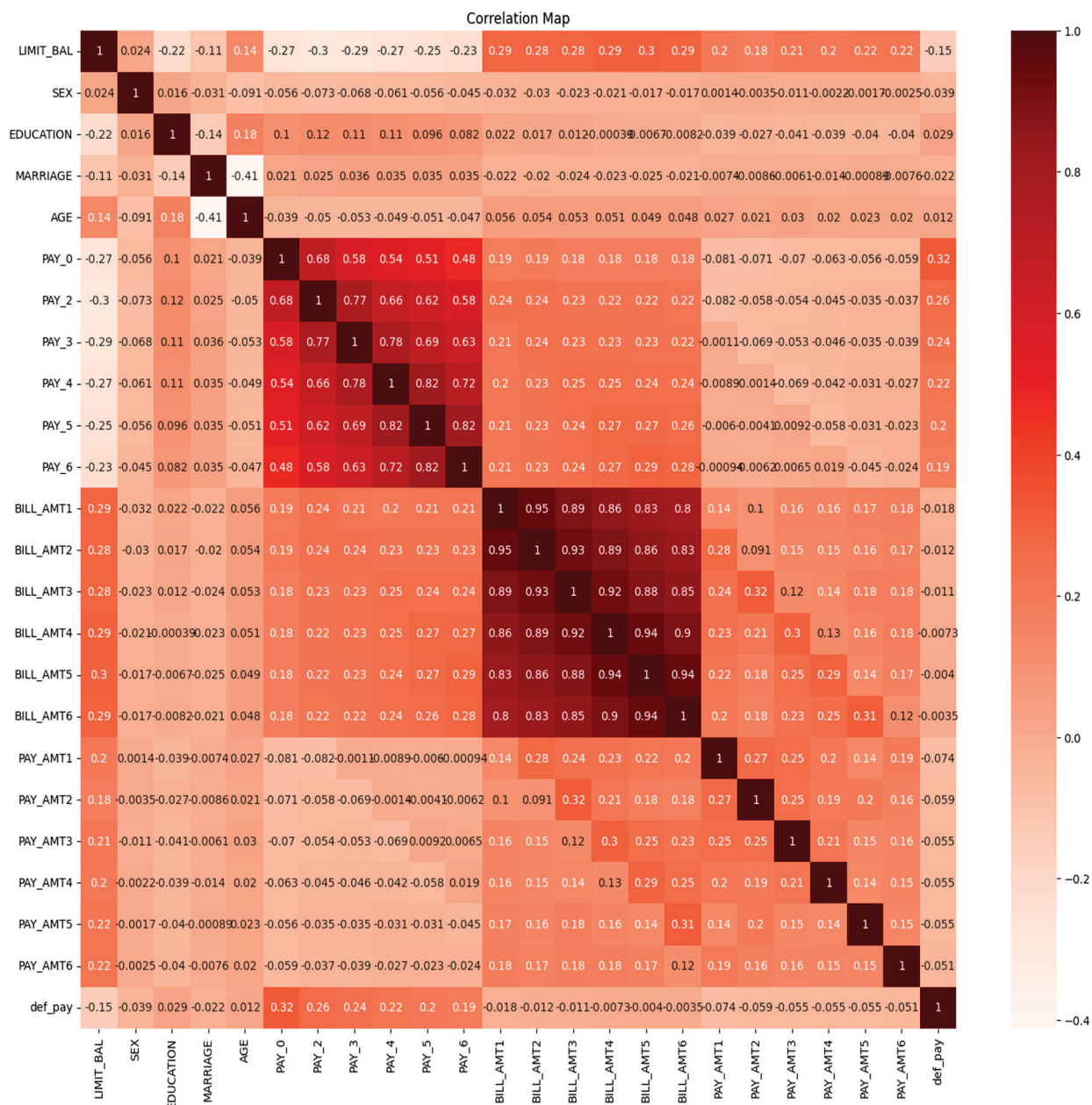


Figure 4. Heat map for the various features of the dataset. Source: Authors' own.

Figure 5 shows the relationship between the generated bill amount (Y-axis) and the corresponding payment made (X-axis) month-wise for 6 months. Since a maximum number of datapoints along the Y-axis are tightly packed near the scale zero of the X-axis in all six plots, it can be inferred that there was a greater proportion of clients for whom the bill amount was high, and at the same time the payment against the bill amount was very low. This indicated that the dataset contained significant details about delayed payments or default cases every month.

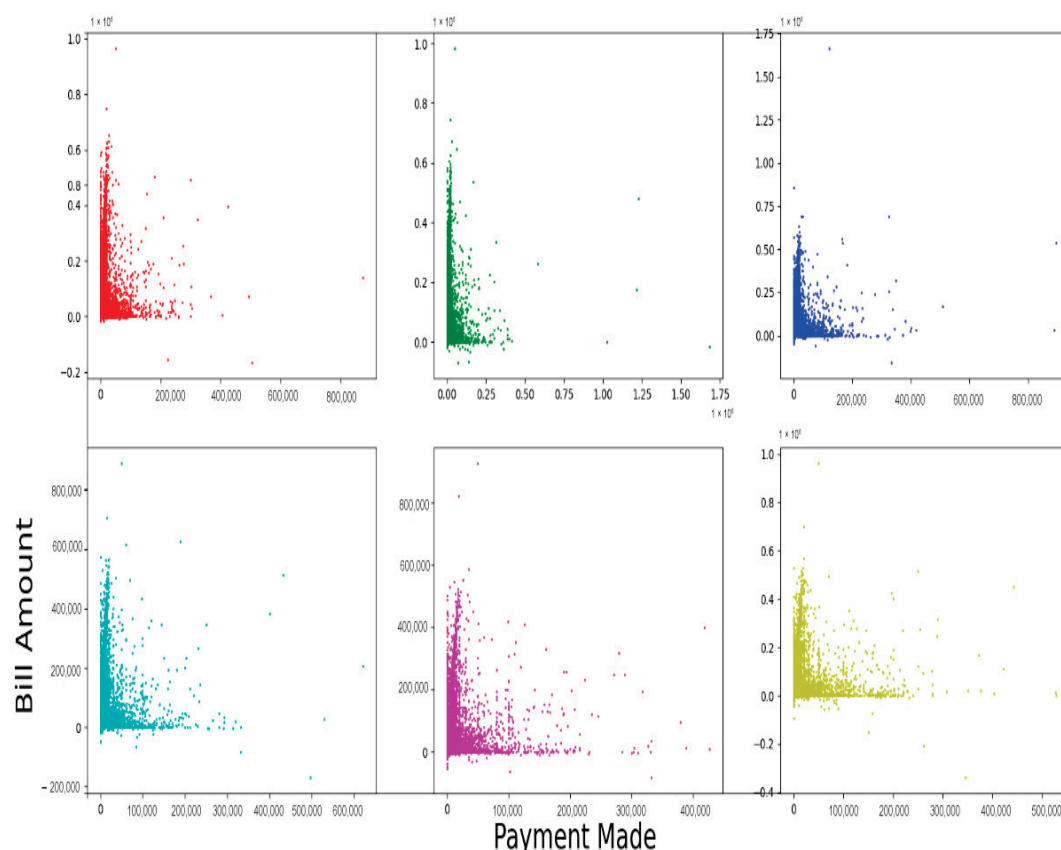


Figure 5. Relationship between the bill amount and the payment made. Source: Authors' own.

4.3. Confusion Matrix Analysis

The confusion matrices for the various models are presented in Table 4, and the metrics for the various models are given in Table 5. The values displayed in Table 5 are the average values of the cross-validated scores performed 10-fold using the K-fold cross-validation technique. The prediction accuracy of the deep neural network was at 81.80%, which was better than all the other models. The accuracy of the modern methods like XGBoost, RF, and DNN was marginally better than the traditional models like LDA, LR, and SVM. The modern methods performed well in predicting the sensitivity, but the traditional methods were better in terms of specificity. The precision score of 0.7047 for the SVM model was better in comparison with all other models. The F1-score value of 0.4820 of the DNN model was the best in comparison with the other models, and the modern methods outperformed the traditional methods in terms of the F1 score. Also, the G-mean value of 0.6027 of the DNN model was the best when compared with all other models, and the modern methods outperformed the traditional methods in terms of the G-mean score also.

Table 4. Confusion matrix for the various models.

LDA			LR			SVM		
Actual	Prediction		Actual	Prediction		Actual	Prediction	
	0	1		0	1		0	1
0	4529	158	0	4549	138	0	4560	127
1	988	325	1	1002	311	1	1010	303

XGBoost			RF			DNN		
Actual	Prediction		Actual	Prediction		Actual	Prediction	
	0	1		0	1		0	1
0	4406	281	0	4417	270	0	4400	287
1	819	494	1	832	481	1	805	508

Source: Authors' own.

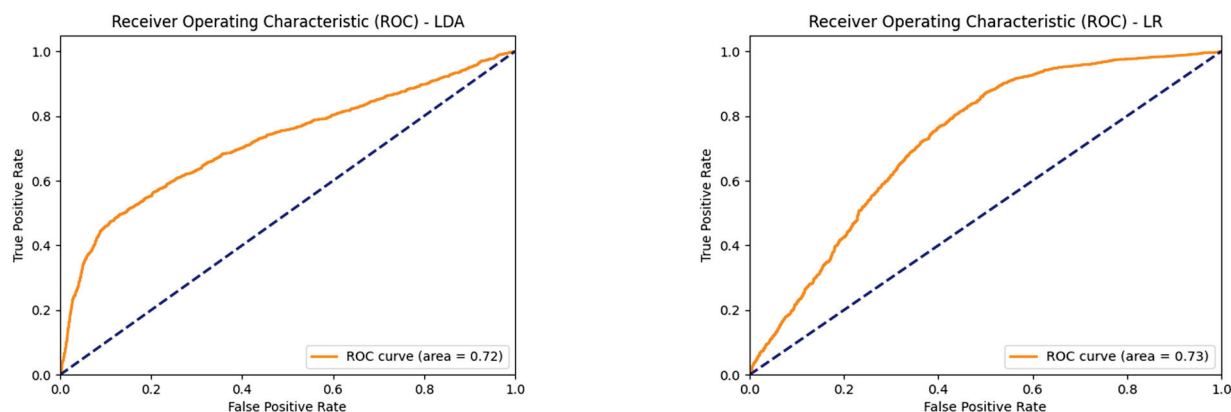
Table 5. Performance metrics for the various models.

Mertric	LDA	LR	SVM	XGBoost	RF	DNN
Accuracy	0.8090	0.8100	0.8105	0.8167	0.8163	0.8180
Sensitivity or recall	0.2475	0.2369	0.2308	0.3762	0.3663	0.3869
Specifivity	0.9663	0.9706	0.9729	0.9400	0.9424	0.9388
Precision	0.6729	0.6927	0.7047	0.6374	0.6405	0.6390
F1 score	0.3619	0.3530	0.3477	0.4732	0.4661	0.4820
G-mean	0.4891	0.4794	0.4738	0.5947	0.5876	0.6027
AUC	0.72	0.73	0.71	0.77	0.76	0.77

Source: Authors' own.

4.4. Receiver Operating Characteristics (ROCs)

The ROC curve illustrates the classification ability of a binary classifier system as its discrimination threshold level is varied. It is plotted with sensitivity in the Y-axis and specificity in the X-axis (Bewick et al., 2004). A good predictive model will have an ROC curve that is close to the top left corner, indicating a high true positive rate with a low false positive rate. The ROC curves for the various models are plotted in Figure 6. The area under the ROC curve (AUC) measures the area underneath the ROC curve (Bewick et al., 2004). A higher value of the AUC is desirable, and a value close to 1 is considered as ideal. The area under the ROC curve was highest for the DNN model and XGBoost model at 77%, and the AUC was 72% for LDA, 73% for LR, 71% for SVM, and 76% for RF.

**Figure 6.** Cont.

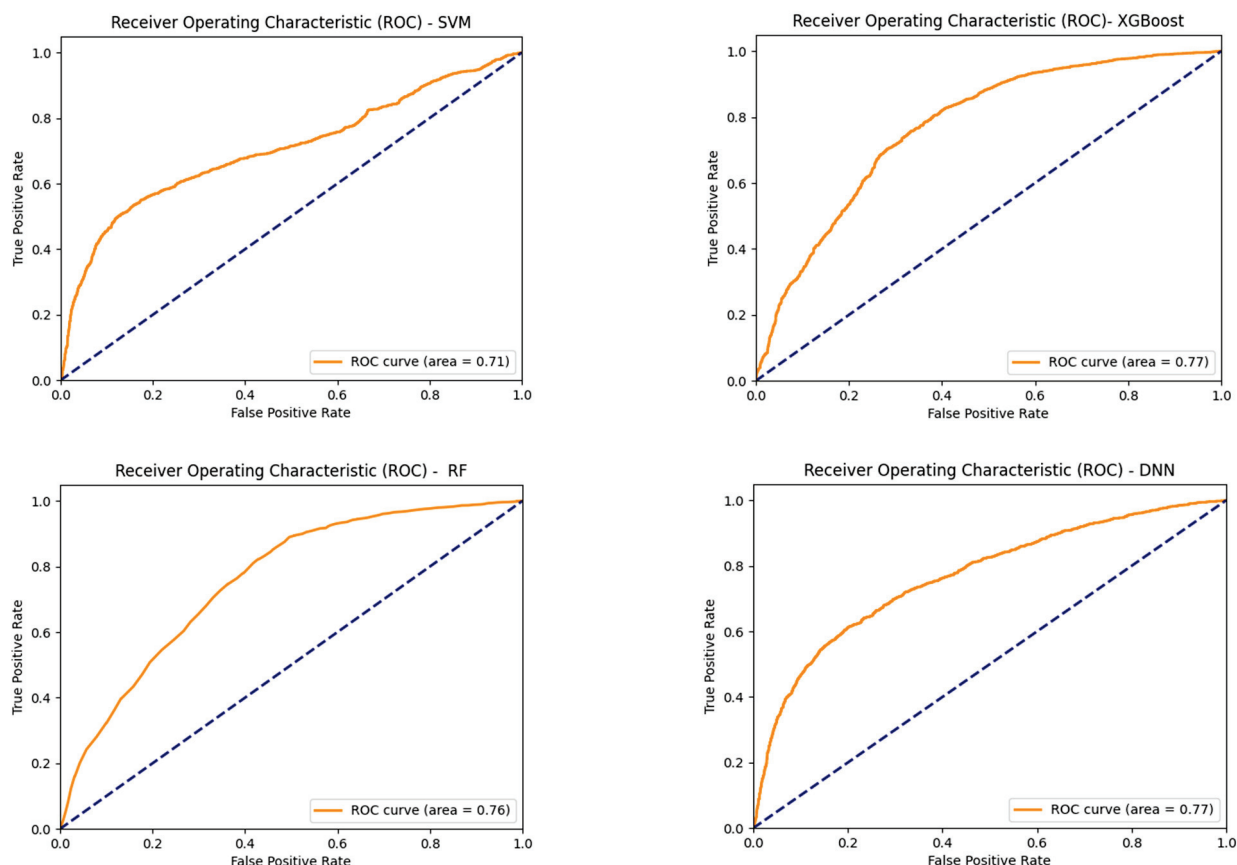


Figure 6. ROC for the various models benchmarked with the random model (blue dotted lines). Source: Authors' own.

4.5. Feature Importance

The feature importance permits the researcher to peek inside the black box of machine algorithms to see which features are critical in informing a good prediction as per the ranking (Musolf et al., 2022). The DNN model was selected to compute the important features since the accuracy of the DNN model was the highest in comparison with all other models. The feature importance for the DNN model based on the weights in the first layer with the F score on the x-axis and features on the y-axis is depicted in Figure 7. The BillSum (sum total of the bill generated for 6 months) emerged as the most important feature, followed by age, payment made (PAY_AMTX) for various months, limit balance, and the PaySum (total sum of the payment made for 6 months). Sex, marital status, and education attainment level were the least important features in predicting the default behavior of the borrower.

4.6. Default Score Calculation

The DNN model had the best accuracy in comparison with all the other models in this study. Hence, the weightage for each feature based on their corresponding F-score value in the DNN model feature importance was the basis for deriving the default score formula. The total F-score value was 4126, and the weightage for each feature was measured by its corresponding F-score value as shown in Figure 7. Based on these parameters the default scoring formula was developed in which each borrower could be assigned a default score as per the equation given below. A score greater than 1 was considered as a good borrower, and a score less than 1 was considered as a bad credit card borrower. Based on the scores the limit balance could be increased or decreased.

$$\text{DefaultScore} = \frac{(\text{PaySum} * 0.0691) + (\text{PAY}_{\text{AMT1}} * 0.1030 + \text{PAY}_{\text{AMT4}} * 0.0962 + \text{PAY}_{\text{AMT6}} * 0.0875 + \text{PAY}_{\text{AMT3}} * 0.0858 + \text{PAY}_{\text{AMT2}} * 0.0858 + \text{PAY}_{\text{AMT5}} * 0.0826)}{(\text{Billsum} * 0.1299) + (\text{LIMIT}_{\text{BAL}} * 0.0892)} \quad (10)$$

The above equation gives a default score that can be classified under several ranges. A higher score indicated good credit utilization and payments made, whereas a lower score indicated either lower credit utilization or default in payments made.

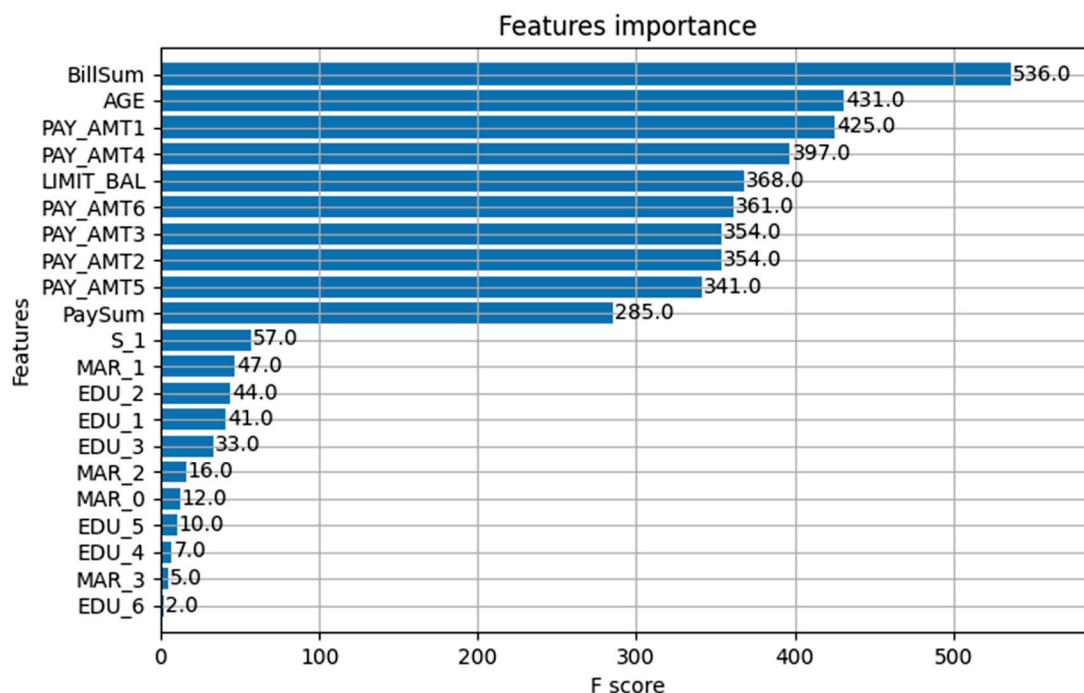


Figure 7. Feature importance for the DNN model. Source: Authors' own.

5. Discussions and Implications

The study results are discussed with previous research findings in this section. The results of this study indicated the superiority of deep neural networks when compared with all other models. The linear models like discriminant analysis and logistic regression also showed satisfactory predictive performances. In a few cases the machine learning methods were marginally better than statistical methods, and in many other metrics, machine learning methods were superior compared with statistical methods.

As evident from the literature, age, income, marital status, gender, and education attainment level were the significant predictors of credit default behavior among borrowers (Ofori et al., 2014). This study confirmed the influence of age, marital status, gender, education attainment level, and income in predicting credit card default behavior as per the feature importance graph. In this study, income was measured with the credit limit provided by the issuer of the card. As per the literature, the past track record of the borrower was also an important predictor of future payments to be made by the potential borrower (Schreiner, 2000). Similar findings were observed in this study since the monthly payments made emerged as the significant important feature.

The cross-validated predictive accuracy of the deep neural network model was 81.80%, which was better than all the other models in this study. The accuracy of the modern methods like XGBoost, RF, and DNN was marginally better than the traditional models like LDA, LR, and SVM. The study was consistent with the findings of Hamdi et al. (2024), Maehara et al. (2024), and Puli et al. (2024). These studies confirmed the superiority of neural network models for improved predictive performance in classification problems.

The area under the ROC curve was highest (77%) for the DNN model and XGBoost model in this study. The findings of this study were consistent with the study results conducted by Hamdi et al. (2024) that displayed the superiority of DNN models with an AUC of 88%. Additionally, the study by Suhadolnik et al. (2023) compared the ROC performance of ten machine learning algorithms and found that the AUC was highest for XGboost at 71.85%, followed by the artificial neural network at 71.41%. Surprisingly, the study by Maehara et al. (2024) found that the AUC for prediction of usage of bank accounts was highest for the random forest model and support vector machine at 81.28%, and the artificial neural network was the lowest performing one at 75.73%. The reason for the deviation was due to the fact that the study by Maehara et al. (2024) was on predicting the bank account usage and not on credit default prediction.

Machine learning outperformed traditional prediction techniques to predict loan defaults and performed significantly well in forecasting recovery rates on nonperforming assets when compared with regression techniques (Bellotti et al., 2021). Also, machine learning and deep learning models had better loan default prediction accuracies when compared with statistical methods like logistic regression, there were no restrictive assumptions on the input data, and it provided the flexibility to change the input criteria with ease (Jayadev et al., 2019). This study supported the findings of Bellotti et al. (2021) and Jayadev et al. (2019) by concluding that machine learning methods had better predictive performance in comparison with traditional methods.

Fintech companies can reduce the cost of lending by taking full advantage of the advancement in digital technology and big data analytics using machine learning methods (Bazarbash, 2019). The main advantage of using machine learning over traditional methods is the improvement in calculating the out-of-sample prediction accuracy, but at the same time these methods suffer with a black box problem without a proper logic on the decision arrived at (Bazarbash, 2019). Hence, feature importance for the deep neural network model was calculated to solve the black box problem by ranking the input parameters according to their importance in the prediction (Musolf et al., 2022). The feature importance showcased that the bill sum and the age of the borrower emerged as the most important features for credit card default prediction in this study.

A good predictive model not only filters the customers based on predictive ability and reduces the credit default risk but also helps to accurately plan the economic capital requirement of the bank, ultimately increasing the profitability (DeVaney, 1999). Also, loss given default is an important parameter to determine the credit default risk. It is defined as the estimated amount that is impossible to recover from an asset in the event of a default, equationally represented as one minus the recovery rate. The loss given default depends on the borrower's ability and willingness to repay, as well as the lending institute's recovery strategies (Thomas et al., 2016). Better prediction accuracy of the loss given default helps the banks accurately calculate the economic capital requirement of the bank resulting in increased profits (Bastos, 2010). Hence, an improvement in the default prediction accuracy ultimately increases the profitability of the organization.

6. Conclusions

The main objective of this study was to compare the prediction accuracy of credit card default behavior using traditional and modern machine learning methods. Traditional methods like discriminant analysis, logistic regression, and support vector machine were compared with modern methods like XGboost, random forest, and deep neural network methods. As per the results of this study, modern machine learning methods outperformed traditional statistical methods in terms of predictive performance measured by the F1 score, G-mean, and AUC. Also, machine learning methods performed marginally better in terms

of prediction accuracy. Among the traditional methods, logistic regression was slightly better than linear discriminant analysis and support vector machines when benchmarked with the predictive performance measured by the area under the receiver operating characteristic curve. In the modern machine learning methods, deep neural networks were overall better than XGBoost and random forest methods. Also, this study found a novel method to calculate the default score using the F-score values of the DNN model's individual features as per their importance. Although the DNN model had the best accuracy in this study, a combination with other models to calculate the weightage of individual features based on averaging the feature importance F-score values can be a scope for future study to improve the default score values.

This study focused on credit card default prediction using various models, and the findings of this study supported the findings of many other articles that confirmed the superiority of machine learning models in terms of predictive performance in comparison with the traditional methods. Even though the study incorporated random forest, XGBoost, and deep neural network, it fell short on an extensive and comprehensive comparison with other gradient boosting algorithms and long short-term memory neural network methods. The comparison could have also studied the regression methods for various models with the calculated error in terms of the root mean square error and the mean absolute percentage error. Also, comparison with econometric methods like autoregressive integrated moving average could have added more insights to this study. The study was also limited to analyzing the dataset from a single database; future studies can focus on combining different datasets from different databases for training and testing the model for better predictive performance.

Author Contributions: Conceptualization, R.B. and B.K.G.; methodology, R.B. and B.K.G.; software, R.B.; validation, R.B. and B.K.G.; formal analysis, R.B. and B.K.G.; investigation, R.B.; resources, R.B. and B.K.G.; data curation, R.B. and B.K.G.; writing—original draft preparation, R.B. and B.K.G.; writing—review and editing, R.B. and B.K.G.; visualization, R.B.; supervision, R.B. and B.K.G.; project administration, R.B. and B.K.G.; funding acquisition, B.K.G. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not Applicable.

Informed Consent Statement: Not Applicable.

Data Availability Statement: The data presented in this study are openly available in the UCI Machine Learning Repository (C55S3H, Yeh, (2016), Default of Credit Card Clients [Dataset], UCI Machine Learning Repository, <https://doi.org/10.24432/C55S3H> (accessed on 9 September 2024), UCI Machine Learning Repository, <https://archive.ics.uci.edu/dataset/350/default+of+credit+card+clients> (accessed on 9 September 2024), 10.24432/C55S3H).

Conflicts of Interest: The authors declare no conflicts of interest.

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Article

Beyond the Traditional VIX: A Novel Approach to Identifying Uncertainty Shocks in Financial Markets

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Abstract: We introduce a new identification strategy for uncertainty shocks to explain macroeconomic volatility in financial markets. The Chicago Board Options Exchange Volatility Index (VIX) measures the market expectations of future volatility, but traditional methods based on second-moment shocks and the time-varying volatility of the VIX often do not effectively to capture the non-Gaussian, heavy-tailed nature of asset returns. To address this, we constructed a revised VIX by fitting a double-subordinated Normal Inverse Gaussian Lévy process to S&P 500 log returns, to provide a more comprehensive measure of volatility that captures the extreme movements and heavy tails observed in financial data. Using an axiomatic framework, we developed a family of risk–reward ratios that, when computed with our revised VIX and fitted to a long-memory time series model, provide a more precise identification of uncertainty shocks in financial markets.

Keywords: asset pricing; volatility; long memory; uncertainty shocks; financial market modeling

1. Introduction

Uncertainty shocks, as introduced by Bloom (2009), are pivotal in understanding the relationship between the stock market volatility and economic outcomes. Bloom (2009) emphasizes the importance of second-moment shocks—uncertainty shocks—in influencing the economy, primarily analyzed through realized and implied option price data. Using the CBOE Volatility Index (VIX) as a proxy for the market expectations of volatility, he quantifies the anticipated fluctuation in the S&P 500 over a 30-day horizon. However, this traditional measure assumes that asset returns follow a symmetric, normal distribution, a limitation that significantly underestimates the impact of extreme market movements.

Empirical evidence from S&P 500 returns reveals that option prices exhibit non-normal distributions with heavy tails, as highlighted by Cont (2000). These heavy tails reflect the disproportionate likelihood of extreme negative or positive market events, challenging the adequacy of the standard deviation as a measure of market uncertainty. Measuring volatility solely through second moments fails to capture these tail risks, leading to incomplete assessments of market stress and underestimating the effects of large shocks. As Kozeniauskas et al. (2018) demonstrates, the heavy tails in financial data amplify uncertainty through disaster risk, magnifying the impact of rare but significant events that deviate from the assumptions of thin-tailed distributions.

The non-Gaussian nature of financial returns requires alternative dispersion measures that incorporate both skewness and kurtosis. By incorporating both the skewness and heavy tails observed in financial markets, it is possible to develop a more comprehensive understanding of the magnitude and persistence of uncertainty shocks, particularly during periods of heightened volatility. Moreover, relying solely on standard measures of volatility, such as the second-moment of VIX, neglects these critical tail risks, rendering traditional uncertainty metrics incomplete.

As an alternative, risk–reward (R/R) ratios provide a more comprehensive framework for assessing uncertainty by explicitly incorporating the asymmetry between potential gains and losses. These ratios evaluate both the right tails (potential gains) and left tails (potential losses), making them particularly valuable in understanding how uncertainty is amplified through extreme market movements. R/R ratios provide a robust framework for managing financial risks by mitigating maximum drawdowns and offering strategic guidance for navigating periods of heightened uncertainty.

To capture these dynamics, we constructed a revised volatility index, the Volatility of VIX (VVIX), derived from a double-subordinated Normal Inverse Gaussian (NDIG) Lévy process. This approach addresses the limitations of the standard VIX by incorporating the stochastic volatility and heavy-tailedness observed in financial data. The NDIG process models the skewness and tail risks in the distributions of option prices, providing a more comprehensive and arbitrage-free measure of implied volatility. The VVIX captures both the persistence and magnitude of uncertainty shocks more comprehensively. For instance, during the March 2020 market crash, the VVIX demonstrated a greater sensitivity to volatility clustering, providing a more detailed and accurate depiction of the risk compared to the traditional VIX. By combining the VVIX with R/R ratios, we propose a novel measure of uncertainty shocks that accounts for variations caused by extreme market movements. This measure integrates the directional aspects of tail risks, extending the understanding of how uncertainty evolves in response to large financial disruptions.

The VVIX captures the shifts in risk-neutral densities caused by geopolitical risks, such as the Russia–Ukraine conflict or potential armed escalations in other regions. These events alter agents’ risk aversion and precautionary savings behaviors, translating as changes in their utility functions. The VVIX also accounts for the rare disaster risks observed during the COVID-19 pandemic, providing a comprehensive measure of market volatility that incorporates all relevant market information. Additionally, the revised index highlights the sectoral or firm-specific dynamics, such as the significant tech-sector sell-offs in early 2022 due to weak earning reports, demonstrating its applicability across various contexts in financial markets.

The remainder of this paper is organized as follows: Section 2 reviews the relevant literature, highlighting the gaps addressed by this study. Section 3 outlines the method used to construct the VVIX and derives performance ratios as novel measures for uncertainty shocks. Section 4 presents the empirical results and discusses their implications for economic and financial systems. Section 5 concludes the paper with a summary of its findings and with directions for future research.

2. Literature Review

This paper contributes to the literature by presenting a robust framework for capturing uncertainty shocks through the integration of heavy-tailed dynamics, skewness, and volatility clustering into the revised VIX (VVIX). Bloom (2014) argues that investors demand compensation for higher risk, with greater uncertainty leading to increased risk premia, thereby raising the cost of finance. Consequently, the rise in risk premia can be attributed to stochastic volatility and fat tails, which explain the magnitude of extreme events or

uncertainty. Similarly, Kelly and Jiang (2014) suggest that heavy-tailed shocks to economic fundamentals help rationalize asset pricing behaviors that are otherwise inconsistent with traditional macrofinance theories.

Rietz (1988) was among the first to emphasize the role of fat tails within the context of the rare disaster hypothesis. Building on this idea, Bansal and Yaron (2004) developed a long-run risk model incorporating fat-tailed endowment shocks. Duffie et al. (2000) further elucidated the mechanics of modeling extreme events by employing jump–diffusion processes to account for heavy-tailed distributions. Extending this framework, Shirvani et al. (2021) expanded Mehra and Prescott (2003)’s model to incorporate consumption and dividend growth rates following a fat-tailed distribution. By assuming that the log-growth rates of consumption and dividends adhere to a Normal Inverse Gaussian (NIG) distribution, they demonstrated that the constant relative risk aversion (CRRA) estimates derived from the NIG model were significantly lower than those obtained using a log-normal distribution.

The role of tail risk in amplifying uncertainty has been emphasized by Orlik and Veldkamp (2014), who investigated the fluctuations in macroeconomic uncertainty measures. Similarly, Kozłowski et al. (2020) highlight that agents, while non-parametrically estimating the distribution of shocks from observed data, are influenced by transitory extreme events that induce persistent changes in beliefs and macroeconomic outcomes. The non-normality of the VIX has also been established in several studies. Moghaddam et al. (2019) show that the ratio of implied to realized variance is best captured by heavy-tailed distributions, such as lognormal and power-law distributions, depending on the time frame of the realized variance. Additionally, Ma and Serota (2014) find that the VIX is well-modeled by a generalized inverse gamma distribution, further confirming it is heavy-tailed and non-normal.

While these studies effectively explain the extreme events channel of uncertainty, the role of stochastic volatility in modeling heavy tails remains underexplored. The present paper pioneers an approach that uses stochastic volatility and the heavy tails of asset returns to model the dynamics of financial markets. Additionally, it introduces risk–reward ratios as a novel tool for estimating uncertainty shocks and their implications for macroeconomic volatility in financial markets.

3. Method

3.1. Data

This study employs option prices derived from the daily log returns of the S&P 500 from 2 January 2014 to 28 July 2023. The choice of this extended period ensures that the analysis captures a broad spectrum of market conditions, including episodes of heightened volatility and systemic stress, as well as periods of market stability. A daily frequency has been selected to maintain a sufficient level of granularity, allowing the underlying stochastic processes and time-varying parameters to be estimated with greater precision.

A key feature of the empirical design is the application of a rolling window estimation approach. Specifically, we use a four-year moving window, corresponding to approximately 1008 daily observations (given roughly 252 trading days per year), to re-estimate the parameters governing our NDIG-based volatility model at each step. This rolling window is re-centered periodically to incorporate the most recent observations while excluding the older observations. Econometrically, the rolling window method mitigates challenges arising from structural breaks, model misspecification, and parameter instability over time. By continuously updating the estimation sample, the model can adapt to evolving market conditions, and it more effectively reflects shifts in volatility regimes and the distributional features of returns. Moreover, this approach ensures that parameter estimates and the

resulting uncertainty measures remain aligned with prevailing market conditions rather than relying on a fixed historical sample that may no longer be representative.

While the data starts with January 2014, the figures and empirical results presented in the subsequent sections start with January 2018. This is due to the initial four-year rolling window period (2014–2017) serving as the estimation sample required to obtain the first set of rolling window parameters. Consequently, the reported empirical outcomes cover the six-year period from 2018 to July 2023, reflecting the parameters and uncertainty measures that have incorporated evolving market conditions for a full four-year span prior to each reported estimate. The use of a rolling window estimation approach is particularly advantageous in the context of financial markets characterized by structural breaks and time-varying dynamics. By employing a four-year rolling window, the model parameters are continuously re-estimated, ensuring that the resulting measures are robust to regime changes and reflective of evolving market conditions. This is crucial for constructing measures like the Volatility of VIX (also referred to as the revised VIX), which depend on accurate and timely estimates of the volatility dynamics.

3.2. Modeling the S&P500 Options via Double Subordination

To capture the complex dynamics of S&P500 option prices, we consider a double-subordinated framework. A Lévy subordinator is a non-decreasing Lévy process $\mathbb{T} = (T_t, t \geq 0)$ with $T_0 = 0$. Following P. Carr et al. (2003) and Shirvani et al. (2024), we adopt a double-subordination approach for modeling the S&P500 option price process. The fundamental premise is that incorporating multiple Lévy subordinators into the asset price dynamics allows us to better capture the non-normality and heavy tails observed in empirical returns.

To begin with, we consider a baseline Black–Scholes–Merton (BSM) setting, where the price process S_t for $t \in [0, \tau]$ has the form

$$S_t^{(BSM)} = e^{X_t^{(BSM)}}, \quad t \in [0, \tau], \quad (1)$$

with

$$X_t^{(BSM)} = X_0 + \mu_1(t) + \sigma_1 B_t, \quad \mu_1 \in \mathbb{R}, \sigma_1 > 0, X_0 = \ln(S_0), S_0 > 0, \quad (2)$$

where $(B_t, t \geq 0)$ represents standard Brownian motion. Although the BSM model is foundational, it is well known that option prices on the S&P500 deviate from normality, exhibiting heavy-tailed behavior. In line with the pioneering ideas of Mandelbrot and Taylor (1967) and Clark (1973), a natural extension is to incorporate a single Lévy subordinator into the time dimension of the Brownian motion. This yields the following subordinated log-price process:

$$S_t^{(ss)} = e^{X_t^{(ss)}}, \quad t \in [0, \tau], \quad (3)$$

with

$$X_t^{(ss)} = X_0 + \mu_2(t) + \sigma_2 B_{T(t)}, \quad \mu_2 \in \mathbb{R}, \sigma_2 > 0, \quad (4)$$

where $(T(t), t \geq 0, T(0) = 0)$ is a Lévy subordinator. Incorporating a single subordinator can capture deviations from normality, but may still be insufficient in fully modeling the observed higher-order moments (skewness and kurtosis).

As shown by Shirvani et al. (2021), multiple subordinations can generate processes with even heavier tails and more flexible distributional characteristics. Introducing a second Lévy subordinator provides a richer framework for modeling the dynamics of returns. In this double-subordination setting, the price process S_t is given by

$$S_t = e^{X_t}, \quad t \in [0, \tau], \quad (5)$$

with

$$X_t = X_0 + \mu_3(t) + \gamma U(t) + \rho T(U(t)) + \sigma_3 B_{T(U(t))}, \quad (6)$$

where $X_0 = \ln(S_0)$, $S_0 > 0$, and $(B_t, T(t), U(t); t \geq 0)$ are mutually independent processes. Here, $T(t)$ and $U(t)$ are Lévy subordinators, and B_t is a standard Brownian motion. The process $T(U(t))$ denotes the double subordination; therefore, the resulting Equation (6) is a double-subordinated log-price process.

This construction preserves the bivariate semi-martingale structure and supports the notion of time-changed volatility dynamics and heavy-tailed returns under a risk-neutral measure, adhering to the fundamental asset pricing framework. To model the subordinators, let both $T(t)$ and $U(t)$ be Inverse Gaussian (IG) Lévy processes to ensure they are drawn from a heavy-tailed distribution. Suppose

$$T(1) \sim IG(\lambda_T, \mu_T), \quad U(1) \sim IG(\lambda_U, \mu_U),$$

where the probability density function of $T(1)$ is

$$f_{T(1)}(x) = \sqrt{\frac{\lambda_T}{2\pi x^3}} \exp\left\{-\frac{\lambda_T(x - \mu_T)^2}{2\mu_T^2 x}\right\}, \quad x \geq 0, \mu_T > 0, \lambda_T > 0. \quad (7)$$

By analogy, $U(1)$ shares a similar form with parameters (λ_U, μ_U) . As a result, the log-price process in Equation (6) follows a Normal Double Inverse Gaussian (NDIG) distribution. The characteristic function (c.f.) of X_1 is given by

$$\psi_{X_1}(v) = \mathbb{E}[e^{ivs.X_1}] \quad (8)$$

Expanding the expectation and substituting the probability density function of $T(1)$ and $U(1)$ in Equation (8), we arrive at

$$\exp\left\{ivs.\mu_3 + \frac{\lambda_U}{\mu_U} \left[1 - \sqrt{1 - \frac{2\mu_U^2}{\lambda_U} \left(\frac{\lambda_T}{\mu_T} \left(1 - \sqrt{1 - \frac{\mu_T^2}{\lambda_T} (2ivs.\rho - \sigma_3^2 v^2)}\right)\right)} + ivs.\gamma\right]\right\} \quad (9)$$

The moment generating function (MGF) is then $M_{X_1}(w) = \mathbb{E}[e^{wX_1}]$ for $w \in \mathbb{R}$. The NDIG model in Equation (6), along with its c.f. in Equation (8), introduces eight parameters $(\mu_3, \sigma_3, \gamma, \rho, \mu_T, \mu_U, \lambda_T, \lambda_U)$. Estimating all these parameters directly can be challenging. Following the method of Shirvani et al. (2024), six parameters are estimated while the remaining two are determined by taking expectations, thereby reducing the complexity of the estimation procedure.

Figures 1 and 2 present the last price and daily returns of the S&P 500 index, respectively, providing a critical understanding of the dynamics of market behavior. The last price series highlights a general upward trend punctuated by significant jumps and diffusions, particularly during periods of market stress, such as the crash in March 2020. These abrupt and extreme changes reflect the presence of tail risks—rare but impactful events that traditional Gaussian-based models fail to capture adequately. The daily returns, on the other hand, reveal volatility clustering, a phenomenon where periods of high volatility tend to cluster together and are followed by more high-volatility periods, while periods of low volatility exhibit prolonged calm. Furthermore, the pronounced spikes in returns during extreme events illustrate the heavy-tailed nature of the return distribution, a characteristic that standard thin-tailed, symmetric distribution models cannot account for. These observations justify the need for a more sophisticated modeling framework that incorporates both stochastic volatility and heavy tails.

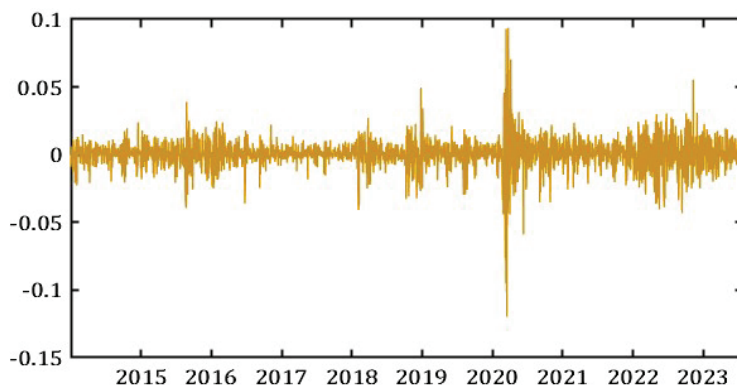


Figure 1. S&P500 daily returns.

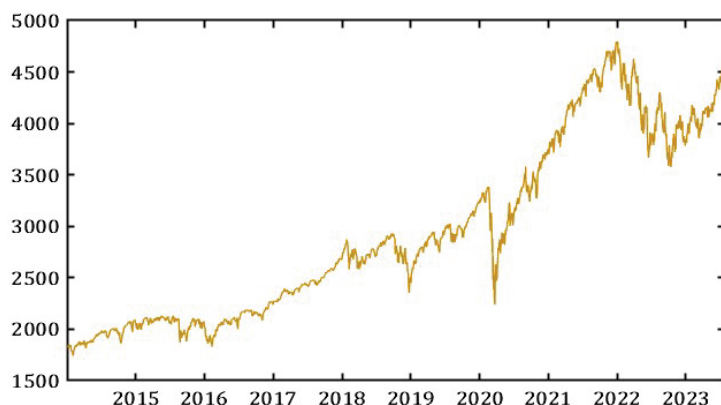


Figure 2. Last price (S&P500).

3.3. NDIG Model for European Call Option Pricing

In the setting of complete markets, where agents can trade a risky asset and a risk-free bond continuously, the pricing of a European call option $\mathcal{C}$ depends on the choice of an Equivalent Martingale Measure $\mathbb{Q}$. Given that the S&P500 options are the underlying of the risky asset S , we assume that the discounted price process $e^{-rt} S_t$, with a non-negative risk-free rate $r \geq 0$, maintains a martingale structure. Following Shirvani et al. (2024), we adopt a minimal conditional martingale measure, ensuring that the no-arbitrage condition is satisfied when pricing European options under this measure.

Figure 3 presents the implied volatility surface obtained from the proposed model, comparing both call and put options. These surfaces demonstrate that the NDIG model can capture the skew and smile effects commonly observed in real market data, providing a comprehensive representation of the volatility structure compared to standard local volatility models.

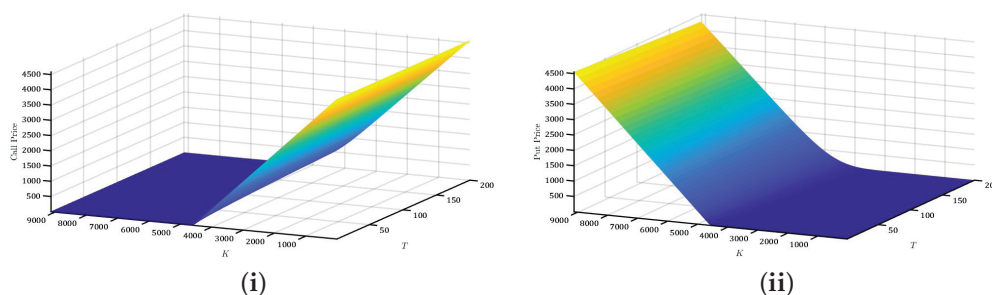


Figure 3. Implied volatility surface. (i) Call price and (ii) put price.

Given that the c.f. of X_t is known from Equation (8), we use the Fast Fourier Transform (FFT) approach of P. P. Carr and Madan (2001) to price options. The FFT method is suitable

when the characteristic function of the log-price is analytically defined. The integral transform for the call price is

$$C(S_0, r, k, \tau) = \frac{e^{-r\tau - ak}}{\pi} \int_0^\infty e^{-ivk} \frac{\psi_{\ln(S_T^{(Q)})}(v - i(a+1))}{a^2 + a - v^2 + i(2a+2)v} dv, \quad (10)$$

where $\psi_{\ln(S_T^{(Q)})}$ is the c.f. of the log-price under the chosen equivalent martingale measure, and a is a damping parameter used to ensure integrability.

P. P. Carr and Madan (2001) presented a method of selecting the parameter a , noting that there is an ‘optimum value’ that balances numerical stability and accuracy. Truncating the integral over a finite domain $[0, v_{\max}]$ introduces a manageable approximation error. To further refine the choice of a , we examine the upper bound $a_{\max}$ derived from the parameters of the NDIG model as follows:

$$a_{\max} = \frac{1}{\sigma_3^2} \sqrt{\rho^2 + \lambda_U \left(1 - \frac{\lambda_U}{4\lambda_T} \sigma_3^2\right)} - \frac{\rho}{\sigma_3^2} - 1 \quad (11)$$

Figure 4 shows the evolution of $a_{\max}$ over time, including a period spanning the highly volatile events of March 2020. Notably, during times of elevated market stress, $a_{\max}$ experiences pronounced shifts. Imposing the constraint $a < 1$ ensures stability in the implied volatility surface obtained from the NDIG model. Finally, the FFT-based pricing framework is applied over multiple strikes K and maturities T . By appropriately selecting a , we achieve stable and economically plausible option prices that reflect the complex distributional properties of S&P500 returns.

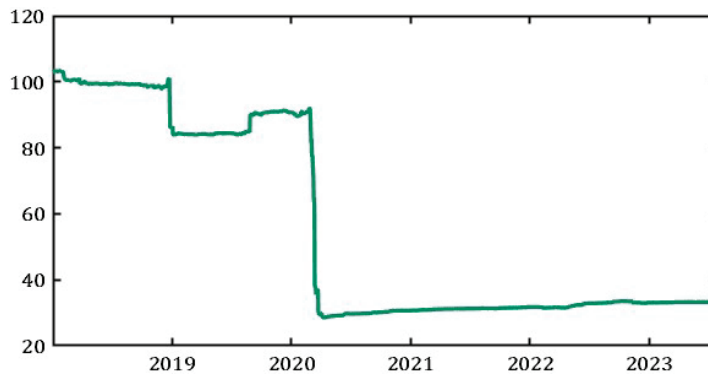


Figure 4. Values for the upper bound $a_{\max}$ computed over the time period from 2 January 2014 to 28 July 2023.

In Figures 5 and 6, we present kernel density estimates of the S&P500 log returns under the NDIG model and compare them to fits of both the normal density and Student’s t . The empirical distribution of S&P500 log returns exhibits pronounced tail thickness which a normal distribution fails to capture. While Student’s t -distribution offers an improvement over normality by introducing heavier tails, it still does not fully replicate the heaviness observed in the data. In contrast, the NDIG model, by incorporating two Lévy subordinators, provides a superior fit to the tail regions, capturing both kurtosis and skewness more accurately. These results lend strong empirical support to the premise that a double-subordinated process, such as NDIG, is better suited for modeling the heavy-tailed and skewed distributions of S&P500 option prices.

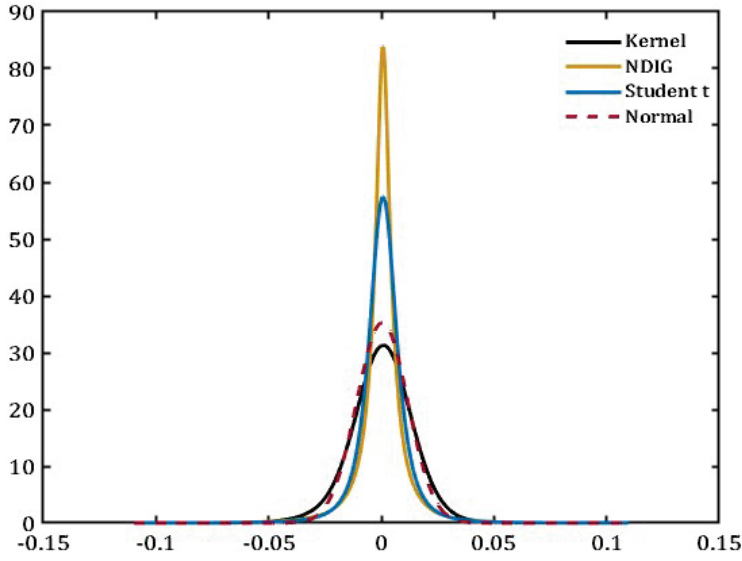


Figure 5. Density fit.

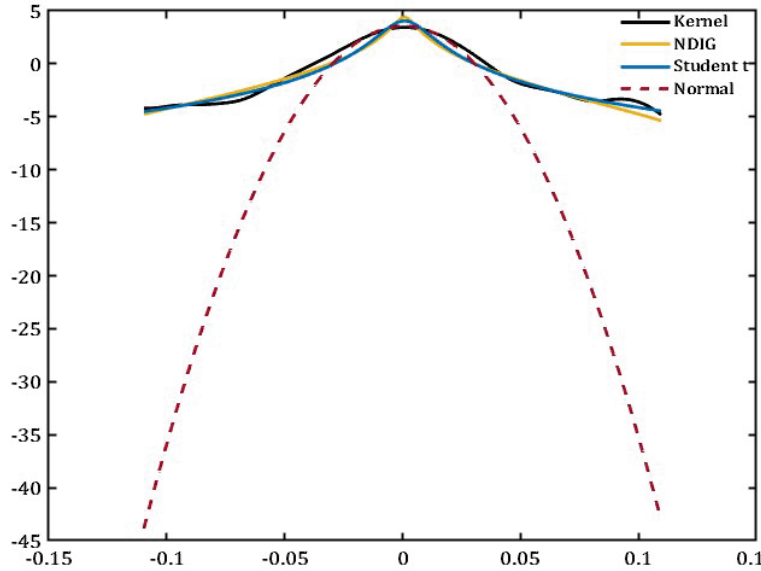


Figure 6. Log-scaled density fit.

3.4. Parameter Estimation

We estimate the parameters of the double-subordinated log-price process by fitting the NDIG model defined in Equations (5)–(9) to the S&P500 log returns in the sample period. The parameter vector is

$$\theta = (\mu_3, \sigma_3, \mu_U, \lambda_U, \mu_T, \lambda_T).$$

In this specification, the subordinators $T(t)$ and $U(t)$ capture the skewness, heavy tails (kurtosis), and stochastic volatility dynamics in the asset returns, aligning with the theoretical considerations outlined earlier.

Following the method employed by Shirvani et al. (2024) for Bitcoin returns, we estimate the first four moments and fit the c.f. of the NDIG model to the empirical distribution of returns. Specifically, the parameter estimates minimize the objective function

$$\min_{\mu_3, \sigma_3, \rho, \lambda_T, \lambda_U} (\Delta M_1)^2 + (\Delta M_2)^2 + (\Delta M_3)^2 + (\Delta M_4)^2 + (\Delta CF)^2. \quad (12)$$

The constraints are based on the deviations of the model-implied moments from the empirical moments of the observed return series p_t . These include the first four standardized moments and the c.f. fit. The moment-based constraints are given by $(\Delta M_1)^2 = 1 - \frac{\mathbb{E}[X]}{\mathbb{E}[p_t]}$. The constraint for the second moment is $\sim(\Delta M_2)^2 = 1 - \frac{\text{Var}[X]}{\text{Var}[p_t]}$. The constraint for the third moment is $\sim(\Delta M_3)^2 = 1 - \frac{\text{Skew}[X]}{\text{Skew}[p_t]}$. The constraint for the fourth moment is $\sim(\Delta M_4)^2 = 1 - \frac{\text{Kurt}[X]}{\text{Kurt}[p_t]}$. $(\Delta CF)^2$ measures the discrepancy between the model-implied and empirical c.f.s as follows:

$$(\Delta CF)^2 = \int_{-\infty}^{\infty} \left(\frac{1}{n} \sum_{j=1}^n e^{ivx_j} - \psi_{X_t}(v, \theta) \right)^2 dv,$$

where $\{x_j\}_{j=1}^n$ are the observed returns, and $\psi_{X_t}(\cdot)$ is the NDIG c.f. Moreover, (ΔCF) depends on the one-to-one correspondence between the cdf and the c.f. as noted in Shirvani et al. (2024). By following Yu (2003) for integrating the c.f., we obtain the parameter estimates shown in Table 1.

Table 1. NDIG parameter estimates for S&P500 log returns.

μ_3	σ_3	μ_U	λ_U	μ_T	λ_T	ρ
0.000782	0.0113	1	0.175	1	9.91	−0.000341

To further assess the temporal stability and robustness of the NDIG model, we re-estimate its parameters over a rolling four-year window and examine their evolution over time. As shown in Figure 7, while the parameters governing the subordinators (μ_U and μ_T) remain relatively stable, others exhibit notable fluctuations. In particular, the drift term (μ_3), the volatility parameter (σ_3), the parameters controlling the heaviness of the tails (ρ), and the variance of the subordinators chosen from the inverse Gaussian distribution (λ_U , and λ_T) vary significantly as market conditions change. This variability underscores the model's capacity to adapt to evolving economic environments and to capture the dynamic nature of volatility, skewness, and heavy tails in the S&P500 options market.

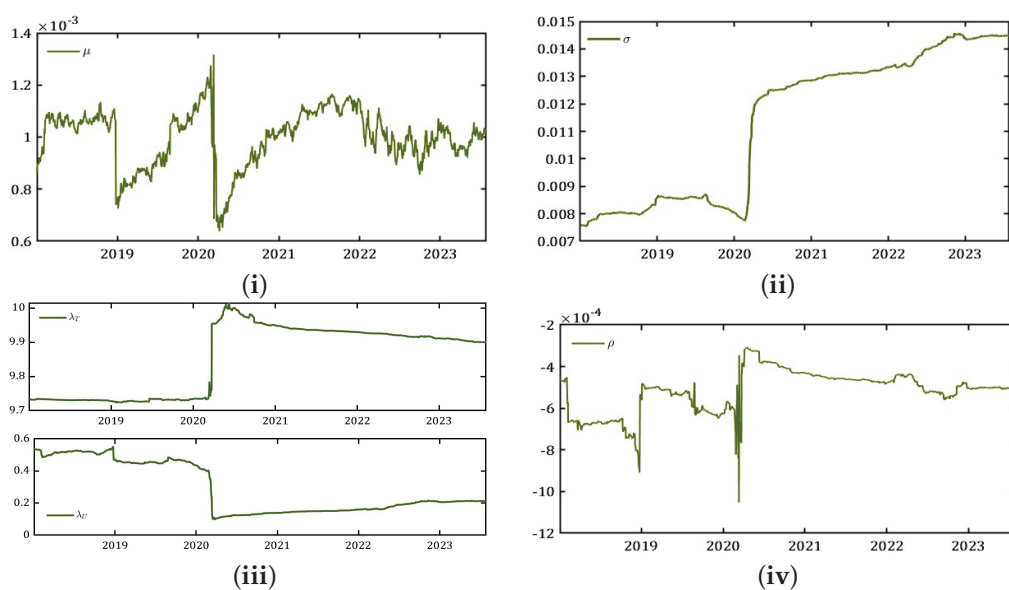


Figure 7. Parameter estimates in a 4-year rolling window: (i) μ_3 , (ii) σ_3 , (iii) λ_T & λ_U , and (iv) ρ .

In addition, Figure 8 compares the theoretical moments derived from the NDIG model with their empirical counterparts under the same rolling window specification. The close

alignment between the theoretical and empirical moments attests to the model's good fit to log returns. Taken together, these results highlight the suitability and flexibility of the double-subordination approach for modeling the complex distributional features observed in S&P500 option price data.

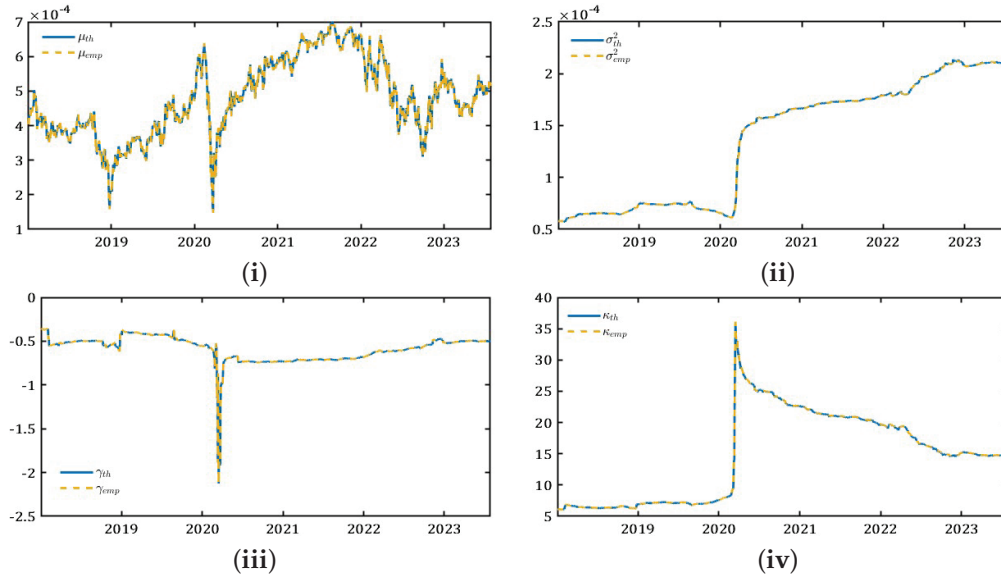


Figure 8. Comparison of the four moments: theoretical vs. empirical $\sim$ (i) $\mathbb{E}[X]$, (ii) $\text{Var}[X]$, (iii) $\text{Skew}[X]$, and (iv) $\text{Kurt}[X]$. ‘Th’: theoretical moments estimated using the fitted parameters. ‘Emp’: empirical moments computed from the S&P500 log returns.

3.5. Revised VIX (Volatility of VIX (VVIX))

The CBOE Volatility Index (VIX) is widely referred to as the “fear gauge” of the market. It measures the market’s expectation of volatility over the next 30 days, as implied by S&P500 option prices. Much of the existing literature on uncertainty shocks relies on capturing volatility through the standard deviation of the VIX or by modeling time-varying volatility clustering as shocks in macroeconomic settings. However, two issues arise. First, using the standard deviation as a measure of volatility implicitly assumes a symmetric distribution. As stated in Section 2 (see Ma & Serota, 2014; Moghaddam et al., 2019), the VIX distribution is non-normal, and relying on a symmetric approximation can understate the uncertainty. Second, a popular approach in the literature is to study the time-varying volatility clustering using models such as GARCH and FIGARCH. These models capture the persistent nature of volatility and can help identify periods of heightened uncertainty. However, they do not fully take into account the heavy tails and asymmetries present in asset return distributions.

Local volatility models, which assume that volatility is a deterministic function of the current asset price and time, are often employed to derive volatility surfaces, and while convenient, these models conflict with fundamental asset pricing principles. They do not accommodate stochastic volatility driven by historical information nor do they maintain a semi-martingale structure. This can lead to theoretical inconsistencies, such as the inability to construct a valid equivalent martingale measure. As a result, local volatility models are not only limited in their descriptive accuracy but also fail to ensure no-arbitrage conditions in the framework of complete markets.

Consider an investor who continuously trades a risky asset and a risk-free bond in a frictionless, complete market. If the return process has two sources of uncertainty—time-varying volatility and fat-tailed distributions—local volatility models fail to provide a proper hedge, forcing the investor to bear risks that cannot be hedged. Moreover, since

local volatility is deterministic, it is typically not a semi-martingale. The lack of a semi-martingale structure undermines the fundamental theorem of asset pricing (see Delbaen & Schachermayer, 1994; Duffie, 2001), preventing the construction of a valid equivalent martingale measure that ensures there are no opportunities for arbitrage.

In contrast, multiple subordinated models, such as the NDIG process used in this paper, capture both the stochastic volatility and the heavy tails of the return distributions. Multiple subordinated processes generally preserve the semi-martingale property, allowing them to be reconciled with no-arbitrage asset pricing principles. Shirvani et al. (2021) stresses the importance of stochastic volatility models for reflecting the heavy-tailed phenomena in the returns. Their work shows that the VIX alone does not fully capture the stochastic dimension and fails to represent the tail behavior critical for an accurate measurement of the uncertainty.

Therefore, as an application of the NDIG-based pricing framework, we construct a revised volatility measure, which will be referred to as the Volatility of VIX (VVIX). The VVIX is derived using a double-subordinated Normal Inverse Gaussian (NDIG) Lévy process to model S&P 500 option returns. This framework differs from the traditional VIX by incorporating two Lévy subordinators mentioned in Sections 3.2 and 3.3. The VIX is formally defined as

$$VIX = 100 \cdot \sqrt{W_1 \sigma_1^2 + W_2 \sigma_2^2}, \quad (13)$$

where W_1 and W_2 are weights corresponding to near- and next-term expirations, normalized such that $W_1 + W_2 = 1$. Similarly, σ_1^2 refers to near-term volatility and σ_2^2 refers to the next-term volatility. While the formula for the VIX aligns with the standard VIX formula specified by the CBOE, the key distinction lies in the computation of the underlying volatility surfaces. Unlike the CBOE's method, which relies on local volatility models, our approach follows Shirvani et al. (2024) by using the NDIG process to estimate these volatilities.

We linearly scale the NDIG-implied volatility estimates to match the scale of the historical VIX, facilitating a direct comparison. Figure 9 presents the normalized revised VIX (VVIX), which incorporates stochastic volatility and accounts for heavy tails. The historical volatility, labeled “STD”, is empirically measured, while the red line represents the theoretical moment of volatility derived from the NDIG model, corresponding to the revised VIX (VVIX). The computation of the VIX (green line) is performed according to Equation (12).

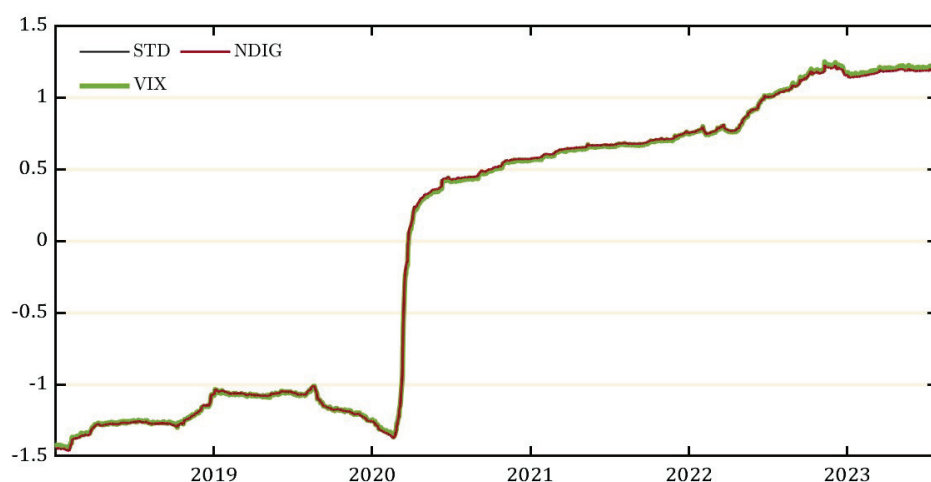


Figure 9. Normalized volatility to match NDIG estimates: revised VIX {Volatility of VIX (VVIX)}.

3.6. Risk–Reward Ratios as a Measure of Uncertainty

Risk–reward (R/R) ratios provide a framework for evaluating the balance between potential gains and losses in markets with volatility and non-normal distributions of returns. By capturing the asymmetry inherent in financial returns, these ratios highlight the importance of controlling for large downside risks rather than relying solely on symmetric measures of dispersion. An axiomatic approach to performance measurement specifies that every R/R ratio should satisfy several key properties as follows: (i) monotonicity, implying that higher returns are always preferred; (ii) quasi-concavity, ensuring that diversification is rewarded; (iii) scale invariance, ensuring that scaling the underlying returns does not change the ratio; and (iv) distribution-based dependence, ensuring that the ratio depends solely on the distribution of the returns.

Let $\mathcal{X}$ be a convex set of random variables defined on a probability space $(\Omega, \mathcal{F}, \mathbb{P})$, and let each $X \in \mathcal{X}$ denote a financial return observed over a time horizon $T \in \mathbb{R}_+$. Consider an R/R ratio of the form

$$\alpha(X) = \frac{\theta(X)^+}{\rho(X)^+}, \quad (14)$$

where $\theta : \mathcal{X} \rightarrow \mathbb{R} \cup \{\pm\infty\}$ measures the reward and $\rho : \mathcal{X} \rightarrow \mathbb{R} \cup \{\pm\infty\}$ measures the risk. Here, $x^+ = \max\{x, 0\}$ and $x^- = -\min\{x, 0\}$. The ratio $\alpha(X)$ should satisfy the following conditions:

1. (M) Monotonicity: $\alpha(X) \geq \alpha(Y)$ for all $X, Y \in \mathcal{X}$ such that $X \geq Y$.
2. (Q) Quasi-concavity: for all $X, Y \in \mathcal{X}$ and $\lambda \in [0, 1]$,

$$\alpha(\lambda X + (1 - \lambda)Y) \geq \min(\alpha(X), \alpha(Y)),$$

thus rewarding diversification and avoiding the concentration of risk.

As noted by Cheridito and Kromer (2013), monotonicity is a minimal requirement for any performance indicator, ensuring that improved returns are always preferred. Quasi-concavity further ensures that diversification is beneficial. If either property is not satisfied, risk may concentrate, as shown in Artzner et al. (1999) for the value-at-risk setting.

In addition, risk–reward ratios can also be interpreted as measures of uncertainty. While volatility alone captures only the dispersion of the returns, risk–reward ratios incorporate both the potential gains and losses relative to their underlying distributions. By doing so, these ratios reflect not just the magnitude of market fluctuations, but also how investors perceive and respond to the asymmetric nature of the outcomes. By accounting for skewness and kurtosis, risk–reward ratios offer a more comprehensive and economically meaningful perspective on uncertainty. However, a key empirical challenge arises when estimating R/R ratios for the revised VIX, while performance ratios over a convex set of random variables assume an independent and identically distributed (i.i.d) framework, financial returns generally exhibit dependence and persistence, particularly in volatility.

To address this, we fit a long-memory time series model to the normalized VVIX, thereby incorporating persistence in both the mean and variance processes. Baillie et al. (1996) introduced the FIGARCH (Fractionally Integrated GARCH) model, demonstrating that standard GARCH models are ill-suited to capturing persistent memory in volatility. Similarly, Hyung and Franses (2002) show that Autoregressive Fractionally Integrated Moving Average or ARFIMA-FIGARCH models outperform traditional ARMA-GARCH models in capturing long memory dynamics in both the mean and the variance, reflecting the persistent influence of past shocks.

Figure 10 compares the residuals obtained from the ARFIMA(1, $d(m)$, 1)-FIGARCH(1, $d(v)$, 1) model with those from a standard ARMA(1,1)-GARCH(1,1) model, both fitted to

the normalized VVIX. The ARFIMA-FIGARCH model demonstrates a clear advantage in capturing the persistent effects and long memory in volatility, which are critical characteristics of financial time series. The fractional differencing terms in the ARFIMA-FIGARCH framework allow for a more gradual decay in autocorrelations, ensuring that the extracted innovations reflect the clustering and persistence commonly observed in market volatility. This is in contrast to the ARMA-GARCH model, which has difficulty in capturing such long-range dependence and often fails to fully capture the dynamic structure of financial market data. These findings underscore the importance of long-memory time series models in financial analysis, particularly for applications requiring the modeling of heavy tails, volatility clustering, and time-varying risk dynamics. The ARFIMA-FIGARCH framework, therefore, provides a more robust and accurate tool for understanding and forecasting uncertainty in the market.

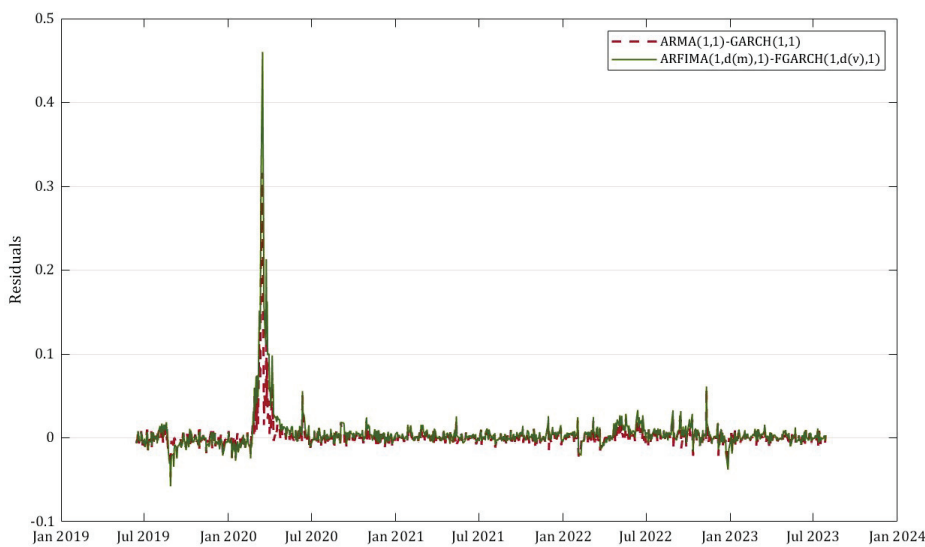


Figure 10. Residuals of the fitted time series models.

Long memory in the mean (captured by ARFIMA) implies that historical values continue to influence future returns over extended horizons. Similarly, long memory in volatility (captured by FIGARCH) implies that periods of heightened turbulence persist for prolonged durations. To incorporate these features, we model the normalized VVIX as follows:

$$ARFIMA(1, d(m), 1) : \phi(L)(1 - L)^{d(m)} z_t = \theta(L) \varepsilon_t, \quad (15)$$

where z_t is the normalized VVIX, $d(m) = 0.268$ is the mean fractional differencing parameter, and ε_t is a white noise innovation.

For the volatility, we use

$$FIGARCH(1, d(v), 1) : \phi(L)(1 - L)^{d(v)} \varepsilon_t^2 = \omega + [1 - \beta(L)] v_t, \quad (16)$$

with $d(v) = 0.01$ capturing the long memory in the volatility.

To evaluate whether the revised VIX and its associated R/R ratios reveal any predictable patterns, we simulate 10,000 NIG scenarios based on the ARFIMA-FIGARCH normal innovations derived from the normalized VVIX. Using these simulated scenarios, we calculate performance measures, including the Rachev ratio and the Stable Tail Adjusted Return (STAR) ratio. Figure 11 demonstrates that these R/R ratios exhibit no discernible or systematic patterns, suggesting the absence of predictable signals within the volatility noise. This finding aligns with the efficient market hypothesis, indicating that the revised VIX

does not introduce exploitable predictability in volatility, thereby preserving the efficiency of the markets.

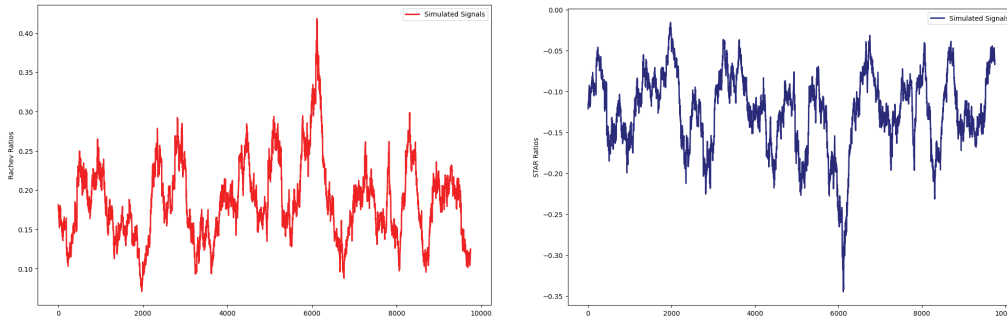


Figure 11. Signal/Noise ratios detected using performance ratios over S scenarios.

4. Results

To identify i.i.d. shocks, we begin by extracting normal innovations from the ARFIMA(1, $d(m)$, 1)-FIGARCH(1, $d(v)$, 1) model defined in Equations (14) and (15). Using these innovations, we then compute the risk–reward (R/R) ratios to isolate uncertainty shocks. Specifically, we consider the following two performance ratios: the Rachev ratio and the Stable Tail Adjusted Return Ratio (STAR ratio). These serve as benchmark metrics for quantifying uncertainty shocks—interpreted here as signals extracted from volatility noise—with the defined data-generating process.

1. Rachev Ratio (RR):

$$RR_{(\beta, \gamma)}(X) := \frac{AVaR_{\beta}(-X)}{AVaR_{\gamma}(X)}, \quad (17)$$

where $AVaR$ denotes the Average Value-at-Risk. More formally,

$$AVaR_{\beta, \gamma}(X) := \frac{1}{\beta} \int_0^{\beta} \left[\max(-F_X^{-1}(u), 0) \right]^{\gamma} du.$$

Here, X denotes the normal innovations obtained from the revised VIX, and β and γ are confidence levels for the right and left tails, respectively. Although the Rachev ratio satisfies monotonicity (M), scale invariance (S), and distribution-based (D) properties, it fails to meet the quasi-concavity (Q) property due to its non-concave numerator.

2. Stable Tail Adjusted Return Ratio (STAR Ratio):

$$STARR_{\gamma}(X) := \frac{\mathbb{E}[X]^+}{AVaR_{\gamma}(X)^+}, \quad (18)$$

where

$$AVaR_{\gamma}(X) = \frac{1}{\gamma} \int_0^{\gamma} VaR_u(X) du.$$

The STAR ratio fully satisfies all four axioms (M, Q, S, D), rendering it axiomatically sound and robust.

Equations (16) and (17) define the benchmark performance ratios used to quantify uncertainty shocks in the ARFIMA-FIGARCH framework. Figure 12 presents these ratios computed over the normal innovations, treating them as an i.i.d. series representing uncertainty shocks. Since the ARFIMA-FIGARCH innovations are not serially correlated, they support the standard macroeconomic assumption that uncertainty shocks are both unexpected and independent over time. In other words, there are no predictable signals in the volatility noise, consistent with the notion that uncertainty should not be forecastable.

Figure 12 presents the Rachev and STAR ratios derived from the ARFIMA-FIGARCH and ARMA-GARCH models, respectively, highlighting their effectiveness in capturing uncertainty shocks. Notably, the ARFIMA-FIGARCH model exhibits pronounced spikes during key market events, such as the COVID-19-induced market crash in March 2020 and the monetary policy tightening in early 2022. These spikes correspond to significant tail risks and volatility clustering in financial markets, as expected under a double-subordinated NDIG framework.

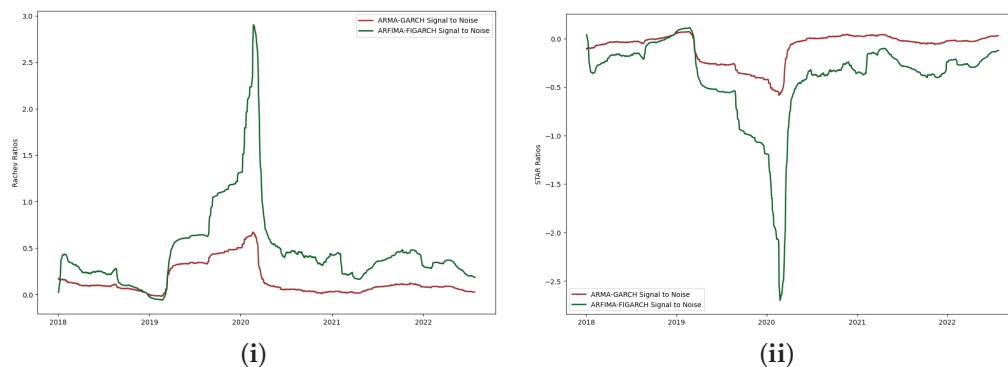


Figure 12. Novel Uncertainty Shocks. (i) Rachev Ratios (ii) STAR Ratios.

The upward spikes in the Rachev ratio reflect heightened tail risk on the left side of the distribution (extreme negative outcomes), while the downward spikes in the STAR ratio correspond to the deterioration in the return-to-risk trade-offs due to the amplified volatility. This contrast arises because the Rachev ratio emphasizes adverse tail events, magnifying the impact of extreme losses, whereas the STAR ratio focuses on the average risk-adjusted returns, which decline sharply under heightened volatility. In contrast, the ARMA-GARCH model produces muted signals, failing to capture the persistence and magnitude of the uncertainty reflected in the data. This comparison underscores the comprehensiveness of our long-memory time series approach in identifying large market disruptions and subtler shifts in investor sentiment and risk aversion.

The pronounced movements or “jumps”, identified as uncertainty shocks, could be interpreted as meaningful signals. Both ratios serve as proxies for the intensity and persistence of uncertainty shocks over time. The ARFIMA-FIGARCH model, capturing long-memory behavior, exhibits pronounced spikes and sharp declines that coincide with major market disruptions (notably in March 2020 and early 2022). In contrast, the ARMA-GARCH-based ratios remain relatively muted, reflecting a less sensitive and more short-term oriented view of uncertainty. These comparisons highlight the capacity of the ARFIMA-FIGARCH approach—combined with the NDIG-based volatility measure—to more accurately detect and quantify the severity and persistence of uncertainty shocks.

Compared to the traditional VIX, our proposed method offers a more comprehensive perspective on market turbulence, while the VIX can effectively detect pronounced episodes of stress—such as the market turmoil triggered by the COVID-19 pandemic in March 2020 or the uncertainty that intensified in early 2022—it relies on modeling assumptions extensively discussed in Section 3.5. In particular, the VIX’s underlying framework, which basically treats returns as if they followed a Normal Inverse Gaussian (NIG) distribution, can limit its ability to discern more intricate patterns of volatility and tail risk.

In contrast, our NDIG-based volatility measure enables the model to incorporate both the timing and magnitude of shocks in a way that better reflects the observed market phenomena. As a result, while the VIX may identify periods of heightened volatility, it can underestimate the true severity of these events or overlook more subtle, yet economically significant, manifestations of uncertainty. For instance, the extreme market turmoil of

March 2020 and the subsequent policy uncertainty in early 2022 are clearly reflected in our model's outcomes. In early 2022, factors such as inflationary pressures, the Federal Reserve's aggressive policy guidance, the Russia–Ukraine conflict, and precipitous declines in technology stocks fueled an environment of heightened uncertainty. Although the VIX recognized heightened volatility, it did not fully take into account the heavy-tailed, persistent features of the underlying return process. In contrast, our NDIG-based approach, supported by the ARFIMA-FIGARCH model, elucidates not only the well-documented macroeconomic events but also previously overlooked properties in the distributional structure of returns.

Figure 13 presents the autocorrelation function (ACF) of the volatility series, highlighting the presence of long-range dependence (LRD) or long memory in the data. The slow, hyperbolic decay of the ACF over the lags demonstrates the long memory processes, as opposed to the exponential decay observed in short memory models like the standard ARMA-GARCH frameworks. This persistence indicates that shocks to volatility have a significant influence over an extended time horizon, consistent with the properties of ARFIMA-FIGARCH. The confidence bands further emphasize that the autocorrelation remains statistically significant over a substantial number of lags. By identifying long-memory, this approach takes into account the enduring nature of volatility clustering and provides a more accurate representation of the dynamics of the market.

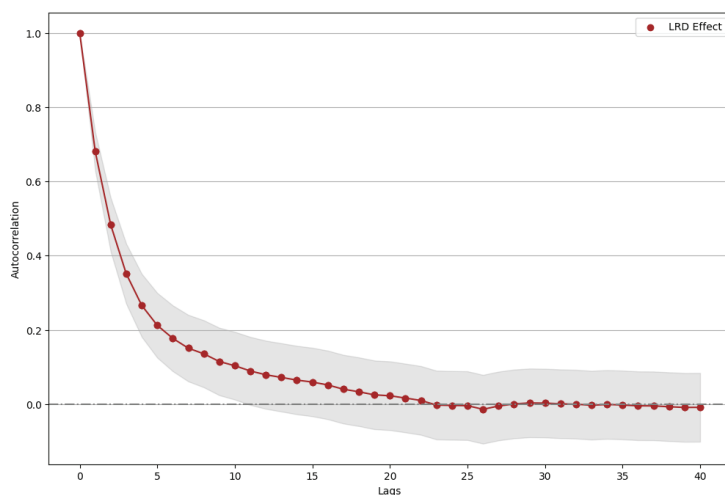


Figure 13. Long-range dependences: decay of the autocorrelation.

Figure 14 presents the Rachev and STAR ratios computed from the normal innovations of the traditional VIX and the revised VIX (VVIX), modeled using the ARFIMA(1, $d(m)$, 1)-FIGARCH(1, $d(v)$, 1) framework. The new measure of uncertainty shocks, denoted as ARFIMA-FIGARCH: revised VIX, captures the more pronounced signals of financial market volatility compared to those extracted from the traditional VIX. The results clearly indicate that the revised method better captures the long-memory effects inherent in financial markets, while these effects remain muted under the traditional VIX approach.

Hence, our framework reveals a more comprehensive portrayal of uncertainty shocks than the traditional VIX. While the VIX remains useful as a volatility gauge, it lacks the flexibility and distributional adaptability of our NDIG-based method. By utilizing R/R ratios, we advance beyond standard volatility measures in financial markets. The findings are more aligned with the fundamental asset pricing principles and offer a deeper understanding of how uncertainty, driven by complex macroeconomic, geopolitical, and sector-specific factors, resonates throughout financial markets.

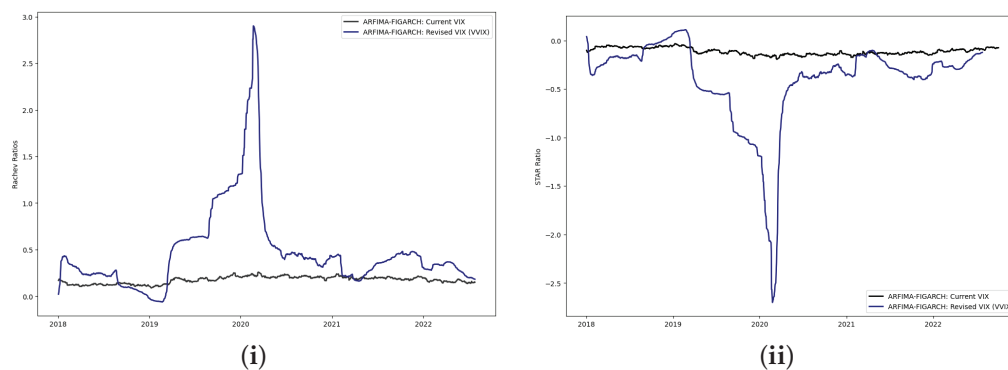


Figure 14. Traditional VIX vs. revised VIX; (i) Rachev ratios, (ii) STAR ratios.

5. Conclusions

This paper contributes to the study of uncertainty shocks in financial markets by introducing a novel method that integrates heavy-tailed distributions and stochastic volatility in asset returns. Using a double-subordinated Normal Inverse Gaussian (NIG) Lévy process to model the log returns of the S&P 500, we developed the Volatility of VIX (VVIX) as a revised volatility index. This new measure captures the complex distributional characteristics of market dynamics more accurately than traditional approaches. By accounting for skewness, kurtosis, and volatility clustering—key features of periods marked by heightened uncertainty—the VVIX provides a more comprehensive understanding of market behavior beyond conventional second-moment measures of volatility.

Our framework further refines the identification of uncertainty shocks by deploying a general family of risk–reward (R/R) ratios on a long-memory time series of the VVIX. These ratios elucidate the relation between risk and return in environments characterized by extreme events and tail risks. In doing so, this approach extends the conventional methods, enabling the more precise modeling of macro-financial linkages, informing risk management strategies, and ultimately improving the understanding of how uncertainty shapes economic outcomes. The VVIX-based method uncovers subtler yet economically meaningful sources of uncertainty, particularly during tumultuous periods. Future research could apply this approach to a broader range of asset classes, investigate its implications for portfolio construction and hedging strategies, and further explore the macroeconomic consequences of uncertainty shocks. Ultimately, this line of inquiry has the potential to yield a deeper understanding of the intricate interplay between uncertainty, asset prices, and economic activity.

Author Contributions: A.J.:data curation, formal analysis, investigation, methodology, resources, software, validation, visualization, writing (original draft), and writing (review and editing); A.S.: formal analysis, methodology, supervision, validation, and writing (review); S.T.R: formal analysis, investigation, methodology, supervision, validation, resources; F.J.F.: supervision, validation, writing (review and editing). All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Data is available upon request.

Conflicts of Interest: The authors declare no conflicts of interest.

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Article

Performance Evaluation of Islamic Banking Services Industry: Evidence from GCC

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Abstract: This study documents the comparative financial performance of the Islamic Banking Services Industry (IBSI) in the Gulf Cooperation Council (GCC) region. After drawing the performance evaluation framework (based on the CAMEL framework), the research conducted data analysis of the Islamic Banking Services Industry (IBSI) in the GCC region for 31 quarters (2013Q4–2021Q4). The analysis examines capital adequacy, asset quality, management performance, earnings, and liquidity management. Objectively classified data trends are reported through graphs. Additionally, the research documents internal determinants of financial performance. Findings suggest that the GCC-IBSI has shown overall progress in achieving primary objectives (commercial performance), including healthy capital adequacy, cost control, equity returns, and liquidity management. Capital adequacy, cost control, and liquidity management significantly contribute to financial performance. Managerial implications include cost control, reduction in non-performing loans, and prudent liquidity management. There exist opportunities in the GCC-IBSI for investors, given the mismatch in demand and supply of Islamic financial services. This study contributes to the literature by documenting findings on the achievements of the primary objective of IBSI in multiple GCC-IBSI markets comparatively.

Keywords: Islamic banking; performance evaluation; financial institutions; financial services

JEL Classification: G2; G21

1. Introduction

The Islamic Financial Services Industry (IFSI) aimed at Islamic Shari'ah compliance recently developed as a niche segment of the financial sector. The IFSI targets the segment of (primarily Muslim) consumers reluctant to use conventional financial services due to mismatch in religious teachings and practices of interest-based financial system. The IFSI is in practice since the last quarter of the 20th century with appreciable results as far as resilience and expansion are concerned. The IFSI turned out to be more resilient than its conventional counterparts during the recent global financial crisis (GFC) (Smolo and Mirakhor 2010; Siraj and Pillai 2012; Hanif and Zafar 2020). According to the Islamic Financial Services Industry Stability Report (IFSISR), by 2022, the industry size has reached a healthy amount of USD 3.25 trillion (IFSB 2023). The IFSI and Sustainable Development Goals (SDGs) complement each other, given the overall philosophy of Islamic finance. Incorporation of Abrahamic religious values into the financial system is the aspiration of the IFSI (Abdulrahman 2010). Broader objectives of Islamic finance include Halal earnings, equitable wealth distribution, financial stability (Chapra 2008; and Ayub 2018), and socio-economic justice (Maudoodi 1941; Abdulrehman 2000). Also, a social role is expected from the IFSI, including corporate social responsibility (CSR) (Sairally 2007), promotion of social values (Obaidullah 2005), socially responsible investments, decrease in poverty (Asutay 2012), and environmental concerns (Saged et al. 2017).

Performance evaluation of an activity is aimed at documenting the results to identify weaker areas in light of preset objectives. However, clarity of objectives to be measured through the process is a prerequisite in developing the performance evaluation mechanism. There are established performance evaluation mechanisms for the conventional banking sector. The most widely used is the CAMELS rating system, which includes evaluation of the sufficiency of capital, strength and quality of assets, capabilities of management in operations, stability and trend in earnings, ability to discharge liabilities at due date, and sensitivity to internal and external events. Global rating agencies (Moody, Fitch, etc.) provide services to assess an institution's financial soundness with the preset mandate of assessing commercial performance and financial stability without assessing the Shari'ah risk.

An interesting question is what additions to the existing CMAELS framework are needed to assess the performance of the Islamic Banking Services Industry (IBSI). The literature carries some appreciable efforts aimed at the performance evaluation of the IBSI. We may classify the studies into three groups.

- First is the financial performance evaluation of the IBSI using conventional models (e.g., see Hanif et al. 2012; Siraj and Pillai 2012; Islam and Ashrafuzzaman 2015; Hazman et al. 2018).
- The second stream of literature develops the performance evaluation mechanism for the IBSI in light of specific objectives of the Islamic financial system (Mohammed et al. 2008, 2015; Mergaliyev et al. 2021).
- Third is the development of *Shari'ah* compliance ratings mechanism for the IBSI—with a focus on IFSI objectives (Ashraf and Lahsasna 2017; Hanif 2018).

Specifically focusing on developing the performance evaluation framework of the IBSI, the literature suggests including specific Islamic finance objectives in addition to traditional measures of commercial performance. Hanif and Farooqi (2023) divide the concept into three sections/levels: primary, secondary, and advanced. The primary objectives include survival and commercial performance within Shari'ah constraints. The secondary objectives include broader economic impact, while the advanced objectives address social aspects.

The GCC (Gulf Cooperation Council) region started Islamic finance in the last quarter of the 20th century. The GCC leads in the provision of Islamic financial services, with more than 50% of the global IBSI assets (IFSB 2022). A significant number of studies exist on the comparative performance evaluation of the IBSI and conventional banking in the region (see inter alia, Samad 2004; AbuLughod 2010; Siraj and Pillai 2012; Sillah and Harrathi 2015; Khokhar et al. 2020; Jaara et al. 2021; and BenSlimen et al. 2022). The overall results of these studies in the GCC region indicate equality in performance, if not better than the conventional industry. However, to the best of our knowledge, no study exists on comparative commercial/financial performance evaluation within IBSI markets in the GCC region for the review period.

The research aims to document the results of achievements of the primary Islamic finance objectives by the leading Islamic banking region, i.e., the Gulf Cooperation Council (GCC). There is a need for continuous documentation of achievements of multiple IBSI markets, given that the IBSI is rapidly growing, and more data are available yearly. Also, the focus of earlier studies on the documentation of comparative performance evaluation has remained within conventional and Islamic banking industries. There is a need to compare the performance of Islamic banking within IBSI markets. The research is expected to fill the gap in the literature by evaluating the comparative performance of the IBSI in the GCC markets, focusing on the achievements of primary objectives (commercial viability). Specifically, the research is intended to answer the following questions:

- Whether the IBSI in the GCC region is stable and carries sufficient capital to remain solvent in the long run (capital adequacy);
- To what extent is the IBSI successful in handling the credit risk (non-performing loans);
- What is the performance of the IBSI's management (cost to income);
- Whether the IBSI remained successful in generating sufficient regular earnings for investors (return on equity);

- Whether the IBSI carries sufficient liquid assets to ensure short-term solvency (liquidity management); and
- Finally, to identify the significant internal contributors to the performance of the IBSI in the GCC region.

The methodology includes calculating financial ratios covering capital adequacy, asset quality, management performance, earnings, and liquidity management by utilising recent financial data for 33 quarters (2013Q4–2021Q4). Averages are compared by equality of means tests. Summary results are presented in tables. Historical trends of specific ratios are presented through graphs. In the second research phase, the internal determinants of profitability are documented. The results carry multiple interesting findings, including IBSI capital adequacy and liquidity management strengths.

The next section summarises the literature on performance evaluation of Islamic finance markets. It then develops an analytical framework and methodology in Section 3. Section 4 reports the findings, while Section 5 concludes this study.

2. Literature Review

Many studies have documented the empirical financial performance of the IBSI globally using available methods. We have evidence from Southeast Asia, South Asia, the Middle East and North Africa (MENA), etc. Starting from Southeast Asia, few studies have compared the performance between conventional and Islamic banking. Using financial ratio analysis, Rosly and Abu Bakar (2003) documented superiority in profitability but was not supported by asset utilisation and investment margin after comparing the performance of Islamic and conventional banks in Malaysia (1996 to 1999). Rozzani and Rahman (2013) documented results for conventional and Islamic banking in Malaysia (2008–2011) through CAMELS, covering 35 banks (conventional 19, Islamic 16). The results indicate similarity in the performance with no significant difference. Another study on the Malaysian banking sector was conducted by Hazman et al. (2018). The sample included ten banks (five from each stream) for the period 2004–2016. As per the results, conventional banking outperforms Islamic banking in performance, based on the CAMEL model.

Another stream of studies has compared commercial performance between full-fledged Islamic banks and conventional banking Islamic windows. Kamaruddin et al. (2008) reported the results from Malaysia (for 1998–2004) on the performance of Islamic banking and conventional banking Islamic windows by application of data envelopment analysis (DEA). The results indicate relatively better cost efficiency than profit generation. In a recent study, Rasli et al. (2020) documented the comparatively better commercial performance and stability of full-fledged Islamic banks and Islamic subsidiaries of conventional banks for eight years (2010–2017). Full-fledged Islamic banks show better performance than subsidiaries of conventional banks. These results are mixed, containing better, equal, and worse performance compared with conventional banking.

A brief review of studies in the South Asian IBSI follows. Ahmad and Hassan (2007) reported comparative results from Bangladesh (1994–2001). Accordingly, Islamic banking leads in liquidity and capital adequacy, shows equality in asset quality, and lags in operating performance. Islam and Ashrafuzzaman (2015) documented similarity for both streams of banking in Bangladesh, by the application of CAMELS testing, in three areas—capital adequacy, management, and earnings; however, the results are different for asset quality. The sample included five banks from each stream of banking (2009–2013). Overall findings indicate either better performance or equal to conventional banking for the Bangladesh IBSI lead.

There are a few citations available on performance measurement of Islamic banking in the Pakistani institutional setting. Ansari and Rehman (2011) documented better performance of Islamic banking than conventional banking in three areas: risk, liquidity, and cost-effectiveness, in the Pakistani IBSI. The sample included three banks from each stream of banking (2006–2009). Islamic banking depicts better credit risk management and solvency while comparatively lagging in profitability and liquidity (Hanif et al. 2012).

The sample included 5 Islamic and 22 conventional banks (2005–2009). Islamic banking depicts superiority over conventional banking in profitability and liquidity for 2007–2009, as concluded by Usman and Khan (2012) after studying three banks from each stream of banking.

Islamic banking shows equality in profitability and better performance than conventional banking in three areas: risk, solvency, and efficiency for 2006–2010 (Latif et al. 2016). The sample comprises five banks from each stream. Qureshi and Abbas (2019) documented the superior performance of Islamic banking in two areas, namely operating performance and liquidity, for the period 2010–2017. The sample included 2 Islamic and 15 conventional banks. Ali et al. (2021) compared the performance of conventional and Islamic banking in Pakistan for 2007–2016 using financial ratio analysis and documented better performance by Islamic banking in two areas, namely asset quality and sensitivity to market risk, whereas conventional banks outperformed Islamic banks in terms of earnings. Although the evidence favours superior management by Islamic banks in the areas of solvency and risk, the findings are mixed. Comparative profitability remained a concern in earlier periods, which was improved later on (Qureshi and Abbas 2019; Latif et al. 2016).

From the MENA region, the results are as follows. Saleh and Zeitun (2007) reported increased profitability, efficiency, and credit expansion in Jordan (2000–2003), while Fayed (2013) found superior performance of conventional banking in Egypt (2008–2010), after studying liquidity, profitability, solvency, and credit risk. Sample size was three Islamic and six conventional banks. The GCC (Gulf Cooperation Council) region is the leader in the provision of Islamic financial services, with more than 50% of the global Islamic Banking Services Industry (IBSI) assets (IFSB 2022). Researchers have focused on measuring the performance of the GCC-IBSI, as depicted by the selected literature review. Samad (2004) concluded from Bahrain that Islamic banking is superior in credit risk management, while similar in liquidity and profitability, after studying a sample of 6 Islamic and 15 conventional banks (1991–2001). Somehow similar results were documented by AbuLughod (2010) by comparing the performance of conventional and Islamic banking from 2000 to 2005 in the GCC region through financial ratio analysis and found no significant difference in profitability and internal growth rate, while the liquidity risk level is low in Islamic banking. Siraj and Pillai (2012) concluded that Islamic banking is more resilient to the financial crisis, as well as outperforms conventional banking in performance in the GCC region (2005–2010). In another study, Sillah and Harrathi (2015) compared the performance of 28 conventional and 20 Islamic banks from the GCC region by applying data envelopment analysis (2006–2012). The findings suggest no difference in efficiency based on constant return to scale; however, variable return to scale suggests that the conventional banks are more efficient than their Islamic counterparts during 2009 and 2010. Likewise, Khokhar et al. (2020) compared the performance of 21 Islamic and 42 conventional banks in the GCC region from 2010 to 2016 and found Islamic banking at par with conventional banking in all terms of efficiency at the industry level. However, BenSlimen et al. (2022) documented that Islamic banking is less cost-efficient than conventional banking after comparing efficiency using stochastic frontier analysis between conventional and Islamic banking in the GCC region from 2006 to 2015. For a longer study period of 2000–2018, it was found that conventional banks are more efficient in profitability in the GCC region (Jaara et al. 2021). The overall results of these studies in the GCC region led to equality in performance, if not better than in conventional industry.

The literature contains studies that compare conventional and Islamic banking's performance in various markets. However, none of the studies has compared the performance of multiple IBSI markets in the GCC region. Given the more similarities than differences in the selected economies, the GCC region is suitable for documenting the comparative performance of six IBSI markets. This research aims to document the comparative financial performance of the IBSI within GCC economies in the areas of capital adequacy, asset quality, management performance, earnings, and liquidity.

3. Analytical Framework

The literature suggests the inclusion of specific Islamic finance objectives in addition to traditional measures (financial performance) in the performance evaluation of the IBSI. The specific objectives include broader macroeconomic objectives and social/ethical objectives. Macroeconomic objectives comprise financial stability and equitability in the distribution of wealth. Financial stability is expected to be achieved by linking financial and real sectors, while applications of profit and loss sharing (PLS) and access to finance are tools to achieve equitable wealth distribution (Chapra 2008). Hanif and Farooqi (2023) articulated the concept of performance evaluation for the IBSI by dividing it into three sections/levels.

- The primary level addresses the survival of Islamic banking by generating sufficient returns within Shari'ah constraints.
- The secondary level addresses broader economic objectives, including financial stability and equitable wealth distribution.
- Finally, the higher level contributes towards the social uplift of the marginal community groups by investing in social sectors.

Micro objectives (primary level) for the IFSI include survival and profitability within Shari'ah constraints. Following the CAMEL framework, the commercial performance of the GCC-IBSI is measured in five areas (Rozzani and Rahman 2013; Ali et al. 2021) (Figure 1 presents an analytical framework).

- Capital—capital adequacy ratio (CAR), total regulatory capital/risk-weighted assets;
- Asset quality—non-performing finance (NPF), gross NPF/total financing;
- Management performance—cost-to-income ratio (CIR), operating costs/gross income;
- Earnings—return on equity (ROE), net income/equity; and
- Liquidity—liquid asset ratio (LAR), liquid assets/total assets.

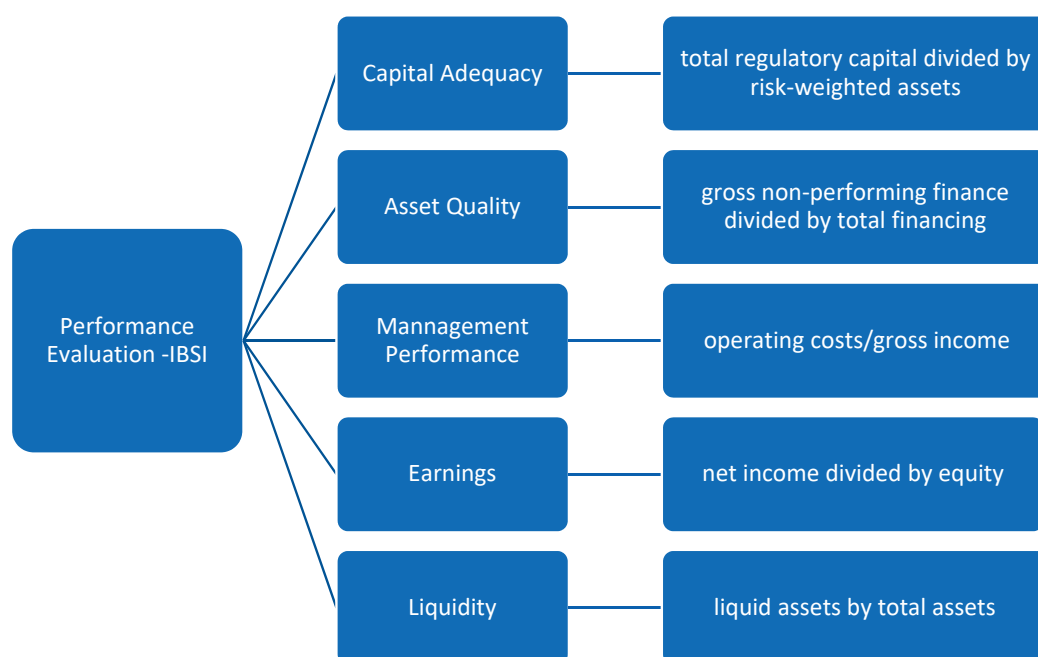


Figure 1. Financial performance evaluation framework—IBSI. Source: Constructed by the author.

Country-wise financial reporting data are obtained from the Islamic Financial Services Board, Prudential, and Structural Islamic Financial Indicators (PSIFIs) for Islamic banks (<https://www.ifsb.org/data-metadata/>). Analysis is carried out on quarterly data from 2013Q4 to 2021Q4. The duration is selected based on the availability of authentic country-wise data from the selected data source. However, the duration is recent and long enough to form an opinion on the performance of selected Islamic banking markets. Results based on objective classification of data are presented through tables and graphs. Graphs

depicting trends in all CAMEL ratios are presented. The averages of all ratios are calculated with standard deviations and coefficients of variation. Tests for means equality among all markets based on a specific financial ratio are completed (Samad 2004; Islam and Ashrafuzzaman 2015).

Finally, a cause-and-effect relationship is determined through panel regression (Jaara et al. 2021). Return on equity (ROE) is used as a performance indicator (dependent variable), while capital adequacy, non-performing finance, the cost-to-income ratio, and the liquidity ratio are used as regressors. The following regression model is tested.

$$ROE_{it} = C + CAR_{it} + NPF_{it} + CIR_{it} + LAR_{it} + \epsilon_{it} \quad (1)$$

where ROE is the return on equity, CAR is the capital adequacy ratio, NPF is the non-performing finance, CIR is the cost-to-income ratio, LAR is the liquid asset ratio, C is a constant/intercept, ϵ represents the error term, the subscript i represents the markets, and the subscript t is for time.

Data are checked for stationarity and autocorrelation. Stationarity of the series is required to run the regression model. Likewise, no two independent highly correlated variables are recommended in the single regression model.

4. Analysis and Findings

Gulf Cooperation Council: The GCC consists of six Arabian Muslim countries (including Saudi Arabia, Kuwait, Bahrain, Qatar, United Arab Emirates, and Oman) and is the Centre of Muslim civilisation with a dominant Muslim population. It was an earlier adopter, promotor, and leader in the modern Islamic financial system, with a significant share of the assets under management of the global Islamic Financial Services Industry.

The following facts depict how the GCC region has played a unique and active role in developing the modern IFSI.

- The first milestone in IFSI history was the establishment of the Islamic Development Bank (IsDB) in Jeddah, KSA, in 1975. IsDB owners include 57 members of the Organisation of Islamic Cooperation (OIC); however, close to 45% of the shareholding is in the GCC region.
- The International Islamic Fiqh Academy (IIFA), established in 1981 in Jeddah, KSA, is a universal scholarly organization (a subsidiary organ of OIC) aimed at studying contemporary life issues and offering solutions through Ijtihad.
- The Accounting and Auditing Organisation for Islamic Financial Institutions (AAOIFI) was established in 1991 in Bahrain to develop and issue standards for the IFSI.
- The International Islamic Financial Market (IIFM) was established in 2002 in Bahrain, focusing on standardizing Shari'ah-compliant financial contracts and product confirmations.
- Dubai Islamic Bank is the oldest private-sector Islamic bank, established in 1975 in Dubai, UAE.
- *JKAU: Islamic Economics* (an international refereed journal), established in 1983 at King Abdulaziz University, KSA, is a pioneer outlet for disseminating IFSI-related academic literature.
- Dubai aims to be an Islamic finance hub (Kane 2014).

Assets under the management of the GCC–Islamic Banking Industry have reached a healthy volume of USD 1212.5 billion, representing more than 50% of global IBSI assets (IFSB 2022). By the end of 2021Q4, the Islamic Banking Services Industry (IBSI) in the GCC consists of 42 fully fledged Islamic banking institutions (IBIs) with a branch network of 1313¹, employing 28,775² professionals. Additionally, there are 12 Conventional Banks with Islamic Windows (CBIWs) with a branch network of 1175, employing 16,033 staff members (IFSB 2022). Figure 2 depicts growth trends in Total Assets (TA) and Total Shari'ah Compliant Financing (TSCF) for IBIs, while Figure 3 is for CBIWs (IFSB 2022). Quarterly growth of assets under IBIs (1%)³ is less than that under CBIW (1.5%) from 2018Q1 onward.

Growth is higher for earlier quarters as the sample growth for IBIs (excluding Bahrain and Qatar) is 2%, and it is 2.64% for CBIW (2013Q4–2021Q4). At the end of the review period 2021Q4, 68% of total assets under IBIs represent TSCF and 11% investment in sukuk. In comparison, a higher percentage of asset concentration (70%) is represented by TSCF and 20% sukuk holding under CBIW. Trend lines show a higher concentration of TSCF compared with total assets (lesser gaps) in IBIs and CBIWs in initial quarters compared with final quarters (larger gaps) during the sample period.

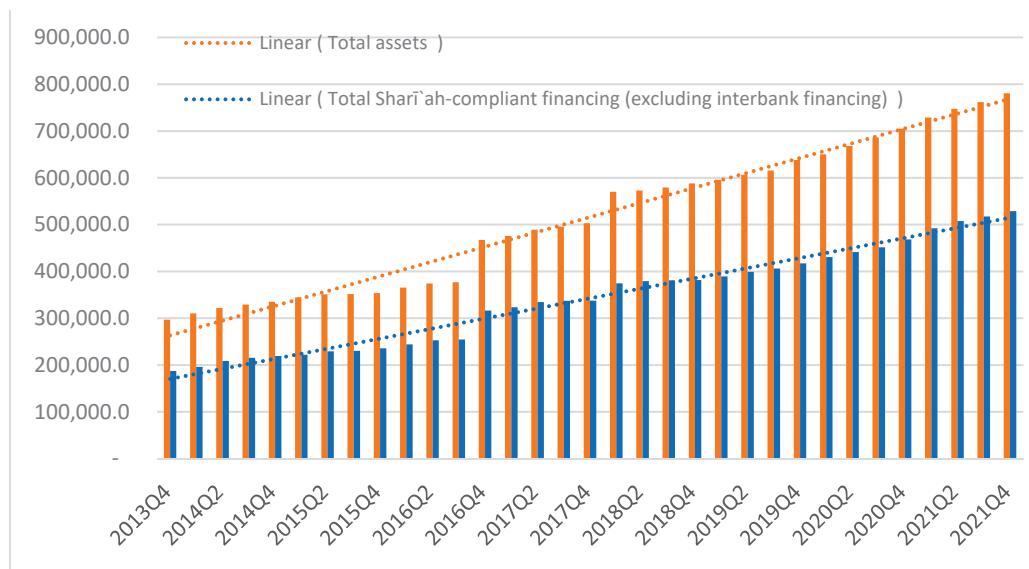


Figure 2. IBIs growth trends—assets and financing (USD million) for 33 quarters (2013Q4–2021Q4). Source: Constructed by the author; data (IFSB 2022).

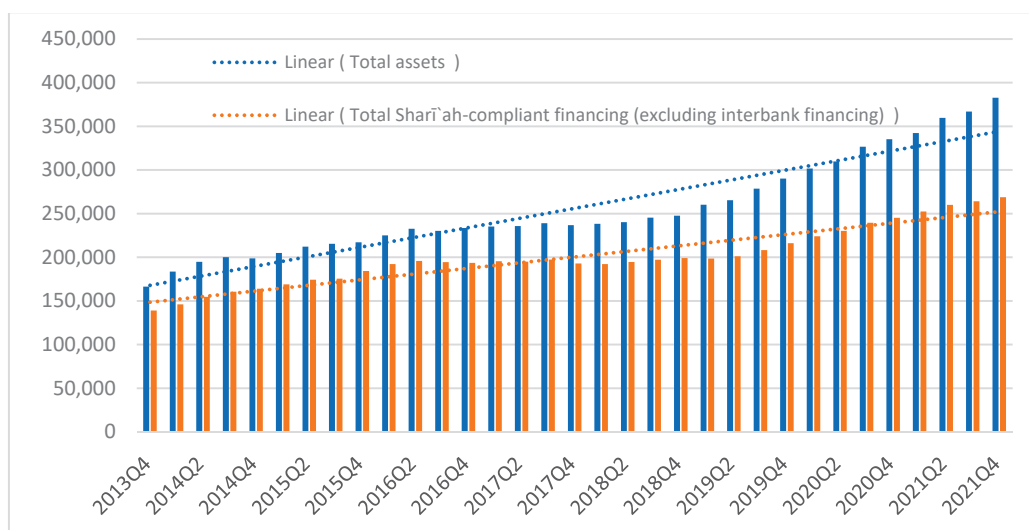


Figure 3. CBIWs growth trends—assets and financing (USD million) for 33 quarters (2013Q4–2021Q4). Source: Constructed by the author; data (IFSB 2022).

Market Share: The GCC region economies hold significant domestic banking market share. By 2021, based on domestic market share, all GCC Islamic banking markets have already achieved systemic importance. A country with a 15% market share in domestic banking assets is included in the list of systemic importance. Five GCC Islamic banking markets have achieved a 20% and above share in the domestic market, while two of them (Saudi Arabia and Kuwait) have more Islamic banking share than conventional banking. Likewise, the GCC Islamic banking markets make a significant contribution (above 50%)

in global Islamic banking assets. The GCC region's asset volume under Islamic banking management is above USD 1200 billion (Table 1).

Table 1. Market Share of GCC Islamic Banking (2021).

Country	Market Share in Domestic Banking Assets	Share in Global Islamic Banking Assets	Volume of Assets USD B
Saudi Arabia	77.2%	30.6%	643.9
Kuwait	51.9%	6.3%	132.6
Qatar	28.1%	6.6%	138.9
UAE	23.9%	10.0%	210.4
Oman	15.3%	0.7%	14.7
Bahrain	21.2%	3.3%	69.4
		57.5%	1209.9
Total Global Islamic Banking Assets			2104.1

Source: Constructed by the author; data (IFSBr 2022).

Micro objectives for the IFSI include survival and being profitable within Shari'ah constraints. The commercial performance of the GCC-IBSI is measured in five areas, namely the capital adequacy ratio (CAR), total regulatory capital/risk-weighted assets; non-performing finance (NPF), gross NPF/total financing; the cost-to-income ratio (CIR), operating costs/gross income; return on equity (ROE), net income/equity; and the liquid asset ratio (LAR), liquid assets/total assets. Summary results are presented in Table 2. Based on the average results, under the CAR performance measure, the Oman IBSI is leading (29%), while the minimum is 16% (Oman CBIW); the NPF score is the highest for Bahrain (11%), while the minimum is less than 1% (Oman IBI and CBIW); Qatar leads in cost control (13%), while the highest CIR is 116% (Oman IBI); KSA leads in ROE (16%), while the least is −0.1% (Oman IBI); the liquid asset ratio is the highest for KSA IBI (28%), and the minimum is 13% (Oman CBIW). The results indicate that managerial attention to profitability and cost control is required in the Oman IBSI, while the matter of NPF is significant in the Bahrain IBSI.

Table 2. Summary Statistics for 33 quarters (2013Q1–2021Q4).

Ratios	Statistics	Bahrain	Kuwait	Oman IBI	Oman CBIW	Qatar	KSA IBI	KSA CBIW	UAE
CAR	Average	18.7%	17.8%	28.8%	16.2%	18.0%	20.1%		17.1%
	St. Dev	1.2%	0.7%	21.2%	3.1%	0.6%	1.0%		1.1%
	Coef. Var	6.6%	4.2%	73.6%	19.1%	3.3%	5.1%		6.2%
NPF	Average	11.0%	2.5%	0.7%	0.7%	1.3%	1.2%	1.4%	6.3%
	St. Dev	2.2%	0.8%	0.9%	0.6%	0.4%	0.2%	0.5%	1.1%
	Coef. Var	20.1%	32.2%	131.1%	88.2%	30.6%	13.6%	39.9%	16.9%
CIR	Average	71.4%	32.5%	115.7%	47.3%	13.3%	49.9%	39.8%	50.7%
	St. Dev	31.0%	8.5%	78.2%	5.6%	0.8%	5.2%	5.6%	2.5%
	Coef. Var	43.4%	26.2%	67.6%	11.8%	6.2%	10.4%	14.1%	5.0%
ROE	Average	8.0%	11.0%	−0.1%	8.7%	11.0%	15.9%		11.3%
	St. Dev	6.5%	2.9%	5.4%	2.2%	5.1%	2.6%		2.5%
	Coef. Var	81.5%	26.1%	−3934.5%	25.5%	46.4%	16.3%		21.8%
LAR	Average	17.2%	31.1%	15.4%	13.2%	26.2%	28.0%		15.3%
	St. Dev	1.7%	2.5%	13.7%	2.9%	8.6%	3.3%		1.2%
	Coef. Var	9.6%	7.9%	88.6%	22.0%	32.9%	11.7%		8.1%

Source: Constructed by the author; data (IFSB 2022).

Capital Adequacy Ratio (CAR): The CAR (measured as total regulatory capital/risk-weighted assets), is an essential financial ratio aimed at judging the sufficiency of capital by a bank required to pass the stress testing. Basel-3 specifies a minimum requirement of 8.0% (Basel 2019). Figure 4 and Table 2 depict comparative results for GCC countries. Much variation is witnessed in the case of the Oman IBSI, with an average CAR of 28.8% (standard deviation 21.22%) ranging from 13% to 81%, followed by the Oman CBIW with an average of 16.2% (standard deviation 3.10%). Trend lines show a downward slope (not much for CBIW), indicating declining trends. In all other cases, the average is well representative of the sample, as depicted by the standard deviation (ranging from 0.59% to 1.23%). The average car (standard deviation) for Bahrain is 18.7% (1.23%), Kuwait 17.80% (0.75%), Qatar 18.0% (0.59%), KSA 20.1% (1.03%), and UAE 17.1% (1.06%). Data for KSA CBIW are not reported in the selected database. The average CAR ranging from 16.2% to 28.8% (higher than the minimum Basel requirement of 8.0%) indicates the financial strength of the IBSI in the GCC region. The equality of means test indicates the differences in the average CAR among various GCC markets, as depicted by standard ANOVA (8.5) and Welch adjusted ANOVA (30.1) statistics with low probability values (close to 0.00) (Table 3).

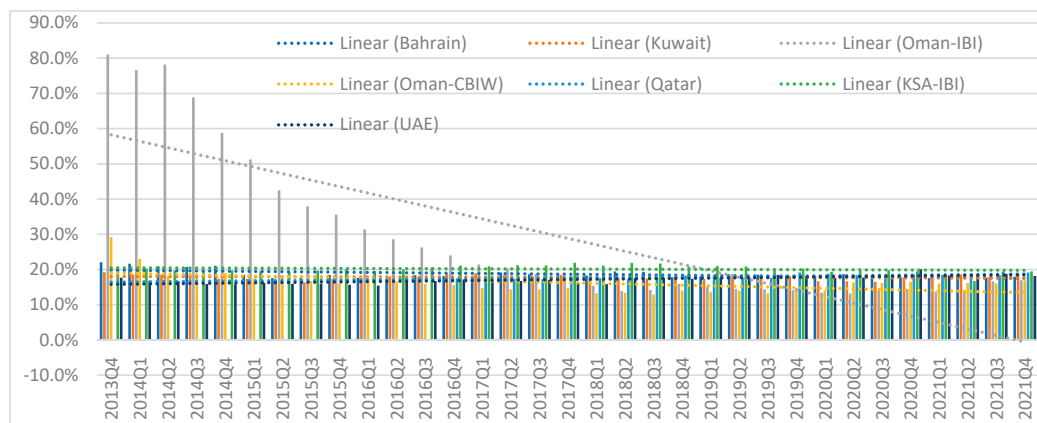


Figure 4. GCC-IBSI capital adequacy ratio (CAR) for 33 quarters (2013Q1–2021Q4). Source: Constructed by the author; data (IFSB 2022).

Table 3. Test for Equality of Means Between Series.

CAR				NPF			CIR			LAR			ROE		
Method	df	Value	Prob	df	Value	Prob	df	Value	Prob	df	Value	Prob	df	Value	Prob
ANOVA	(6, 212)	8.53	0.00	(6, 212)	412	0.00	(6, 212)	28.55	0.00	(6, 212)	42.64	0.00	(6, 212)	46.01	0.00
F-test															
Welch	(6, 92.6)	30.12	0.00	(6, 83.3)	240	0.00	(6, 90.2)	1347	0.00	(6, 86.8)	249.4	0.00	(6, 88.7)	48.09	0.00
F-test *															
Analysis of Var															
Source of Var	df	Sum of Sq.	Mean Sq.	df	Sum of Sq.	Mean Sq.	df	Sum of Sq.	Mean Sq.	df	Sum of Sq.	Mean Sq.	df	Sum of Sq.	Mean Sq.
Between	6	0.358	0.059	6	0.294	0.049	6	18.65	3.108	6	1.007	0.16	6	0.472	0.07
Within	212	1.486	0.007	212	0.025	0.000	212	23.08	0.108	212	0.834	0.00	212	0.363	0.00
Total	218	1.845	0.008	218	0.320	0.001	218	41.73	0.191	218	1.842	0.00	218	0.835	0.00

* Test allows for unequal cell variances. Source: Constructed by the author; data (IFSB 2022).

Non-performing Finance (NPF): Non-performing loans are measured as gross non-performing finance divided by total financing, which measures the credit risk and the company's efficiency in collecting receivables. A lower NPF is an indication of low credit risk and vice versa. As per the results (Figure 5 and Table 2), improvement is depicted in reducing non-performing finance by three countries, namely Bahrain, UAE, and Kuwait. The highest average (11.0%) for the sample period is displayed by Bahrain, followed by UAE (6.3%) and Kuwait (2.5%). Notably, all these countries with higher average non-performing finance have shown significant improvement; for example, in the last quarter, 2021Q4,

NPFs were 6.4% and 1.5% for Bahrain and Kuwait, respectively. Likewise, trend lines indicate a downward slope for Bahrain, Kuwait, and UAE. The average highest NPF for other countries is 1.4% (KSA CBIW), and the average lowest is 0.7% (Oman IBSI). As for the reliability of the average, as a representation of the sample data is concerned, the coefficient of variation (standard deviation/average) is calculated. The highest variation is documented for Oman (IBI 1.31, CBIW 0.88), followed by KSA (IBI 0.14, CBIW 0.40), Kuwait (0.32), Qatar (0.31), Bahrain (0.20), and UAE (0.17). Gross NPFs are below 2% in the last quarter for the sample except for Bahrain (6.4%), UAE (7.1%), and Oman (2.3%), which demands the attention of industry leaders. Also, Oman IBSI, KSA CBIW, and Qatar trend lines show a slightly upward movement. The equality of means test indicates the differences in average NPF among various GCC markets, as depicted by standard ANOVA (412) and Welch-adjusted ANOVA (240) statistics with low probability values (close to 0.00) (Table 3).

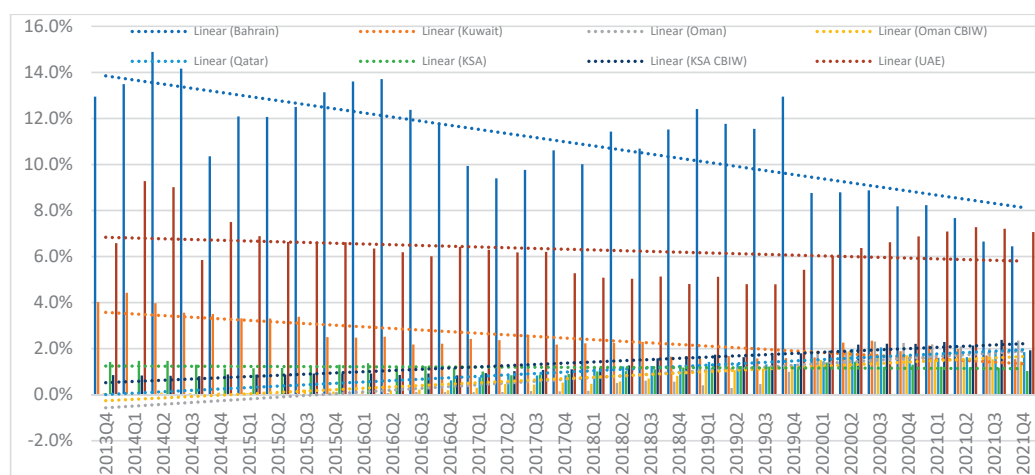


Figure 5. GCC-IBSI non-performing finance (NPF) ratio for 33 quarters (2013Q1–2021Q4). Source: Constructed by the author; data (IFSB 2022).

Cost-to-Income Ratio (CIR): The cost-to-income ratio (CIR) is calculated as operating costs/gross income, aimed at measuring the operating efficiency. A low CIR positively contributes to the generation of healthy ROE and efficient operation of the organization. Comparative results for the GCC-IBSI during the review period are reported in Figure 6 and Table 2. The average CIR is the highest for Oman IBI (115.7%), followed by Bahrain (71.4%) and UAE (50.7%). Notably, trend lines are downward for both countries (Oman and Bahrain), indicating improvement. All other CIRs are below 50.0%, ranging from 49.9% (KSA IBI), 47.3% (Oman CBIW), 39.8% (KSA CBIW), 32.5% (Kuwait—downward trend), to 13.3% (Qatar). CIR trend lines indicate Bahrain downward, Kuwait slightly downward, and Oman IBI significantly downward, while almost straight for Oman CBIW, Qatar, KSA IBI, KSA CBIW, and UAE. The highest coefficient of variation is documented for Oman IBI (0.68), followed by Bahrain (0.43), Kuwait (0.26), KSA CBIW (0.14), Oman CBIW (0.12), KSA IBI (0.10), Qatar (0.06), and UAE (0.05). CV results indicate a good representation of the average of the sample period. While the Qatar IBSI has depicted outstanding performance in cost control, the Oman (IBI) and Bahrain IBSIs need significant attention from decision-makers in cost control. It is encouraging to note that for both Oman and Bahrain, trend lines are downward, indicating that improvement is in progress (e.g., as of 2021Q4, the CIR is 58.5% for Oman IBI and 51.6% for Bahrain). The equality of means test indicates the differences in the average CIR among various GCC markets, as depicted by standard ANOVA (28.55) and Welch adjusted ANOVA (1347) statistics with low probability values (close to 0.00) (Table 3).

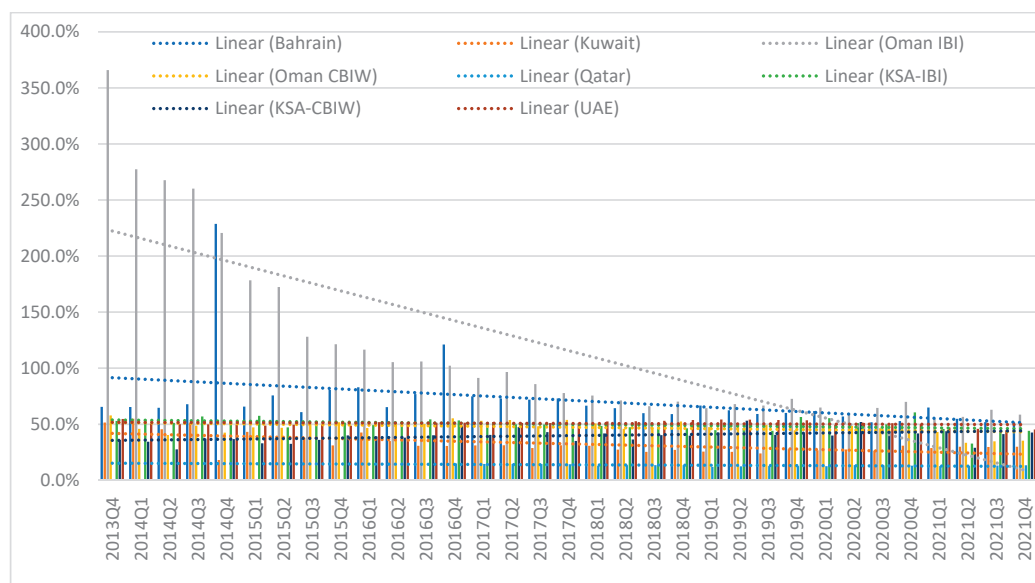


Figure 6. GCC-IBSI cost-to-income ratio (CIR) for 33 quarters (2013Q1–2021Q4). Source: Constructed by the author; data (IFSB 2022).

Return on Equity (ROE): Return on equity is calculated as net income divided by equity, a significant measure of profitability and net returns as a percentage of capital that the business generates for owners. Results for the GCC-IBSI in ROE are presented in Figure 7 and Table 2. Data for KSA CBIW are not reported, while data for Qatar 2016Q4 onward are reported. The average return on equity is the highest for KSA (15.9%), followed by UAE, Qatar, and Kuwait (11.3%, 11.0%, and 11.0%, respectively). The Oman CBIW depicted an average ROE of 8.7%, while Bahrain had 8.0%; the lowest average ROE remained for the Oman IBSI (−0.1%). The coefficient of variations is under 0.5, except for Bahrain at 0.81 and Oman’s IBI at 39.34. Trend lines for Bahrain, UAE, and Oman CBIW are downward; those for KSA and Kuwait are upward; that of the Oman IBI is negative to positive; and that of Qatar is almost straight. The GCC-IBSI has performed well regarding survival goals by depicting positive ROE, except the Oman IBSI, although it has shown progress in recent quarters. Four of the six markets have shown an average ROE in double digits despite the COVID-19 crisis. All ROEs are positive as of 2021Q4, ranging from 6.0% to 19.4%. The KSA IBSI has proven to be a high achiever, while the Oman IBSI needs to improve profitability to remain competitive in the long term. The equality of means test indicates the differences in the average ROE among various GCC markets, as depicted by standard ANOVA (46.01) and Welch adjusted ANOVA (48.09) statistics with low probability values (close to 0.00) (Table 3).

Liquid Asset Ratio (LAR): The liquid asset ratio is calculated by dividing liquid assets by total assets, aimed at measuring the ability of a banking institution to meet its obligations as and when due. Results on the liquidity position of the GCC-IBSI for the sample period (2013Q4 to 2021Q4) are presented in Figure 8 and Table 2. In the case of KSA CBIWs, no data are available, and IBI data are from 2015Q1 onward, while the Qatar data are from 2016Q4 onward. Trend lines indicate a significant decrease for the Qatar and Oman IBIs while a slight decrease for the Kuwait and Oman CBIWs. In the case of Bahrain and UAE, trend lines are almost straight, while the trend line is upward for the KSA IBIs. Kuwait leads in the average LAR (31.1%), followed by KSA (28.0%), Qatar (26.2%), Bahrain (17.2%), the Oman IBIs (15.4%), UAE (15.3%), and the Oman CBIWs (13.2%). Closing figures (2021Q4) for Qatar, Oman IBIs, Oman CBIWs, and Kuwait are 20.8%, 10.2%, 14.5%, and 26.8%, respectively. Liquidity maintenance needs attention in the Oman IBIs. The highest variation is depicted by CV for the Oman IBIs (0.89), Qatar (0.33), the Oman CBIWs (0.22), the KSA IBIs (0.12), Bahrain (0.10), UAE, and Kuwait (0.08), respectively. The average represents the sample well, except for Oman and Qatar. The equality of means test indicates

the differences in the average LAR among various GCC markets, as depicted by standard ANOVA (42.64) and Welch adjusted ANOVA (249.4) statistics with low probability values (close to 0.00) (Table 3).

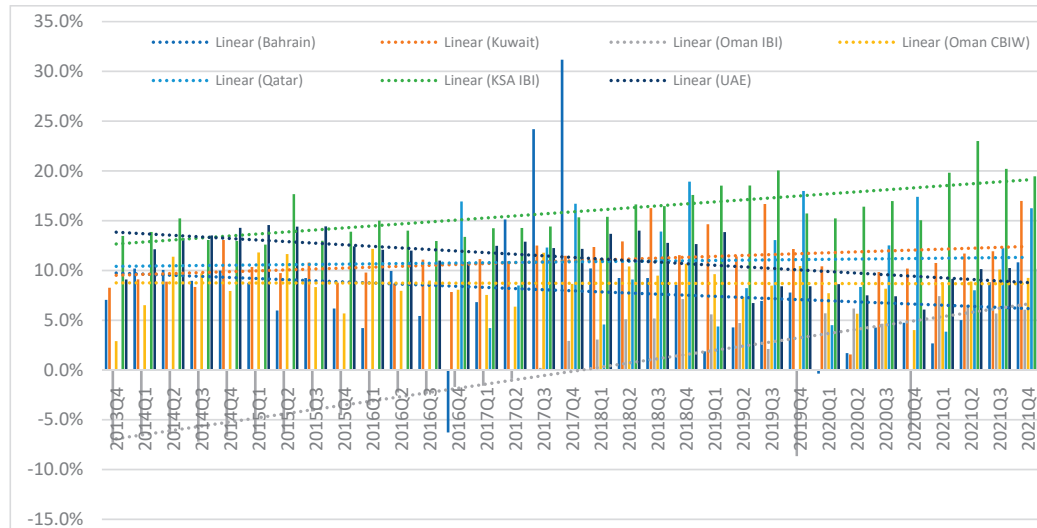


Figure 7. GCC-IBSI return on equity (ROE) for 33 quarters (2013Q1–2021Q4). Source: Constructed by the author; data (IFSB 2022).

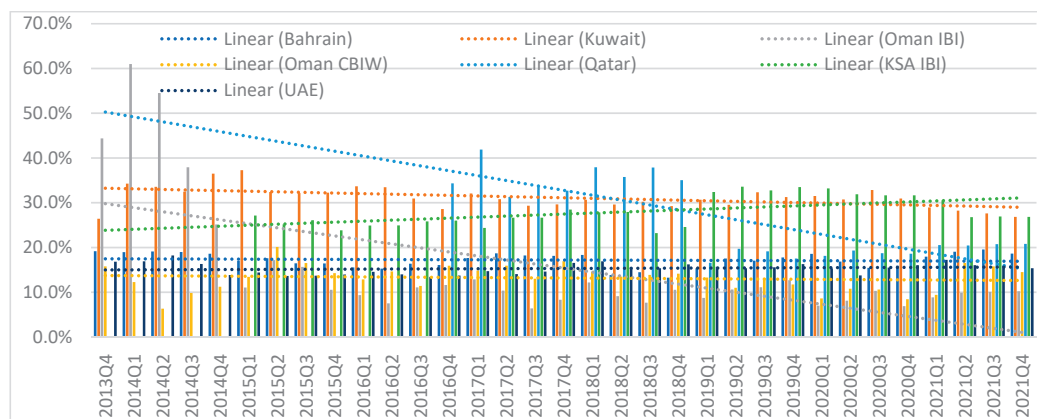


Figure 8. GCC-IBSI liquid asset ratio (LAR) for 33 quarters (2013Q1–2021Q4). Source: Constructed by the author; data (IFSB 2022).

The second phase of analysis consists of determining cause and effect through regression. Which of the internal variables are significant contributors to the financial performance (measured as ROE) of the Islamic banking industry in the GCC region? Certain pre-tests on data are required to run the regression model, including correlation among independent variables and checking for unit roots.

Correlations: The results of the correlations are presented in Table 4. Accordingly, the CAR and the CIR (both independent variables) are highly correlated (81%) and cannot be used in a single regression model. Hence, we have to delete one of them for any regression estimation. In the case of the dependent variable (ROE), two variables (CAR and CIR) depict a negative relationship, while others (NPF and LAR) show a positive relationship. These results indicate that there exist relationships between independent and dependent variables to be confirmed by formal testing through regression equations.

Table 4. Correlation GCC Markets (CAMEL Ratios 2013Q4 to 2021Q4).

	CAR	CIR	DNPF	LAR	ROE
CAR	1.0000				
CIR	0.811	1.0000			
DNPF	−0.009	−0.128	1.0000		
LAR	0.370	0.0058	−0.0462	1.0000	
ROE	−0.431	−0.569	0.0314	0.2569	1.0000

Source: Constructed by the author; data (IFSB 2022).

Stationarity Test: Testing for the unit root is an essential requirement of a regression model. The results are presented in Table 5. Accordingly, all series are stationary at level, except for non-performing finance. NPF is stationary at the first difference; hence, we created D-NPF. Comparative results using ADF and PP unit root tests are calculated. Results are similar under both types of tests.

Table 5. Stationarity Tests.

Variables	ADF-Fisher Chi-Square	Probability *	PP-Fisher Chi-Square	Probability *	Result
CAR	32.8906	0.0030	65.9934	0.0000	I/Level
D-NPF	93.6848	0.0000	136.706	0.0000	I/1
CIR	40.7899	0.0002	80.8968	0.0000	I/Level
ROE	49.2176	0.0000	73.9904	0.0000	I/Level
LAR	48.2465	0.0000	34.4254	0.0018	I/Level

Panel unit root test; Sample: 2013Q4–2021Q4; Exogenous variables: individual effects; user-specified lags: 1. Newey-West automatic bandwidth selection and Bartlett kernel; * Probabilities for Fisher tests are computed using an asymptotic chi-square distribution. Source: Constructed by the author; data (IFSB 2022).

Regression Analysis: Given the high correlation between CAR and CIR, the research estimates two equations by eliminating one variable in each model. Also, due to the higher order of integration, a differenced series (D-NPF) is used in the estimation of regression equations for the NPF series. Furthermore, we rely on the Hausman test to choose between random and fixed effects for panel data regression (Table 6). Results of Hausman tests support the choice of random effect (based on probability values) for both regression equations. The results of the regression analysis are presented in Table 7. Some interesting results emerged through regression estimates. Under both regression models, the adjusted R square is low; likewise, the significant constant (might) indicates that some variables other than the selected explain variations in the ROE. Both the CAR and the CIR carry significant negative coefficients, confirming the hypothesis that higher costs and higher equity contribute to a reduction in the ROE. Surprisingly, non-performance finance is insignificant but has a positive relationship. In model 1, the coefficient is larger (0.47). Finally, liquidity positively contributes to the ROE but is significant under Model 1.

Table 6. Hausman Test—Cross-Section Random Effects.

Test Summary	Chi-Sq. Statistic	Chi-Sq. df	Prob.
Cross-section random with CAR	3.216114	3	0.3595
Cross-section random with CIR	0.967422	3	0.8091

Source: Constructed by the author; data (IFSB 2022).

Table 7. Regression Analysis.

Model-1	Adj. R Square	F Stat	D.W Stat	Constant C	CAR	DNPF	LAR
Coefficients	0.1391	12.36	1.217	0.120	−0.265	0.471	0.122
<i>p</i> Values		0.0000		0.000	0.000	0.270	0.044
T Stat				7.08	−5.46	1.10	2.02
Model-2	Adj. R Square	F Stat	D.W Stat	Constant C	CIR	DNPF	LAR
Coefficients	0.1321	11.70	1.216	0.112	−0.064	0.018	0.079
<i>p</i> Values		0.000		0.000	0.000	0.966	0.168
T Stat				6.047	−5.210	0.042	1.381

Method: Panel EGLS (cross-section random effects). Source: Constructed by the author; data (IFSB 2022).

Variance Decomposition: Finally, we decomposed the variance, and the results are presented in Table 8. According to the results, much of the variation in the ROE is internal. Variations of around 4% in period 1 and around 17% in period 10 are explained by other selected variables, with liquidity accounting for a major share, followed by cost to income variable.

Table 8. Variance Decomposition of ROE.

Period	S.E.	CAR	CIR	DNPF	LAR	ROE
1	0.038	0.072 (0.703)	2.381 (2.389)	0.047 (0.760)	1.106 (1.449)	96.390 (2.974)
4	0.049	0.763 (1.091)	3.814 (2.966)	0.670 (1.463)	4.714 (3.220)	90.037 (4.317)
7	0.050	1.708 (1.496)	4.478 (3.267)	0.735 (1.494)	7.548 (4.378)	85.529 (5.186)
10	0.051	2.460 (1.783)	4.667 (3.326)	0.748 (1.480)	8.887 (4.960)	83.234 (5.734)

Source: Constructed by the author; data (IFSB 2022).

5. Concluding Remarks

This study documents the commercial performance (which is the primary objective and essential for the survival) of the IBSI in the leading markets of the GCC region using quarterly published financial data for 2013Q4–21Q4. The findings show an overall encouraging picture of the industry based on achievements in the areas of capital adequacy, asset quality, management capabilities, earnings, and liquidity during the review period. The average LAR is above 13%, and the average CAR is above 16%, indicating the solvency of the IBSI in the GCC region. The KSA IBSI leads in the ROE, followed by UAE, Qatar, and Kuwait, respectively. Also, Qatar leads in cost control, followed by Kuwait and KSA; however, the CIR is higher for Oman and Bahrain. The average non-performing loans ratio is higher for Bahrain and UAE. Equality of means tests suggest that averages of the CAR, NPF, CIR, ROE, and LAR in selected markets are not similar. Regression results show that cost control and liquidity management significantly contribute to equity returns. The decomposition of variance suggests that much of the variations in the ROE are internal, and other selected factors cause a small variation.

Managerial implications include focusing on cost reduction, non-performing loans, and prudent liquidity management by respective managers in multiple GCC markets. A special managerial focus on the ROE is needed in the Oman IBSI, while due attention to non-performing loans is needed in Bahrain and UAE markets. None of the GCC markets is offering 100% Islamic banking. Shares of Islamic banking as a percentage of domestic banking assets are as follows: Saudi Arabia (77%), Kuwait (52%), Qatar (28%), UAE (24%), Bahrain (21%), and Oman (15%) (IFSB 2022). There are opportunities to expand and reach millions of unserved/underserved residents. The GCC Islamic banking industry offers

promising returns with financial strength for investors interested in halal earnings. Given the similarity of the IFSI's objectives with SDGs, the Islamic financial system is expected to positively contribute to achieving SDGs.

This study's limitations include the consideration of external factors (macroeconomic) as determinants of financial performance in the GCC-IBSI. Also, the contribution of oil revenues to the expansion and growth of the IBSI in the region is an exciting research topic. The future research agenda includes examinations in these areas.

Funding: This research received no external funding. The Article Processing Charge (APC) was funded by Ajman University.

Data Availability Statement: Public Source IFSB.

Conflicts of Interest: The author declares no conflict of interest.

Notes

- ¹ Data for domestic branches not available for Bahrain.
- ² Data for staff are not available for Kuwait and Bahrain.
- ³ Data for Qatar and Bahrain 2016Q4 and 2018Q1 onward, respectively.

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Article

Financial Contagion between German and BRICS Stock Markets under Multiscale Scrutiny

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Abstract: We employ wavelet analysis using the maximum overlap discrete wavelet transform (MODWT) to examine the return and volatility interconnectedness between the German equity market (a prominent representative of the Eurozone market) and the BRICS countries over the period 2005–2017. Specifically, we investigate the presence of the pure form of financial contagion in the stock markets of Brazil, Russia, India, China, and South Africa subsequent to the Eurozone Sovereign Debt Crisis (EZDC). Our results indicate the presence of financial contagion between the Eurozone equity market and its counterparts in South Africa and Russia, characterised by co-movement and volatility spillover effects. This contagion is particularly evident at higher frequencies, suggesting that the transmission of shocks occurs rapidly across these markets in the short term. No financial contagion is observed in the Brazilian, Chinese, and Indian stock markets during the European Sovereign Debt Crisis. The absence of financial contagion observed in these three BRICS countries during the European Sovereign Debt Crisis suggests that policymakers in these countries should prioritise addressing idiosyncratic shock channels.

Keywords: BRICS equity markets; Eurozone Sovereign Debt Crisis; financial contagion; German equity market; subprime crisis; wavelet analysis

1. Introduction

The 1990s will be remembered as a decade marked by multiple financial crises in the developing world. Latin America was the first to be affected, beginning with the 1994 crisis of the Mexican Peso, which subsequently spread to other emerging economies (Herman and Klemm 2019). This Peso crisis was followed by a series of new currency crises that spread across emerging markets in Europe, East Asia, and Southeast Asia. Initially, this propagation received limited attention, as the crises were blamed on poor domestic policies in each affected economy. It was not until the outbreak of more severe crises, such as the 1997 “Asian flu”, the 1998 “Russian cold”, and the 1999 “Brazilian fever”, that academics and financial analysts began to systematically scrutinise their propagation from country to country (Kaminsky and Reinhart 2000). This propagation—if it cannot be explained by economic fundamentals alone—is referred to as financial contagion. Related to financial contagion is the notion of systemic risk.

In the current study, we investigate the pure form of contagion resulting from shocks originating in the German equity market and their transmission to the stock markets of the original BRICS economic bloc members: Brazil, Russia, India, China, and South Africa in the wake of the E Eurozone Sovereign Debt Crisis (EZDC). Pure contagion refers to the transmission of shocks due to reasons that are unrelated to macroeconomic fundamentals, arising solely from irrational phenomena, such as panics, herd behaviour, loss of confidence, and risk aversion.

There are still disagreements among academics regarding the precise definition of contagion and its applicability in instances where two economies share similar macroeconomic fundamentals and direct linkages. The 2008–2009 Global Financial Crisis and the EZDC of 2009–2012 triggered extensive research on financial contagion, with studies revealing evidence of contagion effects across regional stock markets and non-financial assets. Research soon uncovered that the most vulnerable sectors were in emerging Asian and European regions, while developed regions and some sectors across all regions were less affected.

The choice of the original members of the BRICS bloc for this study is based on two factors: first, their geographic diversity, providing a global perspective on contagion transmission; second, their strong partnerships within the BRICS association. As the BRICS expand and their market power grows relative to the G7, understanding their interconnectedness becomes crucial for predicting how future dynamics in developed markets may affect the financial performance of BRICS+ markets and emerging markets in general. Studies have shown that emerging markets are more vulnerable to financial contagion due to factors such as weaker financial institutions, greater reliance on capital inflows, and less developed regulatory frameworks. Given that BRICS countries are predominantly emerging markets, they are more likely to be affected by contagion events originating in developed markets (Kaminsky and Reinhart 2000; Ozkan and Unsal 2012; Gelos and Surti 2016; Ruch 2020).

The choice of Germany as the source (ground zero) market for the analysis of Eurozone financial contagion was motivated by its relatively strong trade and investment connections to BRICS countries. Furthermore, Germany's economy constitutes nearly one-third of the Eurozone's total value (Fröhlich 2021), making the DAX, the German stock market index, a significant barometer of the Eurozone's overall financial health.

Previous studies, such as Ahmad et al. (2013), have also analysed the financial contagion between some fragile economies of the Eurozone and the BRIICKS (i.e., the traditional BRICS countries plus Indonesia and South Korea) by focusing on dynamic conditional correlations (DCC-GARCH) to probe changes in time-varying market correlations. Sizeable increases in cross-market correlations during crises are seen as the main signal of contagion (Dooley and Hutchison 2009; Syllignakis and Kouretas 2011; Yiu et al. 2010). Ahmad et al.'s (2013) multivariate DCC-GARCH results indicated that among the Eurozone economies affected by the debt crisis, Ireland, Italy, and Spain appeared to be most contagious to BRIICKS markets, with South African, Russian, and Brazilian stocks being the most adversely affected.

In a more recent exploration of contagion through financial and non-financial firms during the COVID-19 pandemic, Akhtaruzzaman et al. (2021) also used DCC-GARCH to analyse the heightened cross-correlation between China and G7 markets. Likewise, Nguyen et al. (2022) used the DCC-EGARCH model to study the financial contagion from the US, Chinese, and Japanese markets to emerging Asian markets and found strong contagion during the Global Financial Crisis, but only 3 out of 10 emerging Asian markets were found exposed during the COVID-19 crisis. Similarly, Gunay and Can (2022) applied the same methodology to analyse the financial contagion and identified the US as the leading source of the financial distress, even though the disease itself started in China. Chevallier (2020) used the same methodological approach to document the COVID-19 contagion on financial markets, while Benkraiem et al. (2022) used the copula approach as a more robust method to capture non-linear dependencies and the intensity of the contagion. Bhar and Nikolova (2009), Ganguly and Bhunia (2022), and Kaminsky and Reinhart (2000) analysed the within-BRICS financial market connectedness and the interconnectedness between individual BRICS markets and developed markets. Most of these studies have mainly relied on traditional econometrics tools of time-series modelling, ranging from ARDL to EGARCH.

Among studies using non-traditional econometric analysis to study contagion in BRICS countries, Batondo and Uwilingiye (2022), Gurdgiev and O'Riordan (2021), and

Kannadhasan and Das (2019) used wavelet analysis to detect co-movement at different frequencies. However, all these studies exclusively employed the continuous wavelet transform (CWT) technique, which presents predictive efficiency limitations in the presence of stationary data (Torrence and Compo 1998).

While CWT is renowned for its high frequency and time resolution, making it particularly effective for capturing fine-grained details and localised changes in non-stationary financial data, dealing with stationary data requires a more robust tool. That is why the current study adopts the maximum overlap discrete wavelet transform (MODWT) analysis (a technique pioneered by Percival and Walden (2006)) as a more fine-grained tool to examine the contagion. Because of its ability to denoise the time series and provide accurate information on the frequencies at different timescales, the MODWT analysis can be thus expected to more efficiently detect localised signs of contagion after removing the variations due to noise (Kouzehgar and Eslamian 2023).

MODWT offers several advantages that make it more suitable for our analysis. Firstly, MODWT is particularly well suited for analysing stationary or weakly non-stationary signals, as it prioritises precise time localisation of signal components while balancing frequency resolution and time localisation (Abramovich et al. 1998). In our study, the data stationarity was confirmed through a series of stationarity tests¹ after performing a log transformation. This confirmation further justifies the selection of MODWT over CWT, as CWT is typically more suited to non-stationary data.

Secondly, MODWT offers several other advantages, including enhanced time–frequency resolution, localised interconnectedness, multiscale analysis, the capture of non-linear dependencies, and its robustness to volatility clustering. It also provides an improved computational efficiency and better statistical properties (Ahmad et al. 2013). Put together, all these properties enable a more accurate analysis of transient phenomena and facilitate the extraction of meaningful information for studying financial contagion dynamics. These advantages make MODWT a more appropriate choice for the stationary nature of our data. Additionally, MODWT’s ability to offer greater interpretability and computational efficiency further supports its use in this context.

We, therefore, contribute to the literature on financial contagion by showing not just the existence of an increase in cross-market correlations, but also by analysing both the direction and the intensity of denoised contagion signals at multiple timescales between the stock market of the largest Eurozone economy, Germany, and each of the BRICS markets.

Our main findings indicate signs of financial contagion of the EZDC to the South African and Russian markets. No evidence of similar signs of financial contagion based on heightened short time–frequency similarity was observed for the Brazilian, Chinese, and Indian markets. This resilience may be attributed to domestic economic fundamentals and/or effective policy measures taken to insulate these economies from the crisis.

The remaining sections are structured as follows: Section 2 presents a comprehensive survey of literature on the spillover effects of developed stock markets on emerging markets, and BRICS countries in particular. Section 3 details the methodology employed in this study. Section 4 reports our empirical findings, interpreting the results within the context of existing literature and our research objectives. Section 5 summarises the key findings and concludes the study.

2. Literature Review

In this section, we begin by surveying the literature on various perspectives of financial contagion. We then examine the literature that analyses financial contagion during financial crises originating from developed countries. Next, we focus on the literature related to financial contagion in emerging markets, with particular emphasis on BRICS countries. Lastly, we review some recent empirical studies that utilise wavelet analysis to investigate financial contagion.

2.1. Different Perspectives on Financial Contagion

Financial contagion is characterised by a statistically significant intensification of cross-market correlations following an exogenous shock, beyond what can be explained by fundamental economic linkages. The term contagion started to gain popularity in financial and international economics literature in the wake of the “Asian Flu”, the financial crisis that engulfed Thailand in 1997. The crisis quickly spread through East Asia and later reached Russia and Brazil. Before this crisis, the term “contagion” usually referred to the spread of infectious diseases (Claessens and Forbes 2013). Claessens and Forbes (2013) drew a parallel between financial crisis transmission and epidemiological contagion, noting that both phenomena involve the propagation of adverse effects through direct and indirect channels.

Over the years, the term contagion has gone through a gradual refinement and measurement process. Even though contagions have been documented in various papers, there remains a lack of consensus in the literature regarding the precise definition and measurement of contagion. The definition of contagion provided by Rigobon (2002, p. 3) as “a significant increase in cross-market linkage after a shock to one country or group of countries” has gained widespread popularity. However, it is not universally accepted and is considered narrow by some scholars (Ranta 2010). Closely related to the concept of market contagion is the measure of systemic risk, which gauges changes in tail co-movement to identify the heightened risk for the spreading of financial distress across institutions (Adrian and Brunnermeier 2011). Consequently, the measures of systemic risk, such as the CoVaR proposed by Adrian and Brunnermeier (2011), are at the same time indicators of contagion potential.

2.2. Financial Contagion during Financial Crises

The aftermath of the 2008–2009 Global Financial Crisis (GFC) and the Eurozone Debt Crisis (EZDC) of 2009–2012 spurred significant research on financial contagion. Adrian and Brunnermeier (2011) were among the first to develop contagion indicators, providing valuable tools to measure the risk of contagion in financial markets. Their work highlighted the systemic risks posed by financial institutions during crises, offering a theoretical and empirical basis for understanding contagion dynamics.

Kenourgios and Dimitriou (2015) analysed the contagion effects of the 2008–2009 crisis across ten sectors in six developed and emerging regions, finding evidence of contagion across various regional stock markets, with notable resilience in sectors such as consumer goods, healthcare, and technology in developed Pacific regions. Ahmad et al. (2013) examined how markets in Greece, Ireland, Portugal, Spain, Italy, the USA, the UK, and Japan influenced stock markets in BRIICKS countries (Brazil, Russia, India, Indonesia, China, South Korea, and South Africa) during the EZDC. They observed that Ireland, Italy, and Spain had the highest contagion impact on BRIICKS markets, compared to Greece. Additionally, Brazil, India, Russia, China, and South Africa experienced significant contagion shocks during this period, whereas Indonesia and South Korea showed only interdependence, without contagion effects.

Ahmad et al. (2013) examined the impact of various Eurozone countries on BRICS stock markets during the EZDC, finding significant contagion effects in Brazil, India, Russia, China, and South Africa. Their methodological approach used a bivariate dynamic cross-correlation GARCH model. By contrast, our analysis employs wavelet analysis to exploit its property as a quite sensitive tool to detect contagion direction and intensity. This approach allows for a more detailed examination of the time–frequency characteristics of contagion, revealing short-term transmission effects that may not have been captured by traditional methods.

2.3. Within-BRICS and BRICS-Developed Market Interconnectedness

Emerging markets have borne the brunt of contagion to the greatest extent. Kaminsky and Reinhart (2000) identified three crucial components, termed the “unholy trinity”, that

render emerging markets susceptible to contagion: (i) a sudden reversal in capital inflow, (ii) an unforeseen announcement, and (iii) a leveraged common creditor. Concerning the reversal in capital inflow, Kaminsky and Reinhart (2000) noted that before financial contagion, markets prone to crises witness a surge in international capital inflow, but subsequent to the initial shock, these affected economies encounter an abrupt cessation in capital inflow. Elaborating on surprise announcements, they highlighted that contagion could be explained by an unexpected announcement that triggers a domino effect that consistently catches the financial market off guard. Addressing the role of a common creditor, Kaminsky and Reinhart (2000) emphasised that a leveraged common creditor is often involved, as seen with American banks during crises in Latin America or Japanese banks during crises in (then) emerging Asian economies.

Multiple studies have investigated the interconnectedness of BRICS countries, leading to the identification of two distinct lines of research. The first strand primarily delves into the within-group connectedness of BRICS equity markets. Notably, Kumar et al. (2023) examined the volatility of currency and equity markets during the COVID-19 pandemic and the Russia–Ukraine conflict. His research confirmed the presence of cross-border contagion effects among BRICS member nations, with significant volatility spillover across markets. Kumar et al. (2023) also observed that during the Ukraine conflict, Russian influence notably intensified, while increased spillover was observed among other countries during the pandemic and the conflict. Similarly, Ganguly and Bhunia (2022) utilised GARCH models and ARDL techniques, uncovering a leverage effect unique to the Indian stock market. They identified enduring connections between the Russian and Chinese markets, along with significant linkages between the Indian market and South Africa. Additionally, their ARDL analysis highlighted transient interdependencies extending from the Brazilian market to several others, including links from India to Brazil and South Africa, and from South Africa back to India and Brazil, and from the South African stock market to the Indian stock market.

The second strand of research focuses on the interconnectedness of BRICS equity markets with developed markets. Collectively, the findings of these studies indicate a certain degree of integration between the equity markets of BRICS countries and other developed markets. Sehgal et al. (2019) utilised the ADCC-EGARCH model and a block aggregation technique, revealing moderate cohesion within BRICS equity markets and increased integration during the Global Financial Crisis. Similarly, Bhar and Nikolova (2009), employing the bivariate EGARCH framework, identified varying levels of integration and a negative relationship between India's volatility and that of the Asia-Pacific region, suggesting potential diversification opportunities.

2.4. Using Wavelet Analysis to Model Contagion

Wavelet transform is used to decompose a time series into component series associated with different timescales. Because financial time-series data are observed and collected at regular intervals (discrete points in time), discrete wavelet transform (DWT) is typically employed for scale decomposition (Böckelman 2020). However, depending on the signal's nature, continuous wavelet transform (CWT) might also be used. As a variant of the DWT, the maximum overlap discrete wavelet transform (MODWT) has several advantages over the DWT due to the following features: (i) MODWT can be applied to any sample size, (ii) the characteristics in the original time series are effectively preserved within the multi-resolution analysis, (iii) MODWT is shift-invariant, meaning that an integer shift in the time series results in corresponding shifts in the wavelet and scaling coefficients, and (iv) MODWT provides asymptotically more efficient estimators for wavelet variance (Percival 1995).

Numerous studies have employed wavelet analysis to explore financial contagion within emerging markets. For instance, Kannadhasan and Das (2019) analysed alterations in co-movement dynamics between BRICS countries' stock market returns and those of the United States, both prior to and following the Global Financial Crisis (GFC). Their study

used different wavelet transform techniques for estimating wavelet coherence, wavelet correlation, and wavelet multiple correlation. Continuous wavelet transform (CWT) was used for wavelet coherence, while MODWT was used for wavelet correlation and wavelet multiple correlation. The choice of CWT for wavelet coherence can be attributed to its strength in localised time–frequency analysis, while MODWT is chosen for wavelet correlation and multiple correlation because of its effective handling of boundary issues and robust multiscale analysis capabilities. Kannadhasan and Das (2019) found co-movement at high and low frequencies, with contagion effects detected around the 2008 GFC. In a separate study, Batondo and Uwilingiye (2022) examined co-movement across the BRICS and US stock markets, pinpointing specific periods, such as before the US housing bubble and after the EZDC, where certain shocks triggered pure contagion. Gurdgiev and O’Riordan (2021) investigated cross-contagion between advanced economies and BRICS markets, uncovering bidirectional spillover effects. They concluded that arbitrage opportunities persist in the international equity market vis-à-vis BRICS assets.

2.5. Synopsis

As evidenced in the literature provided above, even though there are various perspectives on the nature and properties of contagion, this phenomenon has been widely covered by research, especially following the COVID-19 crisis. The wavelet approach has been one of the most robust methods used to analyse contagion, and we build on this approach by applying a different type of wavelet analysis in the present study.

3. Data and Methodology

This section provides an overview of the econometric models and data used to study the presence of the pure form financial contagion in the BRICS stock market in the aftermath of the EZDC. The analysis focuses on examining the relationships between the pairwise stock indices of the source market or “ground zero” (Eurozone) and the target market (BRICS).

In this study, the MODWT was utilised to decompose the time-series data of each market into different frequency scales. This approach facilitates the separation of the time series into high- and low-frequency components. To assess the level of similarity or dissimilarity between the frequency components of each market, wavelet correlation was computed. Additionally, wavelet cross-correlation was estimated between the time series of each market pair to identify the degree of association between their frequency components, thereby helping to identify lead–lag relationships between the signals. The presence of financial contagion will be determined based on the presence of high correlation (between the source market and the target market) at lower scales, indicating a shorter time horizon.

3.1. Wavelet Models

The use of wavelet models provides considerable advantages in the analysis of contagion compared to traditional econometric tools. Indeed, wavelet analysis enables a finer decomposition of time-series dynamics to reveal its basic components, much as the Fourier transform shows the constituent frequencies of complex waves, but it also enables to identify the position of a given frequency in time and space (Wilks 2020). By showing similarities between frequencies of wavelets over identifiable portions of the time series, wavelet analysis makes it easier to identify connections between time series or phenomena characterised by similar frequencies. The temporal dynamics of relationships among variables in financial markets can exhibit substantial variation across different timescales. Yet, traditional econometric models typically concentrate on a dual-scale examination—specifically, short-run and long-run dynamics—largely due to inadequate empirical tools. Recently, wavelet analysis has emerged as a notable approach in economics and finance to overcome this limitation (In and Kim 2013). Wavelet analysis offers a more comprehensive and nuanced approach to analysing financial contagion by making use of time-series data decomposed into different frequency components to generate a more precise analysis of

the time-varying nature of financial markets. Additionally, wavelet analysis can handle non-stationary data, which is typical in financial markets. Wavelet analysis also enables multiscale analysis, meaning that it can identify contagion and interdependence patterns at different levels of granularity. Furthermore, wavelet cross-correlation analysis can identify lead–lag relationships between different markets, which can help in identifying the direction of contagion. Overall, wavelet analysis offers a significant improvement over traditional methods that assume stationarity and ignore the time-varying nature of financial data (Hashim and Masih 2015).

Wavelet analysis involves projecting an initial series onto a set of fundamental functions, called wavelets. These wavelets consist of two primary functions: the scaling function, ϕ (also called the father wavelet), and the wavelet function, ψ (referred to as the mother wavelet). The wavelet function ψ can be adjusted in scale and position (translated) to construct a basis for the Hilbert space, $L^2(\mathbb{R})$, of square-integrable functions.

The following functions can define the father and mother wavelets:

$$\phi_{j,k}(t) = 2^{\frac{j}{2}} \phi(2^j t - k) \quad (1)$$

$$\psi_{j,k}(t) = 2^{-\frac{j}{2}} \psi(2^j t - k) \quad (2)$$

where $j = 1, \dots, J$ represents the scaling parameter in a J -level decomposition, and k is a translation parameter ($j, k \in \mathbb{Z}$). The father wavelet portrays the long-term trend of the time series and maintains an integral value of 1. Conversely, the mother wavelet, with an integral value of 0, captures deviations or fluctuations from this trend.

3.2. The Maximal Overlap Discrete Wavelet Transform

The MODWT is a powerful signal-processing technique that builds upon the foundations of the discrete wavelet transform (DWT). Both the MODWT and the DWT are commonly used methods for decomposing time-series data, allowing for analysis at different scales.

While the DWT enables a robust analysis on a uniform frequency band, it does not handle time-variant transforms. The MODWT deals with that issue of time variance, whereby all decomposed layers can keep the same resolution without phase distortion (Xiao et al. 2020). MODWT introduces, therefore, several distinct advantages over traditional DWT methods, as noted by Hashim and Masih (2015): (i) MODWT can accommodate time series of any sample size, irrespective of its dyadic form and size, (ii) at higher scales, it provides enhanced resolution because of data oversampling, (iii) it ensures translation-invariance, meaning wavelet coefficients remain unchanged even in the presence of a circular shift of the time series, and (iv) MODWT yields wavelet variance that is more asymptotically efficient compared to DWT. Because of all these properties, MODWT was selected for the current study as the most suited to handle the complex characteristics of the studied time series.

For a wavelet with a coefficient λ_j and a scale of ω_{ijt} after the MODWT transform, the estimator of the wavelet correlation is specified as follows:

$$\rho_{xy}(\lambda_j) = \text{Corr}(\omega_{ijt}, \tilde{\omega}_{ijt}) = \frac{\text{Cov}(\omega_{ijt}, \tilde{\omega}_{ijt})}{\sqrt{\text{Var}(\omega_{ijt}) \text{Var}(\tilde{\omega}_{ijt})}} \quad (3)$$

where $\tilde{\omega}_{ijt}$ represents a variant of the scale factor ω_{ijt} , adjusted for specific characteristics, such as alignment and normalisation, to enhance interpretability and computation efficiency. The MODWT decomposition of the time series was obtained by applying the Daubechies least asymmetric (LA) wavelet filter of length 8. The LA 8 filter offers a good balance between capturing the details and providing smooth approximations, which makes it a

prime choice for analysis short-run as well as long-run dependencies in financial markets (Gençay et al. 2010).

The structure of the MODWT is particularly useful in distinguishing between contagion and market interdependence. High correlations in the short-term wavelet scales are indicative of contagion, while long-term wavelet correlations may simply signal market interdependence. This distinction is crucial in financial market analysis, as it allows researchers to differentiate between temporary shocks that may lead to contagion and long-term structural relationships between markets (Percival and Walden 2006).

3.3. Wavelet Variance and Wavelet Correlation

The MODWT can be used to decompose the sample variance of a series in a scale-by-scale manner due to its energy-conserving property:

$$\|X^2\| = \sum_{j=1}^{j_0} \|\tilde{W}_j\|^2 + \|\tilde{V}_{j_0}\|^2 \quad (4)$$

From Equation (4) above, we derive a scale-dependent ANOVA using the wavelet and scaling coefficients:

$$\hat{v}_X^2 = \|X^2\| - \bar{X}^2 = \frac{1}{N} \sum_{j=1}^{j_0} \|\tilde{W}_j\|^2 + \frac{1}{N} \|\tilde{V}_{j_0}\|^2 - \bar{X}^2 \quad (5)$$

Wavelet variance is defined for both stationary and non-stationary processes, where $\{X_t: t = \dots, -1, 0, 1, \dots\}$ represents a discrete parameter real-valued stochastic process. Its d -th-order differencing yields a stationary process (Percival and Walden 2006). However, applying d -th-order differencing to a series that is already stationary would result in over-differencing, making the series unnecessarily complex and potentially distorting the data. Therefore, d -order differencing was not applied, as the series were stationary.

$$Y \equiv (1 - B)^d X_t \equiv \sum_{k=0}^d \binom{d}{k} (-1)^k X_{t-k} \quad (6)$$

The derivation is made by using a spectral density function, $S_Y(\cdot)$, with μ_Y as its mean. If $S_X(\cdot)$ denotes the spectral density function for $\{X_t\}$, with $(f) = S_Y(f)/D^d(f)$, and $D(f) \equiv 4\sin^2(\pi f)$, then $\{X_t\}$ can be filtered with a Daubechies MODWT wavelet filter $\{\tilde{h}_{j,l}\}$ of width $L \leq 2d$. The stationary process of the j -th-level MODWT wavelet is then derived by applying the filter:

$$\bar{W}_{j,t} \equiv \sum_{l=0}^{L_j-1} \tilde{h}_{(j,l)} X_{t-1}, \quad t = \dots, -1, 0, 1, \dots \quad (7)$$

Here, $\bar{W}_{j,t}$ represents a random process obtained by filtering $\{X_t\}$ with the MODWT wavelet filter $\{\tilde{h}_{j,l}\}$, and $L_j \equiv (2^j - 1)(L - 1) + 1$.

Considering a series as an outcome of one segment (with values $X_0, \dots, X_{N-1}$) of the process $\{X_t\}$, if $M_j \equiv N - L_j + 1 > 0$, while at the same time $L > 2d$ or $\mu_x = 0$ $E\{\bar{W}_{j,t}\} = 0$, which implies that $v_X^2(\tau_j) = E\{\bar{W}_{j,t}^2\}$, then Equation (8) provides an unbiased estimator of the wavelet variance of scale $\tau_j(v_X^2(\tau_j))$, as suggested by Percival and Walden (2006):

$$\hat{v}_X^2(\tau_j) = \frac{1}{M_j} \sum_{t=L_j-1}^{N-1} \tilde{W}_{j,t}^2 \quad (8)$$

where $\{\tilde{W}_{j,t}\}$ stand for the j -th-level MODWT wavelet coefficients.

$$\left(\tilde{W}_{j,t} \equiv \sum_{l=0}^{L_j-1} \tilde{h}_{(j,l)} X_{t-1 \bmod N}, t = 0, 1, \dots, N-1 \right) \quad (9)$$

It is established that $\hat{v}_X^2(\tau_j)$ asymptotically follows a Gaussian distribution, enabling the formulation of confidence intervals for the estimate (Percival 1995; Dajčman 2013). For the stationary processes $\{X_t\}$ and $\{Y_t\}$, the j -th-level MODWT wavelet coefficients are $\{\overline{W}_{X,j,t}\}$ and $\{\overline{W}_{Y,j,t}\}$, and an unbiased estimator of the covariance, $\hat{v}_{XY}(\tau_j)$, can be specified according to Equation (10), as proposed by Percival (1995):

$$\hat{v}_{XY}(\tau_j) = \frac{1}{M_j} \sum_{t=L_j-1}^{N-1} \tilde{W}_{j,t}^{(X)} \tilde{W}_{j,t}^{(Y)} = \text{cov}\{\overline{W}_{X,j,t}, \overline{W}_{Y,j,t}\} \quad (10)$$

where $M_j \equiv N - L_j + 1 > 0$ represents the number of j -th-level coefficients that are non-boundary coefficients. Likewise, Equation (11) shows the derivation of the correlation estimator for scale τ_j from the wavelet covariance and the square roots of the respective variances:

$$\hat{\rho}_{X,Y}(\tau_j) = \frac{\hat{v}_{X,Y}(\tau_j)}{\hat{v}_X(\tau_j) \hat{v}_Y(\tau_j)} \quad (11)$$

where $|\hat{\rho}_{X,Y}(\tau_j)| \leq 1$. This wavelet correlation resembles the complex coherence, which is its Fourier transform counterpart (Gençay et al. 2003).

The confidence intervals are computed in Equation (12) using the random interval, in line with Percival (1995) and Percival and Walden (2006):

$$\left[\tanh \left\{ h[\rho_{XY}(\tau_j)] - \frac{\Phi^{-1}(1-p)}{\sqrt{N_j-3}} \right\}, \tanh \left\{ h[\rho_{XY}(\tau_j)] + \frac{\Phi^{-1}(1-p)}{\sqrt{N_j-3}} \right\} \right] \quad (12)$$

This method enables accurate capturing of the wavelet correlation, providing an almost full 100 (1 − 2p)% confidence interval.

3.4. Wavelet Cross-Correlation

Within wavelet analysis, wavelet cross-correlation is a technique to assess the degree of connectedness between two time series. This approach allows to elucidate how much one series leads or lags the other by shifting them and computing their (shifted) correlation. This lag exploration helps identify the series whose innovations precede those of the other, thereby establishing a lead–lag relationship. The magnitude and statistical significance of the cross-correlation coefficients provide a measure of the predictive power of one time series over the other.

In analogy to traditional cross-correlation in the time-series domain, which also identifies lead–lag relationships, wavelet cross-correlation seeks to establish lead and lag on a scale-by-scale basis, as in Equation (13), where cross-correlation with lag π for scale τ_j is formulated as:

$$\rho_{\pi,XY}(\tau_j) = \frac{\text{cov}\{\overline{W}_{j,t}^{(X)}, \overline{W}_{j,t+\pi}^{(Y)}\}}{\left(\text{var}\{\overline{W}_{j,t}^{(X)}\} \text{var}\{\overline{W}_{j,t+\pi}^{(Y)}\} \right)^{\frac{1}{2}}} \quad (13)$$

Here, $\overline{W}_{j,t}^{(X)}$ represents the j -th-level wavelet coefficients of the $\{X_t\}$ series at time t , whereas $\overline{W}_{j,t+\pi}^{(Y)}$ represents the j -th-level wavelet coefficients of the $\{Y_t\}$ series lagged

for π units of time. This cross-correlation has values ranging from -1 to $+1$ (i.e., $-1 \leq \hat{\rho}_{\pi,XY}(\tau_j) \leq 1$, for all τ and j), as in its counterpart using the Cauchy–Schwartz inequality.

3.5. Wavelet Coherence

In this study, the concept of wavelet coherence is employed to explore the interplay between the series and assess the degree to which a linear transformation establishes a connection between them. The aim is to probe the level of congruence and dependence linking the two series by applying the wavelet coherence framework. For two time series, the wavelet coherence is specified in Equation (14) as follows:

$$R_n^2(s) = \frac{\left| S\left(s^{-1}W_n^{xy}(s)\right) \right|^2}{S\left(s^{-1}|W_n^x(s)|^2\right)S\left(s^{-1}|W_n^y(s)|^2\right)} \quad (14)$$

In this equation, S represents the smoothing operator, with s being the scale of the wavelet, while $W_n^x(s)$ stands for the continuous wavelet transform of time series X . As for $W_n^y(s)$, it stands for the continuous wavelet transform of the time series Y , whereas $W_n^{xy}(s)$ is the cross-wavelet transform of X and Y (Saiti et al. 2016).

3.6. Data

The dataset consisted of daily closing stock price indices from BRICS and German stock markets, spanning the period from 11 January 2005 to 26 December 2017. This period was chosen because it encompasses the EZDC, which the study aimed to investigate in terms of the transmission of shocks emanating from the Eurozone countries. We used daily data, aligning with the characteristic short-term timeframe of pure contagion, as described by Rigobon (2002). The stock market indices under investigation included Brazil (BOVESPA), China (SSE), India (SENSEX), Russia (RTS), and South Africa (FTSE/JSE). The daily stock price index of the German DAX Composite served as a proxy for the ‘source’ markets. The data were sourced from Thomson Reuters Datastream. The DAX was selected due to its role as an indicator of the health of the German economy and, by extension, the Eurozone countries in continental Europe. Given that Germany’s economy constitutes nearly one-third of the Eurozone’s total value (Fröhlich 2021), the DAX serves as a suitable representation of the broader economic health of continental Europe. In essence, major European indices, such as the CAC 40, tend to exhibit behaviour quite similar to that of the DAX. This similarity stems from their shared exposure to macroeconomic factors affecting the Eurozone and global markets. Taking the CAC 40 as an example, studies have highlighted key characteristics of the CAC 40’s behaviour that are similar to that of the DAX. These include, but are not limited to, (i) the fact that it often moves in tandem with other European indices, particularly the DAX (Trešl and Blatná 2007), (ii) it is heavily weighted towards luxury goods, industrials, and financials, which can influence its overall performance (Euronext 2024), and (iii) as it is denominated in Euros, the CAC 40 can be affected by fluctuations in the Euro’s value against other major currencies (Muller and Verschoor 2006).

For detrending and in order to achieve more stationary time-series data, the daily composite price indices were transformed into natural logarithmic returns, expressed as follows:

$$R_t = [\ln(P_t) - \ln(P_{t-1})] \times 100$$

where P_t is the closing price index recorded for period t , and P_{t-1} is the closing price index recorded for period $t - 1$. The reason for multiplying the expression $\ln(P_t) - \ln(P_{t-1})$ by 100 is due to numerical problems in the estimation part. This did not affect the structure of the model since it is just a linear scaling.

4. Results of Wavelet Analysis

The MODWT analysis carried out in this study applied the Daubechies least asymmetric filter with a filter length of 8 (LA) to investigate financial contagion following the EZDC. The wavelet analysis encompassed 8 scales ranging from 2 days to 18 months, with dyadic increments (2 to 4 days, 4 to 8 days, . . . , and 256 to 512 days). The scales are displayed on the x axis, while correlations are shown on the y axis. The 95% confidence interval was used to establish statistical significance.

The wavelet analysis revealed significantly positive correlations between the DAX index and the indices of the various BRICS stock markets, with the Chinese market being the only exception. These correlations generally increased with the scale of analysis. A noticeable decline at scale 7 was observable, however (except for the Russian market, which showed a decline at scale 5), with a subsequent rebound at scale 8, where their values became higher than 0.6 (see Figure 1). This suggests that dependencies between the Germany and BRICS equity markets persisted for periods longer than a year. Put differently, the German and BRICS equity markets (excluding the Chinese market) displayed significant correlations over long durations, suggesting a high intensity of mutual influence between these respective markets.

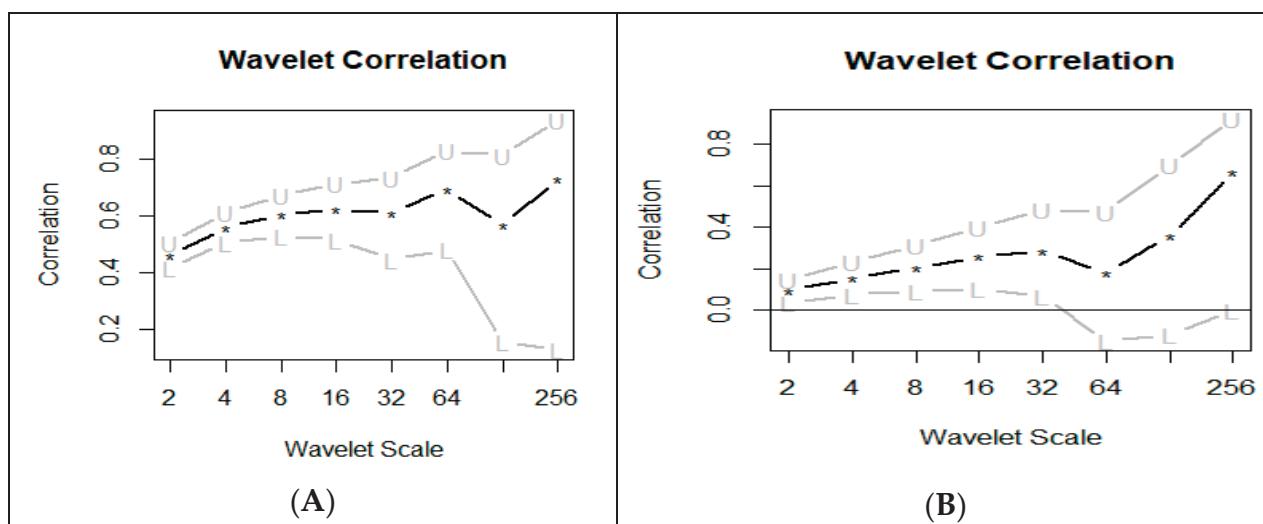


Figure 1. Correlation of DAX with BOVESPA (panel A) and SSE (panel B) at different timescales. (A) Correlation of DAX and BOVESPA at different time scales. (B) Correlation of DAX and SSE at different time scales.

Figure 1 depicts the wavelet correlation between the DAX index and two individual BRICS indices: the BOVESPA index of Brazil (panel A) and the SSE index of China (panel B). Illustrations for other BRICS indices can be provided upon request from the authors. The lines indicate significant correlations between two time series over specific time scales and locations, with thicker lines indicating stronger correlations. Dashed lines indicate boundaries of 5% confidence intervals, with “L” and “U” mark the lower and upper bounds of the correlation. Asterisks highlight points of significant correlation at particular time or frequency points

The study also investigated each MODWT pairwise cross-correlation between the DAX index and respective individual BRICS market indices across various wavelet scales ranging from 1 to 33 days. The analysis found positive and significant cross-correlations at the 4 lowest scales, particularly around the time shifts of $\pi = 9$ and $\pi = -9$. Graphs at these low scales showed a slight right skew, suggesting that the DAX led the individual BRICS indices (see Figures 2 and 3).

At scales 5 and 6, the highest correlations were observed around the time shifts of $\pi = 21$ and $\pi = -21$, although the Chinese stock market showed an exception. Scales 5 and

6 generally exhibited symmetrical distributions, indicating a lack of discernible lead–lag relationships in most cases.

For scale 7, the wavelet cross-correlation was noticeably negative, as can be seen from the graphs of Figures 2 and 3², suggesting that individual BRICS markets led the Eurozone market. Scale 8, however, did not show any clear-cut lead–lag relationship.

Additionally, contemporaneous correlations between the series showed that wavelet correlation coefficients at lag 0 exhibited an anti-correlation relationship. Figures 2 and 3 illustrate cross-correlations between the DAX index and two specific BRICS indices: the BOVESPA index of Brazil and the SSE index of China. Illustrations for other BRICS indices are available upon request from the authors.

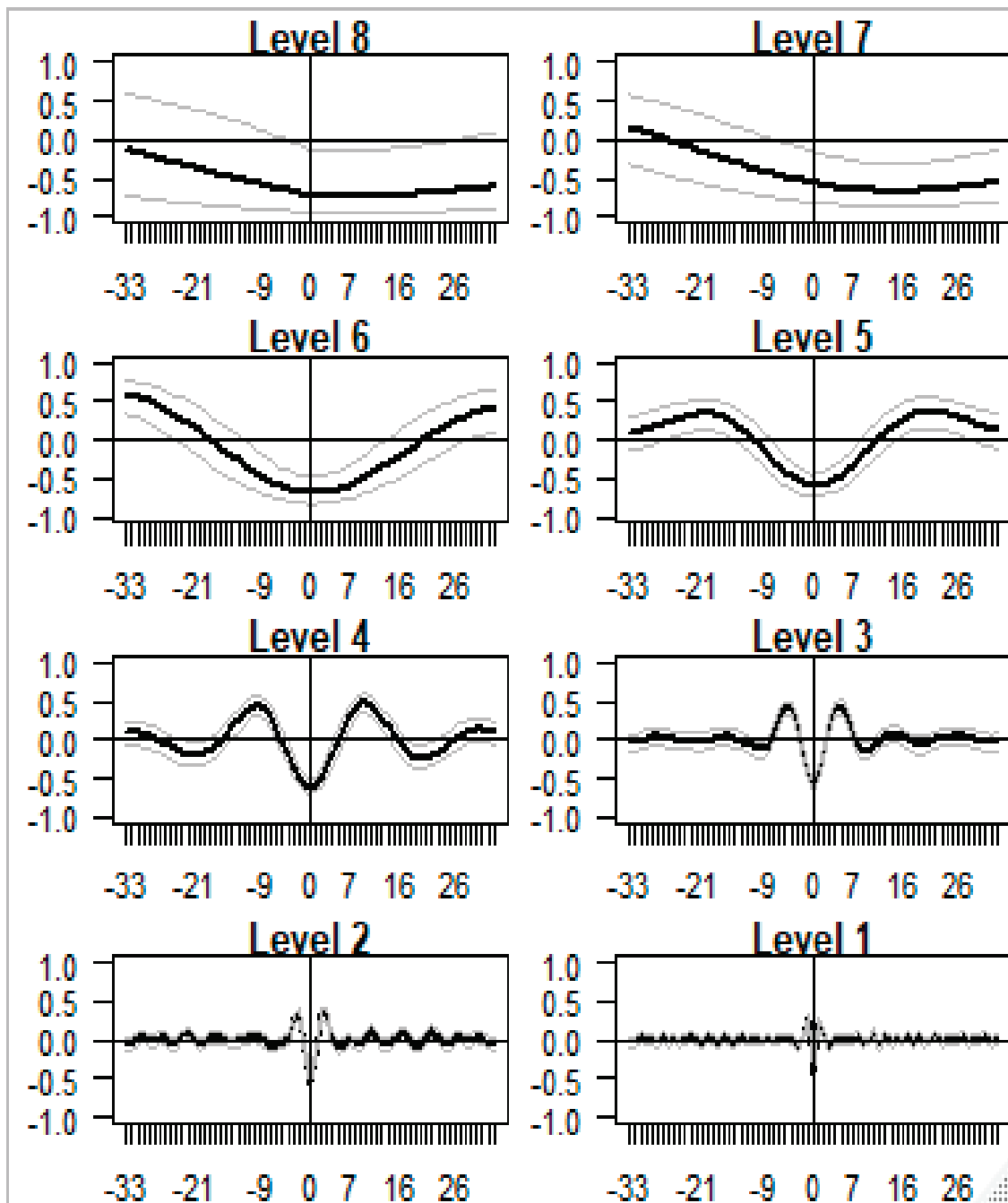


Figure 2. Cross-correlation between the return series of DAX and BOVESPA.

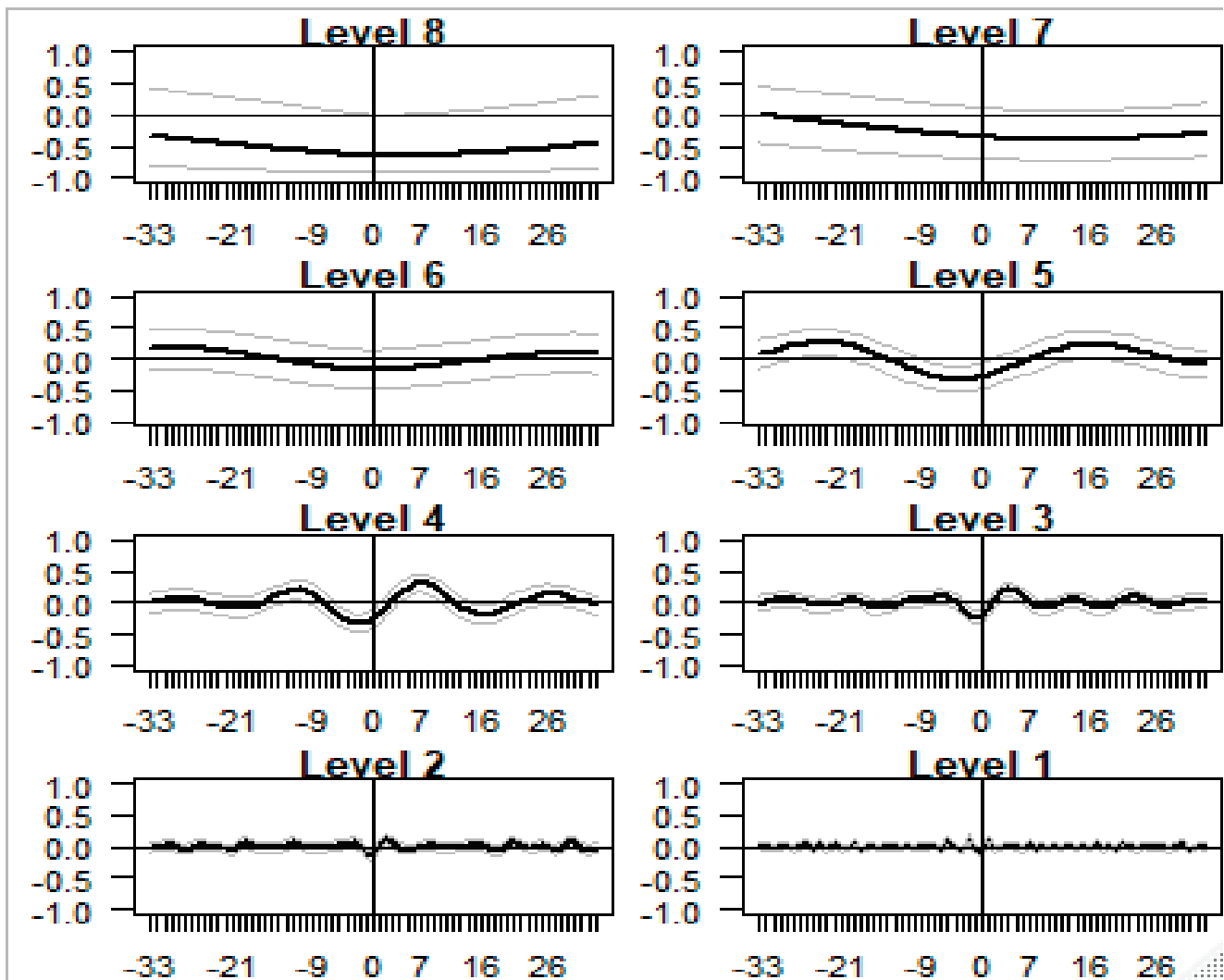


Figure 3. Cross-correlation between the return series of DAX and SSE.

Figures 4–8 present wavelet cross-coherence contour plots comparing the DAX index with each BRICS equity market. The horizontal axis shows calendar time, while the vertical axis represents frequency. The thick black line indicates a 5% significance level estimated using Monte Carlo simulation. The white line demarcates the cone of influence, a region influenced by edge effects.

The heat map, ranging from blue (low coherence) to red (high coherence), represents different levels of correlation. Arrows within the heat map indicate phase relationships:

- Rightward arrows (east): both variables are in phase.
- Leftward arrows (west): variables are out-of-phase.
- Upward arrows (north): the second variable leads the first by 90 degrees.
- Downward arrows (south): the first variable leads the second by 90 degrees.
- Southeast arrows: positive correlation, with the first variable leading.
- Northwest arrows: negative correlation, with the second variable leading.

During the Eurozone crisis (July 2009 to December 2012), most BRICS markets, except China, exhibited higher correlations with the DAX, as indicated by warmer colours. This suggests the presence of contagion, particularly in short-term horizons. Notably, during this period, coherence arrows for most markets pointed southeast, implying a positive correlation, with the DAX leading.

For South Africa and Russia, the southeast-pointing arrows indicated a positive correlation, with the DAX leading. This suggests that changes in the DAX index tended to

precede similar movements in the South African JSE and Russian RTS indices. The high correlations observed in short-term horizons are particularly noteworthy, as they strongly suggested the presence of pure contagion. This means that shocks or disturbances in the Eurozone (and more specifically, in the German) market were quickly transmitted to the South African and Russian markets, indicating a high degree of interconnectedness and interdependence.

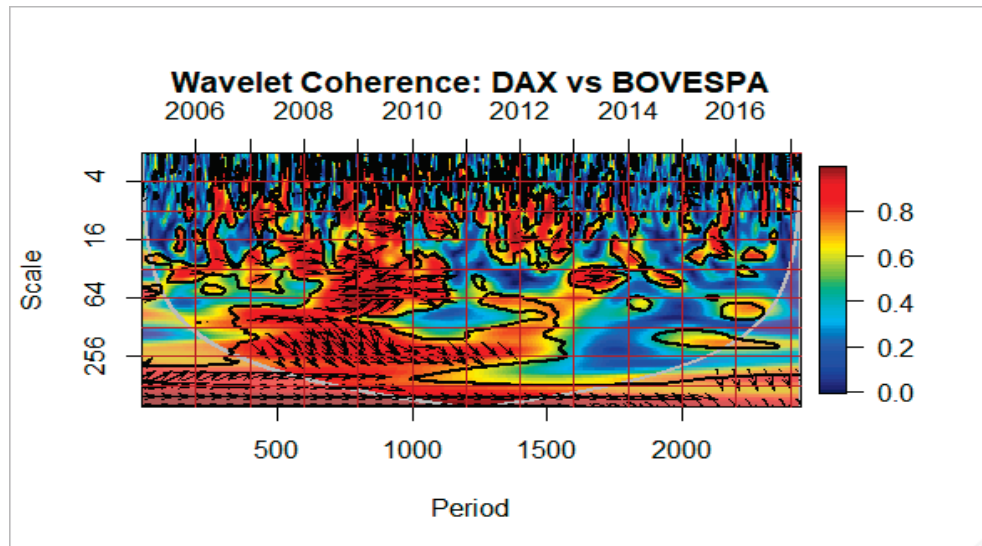


Figure 4. Wavelet coherence between the Eurozone and Brazilian stock markets. Note: → (pointing to the right): the two time series are in phase and move together; ← (pointing to the left): the two time series are out of phase and move in opposite directions; ↑ (pointing upwards): the first time series leads the second; ↓ (pointing downwards): the second time series leads the first.

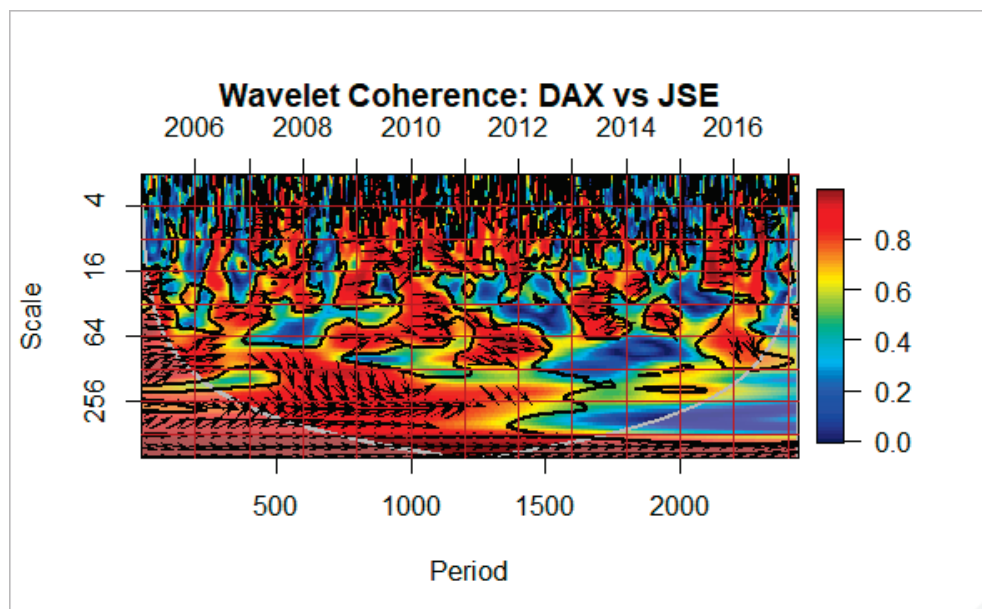


Figure 5. Wavelet coherence between the Eurozone and South African stock markets. Note: → (pointing to the right): the two time series are in phase and move together; ← (pointing to the left): the two time series are out of phase and move in opposite directions; ↑ (pointing upwards): the first time series (DAX) leads the second (JSE); ↓ (pointing downwards): the second time series leads the first.

The strong trading ties between these countries and the Eurozone likely play a significant role in facilitating this contagion. Factors such as trade flows, capital flows, and

investor sentiment can all contribute to the transmission of shocks across borders. Until the war in Ukraine started and sanctions were imposed on Russia, South Africa and Russia had strong connections with Germany as important trade partners, with Germany being the third largest export market for South Africa (after China and the US) and the third largest export market for Russian products (after China and the Netherlands). These connections represent sources of interdependencies that may not be directly captured by the structure of financial markets in normal situations but become sources of systemic risk in times of crisis.

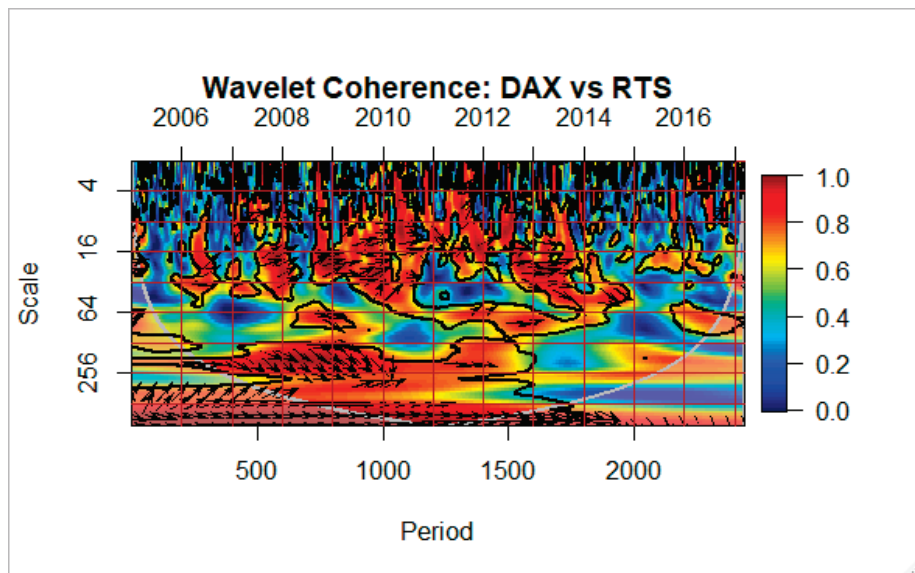


Figure 6. Wavelet coherence between the Eurozone and Russian stock markets. Note: → (pointing to the right): the two time series are in phase and move together; ← (pointing to the left): the two time series are out of phase and move in opposite directions; ↑ (pointing upwards): the first time series (DAX) leads the second (RTS); ↓ (pointing downwards): the second time series leads the first.

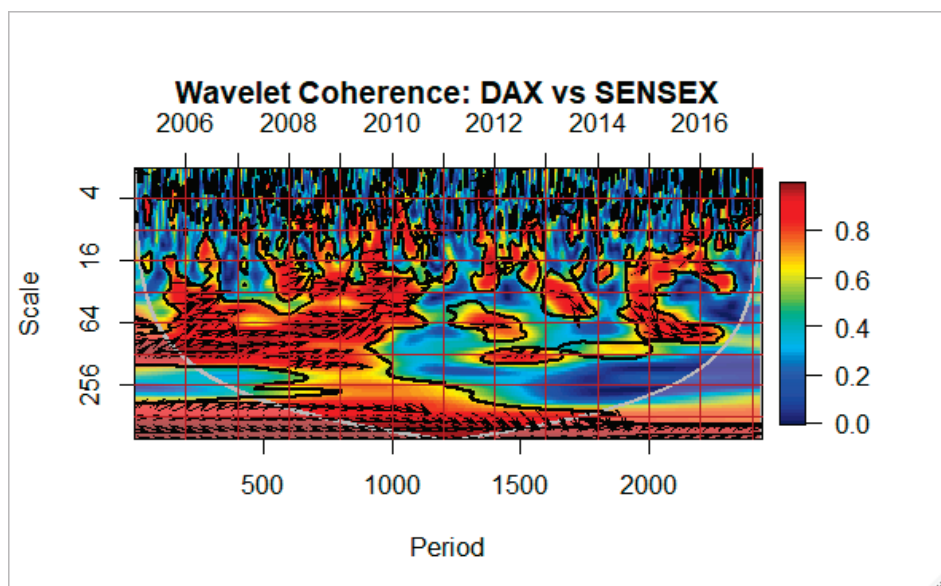


Figure 7. Wavelet coherence between the Eurozone and Indian stock markets. Note: → (pointing to the right): the two time series are in phase and move together; ← (pointing to the left): the two time series are out of phase and move in opposite directions; ↑ (pointing upwards): the first time series (DAX) leads the second (SENSEX); ↓ (pointing downwards): the second time series leads the first.

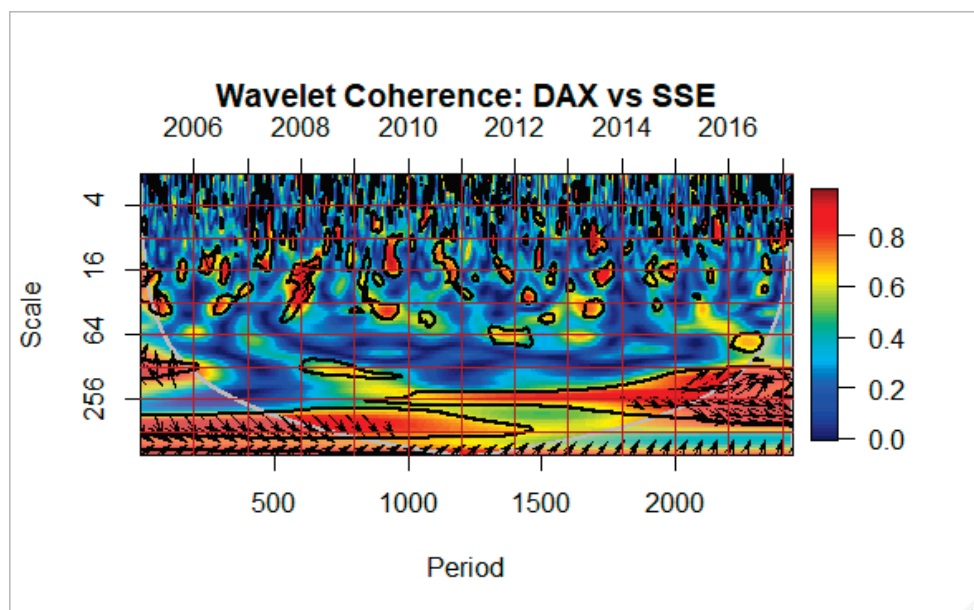


Figure 8. Wavelet coherence between the Eurozone and Chinese stock markets. Note: → (pointing to the right): the two time series are in phase and move together; ← (pointing to the left): the two time series are out of phase and move in opposite directions; ↑ (pointing upwards): the first time series (DAX) leads the second (SSE); ↓ (pointing downwards): the second time series leads the first.

In contrast, the contour plots for DAX with BOVESPA, SENSEX, and SSE showed relatively low short-term correlations (Figures 4, 7 and 8). Significant correlations were observed only in the long-term horizon during the Eurozone crisis, suggesting co-movement driven by market fundamentals. Therefore, the study found no evidence of pure contagion in these three countries during the crisis. Our results imply that investors in Brazil, China, and India might have benefited from portfolio diversification during this period due to the limited impact of Eurozone financial contagion. These findings contradict Ahmad et al. (2013), who reported adverse effects on these markets.

It is worth drawing to the reader's attention that while the MODWT is a particularly robust method that does not necessitate additional robustness checks, it is noteworthy that the data employed in the present study were also utilised in a previous analysis employing the DCC-GARCH model. The DCC-GARCH model corroborated with some of the findings of our current research. The results of these findings were documented by Niyitegeka and Tewari (2021).

5. Conclusions

In evaluating contagion risk, investors should consider non-linear dependencies that extend beyond financial markets, which cannot be easily detected by traditional econometric market correlations. Wavelet analysis provides a suitable tool for denoising the dynamics of financial data and identifying signs of systemic risk and contagion. Policymakers should learn from past experiences to develop optimal policy approaches to insulate their economies from unwanted external volatility.

The present study used the wavelet analysis to examine multiscale interdependence of BRICS equity markets, *vis-à-vis* the German market as a source country in the aftermath of the EZDC. The results of the wavelet cross-correlation analysis brought to light evidence of co-movement and volatility spillover in the low scales, with the DAX index leading the BRICS market indices. For coarse scales, the wavelet cross-correlation was identified as significantly negative, suggesting that the individual BRICS markets led the Eurozone market.

The wavelet coherence results also provided evidence of high correlation at lower scales between the German stock market and individual stock markets in South Africa

and Russia. This is indicative of the presence of financial contagion in these markets. For the Brazilian, Indian, and Chinese stock markets, no correlation was identified in the short-run horizon. This observation led to the conclusion that they suffered no financial contagion induced by the Eurozone crisis. This implies that portfolio diversification could have benefited investors in Brazil, China, and India during the debt crisis, considering the minimal impact of Eurozone financial contagion on these markets.

The study's limitations include a narrow focus on the DAX index as the sole proxy for the Eurozone, which may not fully capture the region's financial diversity, and a restricted analysis that omitted a broad range of emerging markets, potentially leading to an incomplete understanding of global financial integration and contagion effects. For future research, we suggest expanding the scope of this analysis in two key directions. Firstly, including more emerging markets could offer valuable insights into regional contagion effects and the extent of global financial integration. This broader perspective would help in understanding how different regions respond to financial shocks and whether similar integration patterns exist elsewhere.

Secondly, while our study used the DAX to probe contagion from the Eurozone market, incorporating additional major European indices, such as the CAC 40 (France) and EURONEXT index, MIB (Italy), could strengthen the analysis and enhance the generalisability of our findings. This more comprehensive representation of the Eurozone would provide a more nuanced understanding of the contagion dynamics between Europe and the emerging countries.

These expansions in future studies would not only build upon our current findings but also contribute to a more robust understanding of global financial interconnectedness and the transmission of economic shocks across diverse markets.

Author Contributions: Conceptualization, O.N. and A.H.; methodology, O.N.; software, O.N.; validation, O.N. and A.H.; formal analysis, O.N.; investigation, A.H.; resources, O.N.; data curation, O.N. and A.H.; writing—original draft preparation, O.N.; writing—review and editing, O.N. and A.H.; visualization, O.N.; supervision, O.N. and A.H.; project administration, O.N. and A.H.; funding acquisition, O.N. and A.H. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The data were sourced from Thomson Reuters Datastream.

Conflicts of Interest: The authors declare no conflicts of interest.

Notes

- ¹ Augmented Dickey–Fuller (ADF), Phillips–Perron (PP), and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) unit root tests were conducted on the data, and all data were found to be stationary. The results of these tests can be provided upon request.
- ² In this wavelet cross-correlation graph, the black line represents the estimated cross-correlation between two time series at various scales, with each level corresponding to a different frequency band. Lower levels capture short-term fluctuations, while higher levels show longer-term trends. The gray lines depict the confidence intervals, helping assess the statistical significance of the correlation. If the black line falls outside the gray lines, the correlation is significant; otherwise, it is not. The horizontal axis indicates time lags, and the vertical axis measures the strength of the correlation, ranging from -1 to 1 .

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Article

Application of a Robust Maximum Diversified Portfolio to a Small Economy's Stock Market: An Application to Fiji's South Pacific Stock Exchange

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Abstract: In this study, we apply a novel approach of portfolio diversification—the robust maximum diversified (RMD)—to a small and developing economy's stock market. Using monthly returns data from August 2019 to May 2024 of 18/19 stocks listed on Fiji's South Pacific Stock Exchange (SPX), we construct the RMD portfolio and simulate with additional constraints. To implement the RMD portfolio, we replace the covariance matrix with a matrix comprising unexplained variations. The RMD procedure diversifies weights, and not risks, hence we need to run a pairwise regression between two assets (stocks) and extract the R-square to create a P-matrix. We compute each asset's beta using the market-weighted price index, and the CAPM to calculate market-adjusted returns. Next, together with other benchmark portfolios (1/N, minimum variance, market portfolio, semi-variance, maximum skewness, and the most diversified portfolio), we examine the expected returns against the risk-free (RF) rate. From the simulations, in terms of expected return, we note that eight portfolios perform up to the RF rate. Specifically, for returns between 4 and 5%, we find that max. RMD with positive Sharpe and Sortino (as constraints) and the most diversified portfolio offer comparable returns, although the latter has slightly lower standard deviation and downside volatility and contains 94% of all the stocks. Portfolios with returns between 5% and the RF rate are the minimum-variance, the semi-variance, and the max. RMD with positive Sharpe; the latter coincides with the RF rate and contains the most (94%) stocks compared to the other two. An investor with a diversification objective, some risk tolerance and return preference up to the RF rate can consider the max. RMD with positive Sharpe. However, depending on the level of risk-aversion, the minimum-variance or the semi-variance portfolio can be considered, with the latter having lower downside volatility. Two portfolios offer returns above the RF rate—the market portfolio (max. Sharpe) and the maximum Sortino. Although the latter has the highest return, this portfolio is the least diversified and has the largest standard deviation and downside volatility. To achieve diversification and returns above the RF rate, the market portfolio should be considered.

Keywords: portfolio allocation; robust maximum diversified and benchmark portfolios; South Pacific Stock Exchange; small market economy; Fiji Islands

1. Introduction

Portfolio optimization is a critical component of investment management, focusing on maximizing returns while minimizing risk through the careful selection and weighting of assets. The primary goal of this technique is to create an investment portfolio that achieves the best possible balance between expected returns and risk. Portfolio optimization methods, particularly the concept of mean-variance optimization, were pioneered by Markowitz

(1952a, 1952b). His groundbreaking work laid the foundation for modern portfolio theory, introducing a quantitative framework for constructing portfolios. Following Harry Markowitz's pioneering work in 1952, many researchers expanded upon his foundation, developing a variety of advanced strategies for portfolio optimization, each with its own unique approach and methodology (Ghanbari et al. 2023; Kalayci et al. 2019; Milhomem and Dantas 2020; Righi and Borenstein 2018; Salo et al. 2024). Generally, any portfolio strategy aims to create some level of diversification across assets and/or stocks to manage risk. Several studies have been conducted to examine and rationalize different methods of portfolio diversification, and their findings help investors understand the benefits and limitations of diversification (Bielstein et al. 2023; Koumou 2020). However, as noted in the literature, studies on portfolio diversification and investment analysis are generally focused on large and well-developed financial markets, in developed or large emerging economies, mainly because from an investor's perspective, these countries have a vibrant stock market that offers greater liquidity, hence providing the ease of trading. Moreover, higher liquidity in the market can generate scale effects, thus reducing transaction costs, in addition to supporting faster execution of trades (Al Janabi 2021; Andreev 2019; Baumann and Trautmann 2013).

Markets in small economies are generally less liquid, less volatile, and have lesser numbers of participants (listed companies, retail traders and investors, and brokers) than developed markets. With such characteristics of a small market, the task of managing risk and identifying suitable stocks for investment can appear straightforward. However, fewer investors and low volumes of trade can also contribute to a lack of confidence among potential investors to participate in the stock market. Therefore, to support the development and progress of new and infant stock markets, it is vital to identify the nuances present in the market and examine suitable portfolios to educate and inform potential investors. Hence, a contribution of this study is to focus on the small island economy of Fiji's stock market and extend the existing analysis by incorporating newer methods of portfolio construction that can be considered for investment.

The Sustainable Development Goal 8 (SDG 8) emphasizes the need to “improve access to financial services. . .”, and to “strengthen the capacity of domestic financial institutions to encourage and expand access to banking, insurance and financial services for all”.¹ In this regard, the study is relevant and important for both existing and potential investors in small markets, with the view to enhancing financial inclusion and literacy. By focusing on small economies, our research underscores the need for greater financial inclusion for all.

Although Fiji's stock market (South Pacific Stock Exchange—SPX) has been in existence for more than four decades, in a prominent local newspaper, *The Fiji Times*, Singh (2019) documents that from 1979, it operated for some 17 years as Trading Post, with an exchange officer handing trades without any regulatory body, stockbrokers, and dealers. Then, in July 1996, a “open outcry system” or a “call market” was introduced where brokers used a physical trading floor for trading, and later in the same year (December), the first securities market legislation, known as the Capital Markets Development Authority Act (CMDA), was established to formally institute investment advisors, the stock exchange, and the brokers (Whiteside 2016). In 2000, the name of the exchange was changed to the South Pacific Stock Exchange (Saliya 2022), and a Central Share Registry (CSR) was created in 2002. In 2010, SPX launched its electronic trading platform, and in 2016, it launched its web-based online secured portal for shareholders and listed companies. While this progress indicates significant efforts towards development of the stock market in Fiji, the Reserve Bank of Fiji (RBF 2017), in its report on *Financial Sector Development Plan 2016–2025* under Pillar 10, notes that SPX aims to “become the preferred capital market center in the South Pacific”. However, the report (RBF 2017, p. 38) also notes that

“... there are many issues besetting Fiji's capital market. These include small retail investor base, limited financial products, illiquid stock market, high transaction costs, lack of awareness of the capital market and inconsistent application of policy by regulatory agencies”.

Against this background, we extend the earlier studies by applying a newly proposed method—the Robust Maximum Diversified (RMD) portfolio (Bielstein et al. 2023)—and compare the results with a set of benchmark portfolios. Moreover, we also examine the RMD portfolio with additional constraints to generate additional insights. Noting the results, we present alternative approaches for potential investors in small markets to consider diversification and risk management. We analyze all portfolios based on market-adjusted returns. This is because in less liquid markets, changes in asset prices can be due to small volumes traded at a higher frequency, although a large amount of assets may remain untraded for a long time. Hence, considering the responsiveness of asset prices with respect to the market is more informative. Moreover, computing market-adjusted returns informs investors on how the respective asset returns correlate with the overall market performance. Therefore, analysis based on average returns can be misleading, as the returns do not reflect an asset's true performance (relative to the market) (Kumar and Stauvermann 2022).

In this study, we focus on the stock market of a small island economy, Fiji, which at the time of study, comprised 19 listed companies. Some recent studies have provided a comprehensive background on Fiji's stock market and considered a few conventional approaches (Kumar et al. 2022; Kumar and Stauvermann 2022). These studies have laid the groundwork for understanding the dynamics of Fiji's stock market, while noting the challenges and opportunities associated with investing in such a small and relatively less liquid market.

Based on the share price movements, we considered 18 stocks and the stock price data from July 2019 to May 2024. We computed monthly returns for each stock for the period from August 2019 to May 2024 and used these data to estimate each stock's beta. For market return, we use the market-weighted price index published by SPX (SPX 2024a). Using the respective asset's beta, we computed the market-adjusted expected returns and constructed a set of benchmark portfolios (mean-variance, minimum-variance, target ratio, semi-variance, and most diversified portfolios). We then constructed RMD portfolios (Bielstein et al. 2023) and compared them with the benchmark portfolios. The importance of the RMD approach stems from its feature that it does not rely on expected returns or volatilities, and hence it is robust to measurement errors. This is because it uses a pairwise regression between two assets to derive the degree of variation, and then considers the portfolio weights that maximize the unexplained variation of the portfolio.

The study contributes to the literature on small economy finance in the following ways: it provides insights that can enhance the understanding and management of investments in small markets; it highlights the importance of equipping investors with knowledge and tools necessary to make informed decisions, thereby encouraging broader participation in the stock market and other financial activities. This increased participation not only democratizes access to financial markets but also strengthens the overall financial ecosystem. Furthermore, our study supports the objective of promoting financial literacy (education) and provides insights to potential investors and businesses in small markets on navigating the complexities of investing, managing risks more effectively, and ultimately achieving sustainable financial outcomes. Well-informed financial strategies and methods creates greater confidence among investors, and hence support the growth of stock markets and broader economic development goals (Voica 2017; Dash and Mohanta 2024; Kandpal 2020; Kara et al. 2021; Ozili 2022).

The remainder of this paper is organized as follows: Section 2 presents the literature review, providing an in-depth exploration of the investment strategies relevant to this study. Section 3 outlines the materials and methods used in the study, detailing the methodologies applied for portfolio construction and diversification, and introduces the preliminary concepts and benchmarks, setting the foundation for the subsequent analysis. Section 4 presents the analysis and results, where we compare the performance of the newly proposed robust maximum diversified (RMD) portfolios against traditional benchmark portfolios, highlighting key findings and statistical significance. Finally, Section 5 offers the

conclusion, summarizing the study's contributions, discussing the implications for small market economies like Fiji, and suggesting potential areas for future research.

2. Literature Review

Investors have a range of strategies at their disposal when it comes to allocating wealth in the stock markets, each tailored to different levels of engagement and risk tolerance. One common approach is the meticulous selection of individual companies for investment. This strategy often requires a deep dive into fundamental analysis, which involves evaluating a company's financial health, performance metrics, and market position (Hilkevics and Semakina 2019; Narkunienė and Ulbinaitė 2018). In addition to fundamental analysis, ensuring proper diversification across different sectors and asset classes is crucial to mitigate risk and optimize returns (Ahmed et al. 2018). Alternatively, some investors rely on technical analysis to guide their stock selections. This method focuses on patterns in stock price movements and trading volumes, using historical data to forecast future trends and inform investment decisions (García et al. 2018). Another strategy is to manage a portfolio of companies directly, where the selection of companies is performed simultaneously. For investors interested in managing an entire portfolio rather than selecting individual stocks, portfolio management strategies come into play. In this approach, the selection of companies is conducted simultaneously, allowing for a more holistic view of the portfolio's risk and return profile. The following literature survey provides an in-depth exploration of these investment strategies, their underlying principles, and the methodologies employed in their execution.

Markowitz (1952a, 1952b) introduced the concept of portfolio selection based on the trade-off between risk and return. He argued that an investor should not only focus on the expected return of an individual asset but also consider how the asset's return interacts with the returns of other assets in a portfolio. Subsequently, Markowitz proposed the mean-variance optimization framework, where the goal is to construct a portfolio that maximizes expected return for a given level of risk or minimizes risk for a given level of expected return. This approach leads to the identification of the "efficient frontier", a set of optimal portfolios that offer the highest expected return for a given level of risk. Markowitz's work was groundbreaking because it formalized the process of diversification, showing that the risk of a portfolio is not just the sum of the risks of individual assets, but also depends on the correlations between them. This insight has had a profound impact on investment management and laid the groundwork for the development of various financial theories and practices. Later, Markowitz (1991) addressed the foundational principles of portfolio theory, which he originally developed, aiming to clarify how it differs from traditional microeconomic theory. Specifically, he focused on investor behavior under uncertainty, as opposed to the behavior of firms or consumers. The aim of the study was to examine the evolution and refinement of these principles over time, addressing both the practical challenges and the broader applications of portfolio theory, particularly in guiding institutional investors. Moreover, Markowitz (1991) delved into the ongoing relevance of mean-variance analysis in approximating expected utility, while underscoring the need for further research and refinement to enhance the theory's effectiveness in contemporary financial settings. Sharpe (1994) revisited the performance measure he originally introduced in Sharpe (1996), known as the "reward-to-variability ratio" and now widely referred to as the Sharpe ratio, emphasizing its utility in assessing the risk-adjusted performance of mutual funds and other investment portfolios. By acknowledging the measure's evolution and varied terminology over the years, the paper reinforced the Sharpe ratio's position as an essential tool in modern portfolio management.

Elton and Gruber (1997) offered a comprehensive review of the development and evolution of modern portfolio theory from the 1950s to the late 1990s. The authors trace the origins of portfolio theory to Markowitz's (1952a, 1952b) groundbreaking work of the early 1950s, highlighting the introduction of mean-variance optimization, the efficient frontier, and the core principles of portfolio selection. They also discuss the key inputs

necessary for portfolio optimization, such as the estimation of expected returns, variances, and covariances, while addressing the challenges in accurately estimating these parameters. The paper further explored the application of portfolio theory within financial institutions, particularly the complexities of incorporating liabilities and institutional constraints into the analysis, the importance of risk-adjusted returns and the continued relevance of metrics like the Sharpe ratio. The authors concluded that further research is needed to refine the application of portfolio theory in more complex financial environments.

De Athayde and Flôres (2004) addressed the problem of portfolio selection by considering not just the mean and variance of asset returns but also the skewness. The goal of this study was to develop a general methodology for constructing an efficient portfolio set that accounts for the first three moments of asset returns—mean, variance, and skewness. The authors present analytical formulas for determining the efficient surface in a three-dimensional space defined by these moments and explore the geometric properties of this surface. The methodology allows for the computation of optimal portfolio weights, even in cases where the investor is willing to trade off negative skewness for higher expected returns. By expanding on traditional mean-variance analysis, the paper provides a more comprehensive framework for portfolio optimization, addressing situations where asset returns are not normally distributed. The authors also introduced a duality result that plays a crucial role in solving the optimization problem, particularly in cases where the solution may involve multiple local optima.

Markowitz (2010) reflected on the foundational concepts of modern portfolio theory, revisiting key assumptions and their applications in contemporary finance. He discussed the practical use of mean-variance analysis, emphasizing that he never assumed return distributions to be Gaussian or investors' utility functions to be quadratic. Markowitz explored the conditions under which mean-variance analysis is applicable and extended his analysis to newer risk measures like Value at Risk (VaR) and Conditional Value at Risk (CVaR). He also revisits the hypothesis he proposed in 1952 regarding the coexistence of behaviors like buying lottery tickets and insurance by the same economic agents, comparing his utility function to that of prospect theory. Additionally, Markowitz discusses the Capital Asset Pricing Model (CAPM) and critiques some of its foundational assumptions, particularly the unrealistic representation of short positions. Overall, the paper serves as a retrospective and an update on Markowitz's views on portfolio theory, offering insights into both its historical foundations and its relevance to current financial practices.

Maillard et al. (2010) explored an alternative approach to portfolio construction known as the Equally Weighted Risk Contribution portfolio. They analyzed the theoretical properties and practical performance of Equally Weighted Risk Contribution portfolios, which aim to balance the risk contribution of each asset in the portfolio rather than simply equalizing the weights. The Equally Weighted Risk Contribution approach is positioned as a middle ground between the minimum-variance portfolio, which can suffer from concentration issues, and the equally weighted portfolio, which may lack proper risk diversification. The authors delve into the mathematical foundations of Equally Weighted Risk Contribution portfolios, providing both theoretical insights and empirical evidence to support their effectiveness. They compare the Equally Weighted Risk Contribution portfolios with strategies like the $1/n$ and minimum-variance portfolios, through numerical examples and empirical simulations. The study concluded that Equally Weighted Risk Contribution portfolios offer a more balanced risk profile while maintaining competitive performance, making them a valuable tool for investors seeking robust portfolio diversification without excessive concentration in a few assets.

Clarke et al. (2011) focused on the construction and analysis of minimum-variance portfolios, which aim to achieve the lowest possible risk for a given set of assets. They explored the composition of minimum-variance portfolios, particularly under long-only constraints (where no short-selling is allowed). The authors provide an analytic solution for determining the optimal security weights within these portfolios, emphasizing that such portfolios are primarily composed of stocks with lower market betas. The paper also

highlights how high idiosyncratic risk reduces a security's weight but does not eliminate it from the portfolio unless the market beta is high. Furthermore, the study compares these analytic results with empirical data, and finds that the optimization of minimum-variance portfolios often leads to portfolios dominated by low-beta stocks. This finding aligns with the longstanding critique of the Capital Asset Pricing Model (CAPM), which suggests that low-beta stocks can yield returns similar to or even higher than those from high-beta stocks. The authors conclude that minimum-variance portfolio strategies are effective in reducing risk while potentially offering high returns, making them a valuable tool in portfolio management, especially considering the observed anomalies in traditional risk–return relationships.

Boasson et al. (2011) explored the use of a semi-variance framework as an alternative to the traditional mean-variance approach in portfolio optimization. They demonstrated how a semi-variance approach can more effectively measure downside risk in portfolio selection, compared to the traditional mean-variance framework. The authors argued that semi-variance, which only considers return dispersions below the expected value, aligns better with investors' intuitive perceptions of risk, focusing on minimizing losses rather than overall volatility. The study used a sample of exchange-traded index funds (ETFs) to compare portfolios constructed using the mean-semi-variance model with those created using the traditional mean-variance model. The results indicate that portfolios optimized under the mean-semi-variance framework offer potential benefits, such as maintaining or improving expected returns while minimizing downside risk exposure. The findings have practical implications for both individual and institutional investors, particularly those in industries like insurance, where minimizing downside risk is crucial.

Todoni (2015) explored the application of Post-Modern Portfolio Theory (PMPT) in evaluating the risk-adjusted returns of major indices from emerging markets in Central and Eastern Europe over the period 2008–2013. The main goal of this paper is to apply two methods based on PMPT to assess the risk-adjusted returns of five major Central and Eastern European market indices: Romania (BET), Hungary (BUX), Czech Republic (PX), Bulgaria (SOFIX), and Poland (WIG). The study employed the Sortino ratio, a well-known measure to evaluate risk-adjusted return of a portfolio considering only the downside risk. The authors then propose an alternative method that builds on the Sortino ratio by incorporating a “multipliers method” to calculate a global measure of risk, which aims to provide a more nuanced assessment of risk by distinguishing between unrealized return areas and loss areas (negative returns). The analysis was conducted over two sub-periods, 2008–2010 and 2011–2013, highlighting how Central and Eastern European markets responded to the financial crisis. The results show that Hungary consistently outperformed across both methods, while Bulgaria typically exhibited the worst performance. The study concludes by suggesting that the proposed alternative method may offer a more refined measure of risk that better aligns with the realities of investment decision-making, particularly in emerging markets.

Booth and Broussard (2016) explored the application of the Sortino ratio within the context of asset allocation, particularly using Extreme Value Theory (EVT). They assessed the effectiveness of the Sortino ratio, which focuses on downside risk, in optimizing portfolio allocations. The authors compare the performance of portfolios constructed using the Sortino ratio against those optimized with the Sharpe ratio, particularly in environments with significant downside risks, such as during financial crises. The analysis is performed using a dataset that includes U.S. real estate investment trusts (REITs) and the S&P 500 index. The authors also incorporate the EVT to model the extreme returns in the left tail of the distribution, which are crucial in assessing the downside risk more accurately. Their findings indicate that the choice of performance measure (Sortino versus Sharpe) significantly influences the optimal asset allocation, especially under different risk tolerances and market conditions. The results suggest that portfolios optimized using the Sortino ratio, particularly with EVT adjustments, might offer better protection against extreme negative events, making it a valuable tool for investors concerned with downside risk.

Taljaard and Maré (2021) focused on the S&P 500 since 2016 and compared the equally weighted portfolio with the market-capitalization-weighted portfolio. The primary goal of this study was to analyze the reasons behind the underperformance of the equally weighted portfolio relative to the market-cap-weighted portfolio and to propose strategies to mitigate this issue. The authors utilized stochastic portfolio theory to explore the dynamics that contribute to this underperformance. They find that while the equally weighted portfolio typically outperforms over the long term, it has faced significant short-term underperformance due to increased market concentration in the cap-weighted portfolio and reduced diversification benefits. To address these challenges, the study suggested a dynamic approach that involves switching between equal-weighted and cap-weighted portfolios based on a linear regression model that predicts relative performance. This model considers factors such as changes in market concentration and the benefits of diversification, with the aim of optimizing short-term performance while maintaining long-term gains. The findings offer practical insights for improving the performance of equal-weighted portfolios, particularly in volatile or momentum-driven markets.

Surtee and Alagidede (2023) explored an innovative use of the MPT by incorporating different risk–reward ratios beyond the traditional Sharpe and Sortino ratios. They evaluated the effectiveness of the Sterling and Treynor ratios as alternatives to the commonly used Sharpe and Sortino ratios in portfolio optimization. The authors argue that while MPT and the Sharpe ratio have been widely used, these traditional methods may not fully capture the potential for higher returns under varying market conditions. By applying the Sterling and Treynor ratios to MPT, the study finds that these ratios often produce higher-performing portfolios. The paper emphasizes the statistical advantages of using these ratios, particularly in their ability to adapt to different market environments and provide more robust performance metrics compared to traditional methods. The study concludes by suggesting further research into optimizing portfolio performance through the application of these alternative ratios and exploring advanced optimization algorithms to enhance the results.

3. Materials and Methods

3.1. RMD Portfolio

The application of the RMD portfolio is the focus of the study, hence we present the approach as follows (Bielstein et al. 2023). The objective of the RMD portfolio is to maximize the unexplained variation between the asset returns, enhancing diversification by emphasizing assets that behave differently from each other. We consider an asset universe of N assets and compute a sample return over a specific period from $t = 0$ to $t = T$, where $t = 0$ is the starting point for returns, and $t = T$ is the end point for returns. We can then compile the correlation matrix, denoted as C , which presents the pairwise correlations between these asset returns, as follows:

$$C = \begin{bmatrix} 1 & \dots & \rho_{1,N} \\ \vdots & \ddots & \vdots \\ \rho_{N,1} & \dots & 1 \end{bmatrix} \quad (1)$$

The matrix C can be used to derive the explained variations between any two asset returns (say asset 1 and asset 2), which are essentially the R^2 values computed by squaring the correlation coefficient, $\rho_{1,2}$. We compile the R^2 values in a P -matrix, as follows:

$$P = \begin{bmatrix} 1 & \dots & \rho_{1,N}^2 \\ \vdots & \ddots & \vdots \\ \rho_{N,1}^2 & \dots & 1 \end{bmatrix} \quad (2)$$

Alternatively, we can directly compute the R^2 values by taking two asset returns, say assets 1 and 2, and regressing the returns of asset 1 on the returns of asset 2, to determine the proportion of variance of asset 1 explained by asset 2.

Next, we compute the unexplained variation (denoted by the R -matrix), because a diversified portfolio should include assets whose return variations are largely unexplained by other assets. Since the explained variation between any two assets is denoted by R -square values (or matrix P), where $\rho^2 \in [0, 1]$, the unexplained variation between any two assets is computed by $1 - \rho_{1,2}^2$. We can construct the matrix of unexplained variations between the respective pair of asset returns denoted by the R -matrix given below:

$$R = \begin{bmatrix} 0 & \dots & 1 - \rho_{1,N}^2 \\ \vdots & \ddots & \vdots \\ 1 - \rho_{N,1}^2 & \dots & 0 \end{bmatrix} \quad (3)$$

This matrix R represents the unexplained variations between the asset pairs, which the optimization function uses to determine the portfolio weights. The goal is to maximize these unexplained variations, thereby combining assets that exhibit the least correlation with one another. In what follows, the RMD portfolio finds the vector of weights (ω) that maximizes these unexplained variances, subject to full investment and no-short-selling. Hence, the optimization problem is formulated as follows:

$$\max \omega^T R \omega$$

Subject to:

$$\sum_{i=1}^N \omega_i, \text{ and } \omega_i \geq 0, \forall i = 1, \dots, N \quad (4)$$

The term $\omega^T R \omega$ represents the weighted sum of unexplained variations. Maximizing this term means choosing portfolio weights that emphasize assets with minimal correlation to each other, thus maximizing diversification. The constraint $\sum \omega_i = 1$ ensures that the total investment across all assets equals the total capital available for investment. The constraint $\omega_i \geq 0$ ensures that no asset has a negative weight, meaning no short positions are taken in any asset.²

We can compute the R^2 value in Excel[®] using the formula: $=RSQ(\mu_{A1}, \mu_{A2})$, where μ_{A1} and μ_{A2} are the monthly returns of asset 1 and asset 2, respectively. Alternatively, we can obtain the respective R^2 by first computing the correlation between asset 1 and asset 2, $\rho_{1,2}$, and then taking the square of the correlation coefficient, i.e., $\rho_{1,2}^2$. In Excel[®], we can implement this for each pair of assets using the formula: $(=POWER(CORREL(\mu_{A1}, \mu_2), 2))$.

3.2. Benchmark Portfolios

This section is devoted to explaining the benchmark portfolios used in our study. Benchmark portfolios serve as standards or points of reference against which the performance and characteristics of the RMD portfolio can be compared. The following benchmark portfolios are considered.

3.2.1. Equally Weighted (Naïve)

The equally weighted portfolio (1/N) (DeMiguel et al. 2009) allocates an equal proportion of the total investment to each asset, regardless of its individual characteristics. It is robust to estimation errors because it only relies on the number of assets in the portfolio. The primary assumption here is that the assets are uncorrelated, meaning each asset's performance is independent of the others. The equally weighted portfolio can be depicted as follows:

$$\omega_{EW} = \frac{1}{N} \quad (5)$$

where N is the number of assets in the portfolio.

3.2.2. Minimum Variance

The MVP (Clarke et al. 2006; Haugen and Baker 1991) aims to achieve the lowest possible portfolio volatility by minimizing the standard deviation of returns. This approach assumes accurate forecasts of the covariance matrix of asset returns. However, reliance on such forecasts can introduce estimation errors, particularly in large asset universes, leading to potential instability. Moreover, this method may result in overly concentrated portfolios, where a few assets dominate the risk exposure. The MVP can be formulated as follows:

$$\min \left\{ \sigma_p = \sqrt{\omega_{MVP}^T \Sigma \omega_{MVP}} \mid \mu_p = \sum_{i=1}^N \omega_i r_i; \sum_{i=1}^N \omega_i = 1 \right\} \quad (6)$$

where Σ is the $N \times N$ covariance matrix of the asset returns, and r_i is the i th stock's market-adjusted return. Generally, the portfolio with the minimum variance can be computed by $\omega_{min} = \frac{\Sigma^{-1} \mathbf{1}}{\mathbf{1}^T \Sigma^{-1} \mathbf{1}}$, where Σ^{-1} is the inverse covariance of returns matrix. A portfolio's beta-adjusted portfolio mean is given by $\mu_p = \omega' \mu$, and variance is given by $\sigma_p = \omega' \Sigma \omega$, where Σ is the covariance matrix.

3.2.3. Mean Variance (Market)

The individual stock returns are computed as $r_t = \ln\left(\frac{p_t}{p_{t-1}}\right)$, where p_t and p_{t-1} are the individual stock prices for months t and $t - 1$, respectively. Individual asset beta, β_i , represents the trade-off between market return against the individual asset's return over the sample period. Based on the CAPM framework, the annualized return for each stock (μ_{β_i}) is computed as: $\mu_{\beta_i} = r_f + \beta_i (\mu_{mkt} - r_f)$, where r_f is the risk-free rate, assumed equal to 0.0544 (5.44%) in the paper, and μ_{mkt} = average return of the market weighted price index (MWPI) reported by SPX (SPX 2024a). The risk-free rate was selected based on the 1-year government bond yield rate of May 2019.³

With insights earlier studies from on CAPM and maximizing returns with a given risk (standard deviation) (Sharpe 1964; Merton 1972), we derive a market portfolio based on maximizing the Sharpe (1996) ratio, $SR = \left(\frac{\mu_p - r_f}{\sigma_p}\right)$, where μ_p , r_f and σ_p are the portfolio mean, risk-free rate and portfolio standard deviation, respectively. Hence, following Bai and Newsom (2011), we specify the programming problem as

$$\max \left\{ SR = \frac{\mu_p - r_f}{\sigma_p} \mid \mu_p = \sum_{i=1}^N \omega_i r_i; \sigma_p = \sqrt{\sum_{i,j}^N \sigma_{ij} \omega_i \omega_j}; \sum_{i=1}^N \omega_i = 1 \right\} \quad (7)$$

where N is the number of stocks, and σ_{ij} is the covariance between returns of stock i and stock j , and $\bar{r}_i$ is the annualized expected return of stock i , σ_{ij} is the maximum risk level specified by the investor, and ω_i is the weight of stock i in the portfolio. We use the changes in the market-weighted price index to proxy market return and derive beta-adjusted annualized stock returns based on the CAPM framework.

3.2.4. Semi-Variance

Next, we extend the analysis to examine downside risk only. First, we compute the monthly upside risk as $UR_t = \max(\bar{\mu} - \mu_{p_t}, 0)$, where μ_{p_t} is the monthly portfolio return with respect to weight, and $\bar{\mu}$ are the historical monthly returns. The monthly downside risk is given by $DR_t = \max(\mu_{p_t} - \bar{\mu}, 0)$. Then, we compute the annualized downside volatility, as $\bar{\sigma}_D = \sqrt{\frac{\sum_{i=1}^T \max(\mu_{p_t} - \bar{\mu}, 0)^2}{T-1}} \times 12$.

Hence,

$$\min \left\{ \bar{\sigma}_D \mid \bar{\mu}_p = \sum_{i=1}^N \omega_i r_i; \sigma_p = \sqrt{\sum_{i,j}^N \sigma_{ij} \omega_i \omega_j}; \sum_{i=1}^N \omega_i = 1 \right\} \quad (8)$$

3.2.5. Max Target Ratio

With a target return of 6.75% ($T_g = 0.0675$), which was the rate of return offered by Fiji National Provident Fund in 2019,⁴ we compute the Sortino ratio as $Sort = \frac{\bar{\mu}_p - T_g}{\bar{\sigma}_D}$, where $\bar{\sigma}_D$ is the annualized downside volatility. The program for optimization with the T -period sample is as follows:

$$\max \left\{ Sort = \frac{\bar{\mu} - T_g}{\bar{\sigma}_D} \middle| \mu_p = \sum_{i=1}^N \omega_i r_i; \bar{\sigma}_D = \sqrt{12 \left[\frac{\sum_{i=1}^T \max(\mu_T - \mu_i, 0)^2}{T-1} \right]}; \sum_{i=1}^N \omega_i = 1 \right\} \quad (9)$$

3.2.6. Maximum Skewness

Finally, the volatility skewness is defined as $\sigma_v = \frac{\sigma_U^2}{\sigma_D^2}$, where σ_U^2 and σ_D^2 are the variances of upside risk and downside risk, and $\sigma^2 = \sigma_U^2 + \sigma_D^2$. Hence, $0 < \sigma_v < 1$ implies higher downside risk in the portfolio, whereas $\sigma_v > 1$ implies greater upside risk in the portfolio. Hence, the program for maximum volatility skewness is specified as follows:

$$\max \left\{ \sigma_v = \frac{\sigma_U^2}{\sigma_D^2} \middle| \mu_p = \sum_{i=1}^N \omega_i r_i; \sigma_p = \sqrt{\sum_{i,j} \sigma_{ij} \omega_i \omega_j}; \sum_{i=1}^N \omega_i = 1 \right\} \quad (10)$$

3.2.7. Most Diversified Portfolio (MDP)

The MDP (Choueifaty and Coignard 2008) is calculated by comparing the weighted average volatility of the individual assets ($\omega_{MDP}\sigma$) to the total portfolio volatility ($\sqrt{\omega_{MDP}^T \Sigma \omega_{MDP}}$). This method aims to spread investments across assets with varying degrees of volatility and correlation to achieve maximum diversification benefits. The MDP can be depicted as follows:

$$\max \left\{ MDP = \frac{\omega_{MDP}\sigma}{\sqrt{\omega_{MDP}^T \Sigma \omega_{MDP}}} \middle| \mu_p = \sum_{i=1}^N \omega_i r_i; \sigma_p = \sqrt{\sum_{i,j} \sigma_{ij} \omega_i \omega_j}; \sum_{i=1}^N \omega_i = 1 \right\} \quad (11)$$

where σ is an $N \times 1$ vector of the asset return volatilities.

4. Results

4.1. Descriptive Statistics and Asset Betas

This section presents the analysis and results based on historical return data covering 58 months from August 2019 to May 2024.⁵ Table 1 presents a summary profile of the companies listed on the stock exchange. In terms of sector composition, there are two stocks in automotive (TTS and VBH); one each in banking (BCN), education (FBL), insurance (FIL), retail (RBG) and tourism (PDM); three in investment (FHL, KGF and VIL), five in manufacturing and wholesale (PBP, FMF, PGI, APP, RCF); and three in telecommunications and media (ATH, CFL, FTV). The annualized return is calculated using the compound method, considering the share price on the date the company was listed and the share price on 31 May 2024. Furthermore, 13/19 companies have market capitalization below 5%: APP, BCN, CFL, FBL, FIL, FTV, KFL, KGF, PBP, PDM, PGI, RCF and VBH (See Figure 1).

Table 1. Profile of listed stocks on SPX.

Symbol	Name	Date Listed	Sample End Date	Number of Trading Days	Sector	Date Listed Market Closing Price	Market Closing Price on 31 May-2024	Financial Year End	Annualized Return	Market Capitalization in Millions of FJD (% of Market Cap.)
APP	Atlantic & Pacific Packaging Company Ltd.	17-Aug-98	31-May-24	6502.98	Manufacturing and wholesale (Packaging)	\$0.70	\$3.09	30-Jun	5.75%	24.7 (0.72)
ATH	Amalgamated Telecom Holdings Ltd.	18-Apr-02	31-May-24	5577.83	Telecommunications and media (telecommunications and mobile services)	\$1.14	\$2.00	30-Jun	2.54%	1029.0 (30.01)
BCN	BSP Convertible Notes Ltd.	11-May-10	31-May-24	3544.57	Banking (Financial services)	\$5.25	\$31.00	31-Dec	12.63%	95.0 (2.77)
CFL	Communications (Fiji) Ltd.	20-Dec-01	31-May-24	5659.99	Telecommunications (Radio broadcasting)	\$1.15	\$6.17	31-Dec	7.48%	23.4 (0.68)
FBL	Free Bird Institute Ltd.	2-Feb-17	31-May-24	1846.85	Education	\$2.00	\$3.65	31-Dec	8.21%	8.7 (0.25)
FHL	Fijian Holdings Ltd.	20-Jan-97	31-May-24	6899.28	Investment (investment chain)	\$0.18	\$0.95	30-Jun	6.08%	304.6 (8.89)
FIL	FijiCare Insurance Ltd.	7-Dec-00	31-May-24	5920.96	Insurance	\$0.60	\$17.99	31-Dec	14.48%	159.2 (4.64)
FMF	FMF Foods Ltd.	27-Jul-79	31-May-24	11308.93	Manufacturing and wholesale (flour and related products)	\$0.06	\$1.78	30-Jun	7.56%	264.0 (7.70)

Table 1. Cont.

Symbol	Name	Date Listed	Sample End Date	Number of Trading Days	Sector	Date Listed Market Closing Price	Market Closing Price on 31 May-2024	Financial Year End	Annualized Return	Market Capitalization in Millions of FJD (% of Market Cap.)
FTV	Fiji Television Ltd.	24-Apr-97	31-May-24	6834.38	Telecommunications (Television broadcasting)	\$1.02	\$2.00	30-Jun	2.48%	20.6 (0.60)
KFL	Kontiki Finance Ltd.	4-Jul-18	31-May-24	1489.91	Investment (Financial services)	\$1.14	\$1.13	30-Jun	−0.15%	101.1 (2.95)
KGF	Kinetic Growth Fund Ltd.	16-Dec-04	31-May-24	4906.06	Investment (investment chain)	\$1.05	\$1.20	31-Dec	0.69%	4.6 (0.13)
PBP	Pleass Global Ltd.	4-Feb-09	31-May-24	3862.85	Manufacturing and wholesale (Bottled water)	\$0.94	\$7.95	31-Dec	13.93%	56.8 (1.66)
PDM	Port Denarau Marina	14-Aug-19	31-May-24	1209.60	Tourism (Tourism and hospitality)	\$1.40	\$2.30	31-Jul	10.34%	89.2 (2.60)
PGI	Pacific Green Industries	5-Jun-01	31-May-24	5796.69	Manufacturing and wholesale (Furniture)	\$1.90	\$1.08	31-Dec	−2.46%	8.2 (0.24)
RBG	RB Patel Group Ltd.	17-Jul-01	31-May-24	5767.69	Retail (Supermarket chain)	\$0.21	\$3.09	30-Jun	11.75%	463.5 (13.52)
RCF	The Rice Company of Fiji Ltd.	20-Jan-97	31-May-24	6899.28	Manufacturing and wholesale (Rice)	\$0.50	\$9.80	30-Jun	10.87%	58.8 (1.72)
TTS	Toyota Tsusho (South Sea) Ltd.	7-Jun-79	31-May-24	11343.45	Automotive (automotive trading)	\$1.95	\$20.00	31-Mar	5.17%	280.6 (8.19)

Table 1. Cont.

Symbol	Name	Date Listed	Sample End Date	Number of Trading Days	Sector	Date Listed Market Closing Price	Market Closing Price on 31 May-2024	Financial Year End	Annualized Return	Market Capitalization in Millions of FJD (% of Market Cap.)
VBH	V B Holdings Ltd.	1-Nov-01	31-May-24	5693.82	Automotive (property and fleet management)	\$1.28	\$6.00	31-Dec	6.84%	12.8 (0.37)
VIL	Vision Investments Ltd.	29-Feb-16	31-May-24	2080.90	Investment (investment chain)	\$1.70	\$4.09	31-Mar	10.63%	423.4 (12.35)

Notes: Number of trading days per year = 252, and total number of trading days from the day of listing to the sample end date is computed using Excel formula: $= \left(\left(\frac{DAYS(D3,C3)}{365} \right) * 252 \right)$, where D3 = Sample end date and C3 = date the respective company was listed. Annualized return is computed as: $= \left(\left(\frac{H3}{G3} \right)^{\left(\frac{E3}{252} \right)} - 1 \right) * 252$, where H3 is the market closing price on 31 May 2024, G3 = market closing price on the day of listing, and E3 = number of trading days per year. Sun Insurance Company (SUN) was listed on 15 August 2024, hence excluded from the sample. At the time of listing, SUN's market cap was FJD 144 million (4.03%). All the companies are based in and operating in Fiji. Source: authors' own computation and compilation based on data from SPX (2024a; 2024b, p. 3).

Table 2. Descriptive statistics (monthly return data from August 2019 to May 2024).

Statistics	APP	ATH	BCN	CFL	FBL	FHL	FIL	FMF	FTV	KFL	KGF	PBP	PDM	RBG	RCF	TTS	VBH	VIL	DMCWPI
Mean Return	0.013	−0.006	0.006	0.002	0.008	−0.003	0.038	0.002	−0.009	0.004	0.001	0.022	0.011	−0.008	0.004	0.010	−0.0030	0.001	−0.001
Standard Error	0.007	0.008	0.006	0.002	0.009	0.017	0.008	0.015	0.012	0.008	0.001	0.010	0.008	0.013	0.006	0.008	0.004	0.010	0.004
Sample Variance	0.003	0.003	0.002	0.000	0.004	0.018	0.003	0.014	0.009	0.004	0.000	0.006	0.004	0.010	0.002	0.003	0.001	0.006	0.001
Kurtosis	15.004	2.511	4.218	26.266	12.000	1.942	2.142	35.988	14.730	2.524	41.424	17.674	4.544	39.718	30.123	10.773	6.453	10.173	3.140
Skewness	2.792	−0.030	0.708	4.005	1.427	0.730	1.333	4.791	1.561	0.897	6.234	3.702	1.905	−5.520	4.680	2.632	−0.3651	5.84	0.324
Range	0.387	0.363	0.294	0.130	0.547	0.740	0.308	1.122	0.810	0.350	0.045	0.565	0.323	0.892	0.384	0.390	0.194	0.563	0.195
Minimum	−0.088	−0.178	−0.136	−0.034	−0.243	−0.322	−0.069	−0.340	−0.325	−0.168	0.000	−0.121	−0.089	−0.679	−0.095	−0.104	−0.111	−0.245	−0.096
Maximum	0.299	0.185	0.158	0.095	0.304	0.418	0.239	0.782	0.485	0.182	0.045	0.443	0.234	0.213	0.289	0.286	0.083	0.318	0.099
N (Months)	58	58	58	58	58	58	58	58	58	58	58	58	58	58	58	58	58	58	58

Source: authors' own computation based on data from SPX (2024a).

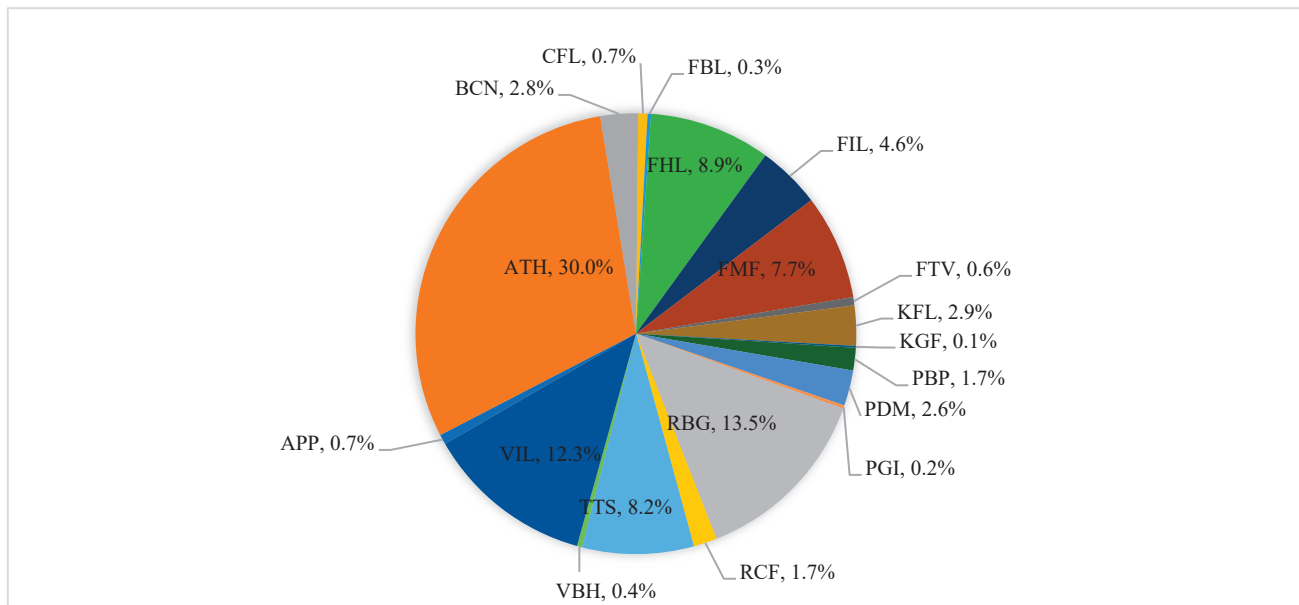


Figure 1. Market capitalization (%). Source: SPX (2024a, 2024b) and authors' own computation.

For analysis, we considered 18/19 companies listed on SPX at the time of study. We excluded one stock because it had no variability in its share price. Table 2 provides the descriptive statistics (mean returns, standard errors, variances, kurtosis, skewness, range, minimum and maximum returns) for the 18 stocks included in our analysis, and the market-weighted price index (MWPI) published by the South Pacific Stock Exchange (SPX). These data are sourced from SPX (2024a), and they form the basis for understanding the performance and risk characteristics of the assets in our portfolio.

Table 3 presents the beta coefficient and the respective p -values, the expected return, standard deviation, and market-adjusted return using the Capital Asset Pricing Model (CAPM). The beta values indicate the sensitivity of each asset's returns to market movements. The statistically significant values of stock beta (denoted by ***, **, *) highlight the strength of the asset's movement with respect to the overall market.

Table 3. Asset return–risk (annualized), adjusted return and trade profile.

Symbol	Beta	p -Value	Expected Return $E(r_i)$	Standard Deviation	Market (CAPM)—Adj. Return, $r_{i,m}$	Number of Trades (Jul 2019–May 2024)	Consideration—FJD [Volume Traded]
APP	0.021	0.928	0.152	0.183	0.053	93	\$201,269 [99,619]
ATH	1.258 ***	<0.001	−0.076	0.205	−0.022	817	\$4,198,696 [2,079,256]
BCN	0.379 **	0.053	0.074	0.156	0.031	307	\$3,381,869 [123,836]
CFL	0.118 *	0.072	0.022	0.052	0.047	88	\$482,651 [75,774]
FBL	−0.043	0.881	0.095	0.228	0.057	93	\$803,486 [266,528]
FHL	1.983 ***	<0.001	−0.031	0.459	−0.063	7016	\$8,286,653 [8,244,432]

Table 3. Cont.

Symbol	Beta	<i>p</i> -Value	Expected Return $E(r_i)$	Standard Deviation	Market (CAPM)—Adj. Return, $r_{i,m}$	Number of Trades (Jul 2019–May 2024)	Consideration—FJD [Volume Traded]
FIL	−0.012	0.963	0.452	0.202	0.055	439	\$4,346,235 [598,217]
FMF	1.591 ***	0.001	0.024	0.407	−0.041	166	\$4,019,393 [2,178,942]
FTV	0.715 *	0.084	−0.110	0.329	0.010	119	\$1,485,997 [363,014]
KFL	0.387	0.160	0.044	0.218	0.030	820	\$10,015,865 [10,190,076]
KGF	0.007	0.808	0.015	0.022	0.054	23	\$90,111.80 [78,481]
PBP	−0.073	0.827	0.262	0.262	0.059	103	\$440,551 [139,544]
PDM	−0.032	0.903	0.136	0.205	0.056	1273	\$36,812,195 [23,808,791]
RBG	−1.131 ***	0.007	−0.095	0.341	0.127	862	\$9,167,304 [2,723,851]
RCF	−0.068	0.731	0.052	0.154	0.059	257	\$761,443 [76,842]
TTS	0.036	0.888	0.124	0.199	0.052	85	\$8,616,426 [605,629]
VBH	−0.101	0.412	−0.036	0.097	0.061	41	\$280,397 [42,590]
VIL	0.996 ***	0.002	0.012	0.267	−0.006	295	\$30,855,896 [7,530,672]

Notes: Average per month market return (change in MWPI) over the sample period is $r_m = -0.055\%$; risk-free rate, $r_f = 5.44\%$ p.a; hence, the monthly rate based on $r_{fj12} = \left\{ (1 + r_f)^{\frac{1}{12}} - 1 \right\} = 0.004424081$; monthly market adjusted return is $r_{i,m} = \left\{ r_{fj12} + \beta_i (r_m - r_{fj12}) \right\}$, and this is annualized as $\bar{r}_{i,m} = \left\{ (1 + r_{i,m})^{12} - 1 \right\}$; ***, **, and * indicates significance at 1%, 5% and 10% level, based on *p*-values. Source: authors' own computation based on data from SPX (2024a).

For example, assets with $\beta > 1$ (ATH—telecommunications and media, FHL—investment, and FMF—manufacturing and wholesale) perform better (worse) than the market if the market moves positively (negatively). Similarly, assets with $0.5 < \beta < 1$ are FTV (telecommunications and media) and VIL (investment), which perform similarly to the market, although proportionately lower than the market. Other stocks with beta $0.1 < \beta < 0.5$ are BCN (banking), CFL (telecommunications and media), KFL (finance), and TTS (automotive), and others are positive but with a small beta ($0 < \beta \leq 0.1$) (APP—manufacturing and wholesale, KGF—investment, and TTS—automotive). On the other hand, just one stock was noted to have $\beta < -1$, which was RBG (retail). Therefore, beta-adjusted annualized returns can provide deeper insight into a stock's performance against its risk profile for potential investors. Subsequently, using beta-adjusted returns can facilitate robust portfolio construction.

Considering the returns, we note that APP has a low beta (0.021), although its annualized average return is 15.2%, with a relatively high volatility (18.3%). Noting the stock's performance against the market, we find that the market-adjusted return is just 1.3%, which is significantly lower than the expected return based on monthly price changes. Examining a few other stocks, we note that some stocks are highly positively correlated with the market (examples: ATH, FHL, FMF), and their market-adjusted returns are higher (in absolute terms) relative to the expected returns. Another observation we make is that

one of the stocks (i.e., PBP—manufacturing and wholesale sector) has a positive average return, but since its beta is negative ($\beta = -0.07$), the market-adjusted return is negative (-0.8%). Interestingly, some stocks with negative beta, such as RBG (retail business) with a $\beta = -1.13$ and VBH (automotive sector) with a $\beta = -0.10$, have negative average returns of -9.5% and -3.6% , respectively. However, the respective annualized market-adjusted returns are positive, with RBG's return of 12.9% and VBH's of 1.5% . Moreover, stocks like FBL (education) and FIL (insurance) have $\beta = -0.043$ and $\beta = -0.012$, respectively. Their respective annualized average returns are 9.5% and 45.2% . However, their market-adjusted returns are 0.6% and 0.5% , respectively.

Furthermore, we note that stocks with betas $+/- 0.1$ range included APP ($\beta = 0.021$), CFL ($\beta = 0.12$), FBL ($\beta = -0.043$), FIL ($\beta = -0.012$), KGF ($\beta = -0.007$), PBP ($\beta = -0.073$), PDM ($\beta = -0.032$), RCF ($\beta = -0.068$), TTS ($\beta = 0.036$) and VBH ($\beta = -0.10$) (Table 3). We note that the p -values of these betas are above the 10% level, hence they are not statistically significant within the 1–10 percent level. Nevertheless, some observations are in order. We note that some of the stocks with low betas have comparatively low numbers of trading over the sample period, and most of them are low-cap stocks with less than 5% over the market capitalization (Table 1). For example (Table 3), the total numbers of trades over the sample period for stocks like APP, CFL, FBL, KGF, TTS and VBH were 93, 88, 93, 23, 85, and 41, respectively. Moreover, some of these stocks have relatively low percentages of market capitalization (below 1%) (APP, CFL, FBL and KGF) (Table 1). Moreover, stocks like FIL, PDM and RCF have small and negative betas, indicating that these stocks' prices tend to move opposite to the market. Moreover, although these stocks (FIL, PDM and RCF) have relatively high numbers of trades (439, 1273 and 257, respectively) and slightly higher percentages of market capitalization (4.64% , 2.60% and 1.72%), we note that for stocks like RCF, the volume traded (76,842) and considerations (FJD 761,443) remain low compared to high beta stocks; and for FIL and PDM, the stocks are traded in large amounts, but infrequently. In any case, a small beta is indicative that the stock prices are not highly sensitive to the overall market.

Next, we construct a portfolio using the RMD method. As mentioned earlier, the P-matrix contains the R-square values obtained from the pairwise regression results between the asset returns (Table 4). Each element P_{ij} in the matrix indicates the proportion of the variance of asset i that is explained by asset j . For example, if we take two stocks, say ATH and APP, then P_{21} represents how much of the variance of ATH is explained by APP. This matrix is essential in understanding the interdependencies and co-movements between different assets. The diagonal elements are 1, indicating that each asset explains its own variance completely. The off-diagonal elements close to 0 suggest low explanatory power between the assets, indicating the potential for diversification. For instance, the low values of $\mathbf{P}$ in most of the off-diagonal elements suggest that the assets have low correlations with each other, hence are favorable for diversification.

As discussed above, the R-matrix is derived from the P-matrix by computing $1 - \rho_{ij}^2$ for each pair of assets (Table 5). This matrix represents the unexplained variations between the asset pairs, and they are crucial for the RMD optimization process. Each element R_{ij} in the R-matrix derived from the pairwise regression denotes the unexplained variations. High values in the R-matrix indicate significant unexplained variation, suggesting that these assets move independently of each other, which is ideal for maximizing diversification. For example, in Table 5, we note that $R_{2,1}$ (where the subscript 2,1 denotes asset in row 2, column 1) is high (0.995). This implies that the relationship between the returns of ATH and APP has a substantial amount of unexplained variation (see Table 4). Because of the close link between correlation and variations, we further confirm this by noting the low correlation coefficient (0.007, Table 6) between the two asset returns. Thus, including these two assets in a portfolio could enhance diversification.

Table 4. P-Matrix.

	APP	ATH	BCN	CFL	FBL	FHL	FIL	FMF	FTV	KFL	KGF	PBP	PDM	RBG	RCF	TTS	VBH	VIL
APP	1.000																	
ATH	0.005	1.000																
BCN	0.028	0.000	1.000															
CFL	0.398	0.064	0.001	1.000														
FBL	0.133	0.034	0.003	0.013	1.000													
FHL	0.001	0.002	0.011	0.048	0.072	1.000												
FIL	0.006	0.006	0.003	0.002	0.003	0.001	1.000											
FMF	0.013	0.009	0.003	0.001	0.072	0.033	0.019	1.000										
FTV	0.010	0.016	0.005	0.025	0.004	0.000	0.028	0.000	1.000									
KFL	0.000	0.001	0.060	0.001	0.000	0.034	0.022	0.011	0.040	1.000								
KGF	0.001	0.003	0.001	0.009	0.000	0.000	0.000	0.000	0.002	0.001	1.000							
PBP	0.029	0.001	0.001	0.000	0.003	0.001	0.001	0.005	0.001	0.000	0.165	1.000						
PDM	0.000	0.016	0.003	0.004	0.000	0.000	0.015	0.000	0.006	0.016	0.004	0.003	1.000					
RBG	0.000	0.054	0.032	0.005	0.009	0.005	0.003	0.000	0.039	0.000	0.000	0.000	0.020	1.000				
RCF	0.004	0.010	0.000	0.001	0.002	0.000	0.004	0.000	0.007	0.002	0.001	0.001	0.000	0.006	1.000			
TTS	0.001	0.002	0.001	0.000	0.003	0.001	0.000	0.002	0.002	0.054	0.001	0.000	0.021	0.002	0.005	1.000		
VBH	0.006	0.000	0.001	0.002	0.000	0.046	0.006	0.000	0.008	0.015	0.000	0.000	0.001	0.003	0.219	0.009	1.000	
VIL	0.001	0.012	0.003	0.000	0.007	0.000	0.003	0.000	0.015	0.099	0.000	0.000	0.006	0.001	0.023	0.105	0.001	1.000

Source: Authors' own computation based on data from SPX (2024a).

Table 5. R-Matrix.

	APP	ATH	BCN	CFL	FBL	FHL	FIL	FMF	FTV	KFL	KGF	PBP	PDM	RBG	RCF	TTS	VBH	VIL
APP	0.000																	
ATH	0.995	0.000																
BCN	0.972	1.000	0.000															
CFL	0.602	0.936	0.999	0.000														
FBL	0.867	0.966	0.997	0.987	0.000													
FHL	0.999	0.998	0.989	0.952	0.928	0.000												
FIL	0.994	0.994	0.997	0.998	0.997	0.999	0.000											
FMF	0.987	0.991	0.997	0.999	0.928	0.967	0.981	0.000										
FTV	0.990	0.984	0.995	0.975	0.996	1.000	0.972	1.000	0.000									
KFL	1.000	0.999	0.940	0.999	1.000	0.966	0.978	0.989	0.960	0.000								
KGF	0.999	0.997	0.999	0.991	1.000	1.000	1.000	1.000	0.998	0.999	0.000							
PBP	0.971	0.999	0.999	1.000	0.997	0.999	0.999	0.995	0.999	1.000	0.835	0.000						
PDM	1.000	0.984	0.997	0.996	1.000	1.000	0.985	1.000	0.994	0.984	0.996	0.997	0.000					
RBG	1.000	0.946	0.968	0.995	0.991	0.995	0.997	1.000	0.961	1.000	1.000	1.000	0.980	0.000				
RCF	0.996	0.990	1.000	0.999	0.998	1.000	0.996	1.000	0.993	0.998	0.999	0.999	1.000	0.994	0.000			
TTS	0.999	0.998	0.999	1.000	0.997	0.999	1.000	0.998	0.998	0.946	0.999	1.000	0.979	0.998	0.995	0.000		
VBH	0.994	1.000	0.999	0.998	1.000	0.954	0.994	1.000	0.992	0.985	1.000	1.000	0.999	0.997	0.781	0.991	0.000	
VIL	0.999	0.988	0.997	1.000	0.993	1.000	0.997	1.000	0.985	0.901	1.000	1.000	0.994	0.999	0.977	0.895	0.999	0.000

Source: Authors' own computation based on data from SPX (2024a).

Table 6. Correlation (C-matrix).

	APP	ATH	BCN	CFL	FBL	FHL	FIL	FMF	FTV	KFL	KGF	PBP	PDM	RBG	RCF	TTS	VBH	VIL	MCWPI
APP	1.000																		
ATH	0.070	1.000																	
BCN	0.167	0.021	1.000																
CFL	0.631	0.253	−0.035	1.000															
FBL	0.365	0.185	−0.053	0.112	1.000														
FHL	−0.033	−0.042	0.106	0.218	−0.269	1.000													
FIL	−0.078	−0.075	−0.050	−0.041	−0.052	0.023	1.000												
FMF	−0.113	0.094	0.053	0.024	−0.268	0.181	0.139	1.000											
FTV	−0.099	0.127	0.074	0.159	0.060	−0.009	−0.167	−0.021	1.000										
KFL	0.003	0.024	0.245	−0.037	−0.003	0.183	−0.149	0.103	0.201	1.000									
KGF	−0.029	0.052	−0.027	−0.096	−0.018	0.006	−0.016	−0.006	−0.043	−0.025	1.000								
PBP	0.170	−0.034	−0.025	0.006	0.055	−0.031	−0.025	−0.070	−0.032	0.008	0.406	1.000							
PDM	−0.015	−0.127	0.056	0.067	0.018	0.021	−0.123	−0.020	0.075	0.128	−0.063	−0.052	1.000						
RBG	0.004	−0.232	−0.180	−0.068	0.094	−0.071	−0.052	−0.020	−0.198	0.015	0.007	0.017	0.141	1.000					
RCF	0.061	−0.099	0.014	−0.031	−0.047	0.005	0.062	0.018	0.083	0.039	−0.028	−0.030	−0.007	0.080	1.000				
TTS	0.039	−0.047	0.036	0.009	0.051	−0.022	−0.006	0.041	0.050	0.231	−0.035	−0.012	0.145	−0.049	0.071	1.000			
VBH	0.075	0.012	−0.035	0.042	0.010	−0.214	−0.076	−0.019	0.088	0.121	0.021	0.016	−0.027	−0.052	−0.468	−0.095	1.000		
VIL	0.034	0.110	0.057	0.018	0.081	0.018	−0.057	−0.011	0.123	−0.315	0.005	−0.008	−0.075	−0.038	−0.151	−0.325	−0.024	1.000	
MCWPI	0.012	0.648	0.256	0.238	−0.020	0.455	−0.006	0.411	0.229	0.187	0.033	−0.029	−0.016	−0.350	−0.046	0.019	−0.110	0.394	1.000

Source: Authors' own computation based on data from SPX (2024a).

In Tables 6 and 7, we also present the correlation (C-matrix) and the covariance matrices, respectively. The correlation matrix (Table 6) displays the correlation coefficients (ρ_{ij}), indicating how (the direction) the returns of two assets move relative to each other, with values ranging from -1 to 1 . Low correlation values suggest that combining these assets could enhance diversification. In Table 7, we present the covariances (σ_{ij}) between asset returns, which measure the degree to which two assets' returns change together. These matrices form the foundation for constructing mean-variance type portfolios, including the RMD portfolio.

Table 7. Covariance Matrix.

	APP	ATH	BCN	CFL	FBL	FHL	FIL	FMF	FTV	KFL	KGF	PBP	PDM	RBG	RCF	TTS	VBH	VIL
APP	0.033																	
ATH	0.003	0.042																
BCN	0.005	0.001	0.024															
CFL	0.006	0.003	0.000	0.003														
FBL	0.015	0.009	−0.002	0.001	0.052													
FHL	−0.003	−0.004	0.008	0.005	−0.028	0.211												
FIL	−0.003	−0.003	−0.002	0.000	−0.002	0.002	0.041											
FMF	−0.008	0.008	0.003	0.001	−0.025	0.034	0.011	0.166										
FTV	−0.006	0.009	0.004	0.003	0.004	−0.001	−0.011	−0.003	0.108									
KFL	0.000	0.001	0.008	0.000	0.000	0.018	−0.007	0.009	0.014	0.047								
KGF	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000							
PBP	0.008	−0.002	−0.001	0.000	0.003	−0.004	−0.001	−0.007	−0.003	0.000	0.002	0.069						
PDM	−0.001	−0.005	0.002	0.001	0.001	0.002	−0.005	−0.002	0.005	0.006	0.000	−0.003	0.042					
RBG	0.000	−0.016	−0.010	−0.001	0.007	−0.011	−0.004	−0.003	−0.022	0.001	0.000	0.002	0.010	0.116				
RCF	0.002	−0.003	0.000	0.000	−0.002	0.000	0.002	0.001	0.004	0.001	0.000	−0.001	0.000	0.004	0.024			
TTS	0.001	−0.002	0.001	0.000	0.002	−0.002	0.000	0.003	0.003	0.010	0.000	−0.001	0.006	−0.003	0.002	0.040		
VBH	0.001	0.000	−0.001	0.000	0.000	−0.010	−0.001	−0.001	0.003	0.003	0.000	0.000	−0.001	−0.002	−0.007	−0.002	0.009	
VIL	0.002	0.006	0.002	0.000	0.005	0.002	−0.003	−0.001	0.011	−0.018	0.000	−0.001	−0.004	−0.003	−0.006	−0.017	−0.001	0.071

Source: Authors' own computation based on data from SPX (2024a).

In Table 8, we present 10 different portfolios. These include equally weighted (1/N) (column I), minimum variance (column II), market portfolio (column III), semi-variance (column IV), maximum Sortino (based on target return of 6.75%) (column V), and maximum volatility skewness (column VI). In column VII, we present the newly proposed maximum RMD portfolio (column VII) and its variations, i.e., RMD portfolio with positive Sharpe (column VIII), and RMD portfolio with Sharpe and Sortino ratios exceeding the risk-free rate and target rate, respectively (column IX); and in column IX, we present the most diversified portfolio.

Table 8. Portfolios under different methods and scenarios.

	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)	(IX)	(X)
Statistics	1/N (Equally Weighted)	Minimum Variance	Max Sharpe (CAPM)	Semi- Variance (min. Downside)	Max Sortino (CAPM)	Max. Vol Skewness (U/D)	Max. RMD	Max. RMD with Positive Sharpe	Max. RMD with Positive Sharpe ($\geq$ RF) and Sortino ($\geq$ TR)	Most Diversified Portfolio
Unadjusted return (annual)	0.0619	0.0239	−0.0075	0.0153	−0.0950	0.0394	0.0637	0.0798	0.0704	0.0443
CAPM-adjusted return (annual) (μ_p)	0.0359	0.0523	0.0786	0.0539	0.1274	0.0030	0.0341	0.0544	0.0426	0.0464
Standard deviation (σ_p)	0.0589	0.0175	0.1032	0.0213	0.3406	0.2046	0.0600	0.0604	0.0551	0.0318
Sharpe ratio (CAPM)	−0.3384	−0.1011	0.2348	−0.0255	0.2144	−0.2511	−0.3393	0.0010	0.7741	1.4578
Sortino ratio (CAPM)	−0.8419	−1.8969	0.1224	−3.3462	0.1917	−0.8499	−0.8425	−0.2724	0.0675	0.2898
Downside volatility (σ_{pD})	47.18%	33.39%	65.02%	16.34%	69.80%	28.54%	46.90%	56.51%	50.13%	48.82%
Volatility skewness (Up-variance/ Down variance)	1.2538	3.9796	0.2896	26.201	0.1872	6.2719	1.2823	0.5950	0.9894	1.099
RMD coefficient	0.9295	0.4976	0.6295	0.0479	0.000	0.6246	0.9303	0.9184	0.92812	0.8558
Diversification Ratio (<i>Div. ratio</i>)	3.7577	2.8710	1.7876	1.1508	1.0000	1.5505	3.7507	3.3480	3.8872	4.6486
Asset	Weights									
APP	0.056	0.000	0.000	0.000	0.000	0.000	0.039	0.044	0.041	0.000
ATH	0.056	0.000	0.000	0.000	0.000	0.079	0.057	0.020	0.042	0.047
BCN	0.056	0.016	0.000	0.001	0.000	0.000	0.062	0.058	0.061	0.045
CFL	0.056	0.141	0.000	0.008	0.000	0.000	0.044	0.055	0.049	0.021
FBL	0.056	0.003	0.000	0.000	0.000	0.277	0.052	0.072	0.060	0.034
FHL	0.056	0.000	0.000	0.000	0.000	0.000	0.056	0.000	0.031	0.027
FIL	0.056	0.015	0.043	0.001	0.000	0.000	0.063	0.076	0.069	0.055
FMF	0.056	0.000	0.000	0.000	0.000	0.512	0.061	0.016	0.042	0.011
FTV	0.056	0.000	0.000	0.000	0.000	0.000	0.058	0.042	0.051	0.010
KFL	0.056	0.005	0.000	0.000	0.000	0.000	0.049	0.051	0.050	0.003
KGF	0.056	0.688	0.000	0.976	0.000	0.000	0.059	0.068	0.064	0.239
PBP	0.056	0.000	0.024	0.000	0.000	0.004	0.058	0.071	0.063	0.025
PDM	0.056	0.009	0.000	0.001	0.000	0.072	0.063	0.075	0.068	0.036
RBG	0.056	0.005	0.279	0.001	1.000	0.033	0.059	0.117	0.082	0.033
RCF	0.056	0.034	0.166	0.003	0.000	0.000	0.055	0.066	0.060	0.109
TTS	0.056	0.013	0.012	0.001	0.000	0.000	0.058	0.071	0.063	0.055
VBH	0.056	0.057	0.475	0.005	0.000	0.022	0.052	0.068	0.060	0.204
VIL	0.056	0.012	0.000	0.001	0.000	0.000	0.055	0.029	0.045	0.047
Number of stocks in portfolio (%)	100%	72%	33%	50%	6%	39%	100%	94%	100%	94%

Source: Authors' own computation based on specific method and data from SPX (2024a).

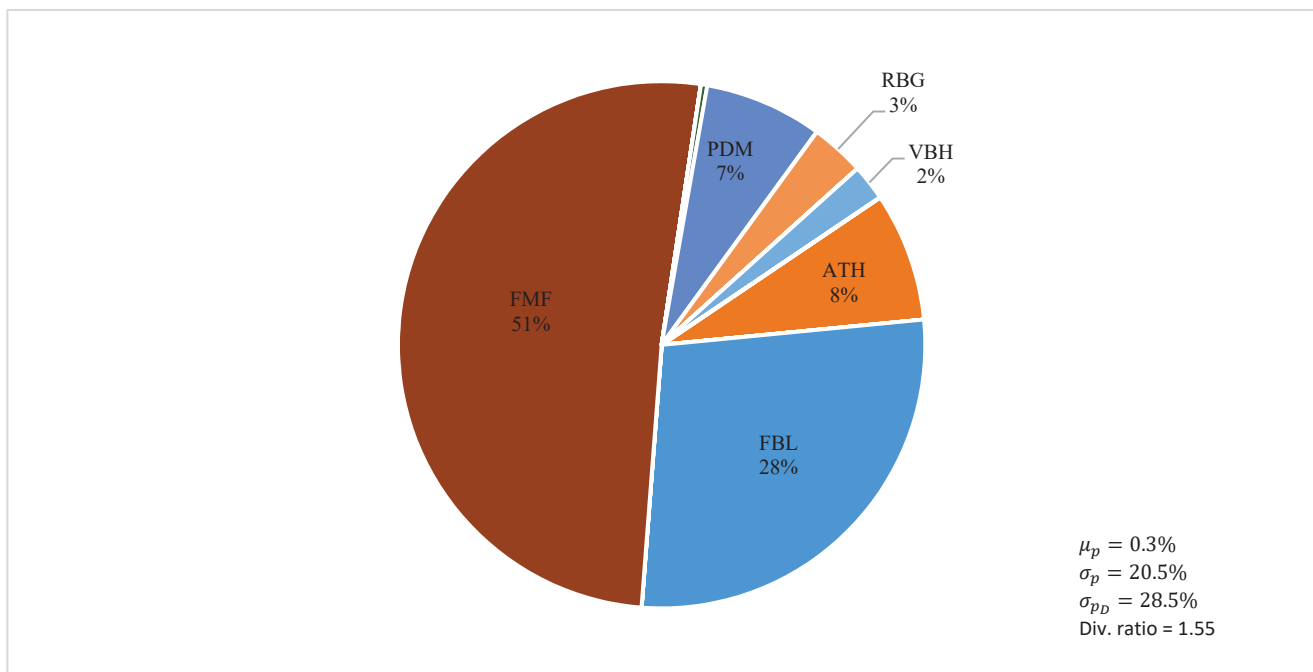
From these portfolios, we observe that three portfolios comprising 100% of the stock are the 1/N ($\mu_p = 3.6\%$, $\sigma_p = 5.9\%$) (column I), max. RMD ($\mu_p = 3.4\%$, $\sigma_p = 6.0\%$) (column VII), and max. RMD with positive Sharpe and Sortino ($\mu_p = 4.26\%$, $\sigma_p = 5.5\%$) (column IX), with diversification ratios of 3.58, 3.75 and 3.89, respectively. However, these portfolios offer returns below the RF rate (of 5.44%), indicating that investing in all the stocks (100%) in either of the two portfolios (1/N and max. RMD) is not desirable. We noted that two portfolios—the max. Sortino (column V) and max. volatility skewness (column VI) have high standard deviations of 34.1% and 20.5%, respectively, and the respective returns are 12.7% and 0.3%. These two portfolios comprise 6% and 39% of the total stocks with diversification ratios of 1.0 and 1.6, respectively.

Moreover, a negative coefficient of Sharpe ratio could indicate possible underperformance of portfolios, and a negative Sortino ratio could indicate an ‘unfair’ risk–reward outcome. In our case, we note that when relaxing constraints on the Sharpe and Sortino ratios, there are five portfolios with negative Sharpe ratios (1/N, minimum variance, semi-variance, maximum volatility skewness, and max. RMD), and six portfolios with negative Sortino ratios (1/N, minimum variance, semi-variance, max. volatility skewness, max. RMD, and max. RMD with positive Sharpe).

Next, we analyze the portfolios against the RF rate (5.44%). We consider portfolios that offer returns similar to the RF rate, below the RF rate and above the RF rate.

4.2. Portfolios below the RF Rate and below 4%

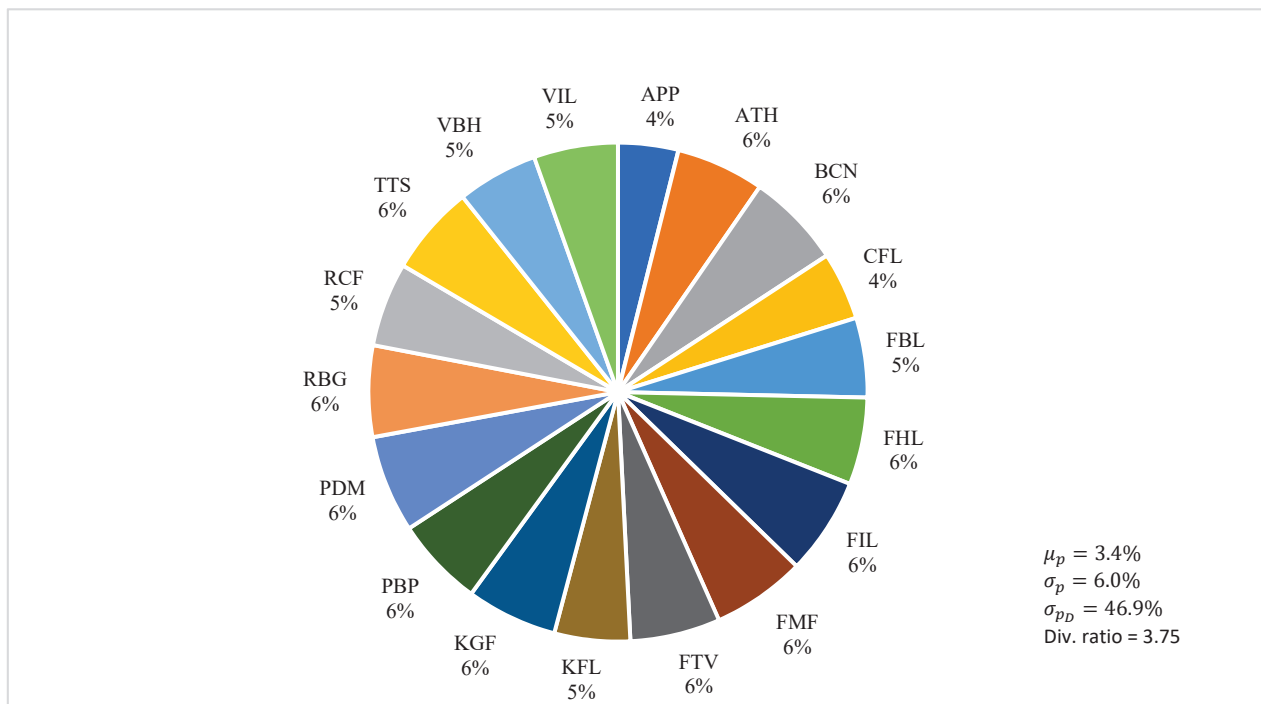
We find three portfolios have returns below the RF rate. These are, max. volatility skewness (column VI), max. RMD (column VII) and 1/N (column I). The portfolio that is farthest away from the RF rate is the max. volatility skewness (column VI), with a return and standard deviation of 0.3% and 20.5%, respectively. This portfolio comprises 39% of all the stocks, with a relatively large allocation in FMF and FBL, and a diversification ratio of 1.55 (see Figure 2a).



Source: Authors' own estimation

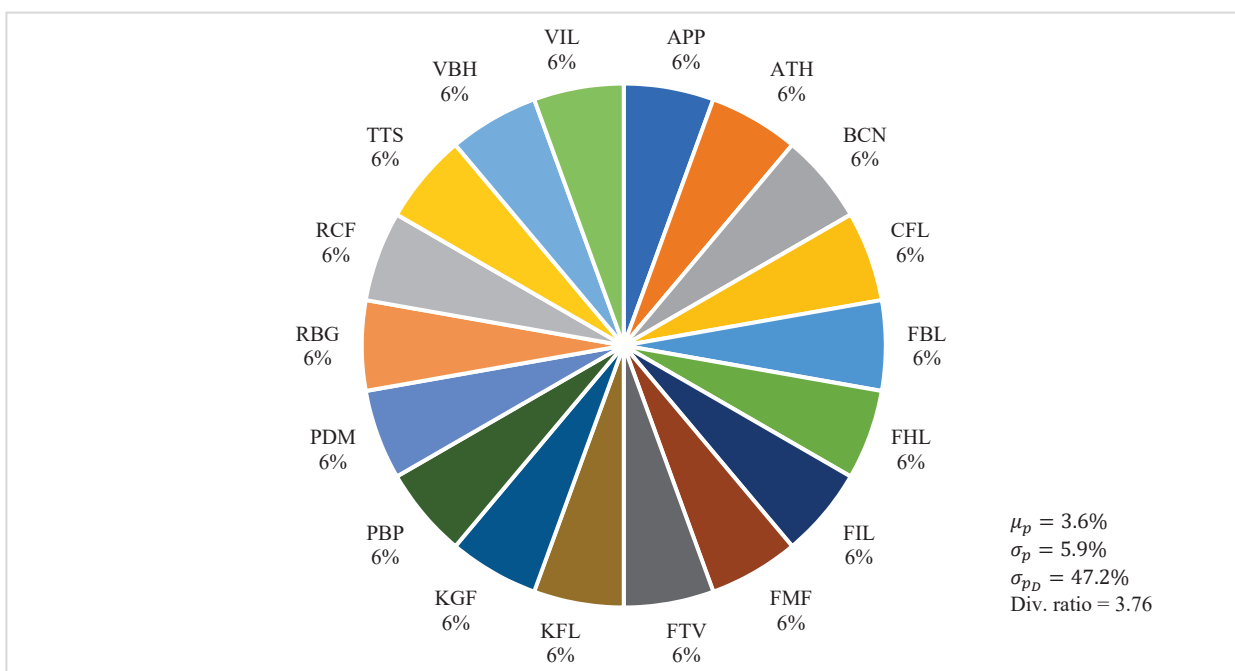
(a)

Figure 2. Cont.



Source: Authors' own estimation

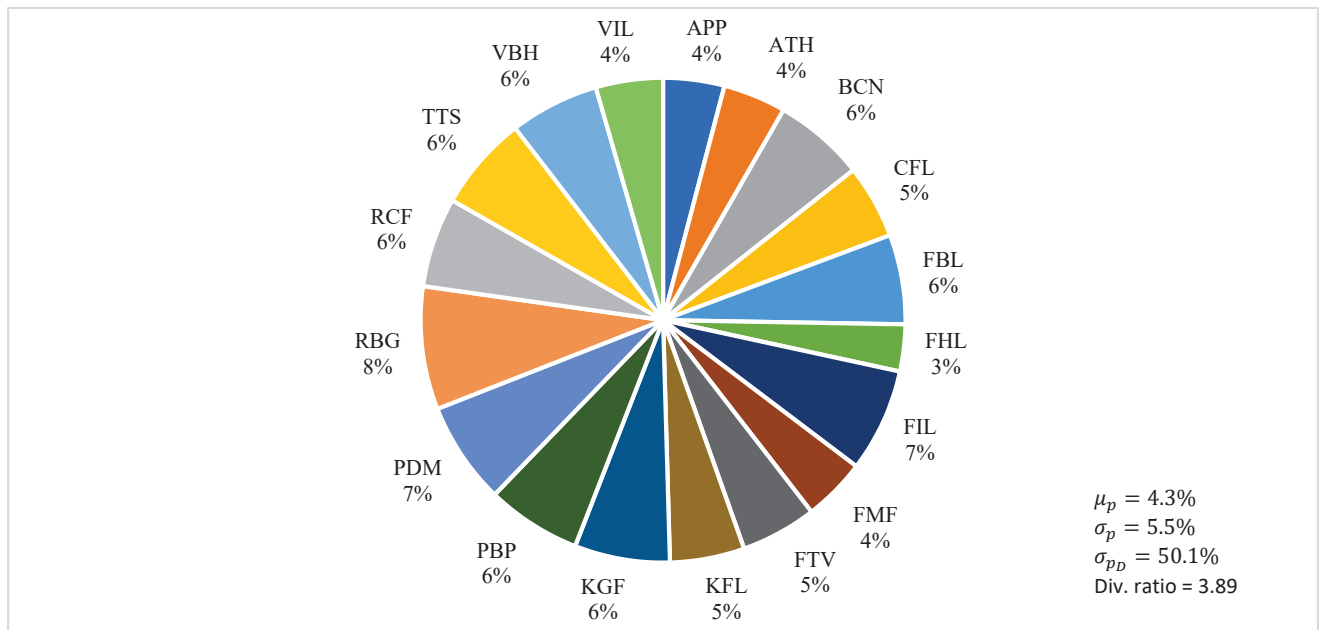
(b)



Source: Authors' own estimation

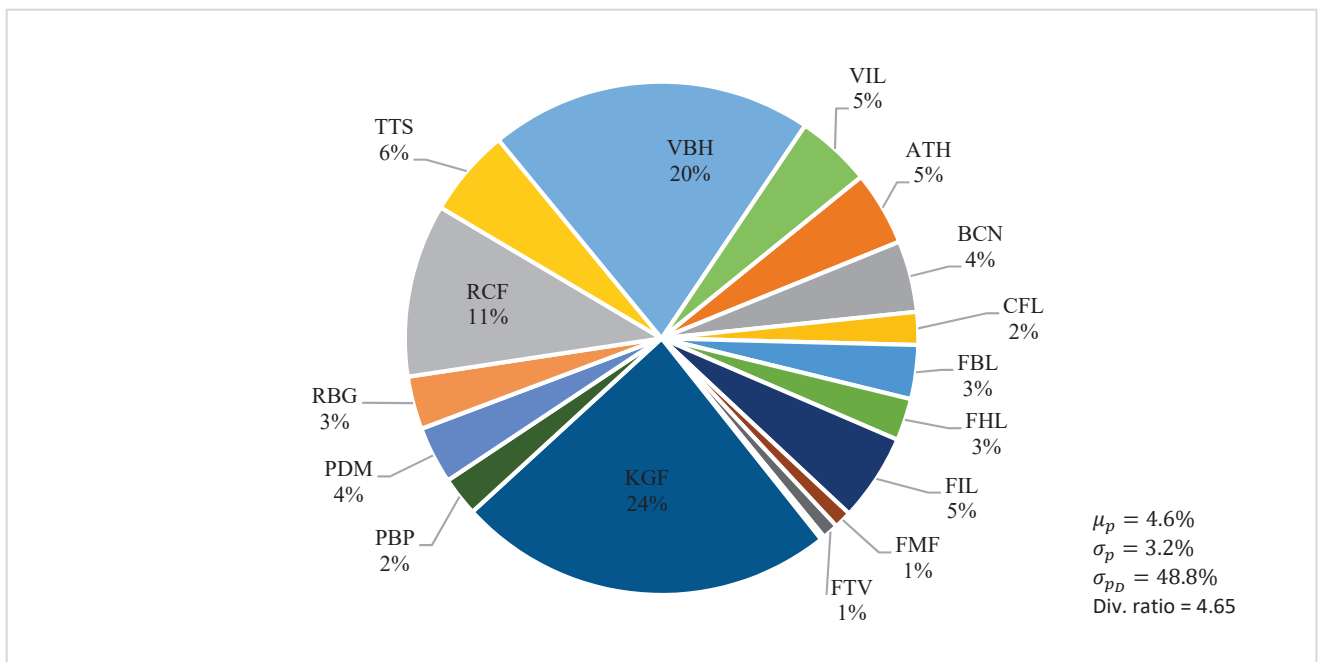
(c)

Figure 2. Cont.



Source: Authors' own estimation

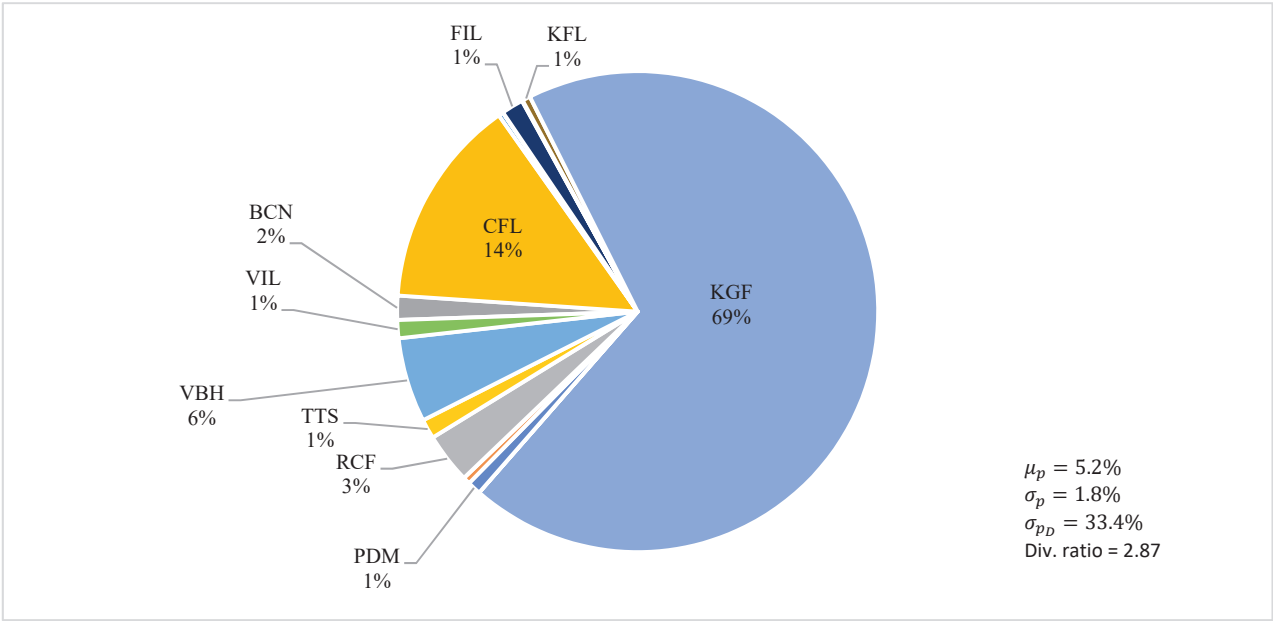
(d)



Source: Authors' own estimation

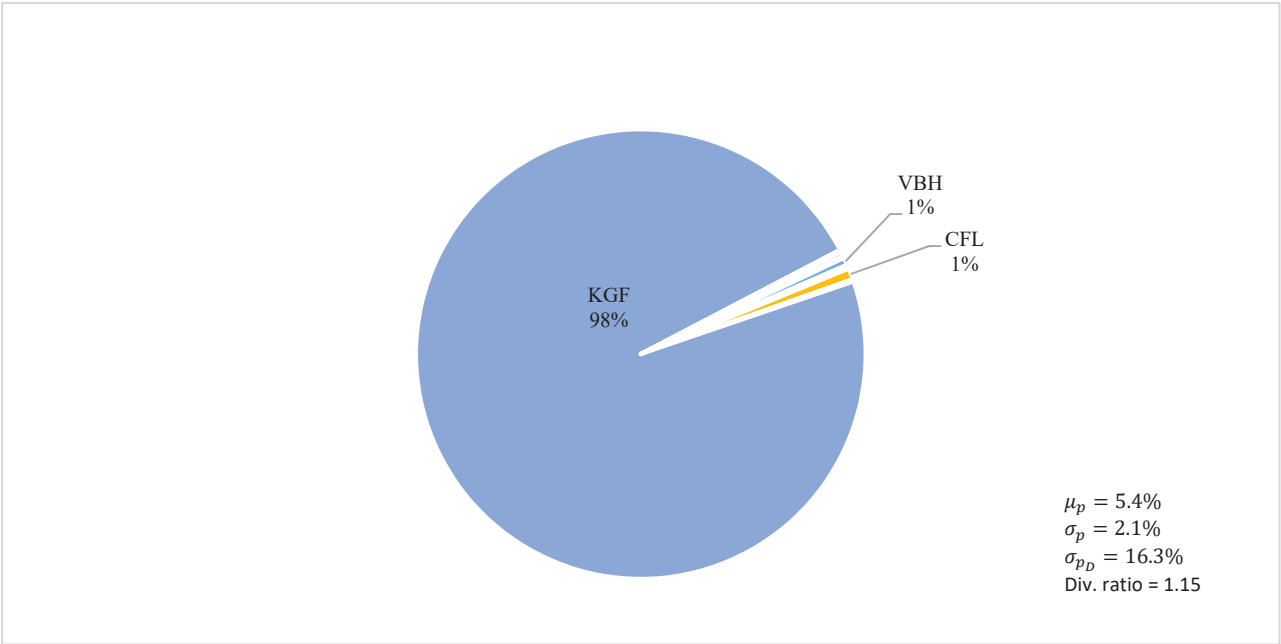
(e)

Figure 2. Cont.



Source: Authors’ own estimation

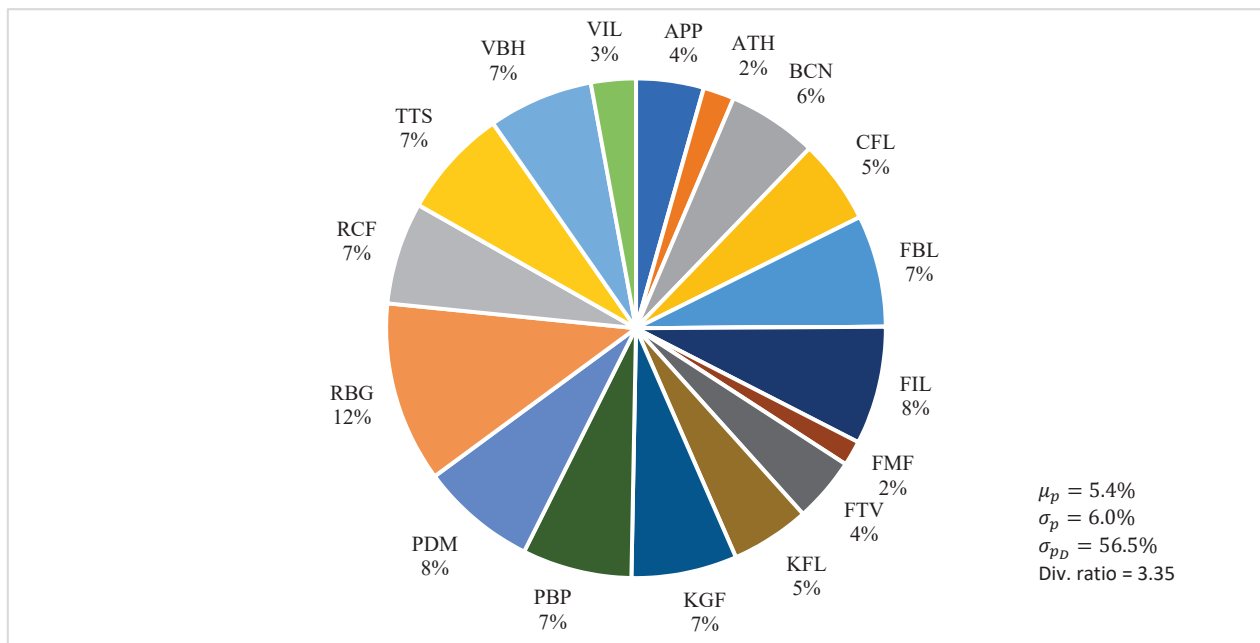
(f)



Source: Authors’ own estimation

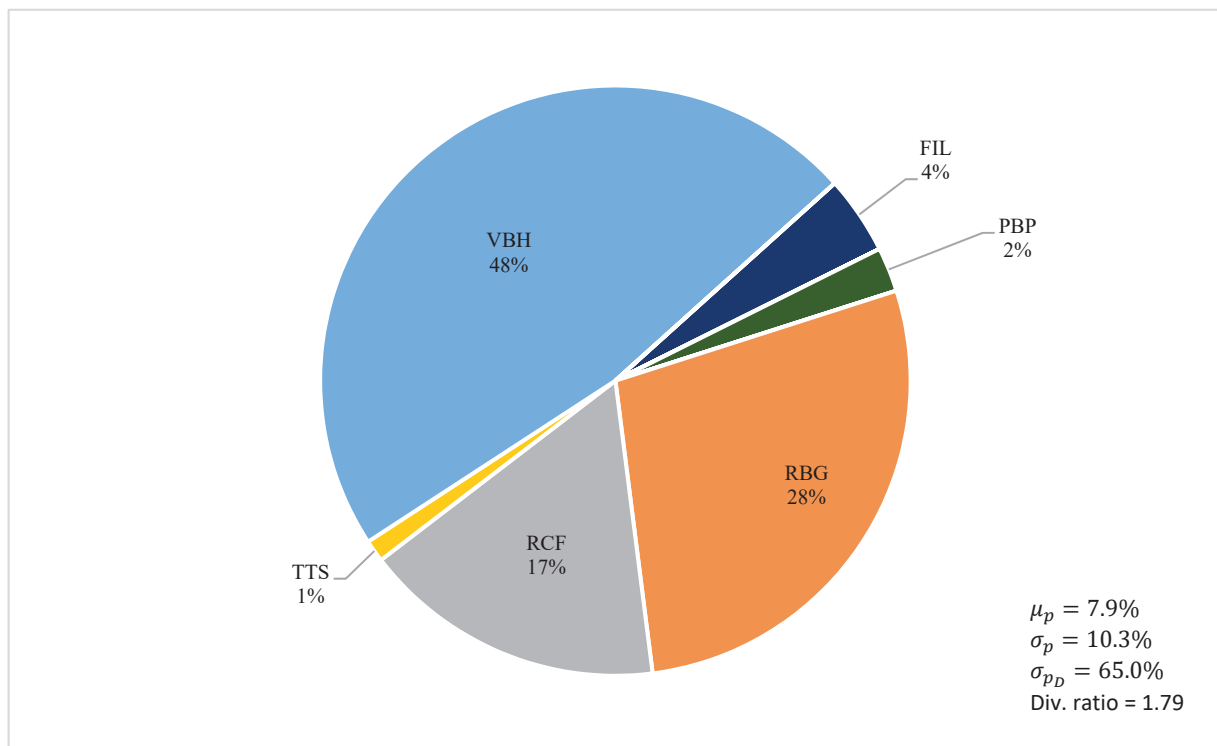
(g)

Figure 2. Cont.



Source: Authors' own estimation

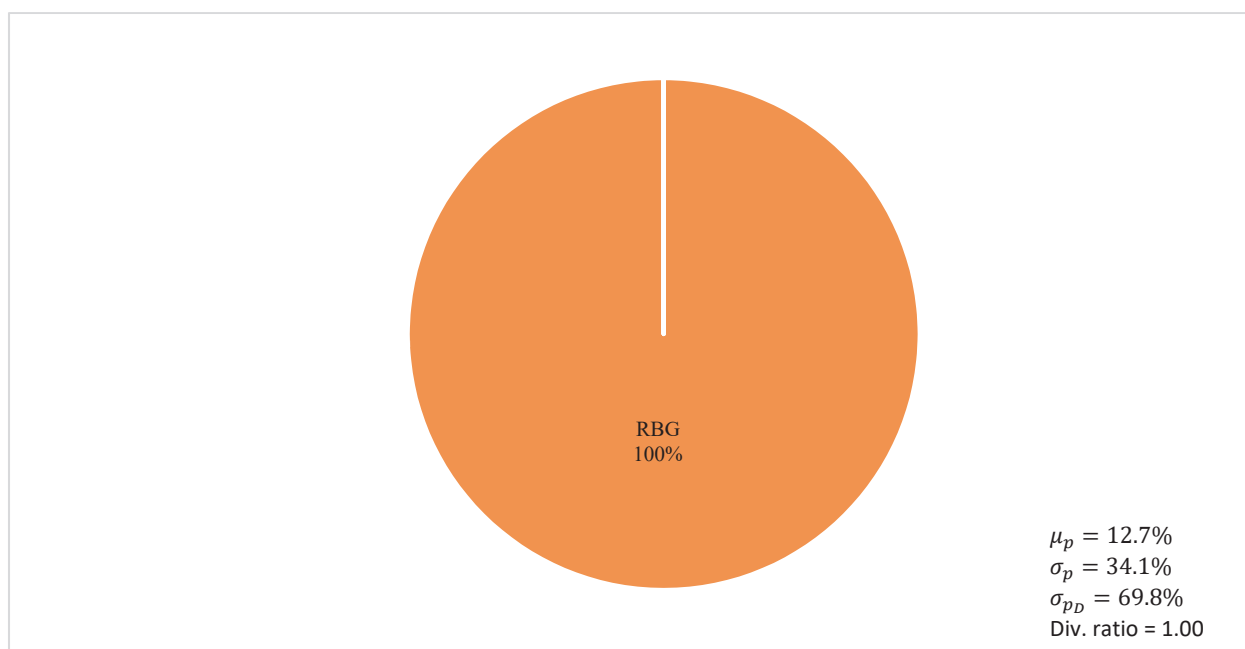
(h)



Source: Authors' own estimation

(i)

Figure 2. Cont.



Source: Authors' own estimation

(j)

Figure 2. (a) Max. volatility skewness. (b) Max. RMD portfolio. (c) 1/N portfolio. (d) Max. RMD with positive Sharpe and Sortino. (e) Most diversified portfolio. (f) Minimum variance portfolio. (g) Semi-variance portfolio. (h) Max. RMD with positive Sharpe. (i) Market portfolio (Max. Sharpe). (j) Maximum Sortino.

Next is the max. RMD portfolio (column VII), which comprises 100% (all) of the stocks and yields a return of 3.4% and standard deviation of 6.0% (Figure 2b). Compared to the equally weighted (1/N) portfolio, we note that the max. RMD portfolio yields a marginally lower return (column I, Figure 2c), although both portfolios' returns are below the RF rate.

4.3. Portfolios between 4 and 5% and below RF Rate (5.44%)

Next, we examine the portfolios that offer returns closer to the RF rate. We find that two portfolios could potentially achieve a return between 4 and 5%. These are the max. RMD with positive Sharpe and Sortino ($\mu_p = 4.3\%$, $\sigma_p = 5.5\%$) (column IX) and the most diversified portfolio ($\mu_p = 4.6\%$, $\sigma_p = 3.2\%$) (column X). As noted from the respective figures, the max. RMD with positive Sharpe and Sortino comprises all the stocks, although the distribution is slightly uneven (Figure 2d), whereas the most diversified portfolio comprises 94% of all the stock, with a relatively greater proportion allocated to VBH, KGF and RCF (Figure 2e). In both portfolios, we note positive Sharpe and Sortino ratios (although the former is based on setting the constraints explicitly), indicating relatively good portfolio performance and reasonable risk-reward tradeoffs.

4.4. Portfolios above 5% and below the Risk-Free Rate

We note that three portfolios yield returns above 5% p.a. These are minimum variance ($\mu_p = 5.2\%$, $\sigma_p = 1.8\%$, column II), semi-variance ($\mu_p = 5.4\%$, $\sigma_p = 2.1\%$, column IV) and max. RMD with positive Sharpe ($\mu_p = 5.4\%$, $\sigma_p = 6.0\%$, column VIII). These portfolios comprise 72%, 50% and 94% of the total stocks, respectively. Both the minimum variance (Figure 2f) and semi-variance (Figure 2g) indicate a relatively large allocation to KGF. Moreover, both the minimum variance and semi-variance portfolios have negative Sharpe ratios, with returns marginally lower than the RF rate, and the latter portfolio is relatively less diversified (Div. ratio = 1.15). The max. RMD portfolio was constrained by setting the Sharpe ratio to be positive (column VIII). In this case, we could obtain a return of

5.4%, which coincided with the RF rate, with a relatively high diversification ratio (Div. ratio = 3.35) (Figure 2h). Moreover, using a positive Sharpe ratio as a guide, this portfolio (max. RMD with positive Sharpe) performed better than seven other portfolios (1/N, minimum variance, semi-variance, max. volatility, max. RMD, max. RMD with positive Sharpe and Sortino, and most diversified portfolio).

4.5. Portfolios above the Risk-Free Rate (5.44%)

Next, we examine portfolios with returns higher than the risk-free rate. We find that two portfolios meet this criterion. We note that the market portfolio (column III) offers a return of 7.9%, with standard deviation of 10.3% (Sharpe ratio = 0.23, Sortino ratio = 0.12). This portfolio comprises 33% of all the stocks, has downside volatility of 65.0%, and a diversification ratio of 1.79 (see Figure 2i). The other portfolio is the max. Sortino (with target return of 6.45%), which offers a return of 12.7%, with standard deviation of 34.0% (column V). However, this portfolio is least diversified (Div. ratio = 1.0), comprising only one stock (RBG) (Figure 2j). While the return is higher than that of all the other portfolios, we note that this portfolio has the highest downside volatility (69.8%), lowest volatility skewness (0.19), and is the least robust (RMD coefficient = 0.00).

5. Conclusions

In this study, we implemented a newly proposed method of portfolio construction proposed by Bielstein et al. (2023), in a small country's stock market. While earlier studies have examined the small market using different methods, we differentiate this study in the following ways. First, earlier studies have used lower values for the risk-free and target rates (scenarios (see Kumar et al. 2022 and Kumar and Stauvermann 2022)). We considered a relatively high risk-free rate (5.44% p.a.) and target rate (6.75% p.a.), based on the 1-year government bond rate and superannuation rate of 2019 (starting period of our sample), respectively. Second, we have illustrated the applicability of Bielstein et al.'s (2023) RMD approach, in addition to including additional constraints like ensuring positive Sharpe and Sortino ratios. Additionally, using the recent data (from August 2019 to May 2024), we computed the CAPM-adjusted return for each stock based on the market-weighted price index (MWPI), and simulated different portfolios.

To keep the analysis manageable, we have separated the portfolios into four main categories. Considering the risk-free rate, we divided the portfolios into below 4%, between 4–5%, between 5% and the risk-free rate, and above the risk-free rate. We note that the max. RMD and 1/N portfolios provide comparable returns (3.4–3.6%) and contain all the stocks in the sample, although the latter is simpler to implement. To secure returns between 4 and 5%, we find that max. RMD with positive Sharpe and Sortino (as constraints) and the most diversified portfolio offer comparable returns (4.5–4.6%), although the latter has slightly lower standard deviation and downside volatility and contains 94% of all the stocks. Next, for portfolios with returns between 5% and the risk-free rate, we obtained three portfolios—the minimum variance, the semi-variance and the max. RMD with positive Sharpe; the latter coincides with the risk-free rate and contains the largest number (94%) of the stocks compared to the other two. Therefore, if diversification is the objective of an investor with at most a risk-free rate of return, then max. RMD with positive Sharpe can be considered. On the other hand, depending on the level of risk-aversion of an investor, the minimum-variance or the semi-variance portfolio can be recommended, with the latter having the lowest downside volatility.

We find two portfolios with returns above the risk-free rate—the market portfolio (max. Sharpe) and the maximum Sortino. Both portfolios are comparable in terms of the downside volatility (65–70%). Moreover, the latter portfolio (max. Sortino) yields the highest return (12.7%), although this portfolio is the least diversified (contains just a single stock), with the largest standard deviation and downside volatility among all the portfolios. On the other hand, the market portfolio (max. Sharpe) offers a return of 7.9%, with a reasonable level of diversification (contains 33% of the total stock). Therefore, investors

with appetite for risk, diversification, and returns above the risk-free rate can consider the market portfolio as a suitable alternative.

While the results offer interesting insights, some caveats are in order. We have used the risk-free (1-year government bond) rate and the target return of the superannuation fund rate for the year 2019. However, we have noted that in subsequent years, there were significant declines in the 1-year government bond rates. The 1-year government bond rates for the years 2019, 2020, 2021, 2022, 2023 and 2024 were 5.44%, 3.22%, 1.01%, 0.14%, 0.13% and 0.93% (averaging around 1.74%). Furthermore, the savings rates on deposits offered by banks were 1.32% in 2018, 1.10% in 2019, 0.54% in 2020, 0.42% in 2021, 0.39% in 2022, 0.38 in 2023⁶ and 0.31% in 2024 (averaging around 0.64%).⁷ Based on the two average rates (savings and 1-year government bond), one can consider using the average of these rates as a relatively conservative risk-free rate. Similarly, the average of the interest rate offered by the superannuation fund from 2019 to 2024 can be applied to the target return.⁸ We also acknowledge that our stock price data are from August 2019 to May 2024, which, although providing a substantial period for analysis, may not capture long-term market trends and behaviors. Market conditions and economic factors can vary significantly over different time periods, and a longer dataset might provide more robust conclusions. Although the study's focus on market-adjusted returns is a significant strength, it also introduces complexity in the analysis. In computing the market-adjusted return for each stock based on the CAPM framework, it must be noted that the returns are sensitive to the chosen market index (i.e., how the index was selected and/or constructed) and its performance, and the choice of the risk-free rate, which could introduce biases or inconsistencies, especially in less liquid markets where index performance can be heavily influenced by a few large trades or specific sectors (and firms) and the government bond rates fluctuate significantly. We also note that at the time of completing this study, SPX listed a new company (SUN Insurance Limited—SUN) on 15 August 2024, which makes up 4.39% of the total market capitalization. This newly listed company is not included in the sample, although it is possible that SUN (in the insurance sector) may alter investor sentiments and behavior, hence impacting the overall market performance. Moreover, while the study emphasizes financial inclusion and literacy, the practical implementation of the proposed RMD portfolio in small markets requires careful consideration of domestic investor behavior, regulatory environments, and market infrastructure. The recommendations and findings might need adjustments to fit the specific regulatory and operational constraints of small markets. Noting these considerations, the portfolios presented in this study should be considered instructive only, supporting learning and exploration of the different methods of investment analysis. However, the results should not be treated as financial advice.

In conclusion, this study advances the understanding of portfolio optimization in small markets and provides the degrees of diversification and risk–return outcomes from different portfolios. Additionally, portfolios based on the RMD and RMD with additional constraints are compared with a set of benchmark portfolios. Nevertheless, noting the limitations of the study, further research to validate and extend the results in different market contexts and over longer time periods will provide additional insights. Moreover, future research could explore the feasibility and practical implications of implementing advanced portfolio strategies in small market environments, considering local market characteristics and investor needs.

Author Contributions: Conceptualization, R.R.K., H.G. and P.J.S.; methodology, R.R.K.; formal analysis, R.R.K.; writing—R.R.K., H.G. and P.J.S.; writing—review and editing, R.R.K., H.G. and P.J.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research receives no extra funding.

Data Availability Statement: Stock price data is available on the South Pacific Stock Exchange (SPX) website.

Acknowledgments: The authors thank the reviewers for their valuable comments and suggestions. All remaining errors are ours. Peter J. Stauvermann thankfully acknowledges the financial support of the Changwon National University 2023–2024 for ongoing research work.

Conflicts of Interest: The authors declare no conflict of interest.

Notes

- ¹ <https://www.un.org/sustainabledevelopment/economic-growth/#:~:text=Goal%20%20is%20about%20promoting,global%20economy%20under%20serious%20threat> (accessed on 29 August 2024).
- ² The no-short-selling assumption is highly relevant to Fiji's stock market.
- ³ <https://www.rbf.gov.fj/bond-pricelist-and-yield-curve-2018-2019/#1608590112383-909852ff-3554> (accessed on 29 August 2024).
- ⁴ The choice of the target ratio is based on the interest earned on superannuation fund in 2019. <https://www.parliament.gov.fj/wp-content/uploads/2019/11/Fiji-National-Provident-Fund-2019-Annual-Report.pdf> (accessed on 29 August 2024).
- ⁵ Please note that SUN Insurance Company Ltd. (SUN) was listed on 15 August 2024, hence not included in the sample.
- ⁶ <https://www.parliament.gov.fj/wp-content/uploads/2023/11/129-Reserve-Bank-of-Fiji-Annual-Report-August-2022%E2%80%932023.pdf> (accessed on 29 August 2024).
- ⁷ <https://knoema.com/data/fiji+savings-rate#:~:text=Savings%20rate%20of%20Fiji%20fell,per%20annum%20in%20May%202024> (accessed on 29 August 2024).
- ⁸ <https://www.rbf.gov.fj/category/bond-price-list-new/> (accessed on 29 August 2024).

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Article

Trading Volume Concentration across S&P 500 Index Constituents—A Gini-Based Analysis and Concentration-Driven (Daily Rebalanced) Portfolio Performance Evaluation: Is Chasing Concentration Profitable?

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Abstract: The period from January 2020 to December 2022 was marked by a confluence of major events, including the COVID-19 pandemic, the Russia–Ukraine war, the energy crisis, surging inflation, Federal Reserve policy shifts, and banking turmoil, which collectively fueled heightened market volatility, risk management needs, and speculative trading opportunities, leading to volatile swings in trading volume concentration across financial markets, with periods of significant increases followed by rapid declines. This paper examines the variation in the concentration of trading volume across the full spectrum of S&P 500 companies, with a focus on explaining the reasons behind the stochastic changes in trading volume concentration. We analyze different concentration measurement methods, including the power law exponent, the Herfindahl–Hirschman Index, and the Gini-based Trading Concentration Index (TCI). The research employs a novel experimental design, comparing a concentration-driven portfolio, rebalanced daily based on the top 30 stocks by trading volume, against the S&P 500 benchmark. Our findings reveal that the Gini-based TCI fluctuated between 55.98% and 77.35% during the study period, with significant variations coinciding with major market events. The concentration-driven portfolio outperformed the S&P 500, achieving an annualized return of 10.66% compared to 5.89% for the index, with a superior Sharpe ratio of 0.325 versus 0.19. This performance suggests that following trading volume concentration can yield above-average results. However, this study also highlights the importance of understanding and managing the risks associated with concentrated portfolios. This study contributes to the literature on market dynamics and offers practical insights for investors and fund managers on optimizing portfolio strategies in response to evolving concentration patterns in financial markets.

Keywords: trading volume concentration; S&P 500 index; Gini-based Trading Concentration Index (TCI); Gini index; Trading Concentration Index (TCI); financial market concentration; risk–return analysis; experimental portfolio design

1. Introduction

The phenomenon of trading volume concentration has been observed across various domains, and particularly in financial markets (Balakrishnan et al. 2008; Shankar et al. 2020) and cryptocurrencies (Doğan and Yalçintaş 2023; Metelski and Sobieraj 2022). Similarly, in the technology sector, market dominance by a few major players has been a subject of ongoing debate and scrutiny (Armoogum et al. 2022; Mayer-Foulkes and Hafner 2023). This trend is characterized by a convergence of interest and activity around a limited set of assets or entities, often driven by herd behavior and the pursuit of short-term gains (Terranova and Turco 2022). The research conducted by Balakrishnan et al. (2008) revealed

that the distribution of daily stock trading volumes exhibits power law characteristics, indicating that daily trading had become more concentrated in a small set of stocks over time. Furthermore, Shankar et al. (2015, 2020) modeled the distribution of daily trading volumes as a power law function and used the power law exponent, also referred to as the Trading Concentration Index (TCI), as a measure of trading volume concentration. Their research revealed that while trading concentration for non-S&P 500 stocks has steadily increased since the 1960s, the concentration for S&P 500 stocks has actually decreased since the mid-1970s, coinciding with the introduction of index funds. This divergence in trading patterns highlights the significant impact of financial innovations like index funds on stock market dynamics.

The underlying drivers of concentration can be multifaceted. One such driver, as described by Palley (1995), is the pursuit of perceived safety in numbers. Palley (1995) provides a formalization of managerial herd behavior driven by this pursuit, supported by individual risk aversion and relative performance-based remuneration. Other drivers include the influence of social media and online communities (Hagar and Shaw 2022), and the desire for quick gains in volatile markets (Batrinca et al. 2018). Some studies provide insights into the underlying drivers of trading volume concentration in financial markets, which could be related to trading strategies in volatile markets (Ananzeh 2015; Davidsson 2014). They highlight that factors such as the significant relationship between trading volume and market volatility (Ananzeh 2015), and the strong correlation between volume, volatility, and return momentum in global financial markets (Davidsson 2014) play crucial roles in understanding these dynamics. Additionally, the asymmetry in price-volume relations, volatility features, and the impact of day-of-the-week patterns on trading volume (Batrinca et al. 2018; Maki 2024) further emphasize the influence of quick gains in volatile markets on trading volume concentration. These findings suggest that the desire for rapid profits in fluctuating market conditions significantly contributes to the concentration observed in trading volume on financial markets.

There is also evidence that trading volume concentration can elevate systemic risks and contribute to market distortions or bubbles. The presence of crowded trades among similarly trading peers can influence asset price dynamics, potentially creating systemic risk (van Kralingen et al. 2021). It is important to note that the impact of trading volume on stock return volatility has been explored, revealing a direct relationship between trading volume and stock return volatility across various quantiles (Tsagkanos et al. 2021). Furthermore, incorporating trading volume into volatility forecasting models has shown to enhance the performance of Value at Risk (VaR) models, especially during crisis periods, indicating the significance of trading volume in assessing market risk and volatility (Slim 2016). These findings suggest that trading volume concentration plays a crucial role in exacerbating systemic risks and market distortions, highlighting the importance of monitoring and managing trading activities to maintain market stability. To mitigate the risks associated with trading concentration, diversification strategies and a broader understanding of market dynamics are crucial.

The question of whether trading volume concentration across the 500 S&P 500 constituents has increased or decreased over time has also been a subject of debate in the literature (Balakrishnan et al. 2008; Shankar et al. 2020; Amundi 2023). Different studies have presented contrasting findings, and it is essential to examine the evidence from various sources to gain a comprehensive understanding of this issue. One perspective suggests that trading concentration across the S&P 500 constituents has decreased due to the popularity of index funds and exchange-traded funds (ETFs) that facilitate investment in the entire basket of stocks comprising the index. This view is supported in the Shankar et al.'s (2020) study, that found that the TCI for the S&P 500 stocks exhibited an inverted V-shaped pattern. The TCI increased from 1960 to 1975, indicating increasing trading concentration. However, after the introduction of S&P 500 index funds in 1975, the TCI for the S&P 500 stocks steadily decreased, suggesting a more even distribution of trading activity across all 500 stocks. Hegde and McDermott (2003) found that the trading volume

and institutional investor interest in stocks added to the S&P 500 index increased immediately after their inclusion, primarily due to the index inclusion itself. This finding suggests that index funds and ETFs play a significant role in driving trading volume and liquidity changes for S&P 500 constituents. On the other hand, some studies have argued that trading concentration across the S&P 500 stocks has increased over time, contradicting the findings mentioned above (Amundi 2023). This perspective is supported by Balakrishnan et al. (2008) who modeled the distribution of daily stock trading volumes as a power law function and found that the power law exponents steadily increased from 1962 to 2005, indicating that daily trading had become more concentrated in a small set of stocks over time. Also, Gabaix (2009) found that the distribution of firm sizes and trading volumes often follows a power law distribution, with a small number of firms or stocks accounting for a disproportionately large share of the total. Specifically, Gabaix et al. (2006) focused on institutional investors and their impact on stock market volatility, contributing to our understanding of power law dynamics in financial markets. It is important to note that these contrasting findings may be attributed to differences in the time periods analyzed, the specific measures of trading concentration used, and the methodologies employed. Additionally, some studies have focused on the entire stock market, while others have specifically examined the stocks from the S&P 500 index. To reconcile these conflicting perspectives, it is necessary to consider the potential impact of various factors, such as the increasing popularity of index funds and ETFs, changes in market structure and regulations, and the evolving investment strategies of institutional and individual investors. The fact of the matter is, that an increasing popularity of index funds and ETFs influences the stock selection by institutional investors, impacting trading volume in specific stocks (Duffy et al. 2019; Alina-Cristina 2018). Research by Kang (2023) demonstrates that higher ETF ownership weakens return reversals, indicating a shift in trading patterns (Kang 2023). Additionally, Huang et al. (2021) find that industry ETFs reduce post-earnings-announcement drift, enhancing market efficiency and influencing trading behavior (Huang et al. 2021). Moreover, Hu et al. (2020) highlight that large institutions, particularly those with high index fund ownership, opt to lend shares rather than cast votes, affecting trading volumes in stocks with significant index ownership (Hu et al. 2020). Also, Shu (2013) highlights that institutional trading volume plays a crucial role in stock market anomalies, showing a decrease in anomalies like price momentum and the value premium as institutional trading volume increases (Shu 2013). These studies suggest that the rise of index funds and ETFs alters institutional investors' portfolio choices and trading activities, ultimately impacting trading volumes in specific stocks. On the flip side, Del Rio and Santamaria's (2010) study contrasts with the US evidence, indicating that differences in investor type do not significantly impact trading volume dynamics, but mutual funds ownership levels can influence autocorrelation in trading volume (Del Rio and Santamaria 2010). It is important to note the role of both institutional (Griffin et al. 2011) and individual investors (Welch 2022; Ülkü et al. 2023) in driving trading volume concentration. As highlighted by Welch (2022) and Ülkü et al. (2023), retail investors also contribute significantly to trading volume concentration, challenging the notion that this phenomenon is driven solely by institutional players. These studies have shown that this is particularly applicable to the period under investigation in this study, namely the post-COVID-19 era.

It is also important to mention the study by Hoekstra and Güler's (2022) who studied the mediation effect of trading volume, revealing that it mediates the relationship between investor sentiment and stock returns, particularly evident in the case of Tesla and the MSCI World Index (Hoekstra and Güler 2022). Additionally, Wei's (2009) work on Taiwan's institutional trading volume demonstrates its impact on the stock market index through volatility effects and causality, emphasizing the significant relationship between trading volume and stock index returns (Wei 2009).

Based on what was presented above, the following hypotheses are formulated: (1) trading volume concentration across the S&P 500 index constituents exhibits significant stochastic changes in response to major economic events and market conditions; (2) chasing trad-

ing volume concentration can be a profitable strategy for investors, potentially outperforming the S&P 500 index; (3) a concentration-driven portfolio offers a competitive risk–return profile compared to the S&P 500 index; (4) the level of trading volume concentration, as measured by various metrics (e.g., percentage of volume accounted for by top companies, disparity indices), provides valuable insights into market dynamics and investor behavior. These hypotheses form the foundation for this study’s investigation into trading volume concentration trends, profitability in chasing trading volume concentration, and implications for portfolio management and risk mitigation strategies. The overview of the literature presented above highlights a research gap in understanding the dynamics of trading volume concentration across the S&P 500 constituents, particularly in light of recent market events and the evolving landscape of institutional (Griffin et al. 2011) and retail investing (Welch 2022; Ülkü et al. 2023). This study aims to address this gap by examining the variation in trading volume concentration across S&P 500 stocks from January 2020 to December 2022, a period marked by significant market volatility and major global events. The study employs various concentration measurement methods, including the power law exponent, the Herfindahl–Hirschman index, and Gini-based TCI, and introduces a novel experimental design, comparing a concentration-driven portfolio, rebalanced daily based on the top 30 stocks by trading volume, against the S&P 500 benchmark. The whole research is motivated by the hypothesis that following trading volume concentration may yield higher returns compared to the S&P 500 index itself. This hypothesis is grounded in the observation that increased trading volume among top-ranked stocks is associated with heightened investor interest (Welch 2022), which should be reflected in their valuations.

The structure of this article is as follows. Section 2 presents various methods for measuring trading volume concentration, including mathematical notations to facilitate better understanding and comparison of different approaches. Additionally, Section 2.2 outlines the ‘experimental design’ and ‘data analysis methodology’. Section 3 provides a detailed discussion of the results, featuring a figure (chart) for the Gini-based TCI and a comparison of ‘power law exponent’, HHI, and Gini-based TCI methods. This section also analyzes concentration levels at different points along the spectrum of trading volume concentration distribution, examining combinations such as the top 10, 30, 75, and 250 stocks by trading volume and their corresponding percentiles. Furthermore, it presents a comparative analysis of the concentration-driven (daily rebalanced) portfolio results (PnL) versus the S&P 500 (PnL), along with a risk–return analysis. It also includes a qualitative assessment of portfolio changes in relation to significant market events, such as the COVID-19 pandemic, the Russia–Ukraine war, the energy crisis, inflation spikes, Federal Reserve policy shifts, and banking sector turbulence, providing context for the observed changes in trading volume concentration and portfolio composition (constituents). Section 4 is dedicated to discussing the results in context, while Section 5 presents the conclusions drawn from the entire study.

2. Materials and Methods

The data utilized in this study were sourced directly in R using the *quantmod* and *tidyquant* packages. The dataset comprises historical stock data for the 500 companies constituting the S&P 500 index. The process involved retrieving data for each company within the index from 2 January 2020 to 30 December 2022, encompassing a total of 756 trading sessions over a span of three years. The dataset encompasses a comprehensive view of stock market dynamics within the S&P 500 index over a three-year period. With each company’s historical stock data captured for every trading session during this timeframe, the dataset provides a rich source of information for analyzing trading concentration and market trends within the index. This robust dataset forms the foundation for conducting an in-depth analysis of trading volume concentration dynamics, presenting comparative analysis of the concentration-driven (daily rebalanced) portfolio results (PnL) versus the S&P 500 (PnL), along with a risk–return analysis, and finally making a qualitative assessment of portfolio changes in relation to significant market events over the specified study period.

2.1. The Power Law Exponent, HHI and Gini-Based TCI as Measures of Trading Concentration

In the realm of financial markets, understanding the concentration of trading activity is crucial for assessing market dynamics, liquidity, and potential systemic risks. Three prominent methods have emerged to quantify this concentration: the power law exponent, the Herfindahl–Hirschman Index (HHI), and the Gini-based Trading Concentration Index (TCI). Each of these measures offers unique insights into the distribution of trading volumes across stocks, particularly within the context of the S&P 500.

Naldi (2003) and Balakrishnan et al. (2008) were the first to demonstrate that the power law exponent could be used as a general measure of market concentration, with larger exponent values indicating greater concentration. Traditionally, the HHI has been used to measure market concentration. However, Naldi (2003) and Balakrishnan et al. (2008) found that the power law exponent is more useful for studying changes in concentration than the HHI measure when dealing with a large number of observations, as the extreme elasticity of the HHI obscures trends over time.

Naldi (2003), Balakrishnan et al. (2013), and Shankar et al. (2020) argue that the power law distribution can be specifically applied used to model the phenomenon whose distribution can be ranked by a metric of size. More specifically, the power law exponent, as employed by Balakrishnan et al. (2013) and Shankar et al. (2020), is derived from the observation that trading volumes often follow a power law distribution. This approach models the relationship between trading volume and its rank as:

$$\log(R_{i,t}) = \alpha_t - \beta_t \log(V_{i,t}) \quad (1)$$

where

- $R_{i,t}$ is the volume rank of stock i on day t ;
- $V_{i,t}$ is the trading volume of stock i on day t ;
- α_t is the intercept term for day t ;
- β_t is the slope coefficient for day t , representing the power law exponent (Trading Concentration Index);
- i is the index for individual stocks (1 to 500 for S&P 500);
- t is the index for trading days.

This formulation expresses the log-linear relationship between a stock's trading volume rank and its actual trading volume on a given day. The power law exponent β_t quantifies the degree of concentration in trading volumes across stocks, with higher values indicating greater concentration. Scientific evidence from various research papers supports the extensive utilization of power law distributions in modeling economic and financial phenomena (Gabaix et al. 2003; Gabaix 2009). Studies have shown that power law distributions explain processes in economics and finance, reflecting extreme events like debt distress in emerging countries (Akhundjanov and Chamberlain 2019; Dufrénot and Paret-Onorato 2016). Furthermore, investigations into wealth distribution among billionaires have revealed that the upper tail of wealth data follows a power law distribution, indicating a statistical understanding of wealth disparity (Asif et al. 2021). Additionally, analyses on the wealth of the richest individuals have verified that power law behavior is present in only 35% of the datasets, often coexisting with rival distributions like log-normal or stretched exponential distributions (Brzezinski 2014). Axtell (2001) found that the distribution of firm sizes in the US follows Zipf's law, a special case of the power law, with a power law exponent of 1.0. However, the study by Kondo et al. (2023) demonstrates that a lognormal distribution or a convolution of lognormal and non-Zipf Pareto distributions better describe the US economy, deviating from Zipf's law (Kondo et al. 2023). Additionally, Asif et al. (2021) found that the distribution of wealth among billionaires follows a power law distribution with exponents ranging from 1.306 to 1.571, indicating a more evenly distributed wealth than suggested by Zipf's law (Asif et al. 2021). Furthermore, Medrano-Adan and Salas-Fumás (2018) argue that the conditions for the firm size distribution to follow a power law are more restrictive than commonly believed, challenging

the assumption of a Zipf distribution in the US (Medrano-Adan and Salas-Fumás 2018). Gopikrishnan et al. (1999) and Nirei et al. (2020) showed that the distribution of trading volume for individual stocks obeys a power law function. I. . Various research papers discussed the application of power law analysis in different fields, showcasing its relevance in understanding economic structures and relationships (Vogel 2022). Additionally, some studies focused on power law distributions in financial instruments and market capitalization across stock exchanges, highlighting fluctuations in power law exponents and their relation to fundamental values of stocks (Tuncay 2020; Mizuno et al. 2016). Furthermore, power law behavior was observed in traffic distribution on road segments, emphasizing the robustness of such patterns in urban traffic simulations (Umemoto and Ito 2018).

The Herfindahl–Hirschman Index (HHI), originally developed to measure market concentration (Hirschman 1964), can be adapted to assess trading volume concentration:

$$HHI = \sum_{i=1}^n s_i^2 \quad (2)$$

where

- $s_i = \frac{V_i}{\sum_{j=1}^n V_j}$, and n is the total number of stocks (e.g., 500 for S&P 500),
- s_i is the market share of stock i 's trading volume,
- V_i is the trading volume of stock i , and
- $\sum_{j=1}^n V_j$ is the total trading volume across all stocks.

This formulation expresses the HHI as the sum of squared market shares of trading volumes, providing a measure of concentration that ranges from $\frac{1}{n}$ (perfect equality) to 1 (complete concentration), where s_i is the market share of stock i 's trading volume. The HHI is particularly sensitive to the distribution of trading volume among the most actively traded stocks, providing a measure of concentration that emphasizes the impact of dominant players in the market.

In turn, the Gini-based Trading Concentration Index (TCI), derived from the Gini coefficient commonly used in income inequality studies (Gini [1912] 1955), offers a comprehensive view of trading volume distribution:

$$G = 1 - 2B \quad (3)$$

where

- G is the Gini coefficient (TCI in our case);
- B is the area under the Lorenz curve, representing the cumulative proportion of trading volume against the cumulative proportion of stocks. The area B is calculated using:

$$B = \frac{1}{n} \sum_{i=1}^n \frac{\sum_{j=1}^i y_j}{\sum_{j=1}^n y_j} \quad (4)$$

where

- n is the number of stocks (500 for S&P 500),
- y_j is the trading volume of stock j , and
- Stocks are ordered from lowest to highest trading volume.

It is important to note, that traditionally the Gini index is used as a measure of statistical dispersion intended to represent the income or wealth distribution of a nation's residents (Gini [1912] 1955). When adapting it to the actual distribution of trading volume across different companies it can be visualized as in Figure 1 below.

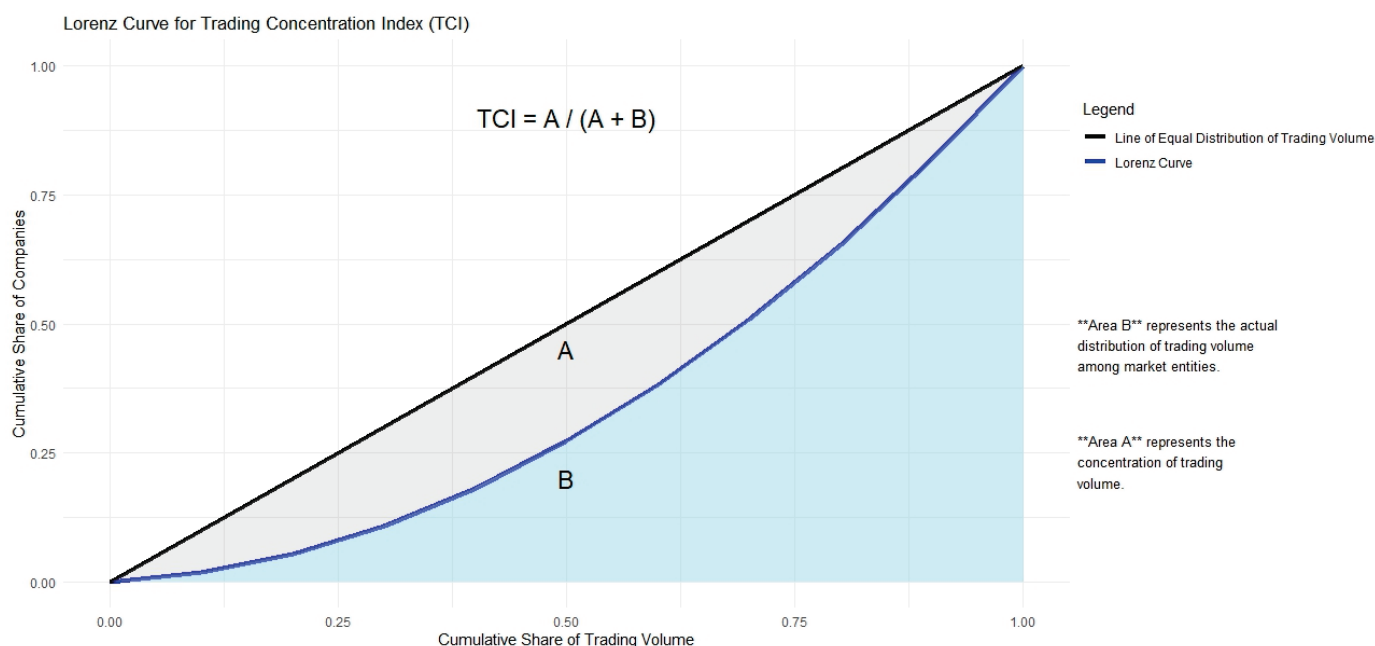


Figure 1. Lorenz curve visualizing the concentration of trading volume among S&P 500 companies. Source: own elaboration in R 4.3.1. Note: A larger B area indicates a more evenly distributed trading volume, and a larger A area indicates higher concentration of trading volume among fewer S&P 500 stocks. The A+B area represents the hypothetical distribution of trading volume in case of perfect equality (always equals 0.5, i.e. half of the unit square area).

In the context of adapting the Lorenz curve and Gini index concepts to measure trading concentration using the TCI, the surface between the Lorenz curve and the line of equal distribution of trading volume (in Figure 1 above) represents the degree of concentration in the distribution of trading volume across stocks. The line of equal distribution of trading volume is the 45-degree diagonal line, representing the case where all stocks have an equal share of the total trading volume. The Lorenz curve represents the actual cumulative distribution of trading volume across the ranked stocks. The area between the Lorenz curve and the line of equal distribution of trading volume can be viewed as the area of inequality in trading volume distribution. This area quantifies the deviation of the actual trading volume distribution from the ideal case of perfect equality, where each stock accounts for an equal share of the total trading volume. A larger area between the Lorenz curve and the line of equal distribution of trading volume indicates a higher degree of trading volume concentration, where a small subset of stocks accounts for a disproportionately large share of the total trading volume. Conversely, a smaller area between the two lines suggests a more even distribution of trading volume across all stocks. The TCI is derived from this area, with higher TCI values corresponding to a larger area of trading volume concentration and lower TCI values indicating a more equal distribution of trading volume activity. Therefore, the surface between the Lorenz curve and the line of equal distribution of trading volume can be appropriately labeled as the “area of trading volume concentration” or the “area of inequality in trading volume distribution”, representing the degree of unevenness or concentration in the distribution of trading volume across stocks. The Gini-based concentration index (TCI) ranges from 0 (perfect equality, where every stock accounts for the same share of trading volume) to 1 (maximum inequality, where one individual or a very small group holds all the share of trading volume).

While each method has its merits, the Gini-based TCI emerges as a particularly robust and insightful measure for investigating trading volume concentration across all 500 S&P 500 stocks. This preference is rooted in several key advantages: its strong theoretical foundation in economic theory, sensitivity to trading volume distribution, resilience against outliers, and normalized comparability. The measure’s range between 0 and 1

allows for intuitive interpretation, further enhancing its appeal. Unlike the power law exponent, which primarily focuses on the tail of the distribution, or the HHI, which is more sensitive to the largest players, the Gini-based TCI considers the entire distribution of trading volumes. This comprehensive approach ensures that concentration changes across all levels of trading activity are captured, providing a more nuanced understanding of market dynamics. The Gini-based (TCI) coefficient's output range of $[0,1]$ allows for straightforward interpretation and comparison across different time periods or market conditions. This normalization facilitates the identification of trends and anomalies in trading concentration over time. While extreme trading volumes can significantly impact both the power law exponent and HHI, the Gini-based TCI is less susceptible to such outliers (which is reflected in Figure 2).

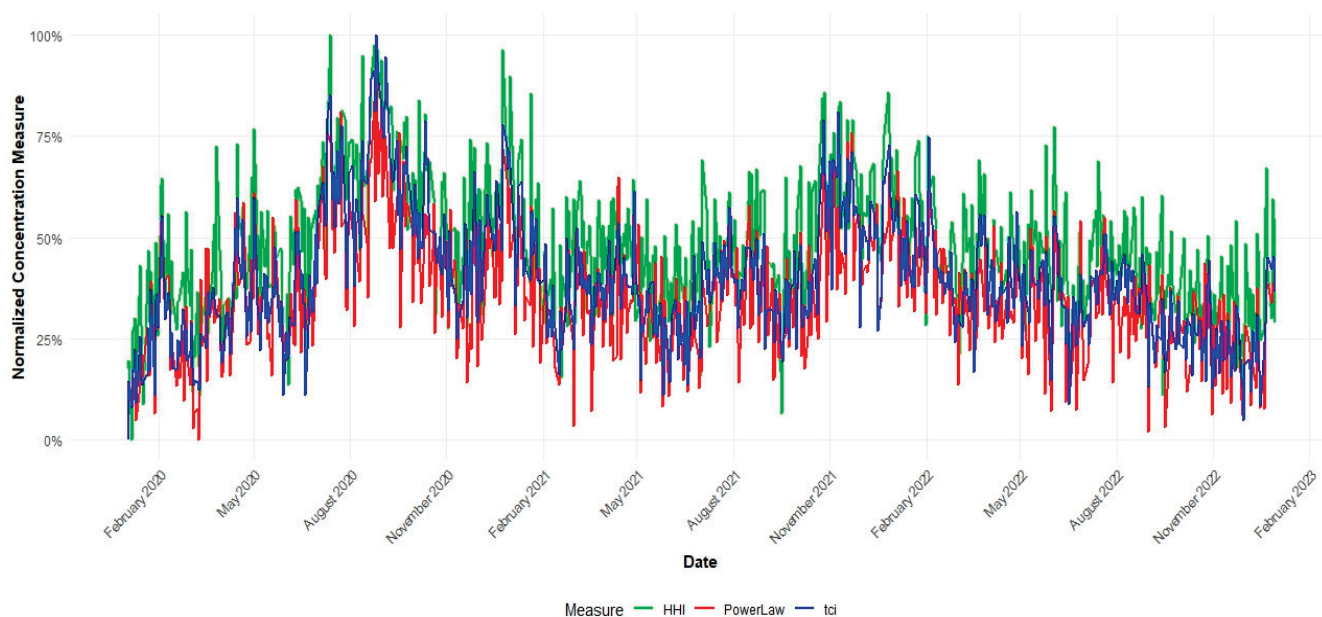


Figure 2. Comparison of different trading volume concentration measures for S&P 500 companies, i.e., with the use of the power law exponent, HHI and Gini-based TCI (all charts are normalized which facilitates the comparative analysis). Source: own elaboration in R 4.3.1.

This robustness of Gini-based TCI ensures that as a measure of trading volume concentration it remains stable and informative even in the presence of occasional trading volume spikes or anomalies (see Figure 2). The Gini coefficient's strong theoretical foundation in inequality studies translates well to the analysis of trading volume concentration. Its mathematical properties, including the principle of transfers (i.e., the Pigou-Dalton transfer principle) (Cowell 2000), make it particularly suitable for assessing the distribution of a finite resource (trading volume) among a fixed set of entities (S&P 500 stocks). The Gini-based TCI provides an intuitive measure of concentration that can be easily communicated to both technical and non-technical audiences. Its visual representation through the Lorenz curve offers additional insights into the nature of trading volume distribution.

From a mathematical perspective, the Gini-based TCI's calculation involves evaluating the area between the Lorenz curve and the line of perfect equality. This approach inherently captures the cumulative effects of trading volume distribution, providing a more comprehensive measure of concentration than methods that rely on specific distributional assumptions or are overly sensitive to particular segments of the market. And while the power law exponent and HHI offer valuable insights into specific aspects of trading volume concentration, the Gini-based TCI provides a more holistic and robust measure for analyzing the S&P 500 market. Its ability to capture concentration effects across the entire distribution of stocks, coupled with its normalized output and strong theoretical founda-

tion, makes it an ideal tool for researchers and practitioners seeking to understand and monitor trading volume concentration in this critical market index.

2.2. Experimental Design and Data Analysis Methodology

This study employed a quantitative approach to test the hypothesis that a portfolio based on trading volume concentration outperforms the S&P 500 index. The experiment focused on all 500 companies in the S&P 500 index over a three-year period from 2 January 2020 to 30 December 2022, encompassing 756 trading sessions. After analyzing various combinations of concentration levels, we determined that the most representative measure of trading volume concentration was the combination of the top 30 companies with the highest trading volume and the 50th percentile. Consequently, our experimental portfolio consisted of the 30 stocks with the highest daily share of total trading volume among all 500 S&P 500 companies. The portfolio was rebalanced daily, with stocks falling out of the top 30 being sold and replaced by new entrants. This approach ensured that the portfolio remained ‘concentration-variant’, reflecting changes in overall trading volume concentration. The concentration level for the top 30 stocks fluctuated between approximately 38% and 64% of the total trading volume (for all 500 S&P 500 companies) during the study period. To maintain consistent risk management and allow for a more direct comparison with trading volume concentration changes, we opted for a fixed number of stocks (30) rather than a fixed concentration level. This decision was based on the premise that a constant number of stocks with varying concentration would better represent the dynamics of trading volume concentration than a fixed concentration level with a variable number of stocks.

The study also included a qualitative assessment of portfolio changes in relation to significant market events, such as the COVID-19 pandemic, the Russia–Ukraine war, the energy crisis, inflation spikes, Federal Reserve policy shifts, and banking sector turbulence. This analysis aimed to provide context for the observed changes in trading volume concentration and portfolio composition.

To evaluate the performance of the concentration-based portfolio against the S&P 500 index, we conducted a comprehensive risk–return analysis. This included calculating and comparing key metrics such as Annualized Return, Annualized Standard Deviation, Annualized Sharpe Ratio (with a risk-free rate of 1%), Maximum Drawdown, Value at Risk (VaR) at 95% confidence level, and Conditional Value at Risk (CVaR) at 95% confidence level.

The experiment’s design allowed for a robust comparison between the daily rebalanced, concentration-based rotational portfolio and the S&P 500 index. This approach enabled us to test our hypothesis and draw scientific inferences about the potential benefits of following trading volume concentration as an investment strategy.

3. Results

Utilizing the R programming language and applying the equations presented in Section 2.1, specifically Equations (3) and (4), we conducted a visualization of the trading volume concentration index. This visualization was based on the theoretical considerations of the Gini-based TCI index discussed in this Section 2.1 and the aforementioned mathematical notations. The R environment provided a robust platform for implementing these complex calculations and generating graphical representations (visualizations) of the trading volume concentration measures. By leveraging the computational power of R and the theoretical framework established by the Gini index, we were able to create a comprehensive visual representation of trading volume concentration across the S&P 500 constituents. This approach allowed for a nuanced analysis of trading volume concentration patterns, enabling us to identify trends and anomalies in trading volume distribution over the study period. The resulting visualizations (shown in Figure 3) offer valuable insights into the dynamics of trading volume concentration and serve as a foundation for our subsequent analyses.

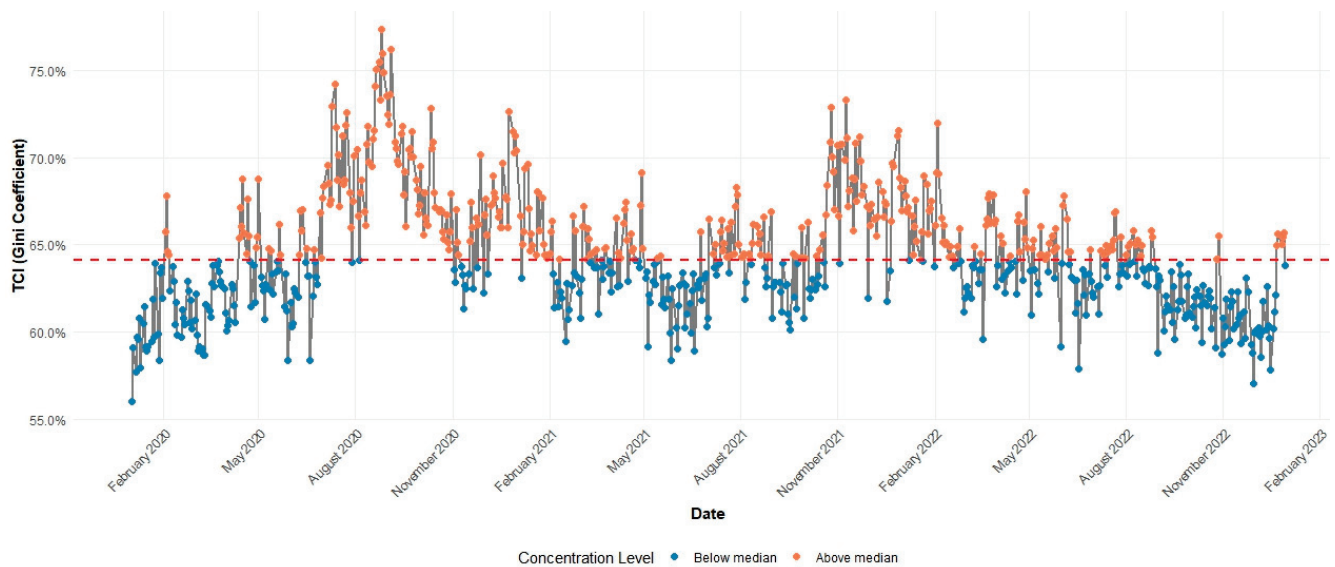


Figure 3. The Gini-based Trading Concentration Index (TCI) of S&P 500 stocks (2020–2022). Source: own elaboration in R 4.3.1.

The results of our analysis reveal that the Gini-based trading volume concentration (TCI) fluctuated within a range of 55.98% to 77.35% throughout the study period. This metric provides valuable insights into market dynamics, allowing us to identify periods when the TCI was above or below its median for the entire timeframe. These findings also enable the identification of key market reversal days (i.e., trading sessions). Notably, TCI readings were low prior to early March 2020, after which the onset of the pandemic and subsequent Federal Reserve actions to increase system liquidity fueled a technology-driven bull market, resulting in rising trading volume concentration levels. This trend culminated in concentration peaks during the latter half of August 2020, with the aforementioned highest reading of 77.35% for the entire study period. Subsequently, we observed a downward trend until May 2021, followed by another increase until November 2021, then a declining trend until June 2022, a rapid one-month increase from June to July 2022, and finally another decline until December 2022. While numerous short-term swings could be identified, the primary objective of this study is to demonstrate the effectiveness of tools like the Gini-based TCI in assessing trading volume concentration, rather than providing an exhaustive analysis of market fluctuations.

To better understand the dynamics of trading volume concentration, measured as the share of individual stocks ranked from highest to lowest trading volume, we analyzed various combinations and points along this distribution. Specifically, we examined four key combinations: (1) the top 10 stocks by trading volume and the 25th percentile, (2) the top 30 stocks and the 50th percentile, (3) the top 75 stocks and the 75th percentile, and (4) the top 250 stocks (representing half of the S&P 500 index) and the 90th percentile. These combinations were chosen to provide a comprehensive view of the concentration distribution across different levels of market depth. By examining these diverse points along the spectrum, we aimed to identify patterns and thresholds that could inform our understanding of trading volume concentration and its potential impact on portfolio performance. Figures 4–7 below illustrate these combinations for different points of the distribution, offering a visual representation of how trading volume concentration varies across different subsets of the S&P 500 index. Analyzing different percentiles, such as the 25th, 50th, 75th, and 90th, allows to examine the distribution of trading volume concentration more comprehensively. This approach can reveal potential skewness, kurtosis, or other distributional properties that might be overlooked by focusing solely on central tendencies or specific quantiles. Additionally, examining different combinations, allows to potentially identify companies or groups of companies that exhibit unusual or extreme trading volume pat-

terms, providing qualitative insights into market dynamics, investor behavior, or other factors influencing trading activity. Having multiple combinations also facilitates comparisons and benchmarking of concentration levels across different segments of the S&P 500 index. For example, it allows to compare the concentration levels of the top 10 companies with the top 30 or top 75 companies, providing a more nuanced understanding of the distribution.

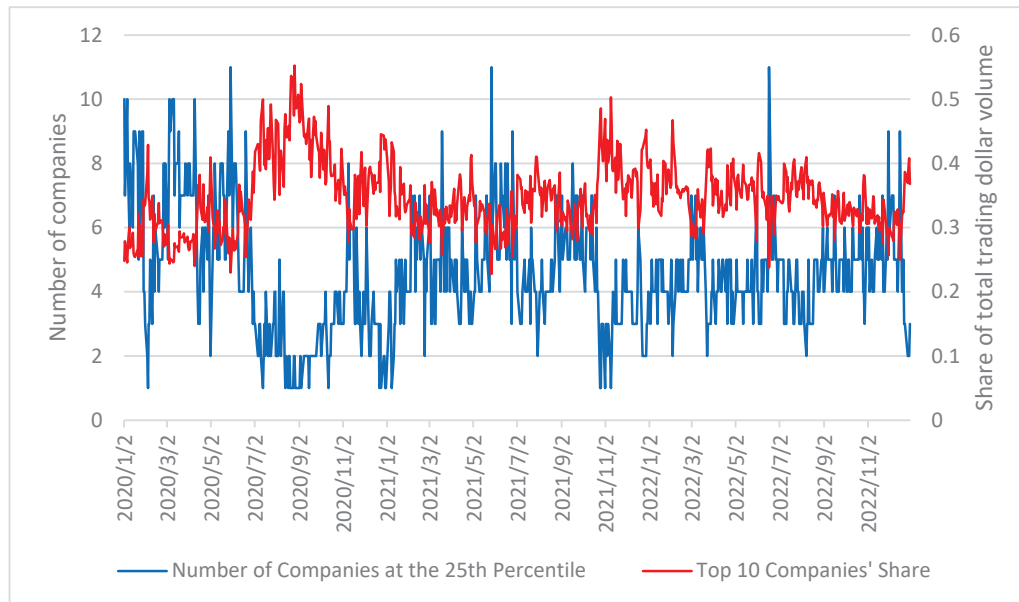


Figure 4. Trading volume concentration in the S&P 500: Top 10 companies' share vs. Number of companies at the 25th percentile (from 2 January 2020 to 30 December 2022, encompassing a total of 756 trading sessions over a span of three years). Source: own elaboration.

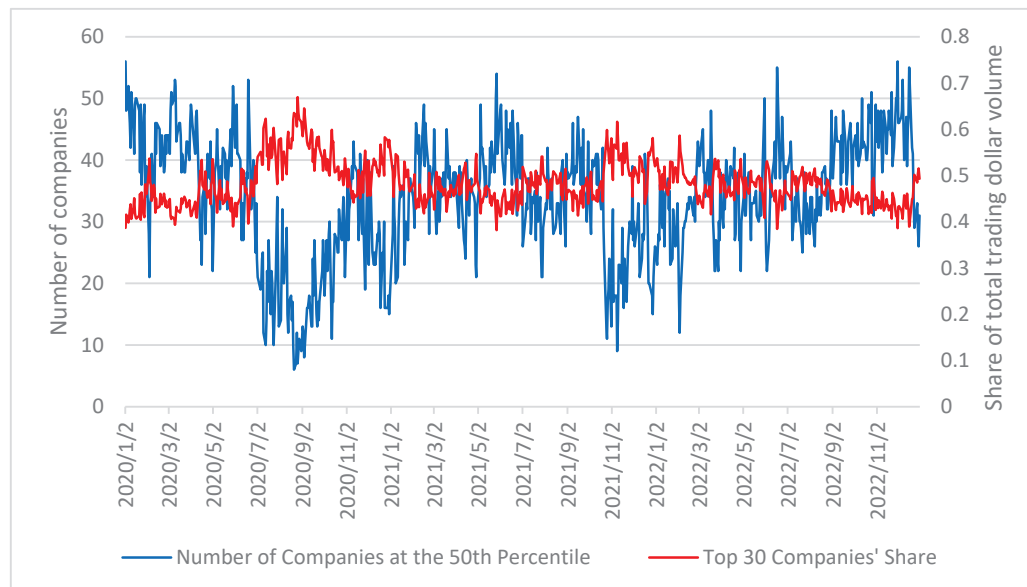


Figure 5. Trading volume concentration in the S&P 500: Top 30 companies' share vs. Number of companies at the 50th percentile (from 2 January 2020 to 30 December 2022, encompassing a total of 756 trading sessions over a span of three years). Source: own elaboration.

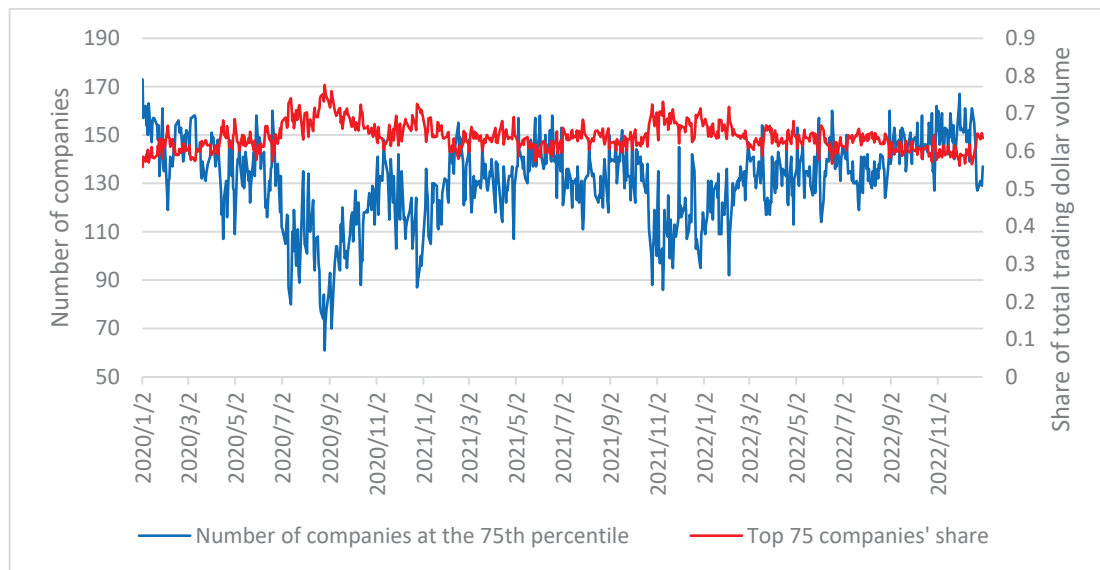


Figure 6. Trading volume concentration in the S&P 500: Top 75 companies' share vs. Number of companies at the 75th percentile (from 2 January 2020 to 30 December 2022, encompassing a total of 756 trading sessions over a span of three years). Source: own elaboration.

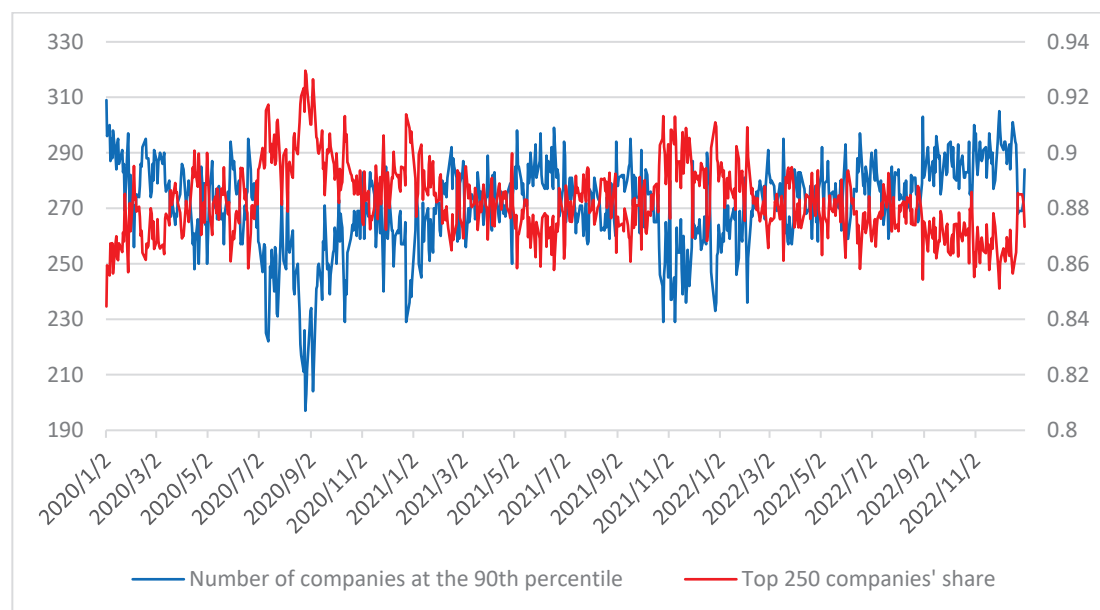


Figure 7. Trading volume concentration in the S&P 500: Top 250 companies' share vs. Number of companies at the 90th percentile (from 2 January 2020 to 30 December 2022, encompassing a total of 756 trading sessions over a span of three years). Source: own elaboration.

The top 10 companies (stock) with the highest trading volume and 25th percentile—this combination provides insights into the concentration levels at the lower end of the distribution, capturing the trading volume dynamics of the companies with relatively higher trading activity. It allows to identify potential outliers or anomalies among the smaller companies and understand their impact on the overall trading volume concentration (see Figure 4).

Analyzing the top 30 companies and the 50th percentile offers a balanced view of the concentration levels, encompassing a significant portion of the trading volume while also considering the distribution's central tendency (see Figure 5). This combination is particularly useful for benchmarking and comparing concentration levels across different time periods or market conditions.

In turn, by examining the top 75 companies and the 75th percentile, we gain a comprehensive understanding of the concentration levels at the upper end of the distribution (see Figure 6). This combination is valuable for identifying potential pockets of high concentration among the larger and more actively traded companies, which can have significant implications for market dynamics and investor behavior.

Finally, analyzing the top 250 companies, which represent half of the S&P 500 index, and the 90th percentile provides a broad perspective on the concentration levels across a substantial portion of the index (see Figure 7). This combination is particularly useful for assessing the overall distribution of trading volume and identifying potential skewness or kurtosis in the data.

This comprehensive approach captures different aspects of the distribution, identifies potential anomalies, facilitates comparisons, and ensures the reliability and generalizability of the findings, ultimately contributing to a deeper understanding of the market dynamics and investor behavior. Based on the results, it is important to note, that the trading volume concentration phenomenon observed in the S&P 500 index stocks is an intriguing and multifaceted occurrence. In early 2020, specifically from the beginning of March, there was a notable increase in the concentration of trading activity (measured as the share of total dollar volume) among the stocks comprising the S&P 500 index. More precisely, the number of stocks accounting for 50% of the total trading volume across all 500 S&P 500 companies decreased from 52 at the start of March to just 6 by the end of August 2020 (a span of approximately 6 months, from 10 March to 21 August) [as shown in Figure 5]. In other words, by late August 2020, a mere 6 out of the 500 S&P 500 stocks were responsible for generating half of the total trading volume across the entire index. This concentration pattern repeated itself in 2021. Starting from 27 May 2021, when 54 stocks accounted for 50% of the trading volume, the concentration level steadily increased until 9 November 2021, when only 9 stocks were responsible for generating half of the total trading volume. From November 2021 until the end of 2022, the trading concentration began to decline again. By December 2022, more than 50 stocks were needed to account for 50% of the total trading volume across the S&P 500 index, indicating a more even distribution of trading activity. Alternatively, the share of trading volume attributed to the top 30 stocks decreased from over 60% to approximately 40%, as illustrated in Figure 5.

All the results illustrated in Figures 4–7, which depict trading volume concentration measured as the share of individual stocks in total trading volume (ranked from top to bottom with the highest to lowest share in total trading volume), are summarized in Table 1 for key reversal days when trading volume concentration peaked or bottomed out. These figures present various combinations and distribution levels, including the top 10 stocks by trading volume and the 25th percentile, the top 30 stocks and the 50th percentile, the top 75 stocks and the 75th percentile, and the top 250 stocks (representing half of the S&P 500 index) and the 90th percentile. Table 1 provides a comprehensive overview of these concentration metrics for the critical market turning points, allowing for a detailed comparison of how different segments of the market contribute to overall trading volume concentration during pivotal moments in the study period. This consolidated presentation facilitates a more detailed understanding of the relationship between market depth and trading volume concentration at key junctures in the market cycle.

Table 1. Trading volume concentration among the S&P 500 companies: distribution spectrum analysis at key reversal dates.

	10 March 2020	21 August 2020	27 May 2021	9 November 2021	17 June 2022	22 July 2022	7 December 2022
Top 10 Companies' Share	0.245829	0.536322527	0.227957801	0.503002991	0.237884131	0.406429329	0.279420471
Number of Companies at the 25th Percentile	10	1	11	1	11	3	7
Top 30 Companies' Share	0.393185145	0.635096283	0.381975163	0.61599916	0.384175257	0.518350563	0.406214409
Number of Companies at the 50th Percentile	53	6	54	9	55	25	53

Table 1. Cont.

	10 March 2020	21 August 2020	27 May 2021	9 November 2021	17 June 2022	22 July 2022	7 December 2022
Top 75 Companies' Share	0.573965619	0.746440805	0.573302986	0.730776668	0.566539724	0.659021436	0.566599586
Number of Companies at the 75th Percentile	158	77	157	86	160	119	161
Top 250 Companies' Share	0.865843702	0.920429479	0.862344887	0.913062896	0.858169444	0.890448254	0.860801235
Number of Companies at the 90th Percentile	288	217	293	229	297	262	294

Source: own elaboration.

The data strongly suggest a positively skewed (right-skewed) distribution of trading volume across S&P 500 companies. This is evident from the fact that a small number of companies (top 10 or top 30) consistently account for a disproportionately large share of the trading volume. For instance, on 21 August 2020, the top 10 companies accounted for 53.63% of the volume, indicating a long right tail in the distribution. The large difference between the share of trading volume for the top 10 companies and the median (50th percentile) suggests a heavy-tailed distribution. This is characteristic of a distribution where extreme values are more probable than in a normal distribution. The concentration of volume in the top companies, particularly during high trading volume concentration periods, indicates a distribution with high kurtosis. This means the distribution has fatter tails and a higher, sharper peak compared to a normal distribution. The data show that the median trading volume is significantly lower than the mean. This can be inferred from the fact that the 50th percentile (median) consistently includes many fewer companies than would be expected if the distribution were symmetric, indicating that the bulk of the distribution is shifted towards lower trading volumes. The wide swings in trading volume concentration levels between dates (as shown in Table 1 above) suggest a distribution with high variability and a large standard deviation. The standard deviation appears to change over time, being larger during high concentration periods. Therefore, the distribution shape appears to change over time. During high concentration periods (e.g., 21 August 2020), the distribution is more extremely skewed and peaked. In contrast, during lower concentration periods (e.g., 10 March 2020), the distribution becomes relatively less skewed and more spread out. The relationship between the cumulative share of trading volume and the number of companies often follows a pattern reminiscent of a power law distribution, which is common in many natural and economic phenomena (Naldi 2003; Balakrishnan et al. 2013; Shankar et al. 2020).

Moreover, Table 1 shows a cyclical pattern of concentration, with alternating periods of high and low concentration. This is evident across all metrics, but particularly pronounced for the Top 10 Companies' Share. The highest levels of concentration occurred on 21 August 2020, and 9 November 2021. On these dates, the Top 10 Companies' Share exceeded 50% of trading volume, indicating significant market dominance by a small number of companies. The following dates: 10 March 2020, 27 May 2021, and 17 June 2022, show relatively lower concentration levels. During these periods, trading volume was more evenly distributed across all 500 S&P 500 stocks. What is important to note is that there are instances of rapid shifts in concentration, particularly between 17 June 2022, and 22 July 2022. This suggests periods of market volatility or significant events affecting trading patterns.

Also, there is a consistency across different metrics (different combination of the top k number companies' share vs. number of companies at the n-th percentile). The patterns observed in the Top 10 companies' share are generally mirrored in the other metrics, indicating that concentration trends affect different segments of the market similarly. As the share of trading volume for top companies increases, the number of companies at various percentiles decreases. This inverse relationship is particularly evident at the 25th and 50th percentiles. The Top 250 companies' share remains relatively stable compared to other metrics, suggesting that larger companies maintain a consistent share of trading volume

even during periods of high concentration. The fluctuations in the number of companies at different percentiles provide insights into market breadth. Lower numbers indicate periods of narrower market participation, while higher numbers suggest broader market engagement. These observations suggest that the S&P 500 experienced significant shifts in trading volume concentration during the studied period, with alternating phases of high concentration and more distributed trading. These patterns may reflect broader market trends, economic events, or changes in investor behavior, and could have implications for market efficiency, liquidity, and overall index performance.

To further illustrate and comprehend the trading volume concentration of S&P 500 stocks, Table 2 presents the trading volume concentration results for the top 30 stocks with the highest trading volume on key dates (trading sessions) where significant extremes in trading volume concentration were observed. This provides an alternative perspective to the information depicted in Figures 3–7. Table 2 allows for a qualitative assessment of why specific companies appeared in this top 30 list, which, as previously emphasized, represents the most representative metric (concentration distribution level) among the four combinations illustrated in Figures 4–7. This detailed breakdown enables a deeper understanding of the factors driving concentration during critical market periods and offers insights into the dynamics of stock selection within the highest volume segment of the 500 S&P 500 stocks. By examining these key dates, we can better contextualize the shifts in trading volume concentration and their potential implications for market behavior and investment strategies.

Table 2. Trading volume concentration among the S&P 500 stocks: Top 30 companies by date (key reversal dates).

Rank\Date	10 March 2020	21 August 2020	27 May 2021	9 November 2021	17 June 2022	22 July 2022	7 December 2022
1	AAPL 0.065767	TSLA 0.175911	TSLA 0.04951	TSLA 0.201085	TSLA 0.048192	TSLA 0.13048	TSLA 0.071953
2	AMZN 0.04361	AAPL 0.167887	AAPL 0.035281	NVDA 0.065906	AAPL 0.042472	AAPL 0.047588	AAPL 0.048241
3	MSFT 0.033986	NVDA 0.05064	NVDA 0.026803	AMZN 0.051055	MSFT 0.025607	NVDA 0.043052	AMZN 0.029569
4	TSLA 0.032521	AMZN 0.046903	AMZN 0.024621	AMD 0.04873	AMZN 0.025434	META 0.033388	NVDA 0.02947
5	META 0.014118	MSFT 0.030834	META 0.020279	PYPL 0.043697	NVDA 0.024022	AMD 0.031417	MSFT 0.024571
6	NVDA 0.012247	META 0.016567	MSFT 0.018124	AAPL 0.028467	AMD 0.020596	AMZN 0.029182	AMD 0.020378
7	GOOGL 0.011306	AMD 0.016158	GOOG 0.013929	MSFT 0.023794	GOOGL 0.01321	MSFT 0.026388	META 0.016478
8	AMD 0.011179	BA 0.011334	BA 0.013732	META 0.019572	XOM 0.013354	GOOGL 0.02444	GOOGL 0.01447
9	GOOG 0.010805	GOOGL 0.010959	PG 0.013295	F 0.01103	CVX 0.012668	GOOG 0.022313	GOOG 0.012448
10	BAC 0.01029	V 0.00815	GOOGL 0.012384	GOOGL 0.009667	KDP 0.011815	NFLX 0.018181	NFLX 0.011843
11	JPM 0.010121	NFLX 0.007709	F 0.012353	GE 0.009294	ON 0.011731	VZ 0.011996	XOM 0.010208
12	BA 0.009749	INTC 0.006813	CRM 0.010313	MRNA 0.008629	GOOG 0.011265	INTC 0.007508	PYPL 0.009023
13	V 0.009512	HD 0.006242	KO 0.009762	GOOG 0.008372	JPM 0.008387	AXP 0.00659	CRM 0.008273
14	NFLX 0.008948	BAC 0.005487	CSCO 0.008854	V 0.008182	ADBE 0.008204	ISRG 0.006465	V 0.008084
15	DIS 0.008675	DE 0.005135	ABBV 0.008827	QCOM 0.006847	BRK-B 0.007439	MU 0.006303	BAC 0.007913

Table 2. Cont.

Rank\Date	10 March 2020	21 August 2020	27 May 2021	9 November 2021	17 June 2022	22 July 2022	7 December 2022
16	XOM 0.00848	ADBE 0.005	AMD 0.008375	ABNB 0.00586	AMGN 0.007387	XOM 0.006244	UNH 0.007594
17	MCK 0.007847	PYPL 0.004788	WMT 0.007953	BAC 0.00575	HD 0.007001	T 0.006138	JPM 0.007579
18	MA 0.007373	JPM 0.004752	GE 0.007883	UBER 0.005081	OXY 0.006886	BA 0.005564	HD 0.006347
19	BRK-B 0.00716	CRM 0.004747	UBER 0.007749	MU 0.005057	V 0.006881	HCA 0.005154	BRK-B 0.006202
20	UNH 0.006665	WMT 0.004356	JPM 0.007683	BA 0.005037	MRK 0.006699	QCOM 0.005126	ENPH 0.005896
21	T 0.006564	TGT 0.004332	DIS 0.00723	MA 0.004866	INTC 0.006334	CMCSA 0.004755	CVX 0.005875
22	CSCO 0.006546	NOW 0.004198	GM 0.00602	PFE 0.004704	CSCO 0.006214	PYPL 0.004648	ABNB 0.005678
23	GILD 0.006466	XOM 0.004179	ACN 0.005973	WFC 0.004697	BAC 0.006164	ADBE 0.004492	BA 0.005087
24	ADBE 0.006416	JNJ 0.004101	MS 0.00587	JPM 0.004456	BMJ 0.006154	UNH 0.004469	WFC 0.005026
25	INTC 0.006379	BRK-B 0.003964	WFC 0.005925	DIS 0.004245	UNH 0.005725	COST 0.004418	JNJ 0.00496
26	VZ 0.006271	QCOM 0.003857	MS 0.00587	CVX 0.004221	MPC 0.005606	CCL 0.004311	COST 0.004904
27	CVX 0.006218	PFE 0.003751	XOM 0.005848	C 0.004184	COP 0.005502	NEE 0.004281	DIS 0.004684
28	CMCSA 0.006157	MA 0.003609	MA 0.005835	XOM 0.004143	WFC 0.005459	AVGO 0.004242	PG 0.004555
29	CRM 0.005967	LRCX 0.003607	MRNA 0.005795	UNH 0.004102	PG 0.005436	BAC 0.004199	MRK 0.00447
30	C 0.005842	JNJ 0.003964	ACN 0.005973	UBER 0.005081	AVGO 0.004242	COST 0.004418	C 0.004437
Sum (Σ)	0.393185	0.635096	0.381975	0.615999	0.384175	0.518351	0.406214

Source: own elaboration in R.

The results of the experimental design described in Section 2.2 are presented in Figures 8 and 9, as well as in Table 3. To recap, this study employed a quantitative approach to test the hypothesis that a portfolio based on trading volume concentration outperforms the S&P 500 index. The experiment focused on all 500 companies in the S&P 500 index over a three-year period from 2 January 2020 to 30 December 2022, encompassing 756 trading sessions. Our experimental portfolio consisted of the 30 stocks with the highest daily share of total trading volume among all S&P 500 companies, rebalanced daily to maintain a ‘concentration-variant’ approach. Figure 8 specifically illustrates the Profit and Loss comparison (i.e., the PnL) curve for both the concentration-driven (daily rebalanced) rotation portfolio and the S&P 500 index over the entire study period. This visual representation allows for a direct comparison of the performance of our experimental portfolio against the benchmark index, providing a clear illustration of the potential benefits or drawbacks of the concentration-based investment strategy. The PnL curves offer insights into the cumulative returns of both approaches, highlighting periods of outperformance or underperformance and allowing for a comprehensive evaluation of the effectiveness of the trading volume concentration strategy in various market conditions throughout the three-year study period.

Table 3 presents a comprehensive comparative risk–return analysis between the experimentally designed portfolio, which daily reallocates funds from stocks falling out of the top 30 highest trading volume to new entrants, and the S&P 500 index as a benchmark.

This analysis provides quantitative metrics to evaluate the performance and risk characteristics of the concentration-driven strategy against the broader market index.

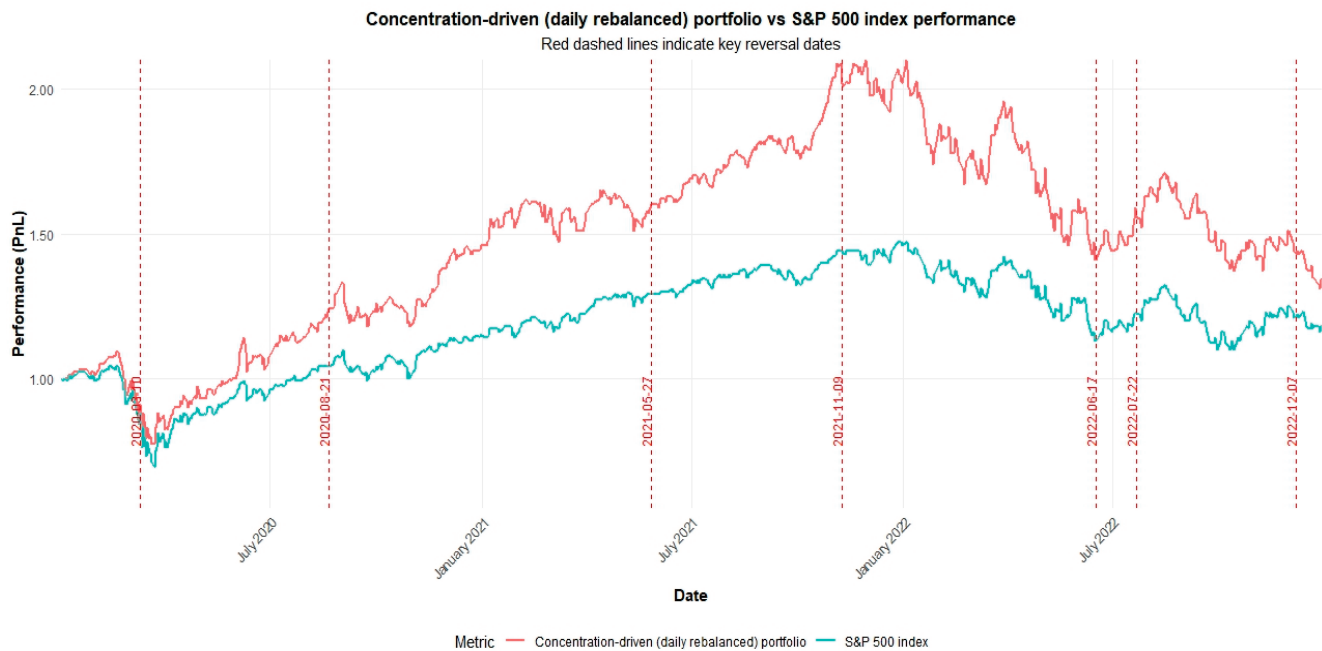


Figure 8. Profit and Loss comparison (PnL): concentration-driven (daily rebalanced) rotation portfolio vs. S&P 500 benchmark; Note: This figure presents a comparison of Profit and Loss (PnL) between the Concentration-Driven (daily rebalanced) Rotation Portfolio and the S&P 500 Index over the entire study period, spanning from 2 January 2020 to 30 December 2022. Source: own elaboration in R 4.3.1.

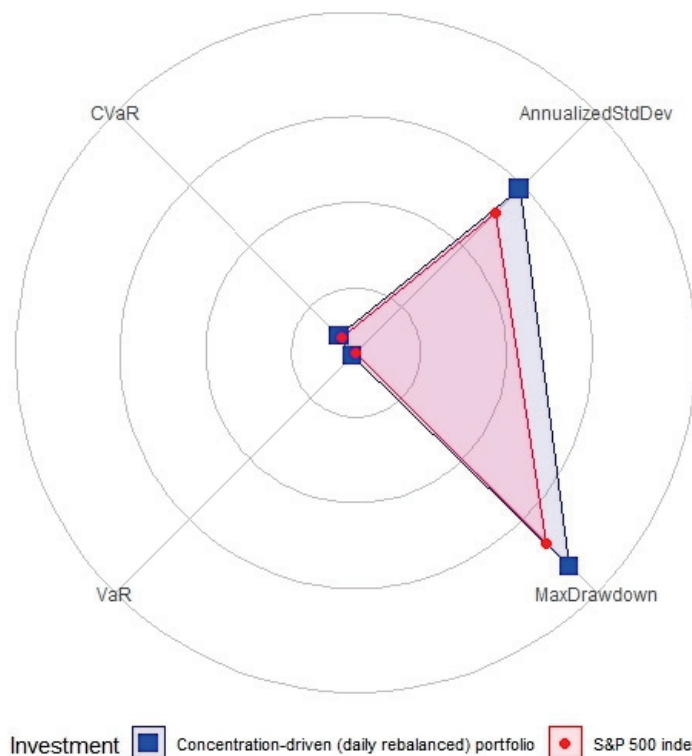


Figure 9. Radar chart: risk metrics comparison between concentration-driven portfolio and S&P 500 index. Source: own elaboration.

Table 3. Comparative risk–return analysis. Concentration-driven portfolio vs. S&P 500 index.

Metric	Concentration-Driven (Daily Rebalanced) Portfolio	S&P 500 Index
Annualized Return	0.1066	0.0589
Annualized Std Dev	0.2943	0.2548
Annualized Sharpe ($R_f = 1\%$)	0.325	0.19
Max Drawdown	0.377049	0.33925
VaR (95%)	−0.03053	−0.02479
CVaR (95%)	−0.05235	−0.04841

Source: own elaboration.

Figure 9 visualizes the same results as Table 3 but in the form of a radar chart, offering a more intuitive understanding of the portfolio strategy’s advantages. This graphical representation allows for a quick and clear comparison across multiple performance and risk dimensions, effectively illustrating the potential benefits of pursuing concentration in S&P 500 stocks as an investment strategy.

The comparative analysis of the concentration-driven portfolio (with its constituents rebalanced daily based on top 30 companies with the highest share of trading volume) and the S&P 500 index yields several noteworthy observations (as shown in Table 3 and Figures 8 and 9). Firstly, the portfolio demonstrates a superior annualized return of 10.66%, compared to the S&P 500’s 5.89%. This represents an outperformance of 477 basis points, indicating a substantially higher rate of capital appreciation for the concentration strategy. Secondly, the portfolio exhibits a higher annualized standard deviation (29.43%) relative to the S&P 500 (25.48%). This suggests that the concentration strategy experiences greater volatility, which is consistent with the expectation that a more concentrated portfolio may be subject to larger price fluctuations. Thirdly, the portfolio’s Sharpe ratio (0.325) surpasses that of the S&P 500 (0.19) by a considerable margin. This indicates that the concentration strategy provides a more favorable risk-adjusted return, delivering a higher excess return per unit of volatility. Fourthly, the portfolio’s maximum drawdown (37.70%) is moderately higher than that of the S&P 500 (33.92%). This metric reveals that the concentration strategy experienced a slightly larger peak-to-trough decline during the observation period, suggesting potentially higher downside risk. Fifthly, the portfolio’s VaR (−3.05%) is marginally higher in absolute terms compared to the S&P 500 (−2.48%). This implies that, with 95% confidence, the worst daily loss for the portfolio is expected not to exceed 3.05%, whereas for the S&P 500 it is 2.48%. Finally, the portfolio’s CVaR (−5.24%) is slightly higher in absolute terms than the S&P 500’s (−4.84%). This indicates that, in the worst 5% of cases, the average loss for the portfolio is expected to be 5.24%, compared to 4.84% for the S&P 500.

In conclusion, the empirical evidence suggests that the concentration-driven (daily rebalanced) rotating portfolio significantly outperforms the S&P 500 in terms of absolute returns and risk-adjusted performance (as measured by the Sharpe ratio). However, this outperformance is accompanied by moderately higher volatility and slightly elevated downside risk metrics. The strategy appears to offer a compelling risk–return tradeoff for investors who can tolerate the additional volatility in pursuit of higher returns. It is important to note that these findings are based on historical data and may not be indicative of future performance.

4. Discussion

Concentration has become an increasingly prevalent phenomenon across various domains of life, reflecting a fundamental shift in how resources, attention, and power are distributed. This trend is evident in numerous fields, from wealth distribution (Marcinkowski 2019; Kim 2021; Kaymak et al. 2022) to market dynamics, and even in urban development patterns (Melchiorri et al. 2018; Umemoto and Ito 2018). In the realm of technology, concentration is particularly pronounced (Armoogum et al. 2022; Mayer-Foulkes and Hafner

2023). As illustrated in Table 4, the dominance of a few key players in the tech industry is striking.

Table 4. Concentration in technology.

Authors	Contribution
Armoogum et al. (2022)	Evidence of Big Tech firms like Apple (Cupertino), Google (Mountain View), Amazon (Seattle), Microsoft (Redmond) dominating markets, leading to monopolistic concerns due to their unassailable positions and lack of significant rivals.
Mayer-Foulkes and Hafner (2023)	Evidence of how monopolistic sectors, like major tech giants, drive innovation and market power, leading to inequality and inefficiency in the economy due to a technology gradient.
Bhattacharya and Innes (2007)	Evidence addressing concerns about monopolistic practices in the technology sector.
Kuzminov and Gerashchenko (2022)	The analysis highlights concerns about monopolistic practices by major tech giants like Apple, Google, Amazon, and Microsoft due to their market dominance, raising issues of competition and regulation.
Veugelers (2018)	Evidence indicating high concentration in R&D spending among top firms, especially in digital sectors like tech. US firms dominate, posing challenges for Europe in technological advancement.
Hashem and Su (2015)	Industry concentration negatively impacts stock returns, indicating competitive industries yield higher risk-adjusted returns. This aligns with concerns about monopolistic practices in concentrated sectors like the technology industry.
Aw et al. (2018)	Industry concentration, especially in highly concentrated sectors like technology, tends to result in higher profitability and expected stock returns, supporting concerns about monopolistic practices and lack of competition.
Dolata (2017)	Market concentration in the technology sector is evident through the dominance of major tech giants like Apple, Google, Amazon, and Microsoft, raising concerns about monopolistic practices and limited competition.

Source: own elaboration.

This concentration aligns with the “winner-takes-all” dynamics observed in digital markets (Borsenberger 2014; Boussard and Lee 2020; Hagar and Shaw 2022). For example, Hagar and Shaw’s (2022) study on attention markets demonstrates attention concentration patterns consistent with cumulative advantage, a key aspect of “winner-takes-all” dynamics. The rise of platform economies and network effects has led to the emergence of tech giants that capture a disproportionate share of market value and user attention (Parker et al. 2021; Liu 2023). The drivers behind this concentration trend are multifaceted. In many cases, it stems from a collective pursuit of safety in numbers (Palley 1995), increased impact of social media (Hagar and Shaw 2022), and a tendency to gravitate towards perceived winners (Boussard and Lee 2020). In financial markets, this often translates to investors pursuing volatility (Batinca et al. 2018) and flocking to investments that are in the spotlight, reinforcing the concentration of trading volumes in certain stocks.

This study focuses on measuring and analyzing trading volume concentration across all 500 S&P 500 stocks. While various methods exist for quantifying concentration, including the power law exponent and the Herfindahl–Hirschman Index (HHI), we opted for the Gini-based Trading Concentration Index (TCI). As demonstrated in Figures 2 and 3, the Gini-based TCI provides a more nuanced and responsive measure of trading volume concentration compared to other methods (as shown in Figure 2). This approach allowed to capture the dynamic nature of concentration in financial markets more effectively. The results, as shown in Figure 3, reveal that the Gini-based TCI for the S&P 500 fluctuated between 55.98% and 77.35% over the study period, with the highest concentration observed in August 2020. This peak coincided with heightened interest in technology stocks, particularly those benefiting from the pandemic-induced shift to remote work and digital services (Sugiana et al. 2022; Kamdjoug et al. 2023). Table 5 provides insights into the specific com-

panies driving this concentration, highlighting the dominance of tech giants like Apple, Amazon, and Tesla during key periods. A qualitative analysis of the data presented in Table 5 offers valuable insights into the changing dynamics of trading volume concentration. It allows to identify patterns in which sectors and companies attract the most trading activity during different market conditions and events.

Table 5. Qualitative analysis of trading volume concentration among the S&P 500 companies.

Time Period	Qualitative Assessment of the TOP 30 Trading Volume Concentration Constituents
Pre-COVID-19 (10 March 2020)	On 10 March 2020, the trading volume concentration was relatively low, with the top 30 companies accounting for 39.32% of the total trading volume. This period can be considered pre-COVID-19, as the pandemic had not yet significantly impacted the markets. The top companies during this time were a mix of large-cap tech giants (AAPL, AMZN, MSFT, GOOGL), financial institutions (JPM, BAC), and consumer discretionary stocks (TSLA, DIS). This suggests that investors were broadly diversified across different sectors, with no clear sector dominance.
COVID-19 Market Crash (21 August 2020)	As the COVID-19 pandemic unfolded, the trading volume concentration spiked to its highest level, with the top 30 companies accounting for 63.51% of the total trading volume. This concentration was driven by a shift towards large-cap tech stocks, particularly TSLA, AAPL, and NVDA. The surge in trading volume for these companies can be attributed to several factors: (1) investors sought refuge in large, well-established tech companies during the market turmoil, (2) the pandemic accelerated the adoption of technology, boosting the demand for products and services offered by these companies, (3) retail investors, who were increasingly active during the pandemic, were drawn to the high-profile tech stocks.
Post-COVID-19 Recovery (27 May 2021)	As the markets recovered from the COVID-19 crash, the trading volume concentration decreased to 38.20%, the lowest level observed in the data. This period saw a more balanced distribution of trading volume across sectors. The top companies included a mix of tech giants (TSLA, AAPL, NVDA, AMZN, MSFT), consumer discretionary stocks (TSLA, ABNB), and some financial institutions (JPM, BAC). The decrease in concentration suggests that investors were more willing to take on risk and diversify their holdings across different sectors.
Inflation Concerns (9 November 2021)	Trading volume concentration increased again, reaching 61.60% on 9 November 2021. This period was marked by growing concerns about inflation and the Federal Reserve's potential policy responses. The top companies during this time were predominantly large-cap tech stocks (TSLA, NVDA, AMZN, MSFT, META), with some exposure to consumer discretionary (TSLA) and financial sectors (JPM). The concentration in tech stocks suggests that investors were seeking companies with strong growth potential and the ability to withstand inflationary pressures.
Recession Fears (17 June 2022)	As recession fears mounted, the trading volume concentration decreased to 38.42%, the second-lowest level observed. This period saw a more balanced distribution of trading volume across sectors, similar to the post-COVID-19 recovery period. The top companies included a mix of tech giants (TSLA, AAPL, MSFT, AMZN, NVDA), energy stocks (XOM), and some financial institutions (JPM, BAC). The decrease in concentration suggests that investors were diversifying their holdings to mitigate the potential impact of a recession.
Continued Volatility (22 July 2022)	Trading volume concentration spiked again, reaching 51.84% in July 2022. This period was characterized by continued market volatility and uncertainty. The top companies were predominantly large-cap tech stocks (TSLA, AAPL, NVDA, META, AMZN, MSFT), with some exposure to consumer discretionary (TSLA) and financial sectors (JPM, BAC). The concentration in tech stocks suggests that investors were seeking companies with strong fundamentals and growth potential, despite the market turmoil.
Recession Concerns Persist (7 December 2022)	As recession concerns persisted, the trading volume concentration decreased to 40.62%, a level similar to the pre-COVID-19 period. This period saw a more balanced distribution of trading volume across sectors. The top companies included a mix of tech giants (TSLA, AAPL, NVDA, AMZN, MSFT), energy stocks (XOM), and some financial institutions (JPM, BAC). The decrease in concentration suggests that investors were diversifying their holdings to mitigate the potential impact of a prolonged economic downturn.

Source: own elaboration.

The core of this study involves an experimental design comparing the performance of the concentration-driven (rebalanced-daily) portfolio against the S&P 500 index. This portfolio, rebalanced daily to include the 30 stocks with the highest trading volumes, significantly outperformed the S&P 500 index benchmark. The concentration-driven portfolio achieved an annualized return of 10.66%, compared to the S&P 500's 5.89%. This outperformance is particularly noteworthy given the general difficulty fund managers face in beating the S&P 500 index. As illustrated in Figures 8 and 9, and Table 3 (in the Section 3), the

concentration-driven portfolio not only delivered superior returns but also demonstrated favorable risk-adjusted performance metrics. The portfolio exhibited a higher Sharpe ratio and only slightly higher maximum drawdown compared to the S&P 500, indicating a better risk–return profile. These findings suggest that from a fund manager’s perspective, following trading volume concentration can yield above-average results.

The study contributes to the literature on trading volume concentration and financial markets in several ways. Firstly, it provides insights into effective methods for measuring concentration. Secondly, it demonstrates the stochastic nature of concentration in financial markets. It builds upon and extends previous studies in this field. For instance, Balakrishnan et al. (2008, 2013) showed that daily trading had become more concentrated in a small set of stocks over time, while Shankar et al. (2020) found that the Trading Concentration Index (TCI) for S&P 500 stocks decreased after the introduction of index funds in 1975, suggesting more evenly distributed trading activity. Our findings complement these studies by providing a more comprehensive analysis of trading volume concentration and its implications for portfolio management. The study also aligns with recent industry observations, such as those reported by Amundi (2023), which highlight the increasing importance of understanding market concentration for effective investment strategies. Our results suggest that monitoring trading volume concentration can serve as a valuable indicator for market entry and exit points, risk hedging, and overall portfolio management.

Notably, even during periods of significant market stress, such as the consecutive days of 5% declines in the S&P 500 index in March 2020, the concentration-driven portfolio demonstrated greater resilience. As shown in Figure 8, the profit and loss (PnL) curve of the concentration-based portfolio outperformed the S&P 500 index during these turbulent times.

Finally, it is important to note that the study has several limitations that should be considered when interpreting its results. Firstly, the research focuses solely on the S&P 500 stocks, which may not be representative of broader market trends or smaller cap stocks. While the study does not capture the trading volume concentration in stocks outside the S&P 500, it is important to note that significant trading volume can concentrate in smaller or mid-cap companies (as was the case for “meme stocks”: GameStop (GME), AMC Entertainment (AMC), and Bed Bath & Beyond (BBBY) during the post-COVID-19 bull market), which are not part of the S&P 500 index (notably, during the period under study, individual investors, as highlighted by Welch (2022) and Ülkü et al. (2023), often generated high trading volumes on such stocks, as many retail investors were confined at home with ample time to implement their own strategies, frequently outperforming institutional investors). For example, the highest dollar trading volume for GME shares occurred on 27 January 2021. On that day, the stock price reached a maximum of USD 347.51, and the trading volume was approximately 93.7 million shares, which translates to a dollar trading volume of approximately USD 32.5 billion. For comparison, the most liquid stocks, such as Apple, Microsoft, Amazon, and Tesla, can achieve daily trading volumes of USD 5–15 billion under normal market conditions. Furthermore, the three-year period from January 2020 to December 2022 covered in the study was marked by exceptional market conditions, including the COVID-19 pandemic, which may limit the generalizability of findings to more typical market environments. Additionally, the concentration-driven portfolio strategy, while outperforming the S&P 500 benchmark, does not account for several real-world trading costs. Although many brokerage firms have reduced or eliminated commissions on stock trades, other costs such as bid-ask spreads, market impact costs, opportunity costs, and taxes still apply. Bid-ask spreads can incur costs, especially for stocks with lower liquidity. Large trades can move the market price, leading to less favorable prices (market impact costs). The time it takes to execute trades at desired prices can result in missed opportunities (opportunity costs or slippage costs). Lastly, capital gains taxes can affect the net returns from trading, particularly for short-term trades. The study’s reliance on daily trading volume data may not capture intraday trading patterns or the impact of after-hours trading. Furthermore, the research does not fully explore the potential

causes of changes in trading volume concentration, such as the influence of algorithmic trading or the growing popularity of passive investment strategies. The experimental design used in the study is theoretical, assuming that trades can be executed exactly at closing prices. In practice, the execution of large trades by a hedge fund attempting to implement the strategy may not occur at these prices due to the size of the transactions, leading to potential discrepancies between theoretical and actual performances. Lastly, while the study employs multiple concentration measures, including the power law exponent, the Herfindahl–Hirschman index, and Gini-based TCI, it does not exhaustively compare these methods or validate their effectiveness across different market conditions or time horizons. This last issue could be addressed as a subject for future research by other scholars, providing a more comprehensive comparison and validation of these concentration measures under various market conditions and over different time periods.

All in all, this study underscores the significance of trading volume concentration in financial markets and its potential as a basis for effective investment strategies. By providing a comprehensive analysis of concentration dynamics in the S&P 500, the study contributes to a deeper understanding of market behavior and offers insights that can inform more sophisticated approaches to portfolio management and risk assessment in an increasingly concentrated financial landscape.

5. Conclusions

This study was inspired by the pervasive phenomenon of concentration observed across various domains, from financial markets to technology and urban development. The background of this research is rooted in the recognition that concentration has become increasingly prevalent in many aspects of modern life, particularly in financial markets. The period from January 2020 to December 2022 was marked by significant events such as the COVID-19 pandemic, Russia–Ukraine war, the energy crisis, surging inflation, Federal Reserve policy shifts, and banking turmoil, which collectively fueled heightened market volatility and trading volume concentration fluctuations.

The research employed a comprehensive methodological approach to analyze trading volume concentration across the 500 S&P 500 stocks. Various methods for measuring and assessing concentration were presented, including indicators based on the power law exponent, the Herfindahl–Hirschman Index (HHI), and the Gini-based Trading Concentration Index (TCI). Figure 2 in the study illustrates the differences between these concentration measurement methods. Notably, the Gini-based TCI revealed that concentration fluctuated between 55.98% and 77.35% during the study period. The research also conducted a purely statistical evaluation of concentration levels at different points along the spectrum of trading volume concentration distribution, analyzing combinations such as the top 10 stocks by trading volume and the 25th percentile, top 30 stocks and 50th percentile, top 75 stocks and 75th percentile, and top 250 stocks (half of the S&P 500) and 90th percentile. This statistical assessment led to the conclusion that the combination of the top 30 stocks by trading volume and the 50th percentile was most representative of the trading volume concentration phenomenon.

Based on these findings, the experimental design for testing the research hypotheses involved creating a portfolio that mimicked concentration by consisting of the 30 stocks with the highest daily share of total trading volume among all 500 S&P 500 companies. This approach was chosen to ensure the portfolio remained “concentration-variant”, reflecting changes in overall market trading volume concentration. The decision to use a fixed number of stocks (30) rather than a fixed concentration level was made to better manage risk and provide a more direct comparison with concentration changes.

The comparison between the concentration-driven (daily rebalanced) portfolio and the S&P 500 index benchmark yielded significant results. The concentration-driven portfolio demonstrated superior performance across several risk–return metrics. Specifically, the portfolio achieved an annualized return of 10.66% compared to the S&P 500’s 5.89%. The annualized standard deviation was moderately higher for the portfolio (29.43%) than

for the S&P 500 (25.48%), indicating somewhat higher volatility. However, the portfolio's annualized Sharpe ratio (0.325) surpassed that of the S&P 500 (0.19), suggesting a more favorable risk-adjusted return. The maximum drawdown for the portfolio (37.70%) was moderately higher than the S&P 500 (33.92%), while the Value at Risk (VaR) at 95% confidence level was -3.05% for the portfolio compared to -2.48% for the S&P 500. The Conditional Value at Risk (CVaR) at 95% was -5.24% for the portfolio versus -4.84% for the S&P 500.

The implementation of the proposed strategy in the experimental design required substantial programming work and time investment. However, this effort was justified by the interesting results obtained, which expand scientific knowledge about concentration in financial markets. This article includes numerous proprietary figures and tables, enhancing its value with visual representations of complex data patterns. Additionally, a qualitative assessment of the concentration-driven portfolio's composition was conducted to better understand the temporal synchronization of concentration fluctuations and the underlying factors driving these changes. This analysis helps elucidate why certain stocks entered or exited the portfolio during different market phases, contributing to a deeper understanding of the relationship between market events, trading volume concentration, and portfolio performance. Overall, this comprehensive study provides valuable insights into the dynamics of trading volume concentration and its potential implications for investment strategies in the S&P 500 market.

Author Contributions: Conceptualization, D.M.; methodology, D.M. and J.S.; validation, J.S.; investigation, D.M. and J.S.; resources, D.M. and J.S.; data curation, D.M.; writing—original draft preparation, D.M. and J.S.; writing—review and editing D.M. and J.S.; visualization, D.M.; supervision, J.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The data were collected from [<https://finance.yahoo.com> and the quantmod and tidyquant packages in R 4.3.1] and transformed into a panel data frame. We confirm that the data, models and methodology used in the research are proprietary, and the derived data supporting the findings of this study are available from the first author on request.

Conflicts of Interest: The authors declare no conflicts of interest.

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Article

Modeling and Forecasting Historical Volatility Using Econometric and Deep Learning Approaches: Evidence from the Moroccan and Bahraini Stock Markets

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Abstract: This study challenges the prevailing belief in the necessity of complex models for accurate forecasting by demonstrating the effectiveness of parsimonious econometric models, namely ARCH(1) and GARCH(1,1), over deep learning robust approaches, such as LSTM and 1D-CNN neural networks, in modeling historical volatility within pre-emerging stock markets, specifically the Moroccan and Bahraini stock markets. The findings suggest reevaluating the balance between model complexity and predictive accuracy. Future research directions include investigating the potential existence of threshold effects in market capitalization for optimal model performance. This research contributes to a deeper understanding of volatility dynamics and enhances forecasting models' effectiveness in diverse market conditions.

Keywords: historical volatility; pre-emerging markets; ARCH-GARCH models; deep learning approaches; LSTM network; 1D-CNN network

1. Introduction

In today's rapidly evolving financial landscape, accurate forecasting of market volatility is crucial for investors and policymakers alike. Volatility, according to Granger and Poon (2001), denotes the degree of variability or dispersion of returns for a given security or market index over a specific period, while market volatility, according to Narula (2022), refers to the degree of variation in trading prices over time. Therefore, historical volatility serves as a gauge of the magnitude of past movements in a financial market and provides valuable insights into the market's behavior over time. Understanding market volatility allows investors to predict patterns and future market movements and potentially earn profits (Burtniak and Suduk 2022; Li 2021). Predicting market volatility allows policymakers to effectively utilize fiscal and monetary policies to reduce systematic risk and then enhance their ability to stabilize financial markets (Yu et al. 2018).

The study of market volatility is vital due to its profound impact on financial decision-making. High volatility often signals increased risk and uncertainty, affecting investment strategies, portfolio management, and risk assessment. Conversely, low volatility may indicate stability but could also reflect a lack of market movement, influencing liquidity and trading activity. By accurately modeling and forecasting volatility, stakeholders can better manage these risks, optimize their investment portfolios, and make informed decisions that enhance market efficiency and stability.

Given the importance of precise volatility modeling and forecasting, it is imperative to explore and evaluate different modeling approaches. Traditional econometric models, such as ARCH and GARCH, have been the cornerstone of volatility analysis and forecasting (Bhowmik and Wang 2020). However, the advent of advanced machine learning and deep learning techniques has opened new avenues for improving forecast accuracy

(Chahuán-Jiménez 2024; Ma et al. 2024; Zhang et al. 2023; Thakkar and Chaudhari 2021; Livieris et al. 2020).

This study aims to contribute to the understanding of deep learning models in volatility modeling and forecasting by comparing their performance with traditional econometric models. Specifically, we examine historical volatility in the Moroccan and Bahraini stock markets, offering a comparative analysis of these methodologies. The inclusion of both markets allows for an assessment of potential differences in market structures, regulatory landscapes, and investor behaviors, providing a more comprehensive understanding of volatility dynamics in these emerging economies.

To our knowledge, this study is the first to model and forecast historical volatility in the context of pre-emerging markets in the MENA region using both econometric and machine learning approaches. Conventionally, researchers have shown a greater interest in modeling and forecasting returns, often prioritizing this over volatility. With the advent of artificial neural networks, research on forecasting returns has increased significantly, primarily because investors are more interested in returns. Despite this, understanding and predicting market volatility remains crucial. Volatility provides insights into the risk and stability of financial markets, which are essential for effective risk management and decision-making. In this study, we aim to address this gap by presenting a comprehensive review of the literature on volatility modeling, highlighting key econometric and machine learning techniques commonly employed in financial forecasting. This is followed by an overview of the Moroccan and Bahraini markets, emphasizing their unique characteristics, regulatory frameworks, and microstructure.

Our methodology section details the data sources, model specifications, and evaluation criteria used for performance assessment. We conduct an empirical analysis of historical volatility patterns in the Moroccan and Bahraini stock markets, comparing the forecasting precision of ARCH and GARCH models with that of LSTM and CNN architectures. Through this comparative analysis, we aim to identify the strengths and limitations of each approach, providing actionable insights for market practitioners and policymakers.

The findings of this study enrich the existing literature on volatility forecasting by providing empirical evidence on the performance of econometric and deep learning models in pre-emerging markets. Our research has significant implications for portfolio management, risk assessment, and financial decision-making in both academic and practical domains.

2. Literature Review

Studying the volatility of an asset or a financial market stands as one of the central pillars of modern financial research (Bhowmik and Wang 2020). This emphasis has only intensified since the market crash of 1987, which underscored the critical importance of understanding and effectively managing market volatility (Schwert 1990). As investors and policymakers grappled with the aftermath of this significant event, there was a heightened awareness of the profound impact that fluctuations in asset prices can have on financial stability, economic growth, and investor confidence. Consequently, researchers have increasingly focused on developing sophisticated models and analytical tools to better comprehend and predict market volatility, aiming to provide insights that can inform more robust risk management strategies and investment decisions.

Since the publication of the seminal paper of Engle (1982) introducing a new class of stochastic processes called autoregressive conditional heteroscedastic (ARCH) processes to estimate the variance of United Kingdom inflation, various studies have explored the effectiveness of different ARCH and GARCH family models in estimating volatility within stock markets. These models have demonstrated their efficacy in capturing the dynamics of asset volatility and also aggregate stock market volatility, due to their ability to capture the time-varying nature and clustering of volatility in financial time series data (Engle et al. 2013). Additionally, researchers have proposed distributed models to better characterize the thick tail of daily return rates. Engle (1982) initially introduced the autoregressive conditional heteroscedasticity model (ARCH model) to account for possible

correlations in the conditional variance of prediction errors, later extended by Bollerslev (1986) into the generalized autoregressive conditional heteroskedastic model (GARCH model). Subsequently, the GARCH model evolved into a family of models, including both linear (symmetric) and nonlinear (asymmetric) variants (such as EGARCH, TGARCH, or APARCH) to accommodate various characteristics of volatility.

Moreover, the GARCH framework accommodates the phenomenon of volatility persistence, where past volatility levels influence future volatility, making it particularly suitable for modeling the dynamics of financial market data (Alqaralleh et al. 2020). Additionally, the flexibility of the GARCH model in capturing both short- and long-term volatility patterns makes it a versatile tool for researchers seeking to understand and predict market dynamics (Bhowmik and Wang 2020). Overall, the GARCH model's ability to capture the complex dynamics of volatility, including its time variation and persistence, makes it a preferred choice for many researchers in financial econometrics.

In the realm of modeling and forecasting stock market volatility, particularly in emerging and pre-emerging markets, empirical investigations into different GARCH models have yielded contradicting outcomes. On the one hand, a plethora of studies have shown that nonlinear models, especially the EGARCH model, outperformed their linear counterparts in capturing and predicting the conditional variance across short- and long-term horizons (Lin 2018; Abdalla and Winker 2012; Liu and Hung 2010; Alberg et al. 2008; Selçuk 2005; Chong et al. 1999). However, Al Rahahleh and Kao (2018) evaluated the forecasting performance of six linear and nonlinear GARCH-class models considering the Tadawul All Share Index (TASI) and the Tadawul Industrial Petrochemical Industries Share Index (TIPISI) for petrochemical industries in the Saudi Stock Market, using daily price data from 10 September 2007 to 26 February 2015. Their findings indicate that the asymmetric power ARCH (APARCH) model is the most accurate for forecasting volatility in both indices.

By contrast, limited evidence in the literature supports the efficacy of linear or symmetric volatility models, especially within the context of emerging markets (Srinivasan and Ibrahim 2010; Gaio et al. 2014). However, the literature has prominently highlighted the effectiveness of the parsimonious linear GARCH(1,1) model with a generalized distribution of residual, particularly in capturing the intricate dynamics of volatility within financial markets. Numerous empirical studies have underscored the model's robustness and predictive power, emphasizing its ability to effectively model the volatility clustering and the conditional variance of asset returns and time series data across various time horizons (Zabiulla 2015; Abdalla and Winker 2012; Joshi 2010; Gokcan 2000).

In line with this, Sharma et al. (2021) conducted a comprehensive study comparing linear and nonlinear GARCH models for forecasting volatility in major emerging countries, namely China, India, Indonesia, Brazil, and Mexico. Using data from January 2000 to December 2019 and incorporating structural breaks due to the 2008 financial crisis, their findings indicate the superiority of the GARCH(1,1) model for volatility forecasting, with insignificant leverage effects.

More recently, numerous studies have delved into the realm of modeling and forecasting market volatility through the lens of deep learning models. Moon and Kim (2019) proposed an accurate algorithm for forecasting stock market indices and their volatility using the long short-term memory (LSTM) deep learning algorithm. Their study examines data from five stock market indices—S&P 500, NASDAQ, German DAX, Korean KOSPI200, and Mexico IPC—over a seven-year period from 2010 to 2016. Their results indicate that the highest prediction performance is achieved using a hybrid momentum approach, which considers the difference between the price and the moving average of past prices, for both market index and volatility predictions. Notably, unlike stock indices, the prediction accuracy for volatility does not depend on other financial variables such as open, low, high prices, or volume, but solely on the volatility itself. Lin and Sun (2021) introduced the SP-M-Attention model, a sparsely optimized, multi-headed, self-attentive neural network designed for volatility prediction, demonstrating superior performance across various financial forecasting tasks and highlighting its potential applicability to diverse time series

problems beyond finance. Cho and Lee (2022) addressed volatility forecasting in the stock market using asymmetric fractality features with deep learning algorithms. Their study introduces a novel approach employing asymmetric Hurst exponents to capture long-range dependence behavior, showing superior predictive power during high volatility periods, such as the COVID-19 pandemic in 2020.

Comparative research has pitted deep learning-based forecasters, including Multi-layer perceptrons, recurrent neural networks, temporal convolutional networks, and the temporal fusion transformer, against traditional econometric models like GARCH ones (Ge et al. 2023). These investigations have frequently revealed the superior predictive performance of deep learning architectures in capturing intricate long-range dependencies, often surpassing the performance of classical approaches in volatility forecasting in financial markets (Sahiner et al. 2023). In this context, Jia and Yang (2021) utilized deep neural network (DNN) and long short-term memory (LSTM) models to forecast stock index volatility. They introduced a likelihood-based loss function to enhance forecasting accuracy, demonstrating that their LSTM model outperforms econometric models and other deep learning approaches using distance loss functions.

Moreover, the integration of deep learning algorithms such as LSTM and GRU with sentiment data has yielded remarkable advancements, showcasing substantial improvements over GARCH models (Yu et al. 2023). Furthermore, the amalgamation of optimized variational mode decomposition with deep learning frameworks like DBN, LSTM, and GRU has unveiled enhanced predictive capabilities applicable across both emerging and developed markets (Cai et al. 2023). These collective findings underscore the efficacy of deep learning models in adeptly modeling and forecasting market volatility, illuminating their pivotal role in this domain.

However, studies focusing on the prediction of volatility in emerging and pre-emerging markets using deep learning methods remain relatively modest. Researchers often concentrate on developed markets, which are known for their high volatility and availability of high-frequency data.

3. Overview of the Moroccan and Bahraini Stock Markets

3.1. Casablanca Stock Exchange (CSE)

Established in 1929, the Casablanca Stock Exchange (CSE) is the third oldest market-place in Africa, playing a central role in the regional economy. Over the years, the exchange has undergone significant transformations to modernize its operations and align with international standards. In 1995, a management company was established, entrusted with overseeing the stock exchange, operating under specifications approved by the Ministry of Finance. This move marked a pivotal moment in the evolution of the CSE, setting the stage for enhanced governance and strategic management. The regulatory environment is overseen by the Moroccan Capital Market Authority (AMMC), which ensures compliance with market regulations and investor protection, further bolstering the exchange's credibility and stability. Despite these advancements, the CSE continues to face challenges in terms of liquidity, market depth, and market activity, necessitating ongoing efforts to strengthen market infrastructure and improve investor confidence.

With 77 listed companies as of the end of 2023, the Casablanca Stock Exchange (CSE) operates as a continuous market, characterized by the continuous matching of buy and sell orders throughout the trading day. Additionally, the CSE features an opening and closing fixing, which serve as reference points for the market at the beginning and end of each trading session. Driven by orders and facilitated by an intricate order book system, the market ensures that buy and sell orders are executed efficiently, contributing to market transparency and fair pricing.

3.2. Bahrain Bourse (BHB)

Transitioning to the Arabian Peninsula and venturing into the Asian continent, we explore the Bahrain Bourse, a younger financial institution established in 1987, character-

ized by its unique blend of traditional Islamic finance principles and modern investment practices. Despite its relatively recent inception, the Bahrain Stock Exchange has rapidly emerged as a significant player in the region's financial landscape, with 42 listed companies as of the end of 2023.

In the Bahraini equity market, the order-driven mechanism, married to continuous auctions, serves as the backbone of trading activities, fostering efficient price discovery. Market participants, including individual investors, institutional traders, and foreign entities, have direct access to the trading platform, enabling them to place orders according to their investment strategies and market outlook. This decentralized approach promotes market depth and liquidity, as the continuous matching of orders facilitates swift execution and minimal price impact.

While the Bahraini market primarily operates as an order-driven system, it also incorporates elements of a quote-driven market, especially in the presence of market makers. These entities provide liquidity by quoting bid and ask prices for certain securities, helping to narrow spreads and improve market efficiency. However, the order-driven nature remains predominant, emphasizing the importance of investor orders in driving market dynamics and price formation.

However, the Bahraini equity market faces certain difficulties. One challenge is the limited number of listed companies, which can restrict investment choices and diversification opportunities for investors. Furthermore, market liquidity can vary across different securities, impacting trade execution and price stability, especially for less liquid stocks.

In fine, both the Moroccan and Bahraini markets are classified as pre-emerging markets by MSCI (Morgan Stanley Capital International), indicating their status as evolving financial hubs with potential for growth and development. Despite facing challenges, they offer promising investment opportunities for those seeking exposure to emerging economies. As they continue to implement reforms and enhance infrastructure, these markets are positioned to attract greater investment inflows in the future.

4. Materials and Methods

In this study, we embarked on a comparative analysis of volatility modeling and forecasting techniques, drawing insights from both econometric and deep learning methodologies. To achieve this goal, our methodology consisted of employing a combination of traditional econometric methods, namely autoregressive conditional heteroscedasticity (ARCH) and generalized autoregressive conditional heteroscedasticity (GARCH) models, alongside cutting-edge deep learning architectures such as long short-term memory (LSTM) and convolutional neural network (CNN) models. The subsequent sections present and elaborate on the various approaches utilized in this study for volatility modeling and forecasting in the two markets.

4.1. Econometric Approach

4.1.1. The Autoregressive Conditional Heteroscedastic (ARCH) Model

ARCH models involve time series characterized by changing volatility over time (heteroscedasticity), which is conditional on the autocorrelation of previous lags (autoregressive conditional). Referring to the seminal paper by Engle (1982), a variable Y_t follows an ARCH (p) process if

$$y_t | \psi_{t-1} \sim N(0, h_t) \quad (1)$$

$$h_t = \alpha_0 + \sum_{i=1}^p \alpha_i y_{t-i}^2 \quad (2)$$

where ψ_{t-1} is the information set available at time $t - 1$, h_t is the conditional variance function, p is the order of the ARCH process, and α is a vector of unknown parameters.

To guarantee positive variance, the parameters must satisfy some conditions, such that $\forall t \in \mathbb{Z}, \alpha_0 > 0$ and $\alpha_i > 0$. Furthermore, the recent past is assumed to have more influence than older lags, so $\alpha_1 > \alpha_2 > \dots > \alpha_p$.

For estimation using our ARCH model, we followed the steps indicated in Figure 1.

Step 1	•Checking for stationarity using a unit root test.
Step 2	•Estimating the mean equation using an ARIMA model.
Step 3	•Checking for ARCH effect using a heteroscedasticity test.
Step 4	•Estimating the variance equation using an ARCH model.

Figure 1. Illustration of ARCH model estimation steps.

4.1.2. The Generalized Autoregressive Conditional Heteroscedastic (GARCH) Model

GARCH models were introduced in 1986 by Bollerslev as an extension of ARCH models. They incorporate both autoregressive and moving average terms in the volatility equation. In addition to past squared residuals, GARCH models also include lagged conditional variances in the model specification. This allows them to capture both short-term volatility clustering and long-term persistence in volatility, making them more flexible and capable of modeling various volatility patterns observed in financial time series (Francq and Zakoian 2019).

Moreover, GARCH models provide a parsimonious alternative to high-order ARCH models, which can become problematic when estimating many ARCH effects (Bhowmik and Wang 2020).

The formalities of GARCH models involve both terms p and q , whereas in ARCH, you only have the p term. So, a variable Y_t follows a GARCH (p,q) process if

$$y_t|\psi_{t-1} \sim N(0, h_t) \quad (3)$$

$$h_t = \alpha_0 + \sum_{i=1}^p \alpha_i y_{t-i}^2 + \sum_{i=1}^q \beta_i h_{t-i} \quad (4)$$

where $\alpha_0 > 0, \alpha_i > 0$ and $\beta_i > 0$.

For estimation using our GARCH model, we followed the steps shown in Figure 2.

Step 1	•Estimating the mean equation using an ARIMA model.
Step 2	•Checking for ARCH effect using a h�eteroscedasticity test.
Step 3	•Re-estimating the model including the appropriate ARCH and GARCH components.
Step 4	•Conducting diagnostic tests.

Figure 2. Illustration of GARCH model estimation steps.

In summary, the conditional variance equation in ARCH and GARCH models serves to capture the time-varying nature of volatility in financial market data. This specification is essential in financial contexts, where analysts seek to predict future volatility based on past observations and information. In these models, the conditional variance at each time point is estimated as a weighted average of several components (Abdalla and Winker 2012).

Firstly, a long-term average (represented by the constant term) provides a baseline estimate of volatility. Secondly, the GARCH term incorporates information from the previous period's forecast variance, contributing to the persistence of volatility over time. Finally, the ARCH term captures the impact of unexpected asset returns on volatility, adjusting the estimate of variance based on the magnitude and direction of these returns. This dynamic interplay between past volatility, current information, and unexpected returns allows ARCH and GARCH models to effectively capture the complex dynamics of financial market volatility.

4.2. Deep Learning Approach

If in the econometric approach, volatility is modeled as the conditional variance using ARCH and GARCH models, in the neural network approach, volatility is approximated by the standard deviation of daily logarithmic returns (close-to-close) for both indices. This is a straightforward calculation and a widely recognized measure of volatility in finance, offering an intuitive interpretation as it directly represents the magnitude of typical price fluctuations. This approach not only provides a clear and intuitive measure of volatility but also facilitates a comparison of model performance across different methodologies. Consequently, these series will serve as inputs for the LSTM and CNN models.

4.2.1. LSTM Network

Modeling and predicting future values of time series using artificial neural networks presents a challenge in retaining past information for accurate forecasting. Recurrent neural networks (RNNs) address this challenge by incorporating memory mechanisms in their hidden layers, allowing them to store and recall past states. However, simple RNNs are prone to gradient explosion, where gradients grow uncontrollably during training, affecting model stability (Kanai et al. 2017). To overcome this limitation, long short-term memory (LSTM) networks were developed. LSTM networks feature gated mechanisms that regulate the flow of information, preventing gradient explosion and enabling effective long-term memory retention. These networks learn to prioritize relevant information for prediction, enhancing forecasting accuracy. LSTM networks have proven effective for financial time series forecasting due to their ability to handle sequential data and long-term dependencies (Yu et al. 2019). However, training an LSTM network requires careful parameter selection to optimize performance (Sako et al. 2022).

In our study, we developed and trained a neural network with a range of parameters, as depicted in Table 1.

Table 1. LSTM network parameters.

Network Parameters	Values
Data standardization formula	$x' = (x - \mu) / \sigma$
Optimization algorithm	Adam
Number of iterations (epochs)	250
Gradient threshold	1
Initial learning rate	0.005
Learning rate drop period	125
Learning rate drop factor	0.2
Number of hidden layers	100
Training rate	0.9
Testing rate	0.1

We trained the LSTM model over 250 epochs, where each epoch represents one complete pass through the dataset during training. A gradient threshold of 1 was applied to stabilize training by limiting the magnitude of gradients during backpropagation. The optimization algorithm chosen was Adam, known for its efficiency in stochastic optimization tasks. We initialized training with a learning rate of 0.005 and applied a learning rate drop

every 125 epochs with a factor of 0.2 to optimize convergence. The models were structured with 100 hidden layers to capture complex patterns in the data. For evaluation, we used a training rate of 90% and a testing rate of 10% to assess model performance on realized data.

4.2.2. 1D-CNN Network

A convolutional neural network (CNN) is a versatile machine learning algorithm applied extensively in diverse fields, such as image processing, speech recognition, and time series analysis. Originally tailored for image data, CNNs necessitate two-dimensional input. However, given that time series data typically unfold in one dimension, a specialized adaptation known as a one-dimensional CNN has emerged (Markova 2022). This model operates on a single sequence, potentially incorporating multiple convolutional layers and a pooling layer to distill key features. Subsequently, a fully connected dense layer interprets these features, facilitated by a flattening layer to reduce dimensionality. To enhance performance, we meticulously curated and refined parameters using our comprehensive training dataset, with the objective of minimizing prediction errors, as illustrated in Table 2.

Table 2. CNN network parameters.

Network Parameters	Values
Data standardization formula	$x' = (x - x_{min}) / (x_{max} - x_{min})$
Optimization algorithm	Adam
Activation function	ReLU
Number of iterations (epochs)	1000
Gradient threshold	ReLU
Number of filter units	64
Number of kernels	2
Batch size	32
Dense units	1
Training rate	0.9
Testing rate	0.1

We trained the CNN network over 1000 epochs to capture temporal patterns in financial time series data. We utilized the Adam optimizer for efficient stochastic optimization and employed ReLU (rectified linear unit) as the activation function in convolutional layers to introduce nonlinearity. A gradient threshold of ReLU was applied to manage gradients during backpropagation. The CNN architecture featured 64 filter units across 2 kernels to extract spatial features from the input data. We utilized a batch size of 32 for training efficiency and configured the model with 1 dense unit for final output. Training and testing rates were set at 90% and 10%, respectively, to evaluate model performance on distinct datasets.

4.3. Forecast Performance Metrics

The performance of all employed models was evaluated using various metrics, which assessed the disparities between predicted and actual values. The performance metrics were as follows:

- Root mean square error (RMSE):

$$RMSE = \sqrt{\frac{1}{n} \sum_{t=1}^n (\varepsilon_t)^2} \quad (5)$$

- Mean absolute error (MAE):

$$MAE = \frac{\sum_{t=1}^n |\varepsilon_t|}{n} \quad (6)$$

- Mean absolute percentage error (MAPE):

$$MAPE = \left(\sum_{t=1}^n \frac{|\varepsilon_t|}{x_t} \right) / n \times 100 \quad (7)$$

- Quasi-likelihood loss (QLIKE):

$$QLIKE = \frac{1}{n} \sum_{t=1}^n \left(\frac{x_t}{\hat{x}_t^2} - \log \left(\frac{x_t}{\hat{x}_t^2} \right) - 1 \right)$$

where ε_t is the difference between the predicted value and the observed value at time t , i.e., $\varepsilon_t = x_t - \hat{x}_t$, with x_t being the observed value and $\hat{x}_t$ being the predicted value; n is the number of observations.

These metrics served as crucial benchmarks for comparing the effectiveness of each model in forecasting volatility, enabling us to identify the optimal approach for predictive accuracy in the Moroccan and Bahraini stock markets.

5. Data and Descriptive Statistics

For the implementation of our study and the deployment of the selected models, we constructed two series of daily returns related to the performance of the Moroccan All Shares Index (MASI) and the Bahrain All Shares Index (BAX) over a 5-year period from January 2019 to December 2023. The data pertaining to the closing values of both indices were obtained from the Investing.com platform, ensuring reliable and comprehensive data coverage for our analysis.

From these data, the daily logarithmic returns were computed using the following formula:

$$R_{it} = \ln(P_{it}/P_{it-1}) \quad (8)$$

where P_t is the closing price of the index i at time t .

Understanding the data through graphical representation in Figure 3 and descriptive statistics in Table 3 serves as a crucial foundation before proceeding to modeling and forecasting, providing valuable insights into the underlying patterns and characteristics of the datasets.

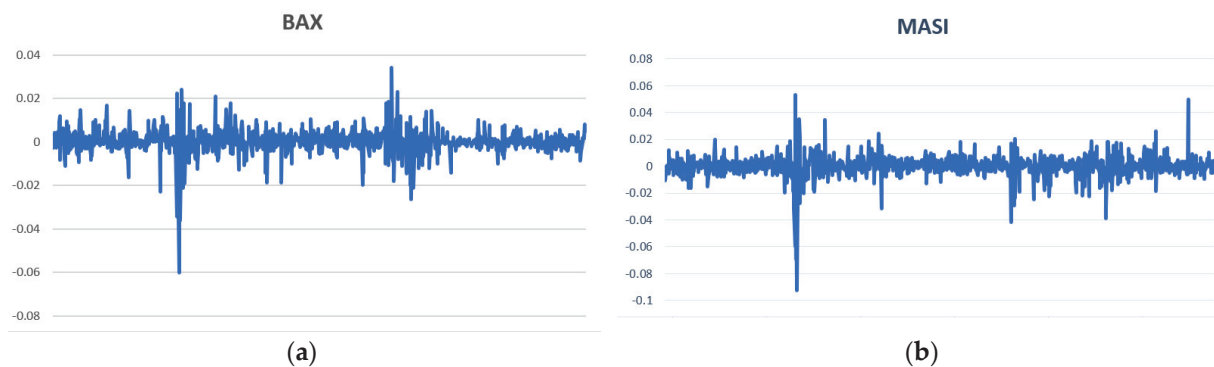


Figure 3. (a) Volatility clustering for BAX; (b) volatility clustering for MASI.

The descriptive statistics reveal insightful characteristics of the daily returns for the BAX and MASI. Notably, while the average daily return for BAX stands at 0.000321, MASI exhibits a slightly lower average return of 5.39×10^{-5} . Both distributions display negative skewness, implying a left-skewed distribution with longer tails on the left side. Additionally, the high kurtosis values suggest heavier tails and more peaked distributions compared to a normal distribution, indicating greater volatility and potential for extreme returns. Furthermore, the Jarque–Bera test results decisively reject the hypothesis of normality for both indices, emphasizing the non-normal nature of their return distributions. Overall, it is noteworthy that there are no significant differences between the statistical

characteristics of the two series, a point further reinforced by observing the graphical representations of the two datasets.

Table 3. Descriptive statistics of the BAX and MASI return series.

Statistics	Variables	
	BAX	MASI
Number of observations	1226	1247
Mean	0.000321	5.39×10^{-5}
Median	0.000391	0.000211
Maximum	0.034233	0.053054
Minimum	−0.060013	−0.092317
Std. Dev.	0.005505	0.008083
Skewness	−1.636707	−1.892897
Kurtosis	21.89118	28.00946
Jarque–Bera	18777.81	33243.21
Probability	0.000000	0.000000
Normality hypothesis	Rejected	Rejected

6. Empirical Results and Discussion

6.1. Empirical Results

6.1.1. Testing for Stationarity

To test the stationarity of our two-return series, we employed the augmented Dickey–Fuller (ADF) unit root test. This test is commonly used to determine whether a time series is stationary or nonstationary by assessing the null hypothesis regarding the presence of a unit root in the data. The results of the test are summarized in the Table 4 below, providing insights into the stationarity properties of the BAX and MASI return series.

Table 4. Stationarity test results for the BAX and MASI return series.

Variables	ADF Test	T-Statistics	p-Values	Hypothesis
BAX	Intercept	−15.88660 *	0.0000	Null hypothesis rejected
	Trend and intercept	−15.88105 *	0.0000	Null hypothesis rejected
	None	−15.81436 *	0.0000	Null hypothesis rejected
MASI	Intercept	−21.16787 *	0.0000	Null hypothesis rejected
	Trend and intercept	−21.15932 *	0.0000	Null hypothesis rejected
	None	−21.17456 *	0.0000	Null hypothesis rejected

Notes: * indicates significance at the 5% level.

The augmented Dickey–Fuller (ADF) test results indicate that the null hypothesis for both the BAX and MASI return series is rejected across all specifications. This suggests that the return series for both indices are stationary at level, indicating that they exhibit stable mean and variance over time.

6.1.2. Mean Equation Specification

To model the mean equation of both the Moroccan and Bahraini stock indices, we began with an analysis of the correlogram and evaluated various ARMA specifications. This process led us to select the ARMA(1,1) model as the most suitable, effectively capturing both the autoregressive and moving average components present in the daily return series. Initial empirical tests and iterative refinements confirmed the adequacy of the ARMA(1,1) model in representing the underlying dynamics of our stock market data. This robust representation of the conditional mean is crucial for our subsequent volatility modeling using ARCH and GARCH approaches. By accurately modeling the conditional mean, we can effectively isolate and analyze the volatility clustering effects that are central to our study.

6.1.3. Testing for Heteroscedasticity

We conducted the heteroscedasticity test using the ARCH effect specification, under the null hypothesis of no existing ARCH effect in the residual of ARMA(1,1) equation up to 1 lag. The results for both series are summarized in Table 5.

Table 5. Heteroscedasticity test results for the BAX and MASI residual return series.

	F-Statistics	Prob.	Chi Square-Statistics	Prob.	Hypothesis
BAX	182.6009 *	0.0000	159.1391 *	0.0000	Null hypothesis rejected
MASI	37.99301 *	0.0000	36.92633 *	0.0000	Null hypothesis rejected

Notes: * indicates significance at the 5% level.

The results of the ARCH test, as indicated by the F statistics and chi-square statistics, reveal that the null hypothesis of no ARCH effect is rejected for both the BAX and MASI residual series. This suggests a pattern of volatility clustering, where significant changes are often succeeded by further significant changes, regardless of their direction, while minor changes tend to be followed by additional minor changes (Joshi 2010). Such findings have significant implications for modeling and forecasting, as ignoring heteroscedasticity can lead to biased parameter estimates and inaccurate predictions.

6.1.4. Estimation Results

Table 6 summarizes the predictive performance of the various models employed in our analysis. The selection of the ARCH(1) and GARCH(1,1) models was based on their ability to capture time-varying volatility in our financial return series. In our analysis, we extended the lag length beyond the first lag, observing that additional lags did not contribute significantly to the ARCH effect. This observation was validated by conducting the ARCH-LM test statistics at various lag lengths. The statistically insignificant p-values obtained for lag lengths beyond the first lag suggest that there is no ARCH effect remaining in the models. This implies that the chosen ARCH(1) and GARCH(1,1) specifications adequately capture the dynamics of volatility in the BAX and MASI return series.

Table 6. Historical volatility prediction: comparative analysis for different models.

	ARCH(1)		GARCH(1,1)		LSTM		1D CNN	
	BAX	MASI	BAX	MASI	BAX	MASI	BAX	MASI
RMSE	0.0055	0.0081	0.0055	0.0081	0.0447	0.0810	0.0447	0.0812
MAE	0.0033	0.0049	0.0034	0.0049	0.0346	0.0453	0.0346	0.0455
MAPE (%)	154.913	166.035	161.52	157.854	86.638	88.013	86.145	89.399
QLIKE	−10.5157	−9.1930	−10.697	−9.0178	−3.1953	−3.0442	−3.1316	−3.0701

Observing the results, ARCH(1) and GARCH(1,1) models perform better in terms of RMSE, MAE, and QLIKE, indicating that they provide more accurate volatility predictions for both BAX and MASI.

LSTM and 1D CNN models have higher errors (RMSE and MAE) and less negative QLIKE values, suggesting they are less suitable for this specific volatility forecasting task.

Despite the high MAPE for ARCH and GARCH, their lower absolute errors and QLIKE values make them preferable over neural network models in this context.

These findings suggest that the parsimonious ARCH and GARCH models are more effective in capturing the volatility dynamics of the BAX and MASI compared to the more complex LSTM and CNN models. Despite their computational complexity, the deep learning models do not exhibit superior predictive performance in this context.

6.2. Discussion

At first glance, our results may appear striking. The outperformance of parsimonious econometric models over robust deep learning models may seem counterintuitive, especially given the complexity and computational power associated with deep learning algorithms.

These results deviate from findings in several studies, such as the study by Petrozziello et al. (2022), which demonstrated the superiority of LSTM networks over various traditional GARCH models in predicting volatility for the NASDAQ 100 index. Similarly, in line with this perspective, Liu (2019) demonstrated that LSTM networks can provide superior predictions for longer time intervals compared to GARCH models.

Our findings, however, contradict these studies, demonstrating the effectiveness of simplistic models in volatility modeling and prediction. Thus, we align with researchers who emphasize the particular performance of the linear GARCH(1,1) model in capturing financial market volatility dynamics (Tripathy and Garg 2013). In addition, we highlight the remarkable performance of the parsimonious ARCH(1) model, which further strengthens our argument for the efficacy of simplistic models in volatility analysis.

However, we emphasize that our results hold true within the specific context of pre-emerging markets, which are already characterized by a lack of dynamism and liquidity. Additionally, it is important to note that we did not encounter similar studies within this particular context to facilitate comparison.

In conclusion, our findings underscore the crucial balance between model complexity and predictive accuracy in volatility forecasting within financial time series analysis. While many researchers advocate for the unconditional superiority of artificial neural network models in financial time series modeling and prediction, there is a growing recognition of the need for a deeper understanding of data characteristics. Aminimehr et al. (2022) label this realization as “inconsistency” and argue that the success of neural networks over econometric methods often stems from improper model implementation. In fine, despite significant advancements in this field, it is essential to acknowledge the continued effectiveness of less complex traditional methods.

7. Conclusions and Perspectives

In conclusion, we emphasize that our study sheds light on the nuanced relationship between model complexity and predictive accuracy in historical volatility forecasting within the context of pre-emerging markets. Our results advocate reevaluating the need for complex models, suggesting that simpler models may offer more precise results, and challenging the prevailing assumption that increased complexity is always necessary for accurate forecasts.

Our study has significant implications for both academics and practitioners. It suggests that in pre-emerging markets, where data quality and quantity might be limited, simpler models such as GARCH(1,1) can outperform more complex neural network-based models. This challenges the conventional wisdom that increasing model complexity invariably enhances predictive accuracy. By demonstrating that simpler models can be more effective in certain contexts, we provide a compelling case for the strategic selection of forecasting models based on the specific characteristics of the market being analyzed.

Looking ahead, an intriguing avenue for future research involves investigating the potential existence of a threshold effect. Specifically, exploring whether there is an optimal market capitalization threshold beyond which neural network models might demonstrate superior forecasting quality. Given the established superiority of neural networks in predicting volatility, returns, and prices in more developed markets, as documented in the literature, exploring this threshold effect could provide valuable insights into the applicability of deep learning approaches in different market conditions. Such research could involve a comparative analysis of various market segments, ranging from small-cap to large-cap stocks, to identify the precise conditions under which the benefits of neural network models become apparent.

Moreover, future studies could extend our analysis by incorporating other emerging and pre-emerging markets, as well as different asset classes. This broader scope would help determine whether our findings are generalizable across various financial contexts or specific to the markets we studied. Additionally, incorporating high-frequency data, where available, could provide further insights into the dynamic nature of volatility and the performance of different models over shorter time horizons.

In summary, our findings underscore the ongoing debate surrounding the choice of model complexity in financial time series analysis in general and historical volatility in particular and highlight the need for further exploration into the interplay between market characteristics and predictive modeling techniques. By addressing these gaps, future research can contribute to a more comprehensive understanding of volatility dynamics and enhance the effectiveness of forecasting models in diverse market environments and conditions. Our study serves as a foundational step in this direction, encouraging continued investigation into the optimal balance between model simplicity and complexity in financial forecasting.

Author Contributions: Both authors contributed equally to the work, including conceptualization, methodology, data analysis, and writing of the manuscript. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The data used in this study are publicly available and accessible through the website <https://www.investing.com/> (accessed on 14 March 2024).

Conflicts of Interest: The authors declare no conflicts of interest.

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Article

Determinants of Bank Profitability—Do Institutions, Globalization, and Global Uncertainty Matter for Banks in Island Economies? The Case of Fiji

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Abstract: The objective of this study is to examine the influences of institutions, globalization, and world uncertainty on bank profitability in small developing economies. Consequently, we emphasize the significance of both bank-specific and other external factors influencing bank profitability. The empirical estimation is based on seven banks in Fiji—a small island economy—over the period 2000–2021. Together with bank-specific and macro factors, we account for institutions, globalization, and world uncertainty in analyzing the determinants of bank profitability. The study uses the fixed-effect estimation method. From the results, we observe that bank-specific variables, like the net interest margin, non-interest income, bank size, and capital adequacy ratio, are positively associated with bank profitability. Non-performing loans and credit risk are negatively associated with bank profitability. Macro variables, such as real GDP growth and remittances, have positive effects on bank profitability. Institutional factors, such as government effectiveness and voice and accountability, are positively associated with bank profitability. Regarding globalization, we find that it supports bank profitability. Global uncertainty and the Global Financial Crisis (2007–2008) are positively associated with profitability, whereas the global pandemic (COVID-19) is negatively associated. This study underscores the need to analyze the bank performance with factors beyond those reported in financial statements to derive a comprehensive understanding and appreciation of the complex nature of banking operations.

Keywords: bank profitability; institutions; globalization; COVID-19; fixed effect; island economies; South Pacific; Oceania; Fiji

1. Introduction

Banks play a pivotal role in financing economic activities, thereby supporting the development of various market segments. A profitable banking sector can be both resilient to shocks (Athanasoglou et al. 2008) and, at times, benefit from antifragility that often arises from tail events¹. One of the main roles of commercial banks is to support deposit mobilization and credit extension. Banks pay interest to deposit holders and charge interest to borrowers while ensuring a sufficient margin to support revenue and profit growth. To maximize their earnings and returns, banks organize their assets and liabilities while considering a range of factors that can affect their profitability.

Previous studies on countries' bank profitability (Short 1979; Bourke 1989; Molyneux and Thornton 1992; Demirgüç-Kunt and Huizinga 2000) mainly focused on bank-specific

and macroeconomic factors. Recent studies on bank profitability have extended the analysis to include additional pertinent dimensions, such as globalization and institutions. However, these studies are based on emerging and developed economies with well-developed financial markets (Kanapiyanova et al. 2023; Athari and Bahreini 2023; Yakubu and Musah 2022; Yakubu and Bunyaminu 2022; Apergis 2014, 2019, 2022, 2023; Apergis and Polemis 2016; Apergis and Lau 2017; Horobet et al. 2021).

Globalization can be characterized as a process for intensifying global economic integration, encompassing global governance structures, and inducing interconnected social and environmental changes (Martens and Raza 2010). The speed of globalization is tracked by the flows of foreign direct investments, expansion of international trade, and evolving political and social connections accompanying growing economic integration, along with growth in the foreign exchange market (Gaston and Khalid 2010).

From a social perspective, globalization has the potential to disrupt barriers and norms. It breaks down geographical barriers in social and cultural setups, streamlines the spread of ideas and technologies, enhances technological utilization, and fosters the amalgamation of markets and nation states (Walter 2021; Albrow 1996; Friedman 2000; Beck and Levine 2004). Globalization sparks the development of information and communication technologies, dismantles trade barriers, dissects production processes, and reduces communication and transportation costs (Gaston and Khalid 2010).

Institutions can play a crucial role in reducing problems related to adverse selection and moral hazard that commonly arise in the credit market. A robust institution can enhance lending terms and conditions, thereby improving loan repayments (Bae and Goyal 2009). Moreover, robust institutions can significantly improve the effectiveness of bank regulation and supervision, creating an environment conducive to financial stability (Bermpei et al. 2018).

Such institutions lead to a transparent and reliable lending environment, improving loan repayment and mitigating potential losses for banks. Additionally, when institutions promote a culture of compliance and accountability, banks become better equipped to navigate regulatory requirements. Effective regulatory frameworks within strong institutional settings not only strengthen banks against financial shocks but also foster a more resilient and competitive banking sector. This encourages economic growth and stability on a broader scale.

Against this backdrop, our study focuses on the banking sector of Fiji, an island economy, over the period from 2000 to 2021. Island nations often face vulnerabilities stemming from various shocks and events, including adverse effects of climate change, such as sea-level rise, unexpected weather patterns (periods of heat and cold), and natural disasters, like tsunamis, cyclones, droughts, and floods. Moreover, many small island economies are geographically remote from larger financial markets. Consequently, the impacts of global uncertainty and shocks appear as secondary effects. As these vulnerabilities materialize, they adversely impact economic activities, making bank performance and profitability significant and concerning topics of discussion.

In this study, we contribute to the understanding of the determinants of bank profitability by incorporating the influences of globalization, institutions, and global uncertainty. The institutional variables encompass the control of corruption, government effectiveness, rule of law, regulatory quality, political stability, and voice and accountability. Globalization variables include economic, social, and political dimensions. Notably, our sample period covers the Global Financial Crisis (GFC) and the COVID-19 pandemic, and we control for these events as well.

Through a detailed analysis, we expand the existing literature on bank profitability within small island economies. Examining how globalization and institutions influence banks' financial performance amid uncertainty whilst accounting for events, like the GFC and COVID-19 pandemic, can provide insights for policymakers, economists, banking institutions, and regulators.

For bank managers and analysts aiming at profit optimization, risk management, and financial stability, examining factors beyond financial statements is essential for informed managerial decision-making. Henceforth, our study considers factors influencing bank profitability beyond those reported in financial statements. The rest of the paper is structured as follows: Section 2 presents the literature and hypotheses, Section 3 details the methodology, and Section 4 discusses the analysis and results. Finally, Section 5 presents the conclusion.

2. Literature Review²

2.1. Bank-Specific Variables

2.1.1. Net Interest Margin (NIM)

Net interest margin (NIM) is a critical financial indicator employed to assess the profitability of banks and other financial institutions. It represents the difference between the interest income earned by a bank and the interest expenses incurred, expressed as a percentage of the average interest-earning assets. A higher NIM indicates a bank's effectiveness in attracting low-cost deposits or charging higher interest rates on loans (Naceur 2003). However, studies have noted mixed results regarding the impact of the NIM on profitability. For instance, in the Indonesian context, Silaban (2017) and Hasan et al. (2020) observed a positive correlation, while Seenaiah et al. (2015) found that the NIM has a negative effect on bank profitability in India³. For our purpose, we hypothesize that

H₁: *NIM is positively associated with bank profitability.*

2.1.2. Non-Interest Income (NII)

Non-interest income (NII) represents the revenue generated by banks through sources other than interest, encompassing fees from services, such as account maintenance, transaction fees, investment banking activities, asset management fees, and trading gains. NII provides banks with an additional stream of revenue beyond traditional interest income, allowing them to diversify their revenue sources and mitigate the impact of interest rate fluctuations. By diversifying their revenue streams, banks can offset declines in interest income during periods of low interest rates. NII can also lead to efficiency gains through economies of scale and scope, improved resource allocation through internal capital markets, and the development of bank-specific competitive advantages (Elsas et al. 2010). However, NII can be more volatile than interest income, as it is often tied to market conditions and the performance of financial markets (Stiroh and Rumble 2006). During periods of economic downturns or market volatility, certain fee-based services may experience reduced demand, negatively impacting banks' profitability. This implies that some components of NII may be exposed to higher risks than interest income.

Furthermore, Ahamed (2017) observed that Indian banks with lower asset qualities tend to derive more benefits from NII compared to banks with higher asset qualities. Nisar et al. (2018) proposed that NII can serve as a proxy for revenue diversification. Analyzing 200 commercial banks in South Asian countries, they found that the total NII positively influences bank profitability and stability. However, mixed effects are observed when specific components of NII are examined. For instance, they noted that fees and commission incomes have a negative impact, while other NII components have a positive impact. Adesina (2021) analyzed 400 commercial banks in 34 African countries over the period 2005–2015 and found that higher NIIs are negatively associated with profitability. In a recent study by Mehzabin et al. (2023), it was noted that NII enhances bank profitability when interest rates are lower. We hypothesize that

H₂: *NII is positively associated with bank profitability.*

2.1.3. Bank Size (BSIZE)

Larger banks can reap the benefits of economies of scale. As banks expand, their fixed costs are distributed across a broader asset base, leading to a reduction in average costs (Aladwan 2015). Larger banks can negotiate more favorable terms with suppliers, access

funds cost effectively, and exert greater influences on interest rates and fees because of their enhanced market power compared to smaller banks. These competitive advantages can bolster their profit objectives. In contrast, smaller banks can gain a competitive edge in terms of profitability by cultivating stronger relationships with local businesses and customers than large banks, granting them access to proprietary information that proves to be valuable in setting contract terms and making sound credit underwriting decisions (Regehr and Sengupta 2016).

Almaqtari et al. (2019) examined 69 banks in India over the period 2008–2017 and found a positive relationship between the bank size (BSIZE) and bank profitability. Similar findings were reported by Jeris (2021) and Isayas (2022) for banks in Bangladesh and Ethiopia, respectively. However, in the case of Nepal, Tharu and Shrestha (2019) observed no significant impact of BSIZE on profitability, while Thi Thanh Thi Thanh Tran and Phan (2020) noted the negative effect of BSIZE on bank profitability in Vietnam.

Accordingly, we hypothesize that

H₃: *BSIZE is positively associated with bank profitability.*

2.1.4. Credit Risk (CRISK)

Credit risk refers to the potential loss that a bank may incur when a borrower fails to fulfill their debt obligations by the due date or upon loan maturity, potentially leading to bankruptcy if the debt is not managed (Poudel 2012). Although lending serves as a primary source of income for banks, it also poses significant threats to bank operations if not analyzed and managed sufficiently. Studies focusing on banks in South Asia (Islam and Nishiyama 2016) and African regions (Bolarinwa et al. 2019; Saleh and Afifa 2020; Abel et al. 2023) noted the negative impact of credit risk (CRISK) on bank profitability. Accordingly, we hypothesize that

H₄: *CRISK is negatively associated with bank profitability.*

2.1.5. Non-Performing Loans (NPLs)

The impact of non-performing loans (NPLs) on bank performance can be analyzed through the lens of asymmetric information theory, which posits that one party in a transactional relationship (the borrower) typically holds more information about the transaction than the other party (the bank) (Mishkin 1992). As a bank's lending decision hinges on the information provided by borrowers, inherent uncertainty regarding loan repayment and creditworthiness can emerge if the borrower's characteristics and actions are not accurately captured (Eichengreen et al. 1998). Consequently, the problem of adverse selection arises when high-quality borrowers are replaced by low-quality borrowers, which can, over time, degrade the overall quality of a bank's loan portfolios, leading to an increase in non-performing loans, asset erosion, and diminished profitability. Studies that have documented a negative effect of NPLs on bank profitability include Kingu et al. (2018) for Tanzania, Çollaku and Aliu (2021) for Kosovo, and Karim et al. (2022) and Begum and Atiq (2023) for Bangladesh. Noting the adverse effect of growing NPLs on bank profitability, we hypothesize that

H₅: *NPLs are negatively associated with bank profitability.*

2.1.6. Capital Adequacy Ratio (CAR)

A high value of the capital adequacy ratio (CAR) may indicate a bank's ability to meet its financial obligations (Rifansa and Pulungan 2022). According to Agbeja et al. (2015), the CAR reflects the bank's capital structure and can serve as a measure against widespread distress in the banking industry. A higher level of capital can support ongoing activities and enhance the potential for business expansion. Additionally, sufficient capital instills confidence in the banking system. Recent studies on banks in Nigeria (Ajayi et al. 2019), Sri Lanka (Chandrasegaran 2020), and Indonesia (Rifansa and Pulungan 2022) have established a positive correlation between the CAR and bank profitability. Henceforth, we test the hypothesis that

H₆: *CAR is positively associated with bank profitability.*

2.1.7. GDP Growth Rate (GDPG)

GDP growth (GDPG) exerts significant influences on the overall economic activity and business expansion through investment channels. A thriving economy fosters the emergence of new businesses and the expansion of existing ones, consequently augmenting the demand for loans and interest income, thereby bolstering bank profitability (Al-Jafari and Alchami 2014; Duraj and Moci 2015). Lutf and Omarkhil (2018) conducted an examination of the macroeconomic determinants of bank profitability in Pakistan and found that GDPG positively impacts bank profitability. Similar findings were observed for banks in Nigeria (Bolarinwa et al. 2019), Nepal (Singh et al. 2021), India (Ali et al. 2022), and Tunisia (Theiri and Hadoussa 2023). Hence, we hypothesize that

H₇: *GDPG is positively associated with bank profitability.*

2.1.8. Remittances (REMs)

Remittances from abroad can augment foreign exchange reserves and enhance the stability of the home country's banking system. Individuals receiving remittances often deposit these funds into their local bank accounts, expanding the bank's pool of funds and enabling the bank to extend loans and engage in investment activities. In one study on banks in Fiji, Chand et al. (2021) found a positive correlation between remittances and bank stability, and in another (Chand et al. 2023), they observed a negative association between remittances and non-performing loans, indicating that remittances support banking operations. Similarly, Ayhan and Toufaili (2021) examined the relationship between remittances and bank profitability for banks in Lebanon, and they found a positive relationship. Subsequently, we hypothesize that

H₈: *REMs are positively associated with bank profitability.*

2.1.9. Institutions

Institutions, also known as the "rules of the game" (North 1990), play a pivotal role in shaping a society's culture, behavior, and economic activities, including financial operations. Sound institutional frameworks, characterized by efficient and effective regulatory and supervisory mechanisms, strong property rights, and an effective legal system, are essential for advancing economic and financial development (Voghouei et al. 2011). A robust rule of law and a low level of corruption are hallmarks of high-quality institutions, promoting greater accountability and stability in the financial sector and facilitating financial liberalization (Chinn and Ito 2006).

Empirical studies have explored the multifaceted relationship between institutions and bank performance. In the case of Ghana, Yakubu (2019) found that a rise in corruption levels negatively impacts bank profitability. Conversely, Bougatef (2017) observed a positive association between corruption and bank profitability in Tunisia. Focusing on stability indicators, Hasan and Ashfaq (2021) analyzed 178 countries from 2000 to 2017 and found that corruption increases non-performing loans and reduces bank profitability. Etudaiye-Muhtar and Abdul-Baki (2020) investigated the impact of the institutional quality on the capital ratios of 79 listed commercial banks from 2000 to 2016, concluding that lower regulatory quality reduces bank capital.

Asteriou et al. (2021) examined the effects of regulation, transparency, and corruption on bank stability and profitability for 326 banks in 19 Eurozone countries from 2005 to 2018. They found that regulation supports bank profitability and stability, while low transparency and corruption decrease bank profitability. Similarly, Nguyen (2022) examined the effects of the institutional quality and rule of law on bank deposits in European countries and found that both factors support bank funding and resilience. Athari and Bahreini (2023) concluded that political stability, regulatory quality, the rule of law, and the control of corruption positively impact Islamic banks' profitability. They further noted that regulatory settings, including their subindices, such as the extent of the disclosure and the ease of

shareholder suits, negatively impact bank profitability. A study by Bashiru et al. (2023) on banks in 33 sub-Saharan African countries reported that an increase in institutional quality is positively associated with bank profitability. From these studies, it becomes clear that institutions play a critical role in shaping the financial landscape and influencing bank performance. Strong institutions, characterized by sound regulatory frameworks, robust property rights, and an effective legal system, are essential for fostering a healthy and stable financial sector.

The World Bank (2023) defines six different institutional indicators: “Control of Corruption” measures the extent to which public power is exercised for private gain, including both petty and grand forms of corruption. The indicator “Government Effectiveness” captures perceptions of the quality of public services, the quality of the civil service and the degree of its independence from political pressures, the quality of the policy formulation and implementation, and the credibility of the government’s commitment to such policies. “Rule of Law” captures perceptions of the extent to which agents have confidence in and abide by the laws of a country and, in particular, the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence. “Regulatory Quality” captures perceptions of the ability of the government to formulate and implement sound policies and regulations that permit and promote private sector development. “Political Stability” measures perceptions of the likelihood of political instability. The indicator “Voice and Accountability” captures perceptions of the extent to which a country’s citizens are able to participate in electing their government, as well as freedom of expression, freedom of association, and free media. Noting the different components of institutions and insights from the above studies, we examine the following hypotheses:

H₉: “Corruption Control” (CC) is positively associated with bank profitability.

H₁₀: “Government Effectiveness” (GE) is positively associated with bank profitability.

H₁₁: “Rule of Law” (RL) is positively associated with bank profitability.

H₁₂: “Regulatory Quality” (RQ) is positively associated with bank profitability.

H₁₃: “Political Stability” (PS) is positively associated with bank profitability.

H₁₄: “Voice and Accountability” (VA) is positively associated with bank profitability.

2.1.10. Globalization Index

Globalization refers to the increasing interconnectedness and integration of economies, cultures, and societies worldwide (Kilic 2015). It recognizes the growing interdependence among countries in terms of trade, investment, technology, and information flow. The Globalization Index, calculated by Dreher (2006) and upgraded by Dreher et al. (2008), consists of three categories of subindices—the economic (EINDEX), social (SINDEX), and political (PINDEX) globalization indices. Considering banks in Jordan, Guesmi et al. (2012) showed that financial globalization (measured by reductions in credit control and entry barriers and by regulatory effectiveness) is negatively associated with bank performance. For banks in Malaysia, Sufian (2012) found that social globalization (information flow, personal contacts, and cultural proximity) supports bank efficiency. Ghosh (2016) examined banks in 169 countries over the period 1998–2013 and noted that globalization reduces profitability but increases cost efficiency. Using data on commercial banks in South Africa over the period 1998–2012, Sufian and Kamarudin (2016) found positive associations of economic integration and trade and a negative association of social globalization with bank profitability. Moreover, for banks in sub-Saharan Africa, Yakubu and Bunyaminu (2022) used financial globalization and trade globalization as measures of economic globalization. They found negative and significant effects of trade and financial globalization on bank profitability. Using these studies as a guide, we investigate the following hypotheses:

H₁₅: EINDEX is positively associated with bank profitability.

H₁₆: PINDEX is positively associated with bank profitability.

H₁₇: *SINDX is positively associated with bank profitability.*

2.1.11. World Uncertainty Index (WUI)

The World Uncertainty Index (WUI), which quantifies the level of uncertainty in the global economy, is based on risk indicators and news (Ahir et al. 2022). A higher index indicates a greater level of uncertainty. Ashraf (2021) examined the impact of the WUI on the loan-pricing decisions of banks in 88 countries from 1998 to 2017. The study notes that a high value of the WUI (global uncertainty) is positively associated with lending rates. Bilgin et al. (2021) investigated the effects of the WUI on the default risks of conventional and Islamic banks. They noted that the relationship between the global uncertainty and default risk was not significant in Islamic banks; however, the relationship was significant for conventional banks that have high income diversification, are of a large size, and are publicly traded. Hence, we test the hypothesis that

H₁₈: *WUI is negatively associated with bank profitability.*

2.1.12. Structural Variables

The Global Financial Crisis (GFC) of 2007–2008 had adverse effects on many banks. The crisis was caused by a combination of factors, including the bursting of the housing price bubble in the US, excessive risk-taking by financial institutions, and the use of complex financial instruments, which reduced consumer confidence in the banking system (Prasad and Reddy 2009). Recognizing the adverse impacts of the GFC on the financial market, we examine the hypothesis that

H₁₉: *GFC is negatively associated with bank profitability.*

The COVID-19 (COVID) pandemic had negative effects on the overall economy, as evidenced by many businesses downsizing their operations, undergoing restructuring, or even shutting down. During events like COVID-19, individuals typically rely on their deposits (drawing down deposits) and, if they have loan obligations, face challenges in meeting their loan repayments. Consequently, some households and businesses end up consolidating or winding up their investments to support basic consumption and livelihood. Such actions tend to reduce a bank's revenue potential. Hence, we hypothesize that

H₂₀: *COVID is negatively associated with bank profitability.*

2.2. Studies on Banking Profitability in Fiji

Although a limited number of studies have delved into various aspects of the banking industry in island economies, like Fiji's, research on bank profitability remains scarce. For instance, Sharma and Gounder (2012) examined the determinants of net interest margins (NIMs) and noted that NIMs are positively associated with interest payments, operating costs, market power, and credit risk but negatively associated with management quality and liquidity risk. In another study, Sharma et al. (2015) found that non-interest income is the only factor that positively influences profitability. However, Krishna et al. (2021) argued that the bank size and exchange rate also support bank profitability, whereas factors like the management efficiency, a broad money supply, and the quality of the regulation reduces bank profitability. Noting the opposing results from these studies and the dearth of comprehensive studies on bank profitability in small economies, like Fiji's, we conduct this study, which considers a more extensive dataset and accounts for the roles of institutions, globalization, and global uncertainty.

3. Methodology

3.1. The Data

This study utilizes data from seven financial institutions (FIs) over the period from 2000 to 2021, with a balanced panel. The sample comprises five commercial banks—Australia and New Zealand Banking Group (ANZ), Bank of the South Pacific (BSP), Bank of the Baroda (BOB), Westpac Banking Corporation (WBC), and Home Finance Corporation

(HFC)—along with two non-bank financial institutions (NBFIs)—Merchant Finance Limited (MFL) and Credit Corporation Fiji Limited (CCFL). Bank-specific variables are sourced from disclosure statements published by the Reserve Bank of Fiji (Reserve Bank of Fiji (RBF) 2023), and variables concerning institutions and other macroeconomic aspects are obtained from Worldwide Governance Indicators and World Development Indicators (World Bank 2023). The three dimensions of the KOF Globalization Index (i.e., economic, political, and social indices) are extracted from <https://datafinder.qog.gu.se/dataset/dr> access on 30 March 2023 (cf. Dreher 2006; Dreher et al. 2008). The WUI index (global uncertainty) is sourced from <https://worlduncertaintyindex.com/data/> access on 30 March 2023 (Ahir et al. 2022; World Uncertainty Index (WUI) 2023). In Table 1, we summarize the dependent and independent variables used for the estimations. All the data (excluding the dummy variables) are log-transformed for regression analysis⁴.

Table 1. Data definitions.

Variable	Definition	Symbol	Expected Sign	Source
Dependent				
Bank Profitability	Return on Assets (Net Profit/Total Assets)	ROA	N/A	RBF
Independent				
<i>Bank Specific</i>				
Net Interest Margin	(Interest Income-Interest Expenses)/Total Assets	NIM	+	RBF
Non-Interest Income	Natural Logarithm of Total Fees and Commissions Received	NII	+	RBF
Bank Size	Natural Logarithm of Total Assets	SIZE	+	RBF
Credit Risk	Total Loans/Total Assets	CRISK	+	RBF
Non-Performing Loans	Bad Debts Divided by Total Loans	NPL	—	RBF
Capital Adequacy Ratio	Sum of Tier 1 Capital and Tier 2 Capital Divided by Risk-Weighted Assets	CAR	+	RBF
<i>Globalization</i>				
Economic	Economic Globalization Index	EINDX	+	KOF
Political	Political Globalization Index	PINDX	+	KOF
Social	Social Globalization Index	SINDX	+	KOF
<i>Institutional</i>				
Control of Corruption	Control-of-Corruption Index	CC	+	WGI
Government Effectiveness	Government Effectiveness Index	GE	+	WGI
Rule of Law	Rule of Law Index	RL	+	WGI
Regulatory Quality	Regulatory Quality Index	RQ	+	WGI
Political Stability	Political Stability Index	PS	+	WGI
Voice and Accountability	Voice-Accounting Index	VA	+	WGI
<i>Macro</i>				
Gross Domestic Product Growth Rate	Annual Percentage Growth Rate of GDP at Market Prices Based on Constant Local Currency	GDPG	+	WDI
Remittances	Worker's Remittances as a Percentage of GDP	REM	+	WDI
<i>Uncertainty</i>				
World Uncertainty Index	Natural Logarithm of World Uncertainty Index	WUI	+	Ahir et al. (2022)
<i>Structural Dummy</i>				
COVID-19	2019-020-2021 were taken as dummy variables for COVID, as these were the years where there was COVID.	COVID	—	WDI
Global Financial Crisis	The financial crisis of 2007–2008 is denoted by a dummy variable.	GFC	—	Authors

Notes: RBF = Reserve Bank of Fiji; WDIs = World Development Indicators; WGIs = Worldwide Governance Indicators; N/A = not applicable. Institutional variables range from −2.5 (weak) to 2.5 (strong) governance performance. Each category of the Globalization Index is measured on a scale of 1–100, where higher values imply greater levels of globalization. *Source:* Authors' compilation.

3.2. Model Specifications

Following a few recent studies (Theiri and Hadoussa 2023; Chand et al. 2021, 2023), we specify the profitability model as follows:

$$ROA_{it} = \alpha + \underbrace{\beta_m X_m}_{m\text{-bankspecific}} + \underbrace{\theta_n G_n}_{\text{Globalization}} + \underbrace{\gamma_p I_p}_{\text{Institutional}} + \underbrace{\omega_q Z_q}_{\text{macro+structural}} + \varepsilon_{it} \quad (1)$$

where ROA_{it} represents bank profitability, as measured by the return on the assets of bank i at time t ; α is a constant; β_m contains the set of coefficients of the bank-specific factors; X_m contains a set of bank-specific factors, m ; θ_n contains the coefficients of the respective n th globalization index, G_n ; γ_p contains the coefficients of the institutional factors, I_p ; ω_q contains the coefficients of the macro and structural (including uncertainty) variables, Z_q (see Table A2); and $\varepsilon \sim N(0, \sigma^2)$ is the error term. Based on Equation (1), the specific model for the estimations can be expressed as follows:

$$\begin{aligned} ROA_{it} = & \alpha + \underbrace{\beta_1 NIM_{it} + \beta_2 NII_{it} + \beta_3 BSIZE_{it} + \beta_4 CRISK_{it} + \beta_5 NPL_{it} + \beta_6 CAR_{it}}_{X_m} \\ & + \underbrace{\theta_1 EINDEX_t + \theta_2 PINDEX_t + \theta_3 SINDEX_t}_{G_n} \\ & + \underbrace{\gamma_1 CC_t + \gamma_2 GE_t + \gamma_3 RL_t + \gamma_4 RQ_t + \gamma_5 PS_t + \gamma_6 VA_t}_{I_p} \\ & + \underbrace{\omega_1 GDPP_t + \omega_2 REM_t + \omega_3 WUI_t + \omega_4 COVID + \omega_5 GFC_t}_{Z_q} + \varepsilon_{it} \end{aligned} \quad (2)$$

For a robust analysis, we estimate six models using the panel's fixed-effect method. In Model (I) we only include bank-specific variables (base model). In Model (II) we extend Model (I) with globalization. In Model (III), we extend Model (I) with globalization and institutional variables. Model (IV) represents the extended version of Model (III) with macroeconomic variables. Next, Model (V) is an extension of Model (IV) with the uncertainty index. Finally, in Model (VI) we extend Model (V) by incorporating structural variables, like "Global Financial Crisis (GFC)" and "COVID-19". Panel data may exhibit group effects, time effects, or both, which can be addressed using either fixed- or random-effect models. Moreover, the fixed-effect regression model assumes differences in intercepts across groups or time periods (Almaqtari et al. 2019; Bolarinwa et al. 2019; Mehzabin et al. 2023). Hence, we determine the suitable estimation approach using the Hausman test (Ali and Puah 2019; Theiri and Hadoussa 2023). In this test, the rejection of the null hypothesis indicates support for the fixed-effect regression model.

4. Empirical Results

The descriptive statistics and correlation matrices are presented in Tables 2 and 3. The fixed-effect model is supported by the results of the Hausman test (see Table 4). There is an overall increasing trend in profits for all the banks, although ANZ, BSP, and WBC have a higher share of bank profits than others. The years 2020 and 2021 marked the episodes of lockdown that were put in place in Fiji because of the COVID-19 pandemic. During this period, we note that bank profitability declined for all the banks. In the year 2022, a positive trend in bank profitability is noted (Figure 1)⁵.

Table 2. Descriptive statistics.

Column 1	Mean	Median	Maximum	Minimum	Standard Deviation	Observations
ROA	0.03	0.02	0.09	−0.03	0.02	154
NIM	0.06	0.04	0.56	0.02	0.05	154
NII	12,572	3741	55,687	0	15,534	154
BSIZE	12.92	13.05	14.94	10.64	1.27	154
CRISK	0.80	0.75	10.77	0.27	0.83	154
NPL	0.01	0.01	0.08	0	0.01	154
CAR	18.74	16.38	39.46	8.81	6.65	154
EINDX	49.85	51.25	53.88	39.88	3.72	154
PINDX	71.32	72.30	77.11	62.80	4.58	154
SINDX	64.50	65.50	69.15	55.41	3.66	154
CC	0.34	0.34	0.74	−0.22	0.30	154
GE	−0.23	−0.19	0.82	−1.17	0.61	154
RL	−0.22	−0.06	0.47	−0.87	0.40	154
RQ	−0.32	−0.32	0.15	−0.97	0.29	154
PS	0.34	0.39	0.92	−0.27	0.37	154
VA	−0.31	−0.04	0.23	−1.11	0.45	154
REM	5.34	5.37	7.84	2.58	1.30	154
GDPG	1.00	1.93	5.60	−17.00	1.95	154
WUI	4.30	4.31	4.61	3.97	0.16	154

Source: Authors' compilation.

Table 3. Correlation matrix.

	ROA	NIM	NII	BSIZE	CRISK	NPL	CAR	EINDX	PINDX	SINDX	CC	GE	RL	RQ	PS	VA	REM	GDPG	WUI
ROA	1																		
NIM	0.68	1																	
NII	−0.28	−0.42	1																
BSIZE	−0.43	−0.59	0.83	1															
CRISK	0.35	0.83	−0.04	−0.22	1														
NPL	0.11	0.36	−0.27	−0.40	0.08	1													
CAR	0.52	0.41	−0.47	−0.58	0.01	0.36	1												
EINDX	0.20	−0.01	0.20	0.28	0.05	−0.21	0.19	1											
PINDX	0.04	−0.11	0.31	0.43	−0.01	−0.12	0.20	0.74	1										
SINDX	0.01	−0.15	0.31	0.44	−0.05	−0.08	0.21	0.73	0.94	1									
CC	−0.25	−0.14	0.09	0.12	−0.08	0.11	−0.05	−0.52	0.05	0.09	1								
GE	−0.15	−0.12	0.08	0.12	−0.05	0.09	−0.05	−0.37	−0.02	0.11	0.74	1							
RL	−0.20	−0.12	0.01	0.03	−0.10	0.07	−0.10	−0.50	−0.23	−0.11	0.64	0.89	1						
RQ	−0.17	−0.12	0.08	0.11	−0.03	0.04	−0.03	−0.42	0.03	0.09	0.81	0.84	0.70	1					
PS	−0.17	−0.14	0.11	0.14	−0.09	0.02	−0.05	−0.38	0.10	0.10	0.77	0.80	0.80	0.80	1				
VA	−0.11	−0.10	0.02	0.03	−0.08	0.06	−0.11	−0.47	−0.15	−0.09	0.66	0.83	0.88	0.72	0.90	1			
REM	−0.02	−0.01	0.06	0.11	0.02	0.15	0.04	0.26	0.09	0.26	−0.19	0.27	0.21	−0.12	−0.03	0.15	1		
GDPG	0.19	−0.13	0.32	0.44	−0.02	−0.12	0.16	0.63	0.94	0.93	0.27	0.26	0.07	0.26	0.33	0.12	0.14	1	
WUI	−0.07	−0.13	0.22	0.29	−0.04	0.07	0.15	0.23	0.57	0.62	0.36	0.32	0.07	0.28	0.28	0.07	0.25	0.55	1

Source: Authors' compilation.

Table 4. Hausman test.

Test Statistic	χ^2 -Stat.	χ^2 -d.f.	Prob.
Random Cross-Section	177.16	5	<0.01 *

Note: * Represents significance at the 0.01 level. Source: Authors' own estimation.

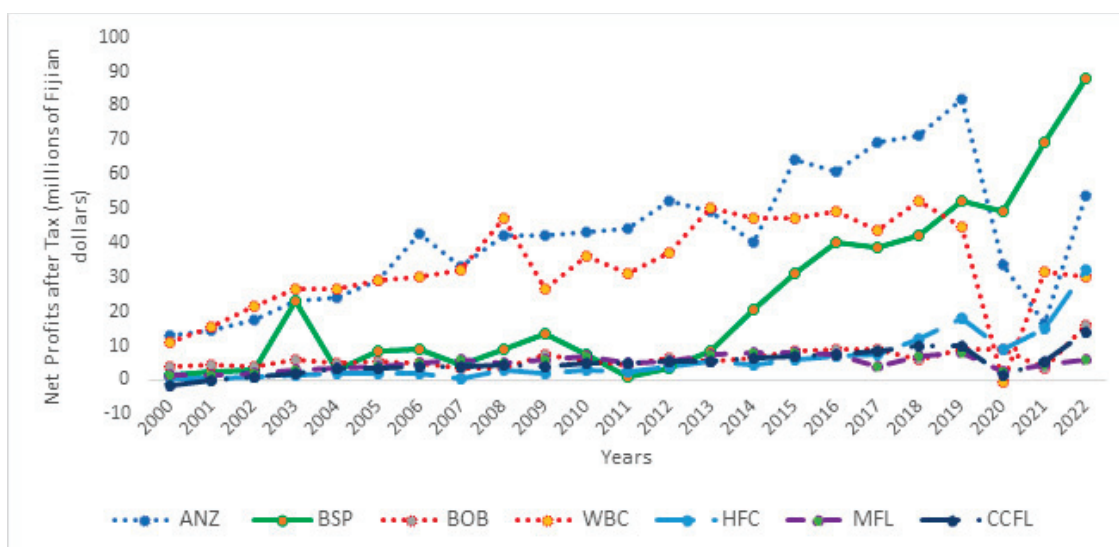


Figure 1. Net profits in millions of FJD.

Table 5 presents the outcomes of the fixed estimations⁶. According to the results, the adjusted R-squared values range between 0.76 and 0.82, signifying that 80 percent of the relationship is explained by the respective models. These findings are discussed in relation to bank-specific, globalization, institutional, and macrostructural variables. It is observed that net interest margin (NIM) demonstrates a positive association with bank profitability (see Models I–VI). This is consistent with existing studies (Silaban 2017; Hasan et al. 2020). Hence, we do not reject H₁. Moreover, the non-interest income (NII) is positive and significant at the 1 percent level (see Models I–VI), which implies that incomes from fees and commissions significantly improve bank profitability, duly supporting H₂. This result is consistent with those in some other studies (Adesina 2021; Nisar et al. 2018; Sharma et al. 2015), which argued that in a low-interest environment, NII can be an important source of revenue. Bank size (BSIZE) is positively associated with bank profitability (see Models I–VI), implying that larger banks have higher profitability because of the high-quality assets deployed in generating consistently high incomes (Aladwan 2015; Almaqtari et al. 2019). Hence, we do not reject H₃. Moreover, we note that the coefficient of the credit risk (CRISK), measured by the ratio of the loans to the total assets, is negative and significant (see Models I–VI). For a developing country, like Fiji, an increase in lending relative to the total assets constrains the banks' liquidity and, hence, negatively influences bank profitability—an outcome, which is consistent with those of previous studies (Abel et al. 2023; Bolarinwa et al. 2019; Islam and Nishiyama 2016). Subsequently, we do not reject H₄.

Additionally, it is observed that Non-Performing Loans (NPLs) exhibit a negative association with bank profitability (see Models I–VI), confirming H₅. Similar to the findings of Kingu et al. (2018), it can be argued that an escalation in non-performing loans constrains bank capital and amplifies losses, hence, exerting an adverse pressure on bank profitability. The coefficient of the Capital Adequacy Ratio (CAR) is positive and significant, suggesting that an increase in CAR positively impacts bank profitability (see Models I–VI). Hence, we do not reject H₆. This result is consistent with findings from other developing countries' banks (Ajayi et al. 2019; Chandrasegaran 2020; Rifansa and Pulungan 2022). The coefficient of the economic growth (real GDP growth rate) is positive and significant (see Models IV–VI). Economic growth provides the necessary condition for banks to grow their investments and expand their revenue-generating activities, thus supporting bank profitability (Al-Jafari and Alchami 2014; Duraj and Moci 2015). Moreover, the coefficient of the REM is positive and significant (see Models IV–VI). Hence, remittances saved as deposits in banks tend to increase the source of funds for banks, which, in turn, supports banks' income-generating (lending and investment) activities. Accordingly, we do not reject H₇ and H₈, respectively.

Table 5. Regression results based on fixed effects: Dependent variable is ROA.

Variable Group	Variable	Model I (Base Model)	Model II	Model III	Model IV	Model V	Model VI
Independent variables	Constant	−0.022574 (0.019505)	−0.029651 (0.019168)	−0.010240 (0.020375)	−0.013794 (0.021314)	−0.062355 * (0.034200)	−0.069791 ** (0.034345)
Bank Specific	NIM	0.620264 *** (0.071475)	0.628529 *** (0.072629)	0.632558 *** (0.075198)	0.623305 *** (0.077281)	0.622594 *** (0.076619)	0.603764 *** (0.077043)
	NII	0.002351 *** (0.000676)	0.002228 *** (0.000663)	0.002423 *** (0.000646)	0.002432 *** (0.000651)	0.002428 *** (0.000645)	0.002586 *** (0.000651)
	BSIZE	0.001115 *** (0.000371)	0.001021 ** (0.000408)	0.001410 * (0.000783)	0.005824 * (0.003175)	0.005021 * (0.003138)	0.0041761 ** (0.002088)
	CRISK	−0.023815 *** (0.003583)	−0.025364 *** (0.003697)	−0.026450 *** (0.003935)	−0.025699 *** (0.004149)	−0.025121 *** (0.004117)	−0.024552 *** (0.004129)
	NPL	−0.590568 (0.084447)	−0.605559 *** (0.089100)	−0.587550 *** (0.088370)	−0.563593 *** (0.101662)	−0.556812 *** (0.100859)	−0.544612 *** (0.101807)
	CAR	0.000207 *** (0.000052)	0.000524 ** (0.000211)	0.0000711 * (0.000042)	0.000491 (0.000257)	0.000448 * (0.000249)	0.000124 * (0.000069)
Globalization Index	EINDX	-	0.000850 * (0.000473)	0.000721 ** (0.000379)	0.000695 * (0.000386)	0.000805 * (0.000473)	0.000704 * (0.000391)
	PINDX	-	−0.000289 (0.000326)	−0.00085 (0.000710)	−0.000261 (0.000821)	−0.000191 (0.000815)	−0.001037 (0.001046)
	SINDX	-	0.001990 *** (0.000698)	0.000991 ** (0.000496)	0.001117 ** (0.000507)	0.000696 * (0.000387)	0.001594 ** (0.000759)
Institutional Variables	CC	-	-	−0.000440 (0.006226)	−0.001802 (0.006651)	−0.003441 (0.006656)	−0.000181 (0.008181)
	GE	-	-	0.007996 ** (0.004310)	0.009241 ** (0.004836)	0.006488 * (0.003816)	0.003032 * (0.001621)
	RL	-	-	−0.006581 * (0.00411)	−0.007010 (0.006200)	−0.003166 (0.006504)	−0.004821 (0.006921)
	RQ	-	-	−0.008022 (0.006105)	−0.009710 (0.006825)	−0.007355 (0.006891)	−0.004947 (0.007287)
	PS	-	-	−0.001498 (0.008067)	−0.001640 (0.008144)	−0.007621 (0.008721)	0.000482 (0.010484)
	VA	-	-	0.007764 *** (0.002773)	0.008151 ** (0.003705)	0.012242 * (0.006553)	0.008597 * (0.004776)
Macro	GDPG	-	-	-	0.000472 *** (0.000188)	0.000109 ** (0.045416)	0.000204 * (0.000113)
	REM	-	-	-	0.000542 * (0.000285)	0.001012 * (0.000562)	0.000847 * (0.002014)
Uncertainty Index	WUI	-	-	-	-	0.014416 * (0.007983)	0.011447 * (0.006359)
Structural Variables	COVID	-	-	-	-	-	−0.012115 ** (0.004846)
	GFC	-	-	-	-	-	0.004731 * (0.002783)
Diagnostics	Adjusted R-Squared	0.759793	0.776952	0.780479	0.797862	0.799489	0.8028391
	F-Statistic	41.3293	36.53015	28.48742	25.70564	25.19892	23.57894
	DW-Statistic	1.364925	1.454027	1.546201	1.552105	1.550164	1.565987
	Observations	154	154	154	154	154	154

Notes: ***, **, and * indicate statistical significances at 1%, 5%, and 10% levels; (-) contains standard errors. Results are based on fixed-effect regression method. *Source:* Authors' own estimation.

Regarding institutions, we find that institution-specific variables, like Government Effectiveness (GE) and Voice and Accountability (VA), have significant and positive relationships with bank profitability (see Models III–VI). Hence, we do not reject H_{10} and H_{14} , respectively. Moreover, these results underscore the importance of the government, and voice and accountability, as critical drivers of bank profitability. Concerning other institutional factors, like Corruption Control (CC), Rule of Law (RL), Regulatory Quality (RQ), and Political Stability (PS), although we observe a negative relationship, these relationships are not statistically significant (see Models III–VI). The non-significant coefficients suggest either a weak (negative) effect, or these factors operate independently of bank profitability.

Regarding globalization, we observe that bank profitability demonstrates a positive association with economic (EINDEX) and social (SINDEX) globalization (see Models II–VI). Based on these positive and significant associations, we do not reject H_{15} and H_{17} , respectively. We note that political globalization is negative but not statistically significant. Economic globalization (EINDEX) reflects the degree of openness in trade and financial activities. In the case of Fiji, we note that trade and financial openness supports bank profitability. With increasing globalization, banks operating in Fiji are in healthier positions to tap into international markets for investment activities and facilitate the trade of goods and services, which enables banks to increase transactions and generate more revenues. Therefore, the effective participation of banks in facilitating global trade supports bank profitability. This result is also consistent with the findings of Rahman et al.'s (2021) analysis on banks in BRICS countries.

Additionally, concerning the impact of social globalization (SINDEX) on bank profitability in Fiji, a positive relationship is observed. Banks in Fiji can benefit from social globalization by proactively investing in building their reputation and brand image and by actively engaging in socially responsible initiatives. Social initiatives, such as community development projects, promoting environmental sustainability, or investing in education and healthcare, are the key areas where banks can create positive impacts. In the long-term, such initiatives can improve the welfare of society and garner customer loyalty and trust. As an example, we note that since 2010, the Bank of the South Pacific (BSP) has invested over FJD 10 million in Fiji through its Corporate Social Responsibility (CSR) program. The bank's expansive CSR program includes supporting and funding education, environmental clean-up, sporting events, and charities at community and national levels (BSP 2021). Other banks and non-financial institutions are also noted to actively participate in supporting community-level initiatives. For example, in the past, larger banks, like ANZ (ANZ 2023) and Westpac, have provided financial support in education, human capital development, and rural banking (scholarships, financial education, and rural banking support). Regarding the relationships between political globalization (PINDEX) and bank profitability and between the political stability index (PS) and bank profitability, we find they are negative although not statistically significant (see Models II–VI). These results are contrary to our hypotheses H_{13} and H_{16} , respectively.

The World Uncertainty Index (WUI), which measures global uncertainty, exhibits a positive and statistically significant relationship with bank profitability (see Models V–VI). This positive association can be attributed to increased global uncertainty leading local investors and businesses to adopt risk-averse behaviors, hence favoring domestic sectors. Higher global uncertainty could also drive individuals and companies to secure deposits and loans and other investment opportunities from a relatively remote economy, like Fiji's. Consequently, banks may experience an influx of deposits, or bank transactions, as well as loans, thus potentially boosting revenues. Furthermore, heightened global uncertainty might prompt banks to exercise caution in lending practices, maintaining high-quality loan portfolios. All these reasons may explain the positive association between global uncertainty and bank profitability. Hence, we do reject H_{18} .

Like the relationship between the WUI and bank profitability, we note that the GFC has positive and significant effects on bank profitability (see Model VI); thus, we reject H_{19} . Moreover, given the remoteness and weak links of Fiji's financial sector to the rest

of the world, and basic financial products and services offered by banks, this result is not surprising. Arguably, with the existing characteristics of Fiji's banking sector, events, like the GFC, tend to encourage investors to seek safer options for their investments, and even consolidate their overseas investments and funds to domestic banks, duly supporting domestic bank operations and profitability.

For the COVID-19 pandemic, we note a negative and significant association with bank profitability (see Model VI). This decline in the profitability ratio (net profit) is also captured in Figure 1, where we saw a drop in bank profitability between 2020 and 2021. The COVID-19 pandemic affected individuals, businesses, and the economy as a whole. In 2020, Fiji's real GDP fell by 15.7% (ADB 2021), and the economy witnessed relatively higher unemployment and financial hardships for both individuals and businesses. Moreover, banks faced with high chances of loan defaults were noted to be under increased pressure to implement repayment holidays and accumulated high non-performing loans—all of which deteriorated their asset quality and, hence, profitability (Badunenko et al. 2022). Hence, based on these results, we do not reject H_{20} .

5. Conclusions

In this study, we focus on the small economy of Fiji from 2000 to 2021. We contribute to the banking literature on bank profitability in small island economies by investigating the effects of globalization, institutions, and global uncertainty. Through this study, we emphasize that the profitability and bank performance analysis should go beyond bank-specific factors.

From these results, we find that globalization, institutions, global uncertainty, and the pandemic (COVID-19) are critical factors for the sound operation and development of a robust and resilient financial sector. Moreover, because of the economy's small size and limited sectors, banks possess a constrained set of portfolios for investment. Hence, analyzing profitability by considering factors beyond financial statements aids in comprehending the intricate environment within which banks operate.

The results derived from this comprehensive model reveal that bank-specific factors, like the net interest margin, non-interest income, bank size, and capital adequacy ratio, support bank profitability, whereas factors like non-performing loans and credit risk have negative effects on bank profitability. Additionally, economic and social globalization, institutional variables (Government Effectiveness and Voice and Accountability), global uncertainty, and the Global Financial Crisis show positive associations with bank profitability. Other factors, such as economic growth and remittances, support bank profitability. According to these results, we emphasize the significance of high economic growth and exploring opportunities to maximize gains from remittance inflows. Therefore, remittances channeled through formal channels (such as banks and money transfer services) can bolster greater financial intermediation⁷. In the realm of social globalization, banks should continue to align their operations with best practices that promote social and green development projects, human capital development, technological advancement, and healthcare initiatives.

Moreover, Fiji, akin to other small countries in the region, grapples with distinctive challenges, including natural disasters, high government debt, inadequate infrastructure, reliance on limited growth sectors, and declining agriculture. This low development, coupled with events like COVID-19, intensifies adverse effects, stalling economic progress and financial sector development. Additionally, susceptibility to frequent natural disasters brings added challenges in commercializing the agricultural sector for large-scale production. Hence, banks need to factor in these events while assessing profitability and lending capacity. Fiji's heavy reliance on its tourism sector (Kumar and Stauvermann 2023) for economic growth not only limits the number of sectors available for banks to diversify their loan portfolios, but the reliance on tourism also reduces the long-term revenue potential, which becomes even more troublesome during events like COVID-19.

Because globalization emerges as a significant force shaping bank profitability, to support banking operations, the Government of Fiji should create an enabling environment

to foster increased trade, attract foreign direct investments, and encourage innovative pathways of economic transactions (mobile and electronic transactions) and greater technology inclusion.

Furthermore, comprehending the dynamics between institutions and bank profitability offers valuable insights into creating specific institutional mechanisms for a stable and robust banking system in small economies. As evident from these findings, specific institutions play a vital role in shaping banking sector operations and profitability. Therefore, the government and the Reserve Bank of Fiji (central bank) should ensure a sound regulatory environment, supportive government policies, and a robust institutional infrastructure. A clear rule of law that supports investment activities, coupled with effective and efficient banking sector regulations and policies, is imperative. Fiji has experienced four political crises (coups d'état) in the past. To foster thriving banks and maintain a healthy performance level, the government must ensure political stability, uphold constitutional norms and the rule of law, promote voice and accountability, and ensure regulatory and policy certainty. The prevailing global uncertainty presents opportunities for banks in Fiji. Hence, banks should recognize this and prudently expand their operations to grow revenue and profit.

Overall, these results highlight the intricate nature of banking sector operations. As such, bank regulators, government entities, and financial managers should recognize the implications of these factors and incorporate them when formulating pertinent policies for sustainable bank operations and the holistic advancement of the financial sector. Considering economic and geopolitical circumstances, banks in small nations, such as Fiji, should meticulously analyze profitability and risk. The assessment of risk and profit should, therefore, adopt a comprehensive perspective to develop more secure strategies that bolster bank resilience and ensure sustainability.

In conclusion, we present the impacts of additional dimensions on bank profitability with certain considerations. It is important to note that these results may not be applicable to other countries, as this study centers on the banking sector of a small economy. Additionally, we acknowledge that the positive correlation between global uncertainty and the global financial crisis could stem from Fiji's limited financial integration with major centers and the small, less-advanced, and less-integrated nature of its banking sector. It is crucial to recognize that economic, political, and regulatory landscapes differ across countries and regions. Consequently, their individual or collective influences might vary for banks operating elsewhere globally. Henceforth, our study comes with its own set of limitations. First, our focus is exclusively on financial institutions engaged in deposit and lending operations. Thus, although our findings hold significance within this realm, they should not be generalized to other financial entities, such as insurance firms, pension funds, or the entire financial system. Second, although our exploration of the linear relationship between bank profit and its determinants yields valuable insights, it is essential to acknowledge the plausibility of non-linear dynamics or presence of threshold levels of key factors. Third, our sample size comprises seven banks over the period 2000–2021. Hence, the sample can be regarded as relatively small. However, we have included the seven banks in the sample because they have consistent data since 2001, available on the central bank's website. The cutoff point of our sample is also contingent upon non-bank factors, which were available up to 2021. Consequently, the small sample size may not capture the full extent of this relationship. Moreover, although we have one more bank (BRED Bank) operating in Fiji, the bank was established in 2012; hence, including BRED Bank in the balanced panel would significantly reduce the sample size. Therefore, future studies could consider these limitations with the possibility for extending this study further, as more data become available. Another important suggestion would be for the Reserve Bank of Fiji to update banks' and other financial institutions' data before 2001 because most of the financial institutions were established decades earlier. Nevertheless, within these limitations, our study presents a comprehensive set of factors, and an objective previously not explored, and offers deeper insight into bank profitability for a small island economy, like Fiji's. These

factors could enrich discussions within the broader context of banking sector management in small island economies.

Author Contributions: Conceptualization, S.A.C., R.R.K., P.J.S. and M.S.; methodology, S.A.C. and R.R.K.; software, S.A.C.; validation, S.A.C., R.R.K., P.J.S. and M.S.; formal analysis, S.A.C., R.R.K., P.J.S. and M.S.; investigation, S.A.C., R.R.K., P.J.S. and M.S.; resources, S.A.C., R.R.K., P.J.S. and M.S.; data curation, S.A.C.; writing—original draft preparation, S.A.C., R.R.K., P.J.S. and M.S.; writing—review and editing, S.A.C., R.R.K., P.J.S. and M.S.; visualization, S.A.C., R.R.K., P.J.S. and M.S.; supervision, R.R.K.; project administration, R.R.K.; funding acquisition, R.R.K. and P.J.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: All data used are publicly available. Links to access the data are provided in the manuscript.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Literature summary table.

Study	Coverage	Sample Period	Method	Summary of Main Findings
Aladwan (2015)	15 commercial banks in Jordan	2007–2017	OLS	Bank Size (+)
Seenaiah et al. (2015)	4 banking groups in India	1995–2012	Fixed Effect	Net Interest Margin (–) Operating Profits (+) Ratio of Wage Bills (+) Non-Performing Loans (+)
Ghosh (2016)	169 developing countries	1998–2013	Fixed Effect and GMM	Concentration Ratio (+) Non-Interest Income (+) Bank Assets-to-GDP (+) Bank Deposits-to-GDP (n.f.) Liquid Assets-to-Deposits (n.f.) Bank Stability (+) Globalization (–) Non-Resident Bank Loans-to-GDP (–) Real GDP Growth (+) Inflation (–) Real GDP Per Capita (–) Real Interest Rate (+)
Islam and Nishiyama (2016)	259 banks in South Asia	1997–2012	Fixed Effect	Capital Adequacy Ratio (+) Non-Performing Loans (–) Liquidity Ratio (–) Credit Risk (–) Productivity Ratio (+) Recurring Earning Power (+) Deposits (+) Bank Size (+) Concentration Ratio (+) Inflation (+) Gross Domestic Product (–)
Menicucci and Paolucci (2016)	35 European banks	2009–2013	Fixed Effect	Bank Size (+) Capital Adequacy Ratio (+) Deposit-to-Asset Ratio (+) Loans (n.f.) Loan Loss Provisions (–)
Sufian and Kamarudin (2016)	30 banks in South Africa	1998–2012	Fixed Effect	Loan Loss Provisions (–) Capital Adequacy Ratio (+) Non-Interest Income (+) Bank Size (+) Gross Domestic Product (–) Inflation (–) Bank Stability (+) Globalization (+) Economic Globalization (+) Social Globalization (–) Political Globalization (n.f.)

Table A1. Cont.

Study	Coverage	Sample Period	Method	Summary of Main Findings
Ahamed (2017)	107 Indian commercial banks	1998–2014	Fixed Effect and Systemic GMM	Concentration Ratio (n.f.) Non-Interest Income (+) Bank Size (+) Capital Adequacy Ratio (+) Loans (+) Loan Loss Provisions (–)
Bougatef (2017)	10 commercial banks in Tunisia	2003–2014	GMM	Corruption Index (+) Bank Size (+) Efficiency (+) Capital Adequacy Ratio (+) Liquidity Ratio (+) Credit Risk (–)
Silaban (2017)	40 Indonesian banks	2012–2016	OLS	Net Interest Margin (+) Capital Adequacy Ratio (n.f.)
Kingu et al. (2018)	16 commercial banks in Tanzania	2007–2015	OLS, Fixed and Random	Non-Performing Loans (–) Liquidity Ratio (–) Capital Adequacy Ratio (+) Gross Domestic Product (–)
Lutf and Omarkhil (2018)	10 banks in Pakistan	2007Q1–2017Q4	ARDL	Gross Domestic Product (+) Inflation (+) Interest Rate (n.f.)
Nisar et al. (2018)	200 commercial banks in South Asia	2000–2014	OLS, Fixed and Systemic GMM	Funding Costs (–) Capital Adequacy Ratio (+) Administrative Expenses (–) Liquidity (+) Investments (+) Bank Size (+) Non-Interest Income (+)
Ajayi et al. (2019)	12 banks in Nigeria	2017	OLS	Capital Adequacy Ratio (+)
Almaqtari et al. (2019)	69 commercial banks in India	2008–2017	OLS, Fixed and Random Effects	Bank Size (+) Capital Adequacy Ratio (n.f.) Loan Ratio (n.f.) Liquidity (n.f.) Deposits (+) GDP Growth Rate (–) Inflation (+) Exchange Rate (–) Interest Rate (–) Financial Crisis (–)
Bolarinwa et al. (2019)	15 commercial banks in Nigeria	2005–2015	OLS, Fixed, Random, and Systemic GMM	Deposits (+) Capital Adequacy Ratio (–) Concentration Ratio (–) Credit Risk (–) Bank Size (+) Gross Domestic Product (–) Inflation (–)
Tharu and Shrestha (2019)	8 banks in Nepal	2013–2018	OLS	Bank Size (n.f.)
Chandrasegaran (2020)	9 banks in Sri Lanka	2008Q1–2019Q3	OLS	Capital Adequacy Ratio (+)
Hasan et al. (2020)	26 Indonesian banks	2007–2018	Fixed Effect	Net Interest Margin (+) Operational Expense Ratio (–) Capital Adequacy Ratio (–) Loan Ratio (+) Non-Performing Loans (–)
Saleh and Afifa (2020)	13 commercial banks in Jordan	2010–2018	GMM	Credit Risk (–) Liquidity Risk (–) Capital Adequacy Ratio (+) Bank Size (–) Loans (+) Efficiency Ratio (+)
Thi Thanh Tran and Phan (2020)	31 commercial banks in Vietnam	2009–2018	GMM	Bank Size (–) Loan Ratio (+) Capital Adequacy Ratio (+) Concentration Ratio (–) Bank Stability (+) Inflation (+) Gross Domestic Product (+)
Adesina (2021)	400 commercial banks in Africa	2005–2015	Fixed and Systemic GMM	Non-Interest Income (–) Human Capital Efficiency (+) Capital Adequacy Ratio (–) Liquidity (+)

Table A1. Cont.

Study	Coverage	Sample Period	Method	Summary of Main Findings
Ayhan and Toufaili (2021)	13 banks in Lebanon	2008–2019	GMM	Remittances (+) Capital Adequacy Ratio (+)
Jeris (2021)	27 banks in Bangladesh	2014–2018	Fixed Effect	Bank Size (+) Cost-to-Income Ratio (n.f.) Capital Adequacy Ratio (+) Loan Ratio (n.f.) Deposit Ratio (+) Loan Loss Provisions (n.f.) Concentration Ratio (–) Gross Domestic Product (–) Inflation (n.f.)
Çollaku and Aliu (2021)	109 commercial banks in Kosovo	2010–2019	OLS	Non-Performing Loans (–) Liquidity Risk (–) Bank Size (+)
Krishna et al. (2021)	7 banks in Fiji	2001–2019	Fixed Effect	Liquidity Ratio (n.f.) Asset Quality (n.f.) Bank Size (+) Management Efficiency (n.f.) Credit Risk (n.f.) Gross Domestic Product (n.f.) Inflation Rate (–) Exchange Rate (+) Money Supply (n.f.) Quality of Regulation (n.f.)
Ali et al. (2022)	21 banks in India	2005–2018	Fixed Effect	Capital Adequacy Ratio (+) Basel Norms (+) Bank Size (+) Credit Risk (–) Liquidity Risk (–) Productivity (+) Cost Efficiency (+) Non-Interest Income (+) Gross Domestic Product (+) Inflation (+) Financial Crisis (–)
Isayas (2022)	14 banks in Ethiopia	2008–2019	GMM	Bank Size (+) Liquidity Ratio (+) Asset Tangibility (+) Capital Adequacy Ratio (+) Leverage (+) GDP (+) Firm's Age (–) Inflation (n.f.)
Karim et al. (2022)	25 commercial banks in Bangladesh	2010–2021	OLS	Non-Performing Loans (–) Liquidity (n.f.) Bank Size (–)
Rifansa and Pulungan (2022)	IV bank listed on the Indonesia Stock Exchange (IDX)	2016–2020	OLS	Capital Adequacy Ratio (+) Non-Performing Loans (–) Loans (+) Operational Costs (–)
Yakubu and Bunyaminu (2022)	40 banks in sub-Saharan Africa	2008–2016	GMM	Financial Globalization (–) Trade Globalization (–) Bank Size (+) Gross Domestic Product (+) Inflation (+)
Abel et al. (2023)	15 banks in Zimbabwe	2009–2019	ARDL	Non-Performing Loans (–) Bank Size (+) Capital Adequacy Ratio (+) Concentration Ratio (+) Inflation (–) Gross Domestic Product (+)
Athari and Bahreini (2023)	29 publicly listed Islamic banks in Saudi Arabia	2003–2017	OLS, Fixed and Random	Bank Size (+) Capital Adequacy Ratio (+) Asset Quality (+) Credit Risk (–) Deposits (+) Domestic Credit (+) Gross Domestic Product (–) Inflation (–) Governance (+)
Bashiru et al. (2023)	33 developing countries	2000–2017	GMM	Financial Development (–) Bank stability (+) Institutional Quality (+)

Table A1. *Cont.*

Study	Coverage	Sample Period	Method	Summary of Main Findings
Mehzabin et al. (2023)	492 banks in Asia	2004–2018	Fixed Effect	Leverage Ratio (–) Bank Size (+) Debt Ratio (+) Non-Interest Income (+) Operating Efficiency (+) Capital Adequacy Ratio (+) Credit Risk (–)
Theiri and Hadoussa (2023)	12 banks in Tunisia	2010–2020	GMM	Digital Transformation (+) Bank Size (+) Capital adequacy Ratio (+)

Notes: (+), (–), and (n.f.) indicate positive, negative, and insignificant effects.

Table A2. Regression results based on ordinary least squares estimation (OLS): Dependent variable is ROA.

Variable Group	Variable	Model I	Model II	Model III	Model IV	Model V	Model VI
Independent Variables	Constant	–0.024524 (0.018404)	–0.028421 (0.016167)	–0.011140 (0.010425)	–0.013794 (0.021314)	–0.071245 (0.04400)	–0.048791 (0.024350)
	NIM	0.585469 *** (0.044677)	0.578189 *** (0.046302)	0.594061 *** (0.075198)	0.572042 *** (0.050514)	0.579471 *** (0.051718)	0.568051 *** (0.052075)
Bank Specific	NII	0.002388 *** (0.000529)	0.002428 *** (0.000549)	0.002474 *** (0.000549)	0.002478 *** (0.000549)	0.002377 *** (0.000569)	0.002505 *** (0.000574)
	BSIZE	0.000672 * (0.000462)	0.001333 ** (0.001123)	0.001140 * (0.000673)	0.000701 * (0.003175)	0.005021 * (0.003138)	0.0041761 ** (0.002088)
	CRISK	–0.022484 *** (0.002522)	–0.022221 *** (0.001309)	–0.023148 *** (0.002691)	–0.024587 *** (0.004237)	–0.02206 *** (0.002839)	–0.021802 *** (0.002843)
	NPL	–0.579628 *** (0.085465)	–0.586160 *** (0.094205)	–0.593314 *** (0.093195)	–0.521920 *** (0.105941)	–0.525681 *** (0.106277)	–0.506717 *** (0.107228)
	CAR	0.000293 * (0.000175)	0.000238 (0.000211)	0.000237 (0.000232)	0.000343 * (0.000242)	0.000414 * (0.000235)	0.000441 * (0.000261)
	EINDX	-	0.000389 * (0.000216)	0.000504 (0.000644)	0.000452 * (0.000662)	0.000805 * (0.000473)	0.000378 (0.000391)
Globalization Index	PINDX	-	–0.000777 (0.000493)	–0.000261 (0.000739)	–0.000421 (0.000821)	–0.000531 (0.000815)	–0.00521 (0.001046)
	SINDX	-	0.000691 * (0.000364)	0.000956 ** (0.000496)	0.000191 * (0.000105)	0.000513 * (0.000312)	0.000594 * (0.000371)
Institutional Variables	CC	-	-	–0.003731 (0.006758)	–0.000642 (0.000697)	–0.005925 (0.007047)	–0.000471 (0.007141)
	GE	-	-	0.010273 ** (0.004321)	0.001350 *** (0.005024)	0.013250 (0.005047)	0.001032 * (0.001621)
	RL	-	-	–0.010881 (0.006164)	–0.001087 (0.006561)	–0.011087 (0.006581)	–0.013561 * (0.007093)
	RQ	-	-	–0.008451 (0.006677)	–0.012381 (0.0073910)	–0.012794 (0.007429)	–0.009634 (0.007895)
	PS	-	-	0.008321 * (0.004894)	–0.001640 (0.008144)	–0.000521 (0.008861)	0.009561 (0.011142)
	VA	-	-	0.007764 *** (0.002773)	0.007151 ** (0.002705)	0.007471 * (0.003932)	0.002655 ** (0.001327)
	GDPG	-	-	-	0.000201 *** (0.000402)	0.000182 * (0.000107)	0.000271 * (0.000143)
Macro	REM	-	-	-	0.000981 ** (0.000363)	0.001012 * (0.000035)	0.001455 (0.002214)
Uncertainty Index	WUI	-	-	-	-	0.003435 (0.004925)	0.008881 (0.007061)
Structural Variables	COVID	-	-	-	-	-	–0.015419 ** (0.000737)
	GFC	-	-	-	-	-	0.0044255 (0.003293)
Diagnostics	Adjusted R-Squared	0.738491	0.730861	0.744742	0.741947	0.744355	0.745675
	DW-Statistic	1.147619	1.144293	1.266	1.251571	1.289995	1.315958
	Observations	154	154	154	154	154	154

Notes: ***, **, and * indicate statistical significances at 1%, 5%, and 10% levels; (–) contains standard errors. Results are based on fixed-effect regression method.

Notes

- ¹ The concept of antifragility supersedes resilience and robustness and refers to conditions in which an entity gains through adverse events (Taleb 2012).
- ² See Table A1 (in the Appendix A section) for a summary of the studies on the determinants of bank profitability.
- ³ However, the study does not provide a theoretical explanation for the negative association. We argue that it is possible that the net interest margin is sufficiently low or sufficiently high; hence, it exhibits a non-linear effect. If too low or too high, an NIM can indicate the mispricing of assets (loans) and liabilities (deposits).
- ⁴ Fiji has seven commercial banks. However, for our analysis, to ensure we have a sufficiently large sample size (2000–2021), we have excluded BRED Bank from the sample because it started operating from 2012.
- ⁵ For bank profitability, the graph demonstrates bank profitability from 2000 to 2022; however, our empirical estimation sample is from 2000 to 2021. This is because data on globalization indices are only available up to 2021. FJD 1 can be approximated as USD 0.45.
- ⁶ The results based on the ordinary least squares method are presented in the Appendix A section (see Table A2) for reference only.
- ⁷ Recently, the country experienced a surge in remittance inflows. In comparison with 2021, in 2022, remittances increased by 25 percent to FJD 1.04 billion (USD 0.52 billion) (Chand 2023).

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Article

Analysis of Factors Affecting the Loan Growth of Banks with a Focus on Non-Performing Loans

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Abstract: The purpose of this paper is to investigate the intertemporal relationship between the non-performing loan ratio and bank lending and to analyze factors affecting loan growth using data from Mongolian commercial banks. There has been a lack of research on Mongolian banks' lending behavior due to their short history. Thus, this paper investigates the effect of the non-performing loan ratio on total loan growth using an ordinary least squares (OLS) regression model with panel data. We used bank-related variables such as the loan-to-deposit ratio, provision-to-gross loan portfolio ratio, equity-to-asset ratio, and liquidity ratio, and economic variables such as the real gross domestic product (GDP) growth rate, interest rate, and inflation rate. The results of this paper show that non-performing loans have a significant negative impact on total loan growth. The implication of this result is that non-performing loans affect banking efficiency, which, in turn, affects financial stability and the real economy. Moreover, high non-performing loans reduce banks' profits. Also, this paper found that loss reserve and the liquidity ratio have a positive effect on total loan growth, while the effects of the loan-to-deposit ratio and the equity capital ratio were not found to be significant. Additionally, from a macro perspective, the inflation rate has a positive effect on the total loan growth rate, while the interest rate has a positive effect on total loan growth rather than a negative effect. And real gross domestic product (GDP) growth does not affect the total loan growth rate.

Keywords: correlation analysis; regression analysis; pooled regression model; Mongolian commercial banks; non-performing loans; total loans

1. Introduction

In Mongolia, there has recently been great continued interest in the financial and banking industries, and the number of related business fields is increasing, but there is still no research on awareness of bank loans, which have a significant impact on the qualitative growth of related businesses. In particular, research on Mongolian bank loans, a representative field in the financial services industry, is very insufficient considering its importance.

The solvency of borrowers decreases due to economic difficulties, and the resulting increase in banks' non-performing loans affects credit supply through three channels (Accornero et al. 2017). The three channels leading to total loan supply are as follows. First, an increase in non-performing loans (NPLs) increases risky assets. This reduces the ratio between equity capital and risk-weighted assets. An increase in non-performing loans increases the risk weight when calculating the expected risk-reward ratio, which may lead the bank to decide to reduce its assets. Second, banks with high non-performing loans may reduce operations due to market pressure. If the increase in non-performing loans is not fully compensated at an appropriate risk level, the bank's external funding cost increases, which is one of the reasons for reducing loan supply. Third, the size of non-performing loans can change a bank's risk-taking attitude. Undercapitalized banks are more sensitive to the "risk-taking channel" of monetary policy and tend to lend to less financially sound

borrowers when interest rates are low. The characteristics of this channel are opposite to those of the above two channels, and banks with high non-performing loans are more interested in lending than their competitors.

Previous studies related to Mongolia's financial industry include CheolMong and Choi (2017)'s comparative study on the efficiency of the Mongolian and Korean banking industries; Ku and Enkhjargal (2021)'s study on the implications of China and Korea's financial system reform on Mongolia's financial system reform; Altanzul and Park (2016)'s study on the impact of consumer expectation discrepancy regarding banking service quality on satisfaction, attitude, trust, and loyalty; and Lim and Dugerjav (2014)'s study on Korean and Mongolian bank service quality and relationship formation. Most previous studies on Mongolian banks have focused on banking service quality, and there has been little research on Mongolian bank lending so far.

Solving the problem of non-performing loans from commercial banks is a task that must be solved in Mongolia, where the financial industry is not on track. Therefore, because it is important to study the continuous lending of Mongolian bank users, this paper investigates the impact of non-performing loans on the total loans of Mongolian commercial banks and their credit supply, and finds micro-factors of banks and macro-factors of economic condition affecting banks' lending behavior.

The structure of this paper is as follows: Section 2 reviews previous studies; Section 3 describes the data used in this study and the research model; the analysis and results are presented in Section 4; and Section 5 provides our conclusions and directions for further studies.

2. Literature Review

The non-performing loan rate refers to the ratio of non-performing loans to the total loan amount and is an important indicator of a bank's vulnerability (Lee and Kim 2020). Recent studies on non-performing loans have focused on the determinants of credit defaulters. Their analyses are largely divided into bank micro-factors (such as loan size, capital, financing level, profit, etc.) and macro-factors (such as GDP, inflation rate, unemployment rate, investment level, etc.). Keeton and Morris (1987) found the determinant of bad loans in the United States between 1979 and 1985 to be the energy sector crisis, and Sinkey and Greenawalt (1991) and Gambera (2000) found the determining factor of bad loans in the United States to be macroeconomic variables. Laeven and Majnoni (2003) studied the factors affecting the stabilization of banks' profits and income using quantitative data from 45 countries. They found that banks have little provision for loan losses during economic downturns and that when the economy is suffering, the size of the bank negatively impacts its operations. Fonseca and González (2008) analyzed factors that improve profits by managing banks' loan loss reserves on a similar topic. They found that when investor protection is strong, banks make less effort to improve profits and there are strong formal and personal controls due to accounting transparency and banking restrictions. In other words, when a country's market system and financial system are strong, banks are well stabilized. Messai and Jouini (2013) studied the determinants of non-performing loans for Spanish, Italian, and Greek banks. They determined that credit supply would increase when unemployment and interest rates rose, and that loan supply would decrease when GDP growth and bank profitability fell. Berrospide and Edge (2010) studied bank lending behavior and the impact of bank assets. Credit growth is considered representative of credit behavior, and capital has been shown to have little effect on the growth of credit. Tomak (2013)'s study on bank lending behavior analyzed the determinants of bank lending using a sample of Turkish banks. These previous studies confirmed that there was a strong correlation between bank credit status and non-performing loans, and the results showed that these non-performing loans had a negative impact on the growth of total loans.

Cucinelli (2015) explains how macro-factors such as gross domestic product (GDP), inflation rate, and unemployment rate, and micro-factors such as loan-to-deposit ratio, equity capital ratio, an appropriate ratio of equity capital to total assets, customer deposit

growth rate, and non-performing loan rate factors affect the total loan growth rate. Lee and Kim (2020) used a VAR model to analyze the factors affecting non-performing loans by dividing them into two parts, macro-variables and micro-variables, similar to Cucinelli (2015), using quarterly data from 2011 to 2019. Lee and Kim (2020) studied the impact of six factors, including GDP and money supply (M2) as macro-factors, and loan-to-deposit ratio, equity capital ratio, bank investment size, and business climate index (BCI) as micro-factors, on the non-performing loan rate, and found that the total production growth rate and non-performing loans showed a positive relationship and the money supply growth rate and the bank non-performing loan rate showed a negative relationship. Lee and Kim (2020) conducted a study using panel data from the Bank of China and the Bank of Korea using the least squares method and a fixed effects model, and found that the non-performing loan ratio improved as the loan-to-deposit ratio increased, and while the asset size was negative for the Bank of China, it was positive for the Bank of Korea. Previous studies related to non-performing loans are summarized in Table 1 below. By synthesizing the variables used in existing studies, this paper analyzes how direct variables related to banks and macroeconomic indicators affect banks' lending behavior.

Table 1. Summary of previous studies related to non-performing loans.

Results	References
The determinant of bad loans in the United States is found to be the energy sector crisis.	Keeton and Morris (1987)
The determinant of non-performing loans in the United States is found to be macroeconomic variables.	Sinkey and Greenawalt (1991), Gambera (2000)
The authors perform research on bank stabilization by analyzing quantitative data from 45 countries. Banks have little provision for loan losses during recessions, and when the economy is tough, we see a negative impact on operations depending on the size of the bank.	Laeven and Majnoni (2003)
The authors analyze factors that improve profits by managing banks' loan loss reserves. Banks are more stable when a country's market and financial systems are strong.	Fonseca and González (2008)
The authors study the determinants of non-performing loans for Spanish, Italian, and Greek banks. Credit supply is expected to increase when unemployment and interest rates rise and decrease when GDP growth and bank profitability fall.	Messai and Jouini (2013)
The authors investigate the impact of bank assets on bank lending behavior. Credit growth is considered representative of credit behavior and capital has little effect on the growth of credit.	Berrospide and Edge (2010)
The macro-factors are gross domestic product (GDP), inflation (INF), and unemployment rate (UNEMP), and the micro-factors are loan-to-deposit ratio (LTD), equity capital ratio (E_TA), an appropriate ratio of equity capital to total assets (TIER_1), and customer deposits. The author conducts a study on how nine factors, such as an increase in loans (DEP), non-performing loans (CR), and DUMMY, affect the total loan growth rate.	Cucinelli (2015)
Macro-factors include gross domestic product (GDP) and money supply (M2), and micro-factors include loan-to-deposit ratio (LDR), capital ratio (CAR), bank capital ratio (WMP), and business climate index (BCI). The author studies 6 influencing factors	Lee and Kim (2020)

3. Data Description and Research Methods

3.1. Data

We used the data of six Mongolian commercial banks, including the Khan Bank, Khas Bank, TDB Bank, Golomt Bank, State Bank, and Capitron Bank (<https://www.mongolbank.mn>, accessed on 1 April 2024). In order to analyze the factors affecting the total loan growth rate of Mongolian banks, financial statements were collected from the websites

of six Mongolian banks from the first quarter of 2016 to the second quarter of 2022. For macro-factors, Mongolian national statistics were used. The information was collected through the committee's website.

3.2. Research Methodology

This paper analyzes data from six banks in Mongolia using a panel regression model by applying the models of Micco and Panizza (2006), Berrospide and Edge (2010), Carlson et al. (2013), and Cucinelli (2015).

Cucinelli (2015) selected gross domestic product (GDP), inflation rate (INF), and unemployment rate (UNEMP) as macro-factors, but in this paper, the central bank's policy interest rate (IR) was selected as a variable instead of the unemployment rate. In addition, Cucinelli (2015) used five micro-factor variables, including loan-to-deposit (LTD) ratio, equity capital ratio (EAR), an appropriate ratio of equity capital to total assets (TIER_1), the increase in customer deposits (DEP), and non-performing loans (NPLs). In this paper, the variables loss reserve (LLP) and liquidity ratio (LR) were considered instead of the appropriate ratio of equity capital to total assets (TIER_1) and the increase in customer deposits (DEP). In other words, the variables introduced earlier, namely non-performing loans (NPLs), loan-to-deposit (LTD) ratio, loss allowance (LLP), equity capital ratio (EAR), and liquidity ratio (LR), were used as micro-factors, and the factors gross domestic product, interest rate, and inflation were used as macro-factors.

Regardless of the cross-sectional and time series characteristics of the panel data, the pooled OLS estimation method uses the same constant coefficient and error term for all units in the panel, the total loan growth rate as the dependent variable, and a model that takes time lag as the independent variables into account.

We used the following regression model to investigate how non-performing loans affect the total loan growth rate using the pooled OLS model:

$$LGR_t = NPL_t + LTD_t + LLP_{t-1} + EAR_{t-1} + LR_{t-1} + GDP_t + IR_t + INF_t + \varepsilon_{it}$$

where loan growth rate is represented by LGR, gross domestic product growth rate by GDP, inflation rate by INF, interest rate by IR, non-performing loan by NPL, loan-to-deposit ratio by LTD, loan loss provision by LLP, equity-to-asset ratio by EAR, and liquidity ratio by LR, and $t - 1$ represents time lag.

Table 2 describes the independent and dependent variables for the regression model. The description of each variable is as follows: Loan growth rate (LGR) is used to measure banks' lending types (Laeven and Majnoni 2003; Gambacorta and Mistrulli 2004; Berrospide and Edge 2010; Alessi et al. 2014). The factors influencing this total loan growth rate were considered micro-and macroeconomic variables of the bank. First, micro-factors such as non-performing loans (NPL) and the loan-to-deposit ratio (LTD), loan loss reserve ratio (LLP), equity adequacy ratio (EAR), and liquidity ratio (LR) were considered as follows. Tomak (2013) argued that an increase in non-performing loans (NPLs) worsens loan ratings and reduces lending by commercial banks. The loan-to-deposit ratio (LTD) is the ratio of loans divided by deposits and is an indicator of how much loans are compared to deposits. Lower loan-to-deposit ratios for financing will reduce dependence on single sources, increase bank assets, and reduce market constraints. So, the coefficient was assumed to be negative. Loan loss provisions (LLPs) or loan loss reserves are funds set aside by banks to cover non-performing loans (loans that are not repaid in full due to customer default or loans that provide less interest income by negotiating a lower interest rate). A loan loss provision is the bank's best estimate of what percentage of the loan may not be repaid. Although loan losses are still a loss asset for the bank, the goal of the loan loss reserve is to protect the bank's cash flow, freeing up funds to service other borrowers and depositors. So, the sign of the expected coefficient in front of this variable is positive. The equity adequacy ratio (EAR) is the ratio of equity capital to total assets, which is included in the equation to detect the correlation between bank capitalization and credit supply. This is a key measure of a bank's solvency. Since banks tend to give out more

loans when their solvency is high, the sign of the coefficient is expected to be positive. The liquidity ratio (LR) is a measure of a commercial bank's ability to repay short-term debt. The liquidity ratio determines how quickly a commercial bank's assets can be converted and used to meet emerging liabilities. The higher the ratio, the easier one's ability to pay off debt and avoid default on payments. So, the sign of the expected coefficient in front of this variable is positive. Next, we considered macro-factors because the operations of the banking sector are highly dependent on economic conditions or macroeconomic factors. The main indicators of macroeconomic factors affecting bank credit supply are usually considered to be GDP, inflation rate, and interest rate (Tomak 2013; Klein 2013). The macro-factors are as follows. Gross domestic product is a macroeconomic indicator and one of the most common measures of overall economic activity. When economic conditions worsen and enter a downward trend, the number of non-performing loans in the banking system increases, resulting in a negative impact on the supply of bank loans. However, high economic growth means that banks supply large numbers of loans to the market. This can increase interest income and assets and improve quality. Therefore, the sign of the coefficient of GDP is expected to be positive. The interest rate is determined by the central bank and is the most important interest rate because it affects all interest rates in the economy. The interest rate is the rate at which the central bank pays or charges for deposits or loans from commercial banks. So, the sign of the expected coefficient in front of this variable is negative. Inflation rate is one of the important macroeconomic indicators. Regarding inflation in bank nominal interest rates and asset valuations, Smith et al. (2003) argued that there are spillover effects. The higher the inflation rate, the higher the nominal interest rate. This will increase banks' interest in lending. Therefore, the sign of the coefficient of inflation rate was predicted to be positive.

Table 2. Variable descriptions and hypotheses.

No.	Category	Variable Symbols	Alternative Hypothesis	References
1	Dependent variable	Loan growth rate (GLR)		Laeven and Majnoni (2003); Gambacorta and Mistrulli (2004); Berrospide and Edge (2010); Alessi et al. (2014)
2	Independent variable	Non-performing loan (NPL)	—	Tomak (2013); Cucinelli (2015)
3	Independent variable	Loan-to-deposit ratio (LTD)	—	
4	Independent variable	Loan loss provision (LLP)	+	
5	Independent variable	Equity adequacy ratio (EAR)	+	Cucinelli (2015)
6	Independent variable	Liquidity ratio (LR)	+	Cucinelli (2015)
7	Independent variable	Gross domestic product (GDP) (year on year)	+	Tomak (2013); Klein (2013)
8	Independent variable	Interest rate (IR)	—	Tomak (2013); Klein (2013)
9	Independent variable	Inflation rate (INF)	+	Tomak (2013); Klein (2013); Smith et al. (2003)

Thus, we hypothesized that the micro-factors of non-performing loans and the loan-to-deposit ratio would have a negative (—) effect on the total loan growth rate, while loan loss provision (LLP, loss reserves), the equity adequacy ratio (EAR), and the liquidity ratio (LR) would have a positive (+) effect. Also, we assumed that (i) the gross domestic product (GDP, year on year) of macro-factors has a positive (+) influence on the total loan growth rate, (ii) the central bank's policy interest rate (IR) has a negative (—) influence on the total loan growth rate, and (iii) inflation (INF) has a positive (+) effect on the total loan growth rate.

4. Results

4.1. Descriptive Statistics

The results of the descriptive statistics of each variable are shown in Table 3 below. The banking sector's average annual growth rate of total loans between 2016 and the second quarter of 2022 was 16.2%, and the average rate of non-performing loans was 7.8%. The annual average of the loan-to-deposit ratio was 88.5%, the annual average of loss reserves was 6.3%, the annual average of the equity capital ratio was 9.5%, the annual average of the liquidity ratio was 37.1%, and the annual average of the gross domestic product rate was 3%. The annual average of the interest rate was 10% and the annual average of inflation was 6.1%.

Table 3. Descriptive statistics.

	Mean	Std	Min	25%	50%	75%	Max
GLR	16.2	19.4	−24.7	5.5	11.2	24	107.7
NPL	7.8	2.8	2	6.1	7.5	9.1	15.3
LTD	85.5	19.6	57	71.6	82	93.8	157.2
LLP	6.3	2.7	2.1	4.3	5.7	7.4	13.2
EAR	9.5	1.8	6.2	7.9	9.3	11	13.3
LR	37.1	11.1	14.7	32	38.9	44.8	57.2
GDP	3	5.7	−10.1	1.5	5.6	8.8	14.8
IR	10	2.5	6	9	10	11	15
INF	6	4.1	−0.1	2.8	6.4	8.1	16.1

4.2. Correlation Analysis

We performed a correlation analysis to determine whether there were relationships among the variables. We used the micro-factor variables with time lag, except the non-performing loan. The correlation coefficient between each variable ranged from −0.018 to 0.831. Here, similar to the correlation analyses above, the largest correlation was found between the non-performing loans and loss reserves at 0.831. The results are shown in Table 4.

Table 4. Correlation analysis (when only micro-factors have time lag, except NPL).

	LGR	NPL	LTD	LLP	EAR	LR	GDP	IR	INF
LGR	1								
NPL	−0.018	1							
LTD	−0.159	0.079	1						
LLP	0.113	0.831 **	0.055	1					
EAR	−0.076	0.172 *	0.175 *	0.303 **	1				
LR	0.237 **	0.092	−0.471 **	0.162 *	0.403 **	1			
GDP	0.204 *	−0.030	0.011	0.058	0.020	0.146	1		
IR	0.213 **	−0.112	0.429 **	−0.130	−0.103	0.037	0.086	1	
INF	0.143	−0.016	−0.170 *	0.072	0.136	−0.049	0.079	−0.296 **	1

* denotes 5% significance with p -value less than 0.05 and ** denotes 1% significance with p -value less than 0.01.

4.3. Results of the Regression Model

We analyzed the regression model with micro-factor time lag variables (except NPL) as follows:

$$\text{LGR}_t = \text{NPL}_t + \text{LTD}_{t-1} + \text{LLP}_{t-1} + \text{EAR}_{t-1} + \text{LR}_{t-1} + \text{GDP}_t + \text{IR}_t + \text{INF}_t + \varepsilon_{it}$$

Table 5 shows the results of the regression model with time lag variables. The R-squared of regression analysis is a statistic that indicates how much the independent variable explains the dependent variable, and was found to be 0.255. The VIP value of the regression analysis was small, less than 4, so there appeared to be no multicollinearity problem.

Table 5. Results of regression analysis (when only micro-factors have time lag, except NPL).

Variables	Unstandardized Coefficient		Standardized Coefficient	<i>t</i> -Value	<i>p</i> -Value	Collinearity Statistic	
	B	Standard Error	Beta			Tolerance	VIF
Const	1.584	12.388		0.128	0.898		
NPL	−2.137	0.979	−0.296	−2.183	0.031	0.287	3.483
LTD	−0.118	0.123	−0.121	−0.963	0.337	0.333	3.007
LLP	3.034	1.016	0.416	2.987	0.003	0.272	3.672
EAR	−2.349	1.178	−0.213	−1.994	0.048	0.465	2.152
LR	0.364	0.213	0.209	1.71	0.089	0.354	2.821
GDP	0.34	0.25	0.103	1.36	0.176	0.921	1.086
IR	2.393	0.753	0.31	3.178	0.002	0.555	1.803
INF	1.003	0.381	0.211	2.636	0.009	0.826	1.211

Dependent variable: loan growth, $R^2 = 0.255$, Adj $R^2 = 0.213$, $F = 6.030$.

It was assumed that non-performing loans would have a negative effect on the increase in total loans, and as a result, the *t*-value was −2.183 and the *p*-value was 0.031, which showed negative significant results. Next, it was assumed that the loan-to-deposit ratio had a negative effect on the increase in total loans, and the results showed that the *t*-value was −0.963 and the *p*-value was 0.337, which was not significant. In addition, it was assumed that loss reserves had a positive effect on the increase in total loans, and the results showed significant results, with a *t*-value of 2.987 and a *p*-value of 0.003. In addition, it was assumed that the equity capital ratio would have a positive effect on the increase in total loans. As a result, the *t*-value was −1.994 and the *p*-value was 0.048, which showed a negative effect, and the assumption that it would have a positive effect was rejected. It was assumed that the liquidity ratio had a positive effect on the increase in total loans, and as a result, the *t*-value was 1.710 and the *p*-value was 0.089, which was found to be significant at 10%.

Next, looking at the results from a macroscopic perspective, it was assumed that gross domestic product had a positive effect on the total loan growth rate, and the results showed that the *t*-value was 1.360 and the *p*-value was 0.176, which was not significant. In addition, it was assumed that the interest rate had a negative effect on the increase in total loans. As a result, the *t*-value was 3.178 and the *p*-value was 0.002, showing a positive effect at 10%, and the assumption of a negative effect was rejected. Lastly, it was assumed that inflation had a positive effect on the total loan growth rate, and the results were found to be significant, with a *t*-value of 2.636 and a *p*-value of 0.009.

4.4. Discussion and Implications

The non-performing loans due to economic difficulties in recent years are likely to see an increase in transaction volume and a rapid increase in bank loans in mid-2022. However, non-performing loans still appear to be at a high level, so it is necessary to reduce non-performing loans, increase lending, and restore financial intermediation.

The implications of this study are as follows. First, the main reason of non-performing loans in Mongolia is the inefficiency of credit collection. It is important to support the market by creating more options for resolving low-quality loans by refusing to bid or participate in transactions. Second, selling non-performing loans is an effective method for efficient debt collection and bankruptcy procedures. This requires banks to completely separate non-performing loans from their balance sheets. However, the negative impact on the banking system remains an unresolved problem in the real economy. Third, a professional asset management system needs to be introduced to alleviate the burden of non-performing loans in the event of a credit soundness crisis, to create an environment in which financial intermediation continues and allows the economy to circulate.

5. Conclusions

This paper analyzed how non-performing loans affect total bank loans using the data of Mongolian banks because non-performing loans are an indicator of credit risk. During economic downturns, there is a tendency to provide large amounts of credit to all business sectors except the banking sector. When the economic situation worsens, production in each sector decreases, and as a result, repayment capacity deteriorates, which becomes the reason for the increase in non-performing loans. Thus, the increase in non-performing loans has a negative impact on credit rating, which leads to a possibility that there will be a lack of financial resources for continued normal operation and market expansion. In other words, an increase in non-performing loans due to economic difficulties can have a negative impact on credit supply, creating a vicious cycle that adversely affects economic recovery and slows down the process.

This paper found the following results: (i) non-performing loans were confirmed to be an important factor in determining the supply of bank loans, and have a negative impact on bank lending behavior or credit supply; (ii) the loan-to-deposit ratio had no significant negative effect on total loan growth; (iii) loss reserves showed a positive effect on total loan growth; (iv) the equity capital ratio showed a negative effect on total loan growth, contrary to our expectation; (v) the liquidity ratio had a positive effect on total loan growth; (vi) gross domestic product had a positive effect on the total loan growth rate, but it was not significant; (vii) the interest rate had a positive effect on total loan growth, contrary to our expectation; (viii) inflation had a positive effect on the total loan growth rate.

The implications of this paper are as follows. First, the main cause of non-performing loans in Mongolia is the inefficiency of credit collection. It is necessary to create more options for resolving poor-quality loans and refusing to bid or participate in transactions. Second, the means of selling non-performing loans is effective in efficient debt collection and bankruptcy procedures. Third, in the event of a credit crisis, an environment needs to be created in which the pressure on non-performing loans in the financial sector can be alleviated.

The limitations of this paper include, first, the inability to secure sufficient data on Mongolian commercial banks, and second, the inability to compare the lending behavior of Mongolian banks with banks in other countries. In the future, we need to compare and analyze the lending behavior of Mongolian banks and the lending behavior of banks in other countries using sufficient data.

Author Contributions: Conceptualization, S.-H.C. and N.A.; methodology and software, N.A.; validation, S.-H.C. and N.A.; formal analysis, S.-H.C. and N.A.; investigation and data curation, N.A. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The data presented in this study are openly available at https://github.com/sehakflower/data/blob/main/jrfm_1year.xlsx (accessed on 1 April 2024).

Conflicts of Interest: The authors declare no conflict of interest.

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Article

Transformation of the Ukrainian Stock Market: A Data Properties View

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Abstract: This paper investigates the evolution of the Ukrainian stock market through an analysis of various data properties, including persistence, volatility, normality, and resistance to anomalies for the case of daily returns from the PFTS stock index spanning 1995–2022. Segmented into sub-periods, it aims to test the hypothesis that the market's efficiency has increased over time. To do this different statistical techniques and methods are used, including R/S analysis, ANOVA analysis, regression analysis with dummy variables, *t*-tests, and others. The findings present a mixed picture: while volatility and persistence demonstrate a general decreasing trend, indicating a potential shift towards a more efficient market, normality tests reveal no discernible differences between analyzed periods. Similarly, the analysis of anomalies shows no specific trends in the market's resilience to the day-of-the-week effect. Overall, the results suggest a lack of systematic changes in data properties in the Ukrainian stock market over time, possibly due to the country's volatile conditions, including two revolutions, economic crises, the annexation of territories, and a Russian invasion leading to the largest war in Europe since WWII. The limited impact of reforms and changes justifies the need for continued market reform and evolution post-war.

Keywords: stock market; persistence; anomalies; adaptive market hypothesis; R/S analysis; efficient market hypothesis

1. Introduction

One of the fundamental academic theories describing and explaining the behavior of financial markets is the Efficient Market Hypothesis (EMH), developed by Fama (1965). According to this theory, at any given moment, the price of a financial asset equals its fundamental value, making it impossible to make economic decisions that would yield profits from operations with assets in the financial market (so-called “you cannot beat the market” rule).

This is explained by the random nature of price fluctuations in financial markets and by the fact that any discrepancy between the current market price of an asset and its fundamental value will be compensated by the corresponding actions of financial market participants, resulting in the almost instantaneous elimination of any deviation from the fair value (Samuelson 1965).

However, there is much empirical evidence against the EMH: persistence of returns and volatility (Caporale et al. 2019), the existence of price bubbles in the financial markets (Scherbina and Schlusche 2014), various types of market anomalies (Plastun et al. 2019), fat

tails in data, non-randomness of data (Lo and MacKinlay 1988), etc. Ball (2009) showed that during the global financial crisis (2007–2009) the most efficient markets suffered the most significant losses.

As a result, alternative concepts and theories emerged to explain the behavior of financial markets. Among the most commonly known are behavioral finance (Shiller 2003), adaptive market hypothesis (Lo 2004), fractal market hypothesis (Peters 1994), noisy market hypothesis (Black 1986), overreaction hypothesis (De Bondt and Thaler 1985), and many others.

These theories contradict each other; they are based on different assumptions and different methodologies of analysis and typically concentrate on a specific aspect of financial markets. Lo (2004) tried to put them all within a single concept, explaining existing differences with the instability of financial markets.

Evolutionarily, markets move from inefficient (when prices have a non-random nature of changes and there is a fundamental possibility of predicting price movements when information asymmetry is present, when there is an opportunity to make profits) to efficient, when prices are unpredictable, and their movements are random, information asymmetry is minimal, and financial markets are markets of perfect competition (Lo 2004).

This is a basic assumption of the Adaptive market hypothesis (AMH). The rationale for this includes the impact of competition, mutation, reproduction, and natural selections which cause changes in the behavior of financial institutions and market participants, with further transmission to the efficiency of markets.

Kim et al. (2011) showed that return predictability varies in time for the case of the Dow Jones Industrial Average index from 1900 to 2009.

The evolutionary nature of financial markets related to their efficiency was confirmed by Urquhart and Hudson (2013) who explored the persistence of returns in the US, UK, and Japanese stock markets and found evidence in favor of the adaptive market hypothesis. Contrary Hull and McGroarty (2014) could not find evidence of persistence trending down over time, suggesting no increase in market efficiency.

Exploring market anomalies provides an alternative perspective on evolutionary processes. Market anomalies should not exist in efficient markets (Jensen 1978). Kohers et al. (2004) and Plastun et al. (2019) observed the diminishing day-of-the-week effect, supporting market efficiency evolution. Xiong et al. (2019) found varying calendar effects in the Chinese stock market over time.

Lim and Brooks (2011) provide a summary of existing literature on market efficiency evolution. A general conclusion is in favor of the AMH: market efficiency varies over time.

However, the Ukrainian stock market remains relatively underexplored. Plastun et al. (2023) analyzed its efficiency, demonstrating predictability differences between traditional and ESG indices but leaving evolutionary aspects unexplored.

This paper fills this gap by analyzing the evolution of the Ukrainian stock market through data properties. Utilizing data from 1995 to 2022, it tests the hypothesis that market efficiency increases over time using regression analysis with dummy variables, normality tests, persistence analysis (R/S analysis), and various statistical tests, including examinations of anomalies such as the day-of-the-week effect.

The Ukrainian stock market presents a unique subject of analysis due to its tumultuous history, which includes two revolutions, economic crises, significant reforms, and the largest war in Europe since World War II. Examining its evolution may offer valuable insights into the behavior of stock markets in the aftermath of revolutions and during periods of conflict.

2. Materials and Methods

We analyse daily data for the leading Ukrainian stock market index PFTS (First Stock Trading System—Persha Fondova Torgova Systema) (<https://www.pfts.com.ua>, accessed on 10 October 2023). The sample period goes from 1995 to 2022.

In order to explore the evolution of the market overall data set is divided into the following sub-periods: 1995–1999, 2000–2004, 2005–2007, 2008–2009, 2010–2013, 2014–2015, 2016–2019, and 2020–2022. This division is based on key events in the development of

the Ukrainian stock market. For example, 2008–2009—the Global financial crisis and 2020–2022—pandemic period, etc.

We analyze returns computed as follows:

$$R_i = \left(\frac{Close_i}{Open_i} - 1 \right) \times 100\%, \quad (1)$$

where

R_i —returns on the i -th period in percentage terms;

$Open_i$ —open price on the i -th period;

$Close_i$ —close price on the i -th period.

Hypothesis to be tested: The efficiency of the Ukrainian stock market increases over time.

To test this hypothesis the following methods and techniques are used:

- Descriptive statistics (to explore differences between key quantitative characteristics of data sets belonging to different sub-periods);
- Parametric tests (t -tests, ANOVA-analysis) to identify statistically significant differences between data sets belonging to different periods;
- Non-parametric tests (Mann–Whitney, Kruskal–Wallis) to identify statistically significant differences between data sets belonging to different periods;
- Data normality tests (Kolmogorov–Smirnov test) in order to check the random nature of data with further conclusions about the efficiency/inefficiency of the market during the analyzed period;
- Methods to analyze price anomalies (the effect of the day of the week) as signs of market inefficiency;
- R/S analysis to explore data persistence with further conclusions regarding the level of market efficiency during the analyzed period.

In this paper, various statistical tests are employed to assess the statistical significance of differences between specific periods and the overall data set. Depending on the distribution of the data (whether it adheres to a normal distribution or not), both parametric and non-parametric tests are used. Given the diverse nature of the data periods under examination, differences in normality distribution are highly probable. To account for this variability and circumvent the need for extensive preliminary checks (such as data normality tests), a combination of parametric tests (t -test and ANOVA analysis) and non-parametric tests (including the Mann–Whitney test for two groups and the Kruskal–Wallis test for datasets with more than two groups) are applied.

The null hypothesis (H_0) in each case is that the data belong to the same general population, and rejecting this hypothesis suggests that the data originate from different populations. This serves as evidence supporting the presence of statistically significant differences between specific period data and the overall dataset.

To measure the degree of persistence R/S analysis is applied. R/S analysis is one of the most commonly used methodologies to calculate the Hurst exponent for financial data over the last 30–40 years. It was used to analyze persistence in FOREX (Corazza and Malliaris 2002), commodities (Barkoulas et al. 1997; Crato and Ray 2000), cryptocurrency (Caporale et al. 2018), stock markets of different countries: the US stock market (Greene and Fielitz 1977), Chinese (Hja and Lin 2003), Japanese (Batten et al. 2003), Swedish (Lennart and Lyhagen 1998), etc.

There is evidence (Taqqu et al. 1995; Lo 1991) that R/S analysis might be biased. As a result, additional techniques to calculate the Hurst exponent can be applied: modified R/S analysis (Lo 1991), DFA and DMA (Jiang et al. 2019), etc. Still, for the case of financial data standard R/S analysis is actively used even in the most recent studies (Raimundo and Okamoto 2018; Danylchuk et al. 2020; Metescu 2022).

Standard R/S analysis is based on the following algorithm (see Caporale and Plastun 2024 for additional details):

1. A time series of length M is transformed into one of length $N = M - 1$ using logs and converting prices into returns:

$$N_t = \log\left(\frac{Y_{t+1}}{Y_t}\right), t = 1, 2, 3, \dots (M - 1). \quad (2)$$

2. This period is divided into contiguous A sub-periods with length n , such that $A_n = N$, then each sub-period is identified as I_a , given the fact that $a = 1, 2, 3 \dots, A$. Each element I_a is represented as N_k with $k = 1, 2, 3 \dots, N$. For each I_a with length n the average e_a is defined as:

$$e_a = \frac{1}{n} \sum_{k=1}^n N_{k,a}, k = 1, 2, 3, \dots N, a = 1, 2, 3 \dots, A. \quad (3)$$

3. Accumulated deviations $X_{k,a}$ from the average e_a for each sub-period, I_a is defined as:

$$X_{k,a} = \sum_{i=1}^k (N_{i,a} - e_a). \quad (4)$$

The range is defined as the maximum index $X_{k,a}$ minus the minimum $X_{k,a}$, within each sub-period (I_a):

$$R_{Ia} = \max(X_{k,a}) - \min(X_{k,a}), 1 \leq k \leq n. \quad (5)$$

4. The standard deviation S_{Ia} is calculated for each sub-period I_a :

$$S_{Ia} = \left(\left(\frac{1}{n} \right) \sum_{k=1}^n (N_{k,a} - e_a)^2 \right)^{0.5}. \quad (6)$$

5. Each range R_{Ia} is normalized by dividing by the corresponding S_{Ia} . Therefore, the re-normalized scale during each sub-period I_a is R_{Ia}/S_{Ia} . In step 2 above, adjacent sub-periods of length n are obtained. Thus, the average R/S for length n is defined as:

$$(R/S)_n = (1/A) \sum_{i=1}^A (R_{Ia}/S_{Ia}). \quad (7)$$

6. The length n is increased to the next higher level, $(M - 1)/n$, and must be an integer number. In this case, n -indices that include the start and end points of the time series are used, and Steps 1–6 are repeated until $n = (M - 1)/2$.
7. The least square method is used to estimate the equation $\log(R/S) = \log(c) + H \cdot \log(n)$. The slope of the regression line is an estimate of the Hurst exponent H . (Hurst 1951).

The Hurst exponent lies in the interval $[0, 1]$. On the basis of the H values three categories can be identified: the series are anti-persistent, and returns are negatively correlated ($0 \leq H < 0.5$); the series are random, returns are uncorrelated, and there is no memory in the series ($H = 0.5$); the series are persistent, returns are highly correlated, and there is memory in price dynamics ($0.5 < H \leq 1$).

However, the Hurst exponent often hovers around 0.5, complicating the interpretation of results. Additionally, the question of the statistical significance of the obtained results remains open, i.e., whether the Hurst exponent value obtained can be considered reliable.

To address these shortcomings of standard R/S analysis, we propose evaluating the statistical significance of the estimated Hurst exponent. This involves calculating p -values for the Hurst exponent using procedures within the framework of regression analysis. Additionally, confidence intervals are estimated to gain insight into the behavior of the Hurst exponent within its typical range of fluctuations with a certain level of confidence (default set at 95%).

Consequently, the improved version of the Hurst exponent calculation appears as follows: $H = 0.63, p = 0.00; CI = 0.62\text{--}0.64$.

In this scenario, the data exhibit persistence, the Hurst exponent is statistically significant, and the entire confidence range is above 0.5.

Regression analysis with dummy variables serves as an additional method to scrutinize data for statistically significant differences across various periods. Within this methodology, data from two sub-periods are consolidated into a unified data set, distinguishing data assignments to specific subsets through the incorporation of dummy variables.

The model is as follows:

$$R_i = a_0 + a_1 D_{1i} + \varepsilon_i \quad (8)$$

where R_i —is the average value of the overall data set for period i , a_0 —is the average value of the first data set (first sub-period); a_1 —is a coefficient for a dummy variable characterizing its influence on the average value of the overall data set for period i ; D_i —is a dummy variable equal to 0 for the first data sub-period and 1 for the second data sub-period for period i .

3. Results

We start with descriptive statistics (see Table 1).

Table 1. Descriptive statistics for all data and sub-period: the case of the Ukrainian stock market.

Parameter	All Data	1995–1999	2000–2004	2005–2007	2008–2009	2010–2013	2014–2015	2016–2019	2020–2022
Average	0.05%	−0.13%	0.18%	0.21%	−0.09%	−0.02%	−0.04%	0.10%	−0.02%
Standard error	0.03%	0.14%	0.06%	0.05%	0.13%	0.07%	0.09%	0.04%	0.07%
Median	0.06%	0.10%	0.10%	0.19%	−0.10%	−0.04%	−0.05%	0.06%	0.03%
Standard deviation	2.06%	3.12%	2.03%	1.47%	2.96%	2.13%	1.90%	1.24%	1.59%
Sample variance	0.04%	0.10%	0.04%	0.02%	0.09%	0.05%	0.04%	0.02%	0.03%
Excess	10.54	4.13	17.16	3.79	3.48	9.60	12.90	6.13	5.37
Asymmetry	0.00	−0.64	1.01	−0.26	−0.05	0.32	0.66	−0.09	−0.27
Interval	38.05%	26.57%	37.25%	13.40%	24.76%	29.83%	26.94%	15.68%	18.37%
Minimum	−15.90%	−15.90%	−15.11%	−6.94%	−12.37%	−11.62%	−11.73%	−7.99%	−8.45%
Maximum	22.15%	10.67%	22.15%	6.46%	12.38%	18.21%	15.21%	7.69%	9.92%
Count	5895	526	1231	736	494	992	492	860	570

Key data characteristics vary across different periods. Particularly, average returns tend to be negative during crisis periods and positive during non-crisis periods, consistent with evidence from other countries and economic logic: stock markets grow during economic expansions and decline during crises. Regarding volatility (measured in Table 1 by the parameter “standard deviation”), there is a general trend of decreasing volatility, indicating a transition to a more efficient market state. With a greater number of professional participants, the market reacts more appropriately to events without excessive price fluctuations. However, volatility increases during times of crisis, a typical reaction of the stock market.

Figure 1 visually confirms these conclusions, depicting the dynamics of average values and standard deviations.

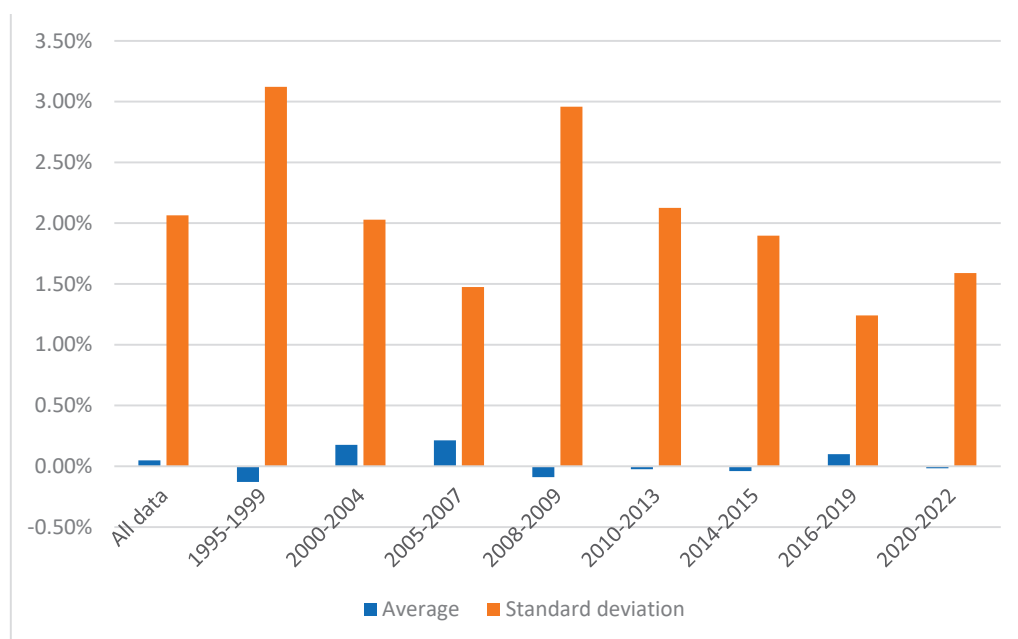


Figure 1. Dynamics of average returns and their standard deviations in the Ukrainian stock market by sub-periods.

Absolute differences, while visually evident, only imply potential distinctions among the data across different periods, as they may lack statistical significance for drawing conclusions about the belonging of the data to different populations. To ascertain the statistical significance of these differences, a series of statistical tests are conducted, encompassing both parametric and non-parametric methods to accommodate possible deviations of data from the normal distribution. The results of the ANOVA analysis (parametric test) and the Kruskal–Wallis tests (non-parametric) are presented in Table 2.

Table 2. Results of ANOVA analysis and Kruskal–Wallis Tests for statistical differences between periods in the Ukrainian Stock Market.

Method	Value	<i>p</i> -Value	Difference Is Statistically Significant
ANOVA analysis	2.67	0.01	Yes
Kruskal–Wallis Tests	25.22	0.00	Yes

As indicated, differences are statistically significant, meaning that not all of the analyzed periods belong to the same population. In other words, some periods demonstrated price behavior that was not typical compared to other periods.

However, based on the results from Table 2, it is not possible to conclude which periods were typical and which were not. To address this question, additional analysis is conducted. Each individual sub-period is explored for differences from the general population (the population, in this case, consisted of all data except for the period being examined). To do this parametric *t*-tests and ANOVA analysis as well as non-parametric Mann–Whitney tests are used. Results are provided in Tables 3–5, respectively.

The results of *t*-tests show that statistically significant differences are observed only during 2005–2007, and in all other periods the data behaved within the framework of the general population.

The data in Table 4 confirm the results of the *t*-tests: the only period that was statistically different from the general population was the period from 2005 to 2007.

ANOVA analysis and *t*-tests are parametric tests, so to avoid potential methodological biases associated with the normality/non-normality of data, a non-parametric Mann–Whitney test is used.

Table 3. Results of *t*-tests for statistical differences between periods in the Ukrainian stock market.

Period	t-Criterion	t-Critical (0.95)	Null Hypothesis	Difference
1995–1999	1.24	1.96	Not rejected	absent
2000–2004	0.87	1.96	Not rejected	absent
2005–2007	3.53	1.96	Rejected	present
2008–2009	0.82	1.96	Not rejected	absent
2010–2013	0.99	1.96	Not rejected	absent
2014–2015	0.54	1.96	Not rejected	absent
2016–2019	1.50	1.96	Not rejected	absent
2020–2022	0.97	1.96	Not rejected	absent

Table 4. Results of ANOVA analysis for statistical differences between periods in the Ukrainian stock market.

Period	F	<i>p</i> -Value	F Critical	Null Hypothesis	Difference
1995–1999	1.55	0.21	3.85	Not rejected	absent
2000–2004	0.75	0.39	3.85	Not rejected	absent
2005–2007	12.50	0.00	3.85	Rejected	present
2008–2009	0.68	0.41	3.85	Not rejected	absent
2010–2013	0.99	0.32	3.85	Not rejected	absent
2014–2015	0.29	0.59	3.85	Not rejected	absent
2016–2019	2.26	0.13	3.85	Not rejected	absent
2020–2022	0.95	0.33	3.85	Not rejected	absent

Table 5. Results of the Mann–Whitney tests for statistical differences between different periods for the case of the Ukrainian stock market.

Period	Adjusted H	d.f.	<i>p</i> -Value	Critical Value	Null Hypothesis	Difference
1995–1999	0.09	1	0.77	3.84	Not rejected	absent
2000–2004	0.27	1	0.60	3.84	Not rejected	absent
2005–2007	18.90	1	0.00	3.84	Rejected	present
2008–2009	1.63	1	0.20	3.84	Not rejected	absent
2010–2013	2.05	1	0.15	3.84	Not rejected	absent
2014–2015	0.45	1	0.50	3.84	Not rejected	absent
2016–2019	3.05	1	0.08	3.84	Not rejected	absent
2020–2022	0.35	1	0.56	3.84	Not rejected	absent

The results of the Mann–Whitney tests confirm the previous findings of parametric tests.

As an additional method to validate the obtained results, regression analysis with dummy variables is employed. In the regression model, Variable X1 represents the coefficient of a dummy variable. The dummy variable takes the value of 1 when the data belongs to a certain period (e.g., 1995–1999, 2000–2004, etc., as indicated in column 1), and 0 otherwise. A *p*-value below 0.05 indicates statistical differences between a specific period from column 1 and the overall data set. The results are presented in Table 6.

Table 6. Results of the regression analysis with dummy variables for statistical differences between periods in the Ukrainian stock market.

Period	F	<i>p</i> -Value	Variable X1	<i>p</i> -Value X1	Difference
1995–1999	1.55	0.21	−0.0017	0.21	absent
2000–2004	0.75	0.38	0.0006	0.38	absent
2005–2007	12.50	0.00	0.0022	0.00	present
2008–2009	0.67	0.41	−0.0011	0.41	absent
2010–2013	0.98	0.32	−0.0008	0.32	absent
2014–2015	0.29	0.59	−0.0005	0.59	absent
2016–2019	2.25	0.13	0.0008	0.13	absent
2020–2022	0.94	0.33	−0.0007	0.33	absent

The results of the regression analysis with dummy variables align with those obtained from the statistical tests: the only period that statistically differs from the overall data set is the period from 2005 to 2007.

Based on the statistical tests and regression analysis with dummy variables, it can be concluded that the only period exhibiting different data properties from the general population is the period from 2005 to 2007. Despite various crises, regulatory changes, and economic shifts, the behavior of prices in the Ukrainian stock market remained relatively consistent across other periods. Apart from the period 2005–2007, there is a lack of evidence indicating qualitative transformations or evolution in the specificity of price fluctuations within the Ukrainian stock market.

A distinct approach to analyzing market efficiency involves examining data persistence. The results of the R/S analysis for the entire data set and sub-periods are presented in Table 7.

Table 7. Results of the persistence analysis for the case of the Ukrainian stock market in different periods.

Period	Hurst Exponent	<i>p</i> -Value	Confidence Interval (95%)	Type of Data
All data	0.65	0.00	0.63–0.66	persistent
1995–1999	0.56	0.00	0.44–0.69	persistent
2000–2004	0.66	0.00	0.64–0.68	persistent
2005–2007	0.63	0.00	0.60–0.66	persistent
2008–2009	0.67	0.00	0.63–0.71	persistent
2010–2013	0.61	0.00	0.58–0.63	persistent
2014–2015	0.56	0.00	0.54–0.58	persistent
2016–2019	0.62	0.00	0.61–0.63	persistent
2020–2022	0.53	0.00	0.49–0.57	random

Overall, the Ukrainian stock market is characterized by the presence of persistence (long-term memory), meaning that past prices contain information about future prices, thus prices in such a market are fundamentally predictable. The visualization of the Hurst exponent dynamics with a trend line is provided in Figure 2.

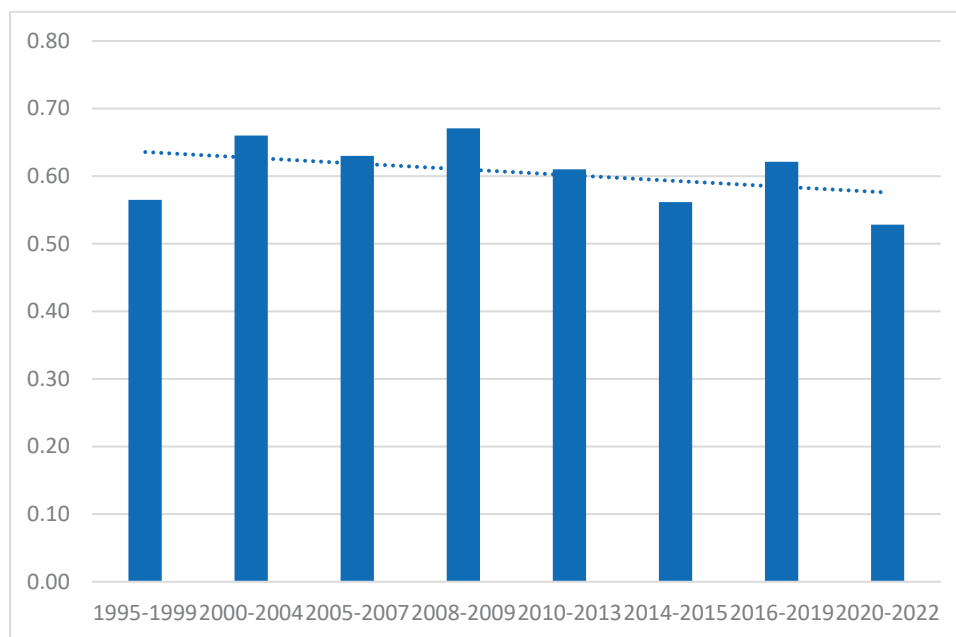


Figure 2. Transformation of persistence in the Ukrainian stock market in time.

As can be seen, there is a certain trend in the dynamics of persistence in the Ukrainian stock market: a decrease in the Hurst exponent values. Essentially, this represents a shift in the specificity of price fluctuations from their fundamental predictability due to the presence of long-term memory to the random nature of price movements, which is typical for an efficient market. Therefore, we have confirmation in favor of certain evolutionary processes in the Ukrainian stock market: it transforms from a less efficient state to a more efficient one.

However, there is only one period (from 2020 to 2022) that can be classified as non-persistent.

An important data property is the type of data distribution (normal/not normal). The normality of data is one of the indicators of an efficient market. Accordingly, the “non-normality” of data is evidence in favor of market inefficiency. Changes in the behavior of this data property can be used as one of the signs of market evolution.

Preliminary conclusions about data normality can be made based on the analysis of descriptive statistics parameters kurtosis and skewness. For a perfectly symmetrical distribution (i.e., normal distribution), the skewness is zero. While there is no strict threshold, skewness values between -1 and 1 (in some sources -0.5 to 0.5) are often considered acceptable for assuming normality. For a normal distribution, the kurtosis is typically around 3. Commonly, excess kurtosis values between -2 and 2 are considered acceptable for assuming normality (George and Mallery 2010; Field 2009). Going beyond these ranges raises doubts about the normality of data distribution.

In Table 8 the values of kurtosis and skewness parameters for each of the analyzed sub-periods are provided.

Table 8. Kurtosis and skewness of data for different periods in the Ukrainian stock market.

Period	Kurtosis	Skewness
All data	10.54	0.00
1995–1999	4.13	−0.64
2000–2004	17.16	1.01
2005–2007	3.79	−0.26
2008–2009	3.48	−0.05
2010–2013	9.60	0.32
2014–2015	12.90	0.66
2016–2019	6.13	−0.09
2020–2022	5.37	−0.27

Skewness across all periods is within the range $[-1..1]$, which is an indication of data normality. However, kurtosis significantly exceeds $[-2..2]$ range in all cases, which, in turn, is a sign of data non-normality.

To eliminate this uncertainty, there are numerous statistical tests for assessing the conformity of data to a normal distribution. One of the most popular ones is the Kolmogorov–Smirnov test. Results are presented in Table 9.

Table 9. Kolmogorov–Smirnov test for different periods in the Ukrainian stock market.

Period	Statistic	d.f.	p-Value
1995–1999	0.123	492	0.000
2000–2004	0.082	492	0.000
2005–2007	0.071	492	0.000
2008–2009	0.094	492	0.000
2010–2013	0.100	492	0.000
2014–2015	0.089	492	0.000
2016–2019	0.086	492	0.000
2020–2022	0.060	492	0.000

Results from Table 9 confirm the normal distribution of the data. Normal distribution was typical for all periods, implying that there were no radical changes in the behavior of this data property in the Ukrainian stock market from 1999 to 2022.

One of the main criticisms against the Efficient Market Hypothesis is the presence of anomalies—typical patterns in price behavior that should not exist in an efficient market but have been empirically identified by researchers. Anomalies range from calendar anomalies (month-of-the-year effect, day-of-the-week effect, Halloween effect, holiday effect, etc.) to anomalies related to small firms and price patterns emerging after abnormal price fluctuations, etc.

Therefore, studying price anomalies can provide additional information about market efficiency. The presence of anomalies is evidence in favor of market inefficiency, while the absence supports market efficiency.

Plastun et al. (2019) explored calendar anomalies in the U.S. stock market and showed that anomalies lost their strength with the development of the U.S. stock market and almost completely disappeared at the beginning of the 21st century. Thus, investigating price anomalies over different periods can offer valuable insights into the evolution and current state of the market in terms of efficiency.

Considering the specifics of the data used in this study (daily data over 2–5-year periods), it is impossible to analyze most anomalies due to their requiring a different data periodicity (monthly, for example) or a larger data set. However, some anomalies can be explored with statistically significant results. One such anomaly is the day-of-the-week effect—one of the most well-known calendar anomalies studied on various markets (stock, currency, commodity, cryptocurrency) in different countries (U.S., Japan, China, etc.) and groups of countries (developed, emerging).

The first step in the analysis for the presence of this anomaly is the visual inspection of average daily returns for specific days of the week (Figure 3).

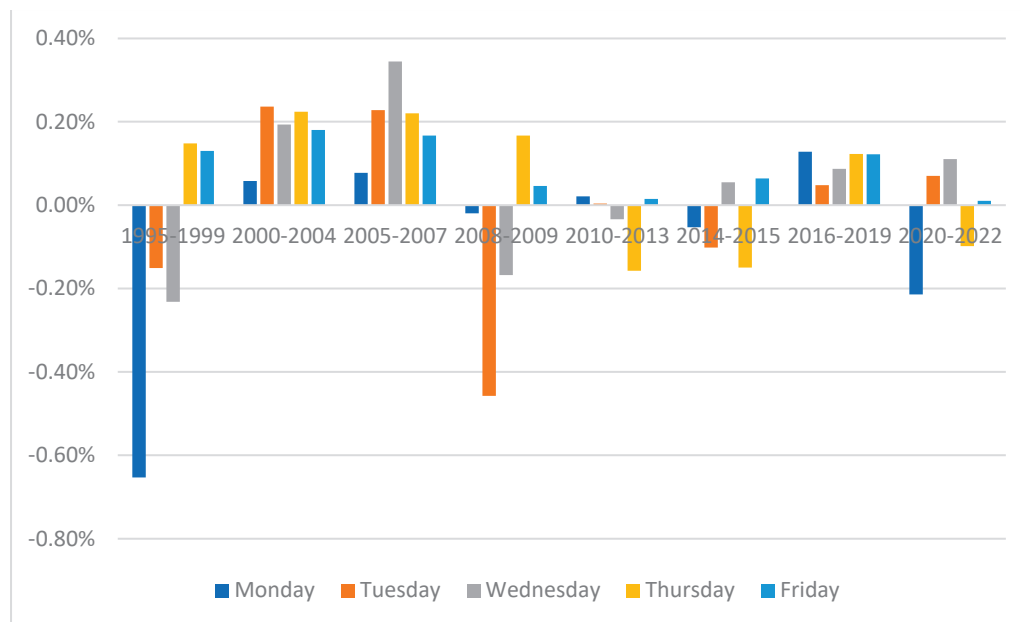


Figure 3. Average Daily Price Fluctuations in the Ukrainian Stock Market by Day of the Week.

As can be seen, the only day when price dynamics were consistently positive (prices increased) was Friday, aligning perfectly with the classical day-of-the-week effect. Regarding another classical feature of the day-of-the-week effect—price declines on Mondays—this effect was vividly observed only in the first and last of the analyzed periods (1995–1999 and 2020–2022, respectively). For the rest of the days, the data were mixed. In certain periods, the dynamics on specific days appeared anomalously strong compared to other days. For

instance, the price decline on Tuesdays during the 2008–2009 period, in absolute terms, was several times greater than the average dynamics on any other day of the week.

Based on visual analysis it cannot be concluded whether the observed differences are statistically significant. Therefore, the next stage of the analysis involves the use of statistical tests to answer the question of whether the differences are statistically significant. For these purposes, both parametric and non-parametric tests are employed.

The results of the *t*-test are presented in Table 10.

Table 10. Testing the statistical significance of day-of-the-week effects: *t*-tests.

Period	t-Criterion (t-Critical (0.95) = 1.96)					Null Hypothesis	Difference
	Monday	Tuesday	Wednesday	Thursday	Friday		
1995–1999	−1.66	−0.04	−0.32	1.17	1.02	Not rejected	absent
2000–2004	−1.17	0.47	0.12	0.37	0.00	Not rejected	absent
2005–2007	−1.17	0.17	1.27	0.11	−0.37	Not rejected	absent
2008–2009	0.22	−1.21	−0.35	0.98	0.58	Not rejected	absent
2010–2013	0.35	0.26	−0.02	−0.98	0.37	Not rejected	absent
2014–2015	−0.06	−0.37	0.63	−0.75	0.74	Not rejected	absent
2016–2019	0.33	−0.62	−0.17	0.22	0.28	Not rejected	absent
2020–2022	−1.21	0.70	0.96	−0.66	0.22	Not rejected	absent

Null hypothesis status is provided for the case of 95% confidence level.

The *t*-test results provide evidence in favor of the absence of statistically significant differences in the price dynamics on different days of the week. All days belong to the same population, indicating that the day-of-the-week effect in the Ukrainian stock market is not confirmed for any of the analyzed periods.

The next parametric test used for additional verification is the ANOVA analysis. The results are presented in Table 11.

Table 11. Testing the statistical significance of day-of-the-week effects: ANOVA analysis.

Period	F	<i>p</i> -Value	F Critical	Null Hypothesis	Difference
1995–1999	1.12	0.35	2.39	Not rejected	absent
2000–2004	0.29	0.89	2.38	Not rejected	absent
2005–2007	0.64	0.64	2.38	Not rejected	absent
2008–2009	0.66	0.62	2.39	Not rejected	absent
2010–2013	0.24	0.91	2.38	Not rejected	absent
2014–2015	0.25	0.91	2.39	Not rejected	absent
2016–2019	0.13	0.97	2.38	Not rejected	absent
2020–2022	0.76	0.55	2.39	Not rejected	absent

Null hypothesis status is provided for the case of 95% confidence level.

The results of the ANOVA analysis are in line with those obtained from the *t*-tests, confirming that no statistically significant differences are detected and providing no evidence of the existence of a day-of-the-week effect in the Ukrainian stock market.

The next step is the use of non-parametrical Kruskal–Wallis Tests (Table 12).

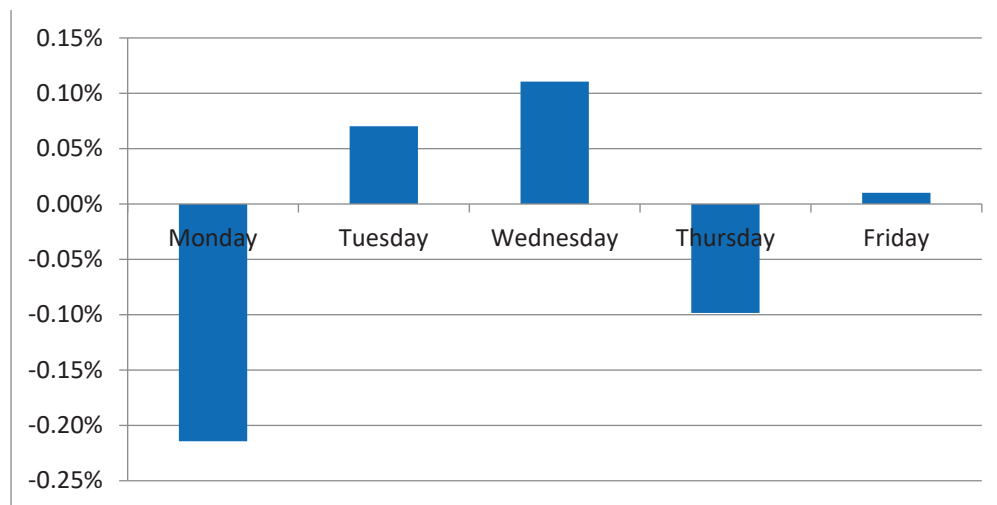
The results of the Kruskal–Wallis tests in general confirmed the conclusions of parametric tests with one exception: during the period 2020–2022, statistically significant differences were observed between different days of the week. However, this conclusion does not specify which days of the week differ from the others.

To clarify this point additional research for this period is provided. Visual analysis (see Figure 4) indicates that Monday is characterized by an anomalously strong price movement compared to other periods, namely a decline in prices.

Table 12. Testing the statistical significance of day-of-the-week effects: Kruskal–Wallis Tests.

Period	Adjusted H	d.f.	p-Value	Critical Value	Null Hypothesis	Difference
1995–1999	5.95	4	0.20	9.49	Not rejected	absent
2000–2004	3.97	4	0.41	9.49	Not rejected	absent
2005–2007	2.88	4	0.58	9.49	Not rejected	absent
2008–2009	1.74	4	0.78	9.49	Not rejected	absent
2010–2013	1.63	4	0.80	9.49	Not rejected	absent
2014–2015	1.36	4	0.85	9.49	Not rejected	absent
2016–2019	0.98	4	0.91	9.49	Not rejected	absent
2020–2022	9.76	4	0.04	9.49	rejected	present

Null hypothesis status is provided for the case of 95% confidence level.

**Figure 4.** Average daily returns in the Ukrainian stock market for the period 2020–2022: the case of days of the week.

As can be seen, returns on Monday were much lower compared with the other days of the week. To see whether this difference is statistically significant parametric ANOVA analysis and non-parametric Mann–Whitney tests are applied. The results of the ANOVA analysis are presented in Table 13.

Table 13. ANOVA analysis for the case of the day-of-the-week effects in the Ukrainian stock market during the period 2020–2022.

Day	F	p-Value	F Critical	Null Hypothesis	Difference
Monday	2.59	0.11	3.89	Not rejected	absent
Tuesday	1.92	0.17	3.89	Not rejected	absent
Wednesday	1.06	0.30	3.89	Not rejected	absent
Thursday	0.36	0.55	3.89	Not rejected	absent
Friday	0.03	0.86	3.89	Not rejected	absent

Null hypothesis status is provided for the case of 95% confidence level.

The results of Table 13 confirm the conclusions of the ANOVA analysis for all days provided in Table 11—there are no statistically significant differences between individual days of the week.

As for the non-parametric Mann–Whitney tests, they are presented in Table 14.

Table 14. Mann–Whitney tests for the case of the day-of-the-week effects in the Ukrainian stock market during the period 2020–2022.

Day	Adjusted H	d.f.	p-Value	Critical Value	Null Hypothesis	Difference
Monday	6.27	1	0.01	3.84	rejected	present
Tuesday	2.39	1	0.12	3.84	Not rejected	absent
Wednesday	5.04	1	0.02	3.84	rejected	present
Thursday	0.22	1	0.64	3.84	Not rejected	absent
Friday	0.00	1	0.98	3.84	Not rejected	absent

Null hypothesis status is provided for the case of 95% confidence level.

Non-parametric tests, unlike parametric ones, indicate that returns on Mondays and Wednesdays differ from the typical price behavior throughout the week. Therefore, there is evidence supporting a day-of-the-week effect during the period 2020–2022, characterized by a presence of negative returns in prices on Mondays and a tendency for the market to demonstrate positive dynamics on Wednesdays.

Considering that throughout all other periods, starting from 1995–1999, anomalies were entirely absent, it can be argued that there is a certain degradation of the Ukrainian stock market from the point of its efficiency.

In general, the analysis of anomalies has shown that the Ukrainian stock market was immune to the day-of-the-week effect. There are no specific trends in their development depending on the period. Thus, the hypothesis that the evolution of the stock market led to an increase in its efficiency in terms of the presence of fewer anomalies has not been confirmed.

4. Discussion

Summarizing the results of the evolution of the Ukrainian stock market, it can be concluded that the level of its efficiency did not demonstrate a clear trend of growth. Existing evidence is mixed, ranging from certain signs of movement towards greater efficiency (R/S analysis and volatility analysis) to clear signs of the degradation of the Ukrainian stock market (movement towards greater inefficiency observed for the case of day-of-the-week effect). Based on these results it is hard to call the last 30 years a development of the Ukrainian stock market.

Partially, this can be attributed to the extremely unstable situation in Ukraine, both economically and politically. The 1990s witnessed a transition from the Soviet economic model to a market-oriented one, during which neither citizens nor companies were familiar with the stock market. The early 2000s saw rapid development in the Ukrainian stock market, but the 2004 revolution marked a significant shift in mentality and development trajectory, impacting the stock market as well. Subsequently, the global financial crisis of 2007–2009, with some time lags, further disrupted the Ukrainian stock market, which has yet to fully recover. Additionally, the revolution of 2013–2014, accompanied by the annexation of Crimea and the onset of war with Russia, led to the physical loss of many industrial companies, plunging the Ukrainian stock market into a new phase of degradation and depression. The full-scale invasion of Russia in 2022 caused the largest war in Europe since WWII, resulting in a one-third loss of Ukrainian GDP and the actual disappearance of the Ukrainian stock market. In 2024, it was only nominally present. Given this tumultuous history, the results of this paper may not be as confusing as they initially appear, and it cannot be conclusively argued that they contradict the AMH.

No wonder the reforms and legislative as well as regulatory changes that took place had little or no impact on the nature of price behavior and the properties of prices as data series. This, in turn, justifies the relevance and necessity of further reforming the Ukrainian stock market and its evolution needs more time.

An additional argument in this favor is that Ukraine's asset price transmission channel is not working. The National Bank of Ukraine primarily operates through other trans-

mission channels, notably the Exchange Rate and Credit Channel. This is mainly because the Ukrainian stock market wields minimal influence over the country's financial system. Hence, it is imperative to prioritize the development of the Ukrainian stock market.

Factors influencing the development of the Ukrainian stock market encompass various aspects, including the end of the war and post-war economic recovery. Additionally, security guarantees and the alignment of Ukrainian legislation with European standards play pivotal roles. Furthermore, the influx of foreign funds is significant, but the establishment of proper stock market infrastructure and business processes is equally crucial. Moreover, the growth of financial literacy among the population and the fostering of an investment culture are essential for market development. Addressing information asymmetry and transparency issues within the Ukrainian stock market are other vital factors. Lastly, introducing new financial products such as futures, options, ETFs (Exchange Traded Funds), and ESG indices contributes to market diversification and growth.

In conclusion, following the war, the Ukrainian stock market is poised to embark on a new trajectory, indicating that the market is still far from achieving efficiency, as evidenced by the findings of this paper.

5. Conclusions

This paper explores the transformation of the Ukrainian stock market through an analysis of various data properties. Daily returns from the leading Ukrainian stock market index PFTS spanning 1997–2022 are examined, with the data set divided into sub-periods to identify differences in data properties. The following hypothesis is tested in this paper: efficiency of the Ukrainian stock market increases over time.

To test this hypothesis a number of data properties are explored: persistence, volatility, normality, and resistance to anomalies. To do these different methods and techniques are used: descriptive statistics, parametric tests (*t*-tests, ANOVA-analysis), non-parametric tests (Mann–Whitney test, Kruskal–Wallis test), data normality tests (Kolmogorov–Smirnov test), R/S analysis, regression analysis with dummy variables.

Volatility (measured by the standard deviation) shows a general decreasing trend, suggesting a shift towards a more efficient market. However, there are no statistically significant differences in returns for different sub-periods, except for the period from 2005 to 2007, which contradicts conclusions from volatility analysis.

The R/S analysis indicates the presence of persistence in the Ukrainian stock market, suggesting that past prices contain information about future prices. Despite this, there is a decreasing trend in Hurst exponent values, indicating a transformation towards a more efficient market and less predictable prices.

Normality tests reveal a normal distribution of daily returns in the Ukrainian stock market across all analyzed sub-periods, with no significant shifts in data properties over time. Similarly, the market shows immunity to the day-of-the-week effect, although there are signs of degradation during the period from 2020 to 2022. Thus, the hypothesis that the evolution of the stock market led to an increase in its efficiency in terms of the presence of fewer anomalies has not been confirmed.

Overall, the results suggest a lack of systematic changes in data properties in the Ukrainian stock market over time, which can be attributed to the country's unstable economic and political situation. Over the past 30 years in Ukraine, there have been two revolutions, numerous economic crises, territorial annexations, and a full-scale Russian invasion, resulting in the largest war in Europe since WWII.

Policy makers can leverage the findings of this paper as a roadmap for their regulatory endeavors. Their primary focus should revolve around post-war economic recovery and ensuring security guarantees. Subsequent efforts should entail harmonizing Ukrainian legislation with European standards, attracting foreign investment, bolstering stock market infrastructure, promoting financial literacy, and introducing innovative financial products such as futures, options, ETFs, and ESG indices.

Furthermore, the results of this paper hold implications for investors, particularly in exploiting abnormal negative returns observed on Mondays in the Ukrainian stock market over recent years. Implementing a straightforward trading strategy of selling on Mondays could yield additional profits, albeit subject to further verification through trading simulations. This avenue presents a promising area for future research, along with exploring other potential price anomalies such as momentum and contrarian effects following abnormal returns, the Month of the Year effect, the Halloween effect, and the Holiday effect.

Moreover, future research directions could include the use of more sophisticated methodologies to investigate data properties. For example, instead of R/S analysis fractional integration methodology can be applied.

Author Contributions: Conceptualization, A.P. and L.H.; methodology, A.P.; software, O.Y.; validation, A.P., O.H. and L.S.; formal analysis, L.H.; investigation, O.Y.; resources, A.P. and L.H.; data curation, A.P.; writing—original draft preparation, A.P., L.H., O.Y., O.H. and L.S.; writing—review and editing, A.P.; visualization, O.H. and L.H.; supervision, A.P.; project administration, L.H.; funding acquisition, A.P. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: Dataset available on request from the authors.

Acknowledgments: Alex Plastun gratefully acknowledges financial support from the University of Liverpool (UK).

Conflicts of Interest: The authors declare no conflicts of interest.

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Article

Stock Overvaluation, Management Myopia, and Long-Term Firm Performance

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Abstract: How does stock overvaluation in secondary financial markets affect long-term firm performance when significant corporate “insiders” seek to realize self-benefit? Using a sample of Chinese listed companies from 2007 to 2018, we find that overvaluation of stock price has a negative impact on long-term firm performance. Moreover, our results show that management myopia mediates the relationship between stock overvaluation and long-term performance. Our study enriches the discussion of stock overvaluation and extends the management myopia literature by considering unique aspects of the irrational behavior of firm decision makers, providing implications for governments to improve their capital market reform and development.

Keywords: stock overvaluation; management myopia; capital market; long-term firm performance

1. Introduction

Promoting the reform of China’s registration-based IPO system and guiding the capital market to reasonable pricing are together a social-concern issue for guaranteeing the sustainable growth of capital market entities. Since the establishment of the China Securities Regulatory Commission (CSRC) in 1992, China has long practiced the approval-based system. IPO-waiting companies take considerable time to list because of the complex recommendation, selection, and approval processes by local authorities and the CSRC. The scarcity of IPOs has made China’s retail investors focus on chasing price trends in secondary markets, providing scholars with an ideal background for studying the economic consequences of stock overvaluation.

Existing research focuses primarily on how prices in primary markets affect firm performance. Owing to the phenomenon known as the “three highs” (high issue price, high P/E ratio, and high excess funds raised) in China’s IPO firms, overvalued equity directly increases the funds that firms raise and facilitates operating and investing activities (Cai et al. 2008; Chan et al. 2004; Li et al. 2018), yet few studies show concern about the real effect of secondary market prices. Some scholars have explored financing roles: stock overvaluation facilitates corporate equity mergers and acquisitions, expands firm size (Shleifer and Vishny 2003), and eases financing constraints (Campello and Graham 2013; Titman 2013); but Bond et al. (2012) have argued that there are three new mechanisms based on information roles—learning, incentive, and irrational behavior. Managers may learn from stock prices and use price information as an anchor for their actions. Surging prices may induce self-confidence and encourage irrational managers to take on more risky investments, which may result in unfavorable outcomes (Chen et al. 2007; Goldstein and Guembel 2008).

The purpose of our study is to draw on and extend Bond et al.’s (2012) research and analyze whether managerial myopia may explain long-term firm performance as a result

of stock overvaluation. In the literature, managerial myopia refers to managers' tendency to invest for short-term gains rather than long-term payoffs (Lavery 1996). As China has a more concentrated ownership structure, price changes tend to trigger myopia among core decision makers, which may have a profound effect on a firm's sustainability when not properly addressed. To the best of our knowledge, few empirical studies have explored the role of managerial myopia within the context of stock overvaluation.

We select Chinese A-share listed companies from 2007 to 2018 to test our hypotheses. Empirical results show that stock overvaluation increases short-term performance but, overall, harms long-term performance. In addition, we test the mediating effect of managerial myopia, where stock overvaluation induces myopia behavior, resulting in a significant performance slump in the long run.

The contribution of this study is as follows. First, we investigate the long-term real effects of stock overvaluation in secondary markets. It is imperative that firms focus on the long run, which shows better capability in resisting environmental threats and achieving sustainable development (Cao et al. 2022; Rostami et al. 2022), and this supplements existing literature on firm performance. Second, based on the information role raised by Bond et al. (2012), this study considers equity sold by corporate insiders and slower R&D growth as new mediators, which is distinguished from previous research that mainly focuses on overinvestment. Third, our findings have implications for practice. Stock market bubbles occasionally occur across countries, destroying a firm's intrinsic value and leading to economic chaos, such as the IT bubble in the United States in the early 2000s and the Chinese stock market crash in 2015. Policy makers should thus accelerate their reform of the registration system in the financial market, increase transparency of information disclosure, and strengthen internal firm governance to alleviate the phenomenon of stock overvaluation that may disrupt the capital market.

2. Literature Review and Hypothesis Development

2.1. Stock Overvaluation and Firm Performance

Stock overvaluation refers to the situation where the market price of a firm's stock is higher than its intrinsic value (Fu et al. 2013). In other words, the stock is trading at a price not justified by the firm's financial performance or future prospects. Several factors may contribute to stock overvaluation: investors are overly optimistic about the stock market, since they are influenced by market sentiment or have non-public information (Seybert and Yang 2012); market bubbles lead to the general overvaluation of stock prices (Dong et al. 2021); or market participants may push up the stock price by market manipulation (Fu et al. 2013).

To resolve the inconsistent findings on the dual effects of stock overvaluation in the literature (Campello and Graham 2013; Jensen 2005; Shleifer and Vishny 2003), we discuss the short- and long-term impacts of stock overvaluations on firm performance. In the short term, firms may perform better when the stock prices are overvalued. An overvalued stock price attracts more investors, increasing a firm's market value and strengthening market position (Goldstein et al. 2013). The focal firms may also benefit from better financing opportunities, trading conditions, and greater market recognition as a result of stock overvaluation (Baker et al. 2003; Shleifer and Vishny 2003). In the long term, however, stock overvaluation overall indicates a negative performance impact. Investors may pursue overvalued stocks for short-term profits, pushing up stock prices, and this delivers favorable signals to the market. However, once large shareholders sell their stocks in quantities and show less concern about a firm's future value (Brown and Cliff 2004), the stock price crashes. Moreover, managers face higher market expectations and assessment pressures when stock prices reach a peak (Goldstein et al. 2013). To maintain overvalued prices, managers may take risks to meet investors' expectations, including overinvestment (Jensen 2005), earning management (Stein 1996), and excessive financial leverage (Bushee 1998). However, the waste and dispersion of resources can result in a decline in return on investment and damage to the firm's competitiveness, thereby reducing its profitability in the long run (Moeller et al. 2005). Therefore, we propose the following hypothesis:

Hypothesis 1. *Stock overvaluation facilitates a firm's short-term performance while hindering future performance in the long term.*

2.2. The Mediating Role of Managerial Myopia

The concept of managerial myopia is argued by Laverly (1996) as “decision-making behavior that maximizes short-term profits, but not long-term profits” in discussing economic short-termism. Two mutually exclusive choices must be decided by managers under intertemporal circumstances: one leads to immediate private benefit in the short term with spending less effort, and the other may bring about more profit in the long run but requires more effort and patience in operating activities. Intuitively, managers are assumed to be entirely rational; they may also take speculative actions for short-term benefit to avoid future uncertainties.

When it comes to stock overvaluation, excessive rising prices allow for more rent-seeking opportunities for management. Bolton et al. (2006) demonstrated that, in a speculative market, managers try to sell overvalued stocks to realize private benefit when their compensation package includes large amounts of stocks. Even where managers are restricted from selling shares, they nonetheless care about the market price because their contracts are in some respects contingent on stock performance. Importantly, in developing economies, stock prices are pushed up by investors' sentiment instead of a firm's intrinsic value. Therefore, managers may lack incentives to invest in a firm's long-run value, since stock prices are less correlated with future growth (Bond et al. 2012). Managers may even make efforts to push up stock price in the short term and create market liquidity by selling their own shares, at the cost of small and medium shareholders (Bolton et al. 2006; Edmans et al. 2017).

For example, LeEco, a Chinese conglomerate listed on the Shenzhen Stock Exchange in 2010, maintains businesses in video streaming, cloud services, and software development. China's investors placed great expectations on LeEco, which set multiple records for being among the most valuable companies on the second-board market. However, Jia Yueting, the chairman of LeEco, insisted on selling his shares for more than CNY 14 billion (USD 2100 million), and showed no interest in the firm's businesses. As a result, LeEco encountered severe financial difficulties due to poor management, and the market value dropped from USD 160 billion to USD 0.7 billion before finally going bankrupt in 2020 (Li and Li 2022).

Secondly, managers may intend to forgo long-term investment programs to maintain short-term stock prices. Managers may use the resources they have at their disposal and their personal authority to influence the size and manner of activities in which the firm invests (Stein 1989). Overvalued stocks tend to be subject to higher market expectations and shareholder pressure (Bolton et al. 2006). As a result, managers are more inclined to choose projects with short maturities and high returns when making investment decisions (Holmström 1999; Narayanan 1985). For long-term investments, approaches such as R&D are not the primary investment objectives of managers (Maritan 2001). Since R&D investment requires a large amount of capital on an ongoing basis, it puts pressure on managers' performance appraisals and cash flow operations (Edmans et al. 2017). There is a high degree of risk and uncertainty as to whether R&D breakthroughs will be realized and translated into products and benefits (Bloom 2007). In addition, R&D benefits take a long time to materialize, and they are primarily intertemporal (Belderbos et al. 2015). As the Chinese proverb says, “A bird in the hand is worth two in the bush”, so that managers are more inclined to seize immediate benefits than rely on nebulous future gains. Therefore, we propose Hypothesis 2:

Hypothesis 2. *Stock overvaluation will lead to managerial myopia.*

Managerial myopia is not exclusively determined by innate and stable personal characteristics; it is also influenced by the environment (Stein 1989). When the stock price is overvalued, myopia is an important feature of management in reducing their

future efforts. Managers place short-term interests above long-term value by ignoring R&D growth, innovation capabilities, talent, market share, and long-term investment returns, and these responses are detrimental to the firm's long-term performance (Bolton et al. 2006; Bond et al. 2012). Therefore, we propose Hypothesis 3:

Hypothesis 3. *Managerial myopia will mediate the relationship between stock overvaluation and long-term performance.*

Our analytical framework is shown in Figure 1, which presents all the hypotheses.

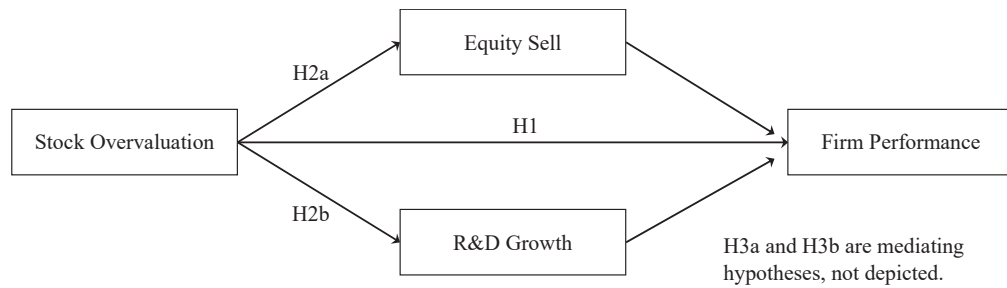


Figure 1. Stock Overvaluation, Managerial Myopia, and Firm Performance.

3. Research Methodology

3.1. Data and Sample

To construct our sample, we started with A-share listed firms on China's Shanghai and Shenzhen Stock Exchanges from 2007 to 2018. Data on stock price and firm fundamentals were derived from the CSMAR database. The following procedures were applied to ensure a representative sample: (1) excluding ST and ST* stocks, which indicate firms are under warnings of delisting; (2) removing firms belonging to the finance and insurance industries; and (3) excluding firms listed for less than one year. Continuous variables were winsorized at the 1st and 99th percentiles to mitigate the influence of extreme value. In total, we obtained a sample of 2444 firms and 16,458 firm-year observations.

3.2. Measures

Dependent variable. The dependent variable is the firm's performance. Following Fairfield et al. (2003), Richardson et al. (2005), and Dechow et al. (2010), we measured the performance effect of overvalued equity on return-on-assets (ROA), which is calculated by a firm's operating income deflated by contemporaneous average total assets. To emphasize our concerns for various time horizons, we regress explanatory variables on ROA in the next 1 to 3 years to study our hypotheses between the short term and the long run.

The independent variable is *Stock Overvaluation*. Rhodes-Kropf et al. (2005) argue that Tobin's Q and market-to-book (M/B) ratio, which are commonly used in firm evaluation, fail to distinguish stock overvaluation from a firm's future growth opportunities. Rhodes-Kropf et al. suggest decomposing the M/B ratio into two parts: (1) *Stock Overvaluation*, defined as the difference between the firm's market value m and the estimated intrinsic value $\hat{v}$, where $\hat{v}$ is calculated using a set of ordinary least squares (OLS) functions that incorporate firm size, leverage, net profit (ni), and an indicator (I) for negative net profit, and (2) *Growth*, measured as a firm's estimated intrinsic value $\hat{v}$ minus book value b , reflecting the firm's future cashflow and growth potential. A large positive value of *Stock Overvaluation* $_{i,t}$ indicates that a firm i 's stock price is overall above its reasonable level in year t . The calculation process is shown in Equation (1):

$$\begin{aligned}
 \ln\left(\frac{M}{B}\right)_{i,t} &= \ln(M_{i,t}) - \ln(B_{i,t}) = m_{i,t} - b_{i,t} \\
 &= (m_{i,t} - \hat{v}_{i,t}) + (\hat{v}_{i,t} - b_{i,t}) \\
 &= \text{Stock Overvaluation}_{i,t} + \text{Growth}_{i,t}
 \end{aligned} \tag{1}$$

where $\hat{v}_{i,t} = f_j(\text{firm size}_{i,t}, \text{leverage}_{i,t}, \text{ni}_{i,t}, I_{i,t})$.
 $= \beta_{0,j} + \beta_{1,j}\text{firm size}_{i,t} + \beta_{2,j}\text{leverage}_{i,t} + \beta_{3,j}\text{ni}_{i,t} + \beta_{4,j}I_{i,t} * \text{ni}_{i,t}$.

In Equation (1), the subscripts i , t , and j denote the firm, year, and industry, respectively, with j representing the industry in which firm i operates. The market-to-book (M/B) ratio is directly retrieved from the CSMAR database, where M , B denote the firm's market capitalization and firm's book value, and the lowercase m , b stand for the logarithm value of M and B .

According to Rhodes-Kropf et al. (2005), the critical issue involves estimating the appropriate $\hat{v}_{i,t}$ for each firm-year observation to break down M/B into *Stock Overvaluation* and *Growth* components. For each industry j , an OLS function f_j with unique parameters β_j should be estimated over the entire research period (i.e., 2007–2018 in this study). This function is designed to capture the specific relationship between a firm's estimated intrinsic value $\hat{v}$, its size, leverage, and profitability within the focal industry. After calculating the numeric value of $\hat{v}$, *Stock Overvaluation* can be directly derived from Equation (1) as the difference between m and $\hat{v}$.

Mediators. We adopted *Equity Sell* and *R&D Growth* as mediators to proxy managerial myopia. First, in China's context, stock holdings are highly concentrated among directors, supervisors, and senior executives (Lakonishok and Lee 2001), where large shareholders own more discourse rights in strategic areas, which is very different from western dispersed ownership structures. We therefore restricted equity selling behavior to significant corporate "insiders", and this is calculated as shares sold by directors, supervisors, and senior management (who own more than 5% of the total shares of the firm) divided by the total shares in the focal year, denoted as *Equity Sell*. Second, followed Edmans et al. (2017), we also used annual growth rate of R&D expenditure (*R&D Growth*) to capture a firm's capability and motivations to invest in long-term strategies.

Control variables. Consistent with existing studies, we controlled several firm-level characteristics, including *Firm Size* (the natural logarithm of a firm's total assets), *Leverage* (a firm's total debt divided by total assets), *Age* (number of years since the firm was listed), *Institution Hold* (the proportion of shares held by institutional investors), *Top 1* (the proportion of shares held by the largest shareholder), *State Hold* (the proportion of shares held by state-owned entities), and *Analyst Coverage* (the number of analysts covering the focal stock divided by 100).

3.3. Statistical Model

We employ firm-level panel regressions to study the relationship between stock overvaluation and firm performance. Industry fixed effect (δ_i) and year fixed effect (η_t) are both controlled in our analysis to mitigate unobserved heterogeneity within industries and years which may independently influence firm performance.

As depicted in Equation (2), the independent variable (*Stock Overvaluation*) is regressed on ROA over the next 1 to 3 years to explore the potential real effect of mispricing across different time horizons. The term $\varepsilon_{i,t}$ represents the regression error. In line with Hypothesis 1, we focus on β_1 and expect $\beta_1 > 0$ in the short term (regressed on next-1-year ROA) and $\beta_1 < 0$ in the long term (regressed on next-3-year ROA):

$$ROA_{i,t+1,t+2,t+3} = \alpha + \beta_1 * \text{Stock Overvaluation}_{i,t} + \beta \text{Controls} + \delta_i + \gamma_t + \varepsilon_{i,t} \quad (2)$$

To investigate the mediating role of *Equity Sell* and *R&D Growth* in the relationship between *Stock Overvaluation* and long-term ROA, we adopt the mediation analysis framework proposed by Baron and Kenny (1986), which involves testing a series of equations as shown in Equations (3)–(5).

First, we examine the effect of *Stock Overvaluation* on the proposed mediators, myopia levels, as indicated by equity sales and R&D investment through Equation (3). Consistent with Hypothesis 2, we posit $\beta_2 > 0$, indicating that *Stock Overvaluation* is associated with higher levels of myopia.

Second, we assess the impact of the mediators (*Myopia*) on the dependent variable (ROA) by testing Equation (4). We anticipate $\beta_3 < 0$, suggesting that higher levels of myopia, which are driven by increased *Equity Sell* and reduced *R&D*, are detrimental to firm performance.

Third, both the mediators (*Myopia*) and the independent variable (*Stock Overvaluation*) are included in Equation (5) to test the full model. According to Hypothesis 3, we expect β_4 , the coefficient for stock overvaluation in the presence of mediators, to be still significant but smaller than β_2 , indicating the impact of stock overvaluation on long-term ROA is partially mediated by the level of myopia.

$$Myopia = \alpha + \beta_2 * Stock\ Overvaluation_{i,t} + \beta Controls + \delta_i + \gamma_t + \varepsilon_{i,t} \quad (3)$$

$$ROA_{i,t+3} = \alpha + \beta_3 * Myopia + \beta Controls + \delta_i + \gamma_t + \varepsilon_{i,t} \quad (4)$$

$$ROA_{i,t+3} = \alpha + \beta_4 * Stock\ Overvaluation_{i,t} + \beta_5 Myopia + \beta Control + \delta_i + \gamma_t + \varepsilon_{i,t} \quad (5)$$

4. Results

Table 1 reports the summary statistics of the variables and their correlations. Variance inflation factors (VIFs) of independent variables ranged from 1.49 to 2.33 and are well below the cutoff of 10, indicating that multicollinearity is not a major concern. The main regressions are presented in Tables 2 and 3.

Table 1. Descriptive Statistics and Correlations.

Variables	Mean	SD	1	2	3	4	5	6	7	8	9	10
1. ROA	0.0379	0.0567										
2. Stock Overvaluation	−0.0002	0.4481	0.1247									
3. Equity Sell	0.0016	0.0088	0.0129	0.0520								
4. R&D Growth	0.8006	1.4670	0.0174	0.0149	0.0407							
5. Firm Size	21.8956	1.2752	0.0327	0.0710	−0.0888	0.0499						
6. Leverage	0.4589	0.2117	−0.3509	−0.0376	−0.1116	−0.0273	0.4161					
7. List Age	9.5094	5.8928	−0.1513	0.0601	−0.1657	−0.0114	0.2277	0.3502				
8. Institution Hold	0.0686	0.0816	0.2840	0.2712	0.0031	0.0400	0.1849	−0.0165	−0.0111			
9. Top 1 Hold	0.3598	0.1524	0.0954	0.0220	−0.0708	−0.0196	0.2703	0.0583	−0.0850	−0.0911		
10. State Hold	0.1872	0.2266	−0.0401	−0.0078	−0.1431	−0.0321	0.3406	0.2239	0.2524	−0.0231	0.4506	
11. Analyst Coverage	0.0709	0.0890	0.3846	0.1786	−0.0067	0.0529	0.4044	−0.0642	−0.1474	0.5139	0.1102	0.0392

Note: Two-tailed tests. Significant at the 0.05 level when Pearson correlations >0.0165 or <−0.0165.

Table 2. Stock Overvaluation and Firm Performance (N = 16,458).

	Model 1	Model 2	Model 3
	ROA _{t+1}	ROA _{t+2}	ROA _{t+3}
Stock Overvaluation	0.0040 *** (0.0014)	0.0013 (0.0014)	−0.0047 *** (0.0016)
Firm Size	−0.0002 (0.0005)	−0.0011 ** (0.0005)	−0.0020 *** (0.0005)
Leverage	−0.0735 *** (0.0029)	−0.0609 *** (0.0028)	−0.0533 *** (0.0031)
List Age	0.0001 (0.0001)	0.0002 ** (0.0001)	0.0004 *** (0.0001)
Institution Hold	0.1021 *** (0.0057)	0.0891 *** (0.0058)	0.0647 *** (0.0066)
Top 1 Hold	0.0406 *** (0.0030)	0.0389 *** (0.0030)	0.0438 *** (0.0034)
State Hold	−0.0083 *** (0.0021)	−0.0067 *** (0.0022)	−0.0025 (0.0023)
Analyst Coverage	0.1489 *** (0.0059)	0.1225 *** (0.0060)	0.1185 *** (0.0068)
Constant	0.0265 ** (0.0121)	0.0484 *** (0.0116)	0.0763 *** (0.0123)
R2	0.255	0.191	0.137

Notes: Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$. Industry and year dummy added.

Table 3. The Mediating Effect of Managerial Myopia (N = 16,458).

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	Equity Sell	ROA _{t+3}	ROA _{t+3}	R&D Growth	ROA _{t+3}	ROA _{t+3}
Stock Overvaluation	0.0008 *** (0.0002)		−0.0045 *** (0.0016)	−0.0747 ** (0.0312)		−0.0045 *** (0.0016)
Equity Sell		−0.1579 *** (0.0542)	−0.1522 *** (0.0541)			
R&D Growth					0.0021 *** (0.0003)	0.0020 *** (0.0003)
Firm Size	−0.0002 *** (0.0001)	−0.0018 *** (0.0005)	−0.0021 *** (0.0005)	0.0089 (0.0133)	−0.0018 *** (0.0005)	−0.0020 *** (0.0005)
Leverage	−0.0006 (0.0004)	−0.0535 *** (0.0031)	−0.0533 *** (0.0031)	0.2128 *** (0.0679)	−0.0538 *** (0.0030)	−0.0537 *** (0.0031)
List Age	−0.0002 *** (0.0000)	0.0004 *** (0.0001)	0.0004 *** (0.0001)	−0.0081 *** (0.0022)	0.0004 *** (0.0001)	0.0005 *** (0.0001)
Institution Hold	0.0004 (0.0009)	0.0606 *** (0.0064)	0.0647 *** (0.0066)	0.7719 *** (0.1699)	0.0588 *** (0.0064)	0.0631 *** (0.0066)
Top 1 Hold	−0.0028 *** (0.0005)	0.0423 *** (0.0034)	0.0433 *** (0.0034)	0.0861 (0.0880)	0.0426 *** (0.0034)	0.0436 *** (0.0034)
State Hold	−0.0018 *** (0.0002)	−0.0027 (0.0023)	−0.0028 (0.0023)	0.0385 (0.0647)	−0.0025 (0.0023)	−0.0026 (0.0023)
Analyst Coverage	−0.0018 * (0.0010)	0.1135 *** (0.0067)	0.1182 *** (0.0068)	−0.1487 (0.1615)	0.1141 *** (0.0067)	0.1188 *** (0.0068)
Constant	0.0072 *** (0.0013)	0.0724 *** (0.0123)	0.0774 *** (0.0123)	0.4492 (0.2858)	0.0702 *** (0.0123)	0.0754 *** (0.0122)
R2	0.071	0.137	0.137	0.090	0.138	0.139

Notes: Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Industry and year dummy added.

Hypothesis 1 predicts that overvalued equity will have a positive performance effect in the short term and a negative effect in the long term. Models 1 and 3 in Table 2 show that the coefficient of stock overvaluation on immediate performance (ROA_{t+1}) is positive ($\beta = 0.0040$, $p < 0.01$), while that on long-run performance (ROA_{t+3}) is significantly negative ($\beta = -0.0047$, $p < 0.01$). This signifies that, as stock overvaluation increases by one standard deviation, the firm's next-period and next-three-period ROA change by +0.179% and −0.211%, respectively. Hypothesis 1 is thus supported.

Hypothesis 2 predicts that overvalued equity leads to managerial myopia, where we should observe more equity sold by significant corporate insiders and lower growth rates in long-term R&D when stock overvaluation is high. As our results in Models 1 and 4 in Table 3 show, the coefficient of stock overvaluation on equity sell is significantly positive ($\beta = 0.0008$, $p < 0.01$), and that on R&D growth is significantly negative ($\beta = -0.0747$, $p < 0.05$). This reveals that a one standard deviation increase in stock overvaluation will increase equity sell by 0.036% of a firm's total shares and decrease R&D growth by 3.35%. Hypothesis 2 is thus supported.

Hypothesis 3 states that managerial myopia mediates the relationship between stock overvaluation and long-run firm performance. Models 2 and 5 in Table 3 support that equity sell overall frustrates long-term performance ($\beta = -0.1579$, $p < 0.01$), and greater investment in R&D accelerates long-term performance ($\beta = 0.0021$, $p < 0.01$). Models 3 and 6 test the mediating effect. Both mediators pass the Sobel test at the 5% significance level, and the proportions of total effect mediated by equity sell and R&D growth are 8.5% and 14.26%, respectively. Hypothesis 3 is thus supported.

Robustness Test

We conducted several additional analyses to ensure the robustness of our findings. First, we used *Return-on-Equity (ROE)* to proxy firm performance and found that the results remain robust (Appendix A.1). Second, we employed two additional measures to proxy for managerial myopia. Following Zhao et al. (2012), we calculated the level of *Earnings Management* by applying the modified Jones model (Appendix A.2).

$$\frac{TA_{i,t}}{A_{i,t-1}} = \beta_0 + \beta_1 * \frac{1}{A_{i,t-1}} + \beta_2 * \frac{(\Delta REV_{i,t} - \Delta REC_{i,t})}{A_{i,t-1}} + \beta_3 * \frac{PPE_{i,t}}{A_{i,t-1}} + \varepsilon_t \quad (6)$$

$TA_{i,t}$ is the total accrued profit; $A_{i,t-1}$ is the total assets at the end of period $t - 1$; $\Delta REV_{i,t}$ is the change in main business income from period t to period $t - 1$; $\Delta REC_{i,t}$ is the change in accounts receivable from period t to period $t - 1$; $PPE_{i,t}$ is the original value of fixed assets at the end of period t . The absolute value of the residuals from the equation was taken as an indicator of managerial myopia. The higher the level of earnings management, the more management tends to embellish financial statements through operational manipulations, indicating an increase in managerial myopia. The results indicated that stock overvaluation significantly increased the level of earnings management, and the increase in earnings management reduced long-term performance, and the mediating effect was also verified. In addition, we applied *Capital Expenditure (CAPEX)* as a proxy for managerial myopia (Appendix A.3), calculated as the net cash outflow from the acquisition of fixed assets, intangible assets, and long-term assets minus the cash inflow from the disposal of these assets, divided by total assets. According to Lavery (1996), managerial myopia might have positive correlations with capital expenditure. However, the results show that the relationship between stock overvaluation and capital expenditure is not significant.

Third, we ran regressions without adding any fixed effect (Appendix A.4). The results that remain unchanged are presented in Appendix A.5. In addition, we controlled the firm fixed effect instead of the industry fixed effect in the regression (Appendix A.5). Similar results were obtained as those obtained in the main analyses. Fourth, we added additional control variables (Appendix A.6). *Cash Flow* represents the firm's cash holdings, calculated as cash reserves divided by total assets. *Duality* indicates the combined role of CEO and chairman. These two variables were selected because they respectively represented the firm's financial robustness and corporate governance structure, both of which had significant impacts on the long-term performance of the company. After incorporating these control variables, both the base regression results and the tests for mediating effects remained significant.

Fifth, we conducted heterogeneity tests using sales growth as a grouping criterion (Appendix A.7). Based on the sales growth median, listed firms were divided into high-growth and low-growth groups. The results indicated that for low-growth listed firms, if the stock price was overvalued by the market, managerial myopia became more pronounced (higher equity sales, lower R&D investment). Correspondingly, stock overvaluation had a more severe impact on these firms' long-term performance. It may be necessary for regulatory authorities to pay closer attention to the issue of stock overvaluation in low-growth firms.

Sixth, we examined the interaction terms between *Institutional Holding*, *Block Holding*, and *SOE Holding* with stock overvaluation (Appendix A.8). Only SOE holding was found to inhibit equity sell in the context of stock overvaluation. Similarly, we used *SOE* as a moderator and found that SOE weakens the relationship between stock overvaluation and firm long-term performance (Appendix A.9). We also find that, when stocks are overvalued, equity selling behavior within SOEs is significantly lower than in non-SOEs. This may be due to the fact that the internal control process of SOEs is more stringent and standardized in the Chinese context, and this has a dampening effect on managerial myopia.

Finally, to further check the robustness of our results, we constructed an instrument variable (IV) to verify our hypotheses (Appendix A.10). We calculate the average level of stock overvaluation within the same industry for a given fiscal year, and we apply this average value as the instrument variable of stock overvaluation. The results remain robust.

5. Discussion

In this paper, we investigate the negative impact of stock overvaluation on firm long-term performance from the perspective of managerial myopia. When the stock price is overvalued, managers may reduce their holdings excessively to obtain a large cash gain directly, and, after the reduction, they care less about the firm's operations and are unwilling to put in more effort to push up the firm's future long-term value. In addition, they may neglect projects that are beneficial to the firm's long-term development, such as R&D growth, while choosing to achieve short-term profits by maintaining an overvalued stock price.

Our results provide evidence that erroneous price signals in the secondary market can affect the motives and decisions of managers, which in turn affects the firm's real operations. This paper considers the characteristics of China's capital market and extends the research related to how the capital market affects the real economy, based on the construction of theoretical models and empirical tests. Unlike those studies based on financing channels in the existing literature, this paper investigates how stock overvaluation may distort the motivation and willingness of managers, which in turn affects corporate decision making, which is more in line with the background of the more stringent equity financing system of China's capital market. The theoretical model and empirical evidence in this paper enrich the literature on managerial myopia and the research on the irrational decision-making effect of stock overvaluation.

This paper also has important practical significance. China's President Xi has emphasized the importance of capital market development and reform in serving the real economy. This paper provides strong evidence supporting the conclusion that the capital market reforms implemented under President Xi's leadership and the Party Central Committee are extremely important for the development of the real economy. These reforms include adhering to capital market reforms, strengthening information disclosure, improving pricing efficiency, and further improving the rules for reducing holdings.

Author Contributions: Conceptualization, J.S., L.W. and Y.S.; methodology, L.W.; software, L.W.; validation, S.W. and Y.S.; formal analysis, L.W.; writing—original draft preparation, J.S. and L.W.; writing—review and editing, Y.S.; supervision, S.W. All authors have read and agreed to the published version of the manuscript.

Funding: We are grateful for the financial support from National Natural Science Foundation of China (NSFC) (72372119).

Data Availability Statement: The database utilized for this research was sourced from the China Stock Market & Accounting Research (CSMAR) platform, accessible at <https://data.csmar.com/>, accessed on 30 March 2024.

Conflicts of Interest: Luyu Wang is employed by the company China UnionPay. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest. The views expressed in this article are solely those of the author and do not represent the views of the institution/organization to which Luyu Wang is affiliated.

Appendix A. Robustness Check*Appendix A.1. Using ROE Instead of ROA*

	Model 1	Model 2	Model 3
	ROE_{t+1}	ROE_{t+2}	ROE_{t+3}
Stock Overvaluation	−0.0029 (0.0034)	−0.0022 (0.0032)	−0.0155 *** (0.0037)
Firm Size	0.0029 ** (0.0013)	0.0011 (0.0013)	−0.0007 (0.0013)
Leverage	−0.0676 *** (0.0078)	−0.0464 *** (0.0072)	−0.0479 *** (0.0075)
List Age	0.0001 (0.0002)	0.0002 (0.0002)	0.0007 *** (0.0002)
Institution Hold	0.2272 *** (0.0132)	0.1937 *** (0.0131)	0.1389 *** (0.0144)
Top 1 Hold	0.0884 *** (0.0070)	0.0812 *** (0.0068)	0.0905 *** (0.0077)
State Hold	−0.0211 *** (0.0052)	−0.0183 *** (0.0051)	−0.0095 * (0.0055)
Analyst Coverage	0.2752 *** (0.0129)	0.2151 *** (0.0131)	0.2158 *** (0.0152)
Constant	−0.0775 ** (0.0303)	−0.0219 (0.0287)	0.0398 (0.0308)
R2	0.151	0.112	0.087

Notes: Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Industry and year dummy added. N = 16,458.

Appendix A.2. Using Earning Management as a Proxy for Myopia

	Model 1	Model 2	Model 3
	Earning Management	ROA_{t+3}	ROA_{t+3}
Stock Overvaluation	0.0070 *** (0.0015)		−0.0060 *** (0.0016)
Earning Management		−0.0163 * (0.0087)	−0.0149 * (0.0087)
Firm Size	−0.0057 *** (0.0006)	−0.0017 *** (0.0006)	−0.0018 *** (0.0006)
Leverage	0.0388 *** (0.0031)	−0.0538 *** (0.0033)	−0.0539 *** (0.0032)
List Age	0.0002 ** (0.0001)	0.0005 *** (0.0001)	0.0005 *** (0.0001)
Institution Hold	0.0058 (0.0071)	0.0590 *** (0.0065)	0.0647 *** (0.0067)
Top 1 Hold	0.0101 *** (0.0037)	0.0412 *** (0.0035)	0.0426 *** (0.0035)
State Hold	−0.0129 *** (0.0027)	−0.0018 (0.0024)	−0.0019 (0.0024)
Analyst Coverage	0.0108 (0.0071)	0.1117 *** (0.0068)	0.1172 *** (0.0069)
Constant	0.1700 *** (0.0129)	0.0702 *** (0.0131)	0.0741 *** (0.0131)
R2	0.089	0.139	0.140

Notes: Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Industry and year dummy added. N = 16,458.

Appendix A.3. Using Capital Expenditure as a Proxy for Myopia

	Model 1	Model 2	Model 3
	CAPEX _{t+3}	ROA _{t+3}	ROA _{t+3}
Stock Overvaluation	−0.0001 (0.0010)		−0.0047 *** (0.0016)
CAPEX		0.0829 *** (0.0108)	0.0829 *** (0.0108)
Firm Size	−0.0006 (0.0004)	−0.0017 *** (0.0005)	−0.0020 *** (0.0005)
Leverage	−0.0004 (0.0020)	−0.0533 *** (0.0030)	−0.0532 *** (0.0031)
List Age	−0.0007 *** (0.0001)	0.0005 *** (0.0001)	0.0005 *** (0.0001)
Institution Hold	0.0384 *** (0.0050)	0.0572 *** (0.0064)	0.0614 *** (0.0066)
Top 1 Hold	0.0017 (0.0026)	0.0426 *** (0.0034)	0.0436 *** (0.0034)
State Hold	−0.0067 *** (0.0017)	−0.0019 (0.0023)	−0.0019 (0.0023)
Analyst Coverage	0.0402 *** (0.0051)	0.1103 *** (0.0067)	0.1152 *** (0.0068)
Constant	0.0581 *** (0.0084)	0.0662 *** (0.0123)	0.0715 *** (0.0123)
R2	0.164	0.139	0.140

Notes: Robust standard errors in parentheses; *** $p < 0.01$. Industry and year dummy added. N = 16,458.

Appendix A.4. Regressions with No Fixed Effect

	Model 1	Model 2	Model 3
	Equity Sell	ROA _{t+3}	ROA _{t+3}
Stock Overvaluation	0.0013 *** (0.0002)		−0.0055 *** (0.0013)
Equity Sell		−0.2016 *** (0.0539)	−0.1841 *** (0.0537)
Firm Size	0.0001 ** (0.0000)	−0.0029 *** (0.0005)	−0.0029 *** (0.0005)
Leverage	−0.0019 *** (0.0003)	−0.0513 *** (0.0028)	−0.0519 *** (0.0028)
List Age	−0.0002 *** (0.0000)	0.0004 *** (0.0001)	0.0005 *** (0.0001)
Institution Hold	−0.0008 (0.0009)	0.0762 *** (0.0065)	0.0836 *** (0.0067)
Top 1 Hold	−0.0028 *** (0.0005)	0.0421 *** (0.0034)	0.0434 *** (0.0035)
State Hold	−0.0030 *** (0.0002)	0.0022 (0.0022)	0.0017 (0.0022)
Analyst Coverage	−0.0037 *** (0.0009)	0.1035 *** (0.0065)	0.1052 *** (0.0065)
Constant	0.0043 *** (0.0010)	0.0856 *** (0.0094)	0.0845 *** (0.0095)
R2	0.046	0.089	0.091

Notes: Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$. Industry and year dummy added. N = 16,458.

Appendix A.5. Using Firm Fixed Effect Instead of Industry Fixed Effect

	Model 1	Model 2	Model 3	Model 4	Model 5
	ROA _{t+1}	ROA _{t+2}	ROA _{t+3}	Equity Sell	R&D Growth _{t+3}
Stock Overvaluation	0.0119 *** (0.0021)	0.0050 *** (0.0019)	−0.0071 *** (0.0023)	0.0011 *** (0.0003)	−0.0849 (0.0555)
Firm Size	−0.0087 *** (0.0018)	−0.0160 *** (0.0017)	−0.0230 *** (0.0017)	0.0001 (0.0001)	−0.1437 *** (0.0380)
Leverage	−0.0177 ** (0.0069)	0.0114 * (0.0062)	0.0288 *** (0.0065)	0.0034 *** (0.0006)	0.3605 *** (0.1359)
List Age	−0.0120 (0.0117)	0.0757 ** (0.0355)	0.0671 (0.0574)	0.0004 (0.0003)	0.1382 (0.0919)
Institution Hold	0.0755 *** (0.0079)	0.0628 *** (0.0075)	0.0260 *** (0.0086)	0.0015 (0.0012)	0.8191 *** (0.2348)
Top 1 Hold	0.0582 *** (0.0107)	0.0518 *** (0.0099)	0.0661 *** (0.0116)	−0.0106 *** (0.0016)	0.2233 (0.2637)
State Hold	0.0035 (0.0052)	0.0053 (0.0045)	0.0062 (0.0046)	0.0015 *** (0.0003)	−0.0602 (0.1619)
Analyst Coverage	0.0582 *** (0.0084)	−0.0016 (0.0077)	−0.0263 *** (0.0093)	−0.0020 (0.0014)	0.0696 (0.2578)
Constant	0.2499 *** (0.0684)	−0.0268 (0.1777)	0.1663 (0.2830)	0.0002 (0.0029)	2.8558 *** (0.8703)
R2	0.061	0.046	0.061	0.024	0.019

Notes: Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Firm and year dummy added. N = 16,458.

Appendix A.6

Appendix A.6.1. Adding Cash Flow and Duality as Control Variables for the Main Regression

	Model 1	Model 2	Model 3
	ROA _{t+1}	ROA _{t+2}	ROA _{t+3}
Stock Overvaluation	0.0040 *** (0.0014)	0.0010 (0.0014)	−0.0046 *** (0.0016)
Firm Size	−0.0003 (0.0005)	−0.0010 ** (0.0005)	−0.0018 *** (0.0005)
Leverage	−0.0595 *** (0.0031)	−0.0481 *** (0.0031)	−0.0411 *** (0.0033)
List Age	0.0001 (0.0001)	0.0002 *** (0.0001)	0.0005 *** (0.0001)
Institution Hold	0.0962 *** (0.0057)	0.0840 *** (0.0058)	0.0596 *** (0.0066)
Top 1 Hold	0.0390 *** (0.0030)	0.0374 *** (0.0031)	0.0425 *** (0.0035)
State Hold	−0.0098 *** (0.0022)	−0.0077 *** (0.0022)	−0.0041 * (0.0024)
Analyst Coverage	0.1460 *** (0.0059)	0.1183 *** (0.0060)	0.1133 *** (0.0068)
Cash Flow	0.0515 *** (0.0037)	0.0485 *** (0.0037)	0.0466 *** (0.0042)
Duality	−0.0026 ** (0.0010)	−0.0012 (0.0010)	−0.0021 * (0.0012)
Constant	0.0120 (0.0122)	0.0316 *** (0.0117)	0.0591 *** (0.0123)
R2	0.265	0.200	0.143

Notes: Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Firm and year dummy added. N = 16,458.

Appendix A.6.2. Adding Cash Flow and Duality as Control Variables for the Mediation Test

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	Equity Sell	ROA _{t+3}	ROA _{t+3}	R&D Growth	ROA _{t+3}	ROA _{t+3}
Stock Overvaluation	0.0009 *** (0.0002)		−0.0045 *** (0.0016)	−0.0680 ** (0.0314)		−0.0045 *** (0.0016)
Equity Sell		−0.1303 ** (0.0538)	−0.1243 ** (0.0538)			
R&D Growth					0.0021 *** (0.0003)	0.0021 *** (0.0003)
Firm Size	−0.0002 *** (0.0001)	−0.0017 *** (0.0005)	−0.0019 *** (0.0005)	0.0087 (0.0135)	−0.0016 *** (0.0005)	−0.0019 *** (0.0005)
Leverage	−0.0016 *** (0.0004)	−0.0415 *** (0.0033)	−0.0413 *** (0.0033)	0.1938 *** (0.0736)	−0.0417 *** (0.0033)	−0.0415 *** (0.0033)
List Age	−0.0002 *** (0.0000)	0.0004 *** (0.0001)	0.0004 *** (0.0001)	−0.0085 *** (0.0022)	0.0005 *** (0.0001)	0.0005 *** (0.0001)
Institution Hold	0.0007 (0.0009)	0.0556 *** (0.0064)	0.0597 *** (0.0066)	0.7343 *** (0.1715)	0.0540 *** (0.0064)	0.0580 *** (0.0066)
Top 1 Hold	−0.0028 *** (0.0005)	0.0412 *** (0.0034)	0.0422 *** (0.0035)	0.1143 (0.0896)	0.0413 *** (0.0034)	0.0423 *** (0.0035)
State Hold	−0.0017 *** (0.0002)	−0.0042 * (0.0024)	−0.0043 * (0.0024)	0.0198 (0.0668)	−0.0040 * (0.0024)	−0.0041 * (0.0024)
Analyst Coverage	−0.0013 (0.0010)	0.1085 *** (0.0067)	0.1132 *** (0.0068)	−0.1448 (0.1639)	0.1090 *** (0.0067)	0.1136 *** (0.0068)
Cash Flow	−0.0040 *** (0.0007)	0.0456 *** (0.0042)	0.0461 *** (0.0042)	−0.0896 (0.0945)	0.0463 *** (0.0042)	0.0468 *** (0.0042)
Duality	0.0000 (0.0002)	−0.0022 * (0.0012)	−0.0021 * (0.0012)	−0.0267 (0.0262)	−0.0022 * (0.0012)	−0.0021 * (0.0012)
Constant	0.0089 *** (0.0013)	0.0555 *** (0.0124)	0.0602 *** (0.0123)	0.4811 (0.2933)	0.0533 *** (0.0123)	0.0581 *** (0.0123)
R2	0.074	0.143	0.143	0.091	0.145	0.145

Notes: Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Firm and year dummy added. N = 16,188.

Appendix A.7. Heterogeneity Test: The Real Effect of Stock Overvaluation with Different Growth Level

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
	ROA _{t+1}		ROA _{t+3}		Equity Sell		R&D Growth	
	HighGrowth	LowGrowth	High Growth	Low Growth	High Growth	Low Growth	High Growth	Low Growth
Stock Overvaluation	0.0126 *** (0.0019)	−0.0057 *** (0.0020)	0.0014 (0.0022)	−0.0106 *** (0.0022)	0.0007 ** (0.0003)	0.0012 *** (0.0003)	−0.0595 (0.0439)	−0.0904 ** (0.0449)
Firm Size	−0.0014 ** (0.0007)	0.0006 (0.0007)	−0.0020 *** (0.0008)	−0.0019 ** (0.0008)	−0.0003 *** (0.0001)	−0.0001 * (0.0001)	0.0118 (0.0182)	0.0081 (0.0193)
Leverage	−0.0802 *** (0.0039)	−0.0691 *** (0.0040)	−0.0622 *** (0.0044)	−0.0456 *** (0.0042)	−0.0004 (0.0007)	−0.0007 (0.0005)	0.0343 (0.0936)	0.3582 *** (0.0973)
List Age	0.0002 ** (0.0001)	0.0003 ** (0.0001)	0.0006 *** (0.0001)	0.0003 ** (0.0001)	−0.0002 *** (0.0000)	−0.0003 *** (0.0000)	−0.0088 *** (0.0031)	−0.0074 ** (0.0031)
Institution Hold	0.0841 *** (0.0072)	0.0997 *** (0.0095)	0.0583 *** (0.0082)	0.0566 *** (0.0115)	0.0004 (0.0012)	−0.0000 (0.0015)	0.6463 *** (0.2044)	1.0318 *** (0.3104)
Top 1 Hold	0.0441 *** (0.0039)	0.0345 *** (0.0045)	0.0483 *** (0.0045)	0.0362 *** (0.0052)	−0.0025 *** (0.0007)	−0.0032 *** (0.0007)	0.1529 (0.1140)	0.0329 (0.1353)
State Hold	−0.0043 (0.0028)	−0.0107 *** (0.0032)	−0.0051 * (0.0030)	−0.0004 (0.0036)	−0.0016 *** (0.0003)	−0.0021 *** (0.0003)	0.1021 (0.0837)	−0.0397 (0.0990)
Analyst Coverage	0.1244 *** (0.0072)	0.1604 *** (0.0095)	0.1096 *** (0.0087)	0.1191 *** (0.0112)	−0.0014 (0.0013)	−0.0017 (0.0016)	−0.1802 (0.2059)	−0.0789 (0.2804)
Constant	0.0542 *** (0.0175)	0.0034 (0.0169)	0.0810 *** (0.0176)	0.0691 *** (0.0173)	0.0086 *** (0.0019)	0.0059 *** (0.0017)	0.2805 (0.3799)	0.4976 (0.4166)
N	8230	8228	8230	8228	8230	8228	8230	8228
R2	0.317	0.204	0.186	0.106	0.070	0.081	0.099	0.094

Notes: Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Firm and year dummy added.

Appendix A.8. The Interaction Effect of Shareholder Structure and Stock Overvaluation

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
	ROA _{t+3}	ROA _{t+3}	ROA _{t+3}	Equity Sell	Equity Sell	Equity Sell	ROA _{t+3}
Stock Overvaluation	−0.0078 *** (0.0019)	−0.0202 *** (0.0033)	−0.0088 *** (0.0019)	0.0008 *** (0.0002)	0.0007 (0.0004)	0.0011 *** (0.0003)	−0.0086 *** (0.0019)
Stock Overvaluation * Institutional Holding	0.0453 *** (0.0140)			0.0009 (0.0016)			
Stock Overvaluation * Block Holding		0.0452 *** (0.0080)			0.0005 (0.0010)		
Stock Overvaluation * SOE Holding			0.0268 *** (0.0048)			−0.0019 *** (0.0005)	0.0266 *** (0.0048)
Equity Sell							−0.1463 *** (0.0539)
Firm Size	−0.0020 *** (0.0005)	−0.0024 *** (0.0005)	−0.0024 *** (0.0005)	−0.0002 *** (0.0001)	−0.0002 *** (0.0001)	−0.0002 *** (0.0001)	−0.0024 *** (0.0005)
Leverage	−0.0530 *** (0.0031)	−0.0527 *** (0.0031)	−0.0524 *** (0.0031)	−0.0006 (0.0004)	−0.0006 (0.0004)	−0.0006 (0.0004)	−0.0525 *** (0.0031)
List Age	0.0005 *** (0.0001)	0.0005 *** (0.0001)	0.0005 *** (0.0001)	−0.0002 *** (0.0000)	−0.0002 *** (0.0000)	−0.0002 *** (0.0000)	0.0004 *** (0.0001)
Institution Hold	0.0574 *** (0.0064)	0.0662 *** (0.0066)	0.0647 *** (0.0066)	0.0003 (0.0009)	0.0004 (0.0009)	0.0004 (0.0009)	0.0647 *** (0.0066)
Top 1 Hold	0.0437 *** (0.0034)	0.0427 *** (0.0034)	0.0436 *** (0.0034)	−0.0028 *** (0.0005)	−0.0028 *** (0.0005)	−0.0028 *** (0.0005)	0.0432 *** (0.0034)
State Hold	−0.0025 (0.0023)	−0.0026 (0.0023)	−0.0031 (0.0023)	−0.0018 *** (0.0002)	−0.0018 *** (0.0002)	−0.0018 *** (0.0002)	−0.0033 (0.0023)
Analyst Coverage	0.1194 *** (0.0068)	0.1184 *** (0.0068)	0.1193 *** (0.0068)	−0.0017 * (0.0010)	−0.0018 * (0.0010)	−0.0018 * (0.0010)	0.1190 *** (0.0068)
Constant	0.0767 *** (0.0123)	0.0836 *** (0.0123)	0.0819 *** (0.0123)	0.0072 *** (0.0013)	0.0073 *** (0.0013)	0.0068 *** (0.0013)	0.0829 *** (0.0123)
R2	0.138	0.139	0.139	0.071	0.071	0.071	0.139

Notes: Robust standard errors in parentheses; *** $p < 0.01$, * $p < 0.1$. Firm and year dummy added. N = 16,458.

Appendix A.9. Using SOE as a Moderator

	Model 1	Model 2	Model 3	Model 4
	ROA _{t+1}	ROA _{t+3}	Equity Sell	ROA _{t+3}
Stock Overvaluation	0.0050 *** (0.0017)	−0.0095 *** (0.0020)	0.0012 *** (0.0003)	−0.0094 *** (0.0020)
Stock Overvaluation X SOE	−0.0034 (0.0021)	0.0117 *** (0.0023)	−0.0011 *** (0.0003)	0.0115 *** (0.0023)
SOE	−0.0088 *** (0.0013)	−0.0055 *** (0.0014)	−0.0012 *** (0.0001)	−0.0057 *** (0.0014)
Equity Sell				−0.1527 *** (0.0540)
Firm Size	0.0001 (0.0005)	−0.0021 *** (0.0005)	−0.0001 ** (0.0001)	−0.0021 *** (0.0005)
Leverage	−0.0731 *** (0.0029)	−0.0519 *** (0.0031)	−0.0006 (0.0004)	−0.0520 *** (0.0031)
List Age	0.0002 ** (0.0001)	0.0005 *** (0.0001)	−0.0002 *** (0.0000)	0.0005 *** (0.0001)
Institution Hold	0.1033 *** (0.0057)	0.0653 *** (0.0066)	0.0006 (0.0009)	0.0654 *** (0.0066)
Top 1 Hold	0.0372 *** (0.0030)	0.0414 *** (0.0035)	−0.0033 *** (0.0005)	0.0409 *** (0.0035)
State Hold	0.0050 * (0.0029)	0.0056 * (0.0031)	−0.0001 (0.0002)	0.0056 * (0.0031)
Analyst Coverage	0.1473 *** (0.0059)	0.1187 *** (0.0068)	−0.0020 ** (0.0010)	0.1184 *** (0.0068)
Constant	0.0227 * (0.0120)	0.0793 *** (0.0122)	0.0064 *** (0.0013)	0.0803 *** (0.0122)
R2	0.257	0.139	0.073	0.140

Notes: Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Industry and year dummy added. N = 16,458.

Appendix A.10

Appendix A.10.1. Using Industry Overvaluation as an Instrumental Variable

	Model 1	Model 2	Model 3	Model 4	Model 5
	ROA _{t+1}	ROA _{t+2}	ROA _{t+3}	Equity Sell	ROA _{t+3}
Industry Overvaluation	0.0108 *** (0.0037)	−0.0015 (0.0037)	−0.0293 *** (0.0046)	0.0020 *** (0.0005)	−0.0290 *** (0.0046)
Equity Sell					−0.1475 *** (0.0542)
Firm Size	−0.0004 (0.0005)	−0.0012 ** (0.0005)	−0.0019 *** (0.0005)	−0.0002 *** (0.0001)	−0.0019 *** (0.0005)
Leverage	−0.0734 *** (0.0029)	−0.0608 *** (0.0028)	−0.0532 *** (0.0031)	−0.0006 (0.0004)	−0.0533 *** (0.0031)
List Age	0.0001 (0.0001)	0.0002 ** (0.0001)	0.0004 *** (0.0001)	−0.0002 *** (0.0000)	0.0004 *** (0.0001)
Institution Hold	0.1044 *** (0.0056)	0.0904 *** (0.0057)	0.0639 *** (0.0063)	0.0009 (0.0009)	0.0640 *** (0.0064)
Top 1 Hold	0.0417 *** (0.0030)	0.0391 *** (0.0030)	0.0422 *** (0.0034)	−0.0026 *** (0.0005)	0.0418 *** (0.0034)
State Hold	−0.0085 *** (0.0021)	−0.0067 *** (0.0022)	−0.0022 (0.0023)	−0.0019 *** (0.0002)	−0.0025 (0.0023)
Analyst Coverage	0.1527 *** (0.0058)	0.1239 *** (0.0059)	0.1145 *** (0.0067)	−0.0009 (0.0009)	0.1143 *** (0.0067)
Constant	0.0274 ** (0.0122)	0.0503 *** (0.0117)	0.0809 *** (0.0124)	0.0075 *** (0.0013)	0.0820 *** (0.0124)
R2	0.255	0.191	0.139	0.071	0.140

Notes: Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$. Industry and year dummy added. N = 16,458.

Appendix A.10.2. Robustness Check—Using Industry Overvaluation as an Instrumental Variable

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	ROA _{t+1}	ROA _{t+2}	ROA _{t+3}	Equity Sell	R&D Growth	ROA _{t+3}
Stock Overvaluation	0.0108 *** (0.0037)	−0.0015 (0.0037)	−0.0293 *** (0.0046)	0.0020 *** (0.0005)	−0.0919 (0.0972)	−0.0289 *** (0.0046)
Equity Sell						−0.1469 *** (0.0542)
R&D Growth						−0.0002 (0.0004)
Firm Size	−0.0004 (0.0005)	−0.0012 ** (0.0005)	−0.0019 *** (0.0005)	−0.0002 *** (0.0001)	0.0124 (0.0132)	−0.0019 *** (0.0005)
Leverage	−0.0734 *** (0.0029)	−0.0608 *** (0.0028)	−0.0532 *** (0.0031)	−0.0006 (0.0004)	0.2114 *** (0.0679)	−0.0533 *** (0.0031)
List Age	0.0001 (0.0001)	0.0002 ** (0.0001)	0.0004 *** (0.0001)	−0.0002 *** (0.0000)	−0.0086 *** (0.0022)	0.0004 *** (0.0001)
Institution Hold	0.1044 *** (0.0056)	0.0904 *** (0.0057)	0.0639 *** (0.0063)	0.0009 (0.0009)	0.7155 *** (0.1665)	0.0642 *** (0.0064)
Top 1 Hold	0.0417 *** (0.0030)	0.0391 *** (0.0030)	0.0422 *** (0.0034)	−0.0026 *** (0.0005)	0.0684 (0.0874)	0.0418 *** (0.0034)
State Hold	−0.0085 *** (0.0021)	−0.0067 *** (0.0022)	−0.0022 (0.0023)	−0.0019 *** (0.0002)	0.0403 (0.0647)	−0.0024 (0.0023)
Analyst Coverage	0.1527 *** (0.0058)	0.1239 *** (0.0059)	0.1145 *** (0.0067)	−0.0009 (0.0009)	−0.2235 (0.1598)	0.1144 *** (0.0067)
Constant	0.0274 ** (0.0122)	0.0503 *** (0.0117)	0.0809 *** (0.0124)	0.0075 *** (0.0013)	0.3960 (0.2850)	0.0817 *** (0.0124)
R2	0.255	0.191	0.139	0.071	0.090	0.140

Notes: Robust standard errors in parentheses; *** $p < 0.01$, ** $p < 0.05$. Industry and year dummy added. N = 16,458.

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Article

Trade Agreements and Financial Market Integration in Latin America and the US

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Abstract: The primary objective of this study is to examine the extent of financial integration between Latin American and US financial markets, particularly in light of recent efforts to foster integration through trade agreements. Spanning from 1 January 1990 to 31 December 2019, the sample focuses on major market indices and key sectors. Financial integration is quantified using a DCC multivariate GARCH model, incorporating a smooth transition model, structural breaks, and regression-based approaches. Results indicate increased comovement with the US for main market indices in Argentina, Chile, Colombia, Mexico, and Peru, while Brazil shows a decrease. Similar trends are observed in sectoral analyses. This study also reveals heightened correlation post-trade agreements. Structural break analysis highlights significant shifts in dynamic correlations for countries with US free trade agreements. These findings support the argument of increased financial integration, bearing significance for portfolio diversification and international policy formulation.

Keywords: trade agreements; international financial integration; comovement; emerging economies; Latin America

JEL Classification: F15; G1; G15; O54

1. Introduction

Financial market integration has been a topic of great interest among academicians and practitioners as it directly impacts investments across the world. Financial integration among countries is significant in many aspects of financial economics. For policymakers, understanding the impact that other countries have on their financial market, hence the country's economy, is of utmost importance. For investors, well-diversified portfolios are created under the idea that correlations are understood, but if these correlations are changing over time, then portfolios should be adjusted based on the time-varying fluctuations of these correlations.

It is important to point out that financial market integration can be measured through several approaches. This investigation focused mainly on one specific measure, comovement, of financial markets. The previous literature has examined the level of comovement within developed countries (Berben and Jansen 2005; Longin and Solnik 1995; Eun and Shim 1989; Shin and Sohn 2006; Rua and Nunes 2009). The results support the argument that market integration is time-varying and that the degree of comovement among financial markets in developed countries is increasing. Most of these studies have focused on financial integration between major developed countries. However, financial market integration between emerging economies has not been examined as thoroughly as developed markets in recent time, even though investors are flocking towards international investments seeking a higher degree of diversification. Forbes and Rigobon (2002) study comovement among international stock markets and find that correlation coefficients are conditional on the examined markets' volatility. In addition, Bekaert and Harvey (1995) show that

some Latin American equity markets tend to have a low correlation with the US, while Johnson and Soenen (2003) show that Latin American markets' comovement with the US is changing in different directions. Also, Fujii (2005) investigate the links between selected Asian and Latin American countries and find significant market connections between the examined Asian and Latin American markets.

There is a substantial amount of recent literature studying the relationship between trade integration and financial integration. Vo (2022) investigates this relationship in Asia using a dataset covering the period from 2001 to 2015. They find a positive and significant bidirectional relationship between international trade integration and international financial integration. Abbasov (2019) found that trade integration has a positive effect on financial integration in both the short and long term for OECD and G20 countries during 2000–2016. Erkut and Sharma (2023) study whether the degree of trade integration in Asia also spills over to financial integration by focusing on Asian trade production networks. Didier et al. (2017) examine the complementarity between trade and financial flows in East Asia and the Pacific. Lim and Breuer (2019) find evidence that after free trade agreements, trade costs have been reduced for nine countries, providing evidence that greater market integration has been achieved in South Korea. Wang et al. (2023) analyze how the deepening of free trade agreements promotes the growth of China's international trade.

Latin American countries have been working to integrate their main financial markets. These efforts have increased access to capital for both domestic and international firms. For example, the creation of the Mercado Integrado Latinoamericano (MILA), which is an integrated exchange that consists of four of the most relevant markets in the region (Chile, Colombia, Mexico, and Peru). With this new integration, stocks from all these countries can be traded by investors in any of the four markets in their original currency. Further, regional cooperation organizations like Latin American Integration Association (ALADI) or Mercosur (South American Common Market) have helped unite these countries in a wide range of factors. These efforts have also focused on aiding economies and financial markets to interact more closely within this region.

In addition, regional trading deals such as the North American Free Trade Agreement (NAFTA), which involves a direct free trade agreement between Canada, the US, and Mexico, was established in 1994. This trade agreement included tariff reductions for a significant number of goods between these countries that were gradually reduced until 2008. In 2019, a new NAFTA deal is being prepared.¹ This was the initial free trade agreement between the US and any Latin American country. The US government has gradually increased trade and cooperation efforts with several countries in this region by creating trade agreements with a significant number of countries in Central and South America.

The US has put in place several bilateral trade agreements with countries in this region. For example, the US government has utilized three main types of trade agreements with countries in the Latin American region, which are: the Trade and Investment Framework Agreement (TIFA), Agreement on Trade and Economic Cooperation (ATEC), and bilateral Free Trade Agreements (FTA). A Trade and Investment Framework Agreement (TIFA) is considered a trade deal that creates a strategic framework to expand trade and resolve any disputes between countries. The Agreement on Trade and Economic Cooperation (ATEC) created between Brazil and the US is a specific agreement between these countries. The ATEC is a unique pact in the sense that it promotes bilateral trade and economic cooperation, but it is not a full free trade agreement. In essence, the agreement is very similar to a Trade and Investment Framework Agreement (TIFA), and it is perceived as a first step towards the creation of a future free trade agreement between both countries. These agreements tend to pave the way for bilateral free trade agreements with the US. A free trade agreement is a trade deal that diminishes barriers of imports and exports. Under a free trade agreement, goods and services can be exchanged across countries' borders with minimal or no government tariffs, quotas, subsidies, or prohibitions. This type of trade pact is the strongest among the three different types the US has used within this region. Nonetheless, all the above-mentioned trade agreements intend to reduce trade and

investment barriers, open markets, and eliminate obstacles between these two countries over time.

Specifically in this region, the US has created three different free trade agreements. NAFTA includes three countries (the US, Mexico, and Canada), while the remaining deals are bilateral free trade agreements. The US has a bilateral free trade agreement with Chile, Colombia, and Peru. Moreover, The United States–Chile Free Trade Agreement (FTA) entered into force on 1 January 2004, but the deal was signed on 6 March 2003. The United States–Colombia Trade Promotion Agreement (FTA) was signed on 22 November 2006, but took about 6 years to put into force on 15 May 2012. Of the bilateral free trade agreements, the Colombian pact took the longest to get implemented after the official signature between the countries. The United States–Peru Free Trade Agreement (FTA) entered into force on 1 February 2009, while it was initially agreed upon on 12 April 2006. On the other hand, the US has also instituted a TIFA and an ATEC with Argentina and Brazil, respectively. On 18 March 2011, the US and Brazil signed an Agreement on Trade and Economic Cooperation (ATEC) to strengthen trade and investment between the two nations. Finally, Argentina and the US signed a bilateral Trade and Investment Framework Agreement (TIFA) on 23 March 2016 to advance trade and market accessibility between both countries.² As a result, these trade agreements have strengthened the ties between the US and these six countries on a wide range of levels, sectors, and industries.

All these integration efforts have been of great importance considering the close geographical proximity between these countries. For instance, Bae et al. (2019) state that most Latin American countries import heavily from the US. According to Bae et al. (2019), the US is the largest importer for all the Latin American countries examined in this paper, which shows these countries are deeply connected in a wide range of levels. According to Forbes and Chinn (2004), trade flows are one of the most relevant determinants of cross-country relations. Basnet and Sharma (2013) examine the integration in terms of macro variables (i.e., GDP, Investment, Trade, and Consumption) between the major Latin American countries, and this study concludes that these countries are getting a higher degree of synchronization both in the short and long term. Consequently, the expectation is that the trade agreements are able to help these countries accelerate integration among the studied stock markets.

Whether the degree of comovement has increased or decreased, it is of great importance to closely examine these correlations to determine how to properly construct portfolios. This has been overlooked due to their market size and slow development. Consequently, this study brings a contribution to the existing literature by examining the degree of financial integration, through market comovement, within the stock markets in Latin America as well as their degree of comovement with the American market. In addition, this investigation helps determine how these trade agreements affect financial market integration and if they have been a direct catalyst for a higher or lower degree of integration.

Finally, the main objectives of this paper are twofold. First, to research the level of financial market integration between the US and the main Latin American markets over time. Second, to explore if the different types of trade agreements between the US and these countries have impacted the comovement of these financial markets. This study concludes that the degree of comovement between the US and the main Latin American countries (Argentina, Brazil, Chile, Colombia, Mexico, and Peru) vary widely. Different sectors and industries are affected differently through the sample, and the trade agreements seem to impact sectors that deal with physical products (basic materials, consumer goods, industrial, financial, and energy) more than the others. In terms of the main market indices, the results show that the integration with the American market index (S&P 500) has increased over time for all the countries except for Brazil, which had a small reduction in correlation during the end of the sample period.

The rest of the study is organized as follows. Sections 2 and 3 present the methodology and data, respectively. Section 4 reports empirical results. Section 5 offers concluding remarks of this study.

2. Methodology

To thoroughly research the correlations between the returns of the different stock markets, this paper investigates the dynamic conditional correlations between the American market index and sector indices with their Latin American counterparts. This approach will help us determine the level of comovement between the market index as well as different sector indices. In addition, a smooth transitional model is introduced to establish the changes in correlation over time, while structural breaks on this correlation are implemented to determine if the signing and/or implementation of the trade agreements had a direct impact on these correlations. Finally, a regression-based approach is considered to study the degree of comovement before and after the signing and/or implementation of the trade agreements.

As previously mentioned, this paper focuses on one of the most used measures of financial integration: comovement between market indices. For asset return volatility, it is shown that large changes in returns in one period tend to be followed by large changes in the following periods. This is called volatility clustering, which usually becomes more evident as the frequency of the data rises. The GARCH class models have proven to be successful in capturing volatility clustering. As shown in previous studies, GARCH models appear to properly account for the stochastic properties of stock returns and correlation, in other words, time-variation and persistence of the variables.

Taking these properties into account, this paper will follow the dynamic conditional correlation (DCC) approach proposed by Engle (2002). The dynamic conditional correlation model can determine how correlations among the examined countries have changed through the studied sample. Therefore, this model can measure comovement between the US and the Latin American financial markets. The DCC-GARCH model follows:

$$r_t = \mu_t + \varepsilon_t, \varepsilon_t | I_{t-1} \rightarrow N(0, H_t) \quad (1)$$

where r_t is a $k \times 1$ vector that consists of the index return series for each market, and H_t is the conditional variance–covariance matrix of the return vector r_t , while $\varepsilon_t | I_{t-1}$ accounts for the information set that considers all the information up to time t . Further, the conditional variance–covariance matrix can be expressed as follows:

$$H_t = D_t R_t D_t \quad (2)$$

and

$$D_t = \text{diag}(\sqrt{h_{1t}}, \sqrt{h_{2t}}) \quad (3)$$

where D_t is the 2×2 diagonal matrix of time-varying standard deviations from the univariate GARCH models with $\sqrt{h_{it}}$ on the diagonal, and R_t is considered the time variant conditional correlation matrix. Thus, we first estimate the univariate volatility model for each market, and the best one is selected using the Akaike Information Criterion (AIC). The considered models include the GARCH model proposed by Bollerslev (1986), EGARCH model proposed by Nelson (1991), TGARCH proposed by Zakoian (1994) and GJR-GARCH of Glosten et al. (1993). Consequently, the residuals of each are specific market are utilized to estimate the dynamic conditional correlation matrix R_t .

The dynamic conditional correlation matrix R_t is expected to change based on a GARCH process and follows:

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1} \quad (4)$$

In this case, Q is the unconditional correlation matrix of the ε 's and follows:

$$Q_t = (1 - a - b) \bar{Q} + a \varepsilon_{t-1}^{-1} \varepsilon'_{t-1} + b Q_{t-1} \quad (5)$$

The parameters a and b represent the effect of preceding shocks and former dynamic correlations. These estimates are obtained from the univariate GARCH estimations, and they satisfy $a + b > 1$.

The bivariate conditional correlation coefficient ρ_{ij} between two markets therefore follows the equation:

$$\rho_{ij} = \frac{(1 - a - b)\bar{Q} + a\epsilon_{t-1}^{-1}\epsilon'_{t-1} + bQ_{t-1}}{\sqrt{(1 - a - b)\bar{Q}_{ii} + a\epsilon_{i,t-1}^2 + bQ_{ii,t-1}}\sqrt{(1 - a - b)\bar{Q}_{jj} + a\epsilon_{j,t-1}^2 + bQ_{jj,t-1}}} \quad (6)$$

In addition, it is important to examine the effects of free trade agreements within the conditional correlations of the US and these Latin American countries. Therefore, the second approach is to use structural breaks within the dynamic conditional correlations between these countries' indices. For this approach, two different structures were used. The first one tested for structural breaks for known dates, which in this case, will be the signing date and implementation or start date. The other structure lets the data determine the structural breaks, and the idea is to establish the breaks and their location in a linear regression framework. Following Bai and Perron (2003), if we assume that the dynamic conditional correlations have m number of breaks ($b_1 \dots b_m$), then we determine the date of any structural breaks by focusing on the breakpoints that minimize the following function:

$$\hat{b}_1 \dots \hat{b}_m = \underset{\hat{b}_1 \dots \hat{b}_m}{\operatorname{argmin}} \operatorname{RSS}_{\hat{b}_1 \dots \hat{b}_m} \quad (7)$$

where RSS is the residual sum of squares that results from the b regressions. These regressions that the following form:

$$y_t = \beta x_t^T + \epsilon_t; (t = 1, 2, \dots, n) \quad (8)$$

In this case, the y_t is the estimated bivariate dynamic conditional correlation series at time t , x_t is a vector of the observations of y_{t-1} , β is the vector of regression coefficients, and ϵ_t is the error term which is assumed to be independent and identically distributed ($0, \delta^2$).

The null hypothesis states that there is no structural break, while the alternative hypothesis is that the regression coefficients vary over time. Therefore, if we reject the null, then we conclude that the estimated structural break is statistically significant. The idea is to determine if a structural change occurred around the trade agreements.

Structural breaks assume that changes in comovement are instantaneous and readily visible. This might not always be the case considering that these markets can gradually integrate rather than at a determined point in time, regardless of external shocks that impact integration. As a result, the structural breaks approach has several limitations that can be mitigated using other methods. One of those methods is the smooth transition model. The idea behind the smooth transition model is to measure the changes in comovement in an extended period rather than at a specific moment in time. This long-term approach gives a better understanding of the movement between the examined markets as the models show the change in comovement over time.

In addition, other researchers have examined DCC-GARCH models with a smooth transition model to detect structure changes in the correlations (Chelley-Steeley 2005; Berben and Jansen 2005; Lin and Teräsvirta 1994). However, a disadvantage of the smooth transition model is that it assumes a single transition period between two long-run means. This model specification can limit the number of structural changes in the correlation in our sample considering the sample covers an extensive amount of time. The smooth transition model is applied to bivariate equity market dynamic conditional correlations, which have been obtained using the previously discussed dynamic conditional correlation (DCC-GARCH) model.

The logistic smooth transition regression model for the conditional correlations time series between the US and the Latin American countries, $\rho_{ij,t}$ estimated earlier, can be expressed as:

$$\hat{\rho}_{ij2t} = \alpha + \beta S_t(\gamma, \tau) + \epsilon_t \quad (9)$$

where ϵ_t is considered a stationary ($I(0)$) process with zero mean. Consequently, the smooth transition between the two examined indices is commanded by the log function $S_t(\gamma, \tau)$. This log function can then be formalized using the following equation:

$$S_t(\gamma, \tau) = 1 + \exp(-\gamma(t - \tau N))^{-1}; (r > 1) \quad (10)$$

where N is the size of the sample. Further, τ establishes the point in which the dynamic conditional correlation changed from pattern one to pattern two. In other words, τ determined the midpoint or the point of change between the dynamic conditional correlations. The midpoint essentially partitions the sample into a section before integration and section after the integration. Therefore, there is a before and an after in terms of average correlation. The α represents the mean of the section of the sample before the midpoint or old structure before integration, while β determines the change in correlations of the sample after the midpoint or turning point, as shown by the smooth transition model. Consequently, if $\beta > 0$, then we can conclude that the newer conditional correlation or the correlation after the midpoint has increased through the sample. On the other hand, if $\beta < 0$, it means that the newer conditional correlation or the correlation after the midpoint has decreased compared to the initial section. As a result, the summation between α and β signifies the mean of the new regime. This method gives us an idea regarding the integration changes over time as well as after the trade agreement.

Although the smooth transition model is able to give us a better representation of the different regimes of correlation, it is also important to note that this approach specifies one single midpoint that serves as the turning point between the changes in correlation. Considering the large time frame, the turning point could appear at any given point in our sample. To determine if dynamic conditional correlations have changed over time, a regression-based approach is taken into consideration. This approach follows:

$$y_t = \alpha_1 + \delta_1 \alpha_2 + \epsilon_t \quad (11)$$

where y_t is the dynamic conditional correlations previously computed, δ is the dummy variable indicating the date after the signing or start date of the trade agreement between the US and the given Latin American country, while α_1 is the constant and α_2 is the coefficient that determines the increase or decrease after the trade agreement. A positive α_2 indicates an increase in correlation after the trade agreement, while a negative α_2 shows a decrease in correlation after the trade agreement. Finally, ϵ_t represents the error term.

3. Data

The data used for this study were collected from DataStream. The most important stock exchange markets in Latin America were selected for this research. The selection was based on market capitalization and data availability and includes the following countries: Argentina, Brazil, Chile, Colombia, Mexico, and Peru. The market indices selected for the mentioned nations are: Merval for Argentina, IBOVESPA or B3 for Brazil, IPSA for Chile, COLCAP for Colombia, IPC for Mexico, and SPBLPGPT for Peru. On the other hand, the two main American market indices in the US were obtained (S&P500 and DJIA).³

In addition, for each country, the main industry sectors were considered. Following the industry classification benchmark (ICB) used by the FTSE for sector and industry classification, the main industry sectors studied are basic materials, consumer discretionary, consumer staples, energy, financials, healthcare, industrials, real estate, technology, telecommunications, and utilities.⁴ However, considering that the healthcare and technology sectors are not present in 4 out of the 7 countries, those were not taken into consideration.

Further, the real estate index is not available for Colombia, while the energy index is not available for Mexico. The idea is to incorporate as many sectors as possible to research how each different sector comoves with the same sectors in the US. The more sectors incorporated, the better one can understand the different changes in correlations with the US.

The data were selected for the period between 1 January 1990 and 31 December 2019. Although some countries only have data available slightly after the selected starting date; if that is the case, the earliest available data are used. From these data, the daily and weekly returns for each index and sector over the entire sample were computed. Moreover, the log daily and weekly returns were considered as well as the daily and weekly raw returns. The results are consistent, but the weekly log returns were used in this study.⁵ To eliminate any possible discrepancies with different currencies and to make the returns more comparable, the returns were calculated in US Dollars. As a result, the weekly log returns in USD were used for the entire analysis.

4. Empirical Analysis

4.1. Preliminary Analysis and Time-Varying Estimation Models

Table 1 presents the summary statistics for every country sorted by industry. The summary statistics show huge variations in returns. Returns range from -25.80% to 86.40% . Also, the volatility of the market in terms of standard deviation of all indices is relatively high during the sample period. Standard deviations range from about 2.20% to 24.01% . In our sample, Colombia is the most vulnerable in terms of returns and standard deviations: it exhibits the highest and lowest returns, and the highest standard deviations among countries. Compared to other countries, the US exhibits the lowest standard deviations and the second highest returns, which show the ideal market conditions.

Figure 1 shows a graphical representation of the returns on the main market indices for each country. A visual representation shows that the market indices for these countries are stationary.⁶ In addition, we generate normality and autocorrelation tests for further analysis.⁷

Billio et al. (2015) show that unconditional correlations performed as well as more sophisticated financial integration measures proposed in the existing literature and, even though many authors have shown that correlation is time varying, the unconditional correlation of each country's main market and sectors indices to determine each country's pairwise correlation without considering the time-variance adjustments. This way one can establish if the correlations have drastically changed during the different time periods. Table 2 shows the correlations among the examined indices. At a first glance, we observe that there are no negative correlations, which indicates that these countries up to a given extent move in the same direction. For the main market index, the highest correlations are between Brazil and Mexico with 0.649 , the US and Mexico with 0.617 . Also, Brazil and the US with 0.574 , and Brazil and Argentina with 0.538 exhibit strong positive correlations as well.

Table 1. Summary Statistics. Table 1 reports summary statistics for Latin American countries and the US. In our Latin American data, we have several Latin American countries including Argentina, Brazil, Chile, Colombia, Mexico, and Peru. We first collect daily financial data and then calculate weekly-based log returns and standard deviations sorted by industries. The sample data period is between 1 January 1990 and 31 December 2019.

	Argentina		Brazil		Chile		Colombia		Mexico		Peru		US	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Market Index	0.059	0.069	0.152	0.058	0.159	0.030	0.097	0.092	0.172	0.045	0.322	0.041	0.141	0.024
Basic Materials	0.047	0.070	0.068	0.055	0.126	0.038	0.199	0.099	0.222	0.050	0.087	0.038	0.119	0.034
Consumer Discretionary	−0.136	0.079	0.149	0.049	0.135	0.041	−0.258	0.105	0.165	0.041	0.249	0.059	0.166	0.024
Consumer Goods	0.104	0.063	0.188	0.047	0.148	0.036	0.049	0.096	−0.115	0.054	0.111	0.034	0.158	0.021
Energy	0.024	0.073	0.170	0.068	0.115	0.042	−0.003	0.102	N/A	N/A	−0.199	0.069	0.099	0.031
Financials	0.054	0.064	0.129	0.054	0.177	0.034	0.063	0.092	0.187	0.048	0.187	0.024	0.142	0.032
Industrials	0.119	0.070	0.198	0.049	0.107	0.038	−0.087	0.056	0.051	0.049	−0.018	0.097	0.176	0.028
Real Estate	−0.004	0.054	0.007	0.055	0.082	0.041	N/A	N/A	−0.022	0.035	0.072	0.020	0.104	0.032
Telecommunications	−0.036	0.064	−0.006	0.053	0.064	0.043	0.024	0.054	0.209	0.048	−0.022	0.066	0.046	0.028
Utilities	−0.086	0.058	0.007	0.055	0.155	0.035	0.864	0.240	0.108	0.041	0.092	0.029	0.084	0.022

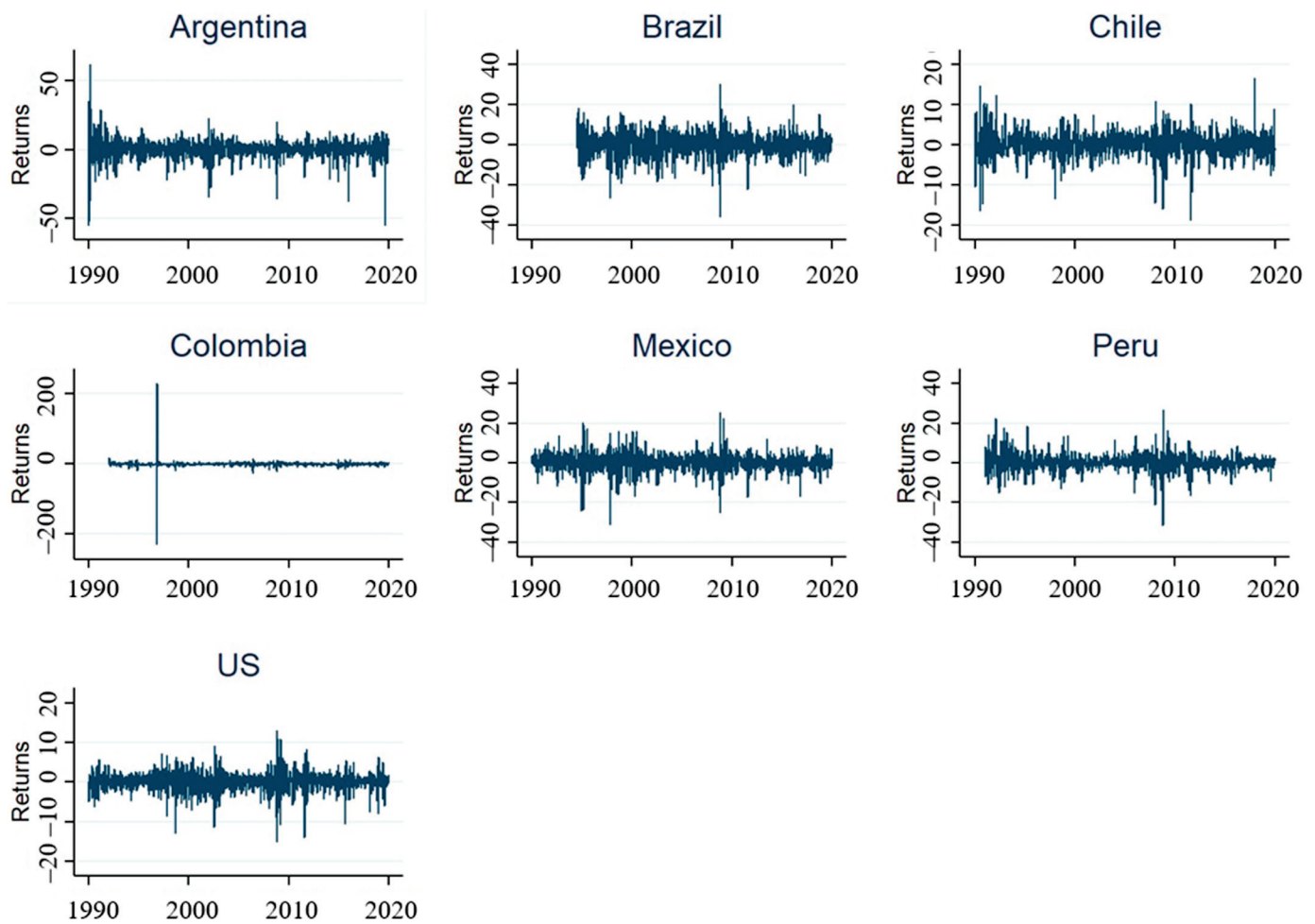


Figure 1. Returns of Latin American and the US market indices. Figure 1 presents returns of Latin American and the US market indices. This is based on weekly-based log returns sample data. The sample period is between 1 January 1990 and 31 December 2019.

Table 2. Unconditional correlations of main market indices and sectors. Table 2 reports unconditional correlations of main market indices and sectors. When we report unconditional correlations of energy and real estate sectors, we exclude Mexico and Colombia, respectively, due to data unavailability. The sample data period is between 1 January 1990 and 31 December 2019.

Main Market Index	Argentina	Brazil	Chile	Colombia	Mexico	Peru	US
Argentina	1.000						
Brazil	0.538	1.000					
Chile	0.468	0.598	1.000				
Colombia	0.109	0.133	0.168	1.000			
Mexico	0.508	0.649	0.536	0.142	1.000		
Peru	0.403	0.514	0.526	0.162	0.472	1.000	
US	0.432	0.574	0.498	0.156	0.617	0.408	1.000
Basic Materials	Argentina	Brazil	Chile	Colombia	Mexico	Peru	US
Argentina	1.000						
Brazil	0.365	1.000					
Chile	0.322	0.559	1.000				
Colombia	0.063	0.108	0.133	1.000			
Mexico	0.362	0.629	0.477	0.111	1.000		
Peru	0.219	0.416	0.370	0.092	0.444	1.000	
US	0.333	0.640	0.503	0.112	0.605	0.394	1.000

Table 2. Cont.

Consumer Discretionary	Argentina	Brazil	Chile	Colombia	Mexico	Peru	US
Argentina	1.000						
Brazil	0.275	1.000					
Chile	0.223	0.395	1.000				
Colombia	0.046	0.092	0.059	1.000			
Mexico	0.301	0.437	0.372	0.075	1.000		
Peru	0.020	0.052	0.022	0.029	0.032	1.000	
US	0.225	0.347	0.393	0.076	0.507	0.030	1.000
Consumer Staples	Argentina	Brazil	Chile	Colombia	Mexico	Peru	US
Argentina	1.000						
Brazil	0.326	1.000					
Chile	0.307	0.370	1.000				
Colombia	0.047	0.122	0.143	1.000			
Mexico	0.303	0.303	0.269	0.110	1.000		
Peru	0.108	0.149	0.147	0.006	0.107	1.000	
US	0.233	0.302	0.305	0.123	0.270	0.072	1.000
Energy	Argentina	Brazil	Chile	Colombia	Peru	US	
Argentina	1.000						
Brazil	0.391	1.000					
Chile	0.300	0.480	1.000				
Colombia	0.294	0.530	0.431	1.000			
Peru	0.159	0.296	0.279	0.302	1.000		
US	0.417	0.667	0.507	0.528	0.334	1.000	
Financials	Argentina	Brazil	Chile	Colombia	Mexico	Peru	US
Argentina	1.000						
Brazil	0.323	1.000					
Chile	0.332	0.532	1.000				
Colombia	0.239	0.451	0.482	1.000			
Mexico	0.284	0.525	0.505	0.422	1.000		
Peru	0.191	0.303	0.328	0.304	0.258	1.000	
US	0.267	0.465	0.442	0.369	0.490	0.222	1.000
Industrials	Argentina	Brazil	Chile	Colombia	Mexico	Peru	US
Argentina	1.000						
Brazil	0.261	1.000					
Chile	0.244	0.424	1.000				
Colombia	0.158	0.332	0.251	1.000			
Mexico	0.239	0.559	0.430	0.330	1.000		
Peru	0.040	0.075	0.092	0.060	0.100	1.000	
US	0.208	0.511	0.396	0.293	0.597	0.124	1.000
Real Estate	Argentina	Brazil	Chile	Mexico	Peru	US	
Argentina	1.000						
Brazil	0.294	1.000					
Chile	0.150	0.385	1.000				
Mexico	0.202	0.422	0.391	1.000			
Peru	0.104	0.110	0.081	0.145	1.000		
US	0.196	0.423	0.430	0.430	0.119	1.000	
Telecommunications	Argentina	Brazil	Chile	Colombia	Mexico	Peru	US
Argentina	1.000						
Brazil	0.371	1.000					
Chile	0.252	0.385	1.000				
Colombia	0.753	0.254	0.222	1.000			
Mexico	0.327	0.606	0.398	0.302	1.000		
Peru	0.090	0.136	0.080	0.028	0.123	1.000	
US	0.262	0.486	0.293	0.238	0.537	0.084	1.000

Table 2. Cont.

Utilities	Argentina	Brazil	Chile	Colombia	Mexico	Peru	US
Argentina	1.000						
Brazil	0.219	1.000					
Chile	0.271	0.491	1.000				
Colombia	0.110	0.451	0.472	1.000			
Mexico	0.120	0.339	0.386	0.390	1.000		
Peru	0.092	0.254	0.143	0.170	0.148	1.000	
US	0.037	0.304	0.238	0.231	0.244	0.081	1.000

In addition, we report correlations between all countries sorted by industry.⁸ We observe all correlations are positive and each country and industry exhibit different levels of connectedness. For example, the basic materials sector the highest correlation is between the US and Brazil with 0.640; for consumer services, the US and Mexico share the strongest relation with 0.507, while for consumer goods, the strongest pairwise correlation is between Chile and Brazil with 0.370. Brazil dominates the energy (and utilities) correlation with the US (and Chile) with correlations of 0.667 (and 0.491). Mexico dominates the correlation with the US in the industrials sector with 0.597.

Now that we have a sense of the pairwise correlations among the countries and their sectors, the univariate generalized autoregressive conditional heteroskedasticity (GARCH) model is considered since all the returns showed autocorrelation. The next step included the estimation of the univariate GARCH model and selecting the best model based on the Akaike Information Criterion (AIC) and Schwarz's Bayesian Criterion (BIC) to determine the best GARCH model based on the estimation of each model. As previously stated, the best model was selected among the traditional GARCH, EGARCH, GJR-GARCH and TGARCH. The model with the lowest AIC (BIC) score will be selected since it shows the best fit.

According to the results in Table 3, GARCH (1,1) is the best model for 11 of the analyzed sectors' returns. EGARCH (1,1) and GJR-GARCH (1,1) are present in 34 and 21 of studied sectors, respectively. Like EGARCH (1,1) and GJR-GARCH (1,1), TGARCH (1,1) also shows the presence of asymmetric effects on these sectors. This indicates that there exist significant asymmetric effects on time series. For example, the EGARCH (1,1) model predominates in Argentina, Brazil, Mexico, and the US. Also, GJR-GARCH (1,1) predominates within sectors, indicating that most countries and sectors react differently to good and/or bad news. Before moving to the conditional correlation approach, we generate normality tests for the residuals and the squared residuals of the models.⁹

Table 3. Univariate GARCH Models. Table 3 reports traditional GARCH, EGARCH, GJR-GARCH, and TGARCH models and their parameters sorted by industry. The sample data period is between 1 January 1990 and 31 December 2019.

Argentina	Model Selected	ω	θ	Z	δ
Main Index	EGARCH	0.219 ***	−0.068 ***	0.263 ***	0.941 ***
Basic Materials	GARCH	1.351 ***	0.130 ***	N/A	0.843 ***
Consumer Discretionary	EGARCH	0.256 ***	0.019 *	0.355 ***	0.942 ***
Consumer Goods	GJR-GARCH	1.861 ***	0.162 ***	0.087 ***	0.758 ***
Energy	EGARCH	0.273 ***	−0.061 ***	0.326 ***	0.930 ***
Financial	EGARCH	0.140 ***	−0.021 ***	0.232 ***	0.965 ***
Industrials	EGARCH	0.154 ***	−0.150 *	0.352 ***	0.963 ***
Real Estate	GJR-GARCH	1.436 ***	0.106 ***	−0.052 ***	0.869 ***
Telecommunications	EGARCH	0.432 ***	−0.098 ***	0.250 ***	0.885 ***
Utilities	GJR-GARCH	0.565 ***	0.086 ***	0.065 ***	0.880 ***

Table 3. Cont.

Brazil	Model Selected	ω	θ	Z	δ
Main Index	EGARCH	0.145 ***	−0.075 ***	0.174 ***	0.958 ***
Basic Materials	EGARCH	0.102 ***	−0.063 ***	0.198 ***	0.970 ***
Consumer Discretionary	EGARCH	0.227 ***	−0.065 ***	0.178 ***	0.929 ***
Consumer Goods	GJR-GARCH	0.856 ***	0.144 ***	−0.010 ***	0.839 ***
Energy	EGARCH	0.205 ***	−0.061 ***	0.180 ***	0.946 ***
Financial	GJR-GARCH	26.370 ***	0.352 ***	−0.327 ***	−0.093 **
Industrials	GJR-GARCH	1.082 ***	0.126 ***	−0.076 ***	0.861 ***
Real Estate	EGARCH	0.084 ***	−0.056 ***	0.139 ***	0.976 ***
Telecommunications	EGARCH	0.147 ***	−0.064 ***	0.183 ***	0.955 ***
Utilities	EGARCH	0.084 ***	−0.056 ***	0.139 ***	0.976 ***
Chile	Model Selected	ω	θ	Z	δ
Main Index	GJR-GARCH	1.632 ***	0.220 ***	0.023 ***	N/A
Basic Materials	GJR-GARCH	0.389 ***	0.111 ***	−0.035 ***	0.880 ***
Consumer Discretionary	GARCH	3.285 ***	0.156 ***	N/A	0.651 **
Consumer Goods	GJR-GARCH	0.199 ***	0.115 ***	−0.047 ***	0.897 ***
Energy	GJR-GARCH	1.130 ***	0.117 ***	−0.059 ***	0.843 ***
Financial	GJR-GARCH	0.302 ***	0.137 ***	−0.091 ***	0.890 ***
Industrials	GJR-GARCH	0.268 ***	0.135 ***	−0.045 ***	0.877 ***
Real Estate	EGARCH	0.196 ***	−0.028 **	0.221 ***	0.937 ***
Telecommunications	GJR-GARCH	0.429 ***	0.098 ***	−0.037 ***	0.902 ***
Utilities	EGARCH	0.112 ***	−0.044 ***	0.212 ***	0.954 ***
Colombia	Model Selected	ω	θ	Z	δ
Main Index	GARCH	49.422 ***	0.072 ***	N/A	−0.008 *
Basic Materials	GARCH	−0.108 ***	−0.001 ***	N/A	1.000 ***
Consumer Discretionary	GARCH	0.014 ***	−0.002 ***	N/A	1.003 **
Consumer Goods	TGARCH	−0.008 ***	−0.005 ***	N/A	1.000 ***
Energy	EGARCH	3.607 ***	0.851 ***	1.251 ***	0.168 ***
Financial	EGARCH	0.477 ***	−0.271 ***	−0.148 ***	0.856 ***
Industrials	EGARCH	0.068 ***	−0.045 ***	0.200 ***	0.982 ***
Telecommunications	GJR-GARCH	11.067 ***	0.175 ***	0.212 ***	0.383 ***
Utilities	GARCH	0.010 ***	−0.001 ***	N/A	0.999 ***
Mexico	Model Selected	ω	θ	Z	δ
Main Index	EGARCH	0.167 ***	−0.113 ***	0.220 ***	0.943 ***
Basic Materials	GJR-GARCH	1.108 ***	0.128 ***	−0.063 ***	0.854 ***
Consumer Discretionary	EGARCH	0.127 ***	−0.071 ***	0.216 ***	0.955 ***
Consumer Goods	EGARCH	0.210 ***	−0.173 ***	0.328 ***	0.942 ***
Financial	EGARCH	0.110 ***	−0.096 ***	0.213 ***	0.966 ***
Industrials	EGARCH	0.208 ***	−0.096 ***	0.198 ***	0.934 ***
Real Estate	GARCH	2.180 ***	0.088 ***	N/A	0.726 ***
Telecommunications	EGARCH	0.169 ***	−0.084 ***	0.198 ***	0.947 ***
Utilities	TGARCH	N/A	N/A	N/A	N/A
Peru	Model Selected	ω	θ	Z	δ
Main Index	GJR-GARCH	0.630 ***	0.147 ***	0.044 ***	0.799 ***
Basic Materials	EGARCH	0.113 ***	−0.048 ***	0.214 ***	0.959 ***
Consumer Discretionary	GARCH	0.213 ***	0.025 ***	N/A	0.970 ***
Consumer Goods	GARCH	0.014 ***	0.083 ***	N/A	0.935 ***
Energy	GARCH	26.500 ***	0.198 ***	N/A	0.257 ***
Financial	EGARCH	0.116 ***	0.003 ***	0.364 ***	0.944 ***
Industrials	EGARCH	5.186 ***	0.317 ***	−0.021 ***	−0.149 ***
Real Estate	EGARCH	0.021 ***	−0.047 ***	0.074 ***	0.997 ***
Telecommunications	GARCH	3.557 ***	0.337 ***	N/A	0.703 ***
Utilities	GJR-GARCH	0.224 ***	0.095 ***	−0.062 ***	0.906 ***

Table 3. Cont.

US	Model Selected	ω	θ	Z	δ
Main Index	EGARCH	0.117 ***	−0.163 ***	0.236 ***	0.924 ***
Basic Materials	GJR-GARCH	0.317 ***	0.130 ***	−0.087 ***	0.880 ***
Consumer Discretionary	EGARCH	0.132 ***	−0.156 ***	0.260 ***	0.917 ***
Consumer Goods	EGARCH	0.086 ***	−0.126 ***	0.201 ***	0.935 ***
Energy	EGARCH	0.111 ***	−0.099 ***	0.201 ***	0.950 ***
Financial	GJR-GARCH	0.282 ***	0.179 ***	−0.126 ***	0.847 ***
Industrials	EGARCH	0.108 ***	−0.139 ***	0.183 ***	0.942 ***
Real Estate	GJR-GARCH	0.334 ***	0.192 ***	−0.123 ***	0.825 ***
Telecommunications	GJR-GARCH	0.149 ***	0.098 ***	−0.089 ***	0.920 ***
Utilities	EGARCH	0.076 ***	−0.041 ***	0.254 ***	0.952 ***

Notes: *, **, and *** indicate a significance at the 10%, 5%, and 1% levels, respectively.

As previously stated, the DCC-GARCH model will be a bivariate model, with the US market and US sectors being paired with their respective counterpart from the Latin American countries (Argentina, Brazil, Chile, Colombia, Mexico, and Peru). That is, the US will be paired with each Latin American country's index to determine their comovement. The estimates of the dynamics on the conditional correlations are shown in Table 4. The coefficients among the different sectors and countries are quite similar. We observe that coefficients a are relatively small (with the except of a couple of the coefficients), indicating that conditional volatility does not change very rapidly. Coefficients b are much larger than coefficients a , indicating gradual fluctuations over time. We confirm that the estimated coefficients a and b satisfy the stationary conditions for all the variance and covariance processes.

Table 4. DCC GARCH Model—US and Latin American Countries. Table 4 reports the estimates of the DCC-GARCH model. In all six tables, the US will be paired with each Latin American country's index to determine their comovement.

Argentina and US			Brazil and US		
	a	b		a	b
Market Index	0.032 **	0.941 ***	Market Index	0.069	0.923 ***
Basic Materials	0.031 **	0.948 ***	Basic Materials	0.067 ***	0.931 ***
Consumer Discretionary	0.053 **	0.829 ***	Consumer Discretionary	0.018 ***	0.981 ***
Consumer Goods	0.023 *	0.946 ***	Consumer Goods	0.043 **	0.847 ***
Energy	0.029 ***	0.949 ***	Energy	0.072 ***	0.918 ***
Financials	0.029	0.925 ***	Financials	0.029 **	0.975 ***
Industrials	0.007	0.971 ***	Industrials	0.063 ***	0.935 ***
Real Estate	0.024 **	0.958 ***	Real Estate	0.047 *	0.880 ***
Telecommunications	0.029 ***	0.937 ***	Telecommunications	0.053 **	0.904 ***
Utilities	0.021 *	0.948 ***	Utilities	0.035 ***	0.955 ***
Peru and US			Chile and US		
	a	b		a	b
Market Index	0.035	0.914 **	Market Index	0.034 **	0.952 ***
Basic Materials	0.033 *	0.966 ***	Basic Materials	0.054 ***	0.944 ***
Consumer Discretionary	0.027 **	0.965 ***	Consumer Discretionary	0.017 ***	0.977 ***
Consumer Goods	0.009	0.126	Consumer Goods	0.047 ***	0.921 ***
Energy	0.038 *	0.911 ***	Energy	0.044 *	0.946 ***
Financials	0.019 **	0.978 ***	Financials	0.059 ***	0.927 **
Industrials	0.01	0.967 ***	Industrials	0.049 ***	0.945 ***
Real Estate	0	0.991 ***	Real Estate	0.012 *	0.984 ***
Telecommunications	0.001	0.994 ***	Telecommunications	0.037	0.527 **
Utilities	0.003	0.986 ***	Utilities	0.029 ***	0.958 ***
Colombia and US			Mexico and US		
	a	b		a	b
Market Index	0.015 ***	0.980 ***	Market Index	0.050 ***	0.947 ***
Basic Materials	0.696 ***	0.035	Basic Materials	0.058 ***	0.938 ***
Consumer Discretionary	0.008	0.994 ***	Consumer Discretionary	0.044	0.934 ***
Consumer Goods	0.195	0.520 **	Consumer Goods	0.067 *	0.918 ***
Energy	0.033 **	0.964 ***	Financials	0.062 ***	0.878 **
Financials	0.265 **	0.114	Industrials	0.064 ***	0.935 ***
Industrials	0.053 **	0.917 ***	Real Estate	0.098 **	0.856 ***
Telecommunications	0.142 **	0.189	Telecommunications	0.043 ***	0.941 ***
Utilities	0.011 *	0.975 ***	Utilities	0.005	0.982 ***

Notes: *, **, and *** indicate a significance at the 10%, 5%, and 1% levels, respectively.

Table 5 presents the summary statistics of the bivariate conditional correlations between the US and each of the respective Latin American markets. It is important to notice that similar to the unconditional correlations, we find that all the Latin American indices studied have an average positive correlation with the US indices. In terms of the market index, on average, Mexico has the highest conditional correlation with the US with 0.532, and Colombia has the lowest mean conditional correlation relative to the US with 0.182, indicating that Mexican market tends to comove with US markets relatively more compared to the remaining Latin American countries. This is not surprising since Mexico has engaged in a free trade agreement with the US since 1994. Also, the geographical proximity to the US is significant for their strong comovement. On the other hand, Colombia has the lowest conditional correlation, which should imply higher diversification gains to an American investor relative to the rest of Latin America nations. Moreover, the ranking shows that the more developed countries (Argentina, Brazil, and Mexico) within this group have a higher positive dynamic conditional correlation with the US than the relatively less developed countries (Colombia and Peru). Lastly, we observe that more developed countries (Argentina, Brazil, and Mexico) tend to have a higher correlation with the US than relatively less developed countries (Colombia and Peru). These findings show where American investors can get portfolio diversification benefits with Latin American countries and their sectors as well.¹⁰

Table 5. Summary statistics of bivariate conditional correlation. Table 5 reports the summary statistics of bivariate conditional correlation. In Table 5, we only report the main market index.

Country List	Mean	Median	Min	Max	SD
Argentina and US	0.382	0.380	−0.001	0.741	0.126
Brazil and US	0.514	0.528	−0.075	0.870	0.189
Chile and US	0.377	0.400	−0.029	0.669	0.146
Colombia and US	0.182	0.189	−0.069	0.424	0.126
Mexico and US	0.532	0.588	−0.124	0.861	0.213
Peru and US	0.267	0.273	−0.057	0.644	0.093

The dynamic conditional correlation for the main market indices between the US and the examined countries can be seen in Figure 2. All graphs show two lines that denote the signing date of the trade agreement with the US, while the second line shows the point in time in which the trade deal started and was implemented. A visual examination of the Argentina–US conditional correlation shows that conditional correlation has increased from the start of the sample (1990) and mostly increased through time. Some of the abrupt changes can be attributed to the several financial problems related to currency issues as well as default problems that Argentina has encountered in the last 15 years. Brazil has a very low correlation and large spikes on the beginning of the sample, which coincide with the implementation of the Real as the nation’s currency (replacing the cruzeiro real). However, we observe an upward trend and a significant increase in correlations, especially during the financial crisis and the years after that. For Chile, we observe that comovement was low at the beginning of the sample but gradually increased while the country started liberalizing its market. Colombia shows a low correlation with the US for the first 10 years but has a significant bump in correlation close to the signing of the bilateral free trade agreement with the US. After that considerable rise, the correlations seem to stabilize during the new range. In 2016, Colombia experienced high inflation and lowered GDP growth. This matches the movements shown in the graph of the dynamic conditional correlation. Mexico shows a different story than the rest of the countries. It seems that comovement between the US and Mexico has been significantly strong over most of the sample. However, the later part of the sample correlation between these countries suffers a significant downward trend for a short period. Although it does not involve any specific crisis or country specific turmoil, it does conform with the initial stages of negotiation of a new trade agreement. During this time, several negotiation talks failed to move the new

agreement forward and talks of eliminating free trade between Mexico and the US were surfaced. After long negotiations occurred, a new deal was signed, and the graphs shows the correlation bouncing back to previous values. Lastly, Peru has been a relatively small market in Latin America that has started growing in the last 10 years. The graph of the conditional correlation shows that comovement was relatively low and has a gradual trend towards a higher degree of comovement. The graphs for the remaining sector indices show similar effects to the ones shown on the main market indices.

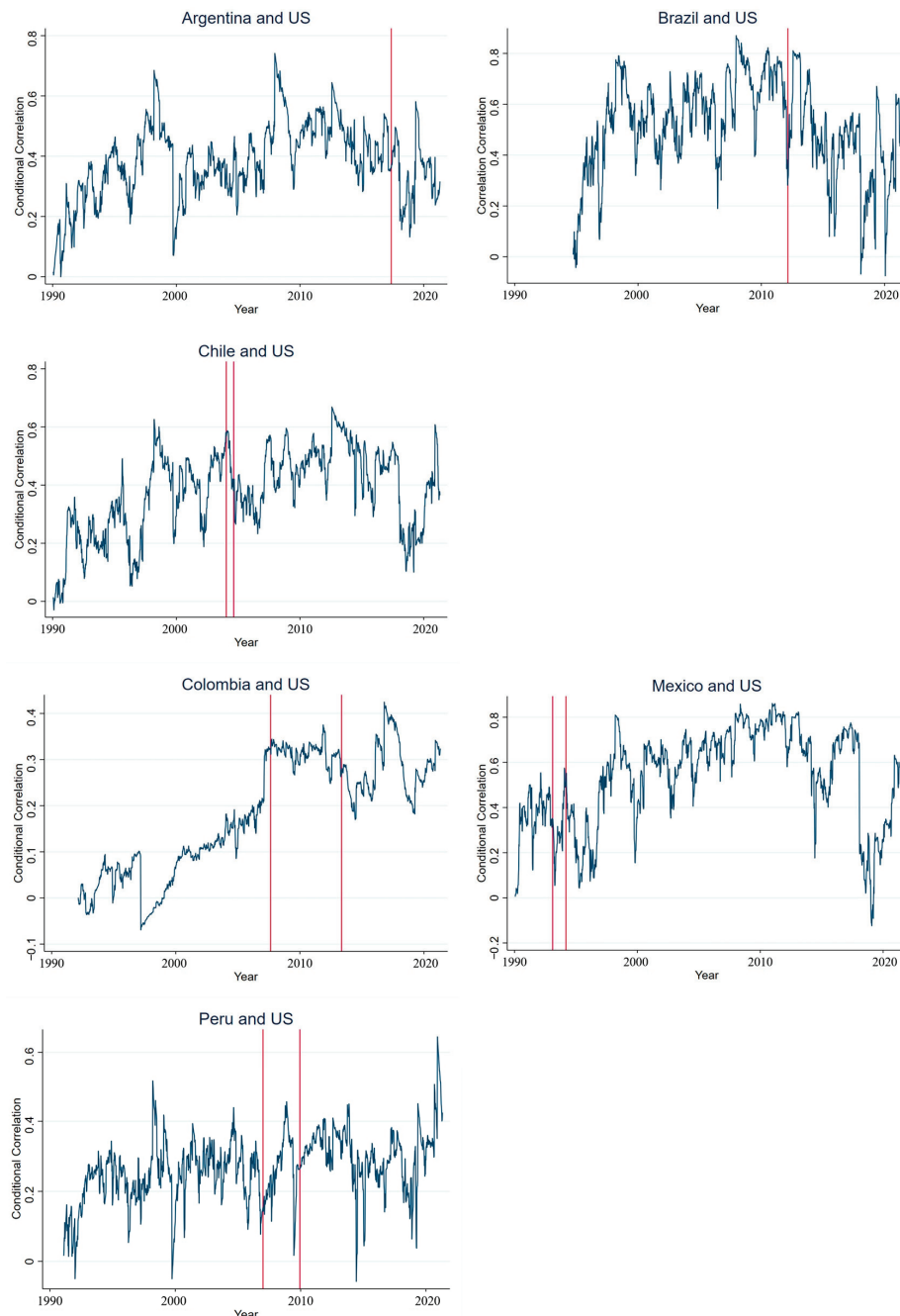


Figure 2. Conditional correlation of latin american market indices and the US market index returns. Figure 2 presents the dynamic conditional correlation for the main market indices between the US and the examined countries: Argentina, Brazil, Chile, Colombia, Mexico, and Peru. We also show (red) lines that denote the trade agreement signing date with the US. Two separate lines indicate that the signing date and implemented dates are different.

4.2. Smooth Transition Model

The smooth transition model on the dynamic bivariate conditional correlation between the US and the examined Latin American countries was computed.¹¹

The results of the smooth transition estimation are shown in Table 6. The smooth transition model estimates the average correlation between two different regimes. The term α is the average correlation of the first (old) regime, while β is the change in correlation of the second (new) regime. Consequently, $\alpha + \beta$ is an indicator of the average correlation of the second (new) regime. The term γ establishes the slope of the transition curve. The higher the values of γ , the more drastic the change between the two correlations (old and new) regimes. Lastly, τ shows the midpoint or turning point of the transition curve.

Table 6. The estimated smooth transition model. Table 6 presents the smooth transition model to estimate the average correlation between two different regimes.

Argentina and US	α	β	γ	T	Midpoint
Market Index	0.378 ***	0.094 *	633 ***	0.449 ***	Jun-03
Basic Materials	0.293 ***	0.008	242 ***	0.292 ***	Sep-98
Consumer Discretionary	0.193 ***	−0.084 *	13.300	0.566 ***	Dec-06
Consumer Goods	0.240 ***	0.011 *	316.00	0.223 ***	Oct-96
Energy	0.341 ***	−0.024 ***	581 ***	0.467 ***	Jan-04
Financials	0.317 ***	−0.010 *	434 **	0.325 ***	Oct-99
Industrials	0.262 ***	−0.095	31.8 **	0.476 ***	Apr-04
Real Estate	0.222 ***	0.244 ***	4.13 ***	0.584 ***	Jul-07
Telecommunications	0.246 ***	0.417	7.77 **	0.889 *	Aug-16
Utilities	0.183 ***	0.018 ***	66.3 ***	0.228 ***	Oct-96
Brazil and US	α	β	γ	T	Midpoint
Market Index	0.513 ***	−0.064 **	1116 ***	0.554 ***	Jan-04
Basic Materials	0.536 ***	−0.010 **	786 ***	0.656 ***	Aug-09
Consumer Discretionary	0.318 ***	−0.624	111 **	0.682 ***	Jun-10
Consumer Goods	0.277**	0.055	76.70	0.152 ***	May-95
Energy	0.492 ***	−0.006 **	506	0.523 ***	Sep-05
Financials	0.339 ***	−0.015	98	0.272 ***	Mar-95
Industrials	0.402 ***	−0.014 **	582	0.371 ***	Feb-01
Real Estate	0.323 ***	−0.077 *	227	0.484 ***	Apr-99
Telecommunications	0.374 ***	−0.018 *	21.9 ***	0.305 ***	Feb-99
Utilities	0.184 ***	0.114 ***	355 ***	0.052 ***	Jul-91
Chile and US	α	β	γ	T	Midpoint
Market Index	0.358 ***	0.024	51.3 ***	0.262 ***	Nov-97
Basic Materials	0.04	0.348 ***	116 ***	0.142 ***	Mar-94
Consumer Discretionary	0.239 ***	0.099 **	149 ***	0.019 ***	Aug-90
Consumer Goods	0.254 ***	0.523 ***	12.3 ***	0.780 ***	May-13
Energy	0.199 ***	0.060 ***	125 ***	0.025 ***	Oct-90
Financials	0.250 ***	0.055	13.2 ***	0.137 *	Jan-94
Industrials	−0.059	0.319 ***	434 ***	0.173 ***	Apr-95
Real Estate	0.140 ***	0.015 ***	377 ***	0.081 ***	May-92
Telecommunications	0.247 ***	−0.009 ***	99.3 ***	0.142 ***	Apr-94
Utilities	0.198 ***	0.042 ***	6.90 ***	0.065 *	Dec-91

Table 6. Cont.

Colombia and US	α	β	γ	T	Midpoint
Market Index	0.080 ***	0.166 **	21.2 ***	0.211 *	Dec-95
Basic Materials	0.049 **	−0.739 ***	8.62 ***	0.805 ***	Feb-14
Consumer Discretionary	0.014 *	0.069 ***	21.9 ***	0.006	Sep-91
Consumer Goods	0.120 ***	−0.034 ***	213 ***	0.265 ***	Dec-97
Energy	0.175 ***	0.029 *	674 ***	0.119 **	Jul-93
Financials	0.108 ***	−0.379**	19 ***	0.797 ***	Nov-13
Industrials	0.292 ***	0.004 *	812 ***	0.241 ***	Mar-97
Telecommunications	0.226 ***	0.071 ***	26.0 ***	0.506 ***	Jan-05
Utilities	0.115 ***	0.216	9.14 ***	0.508 ***	Mar-05
Mexico and US	α	β	γ	T	Midpoint
Market Index	0.512 ***	0.122 *	277 ***	0.375 ***	Mar-01
Basic Materials	0.348 ***	0.144 ***	151 **	0.161 **	Oct-94
Consumer Discretionary	0.376 ***	0.051	63	0.224 ***	Sep-96
Consumer Goods	0.157 ***	0.131 ***	502 ***	0.040 ***	Mar-91
Financials	0.261 ***	0.08	417 ***	0.045 ***	Apr-91
Industrials	−0.152	0.622 ***	95 ***	0.119 ***	Jul-93
Real Estate	0.334 ***	0.057 **	37.2 ***	0.211 ***	Apr-96
Telecommunications	0.349 ***	0.040 **	39.9 ***	0.298 ***	Nov-98
Utilities	0.192 ***	−0.344	15.8 **	0.422 *	Aug-02
Peru and US	α	β	γ	T	Midpoint
Market Index	0.261 ***	0.213 **	65.5 ***	0.303 ***	Feb-99
Basic Materials	0.276 ***	0.099 ***	4.55 **	0.328 **	Jul-98
Consumer Discretionary	0.219 ***	−0.139 **	255 ***	0.114 ***	May-93
Consumer Goods	0.102 ***	0.012 ***	84.2 ***	0.235 ***	Jan-97
Energy	0.259 ***	0.034	254 ***	0.249 ***	Jul-96
Financials	0.142 ***	0.066 ***	12.5 ***	0.471 ***	Feb-04
Industrials	0.144 ***	0.495 ***	13.3 ***	0.552 ***	Jul-06
Real Estate	0.052 ***	0.002	681 ***	0.102 **	Dec-91
Telecommunications	0.074 ***	0.016	516 ***	0.086 ***	May-92
Utilities	0.109 ***	0.318	6.69 ***	0.776	Apr-14

Notes: *, **, and *** indicate a significance at the 10%, 5%, and 1% levels, respectively.

For the market index comovement between the US and Argentina, the first regime has an average correlation of 0.378, while the second regime has correlation of 0.472. This would be clear evidence that comovement has increased during the sample period. The midpoint was in mid-2003, and it shows a large γ , which signifies a more abrupt change in correlations. On the other hand, Brazil shows an average correlation of 0.513 on the first part of the sample, but the second regime reduces by 0.064, resulting in a decrease in comovement in the second regime. The market index in Chile shows a 0.358 correlation for the first regime and a 0.024 correlation for the second regime. For Colombia, the midpoint was in the earliest part of the sample in late 1995. The correlation regimes moved from 0.080 to 0.246. Mexico also shows a similar story with an old regime correlation of 0.512 and with a new correlation regime of 0.634. In this case, the midpoint occurred in early 2001. Peru shows an old regime correlation of 0.261 and a new correlation regime of 0.474, which is the biggest increase in correlation among the main market indices. From all the countries' main indices, all increased their level of comovement with the US in the smooth transition approach except Brazil. We conclude that the degree of comovement mostly increased. In terms of all the different sectors across the Latin American countries, the results show that the majority of the indices exhibit an increase in correlation from the old regime to the new one, indicating that different countries and sectors have shifted differently over the entire sample, but most of the countries show a significant increase.

Employing the smooth transition model, we observe that the comovement between the US and Latin American countries (except Brazil) has increased during the sample period.

One downside of this model is that we only consider one midpoint of the entire sample of 30 years. To check robustness of the smooth transition model, we generate tests for a unit root on the residuals of the model.¹² We confirm that the smooth transition model is appropriate for the evaluated series.

4.3. Structural Breaks

The structural break analysis was divided into two main approaches. The first included testing known dates that includes considering if structural breaks are present during the signing date as well as during the established start date of the bilateral trade agreements. The second approach tested for unknown structural breaks. In Table 7 Panel A, we report results for the structural breaks around the signing and start dates of the dynamic conditional correlations, showing the presence of structural breaks in some of the main indices.

Table 7. Structure breaks and regression analysis. In Table 7, we report structural breaks with known dates (Panel A) and unknown dates (Panel B). Also, the regression analysis was taken to examine directly if the dynamic conditional correlation between these countries has changed after the signing and implementation of each trade agreement (Panel C).

Panel A. Structure Breaks—Known Dates		
Country List	Sign Date	Start Date
Argentina and US	3.737	3.737
Brazil and US	3.841	3.841
Chile and US	5.621 *	2.841
Colombia and US	5.833 **	3.353
Mexico and US	6.602 **	7.204 **
Peru and US	6.577 **	6.920 **
Panel B. Structure Breaks—Unknown Dates		
Country List	Number of Breakpoints	Estimated Break Dates
Argentina and US	5	07-1994; 04-1999; 05-2006; 01-2011; 04-2016
Brazil and US	5	04-1998; 07-2002; 05-2006; 02-2011; 03-2016
Chile and US	5	01-1997; 06-2003; 05-2006; 11-2010; 07-2015
Colombia and US	5	12-1997; 03-2002; 08-2006; 02-2011; 04-2015
Mexico and US	5	07-1996; 05-2011; 05-2006; 01-2011; 07-2015
Peru and US	5	07-1997; 07-2002; 04-2006; 05-2011; 08-2015
Panel C. Regression Analysis		
Country List	Sign Date	Start Date
Argentina and US	0.051 ***	0.051 ***
Brazil and US	−0.122 ***	−0.122 ***
Chile and US	0.118 ***	0.115 ***
Colombia and US	0.212 ***	0.135 ***
Mexico and US	0.202 ***	0.225 ***
Peru and US	0.060 ***	0.065 ***

Notes: *, **, and *** indicate a significance at the 10%, 5%, and 1% levels, respectively.

We observe structural breaks for Chile, Colombia, Mexico, and Peru, while the other two (Argentina and Brazil) do not exhibit a structural break after the signing or start dates of their trade agreements. This coincides with the countries that have a stronger trade agreement with the US. It is important to recall that Colombia, Chile, Mexico, and Peru have a full bilateral free trade agreement, while Argentina and Brazil have trade agreements that are not completely free trade agreements, hence their strength is weaker relative to a full free trade agreement. Some specific sectors such as materials, consumer goods, financial, energy, and industrial exhibit the highest number of structural breaks during the sign and start dates, indicating that such industries in Latin America tend to have a higher level of commercial connection with the US.¹³

In addition, we report unknown structure breaks in Table 7 Panel B. Contrary to the known structural breaks, the unknown structural break approach used by Bai and Perron (2003) tests for a specified number of breaks in the bivariate dynamic conditional correlation. In this case, the unknown structural breaks were limited to five but would incorporate more than five if these breaks were present. The results of the unknown structural breaks show a very similar story to the one from the known structural breaks (signing and start dates). It is also important to consider that several unknown breaks are very close to the signing and start dates. Although the structural breaks are not on the exact same date, according to the data, there is a break present near that specific date. This can be attributed to the trade agreements considering there are significant or major events that could produce such a shock on the correlation between these countries in that given time. As mentioned previously and as shown by the analysis, the impact on the bivariate dynamic conditional correlation might not be shown immediately but over a more prolonged period of time. Therefore, the smooth transition model was considered to study how the correlations have changed over the sample period.

Lastly, to examine directly if the dynamic conditional correlation between these countries has changed after the signing and implementation of each trade agreement, a regression approach was taken. The idea is to use the dynamic conditional correlation as the dependent variable, and an indicator variable determines the creation and implementation of the trade agreements. In Table 7, Panel C presents the coefficients of the model, and we observe that after the respective bilateral trade agreements between the US and Argentina, Chile, Colombia, Mexico, and Peru have increased comovement in the main market indices between these countries. Also, the US and Brazil's dynamic conditional correlation shows a negative and significant coefficient that signifies that the comovement between the US and Brazil has fallen after the implementation of their trade agreement.

5. Conclusions

The main objective of this study was to empirically investigate if the comovement between main stock indices of Argentina, Brazil, Colombia, Chile, Mexico, and Peru have shown greater or lower comovement in relation to the US financial markets. We conclude that main market indices of Argentina, Chile, Colombia, Mexico, and Peru have increased their correlation with the main market index in the US after the respective bilateral trade agreements. In addition, the results indicate that the integration with the US market index has increased over time for all the countries except for Brazil, which had a small reduction in correlation during the end of the sample period. The results of the smooth transition model also provide support for the previous claims.

The lower values and lack of structural breaks around Argentina and Brazil can be partly explained by the type of trade agreement. Considering that the agreements that Argentina and Brazil signed with the US are not full free trade agreements, the impact on financial market integration seems lower. On the contrary, the countries that do have a free trade agreement (Chile, Colombia, Mexico, and Peru) with the US have shown a higher number of structural breaks around the signing and implementation dates of these treaties. In addition, the regression-based approach shows the comovement between Latin American and the US financial markets.

The results show evidence that the financial market integration between these countries is varying consistently over time, so close attention must be taken. The implication of the study for policy makers can be stated as an increase in the level of correlations between Latin American and the US financial markets means that financial market disturbances in the US are more likely to be transmitted to these countries, which may have adverse consequences for the stability of the financial systems involved. On the other hand, a higher degree of comovement implies that optimal portfolios have changed as a result of the correlation variation; hence, investors will have to adjust their portfolios accordingly. The results support the idea that financial market integration in the region is increasing overall as well as the argument that the US has become more integrated with this region

over time. Our main limitation is access to data for other Latin American countries. It will be beneficial to have further investigations including other Latin American countries for future research.

Author Contributions: Conceptualization, O.F.I.; methodology, O.F.I.; software, O.F.I. and S.S.; validation, O.F.I. and S.S.; formal analysis, O.F.I. and S.S.; investigation, O.F.I. and D.Z.; resources, O.F.I. and D.Z.; data curation, O.F.I.; writing—original draft preparation, O.F.I., S.S. and D.Z.; writing—review and editing, D.Z.; visualization, S.S.; supervision, S.S. and D.Z.; project administration, D.Z. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: Data is available upon request.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A. Free Trade Agreements

Trade Partners	Signed Date	Starting Date	Type of Agreement
Argentina-US	2016-03-23	2016-03-23	Trade and Investment Framework Agreement
Brazil-US	2011-03-18	2011-03-18	Agreement of Economics Trade and Cooper
Chile-US	2003-06-06	2004-01-01	Free Trade Agreement
Colombia-US	2006-11-22	2012-05-15	Free Trade Agreement
Mexico-US	1992-12-17	1994-01-01	Free Trade Agreement
Peru-US	2006-04-12	2009-02-01	Free Trade Agreement

Appendix B. ICB-FTSE Actuaries (Sector and Industry Classification)

Sectors	Industries Included
Basic Materials	Chemicals Foyster and Paper Industrial Metals and Mining
Consumer Staples	Automobile Food Producers Beverages Leisure and Personal Goods Household Goods and Home Construction Tobacco
Consumer Discretionary	Food and Drug Retailers General Retailers Media Travel and Leisure
Energy	Oil and Gas Coal Alternative Energy
Financials	Banks Financial Services Insurance
Industrials	Construction and Materials Aerospace and Defense General Industrials Electrical Equipment Industrial Engineering and Support Services Industrial Transportation
Real Estate	Real Estate Investments and Services Real Estate Investment Trusts (REITs)
Telecommunications	Fixed Line Telecommunications Mobile Telecommunications
Utilities	Electricity Gas, Water and Multi-Utilities Waste and Disposal Services

Appendix C. Summary Statistics of Bivariate Conditional Correlation

Argentina and US	Mean	Median	Min	Max	SD
Market Index	0.382	0.380	−0.001	0.741	0.126
Basic Materials	0.297	0.300	−0.064	0.706	0.152
Consumer Discretionary	0.192	0.186	−0.374	0.633	0.097
Consumer Goods	0.248	0.239	−0.021	0.536	0.094
Energy	0.339	0.342	0.008	0.743	0.122
Financials	0.313	0.317	−0.339	0.693	0.104
Industrials	0.259	0.262	−0.006	0.397	0.054
Real Estate	0.220	0.227	−0.119	0.491	0.113
Telecommunications	0.248	0.252	−0.077	0.556	0.099
Utilities	0.183	0.174	−0.167	0.513	0.095
Brazil and US	Mean	Median	Min	Max	SD
Market Index	0.514	0.528	−0.075	0.870	0.189
Basic Materials	0.535	0.569	−0.225	0.911	0.256
Consumer Discretionary	0.318	0.338	−0.122	0.614	0.182
Consumer Goods	0.321	0.327	−0.019	0.627	0.079
Energy	0.493	0.505	−0.157	0.892	0.223
Financials	0.329	0.317	−0.078	0.676	0.147
Industrials	0.393	0.424	−0.454	0.771	0.222
Real Estate	0.325	0.327	−0.011	0.763	0.098
Telecommunications	0.363	0.371	−0.036	0.719	0.164
Utilities	0.298	0.279	−0.023	0.706	0.164
Chile and US	Mean	Median	Min	Max	SD
Market Index	0.377	0.400	−0.029	0.669	0.146
Basic Materials	0.387	0.400	−0.169	0.889	0.231
Consumer Discretionary	0.337	0.360	−0.027	0.586	0.132
Consumer Goods	0.255	0.250	−0.159	0.599	0.141
Energy	0.258	0.278	−0.312	0.071	0.196
Financials	0.293	0.320	−0.353	0.841	0.227
Industrials	0.261	0.283	−0.272	0.700	0.189
Real Estate	0.154	0.133	−0.023	0.449	0.105
Telecommunications	0.237	0.238	0.013	0.412	0.039
Utilities	0.237	0.237	−0.198	0.697	0.144
Colombia and US	Mean	Median	Min	Max	SD
Market Index	0.182	0.189	−0.069	0.424	0.126
Basic Materials	0.048	0.039	−0.684	0.835	0.105
Consumer Discretionary	0.081	0.088	0.004	0.101	0.021
Consumer Goods	0.119	0.112	−0.444	0.677	0.112
Energy	0.211	0.219	−0.275	0.669	0.211
Financials	0.107	0.102	−0.707	0.818	0.129
Industrials	0.291	0.285	−0.137	0.706	0.149
Telecommunications	0.155	0.152	−0.557	0.703	0.104
Utilities	0.118	0.114	−0.082	0.282	0.073
Mexico and US	Mean	Median	Min	Max	SD
Market Index	0.532	0.588	−0.124	0.861	0.213
Basic Materials	0.493	0.487	−0.228	0.921	0.241
Consumer Discretionary	0.426	0.46	−0.031	0.723	0.147
Consumer Goods	0.287	0.293	−0.389	0.797	0.233
Financials	0.357	0.357	−0.553	0.806	0.151
Industrials	0.467	0.491	−0.291	0.881	0.244
Real Estate	0.341	0.319	−0.145	0.898	0.195
Telecommunications	0.381	0.391	−0.105	0.733	0.159
Utilities	0.182	0.199	0.003	0.247	0.051
Peru and US	Mean	Median	Min	Max	SD
Market Index	0.267	0.273	−0.057	0.644	0.093
Basic Materials	0.284	0.289	−0.263	0.686	0.205
Consumer Discretionary	0.079	0.059	−0.171	0.411	0.094
Consumer Goods	0.102	0.107	0.126	0.243	0.01
Energy	0.278	0.284	0.015	0.572	0.088
Financials	0.174	0.147	−0.087	0.442	0.132
Industrials	0.146	0.123	−0.022	0.327	0.058
Real Estate	0.521	0.056	0.005	0.072	0.015
Telecommunications	0.073	0.081	0.004	0.085	0.018
Utilities	0.113	0.11	0.013	0.179	0.031

Appendix D. ADF Statistics of Conditional Correlation before Fitting the Smooth Transition Model

Argentina and US	Levels	First Difference	Brazil and US	Levels	First Difference
Market Index	−1.174	−16.888 ***	Market Index	−1.359	−21.711 ***
Basic Materials	−1.643	−20.316 ***	Basic Materials	−1.474	−28.831 ***
Consumer Discretionary	−1.630	−12.104 ***	Consumer Discretionary	−0.644	−13.58 ***
Consumer Goods	−1.637	−24.073 ***	Consumer Goods	−0.721	−11.542 ***
Energy	−1.215	−24.346 ***	Energy	−0.739	−10.053 ***
Financials	−1.549	−23.020 ***	Financials	−0.809	−25.412 ***
Industrials	−0.246	−27.616 ***	Industrials	−1.532	−26.809 ***
Real Estate	−1.566	−27.085 ***	Real Estate	−1.024	−10.813 ***
Telecommunications	−1.628	−23.054 ***	Telecommunications	−1.481	−13.277 ***
Utilities	−1.511	−26.899 ***	Utilities	−1.557	−26.593 ***
Peru and US	Levels	First Difference	Chile and US	Levels	First Difference
Market Index	−0.895	−14.398 ***	Market Index	−0.984	−16.497 ***
Basic Materials	−1.001	−19.423 ***	Basic Materials	−1.533	−29.545 ***
Consumer Discretionary	−1.594	−26.182 ***	Consumer Discretionary	−0.543	−27.044 ***
Consumer Goods	−0.168	−12.765 ***	Consumer Goods	−2.150	−23.732 ***
Energy	−0.687	−12.582 ***	Energy	−1.615	−28.489 ***
Financials	−0.837	−15.449 ***	Financials	−1.253	−20.936 ***
Industrials	−0.690	−15.800 ***	Industrials	−1.455	−28.683 ***
Real Estate	2.115	−17.686 ***	Real Estate	−1.111	−22.516 ***
Telecommunications	0.669	−3.916 ***	Telecommunications	−0.313	−13.141 **
Utilities	0.144	−25.890 ***	Utilities	1.601	−23.981 ***
Colombia and US	Levels	First Difference	Mexico and US	Levels	First Difference
Market Index	−0.243	−26.519 ***	Market Index	−1.094	−28.735 ***
Basic Materials	−1.607	−13.890 ***	Basic Materials	−1.481	−29.480 ***
Consumer Discretionary	1.627	−29.878 ***	Consumer Discretionary	−1.121	−24.458 ***
Consumer Goods	−1.585	−12.938 ***	Consumer Goods	−1.491	−29.806 ***
Energy	−1.136	−27.769 ***	Financials	−1.490	−11.016 ***
Financials	−1.452	−17.005 ***	Industrials	−1.605	−28.875 ***
Industrials	−1.464	−24.346 ***	Real Estate	−1.606	−12.391 ***
Telecommunications	−1.001	−11.719 ***	Telecommunications	−1.363	−23.996 ***
Utilities	−1.437	−17.889 ***	Utilities	0.364	−12.750 ***

Notes: *, **, and *** indicate a significant at the 90%, 95%, and 99% levels, respectively.

Appendix E. ADF Statistics on the Residuals of the Smooth Transition Model

Argentina and US	ADF Statistic	First Difference
Market Index	−23707 ***	0
Basic Materials	−39.686 ***	0
Consumer Discretionary	−15.701 ***	0
Consumer Goods	−17.719 ***	0
Energy	−18.587 ***	0
Financials	−17.462 ***	0
Industrials	−9.513 ***	0
Real Estate	−14.201 ***	0
Telecommunications	−22.893 ***	0
Utilities	−13.501 ***	0
Brazil and US	ADF Statistic	First Difference
Market Index	−37.345 ***	0
Basic Materials	−36.450 ***	0
Consumer Discretionary	−35.680 ***	0
Consumer Goods	−20.919 ***	0
Energy	−37.837 ***	0
Financials	−16.042 ***	0
Industrials	−17.058 ***	0
Real Estate	−17.252 ***	0
Telecommunications	−21.740 ***	0
Utilities	−21.460 ***	0

Chile and US	ADF Statistic	First Difference
Market Index	−17.547 ***	0
Basic Materials	−41.524 ***	0
Consumer Discretionary	16.487 ***	0
Consumer Goods	−17.464 ***	0
Energy	−22.666 ***	0
Financials	−14.820 ***	0
Industrials	−3.776 *	0
Real Estate	−14.445 ***	0
Telecommunications	−39.473 ***	0
Utilities	−23.752 ***	0
Colombia and US	ADF Statistic	First Difference
Market Index	−37.353 ***	0
Basic Materials	−38.196 ***	0
Consumer Discretionary	−20.335 ***	0
Consumer Goods	−38.595 ***	0
Energy	−14.734 ***	0
Financials	−37.817 ***	0
Industrials	−34.054 ***	0
Telecommunications	−28.935 ***	0
Utilities	−37.999 ***	0
Mexico and US	ADF Statistic	First Difference
Market Index	−18.009 ***	0
Basic Materials	−41.211 ***	0
Consumer Discretionary	−24.302 ***	0
Consumer Goods	−15.251 ***	0
Financials	−17.801 ***	0
Industrials	−14.113 ***	0
Real Estate	−22.406 ***	0
Telecommunications	−12.365 ***	0
Utilities	−12.750 ***	0
Peru and US	ADF Statistic	First Difference
Market Index	−14.878 ***	0
Basic Materials	−36.304 ***	0
Consumer Discretionary	−14.371 ***	0
Consumer Goods	−36.733 ***	0
Energy	−13.370 ***	0
Financials	−9.389 ***	0
Industrials	−38.098 ***	0
Real Estate	−27.153 ***	0
Telecommunications	−11.879 ***	0
Utilities	−21.090 ***	0

Notes: *, **, and *** indicate a significant at the 90%, 95%, and 99% levels, respectively.

Notes

- 1 The new deal is now known as the USMCA (US-Mexico-Canada Agreement) and it was implemented in 1 July 2020. Although the new deal is within the scope of this research, it is out of the research sample and time frame.
- 2 Detailed information about the implementation and creation of each Trade Agreement is given in Appendix A.
- 3 The results shown in this study used the S&P500. DJIA was used and showed very similar results.
- 4 Appendix B shows the sectors with their respective industries as per the ICB-FTSE classification.
- 5 Although the results are similar, the weekly approach was used to accommodate for any potential biases regarding holidays, exchange operational days and time differences.
- 6 We conduct an Augmented-Dickey-Fuller (ADF) test and confirm that the given time-series are stationary.
- 7 We generate wilk-Shapiro (Normality) and Ljung-Box Q (Autocorrelation) tests. The results are available upon request.
- 8 When we report unconditional correlations of energy and real estate sectors, we exclude Mexico and Colombia, respectively, due to data unavailability.
- 9 Normality tests for residuals and squared residuals are available upon request.
- 10 Appendix C provides the summary statistics of the bivariate conditional correlations between US and each of the respective Latin American markets sorted by industry.
- 11 Appendix D provides ADF statistics before fitting the smooth transition model. We confirm that a smooth transition model can be used on dynamic conditional correlations.
- 12 The assumption behind the smooth transition model is that the residuals should be stationary to be a good fit for the data: An Augmented-Dickey Fuller test was conducted on the residuals and all the results show that the residuals are stationary. Appendix E provides all results.

- ¹³ In Table 7, we only report the results based on the market index between countries. Sectors information is reported separately and is available upon request.

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Article

The Effects of Geopolitical Risk on Foreign Direct Investment in a Transition Economy: Evidence from Vietnam

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Abstract: Foreign direct investment (FDI) is a key driver of economic development of both developed and developing countries. Understanding and having insights into the factors that motivate increased FDI are very important for both academics and policy makers. A key factor that multinationals incorporate in their decisions on FDI is geopolitical risk (GPR). Therefore, this study is devoted to investigating the short-term and long-term effects of GPR on FDI in Vietnam. Data used in this study are the yearly geopolitical risk index, FDI, and other control variables covering the period from 1986 to 2021. Using the autoregressive distributed lag (ARDL) bounds testing approach, the empirical results confirm that geopolitical risk (GPR) has a significantly negative effect on FDI in Vietnam in the long term. Specifically, in the long term, 1 percent increase in the GPR index is associated with 5.7983 percent decrease in Vietnam's FDI. In addition, the results derived from the ARDL model indicate that in the short term, GPR has a significantly positive effect on the FDI for the one-year lag, meaning that an increase in the GPR index leads to an increase in FDI. Moreover, the results derived from the error correction model (ECM) indicate that 42.89% of the disequilibria from the previous year are converged and corrected back to the long-run equilibrium in the current year. Based on the findings, some policy implications are drawn for policymakers to mitigate the negative effects of GPR on FDI.

Keywords: geopolitical risk; FDI; Vietnam

JEL Classification: F21; F51

1. Introduction

Globally, most all countries want to grow and prosper economically. Foreign direct investment (FDI) into a country and especially a developing country is a key driver of its economic prosperity. Understanding and having insights into the factors that motivate increased FDI are a critical vein of research which sheds light on those actions a country can take to promote the most beneficial FDI for its economy. Multi-national corporations (MNCs) look for those characteristics within a country that will give them the greatest chance of success. But just as importantly, they look at the risks that can undermine their success. Some variables serve to enhance FDI while other variables negatively impact FDI. Countries wanting to increase FDI should promote those areas that increase beneficial FDI while avoiding those issues that inhibit FDI. These factors include everything from geopolitical risk (GPR) to economic, financial, and technological development.

A key factor multinationals incorporate in their decisions on FDI to countries like Vietnam is the GPR of a particular country or region. Research indicates that GPR's impact is more significant for emerging market economies than for developed economies. The question of interest is in what ways and under what conditions GPR most impacts FDI both positively and negatively, and also which components of GPR are most influential on

FDI. There are a number of factors that MNCs look at to evaluate these risks. The International Country Risk Guide Index identifies 12 components of GPR including government stability, socio-economic pressure, investment profile, internal conflict, external conflict, corruption, military influence, religious tensions, law and order, ethnic tension, democratic accountability, and, lastly, bureaucracy quality.

Vietnam is an economy on the verge of moving from a frontier market to an emerging market via its transition from a central planning to a market-based economy with a wealth of economic opportunities. Vietnam's economy has been significantly integrated in the world economy since Doi Moi (Truong and Vo 2023). In addition, foreign direct investment (FDI) inflows to Vietnam have continuously increased during the past few decades. Specifically, the statistics of the World Bank show that Vietnam's FDI inflows increased by nearly 400 times its 1986 value of USD 40 million to USD 15,660 million in 2021.

Many things are driving this development success. Vietnam stands to be a big winner from Western economies looking to disentangle their supply chain exposure to China. First and foremost, MNCs headquartered in the West are looking for countries with a qualified and low-cost labor pool and the infrastructure in place to sustain the MNCs' supply chain needs. However, equally important is the political and legal environment of the country. These risks can easily derail MNCs' plans and cost significant resources. Although the effects of GPR on FDI inflows have been extensively studied in many countries, to our knowledge, no study has investigated the effects of GPR on Vietnam's FDI inflows. Therefore, this study is devoted to exploring the effects of GPR on FDI inflows to Vietnam, a transition economy.

The contributions of this study to the literature are as follows. First, this study enriches our knowledge on the effects of GPR on FDI inflows in a transition economy. Vietnam provides fertile ground for a unique investigation of the effects of GPR on FDI inflows due to the fact that Vietnam's economy has been in the transitional period with a deep and wide integration in the world economy. In addition, Vietnam has adopted the socialist-oriented market economy that is a unique model with its own characteristics in institutions and policies. By pursuing this model, Vietnam has remarkably achieved macro-economic performances in recent decades. Second, by using the ARDL (autoregressive distributed lag) bounds test approach, the short-term and long-term effects of GPR on the FDI are estimated. It is noted that the ARDL approach is proved to have some advantages in comparison with other co-integration techniques. Third, this study employs a comprehensive dataset covering the period from 1986 through to 2021 that allows for an in-depth analysis of both short-term and long-term effects of GPR on FDI.

The findings derived from the ARDL approach indicate that GPR has a significant negative effect on Vietnam's FDI inflows in the long-term. Interestingly, the ARDL model reveals a positive effect of GPR on FDI in the short-term, indicating possible opportunistic FDI by these MNCs during increased GPR. In addition, an analysis using an error correction model shows that nearly half of the previous year's disequilibria converges back in the current year to the long-term equilibria level. Based on the findings, some policy implications are drawn for policymakers in transitional countries, like Vietnam, to mitigate the negative impact of GPR on FDI.

This paper is organized as follows. Section 2 reviews the previous literature while Section 3 provides the data and methodology employed in the analysis. Section 4 contains the results of the analysis. Section 5 discusses the results, and Section 6 concludes the study.

2. Literature Review

The effects of GPR on FDI have been widely investigated and documented in the literature in recent decades. There is a broad array of research examining GPR's influence on FDI for many other countries and regions. Past research has documented that geopolitical risk (GPR) significantly affects FDI. The literature takes a number of different approaches to identify factors that either enhance or diminish the influence of GPR on FDI. Earlier research in this field focuses mainly on the impact of political and economic risks on

FDI. Ramcharan (1999) investigates the effects of political and economic risks on FDI for 26 countries over the period 1992–1994. Using Euromoney's Country Risk Data indexes as indicators of political and economic risks, the author finds a significant negative impact on FDI from increased political and economic risks. Subsequently, Mudambi and Navarra (2003) take a different approach by examining the effect of political traditions within a single country, Italy, to identify multinational FDI locational choices within this particular country. The authors contend that regional political traditions vary substantially across regions within Italy. Using a two-step econometric model, they examine the impact of local government's political orientation on FDI within each region across Italy. Interestingly, the authors find that a transition within the local government towards a center-right political orientation positively impacts regional FDI, while the opposite is true for a change to a center-left political orientation which has a negative influence on regional FDI. The move to a far-left political orientation within a region is mostly associated with a negative change in FDI. Subsequently, Hayakawa et al. (2013) examine the impact of both financial and political risks on FDI inflows for 89 countries over the period 1985–2007. The authors use both the level of these risks and their change over time. Interestingly, the authors find that only political risk and not financial risk adversely affects FDI. For developing countries in the sample, internal conflict, corruption, military influence on politics, and bureaucratic quality were negatively related to FDI. Conversely, the authors not only find that lower financial risk levels do not increase FDI, but that for developing countries, greater financial risk may actually increase FDI. The authors contend that these results are indications of a merger and acquisition fire sale phenomenon surrounding different financial crises. If this is the case, the authors posit that financial risk may have a differing impact on green field FDI versus M&A-motivated FDI. Moreover, in a study that includes 91 countries over the period 2002–2012, Erkekoglu and Kilicarslan (2016) use panel data analysis to examine the influence on FDI of various factors including political risks. The authors identify six political risk variables which are freedom of expression and transparency, political stability and absence of violence, management effectiveness, regulatory quality, rule of law, and prevention of corruption. They also use five control variables that are FDI, consumer price inflation, GDP, exportation of goods and services, and population size. To control for interdivisional correlation, autocorrelation, and heteroscedasticity, the authors use a Driscoll–Kraay fixed-effects model. The findings indicate that FDI is positively associated with the exportation of goods and services, population, and logarithms of GDP. However, political stability and the absence of violence along with administration efficacy negatively impact FDI. Also employing panel data, Weiling and Martek (2021) use 74 developing countries for the period 2008–2017 to delve into the influence of certain political risks on sustainable development and access to clean energy by looking at FDI related to energy investment. The authors find that the risk of investment profile, law and order, religious tensions, and corruption have a significant negative impact on foreign energy investments. But, these factors' influence can be reduced by gross domestic product, economic freedom, and host country energy demand. The authors go on to use clustering techniques to identify commonality within sub-groups of the 74 countries, finding that developing countries will share similar political risk and macro-environmental profiles with some countries but not others. They find five clusters ranging in size from 7 to 25 countries in each similar grouping. Haiti and Iraq were outliers not paired with any cluster.

Following up on the impact of political elections, Julio and Yook (2016) identify national elections as times of political uncertainty and examine US multinational FDI across 43 countries surrounding these elections. The authors find that US multinational FDI drops by 13% on average for the time period just preceding a national election. The more competitive the election, the greater the impact on FDI. They also report that the drop in foreign FDI significantly exceeds any drop in domestic investment over the same period. Once the election is over, FDI then increases as greater political certainty returns. Though greater for emerging markets, the results were also robust for developed countries, indicating that political uncertainty universally affects a country's FDI. Countries identified

as having higher quality legal and political institutional quality have significantly less FDI variation surrounding elections. In another analysis, DesBordes (2010) delves into whether multinationals consider both global and diplomatic risk when considering FDI. The author contends that these risks are different in that diplomatic risk is country-specific based on governmental relations. However, GPR is the same for all multinationals regardless of location. Using modeling from bilateral FDI panel data with included dyadic effects, the author finds that both global and diplomatic political risks negatively impact FDI by US multinationals who demand higher returns when faced with these risks. Similar to GPR, a one-standard-deviation rise in diplomatic risk increases the required return by approximately 0.80%. Also employing a dyadic approach for the period 1980–2000, using a GMM estimator to a gravity model of FDI for 58 countries with 1117 dyads, Li and Vashchilko (2010) examine the impact of military conflicts as a source of political risk and uncertainty on bilateral capital flows. The authors find that for the 18 countries with a per capita real income above USD 12,000, conflicts do not significantly impact capital flows. They also report that security alliances increase cross-border capital flows, with defense pacts having the greatest influence.

From a different perspective, several empirical studies investigate the effects of GPR indexes on FDI. Busse and Hefeker (2007) look at the impact of GPR on FDI across 83 developing countries for the period 1984–2003 using the 12 components of political risk tracked by the Political Risk Services (PRS) group reported in their International Country Risk Guide. These 12 components of political risk include government stability, socio-economic pressure, investment profile, internal conflict, external conflict, corruption, military influence, religious tensions, law and order, ethnic tension, democratic accountability, and, lastly, bureaucracy quality. Using an Arellano–Bond GMM dynamic estimator to control for autocorrelation and endogeneity for the time-series analysis, the authors find that government stability, internal and external conflicts, law and order, ethnic tensions, and bureaucratic quality are highly significant determinants of FDI, while a significant but weaker relationship is found between FDI, corruption, and democratic accountability. Similarly, Al-Khouri and Khalik (2013) examine the impact of political risk on FDI over the period from 1984 to 2011 for the MENA region which consists of the Middle East and North Africa by using the 12 components of political risk tracked by the Political Risk Services (PRS) group. They find that market size and, in some cases, political risk are positively related to the change in FDI. Corruption and external conflict are most correlated with FDI flows for the 12 political risk components. Results show that market size and growth, agglomeration, and openness are all positively related to FDI. The authors further find that bureaucracy and ethnic tension negatively affect FDI. Counterintuitively, the authors report that countries with higher corruption, less democracy, and high internal conflicts are more able to attract FDI. Similar to Al-Khouri and Khalik (2013) and Busse and Hefeker (2007), Rafat and Farahani (2019) also use the 12 political risk indexes from the International Country Risk Guide to study the link between GPR and FDI in Iran over the period 1985–2016. They use a two-stage least squares model and find that of the 12 political risk indexes, external conflict, ethnic tensions, socioeconomic condition, investment profile, and military and religious tensions have a highly significant influence on multinational FDI for Iran. Using a generalized linear model, Fania et al. (2020) examines the influence of GPR on FDI for 16 West African countries. Like previous research, the authors report that the influence of GPR on FDI varies significantly across GPR's sub-components. Taking a different approach from the research using GPR indexes, Jensen (2008) contends that these indexes only indirectly measure the relation between political risk and political institutions. To get a more direct measure, the author uses the political risk insurance agency premiums that multinationals are charged to cover government expropriations and contract disputes. Using this unique metric, the author reports that democratic governments reduce FDI risk for multinationals primarily by placing greater constraints on the executive leaders of the countries. To better explore the relationship between democracies and lower political risk, the author goes on to collect qualitative data from 28 investors, political risk insurers, plant location consultants,

and multinational international lawyers. Overall, the author finds that the possibility of expropriation and other executive policy changes is significantly increased in countries with few constraints on the leader such as Russia, Bolivia, and Venezuela.

More recently, some studies measure the effects of GPR by using the GPR index created by Caldara and Iacoviello (2022) on FDI. Using a pseudo Poisson maximum likelihood estimation for a gravity trade model, Thakkar and Ayub (2022) examine the influence of GPR on bilateral FDI data for 2001–2012 and trade data for 1948–2019. The authors find that their univariate model indicates that for a 10% increase in GPR, there is a significant drop of 3.6% for FDI and a drop of 0.5% for trade. However, for their multivariate model, the results indicate a small increase in trade of 0.04%. Some other recent research includes Nguyen et al. (2022), who examine the influence of GPR on FDI inflows and total factor productivity for 18 emerging market countries over the period 1985–2019. The authors use Granger causality panel data tests along with seemingly unrelated regression models to find that GPR has a significant negative impact on technological progress and FDI. They also find that technological progress and FDI act to mitigate GPR. Furthering the literature on technologies' impact on FDI, using multiple databases, Bussy and Zheng (2023) conclude that greater geopolitical risk and uncertainty also negatively impact FDI. The authors report that good governance shields FDI from GPR. In addition, rather than managing GPR, multinationals with closer geographic, cultural, and commercial relationships often delay FDI at rising GPR. On the technology front, they find that FDI for R&D industries has greater resilience to GPR, hypothesizing that technology is more readily transferred outside the country. Following up, the influence of geopolitical risks on FDI for Turkey over the period 1985–2020 was examined by Altiner and Bozkurt (2023). Using an ARDL bounds test approach, where FDI is the dependent variable and geopolitical risk, growth, globalization, and inflation are the explanatory variables, the authors find (as hypothesized) that an increase in geopolitical risk negatively impacts FDI. For the control variables, inflation negatively affects FDI while higher economic growth and globalization motivate FDI. Moreover, Yu and Wang (2023) also employ a cluster fixed-effects model on a sample of 41 countries over the period 2003–2020 to examine the influence on FDI of GPR obtained from the GPR index created by Caldara and Iacoviello (2022). The authors identify three possibly mitigating motives for FDI that serve to limit GPR. These three control variables are market seeking, natural resource seeking, and strategic resource seeking motives. Overall, they find that GPR significantly reduces FDI which spills over to impact the domestic economy. In addition, they find that all control variables are significant drivers of FDI. In addition, the authors find that these results are robust for sub-sample data. They then use as the core explanatory variable an interaction between GPR and trade dependency, finding that the trade dependency of a country mitigates the negative influence of GPR on FDI. The authors go on to find that GPR has a significant impact on FDI for emerging economies but not developed economies.

Overall, research provides some interesting and generally consistent insights into the factors most likely to positively and negatively impact FDI. Political, economic, and financial factors all have varying positive and negative influences on FDI depending on the country, and as our analysis shows, differ for the short term versus the long term. For example, greater financial risk is generally shown to enhance FDI while most political risks negatively impact FDI. Also, in more developed economies, these variables are muted, while their effects are much more pronounced in emerging market economies that can be far more dependent on FDI. Domestic politics is also shown to influence GPR. Voting that moves a region to the political left wing direction can have a significant negative impact on FDI. Similarly, concentrating too much power in the executive leader position also negatively influences FDI while democracy and a more balanced political power dynamic generally lead to greater FDI. However, counterintuitively, factors such as higher corruption levels and financial risk can motivate higher FDI in some cases. Although the effects of GPR on FDI inflows have been widely studied in many countries, to our knowledge, there are no studies that specifically examine the impact of GPR on FDI for Vietnam. Therefore,

this study adds to the literature by using the ARDL model to investigate the effects of GPR on Vietnam's FDI inflows.

3. Data Sources and Research Methodology

3.1. Data Sources

The data employed in this study are the yearly series of geopolitical risk (GPR) index, FDI, trade openness (TO), and GDP growth of Vietnam, covering the period from 1986 to 2021. This period is selected for this study because Vietnam began a program of comprehensive economic reforms (Doi Moi) in 1986, which marked the opening of its economy (the end of a central planning period of the economy). It is important to note that this study employs the geopolitical risk index that was developed by Caldara and Iacoviello (2022). This index is calculated based on selected words related to geopolitical risk, which are commonly used by journalists when reporting on geopolitical events and threats (Micallef et al. 2023). The GPR index was normalized to 100 from the points on the base year 2000. Specifically, the data sources are presented in Table 1.

Table 1. Data sources.

Data	Data Source
FDI	World Bank (WB)
GPR Index	Caldara and Iacoviello's website (https://www.matteoiacoviello.com , accessed on 30 September 2023)
TO	World Bank (WB)
GDP growth	World Bank (WB)

3.2. Research Methodology

To investigate the effects of geopolitical risk on FDI flows to Vietnam, the following regression model was used in this study:

$$\text{LNFDI}_t = \beta_0 + \beta_1 \text{LNGPR}_t + \text{TO}_t + \text{GDPG}_t + \varepsilon_t \quad (1)$$

where

- LNFDI: Natural logarithm of FDI (USD) in Vietnam.
- LNGPR: Natural logarithm of GPR Index (point).
- TO: Trade openness. The trade openness is computed using the following equation:

$$\text{TO}(\%) = \frac{\text{EX} + \text{IM}}{\text{GDP}} * 100 \quad (2)$$

where

- EX: Total export value (USD) of Vietnam.
- IM: Total import value (USD) of Vietnam.
- GDP: Gross domestic product (USD) of Vietnam.
- GDPG (%): Gross domestic product growth rate of Vietnam.

To investigate the short-run and long-run effects of GPR on FDI in Vietnam, this study employs an autoregressive distributed lag (ARDL) model which was developed by Pesaran et al. (2001). The ARDL model has some advantages compared to other co-integration methods. The prominent advantage of this model over other alternative co-integration methods is that an error correction model (ECM) can be estimated from the ARDL model, and hence the short-run and the long-run effects of explanatory variables on the dependent variable can be simultaneously computed. In addition, this approach does not require that all variables in the model have the same integration order. Instead, it only requires that all variables are integrated to the order of purely zero, purely one, or a combination of both. Moreover, the ARDL approach is relatively more robust and reliable than other approaches in the case of small observations like this study. However, this

approach has several disadvantages. First, this approach is based on the assumption that the relationship between the dependent variable and independent variables is symmetric (linear), meaning that a decrease and an increase in independent variables has the same effect on the dependent variable with the same magnitude. Second, this technique cannot be applied to the model that requires one of the variables to be integrated to the order 2 or I(2).

3.2.1. Unit Root Test

As mentioned above, the ARDL bounds test requires that all variables are integrated to the order of purely zero [I(0)], purely one [I(1)], or a combination of both. Therefore, before performing the bounds test, the order of integration of all variables should be examined by using unit root tests. This study employs the ADF (augmented Dickey–Fuller) and Phillips–Perron tests to examine whether the studied variables are stationary or not.

3.2.2. ARDL Bounds Test for Co-Integration

Before estimating the short-run and long-run effects of GPR on Vietnam's FDI, co-integration tests should be performed as a required condition. In order to examine the co-integration between variables, this study employs the bounds test. The bounds test of co-integration is estimated using the following equation:

$$\Delta LNFDI_t = \beta_0 + \sum_{i=1}^{q_1} \beta_{1i} \Delta LNFDI_{t-i} + \sum_{i=0}^{q_2} \beta_{2i} \Delta LNGPR_{t-i} + \sum_{i=0}^{q_3} \beta_{3i} \Delta TO_{t-i} + \sum_{i=0}^{q_4} \beta_{4i} \Delta GDPG_{t-i} + \delta_1 LNFDI_{t-1} + \delta_2 LNGPR_{t-1} + \delta_3 TO_{t-1} + \delta_4 GDPG_{t-1} + \varepsilon_t \quad (3)$$

where Δ represents the first difference of the variables. The null hypothesis (H_0) of the bounds test is $\delta_1 = \delta_2 = \delta_3 = \delta_4 = 0$ (no co-integration in the long-run between variables). If the F-statistic calculated from the bounds test is greater than the critical value of the selected significance level, the null hypothesis is rejected. This means that there is a long-term relationship (co-integration) between the variables in the model. If the long-run equilibrium relationship is confirmed, the short-run and long-run effects of the GPR on the FDI are estimated using Equations (4) and (5), respectively.

$$\Delta LNFDI_t = \alpha_0 + \sum_{i=1}^{q_1} \beta_{1i} \Delta LNFDI_{t-i} + \sum_{i=0}^{q_2} \beta_{2i} \Delta LNGPR_{t-i} + \sum_{i=0}^{q_3} \beta_{3i} \Delta TO_{t-i} + \sum_{i=0}^{q_4} \beta_{4i} \Delta GDPG_{t-i} + \delta ECM_{t-1} + \varepsilon_t \quad (4)$$

$$LNFDI_t = \alpha_0 + \sum_{i=1}^{q_1} \beta_{1i} LNFDI_{t-i} + \sum_{i=0}^{q_2} \beta_{2i} LNGPR_{t-i} + \sum_{i=0}^{q_3} \beta_{3i} TO_{t-i} + \sum_{i=0}^{q_4} \beta_{4i} GDPG_{t-i} + \varepsilon_t \quad (5)$$

4. Empirical Results

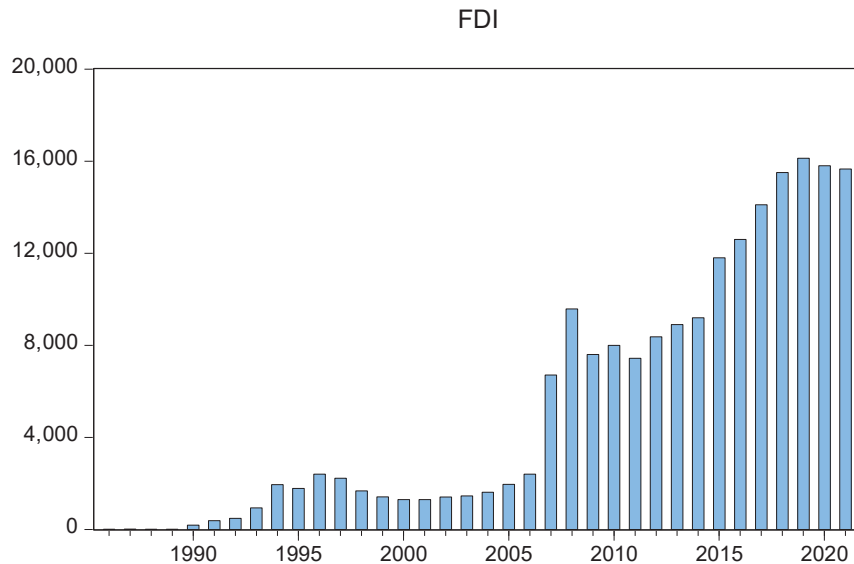
4.1. Vietnam's FDI Inflows and the GPR for the Period 1986–2021

On the basis of the collected data, the descriptive statistics of the Vietnam's FDI inflows and GPR for the period from 1986 to 2021 are computed and summarized in Table 2. It is shown that over the same period, Vietnam's average FDI inflows was USD 5338 million. In addition, Table 2 indicates that Vietnam's FDI fluctuated highly during the sample period, ranging from USD 0.04 million to USD 16,120 million, with a standard deviation of 5494.76. Moreover, Figure 1 illustrates that Vietnam's FDI inflows during the period from 1986 to 2006 is rather small compared with the period 2007–2021. Specifically, the FDI inflow was only 0.04 million USD in 1986. Vietnam's FDI inflows gradually improved since the lifting of US trade embargo against Vietnam in 1994. In particular, Vietnam's FDI inflows significantly increased after Vietnam joined the World Trade Organization (WTO) in 2007. In fact, Figure 1 shows that Vietnam's FDI inflows increased from USD 6700 million in 2007 to USD 16.120 million in 2019. However, Vietnam's FDI inflows slightly decreased during the period 2020–2021 due to the COVID-19 pandemic.

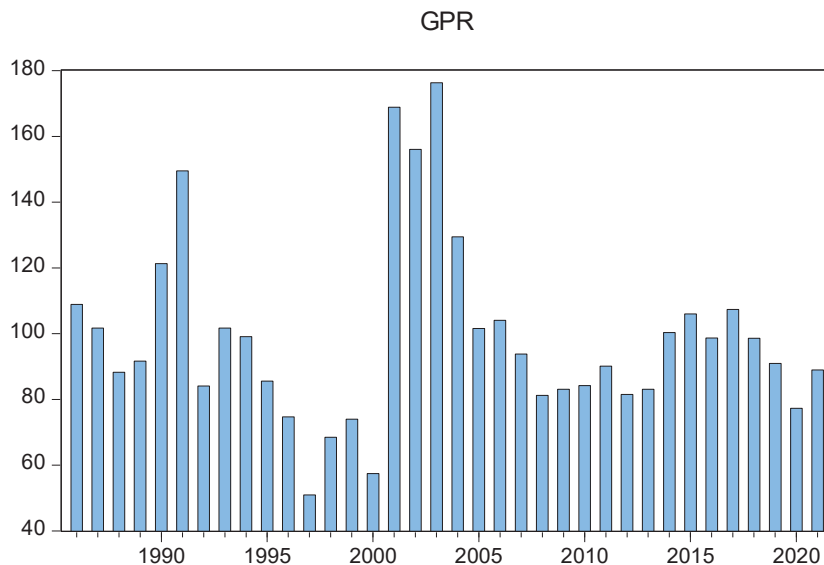
Table 2. Summary statistics of Vietnam's FDI and GPR (1986–2021).

Variables	Obs.	Mean	Min.	Max.	Std. Dev.
FDI (million USD)	36	5338.04	0.04	16,120.00	5494.76
GPR (point)	36	98.83	50.91	176.30	27.88

Source: Own calculation on the basis of data obtained from the WB and Caldara and Iacoviello's website (<https://www.matteoiacoviello.com>, accessed on 30 September 2023).

**Figure 1.** Vietnam's FDI inflows during the period 1986–2021.

In addition, Table 2 indicates that the GPR index mean for the period from 1986 to 2021 is 98.83 points, ranging from 50.91 points to 176.30 points. Specifically, Figure 2 shows that the GPR index fluctuated highly during the period from 2000 to 2005. It is important to note that there were some big political events that took place during this period, such as the suicide attacks in the US on 11 September 2001, the Afghanistan War starting on 7 October 2001, and the Iraq War beginning in April 2003. The GPR index reached the highest score in 2003 (176.30 points). The GPR index was rather stable during the period from 2006 to 2021 compared to the previous period.

**Figure 2.** The GPR Index for the period 1986–2021.

4.2. Unit Root Tests

As mentioned above, this study employs the ADF and Phillips–Perron tests to check whether the variables used in the model are stationary as a required condition of the ARDL bounds test. The tests are performed for both cases of constant only and constant with time trend. The results of the tests are summarized in Table 3. The results derived from the ADF and Phillips–Perron tests consistently confirm that the null hypothesis of a unit root is statistically rejected for LNFDI and LNGPR at the level. In other word, the LNFDI and LNGPR variables are integrated to the order zero denoted as $I(0)$. In addition, the results of the ADF and Phillips–Perron tests consistently indicate that the TO series is non-stationary at the conventional significant level of 5 percent. However, when the first differences are applied, the null hypothesis of a unit root is significantly rejected at the one percent level for the series, indicating that it is stationary. It means that TO series is integrated of order 1 or $I(1)$. Moreover, the results of the ADF test reveal that the GDPR series is $I(0)$ while the results of the Phillips–Perron test indicate that this series is $I(1)$. With the evidence, it is concluded that all variables in the model fulfil the requirements of the ARDL bounds test.

Table 3. Results of ADF unit root tests.

Variable	ADF Test		Phillips–Perron Test	
	Constant	Constant with Trend	Constant	Constant with Trend
LNFDI				
Level	−5.77 ***	−5.72 ***	−6.64 ***	−6.73 ***
LNGPR				
Level	−3.26 **	−3.22 *	−3.32 **	−3.27 *
TO				
Level	−1.24 (0)	−2.54	−1.22	−1.36
First difference	−5.38 ***	−5.34 ***	−5.39 ***	−5.39 ***
GDPR				
Level	−3.11 **	−3.25 *	−2.61	−2.67
First difference			−5.41 ***	−5.76 ***

***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.

4.3. ARDL Bounds Test for Co-Integration

As mentioned above, this study employs the bounds test proposed by Pesaran et al. (2001) to determine the long-run relationship among variables in the model. Based on the Akaike Information Criterion, the best model used for the bounds test is ARDL (4,2,4,4). The results of the bounds represented in Table 4 indicate that the null hypothesis of no co-integration among variables is rejected at the significant level of 1 percent. This means that there is a long-run equilibrium relationship between LNFDI and the regressors. Therefore, it is concluded that the ARDL model can be used to estimate the short-term and long-term effects of GPR on FDI.

Table 4. Results of the bounds test.

	k	F-Statistic	Significance Level	Critical Value	
				Lower Bounds $I(0)$	Upper Bounds $I(1)$
ARDL (4,2,4,4)	3	12.85 ***	5%	3.23	4.35
			1%	4.29	5.61

k indicates the number of regressors. *** represents statistically significance at the 1% level.

4.4. Short-Term and Long-Term Effects of the GPR on Vietnam's FDI

The short-term and long-term effects of GPR and other independent variables on Vietnam's FDI derived from the ARDL model are presented in Tables 5 and 6, respectively. In the short-term, the GPR index has a significantly positive effect on FDI at the one percent

level for the one-year lag. This finding implies that in the short-term an increase in the GPR index leads to an increase in FDI for the one-year lag. In addition, the results reported in Table 5 indicate that TO has a significantly negative effect on the FDI at the five percent level for the three-year lag. Moreover, Table 5 reveals that in the short-term, GDP growth (GDPR) is positively associated with FDI for the three-year lag. This relationship is statistically significant at the one percent level. The implication of this evidence is that in the short-term, an increase in GDPR results in an increase in FDI for the three-year lag. Furthermore, the coefficient of error correction for the model is -0.4289 and significant at the one percent level, indicating that 42.89 percent of the disequilibria from the previous year is converged and corrected back to the long-run equilibrium in the current year.

Table 5. The estimated short-term coefficients.

Variables	Coefficients	t-Statistic
$\Delta \text{LNFDI}(-1)$	0.2113	2.54 **
$\Delta \text{LNFDI}(-2)$	0.1402	1.74
$\Delta \text{LNFDI}(-3)$	0.2808	4.55 ***
ΔLNGPR	-0.4859	-1.03
$\Delta \text{LNGPR}(-1)$	1.4348	3.46 ***
ΔTO	0.0164	4.24 ***
$\Delta \text{TO}(-1)$	0.0003	0.05
$\Delta \text{TO}(-2)$	0.0045	0.78
$\Delta \text{TO}(-3)$	-0.0010	-2.23 **
ΔGDPR	0.0601	1.48
$\Delta \text{GDPR}(-1)$	0.0435	0.75
$\Delta \text{GDPR}(-2)$	-0.0336	-0.52
$\Delta \text{GDPR}(-3)$	0.1427	3.62 ***
$\text{ECM}(-1)$	-0.4289	-6.07 ***

*** and ** indicate significance at the 1% and 5% levels, respectively.

Table 6. The estimated long-term coefficients.

Variables	Coefficients	t-Statistics
Constant	28.4360	8.68 ***
LNGPR	-5.7983	-4.31 ***
TO	0.0443	10.80 ***
GPRG	-0.0464	-0.32

*** indicates significance at 1%.

In addition to estimating the short-term effect, the ARDL approach also allows for the estimation of the long-term effect of GPR on FDI. The results of the long-term of GPR on FDI are summarized in Table 6. It is observed that in the longterm, GPR has a significantly negative effect on FDI at the one percent level. Specifically, in the longterm, a one percent increase in the GPR index is associated with 5.7983 percent decrease in Vietnam's FDI. In addition, the results presented in Table 6 show a significantly positive effect of TO on Vietnam's FDI at the one percent level. However, in the longrun, GPRG has no significant effects on FDI.

4.5. Diagnostic Tests

To check the validity and reliability of the estimated results, the Breusch–Godfrey test for serial correlation, the ARCH test for heteroscedasticity, and the Jarque–Bera test for the normal distribution of residuals are used in this study. The results derived from these tests are presented in Table 7. Specifically, the results of the Breusch–Godfrey test confirm that the null hypothesis of no serial correlation in the model cannot be rejected at the significance level of 5%. Therefore, it is concluded that serial correlation does not exist among the residuals. In addition, the results derived from the ARCH test confirm that the residuals are characterized by homoscedasticity. Moreover, the results of the Jarque–Bera

test indicate that the null hypothesis of residuals having normal distribution cannot be rejected at the conventional significant level of fivepercent. This means that the residuals of the model follow a normal distribution. These diagnostic tests ensure the reliability and validity of the estimated results.

Table 7. Results of autocorrelation, ARCH, and normality tests.

Diagnostic Test	Statistics	<i>p</i> -Value	Conclusions
Autocorrelation (Breusch–Godfrey test) H_0 : No serial correlation	2.006	0.177	Failure to reject H_0
Heteroskedasticity (ARCH test) H_0 : No ARCH effects	0.566	0.458	Failure to reject H_0
Normality test (Jarque–Bera test) H_0 : The residuals are normally distributed.	1.759	0.415	Failure to reject H_0

4.6. Structural Stability Tests

It is important to stress that the ARDL model is sensitive to structural breaks and the variables used in this study are also sensitive to global events. To examine the long-term stability of the coefficients in the model, this study employs the cumulative sum of the recursive residuals (CUSUM) and the cumulative sum of squared recursive residuals (CUSUMSQ) tests proposed by Brown et al. (1975). It is observed in Figure 3 that the plots of CUSUM lie inside the critical bounds at the five percent level of significance. In addition, Figure 4 shows that the plots of CUSUMSQ are almost within the critical bounds at the significance level of 5%. Therefore, it can be concluded that the model used in the study is stable over the sample period.

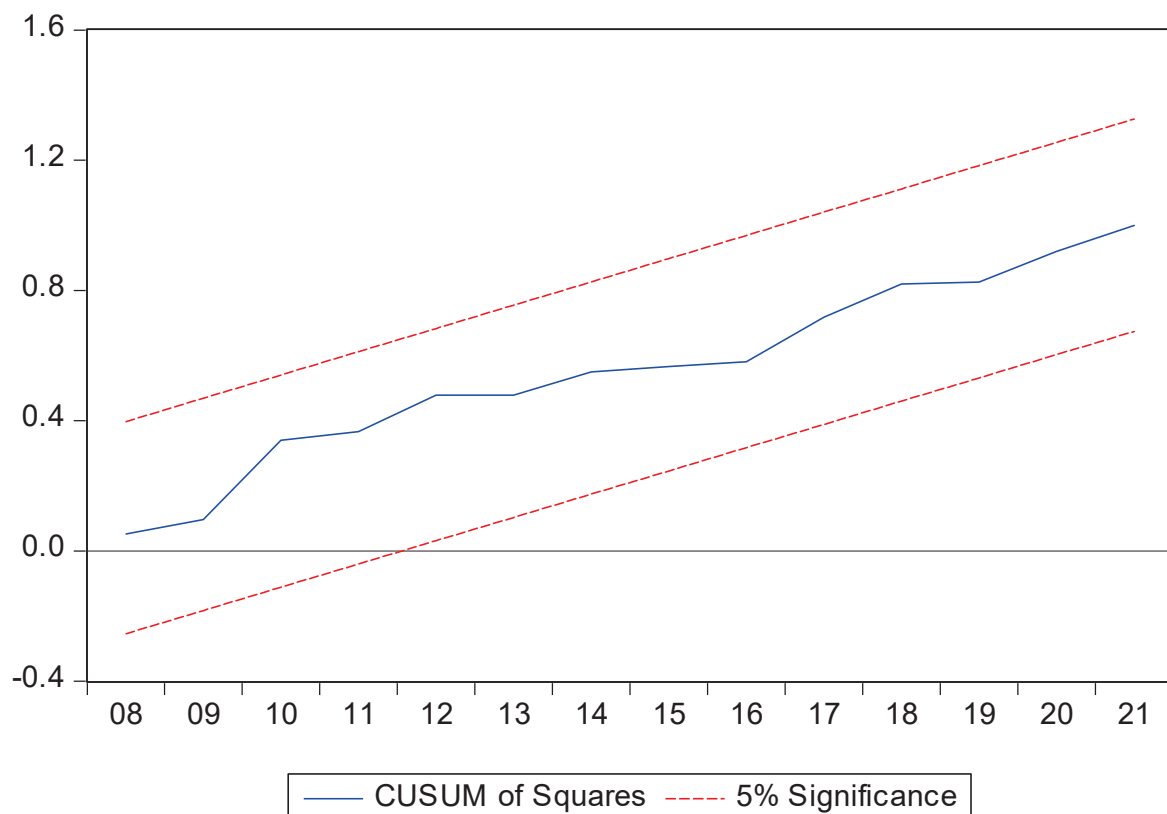


Figure 3. Plots of cumulative sum of recursive residuals.

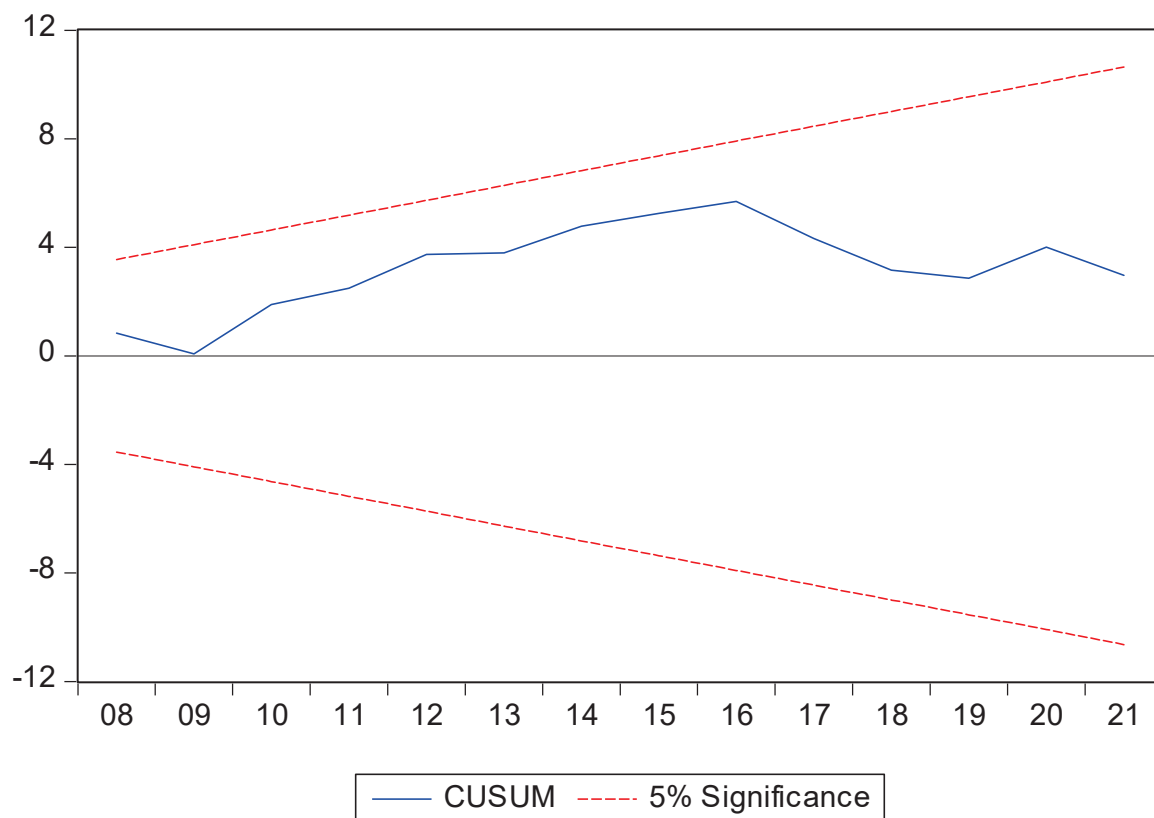


Figure 4. Plots of cumulative sum of squares of recursive residuals.

5. Discussion of the Results

The main finding of the study is that in the longterm, GPR has a significantly negative effect on FDI. In other words, increasing GPR deters FDI inflows. This evidence is consistent with the previous empirical findings of Ramcharran (1999), DesBordes (2010), Hayakawa et al. (2013), Weiling and Martek (2021), Nguyen et al. (2022), Thakkar and Ayub (2022), Bussy and Zheng (2023), and Yu and Wang (2023). The implication of this finding is that in the context of transition economies, GPR could result in potential economic costs for MNCs. Therefore, MNCs postpone outward foreign direct investment if their perception of GPR is high. In addition, the results reveal that trade openness has a significantly positive effect on FDI in both the longterm and shortterm. This finding implies that trade openness plays an important role in attracting FDI inflows. Specifically, an improvement in trade openness is associated with an increase in FDI in both the longterm and shortterm. Finally, the results of the error correction model indicate that nearly half of the previous year's disequilibria converges back in the current year to the long-term equilibria level. The adjustment speed in this case is rather slow. This finding provides an insightful understanding of the adjustment process in FDI flows, which is a valuable reference for policymakers to issue appropriate policies to mitigate the negative impact of GPR on FDI.

Based on the findings, some policy implications can be drawn for policymakers in transitional countries, like Vietnam, to mitigate the negative impact of GPR on FDI. First, governments should prioritize policies that promote political stability as a signal of macro-economic stability to foreign investors. Second, governments should strengthen political and economic cooperation with other countries, focusing on leading nations that contributed to their FDI inflows through proactive diplomatic strategies, the signing of investment agreements, and participation in free trade areas. Third, it is found from the study that TO has a significantly positive effect on the FDI. Therefore, in order to stimulate exports and sustainably improve the trade balance, a managed floating exchange rate policy should be applied. A higher level of the country's trade openness can attract more FDI

inflows. Moreover, by adopting this regime, governments can actively adjust the exchange rate in order to control inflation and absorb most of the foreign shocks or policy changes from developed economies.

6. Conclusions

This study empirically investigates the short-term and long-term effects of GPR on Vietnam's FDI during the period from 1986 to 2021. The empirical findings derived from the ARDL approach confirm that GPR has a significantly positive effect on FDI in the short term for the one-year lag. However, in the long term, GPR has a significantly negative effect on FDI. In other words, an increase in the GPR index is associated with a decrease in Vietnam's FDI inflows. In addition, the results reveal that trade openness (TO) has a significantly positive effect on FDI in both the long term and short term. Moreover, the findings of the ARDL test indicate that in the short term, GDP growth (GDPR) is positively associated with FDI for the three-year lag, but it has no impact on FDI in the long term. Finally, the results of the error correction model show that 42.89% of the disequilibria from the previous year are converged and corrected back to the long-run equilibrium in the current year.

Although this study has enriched our understanding of the effects of GPR on FDI in a transition economy, it still has limitations that should be addressed in future empirical studies. First, in this study, we investigate the effects of GPR on FDI inflows without considering the moderating effects of trade openness and economic growth variables on the association between GPR and FDI inflows. Therefore, future research could focus on the moderating effects of these variables when measuring the impact of GPR on FDI inflows. Second, due to limitations in the data, this study could omit some determinants of the FDI, such as financial development and public governance. With this limitation, future research could investigate the effects of these factors on FDI inflows and their moderating effects on the relationship between GPR and FDI inflows. The third limitation of this study could be the assumption that GPR has symmetric effects on FDI whereas these effects could be asymmetric. Therefore, the symmetric effects of GPR on FDI inflows could be an interesting topic that awaits further research.

Author Contributions: Conceptualization, L.D.T. and H.S.F.; methodology, L.D.T.; software, T.D.P.; formal analysis, L.D.T.; resources, T.D.P.; data curation, T.D.P.; writing—original draft preparation, L.D.T. and H.S.F.; writing—review and editing, L.D.T. and H.S.F.; project administration, L.D.T. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The data that support the findings of this research are available from the corresponding author upon request.

Conflicts of Interest: The authors declare no conflict of interest.

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Article

How Consideration of Future Consequences, Prior Gain or Loss, Personal Risk Profile, and Justification Affect Risk–Payoff Preferences

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Abstract: This study examines (1) how risk–payoff preference can be affected by differences in consideration of future consequences (CFC), prior gain/loss, and personal risk profile, and (2) whether one’s risk–payoff preference may vary with justification prompts. Using an experimental design with 366 undergraduate business students, participants are tasked to make risk–payoff choices in two scenarios, with the combined risk–payoff outcomes serving as the dependent variable. In addition, participants are assessed on their personal risk profiles and also complete the 14-item CFC scale to gauge the propensity to take into account future consequences of their behaviors. Findings show that one who scores low (high) in CFC will prefer lower (higher) risk and payoff. Further, for an individual who scores high in CFC and has a prior gain (loss), he/she will be more inclined to prefer lower (higher) risk and payoff, though this effect is moderated by one’s risk profile. Finally, justification prompts help to reduce one’s propensity toward high risk–payoff, irrespective of prior gain/loss and risk profile considerations. With regard to consumers’ financial choices, particularly in a volatile economic environment, the findings here indicate that prompting for strategic justifications before making decisions can help lower one’s overall propensity toward high risk–payoff choices.

Keywords: consideration of future consequences; prior gain or loss; personal risk profile; justification; payoff

1. Introduction

In this study, consideration of future consequences (CFC) is defined as the importance a person assigns to the immediate versus delayed consequences of their actions (Strathman et al. 1994). In predicting how individual differences in CFC may impact one’s financial decision-making, Joireman et al. (2005) showed that individuals high in CFC are more inclined to use a hypothetical windfall in a fiscally responsible fashion, like exhibiting greater promptness in paying down one’s credit card debt. Howlett et al. (2008) similarly found that consumers who display a higher propensity to consider the future consequences of their behaviors (i.e., higher CFC) will be more likely to make decisions and evaluations that will maximize their future financial well-being. In matters concerning personal finance, one with a higher level of CFC reports a higher likelihood of contributing to a 401 K plan, though this is moderated by one’s self-regulatory state and the level of financial knowledge.

Prior literature concerning aspiration level has also shown that investment choices are largely based on loss aversion, with individuals typically being risk-averse over gains, but risk-seeking over losses (see Payne et al. 1980, 1981). The economic theory of endowment effect posits an asymmetry between gains and losses, whereby loss is considered more aversive than gain of the same size (Kahneman and Tversky 1979). With outcome dispersion or variance often used as a proxy for risk, a greater (lower) risk can portend a lower (higher) probability of an event occurring (see Libby and Fishburn 1977; Payne 2005). Prior research has shown that using lower- (versus higher-) level construal to represent information about near (versus distant) events in the future increases one’s preference for a

higher (lower) probability of a lower (higher) expected payoff (Joireman and Balliet 2004; Sagristano et al. 2002).

Finally, Tetlock (1983, 1985) has found that prompting a more effortful process to justify one's decision choices could attenuate the tendency of making fundamental attribution errors. Applied to one's risk–payoff preference and conditional on one's CFC, prior gain/loss, and risk profile considerations, this study heretofore examines if strategic justification prompts could provide an effective prescription toward reducing one's propensity for making high-risk choices.

Using an experimental design with 366 undergraduate business students, participants are tasked to make risk–payoff choices in two scenarios, with the combined risk–payoff outcomes serving as the dependent variable. In addition, participants are assessed on their personal risk profiles and also complete the 14-item CFC scale to gauge the propensity to take into account future consequences of their behaviors. The findings of this study show that one who scores low (high) in CFC will prefer a lower (higher) risk and payoff. For an individual who scores high in CFC and has a prior gain (loss), he/she will be more inclined to prefer a lower (higher) risk and payoff. In examining the moderation effect arising from one's risk profile, results show that one with high CFC and a prior loss will demonstrate a preference for higher risk regardless of their personal risk profile. On the other hand, one with high CFC and a prior gain will choose the less risky approach if they were risk avoiders, versus the more risky approach if they were risk seekers. Finally, justification prompts help to reduce one's propensity toward high risk and payoff, irrespective of prior gain/loss and risk profile considerations.

Prior studies in financial statement risk assessment have provided theoretical insights by using both decision theory and behavioral variables in explaining investors' decision judgments, as well as investors' biases toward the different labeling and disclosures used in financial instruments (e.g., Koonce et al. 2005a, 2005b). This experimental study makes at least three incremental contributions to risk–payoff decision research. First, from a methodological standpoint, prior research in the areas of risk tolerance and risk-taking have predominantly used archival data from surveys, illuminating the importance of household demographics, individuals' life domains, and portfolio structures as well as a composite of subjective and objective financial knowledge in determining one's financial risk tolerance level or risk-taking propensity (see Grable and Rabbani 2014; Heo et al. 2021; Irandoust 2017; Noman et al. 2023; Rabbani et al. 2021; Schooley and Worden 2016). Experimental studies examining this research stream have also primarily looked at various individual effects, such as the effects of inducing differing time pressures or stressors on risk-taking preferences/behaviors (see, e.g., Cahlikova and Cingl 2017; Kirchler et al. 2017; Kocher et al. 2013). This study uses an experimental setting to further examine a multitude of important constructs on respondents' risk preference decisions.

Second, it extends the findings of earlier studies by introducing the important concept of CFC. Many of our life decisions involve a temporal element that hinges on our ability to look past the immediate and into the future. Contrary to the piecemeal approaches of prior studies in studying various individual concepts, this study consolidates and examines the dynamics of how one's CFC, prior gain/loss, and risk profile may interact with justification requirement to affect risk–payoff judgments. Thus, incorporating CFC within the broader financial decision-making framework can serve as a springboard for more future research involving a temporal dimension. Third, on a practical level, findings of this study indicate that, notwithstanding one's CFC, prior gain/loss, and risk profile, prompting for crucial justifications before making decisions can effectively be used to evoke a more cognitively vigilant mental processing mode, thereby helping to mitigate one's propensity toward making highly divergent, and often risky, choices. Overall, one could take heed of the findings from this study and gain a better understanding of the mechanism shaping one's decision-making processes. From a personal financial planning perspective, this can hopefully help steer investors toward making more reasoned financial choices,

with *lower* overall risks, particularly in a volatile economic environment when investors are more prone to make emotion-driven decisions.

The remainder of this paper is organized into five sections. The next section provides the theoretical background to the study. This is followed by the hypotheses development, research design, analyses, limitations and future research, and finally, the conclusion and implications.

2. Theoretical Background

2.1. Consideration of Future Consequences

Prior research has demonstrated that CFC's immediate-versus-future orientation is a stable personality characteristic with a significant influence on one's domain-specific behavioral outcomes (Murphy et al. 2020; Zimbardo and Boyd 1999). As defined by Strathman et al. (1994), individual differences in CFC reflect "the extent to which people consider the potential distant outcomes of their current behaviors and the extent to which they are influenced by these potential outcomes." Past research has shown an inverse relationship between CFC and temporal discounting, in that one who scores lower in CFC will prefer a smaller but more certain outcome amount, while in comparison, a person who scores higher in CFC will prefer a larger (i.e., higher expected utility) but less certain payoff (Joireman and Balliet 2004; Sagristano et al. 2002).

Related, construal level theory (CLT) proposes that temporal distance changes one's responses to future events by changing the way one mentally represents those events (Liberman and Trope 1998; Trope and Liberman 2000). One will use lower- (higher-)level construal to represent information about nearer (more distant) events in the future. As CLT proposes, in the context of making decision choices, if one thinks of the probability of (immediate) winning as subordinate to (distant) payoffs, then information regarding the probability of winning will be more prominent in construing near-future than distant-future decision choices, whereas information regarding payoffs will be more prominent in construing distant-future than near-future decision choices (Sagristano et al. 2002).

Inducing the near- versus distant-future concepts of CLT to predict how individual differences in CFC may impact one's financial decision-making, Joireman et al. (2005) showed that individuals high in CFC are more inclined to use a hypothetical windfall in a fiscally responsible fashion, like exhibiting greater promptness in paying down one's credit card debt. Howlett et al. (2008) further found that consumers who display a higher propensity to consider the future consequences of their behaviors (i.e., higher CFC) will be more likely to make decisions and evaluations that will maximize their future financial well-being. In matters concerning personal finance, one with a higher level of CFC reports a higher likelihood of contributing to a 401 K plan, though this is moderated by one's self-regulatory state and the level of financial knowledge.

2.2. Prior Gain/Loss and Risk

The phenomenon of mere ownership bias effect is one whereby an object will be regarded more favorably by an owner than by a non-owner (Hoorens et al. 1990). From the mere ownership effect comes the endowment effect phenomenon, the latter defined as an increment in value that accrues to an object when it becomes part of a person's endowment due to ownership (see Heider 1958). As put forth subsequently by Kahneman and Tversky (1979), in economic theory terms, the endowment effect is thought to occur because of the asymmetry between gains and losses, with a loss viewed as more aversive than a comparable gain (Kahneman et al. 1990). This endowment-driven, loss aversion impact on one's preference decisions could change depending on whether one is in a position with a prior gain or loss. Such tendency follows from the tenets of individuals being risk-averse over gains but risk-seeking over losses (Kahneman and Tversky 1979). Intuitively, this could impact one's preference, such that a prior gain (loss) position will evoke a lower (greater) propensity to take on risky investment decisions. When combined with prior

findings related to CFC, one's prior gain or loss should also be considered when tasked to make decision choices.

Several recent research studies have examined the topics of financial risk tolerance (FRT) and risk-taking behavior. Grable and Rabbani (2014) had earlier constructed a risk-tolerance portrait for individuals near retirement, to accurately characterize risk attitudes across seven domains. Focusing on the financial crisis event in 2008, Noman et al. (2023) examined a 2009–2018 data set and found that investors' FRT was associated more with their subjective than their objective financial knowledge, though the relative influence of subjective knowledge increased as the survey periods progress further away from 2008. Schooley and Worden (2016) also used a 2007–2009 panel data set to examine changes in perceived and realized risk tolerance after the financial crisis. They found that households who perceived less risk tolerance (particularly those whose wealth had decreased) were more likely to have reduced their portfolio risk. Single, less educated, self-employed, or unemployed households were also most susceptible to portfolio reduction during this period, and thus may need financial advice to help prevent them from selling too quickly and potentially missing out on gains as the market recovers.

Separately, Rabbani et al. (2021) used a January 2018 to January 2019 data set to compare one's FRT pre- to post- 3 October 2018 (i.e., the date of market high for the year 2018). They found a decrease in FRT levels post-October, with the most acute decrease evident with younger and less financially experienced respondents. There was no significant decrease in FRT post-October though, for those who have worked with financial advisors and counselors. Focusing from the COVID perspective by analyzing a data set from April 2019 to July 2020, Heo et al. (2021) found a general decrease in FRT as a result of the pandemic.

On one's risk-taking propensity, Irandoust (2017) investigated, in the context of Sweden, the effects of factors that may influence the probabilities of one being risk-averse or risk-seeking. Results from questionnaire responses conducted in Sweden during May 2015 showed that one's willingness to take financial risks depended on a multitude of portfolio and personal (i.e., gender, age, education, etc.) factors. Some previous studies have also examined the impact of inducing acute stressors or varying time pressures on risk-taking behaviors, finding inconsistent risk preferences toward gains and losses in response to differing conditions (Cahlikova and Cingl 2017; Kirchler et al. 2017; Kocher et al. 2013).

The normative mean-variance model as posited by Sharpe (1970) is centered on the value of an investment with its expected return (whereby more is preferred to less) and standard deviation (whereby less is preferred to more). In terms of one trying to reach an aspiration (i.e., success) level, the corresponding aim of loss aversion is often emphasized (Payne et al. 1980, 1981). Loss aversion, by definition, emphasizes a greater weighting attached to a negative event (Kahneman et al. 1990). Insofar as availability heuristics is concerned, people often base their predictions of the rate of occurrence within a population on the ease with which an example can be brought to mind (Tversky and Kahneman 1973). In the context of making decision choices, one will thus be more inclined to choose that option with a greater presence of positive outcomes, assuming equal actual expected outcome values for the different options.

Prior studies regarding decisions under uncertainty in finance and risk management have also postulated the importance of risk, in that an investor's emphasis is on avoiding the prospect of not meeting some target rate of return (Mao 1970). Payne (2005) conceptualized risk from the perspective of the overall probability of success or positive outcome in obtaining a certain level of return, thus the focus is on both increasing the overall probability of a gain as well as decreasing the overall probability of a loss. In effect, the higher (lower) the risk, the lower (higher) the probability of a favorable outcome, or conversely, the higher (lower) the probability of an unfavorable outcome. Edwards (1954) similarly showed in his study that the research subjects prefer low probabilities of losing large amounts of money to high probabilities of losing small amounts. Striving to consistently stay above one's aspiration (success) level, Siegel (1957) provided further evidence in this regard.

Earlier studies have so far largely identified the risk construct into two main groups: (1) as mentioned earlier, those conceiving risk as the failure to obtain a certain level of returns, and (2) those conceiving risk as relating to the total dispersion of the outcomes (i.e., measured in terms of the whole distribution variance) (Libby and Fishburn 1977). Since prior evidence has largely suggested that risk is more related to probability and the amount of loss (hence adhering to such decision rules as ‘minimize possible loss’ or ‘maximize possible gain’) (e.g., Slovic 1972), this study varies the level of risk (i.e., with an inverse relationship to the probability of success or a favorable outcome) and examines one’s risky investment decision choices given a prior gain (as compared to a loss or neutral) condition. Hence, controlling for one’s CFC, this study examines whether one’s prior gain/loss and personal risk profile can impact their risk–payoff choices.

2.3. Justification

Justification strategies in investment, shopping, or health-related decisions provide various rich contexts to examine judgment accountability (e.g., Huber et al. 2009; Johnson and Kaplan 1991; Park and Hill 2018; Schippers and Rus 2021; Tetlock 1983), whereby the process of explaining one’s decision to support a chosen option over another could evoke a more cognitively vigilant mental processing mode. One’s fundamental attribution error tendency could also be attenuated when meaningful accountability is introduced (Tetlock 1985; Lerner and Tetlock 1999). In essence, by being mindful and deliberate, in spending enough time to consider as many factors as possible before making a decision, this thought process could potentially reduce the risk of ending up with information-processing failures, thereby minimizing any divergence in one’s decision preference across differing endowment effects.

The main impetus for incorporating strategic justification requirements as an experimental treatment in this study is to examine if this will lead to a reduction in one’s propensity toward making high-risk choices. Using a more effortful process to document one’s formal decision rules will hopefully point to a more effective prescription toward reducing biased and risky choices previously observed. Hence, based on one’s prior gain or loss and personal risk profile, this study further examines if and how a more in-depth cognitive reasoning process impacting one’s choice preference can be evoked through the imposition of a justification requirement.

3. Hypotheses Development

Prior focus on the overall probability of success stemming from aspiration level is evident from studies by Payne and Braunstein (1971), Payne et al. (1980, 1981), and Payne (2005). Results indicate that subjects prefer the option with a higher overall probability of a positive outcome or gain, *ceteris paribus*. Insofar as the endowment effect is concerned, an increment in value is evident as a result of a person’s endowment due to ownership. This arises primarily because of the asymmetry between gains and losses, with a loss generally viewed as more aversive than a comparable gain (Kahneman and Tversky 1979). In this study, the objective is to examine whether one with a prior gain position can accentuate such an endowment-driven, loss-aversion phenomenon, while a prior loss position can conversely mollify such an endowment-driven, loss-aversion phenomenon. Thus, in adherence to prior findings related to the endowment effect, with a prior gain (loss), one will intuitively have greater (lower) loss- and risk-aversion tendencies, hence will be more inclined to prefer decisions with lower (higher) risk.

Individuals with lower CFC will logically prefer a more certain but smaller expected payoff, while a person higher in CFC will comparatively prefer a less certain but larger expected payoff. This study thus addresses the gap in the existing literature by further examining how one’s CFC could induce differing temporal distance perceptions in adherence to the near- versus distant-future construal, which when considered in conjunction with one’s prior gain or loss position, will impact one’s decision choices. Prior research established that one who scores low in CFC is less affected by their prior gain or loss, and will

be more inclined to direct resources away from the options maximizing long-term future benefits toward those options maximizing more certain short-term interests, in effect seeking the less risky (i.e., more certain) option (Joireman and Balliet 2004; Joireman et al. 2005). On the other hand, for those with high CFC, the endowment effect with a longer-term future benefit will likely take precedence (depending on whether one has a prior gain or loss), thus resulting in a stronger response to a loss than to a corresponding gain. Subject to “risk-seeking in the losses” and possibly moderated by one’s personal risk profile, this study also further builds on prior postulation and examines one’s risk–payoff choice preferences, depending on whether one has a prior gain or loss in a high CFC setting. Hypotheses One and Two are henceforth formally stated as:

H1. *One who scores low (high) in CFC will be more inclined to prefer decisions with lower (higher) risk (i.e., higher (lower) probability) and lower (higher) payoff.*

H2a. *One with a prior gain (loss) and who scores high in CFC will be inclined to prefer decisions with lower (higher) risk and lower (higher) payoff.*

H2b. *The effect of prior gain/loss and CFC on risk–payoff preference is moderated by one’s personal risk profile.*

Tetlock (1983) first discussed the construct of accountability in terms of justification, defining it as the social pressure to justify one’s decisions to others. Simonson and Nye (1992) found that, depending on the decision context, accountability can end up improving, degrading, or not changing one’s performance. In enhancing one’s self-critical attention to the judgment process as well as evoking a greater cognizance of the information provided, this study further examines if imposition of a justification requirement will lead to a less biased choice in a high CFC setting, potentially enabling one to pivot toward a decision with lower risk–payoff dynamics. As one documents the formal decision rules to follow, a more de-biased overall outcome should logically eventuate. Hypothesis Three, in imposing a strategic justification requirement, is henceforth formally stated as:

H3. *For one who scores high in CFC, justification prompts will help to reduce the propensity toward high risk–payoff.*

4. Research Design

The objective of this study is to examine the difference in risk–payoff preference between one with a prior gain vis-a-vis one with a prior loss. The experimental design is 3 (prior gain, prior loss, and neutral as control) $\times$ 2 (no justification versus justification requirement) randomized between-subject, with 370 undergraduate business students (recruited over two semesters) from a public university in the U.S., participating in exchange for extra course credits in an undergraduate accounting course. To improve participation, besides being awarded the extra course credits, each participant was entered into a cash lottery draw of USD 25 for each class of participants. Participants in the “justification requirement” condition provided their opinions on the specific reasons they have adopted in regard to their choices. An open-ended response format was used for participants who were prompted to provide justification for their choices. All participants were assessed on their CFC and personal risk profiles after they had indicated their choices. Four participants were removed from the final usable sample for leaving right after the experimental study began or for having not spent any time to reason (when prompted to justify),¹ thereby rendering their subsequent responses invalid with the substantially missing data responses (final sample: $n = 366$, 45% male, 55% female, median age = 20.6).

Part of the experimental instrument regarding the risk choice options was adapted from Sagristano et al. (2002), Payne (2005), and Payne et al. (1980). It started by narrating a synopsis whereby the participant is currently assumed to be in a position of net gain,

neutral, or net loss. Recently, the participant became aware of a prospectus regarding a new investment fund. Each participant is to assume that this new investment fund comes with two options (Choice A or B). To prevent participants' selection from being confounded by order effects, two within-subject scenarios were provided. In Scenario 1, Choice A has a lower risk (i.e., higher probability) of a lower expected payoff as compared to Choice B. Conversely, in Scenario 2, Choice A has a higher risk (i.e., lower probability) of a higher expected payoff as compared to Choice B. Each participant is then tasked to choose whether to invest in Choice A or B for both scenarios. A coding of "1" is used when a participant chooses lower risk and lower payoff, and "2" when one chooses higher risk and higher payoff, hence providing a possible range of 2 (lowest) to 4 (highest) in summing the combined choices made for the two scenarios.² This risk score (i.e., the risk variance spread preference value) will form the dependent variable in our analyses. A copy of the case is found in Appendix A.

All participants completed the adapted 14-item CFC scale (see Joireman et al. 2012, 2006; Strathman et al. 1994), as shown in Appendix B. The 14-item CFC scale contains general statements regarding a person's propensity to take into account future consequences of their behavior. Participants were asked to indicate whether each of the fourteen statements was characteristic of themselves by circling the appropriate number on the scale, ranging from 1 (extremely uncharacteristic) to 7 (extremely characteristic). Uni-dimensionality of items in the composite CFC measurement model was affirmed using factor analysis to ascertain reliability (SRMR = 0.030, RMSEA = 0.045, CFI = 0.995, TLI = 0.993).³ Upon completion of the experiment, each participant answered a post-experimental debriefing questionnaire, eliciting demographic information for use in subsequent covariate testing.

5. Analyses

Analyses of covariates (ANCOVA) ascertain that the following factors exert no qualitative influence on the final results: gender, age, class level, major, GPA, work experience, current investments, personal and family net worth, as well as perceived investment sophistication level (all $p > 0.100$). All participants of the final usable sample completed the adapted 14-item CFC scale (modified from Strathman et al. 1994). Prior research has shown that CFC is a reliable, stable, and valid construct with wide-ranging behavioral implications. In effect, individuals with low (high) CFC attach a high (low) degree of importance to the immediate consequences of their behaviors, and a low (high) importance to the delayed consequences of their behaviors (Joireman et al. 2006). As illustrated in Table 1, the Cronbach alpha value based on standardized items is 0.877 ($p = 0.000$, $DF = 91$). Table 2 also shows the correlation matrix of the 14 items used in the CFC scale administration (with significant p values), hence affirming the reliability of the CFC items used.

Table 1. KMO and Bartlett's test.

Kaiser–Meyer–Olkin measure of sampling adequacy.		0.877
Bartlett's test of sphericity:	Approx. chi-square	1.666×10^3
	Df	91
	Sig.	0.000

To test for Hypothesis 1, an independent sample t -test was performed to compare the group statistics between those with high versus low CFC (by dividing their responses using the CFC scale's midway point).⁴ Evident from Tables 3 and 4, those with low CFC show a significantly lower risk (i.e., higher probability) preference as compared to those with high CFC (low CFC at mean = 2.26 as compared to high CFC at mean 2.83, significantly different at $p = 0.000$).⁵ In effect, the results here indicate that those with low (high) CFC prefer near- (distant-) future preferences for higher (lower) probability, albeit a lower (higher) risk–payoff, thus affirming Hypothesis 1.

Table 2. Inter-item correlation matrix among consideration of future consequences (CFC) items ^a.

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14
C1	1.0	0.317	0.372	0.344	0.110	0.332	0.245	0.186	0.302	0.326	0.403	0.296	0.527	0.552
C2	0.317	1.0	0.233	0.237	0.217	0.298	0.093	0.190	0.132	0.219	0.364	0.297	0.267	0.335
C3	0.372	0.233	1.000	0.684	0.243	0.280	0.183	0.155	0.293	0.361	0.604	0.365	0.335	0.396
C4	0.344	0.237	0.684	1.000	0.287	0.244	0.191	0.148	0.312	0.313	0.555	0.352	0.341	0.386
C5	0.110	0.217	0.243	0.287	1.000	0.042	−0.009	−0.011	0.190	0.241	0.292	0.253	0.039	0.073
C6	0.332	0.298	0.280	0.244	0.042	1.00	0.356	0.200	0.131	0.296	0.389	0.247	0.329	0.388
C7	0.245	0.093	0.183	0.191	−0.009	0.356	1.00	0.239	0.398	0.364	0.272	0.149	0.370	0.313
C8	0.186	0.190	0.155	0.148	−0.011	0.200	0.239	1.00	0.176	0.199	0.219	0.061	0.230	0.238
C9	0.302	0.132	0.293	0.312	0.190	0.131	0.398	0.176	1.000	0.469	0.407	0.296	0.366	0.355
C10	0.326	0.219	0.361	0.313	0.241	0.296	0.364	0.199	0.469	1.000	0.505	0.310	0.366	0.330
C11	0.403	0.364	0.604	0.555	0.292	0.389	0.272	0.219	0.407	0.505	1.000	0.469	0.394	0.425
C12	0.296	0.297	0.365	0.352	0.253	0.247	0.149	0.061	0.296	0.310	0.469	1.000	0.294	0.294
C13	0.527	0.267	0.335	0.341	0.039	0.329	0.370	0.230	0.366	0.366	0.394	0.294	1.00	0.646
C14	0.552	0.335	0.396	0.386	0.073	0.388	0.313	0.238	0.355	0.330	0.425	0.294	0.646	1.000
Sig. (1-tailed)	C1		0.000	0.000	0.018	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	C2	0.000		0.000	0.000	0.000	0.038	0.000	0.006	0.000	0.000	0.000	0.000	0.000
	C3	0.000	0.000		0.000	0.000	0.000	0.002	0.000	0.000	0.000	0.000	0.000	0.000
	C4	0.000	0.000	0.000		0.000	0.000	0.002	0.000	0.000	0.000	0.000	0.000	0.000
	C5	0.018	0.000	0.000	0.000		0.211	0.432	0.415	0.000	0.000	0.000	0.230	0.083
	C6	0.000	0.000	0.000	0.000	0.211		0.000	0.000	0.006	0.000	0.000	0.000	0.000
	C7	0.000	0.038	0.000	0.000	0.432	0.000		0.000	0.000	0.000	0.002	0.000	0.000
	C8	0.000	0.000	0.002	0.002	0.415	0.000	0.000		0.000	0.000	0.122	0.000	0.000
	C9	0.000	0.006	0.000	0.000	0.000	0.000	0.000	0.000		0.000	0.000	0.000	0.000
	C10	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000		0.000	0.000	0.000
	C11	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000		0.000	0.000
	C12	0.000	0.000	0.000	0.000	0.000	0.002	0.122	0.000	0.000	0.000	0.000		0.000
	C13	0.000	0.000	0.000	0.000	0.230	0.000	0.000	0.000	0.000	0.000	0.000	0.000	
	C14	0.000	0.000	0.000	0.000	0.083	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Note: ^a Determinant = 0.009.**Table 3.** Test of difference between high and low CFC.

Group Statistics				
	CFC	<i>n</i>	Mean	Std. Deviation
DV	Low	27	2.26	0.526
	High	339	2.83	0.854

Note: DV dependent variable: risk variance spread preference (2: low to 4: high).

Table 4. Independent samples test.

		Levene's Test for Equality of Variances		t-Test for Equality of Means						
		F	Sig.	t	df	Sig. (2-Tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference	
									Lower	Upper
DV	Equal variances assumed	22.309	0.000	−3.393	364	0.001	−0.567	0.167	−0.895	−0.238
	Equal variances not assumed			−5.091	37.961	0.000	−0.567	0.111	−0.792	−0.341

To test for Hypotheses 2, variance tests of between-subject effects were performed on those with high CFC values. Table 5 illustrates the descriptive statistics of the different

factors (personal risk profile,⁶ prior gain/loss, justification requirement, and one's CFC position). Table 6 shows that, among the group with high CFC, those who are risk-seekers will uniformly adopt a more risky preference (i.e., higher risk scores), vis-a-vis that for risk avoiders.

Table 5. Between-subject factors.

Description	Type	<i>n</i>
Risk	Seeker	185
	Avoider	181
Prior	Gain	151
	Neutral	68
	Loss	147
Justification	No	177
	Yes	189
CFC	Low	27
	High	339

Table 6. Descriptive statistics for high CFC responses.

Prior Gain/Loss	Justification	Risk Profile	Mean	Std. Deviation	<i>n</i>
Gain	No	Seeker	3.81	0.397	30
		Avoider	2.06	0.246	30
		Total	2.94	0.941	60
	Yes	Seeker	2.25	0.615	41
		Avoider	2.02	0.152	41
		Total	2.14	0.462	82
	Total	Seeker	2.91	0.941	71
		Avoider	2.04	0.197	71
		Total	2.48	0.807	142
Neutral	No	Seeker	3.76	0.437	15
		Avoider	2.50	0.516	14
		Total	3.15	0.795	29
	Yes	Seeker	3.05	0.405	16
		Avoider	2.12	0.342	14
		Total	2.63	0.598	30
	Total	Seeker	3.39	0.549	31
		Avoider	2.31	0.471	28
		Total	2.88	0.744	59
Loss	No	Seeker	3.82	0.385	38
		Avoider	3.77	0.423	37
		Total	3.80	0.403	75
	Yes	Seeker	3.00	0.250	31
		Avoider	2.03	0.171	32
		Total	2.51	0.533	63
	Total	Seeker	3.45	0.528	69
		Avoider	2.97	0.936	69
		Total	3.21	0.796	138
Total	No	Seeker	3.81	0.395	82
		Avoider	2.92	0.887	82
		Total	3.37	0.816	164
	Yes	Seeker	2.67	0.610	89
		Avoider	2.04	0.204	86
		Total	2.36	0.553	175
	Total	Seeker	3.22	0.771	171
		Avoider	2.47	0.771	168
		Total	2.85	0.856	339

Notes: Dependent variable: risk variance spread preference (2: low to 4: high).

Also shown in Table 6, for those without justification requirement as well as irrespective of the risk profile, with a prior gain (loss), one who scores high in CFC will be significantly more (less) inclined to prefer decisions with a lower risk (mean of 2.94 versus 3.80, $p < 0.010$), thus affirming Hypothesis 2a. Further, in examining the possible moderation effects arising from one's personal risk profile, for participants with a prior loss and without justification prompt, those with high CFC will show a greater propensity to prefer a choice entailing a higher risk regardless of their personal risk profile (mean for risk seekers = 3.82 versus mean for risk avoiders = 3.77, at $p > 0.100$). On the other hand, with a prior gain and without justification prompt, participants with high CFC will choose the less risky approach if they are risk avoiders (mean = 2.06) versus the more risky approach if they are risk seekers (mean = 3.81, at $p < 0.010$). This moderating effect of one's prior gain/loss position with their personal risk profile is also graphically evident from Figure 1, thus affirming Hypothesis 2b.⁷



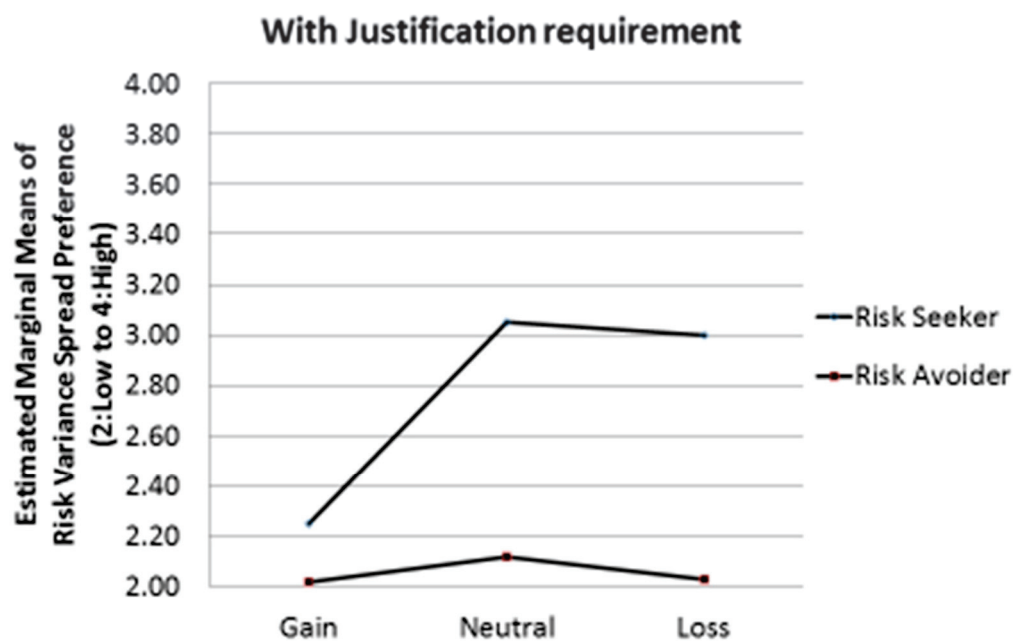
Figure 1. Estimated marginal means of decision choice for one with high CFC.

Finally, in affirming Hypothesis 3, the findings show that when those with high CFC were prompted to provide strategic justifications, an *overall* reduction in one's propensity toward high risk–payoff is evident, irrespective of prior gain/loss and risk profile ($p < 0.010$). Additional analyses also show that, when those with high CFC were prompted to provide their justifications, there was no significant difference in choice preference for risk avoiders with a prior gain versus loss (mean for gain group = 2.02 versus mean for loss group = 2.03, at $p > 0.100$). However, under the same conditions, there is a significant difference in choice preference for risk seekers with a prior gain versus loss (mean for the gain group = 2.25 versus mean for the loss group = 3.00, at $p < 0.010$). This effect is statistically illustrated by the interaction effect of one's prior gain/loss position with the imposition of a justification requirement ($p = 0.000$) in Table 7, and is also graphically evident from Figure 2. Overall, Table 7 shows that insofar as one's prior gain/loss position, imposition of a justification requirement, as well as personal risk profile are concerned, each exerts main and 2-way interaction effects on the dependent variable (all at $p = 0.000$, and with adjusted R-squared = 0.690 affirming a good-fitting model).⁸ A summary of all the findings is shown in Table 8.

Table 7. Tests of between-subject effects for high CFC responses.

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected model	186.385 ^a	8	23.298	102.624	0.000
Intercept	2573.013	1	2573.013	1.133×10^4	0.000
PriorGL (prior gain/loss position)	28.226	2	14.113	62.165	0.000
Justification	61.741	1	61.741	271.961	0.000
RiskProfile	52.518	1	52.518	231.333	0.000
PriorGL $\times$ RiskProfile	5.433	2	2.717	11.966	0.000
PriorGL $\times$ justification	7.642	2	3.821	16.831	0.000
Error	74.91	330	0.227		
Total	3234	339			
Corrected total	267.432	338			

Note: ^a R-squared = 0.697 (adjusted R-squared = 0.690). Dependent variable: risk variance spread preference (2: Low to 4: high).

**Figure 2.** Estimated marginal means of decision choice for one with high CFC.**Table 8.** Summary of findings.

CFC	Prior Gain/Loss	Risk Averter/Seeker	Justification	Risk–Payoff Preference	Tests
Low				Low	H1 ✓
High				High	
High	Gain		No	Lower	H2a ✓
High	Loss		No	Higher	
High	Gain	Avoider	No	Lower	H2b ✓
High	Gain	Seeker	No	Higher	
High	Loss	Avoider	No	Higher	
High	Loss	Seeker	No	Higher	
High	Both Gain and loss	Avoider	Yes	Lower	H3 ✓
High	Gain	Seeker	Yes	Lower	Overall lower
High	Loss	Seeker	Yes	Higher	

6. Limitations and Future Research

The results of this study should be interpreted in light of its contextual limitations. In the name of parsimony, no mention is made in this study to the magnitude of the prior gain or loss amounts nor regarding the timeline for the existing as well as that of the

intended future investments. The time value of money doctrine may affect how one will allocate their wealth. Also, in both experimental scenarios, participants were prompted to choose only one of the two profit options provided, while not provided with any loss option nor with the choice of prorating fractional allocations. Further, since this study was only conducted with an undergraduate business participant pool, with no decision-based monetary incentive at stake, findings may be biased. Future research could potentially explore the generalizability and real-world relevance of these findings across different demographic, cultural, and geographic settings.⁹ Similarly, one can extend this study toward a corporate setting, examining the motivations that may drive managerial decision-making processes. Last but not least, in conducting a laboratory experiment, participants were provided with the probability of achieving the various outcomes in each choice option, *ex ante* would not be feasible in reality.

7. Conclusions and Implications

Overall, in affirming the three hypotheses, one's decision choice preference is shown to be dependent upon CFC inclination, prior gain or loss, as well as personal risk profile. Nonetheless, with justification requirements, there is an overall reduction in one's propensity for making high risk–payoff choices.

In terms of theoretical implications, this study complements prior research of Howlett et al. (2008), Koonce et al. (2005a), as well as Koonce et al. (2005b) by examining choice preference effects of varied CFC profiles in conjunction with other important variables like one's personal risk profile, prior gain or loss, as well as the crucial imposition of a justification requirement. Juxtaposing the construct, consideration of future consequences, with the variables examined in prior research studies, findings here allude to the boundary conditions particularly for individuals with high CFC, whereby only those with a prior gain will manifest endowment effect tendencies. This would, in turn, result in one's aversion toward committing to a higher-risk decision. On the contrary, one with a prior loss would gravitate toward making a higher-risk decision. Further, when a strategic justification requirement is imposed, an overall reduction in one's propensity toward high risk–payoff is evident. Additional analyses also show that the personal risk profile will moderate the effects when a justification requirement is imposed, resulting in a de-biased effect for risk avoiders, while exacerbating the biased effect for risk seekers.

The research findings here hold practical implications, particularly in a volatile economic environment, whereby, with increased pressure, the use of heuristics for investment decision-making may become more prevalent. In matters concerning personal finance, investors should remain leery of potentially misleading and sometimes fraudulent claims from investment scheme promoters during bad economic times, a period when an investor's investment portfolio and psyche could typically take a hit. Many unfortunate human situations unfold in circumstances where people take desperate gambles and potentially turn manageable failures into even greater disasters. Classic quote from the famed Warren Buffett sums it up, 'When the tide goes out, you learn who's been swimming naked.' Capitalizing on investors' weakened morale and cognitive biases as a result of suffering a loss in their existing investment portfolios, marketers will often take advantage of the situation to push investment products that promise greater potential gain (while obfuscating the potential loss), thus entailing a greater level of risk. Despite the observed pitfalls, results from this study's justification prompt exercise show that investors can reduce their propensity for making high risk–payoff choices by exercising greater due diligence through formal, justifying reasoning in strategic areas when rationalizing one's decisions. This mechanism seems to cause risk avoiders to uniformly seek lower risk–payoff choices. On the other hand, for risk seekers, with a justification requirement, those with a prior gain (loss) will now be inclined to make a lower- (higher-) risk decision, although the *overall* risk level undertaken by either risk profile is still significantly decreased as compared to that without the justification requirement.

Ultimately, a conscious effort to strategically justify should uniformly help lower risk in varying degrees, thereby leading to a more reasoned and rational mechanism in decision-making, irrespective of one's CFC, prior gain/loss, and risk profile. From a public interest perspective in personal financial planning, when tasked to make risky decision choices, one could take heed of the findings from this study and strive to conduct a more efficacious deliberation as part of due diligence. Particularly in a volatile economic environment, when investors are more prone to make emotion-driven decisions, this study will hopefully result in an overall greater understanding of the mechanism shaping one's decision-making processes.

Funding: The author acknowledges financial and research support from Washington State University and the University of Northern Iowa.

Data Availability Statement: The raw data supporting the conclusions of this article are available on request from the author.

Conflicts of Interest: The author declares no conflict of interest.

Appendix A

Case Background

Gain condition: You have so far made a gain (resulting in a net positive sum to date).

Neutral condition: You have so far not made a gain or loss (resulting in a breakeven to date).

Loss condition: You have so far made a loss (resulting in a net negative sum to date).

Instruction

Recently, you received a prospectus regarding a new investment fund. With some money on hand to invest, you are now deciding whether to invest in **CHOICE A** or **CHOICE B** (i.e., two possibilities), assuming you know the probabilities of the payoffs for each choice.

For each of the two scenarios below, probabilities of earning the payoffs are listed.

No justification requirement condition:

For each scenario, choose (by circling) only ONE choice you would put your money in.

Scenario 1:

CHOICE A: 60% probability of gaining USD 3000

CHOICE B: 40% probability of gaining USD 4500

Scenario 2: (to be reverse coded)

CHOICE A: 40% probability of gaining USD 12,000, 20% probability of gaining USD 11,000

CHOICE B: 70% probability of gaining USD 6000, 70% probability of gaining USD 4000

Justification requirement condition:

Provide your justification within the box by listing down your reasons, as you assess your choice A or B selection in each of the two scenarios below. After assessing, for each scenario, choose (by circling) only ONE choice you would put your money in.

Box A1

☐

Scenario 1:

CHOICE A: 60% probability of gaining USD 3000

CHOICE B: 40% probability of gaining USD 4500

Scenario 2: (to be reverse coded)

CHOICE A: 40% probability of gaining USD 12,000, 20% probability of gaining USD 11,000

CHOICE B: 70% probability of gaining USD 6000, 70% probability of gaining USD 4000

For both No Justification requirement and Justification requirement conditions:
All participants are assessed their *Consideration of Future Consequences* and *Personal Risk Profiles* after they have circled their choices for both scenarios.

Appendix B

Assessing consideration of future consequences (CFC)
For each of the statements below, indicate **whether or not** the statement is **characteristic of you** based on the 1–7 scale shown below. Please write your answer in the **LEFT SPACE** provided.

1-----	2-----	3-----	4-----	5-----	6-----	7-----
Extremely Uncharacteristic	Moderately Uncharacteristic	Slightly Uncharacteristic	Neutral	Slightly Characteristic	Moderately Characteristic	Extremely Characteristic
___ 1.	I consider how things might be in the future, and try to influence those things with my day-to-day behavior.					
___ 2.	Often, I engage in behaviors to achieve outcomes that may not produce results for many years.					
___ 3. R	I only act to satisfy immediate concerns, figuring the future will take care of itself.					
___ 4. R	My behavior is only influenced by the immediate and short-term outcomes of my actions.					
___ 5. R	My convenience is a big factor in the decisions I make or the actions I take.					
___ 6.	I am willing to sacrifice my immediate happiness or well-being in order to achieve future outcomes.					
___ 7.	I think it is important to take warnings about negative outcomes seriously even if the negative outcome will not occur for many years.					
___ 8.	I think it is more important to perform a behavior with important distant consequences than a behavior with less important immediate consequences.					
___ 9. R	I generally ignore warnings about possible future problems because I think the problems will be resolved before they reach crisis level.					
___ 10. R	I think that sacrificing now is usually unnecessary since future outcomes can be dealt with at a later time.					
___ 11. R	I only act to satisfy immediate concerns, figuring that I will take care of future problems that may occur at a later date.					
___ 12. R	It is more important to me to take care of my day-to-day work that has immediate outcomes than my work that has distant outcomes.					
___ 13.	When I make a decision, I think about how it might affect me in the future.					
___ 14.	My behavior is generally influenced by future consequences.					

R: Reverse-scored items.

Notes

- This is affirmed through a time clock monitored by a third-party researcher during the experimental study. In addition, there is no significant difference in the amount of time spent on both tasks by the participants from both conditions ($p > 0.100$). Justification responses received for both tasks were also quite uniform in length.
- In analyzing the participants' responses, Scenario 2 was reverse-coded. Lower (higher) combined scores for the responses from both scenarios thus indicate a greater affinity for lower (higher) risk and payoff.
- Vilar et al. (2022) and Joireman et al. (2012) have alternatively suggested a two-factor solution (CFC-Future and CFC-Immediate) to the CFC scale. Dichotomizing into two factors, factor analyses similarly affirmed adequate internal reliabilities for both factors and a sufficiently robust model fit.
- A greater number of participants responded in the upper half of the CFC scale (i.e., $n = 339$ for those with averages above '4' on the CFC scale), as compared to those who responded in the lower half of the CFC scale (i.e., $n = 27$ for those with averages below '4' on the CFC scale). Since '4' on the 7-point CFC scale denotes a *neutral* position, and with the upper half denoting *characteristic* and the lower half denoting *uncharacteristic*, this study dichotomizes the high versus low CFC group at the midway point of the CFC scale.
- Mann–Whitney U-testing was performed as a nonparametric alternative, with the results remaining qualitatively unchanged ($p > 0.100$).
- Respondents were asked to self-assess their personal risk profile on a 0 (unwilling to take risks) to 10 (fully prepared to take risks) scale with the following question: "How do you see yourself in financial matters: Are you a person who is fully prepared to take risks or do you try to avoid taking risks?" (adapted from Dohmen et al. (2005)). The 'risk avoider' versus the 'risk seeker' group was differentiated using the midway point of 5 on the scale. Additional testing for the small number of respondents scoring '5' shows

that their subsequent responses were much closer to those of risk avoiders ($p < 0.050$), hence were also counted as risk avoiders. The results of the study remain qualitatively unchanged when this middle group is removed from the test sample ($p > 0.100$).

- 7 Results for risk and payoff are both directionally consistent; Untabulated analyses based on responses from those with low CFC showed that this group exhibits a uniformly greater inclination to prefer decision choices with a lower risk (i.e., higher probability) of a payoff, irrespective of differences in risk profiles as well as prior gain or loss position (all $p > 0.100$).
- 8 Untabulated analyses for those with low CFC show that the earlier observed preference for a lower risk variance spread remains unchanged regardless of whether a justification requirement is imposed or not ($p > 0.100$).
- 9 The sample and the general population data may differ in various dimensions. For instance, according to the U.S. Census Bureau projections' data for 2022, the percentage of the population in the 18–24 age group is 9.4%, the percentage of the male population is 49.6%, and the percentage of persons 18–24 years of age with a Bachelors' degree is 11.4% among that age group (see <https://www.census.gov> (accessed on 27 December 2023)).

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Article

Impact of Financial Factors on the Economic Cycle Dynamics in Selected European Countries

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Abstract: The aim of this paper was to assess the impact generated by the financial market shocks on the economic cycle in European countries. In addition to the studies from the literature, which focus more on the developed economies, this paper also considered the situation at the level of a group of emerging economies to highlight the potential differences. In this sense, it was analyzed how the shocks at the level of the banking sector, those at the level of the capital market, and those at the level of the real estate market influence the dynamics of the economic cycle. Both econometric models for the individual analyses of each state, such as the Bayesian vector autoregression model, and models at the level of groups of states, such as panel regressions, were used for the period 2007–2022. The results showed a strong connection between the dynamics of the financial system and that of the real economy. In addition, the impact of financial factors on the economic cycle tends to be much stronger and more significant in the case of developing countries, compared to developed ones. In this regard, it was recommended that fiscal and monetary policies should be coordinated to generate the expected effect on the economy.

Keywords: economic cycle; shocks; financial factors

1. Introduction

The 2007–2008 global financial crisis (GFC) revealed that, in addition to the study of the economic cycle, a key element that must be considered by economic policymakers is the financial cycle. As could be observed during the GFC, the dynamics of the financial cycle exhibited very strong effects on the real economy, ultimately generating an economic recession.

The purpose of this paper was to identify how financial market shocks influence the economic cycle. This topic is of interest as the nature of the connection between the financial market and the real economy can have an important impact on the effectiveness of the economic policy measures implemented. Thus, the dynamics of the credit market, the capital market, or even the real estate market can scale, or depending on the case, they can massively reduce the effectiveness of economic policy measures.

The interaction between the financial and the economic cycle is more easily noticeable in periods of crisis, when the two types of cycles tend to synchronize, as the results of the study conducted by Haavio (2012) showed. However, it is important to analyze whether the connection between them is maintained in general and also during periods that are not characterized by economic tensions.

According to the studies in the dedicated literature, the dynamics of the financial cycle is the one that determines the dynamics of the economic cycle, two of the papers that reached that conclusion being Gómez-González et al. (2014) but also Shen et al. (2019). Given the above, this study considered that direction within the nexus between financial factors and the dynamics of the economic cycle.

As the experience of the last century has shown, financial crises can begin in different sectors of the financial market. Several crises started from the credit side, the excessive indebtedness of the households or non-financial companies being the generating element of the financial and economic repercussions. Other crises of a financial nature started due to excessive increases in real estate market prices, which ultimately generated a wide spectrum of negative effects at the level of the entire economy. Moreover, the third type of financial crisis started due to the capital market dynamics, with the high volatility leading to the accumulation of important vulnerabilities in the financial market. In this regard, the financial factors used in this study were selected to cover the entire spectrum of the financial system; more precisely, variables that characterize the activity of the banking sector, variables that characterize the dynamics of the capital market, and variables that characterize the dynamics of the real estate market were included.

To investigate whether there are differences in the direction and magnitude of this link, conditional on the level of development of the states, two groups of countries were analyzed. The first is a group consisting of five developing countries from Central and Eastern Europe, namely Romania, Czechia, Poland, Hungary, and Bulgaria, while the second is made up of five developed states from the central-western region of Europe, namely Germany, France, Austria, Spain, and Italy. Comparing the results obtained at the level of the two groups of states, as a general conclusion, the impact of financial factors on the economic cycle tends to be much stronger and more significant in the case of developing states compared to developed ones.

The novelty of this paper comes from enriching the scarce literature related to the link between financial factors and the economic cycle dynamics for developing countries. Different from other works in the literature, which carry out studies on developed economies such as that of the United States of America (Constantinescu and Nguyen (2021), Furlanetto et al. (2019), or Furlanetto et al. (2021)) or on other developed economies such as those in the G7 (de Winter et al. 2021), our paper analyzed the link between the economic cycle and financial factors at the level of the selected European developing countries. Also, in addition to articles in the literature that focus on the evaluation of credit market shocks on the economic cycle (e.g., Bartoletto et al. 2019 and Beltran et al. 2021), in our work, shocks from other financial market sectors, such as the real estate and capital markets, were considered.

In what follows, this paper includes the summary of the results from the correspondent literature on this topic, the description of the research methodology and data used, followed by the results and the conclusions drawn from our study.

2. Literature Review

The papers from the literature exhibit a significant link between the financial cycle and the economic cycle, with financial factors representing important determinants in economic dynamics. In general, the authors determined the economic cycle based on the gross domestic product, and the financial cycle based on indicators from the credit market, real estate market, or capital market.

The work of Karagol and Dogan (2021), which had Turkey as a case study, illustrated that there is a strong connection between the financial cycle and the economic cycle. In this sense, the authors recommend economic policymakers to consider the role that financial factors can have in the efficiency level of the measures adopted by them. In the case of this study, the proxy variables for the dynamics of the financial cycle were not only those regarding the dynamics of credit but also those regarding the dynamics of the capital market.

Important results were also presented in the study of Bartoletto et al. (2019), whose analysis was based on the Italian economy. In this case, the financial cycle was mainly identified through the dynamics of credit. The main results indicated that periods of economic recession associated with credit crunches are much more severe than periods of recession in which credit had no contribution. These authors also found that the response

of the economic cycle to credit shocks was much stronger during contraction periods of the financial cycle.

The paper of Berger et al. (2022) had the USA as a case study. In this work, the financial cycle was identified through credit dynamics and real estate price dynamics. The results of the analysis illustrated that the financial sector had an important role in the dynamics of the economic cycle during the Great Recession. Also, a financial shock can generate a negative correlation between the lagged credit cycle and the contemporaneous economic cycle. In this context, caution was suggested in associating periods of economic expansion with periods of expansion of the financial cycle.

Another approach in determining the cycles is that through the Beveridge–Nelson filter used by Morley and Wong (2020). In addition to the different filtering method, this study also employed Bayesian VAR-type models to identify macroeconomic variables that provide information about the dynamics of the economic cycle. Their results showed that, in addition to economic growth, variables such as the inflation rate but also the unemployment rate have an important impact on the dynamics of the economic cycle. Another work that expands the methodological framework for the analysis of economic and financial cycles is Bulligan et al. (2019), whose study was based on the Italian economy and used multivariate filters to identify the trend and the cyclical components.

The study carried out by Schuller (2020) showed that the analysis of the financial cycle only through credit indicators (e.g., credit to GDP gap) can lead to the false identification of periods of expansion or contraction. In this perspective, it is useful to consider other options of identifying the phases of financial cycles, starting from variables regarding other sectors of the financial market, but also additional filtering methods compared to the standard ones recommended by the BCBS (Basel Committee on Banking Supervision). However, there are also works, such as Beltran et al. (2021), which show that the method of calculating the financial cycle based on credit dynamics, or through the credit to GDP gap indicator, can be optimized to improve its ability to identify the phases of the financial cycle.

Another work, by de Winter et al. (2021), carried out their analysis of the economic and financial cycles at the level of eight developed countries, specifically the seven countries of the G7 (the USA, UK, Japan, Canada, Germany, France, and Italy) but also the Netherlands. The results of this analysis showed that, at the level of all eight economies, there is a high degree of co-movement of the financial cycle, identified through real estate prices, and the economic cycle identified through gross domestic product.

There are also studies that have analyzed the link between the economic cycle and financial factors for a long period of time. In this sense, the study conducted by Constantinescu and Nguyen (2021) can be mentioned, which analyzed the American economy for a period of more than a century. The results of this study confirmed the essential role of financial factors, such as credit, the prices of financial assets, or the real estate market, in the dynamics of the economic cycle. Another study of interest at the level of the USA economy is that of Furlanetto et al. (2019); its results showed that financial shocks represent an important determinant of the gross domestic product dynamics (of investments) but have a limited effect on the dynamics of inflation. The financial shocks identified via the real estate market prices are the ones that play the most important role in the dynamics of the gross domestic product. Another study (Furlanetto et al. 2021) revealed that financial frictions and financial market shocks not only have an important impact on the dynamics of the economic cycle but also on how other determinants influence economic fluctuations.

An important paper analyzing the impact of financial factors on the economic cycle is represented by Christiano et al. (2010). The methodology used was based on a DSGE (dynamic stochastic general equilibrium) model applied at the level of the Eurozone states but also at the level of the USA (United States of America). The results of this study showed that shocks at the level of the financial system are important determinants of economic fluctuations.

Another reference work on this topic is the one of Iacoviello (2015), whose results showed that the impact of financial shocks affecting highly indebted sectors of the economy

accounts for two-thirds of the output collapse during the Great Recession. In their analysis, a DSGE model was used, in which a recession starts as a result of the losses suffered by the banks and their inability to provide enough credit to the real economy. Similarly, Borio et al. (2016) showed that financial factors play a key role in explaining the dynamics of the economic cycle.

Other papers have shown that there is Granger causality between the financial cycle and the economic cycle. In this respect, the study of Sala-Rios et al. (2016), whose analysis was based on data for Spain, showed that the economic cycle was caused by the financial cycle. The financial and economic cycles were determined by means of the Hodrick–Prescott filter, a similar procedure being employed in the present paper.

Another work that studied the connection between financial factors and the economic cycle through causality is that of Aravalath (2020), which used India as its case study for the period 1990–2019. The results also showed that the financial cycle is the one that causes the dynamics of the economic cycle. Another work that reached similar conclusions is that of Gómez-González et al. (2014), with their study having been carried out at the level of a group of South American states.

The link between financial factors and the real economy may differ depending on the phases of the economic cycle. In this sense, in the work of Antonakakis et al. (2015), a study was carried out at the level of the G7 (Group of Seven) states, which showed that the connection between the financial and the economic cycles becomes much closer in periods of recession, compared to periods of economic expansion.

Another work that showed a strong correlation between financial factors, materialized in the financial cycle, and the economic cycle is that of Akar (2016). The analysis was carried out at the level of Turkey for the period 1998–2014, and the results showed that there is a strong and positive correlation between the financial cycle and the economic cycle.

Another perspective of interest is the one regarding the impact of financial factors on the economic cycle, conditioned by the level of development of a state/province. The work of Shen et al. (2019), whose analysis deals with China's situation, showed that, in general, the phases of the financial cycle are the ones that determine the dynamics of the phases of the economic cycle. This result was recorded with a higher frequency and intensity within the richest provinces in the sample.

Another important perspective on the link between financial factors and the economic cycle concerns the period in which the effects of shocks become visible. An analysis at the level of the state of Denmark, carried out in the paper by Grinderslev et al. (2017), showed that the synchronization of the financial cycle with the economic one is felt more strongly in the medium term. Another paper that illustrated a stronger connection between the two types of cycles, in the medium term, is that of Škare and Porada-Rochoń (2020), whose study was based on data for the United Kingdom, using an econometric methodology based on spectral Granger causality. In the same area, a similar result was also discovered for the USA economy by Yan and Huang (2020) using wavelet functions but also VAR-type (vector autoregression) models.

Berger et al. (2020) analyzed the effect of financial factors on the economic cycle by means of Bayesian VAR models. The results of their study showed that the impact of financial factors on the output gap was much stronger in the period after 2000 than in the period before this year. Regarding the direction of influence, the financial cycle shock generates a positive contemporaneous impact on the output gap, but it becomes negative if the lagged effect of this shock is quantified.

However, it should be mentioned that there are also works whose results show a low connection between financial factors and the economic cycle, an example in this sense is the work by Apostoae and Percic (2014), which was carried out based on data for 20 European states. The results of their study showed that, at the level of the analyzed states, there was no causality between the financial cycle and the economic cycle. Other studies have shown that the connection between financial factors and the economic cycle is limited; an example

of this is the work of Ahmad and Sehgal (2018), the authors of which studied a group of countries in the South Asian area by means of dynamic spillover models.

3. Methodology and Data

The objective of this paper was to identify how financial factors influence the economic cycle. In this sense, 2 groups of states were analyzed; the first was a group consisting of 5 developing countries from Central and Eastern Europe, namely Romania, Czechia, Poland, Hungary, and Bulgaria, while the second was made up of 5 developed states from the central-western region of Europe, namely Germany, France, Austria, Spain, and Italy. Data with a quarterly frequency were used, and the period analyzed was between Q4 2007 and Q4 2022.

The financial factors used in this study were selected to cover the entire spectrum of the financial system, more precisely, the activity of the banking sector, the dynamics of the capital market, and the dynamics of the real estate market. To characterize the activity of the banking sector, the dynamics of lending were used for both the household sector and for the sector of non-financial companies. To characterize the dynamics of the capital market, the CLIFS (Country-Level Index of Financial Stress) indicator was used as a proxy, and to characterize the dynamics of the real estate market, a proxy was used for the dynamics of residential property prices (RRE). In addition to financial factors, control variables were also used in the panel data models. In this sense, the harmonized inflation rate was used as well as the dynamics of the stock of private investments at the level of each state.

Credit data were taken from the ECB (European Central Bank) database in nominal quarterly values. For each quarter, the rate of change was calculated, considering the dynamics of the variable in comparison with the same quarter of the previous year, to prevent the non-stationarity problem. In this way, the data series included in the model were the growth rates of lending at the level of the two sectors, households, and non-financial companies. CLIFS data were taken in quarterly format from the ECB database and were used in the analysis in the same way. Regarding the RRE prices, the data were taken in quarterly format from the ECB database directly in the form of percentage change. The inflation rate was taken in the quarterly format directly in the percentage form from the Eurostat database. In the case of private investments, the data were taken in quarterly nominal format from the Eurostat database and were transformed into growth rates based on the dynamics of the variable in comparison with the same quarter from the previous year. Having all the datasets in percentage form, after the proper transformation, helped us to prevent potential econometric issues.

The dependent variable, the economic cycle, was calculated by means of the Hodrick–Prescott filter, the model being described in detail in the following paragraphs, similarly to the procedures applied in the dedicated literature. The input data on nominal gross domestic product, which were later passed through the logarithm operator and filtered, were taken from the Eurostat database. The economic cycle was calculated for the same period with the rest of variables used in the B-VAR (Bayesian VAR) model, specifically between Q4 2007 and Q4 2022.

The econometric programs used for data preprocessing were Eviews and Matlab, and an extensive presentation of the econometric models used has been made below.

In the empirical analysis, in accordance with relevant works, such as Tamási and Világi (2011) or Berger et al. (2020), two types of econometric models were used. On the one hand, Bayesian VAR (B-VAR) models were used to identify the effect caused by shocks in the financial system at the level of each state individually; on the other hand, panel data models were used to identify whether there were significant differences in impact caused by the level of development of the states.

To determine the economic cycle, a Hodrick–Prescott type filter was used. This filter has the property of decomposing a data series (x_t) into two important components: the trend and the cyclical component (Formula (1)):

$$x_t = \tau_t + c_t \quad (1)$$

where τ_t represents the trend of the variable (x_t), and c_t represents its cyclical component. To achieve this decomposition, the loss function presented in Formula (2) was minimized:

$$\sum_{t=1}^T (x_t - \tau_t)^2 + \lambda \sum_{t=2}^{T-1} [(\tau_{t+1} - \tau_t) - (\tau_t - \tau_{t-1})]^2 \quad (2)$$

where λ represents the smoothing parameter. To determine the economic cycle, this parameter was calibrated according to the work of Hodrick and Prescott (1981) to the value of 1.600. This value was determined based on Formula (3):

$$\lambda = \frac{\sigma^2(c_t)}{\sigma^2[(\tau_{t+1} - \tau_t) - (\tau_t - \tau_{t-1})]} \quad (3)$$

After determining the economic cycle, the first type of econometric model was applied, more precisely B-VAR. Different from the classical approach, Bayesian econometrics treats each parameter as a random variable following a distribution, according to Bayes' rule (Formula (4)):

$$\pi(\beta|y) \propto f(y|\beta)\pi(\beta) \quad (4)$$

where $\pi(\beta|y)$ represents the posterior distribution of the parameters conditional on the data, $\pi(\beta)$ represents the prior distribution of the parameters, and $f(y|\beta)$ represents the likelihood function. Thus, an important step of this type of analysis is the selection of a priori distributions of the parameters, with Minnesota-type priors being used in this study. In this case, the likelihood function is represented in Formula (5):

$$f(y|\beta) \propto \exp \left[-\frac{1}{2} (y - \bar{X}\beta)' \bar{\Sigma}^{-1} (y - \bar{X}\beta) \right] \quad (5)$$

The a priori distribution of the vector of coefficients (β) is presented in Formula (6):

$$\pi(\beta) \propto \exp \left[-\frac{1}{2} (\beta - \beta_0)' \Omega_0^{-1} (\beta - \beta_0) \right] \quad (6)$$

Following the substitutions, the posterior distribution of the parameters conditional on the data takes the form:

$$\pi(\beta|y) \propto \exp \left[-\frac{1}{2} (y - \bar{X}\beta)' \bar{\Sigma}^{-1} (y - \bar{X}\beta) \right] \times \exp \left[-\frac{1}{2} (\beta - \beta_0)' \Omega_0^{-1} (\beta - \beta_0) \right] \quad (7)$$

A comprehensive overview of the demonstrations is provided in Dieppe et al. (2016). The BEAR toolbox (Bayesian estimation, analysis, and regression) available for the Matlab program was used to operate B-VAR models.

The second type of model used, for the analysis at the level of the group of developing countries compared to that of developed countries, was panel regression. The mathematical form of the model used is presented in Formula (8):

$$OG_{i,t} = \gamma_1 + \gamma_2 GR\_L\_HH_{i,t} + \gamma_3 GR\_L\_NFC_{i,t} + \gamma_4 CLIFS_{i,t} + \gamma_5 RRE_{i,t} + \gamma_6 HICP_{i,t} + \gamma_7 GR\_PI_{i,t} + \varepsilon_{i,t} \quad (8)$$

where $OG_{i,t}$ represents the output gap in quarter t within state i ; $GR\_L\_HH_{i,t}$ represents the quarterly growth rate of credit granted to households in quarter t within state i ; $GR\_L\_NFC_{i,t}$ represents the quarterly growth rate of credit granted to non-financial companies in quarter t within state i ; $CLIFS_{i,t}$ represents the CLIFS indicator in quarter t within state i ; $RRE_{i,t}$ represents the growth rate of residential real estate prices in quarter t within state i ; $HICP_{i,t}$ represents the harmonized inflation rate in quarter t within state i ; and $GR\_PI_{i,t}$ represents the private investment growth rate in quarter t within state i .

To identify the most suitable type of model to be used, the one with random effects or the one with fixed effects, the Hausmann test was employed in the case of both groups of states.

4. Results and Discussion

Regarding the econometric models, two approaches were used; in a first phase, the impact of the shocks was analyzed at the level of each state through B-VAR-type models, after which, to increase the level of robustness of the results, regression models with panel data were used.

In the case of B-VAR models, the first type of shock analyzed is the one originating from the banking sector, through the credit granted to non-financial companies. The results for the group of countries in the CEE (Central and Eastern European) region are presented in Figure 1.

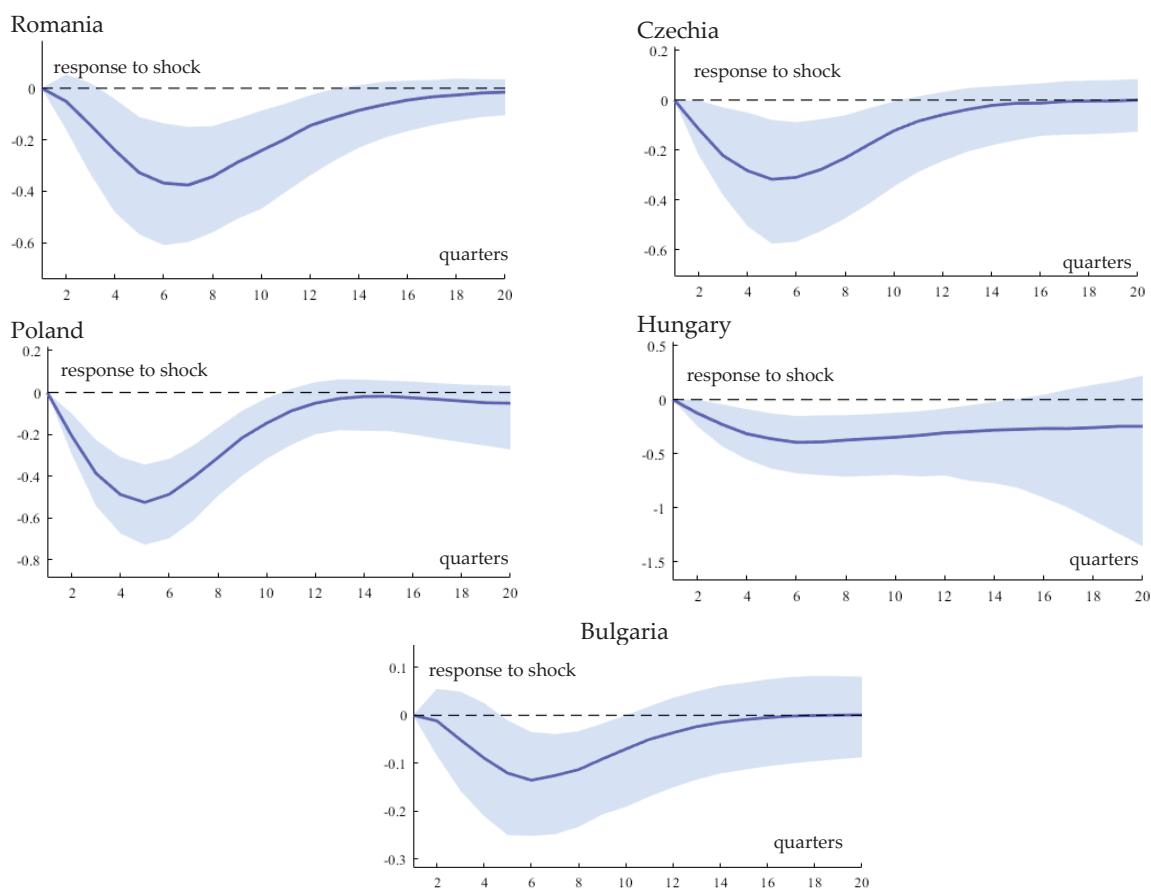


Figure 1. Dynamics of the economic cycle due to the shock on the level of loans granted to non-financial companies in the CEE states. Note: the line represents the response of the economic cycle due to the shock, and the highlighted area represents the 95% confidence interval.

In all five analyzed states (Figure 1), a shock in the level of credit granted to non-financial companies has the effect of reducing the output gap. Thus, if the economic cycle is in an expansion phase, the banking sector shock reduces its amplitude, while if the economy is in a recession phase, the banking sector shock intensifies the negative impact on the economy. A special case is that of Hungary, where, unlike the rest of the states, the impact of the credit shock persisted even after 20 quarters. One of the reasons that could justify this dynamic could be related to the relatively high size of the national banking sector of this state, measured via total domestic banking assets in GDP, at the level of the CEE region. Another reason may be related to the relatively high level of financial intermediation compared to the rest of the analyzed CEE countries.

However, this type of effect is not conditioned via the level of development of the states, as in the case of most developed countries in the central-western region of Europe, analyzed in this paper, the same type of phenomenon was observed (Appendix A). However, special cases regarding this dynamic have been recorded in Spain and France, where the impact of such a shock is relatively low. This was caused by the size of the financial sector of the two countries, which also includes a well-developed capital market. Thus, financial intermediation can be carried out both through banks and through the capital market.

In addition to the shock that occurred at the level of lending to non-financial companies, the impact of a shock that occurred at the level of lending to household segments was also analyzed. In the case of the CEE countries, a shock to the crediting of this sector has the effect, in most states, of a decrease in the output gap (Appendix B). A special case was that of Hungary, where the shock remained persistent even after 20 quarters from the moment of its appearance. This result can also be justified via the relatively high level of financial intermediation in this country, compared to the rest of the states in the region. In the case of most developed states in the central-western region of Europe, the effect is one opposite than for the developing ones (Appendix C). A factor that could argue for this difference is related to the importance of lending to this segment in developed countries, compared to the situation in developing countries. Moreover, the only developed country where a more pronounced response of the economic cycle dynamics was observed, due to the shock, was Spain; however, in this case, the response was also not statistically significant.

The second type of shock analyzed was the one originating from the capital market, in this case, materialized at the level of the financial stress index (CLIFS). The results for the CEE group of states are presented in Figure 2.

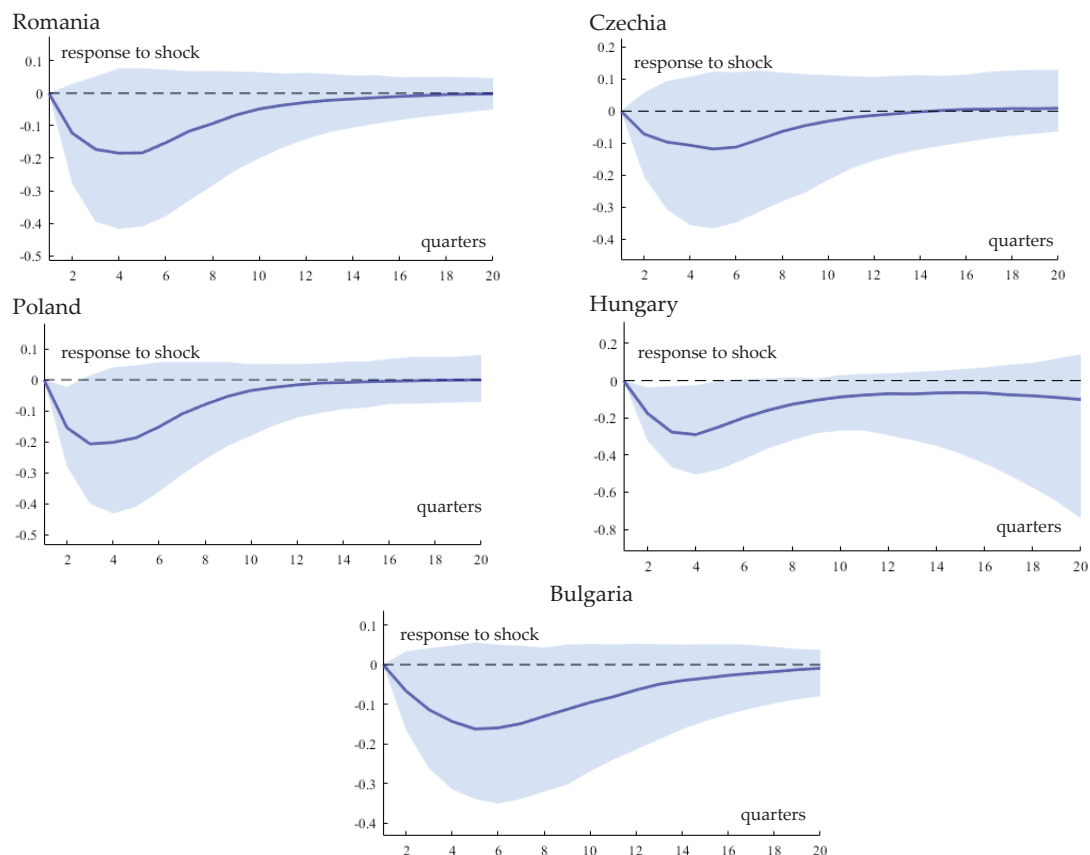


Figure 2. Dynamics of the economic cycle due to the CLIFS shock in the CEE states. Note: the line represents the response of the economic cycle due to the shock, and the highlighted area represents the 95% confidence interval.

A shock at the level of the financial stress index had the effect of reducing the output gap in all five analyzed CEE states. In this sense, during periods of expansion, the shock on the capital market diminishes the amplitude of the economic cycle, whereas during periods of economic recession, the negative impact on the economy is intensified. In this case, a similar trend was observed at the level of all five analyzed developing states. However, this type of effect is not conditioned by the level of development of the states, as in the case of most developed states in the central-western region of Europe, analyzed in this paper, the same type of phenomenon was observed (Appendix D). Also, in this case, a similar trend was observed at the level of all five analyzed developed states.

The third type of shock analyzed was the one originating from the real estate market. The results for the group of CEE states are presented in Figure 3.

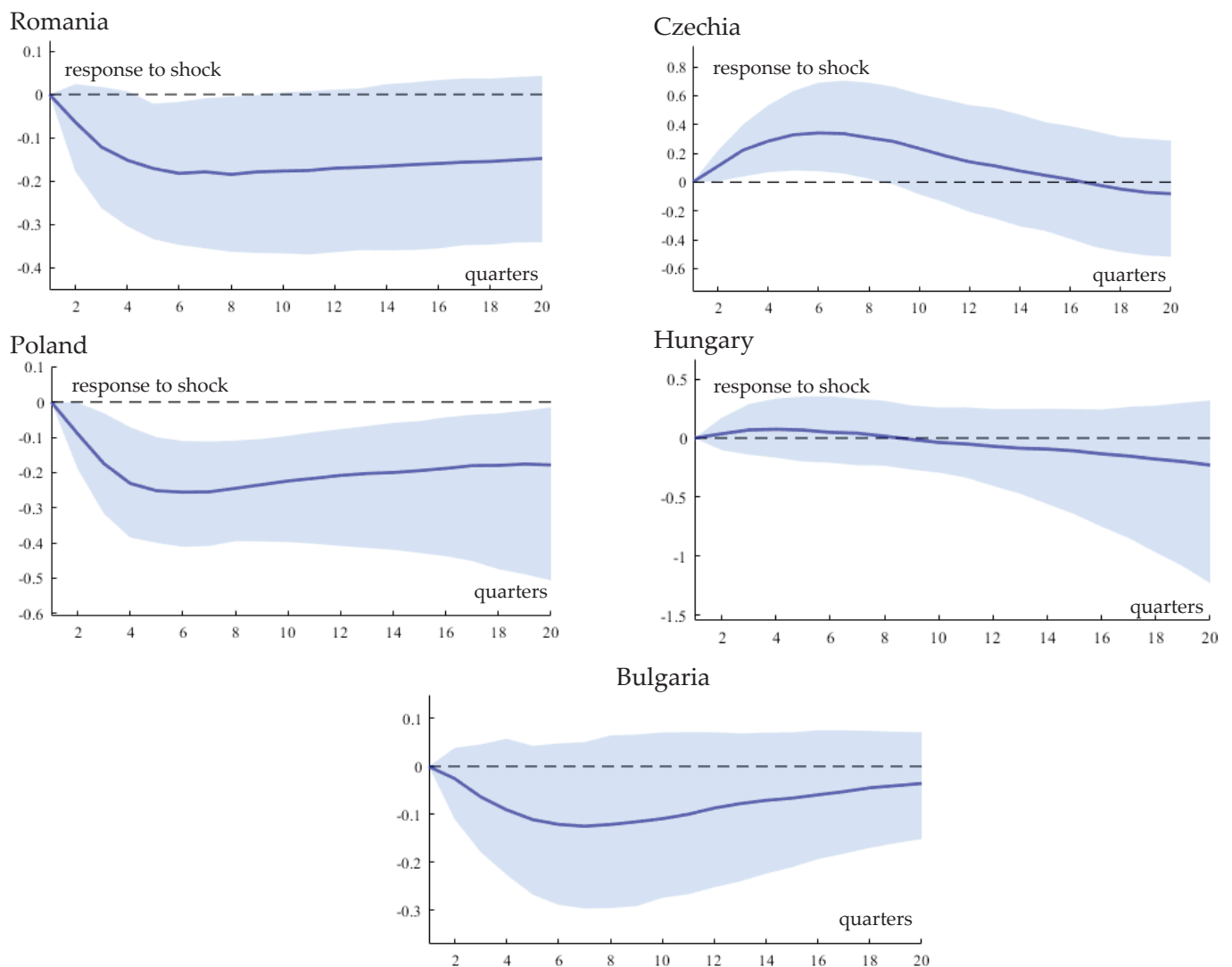


Figure 3. Economic cycle dynamics due to the real estate price shock in CEE states. Note: the line represents the response of the economic cycle due to the shock, and the highlighted area represents the 95% confidence interval.

A real estate price shock exhibits a distinct effect for different CEE states. Thus, if in the case of Romania, Poland, and Bulgaria, the shock materialized in this area generates a decrease in the output gap, in the case of Czechia, the effect is one in total opposition. The explanation of the result for Czechia could be provided by a much higher degree of synchronization of the financial cycle with the economic one in this state. Moreover,

considering these results, the real estate market in this country has a more pronounced impact on the macroeconomic framework, compared to the rest of the states in the region.

In the case of the developed states in the central-western region of Europe, for this type of shock, the effects on the output gap were closer, from the perspective of the direction of influence, to those recorded in Czechia (Appendix E). A special case was registered in Italy, Spain, and France, where real estate prices have a very low influence on the economic cycle dynamics. A reason for this result could be that other factors have a more pronounced impact on the general economic dynamics of these states.

The second method of analysis was carried out in an aggregated manner at the level of the groups of states analyzed by means of models with panel data. The first representation is that of the results for the panel of CEE states (Table 1).

Table 1. Econometric results at the level of the CEE group of states.

Regressor	I	II	III	IV
CLIFS	−0.0203 (0.0159)	−0.0267 (0.016) *	−0.0284 (0.0157) *	−0.0272 (0.0156) *
HH_L		−0.0448 (0.0201) **	−0.0027 (0.0235)	0.0193 (0.0251)
NFC_L			−0.0796 (0.0242) ***	−0.0835 (0.024) ***
RRE				−0.0255 (0.0109) **
INFL	0.0575 (0.078)	0.0495 (0.0774)	0.1386 (0.0806) *	0.186 (0.0824) **
PR_INV	0.0435 (0.0168) **	0.0547 (0.0174) ***	0.0647 (0.0173) ***	0.0629 (0.0171) ***

Note: *—the parameter is statistically significant at the 10% level; **—the parameter is statistically significant at the 5% level; and ***—the parameter is statistically significant at the 1% level. For each of the variables, the estimated parameter is noted, and the standard error level is noted in parentheses. Source of the data: own processing based on data provided by Eurostat and ECB.

In the case of this group of states, four panel regression models were run, in which different financial factors were integrated one by one sequentially. The model whose results were the most significant was IV, in which all the financial factors covered in the analysis were included. Thus, it is observed that an increase in the level of financial stress, materialized via an increase in the CLIFS, has a decreasing effect on the level of the output gap. A similar result was obtained individually for each of the states in this group through B-VAR models.

Another significant result is related to the impact of the dynamics of lending to the segment of non-financial companies. In this sense, an increase in lending to this sector has the general effect of a decrease in the output gap. However, it should be noted that only the increase in lending to the segment of non-financial companies had this effect; the dynamics of lending to the household sector did not significantly influence the dynamics of the economic cycle at the level of this group of states.

The third area analyzed was the impact of the dynamics of the real estate market on the economic cycle. In this sense, an increase in real estate market prices has the effect of a decrease in the output gap. Thus, if the economic cycle is in an expansion phase, the housing market shock reduces its amplitude, while if the economy is in a recession phase, the banking sector shock intensifies the negative impact on the economy.

The second group of states analyzed was that of developed countries from the central-western region of Europe (Table 2).

Similarly, to the situation at the level of the CEE group of states, and within the group of developed states, an increase in the CLIFS has the effect of a reduction at the level of the output gap. However, it should be noted that within this group of states, the impact of this factor is not only much lower in magnitude but also in terms of statistical significance.

Table 2. Econometric results at the level of the group of developed countries.

Regressor	I	II	III	IV
CLIFS	−0.0146 (0.0123)	−0.0142 (0.0123)	−0.0129 (0.0121)	−0.0129 (0.0121)
HH_L		−0.0148 (0.0241)	0.0602 (0.0321) *	0.062 (0.0348) *
NFC_L			−0.0905 (0.0263) ***	−0.0906 (0.0263) ***
RRE				−0.0009 (0.0069)
INFL	−0.0216 (0.0803)	−0.0137 (0.0815)	0.0142 (0.0801)	0.016 (0.0814)
PR_INV	0.1430 (0.0151) ***	0.144 (0.0152) ***	0.1484 (0.0149) ***	0.1474 (0.0167) ***

Note: *—the parameter is statistically significant at the 10% level; and ***—the parameter is statistically significant at the 1% level. For each of the variables, the estimated parameter is noted, and the standard error level is noted in parentheses. Source of the data: own processing based on data provided by Eurostat and ECB.

Regarding the link between the real economy and the banking sector, similarly to the situation in the CEE states, an increase in lending to the non-financial company segment results in a significant reduction in the output gap. In terms of magnitude, the impact of this factor tended to be similar for the two groups of states analyzed.

However, when the impact of the dynamics of credit granted to the households was analyzed, a difference was observed between the two groups of states. If in the case of the CEE states the impact of this factor was insignificant from a statistical point of view, in the case of developed states it is a significant one. The direction of influence was the same; however, it appeared that at the level of developed states, the dynamics of lending to the household segment have a more pronounced impact on the economic cycle.

Regarding the dynamics of the real estate market, the direction of influence is similar in the case of the group of developed countries to that obtained within the group of developing countries. Thus, an elevation in residential real estate market prices results in a decrease in the output gap. However, it should be noted that distinct from the case of CEE states, in the group of developed states the impact of real estate prices on the economic cycle was much lower, even insignificant from a statistical point of view.

Looking comparatively at the results obtained at the level of these two groups of states, as a general conclusion, the impact of financial factors on the economic cycle tends to be much stronger and more significant in the case of developing states, compared to already developed states. One of the arguments supporting this conclusion is related to the level of stability of the economy at the level of the two groups of states. The economies of developing countries are generally much more vulnerable to shocks, whether they are economic or financial, which is why the impact of any dynamic in the financial market is felt more strongly at their level.

Another argument that could support these conclusions is related to the level of development and complexity of the financial system in these two groups of states. A shock arising from the capital market, from the banking sector, or from the real estate market can be absorbed more easily under the conditions of a stable financial system so that the economic effects are diminished. This, on the other hand, is not possible in the same way in the case of states whose financial systems are poorly developed, and whose financial activity depends, to a very large extent, on only one area of the financial system.

5. Conclusions

The main aspect analyzed in this paper was related to the way in which the shocks in the financial system influence the dynamics of the economic cycle. More specifically, we have taken into consideration shocks that come from the banking system through the credit channel, those that come from the capital market and whose effect is to increase the financial stress index, and those that come from the real estate market through residential property prices. At the same time, this study was carried out both at the individual level

of a state and aggregated for the groups of states in CEE and those in the central-western region of Europe.

The papers from the literature mostly showed a significant link between the financial cycle and the economic cycle in developed countries, with financial factors representing important determinants in economic dynamics. In general, the most important financial factors with an impact on the economic cycle dynamics are the ones regarding lending, real estate prices, and the capital market.

The main results of the B-VAR analysis showed that a shock in the level of loans granted to non-financial companies has the effect of a decrease in the output gap in all five CEE states, which are in line with Berger et al. (2022). However, this type of effect was not conditioned by the level of development of the states, as in the case of most developed states in the central-western region of Europe, analyzed in this work, the same type of phenomenon was observed. This result is in line with other studies, such as Constantinescu and Nguyen (2021) and Furlanetto et al. (2021), who have shown that the indicators regarding lending have an important and significant impact on the dynamics of the economic cycle.

Regarding the capital market, a shock at the level of the financial stress index not only had the effect of reducing the output gap in all five CEE states analyzed but also in most of the developed states in the central-western region of Europe. This result is in line with Karagol and Dogan (2021), who identified a significant link between the capital market and economic cycle dynamics. Regarding the housing market, a shock to residential property prices had a distinct effect for different CEE countries in comparison with the developed ones. Thus, in the case of most developing countries, the shock materialized in this area generates a decrease in the output gap; in the case of most developed countries, the effect is one in total opposition. The significant impact of the real estate market dynamics on the economic cycle was also identified in other studies, including Furlanetto et al. (2019) and de Winter et al. (2021).

The results from the panel data model showed that, at the CEE level, the dynamics of the CLIFS indicator, the dynamics of lending to non-financial companies, and the dynamics of residential property prices significantly influence the dynamics of the economic cycle. Within the panel of developed states from the central-western part of Europe, only the dynamics of lending significantly influenced the dynamics of the economic cycle. These results are also in line with Bartoletto et al. (2019), who identified a strong link between lending and the economic cycle.

The practical implications of these results could be useful for economic policymakers, as any measure of monetary policy or fiscal policy that has effects on the activity of the banking sector, on the capital market, or on the dynamics of the activity of the real estate market influences indirectly and the dynamics of the economic cycle at the level of the respective state. In this sense, fiscal and monetary policies should be coordinated to generate the expected effect on the economy. On the contrary, if the direction of influence of the two types of policies is different, one of them being anti-cyclical while the other is pro-cyclical, the level of efficiency of the implemented measures could be significantly reduced.

This analysis can be expanded, in future research, both from the perspective of the countries analyzed and the types of econometric models used. In terms of countries, a future study could consider all EU member states to have a complete picture of how financial factors influence the real economy at the European level. In terms of econometric models, future studies could not only extend the analysis using other methods of filtering and identifying business cycles but also using other financial factors than those included in the analysis to illustrate the interactions between the financial market and the business cycle. Regarding the limitations of this study, we can mention the relatively short period of time analyzed, due to the lack of other historical data available, and the lack of data for other developing states from the CEE region.

Author Contributions: Conceptualization, B.A.D. and R.-A.G.; methodology, B.A.D. and R.-A.G.; software, B.A.D. and R.-A.G.; validation, B.A.D. and R.-A.G.; formal analysis, B.A.D. and R.-A.G.; investigation, B.A.D. and R.-A.G.; resources, B.A.D. and R.-A.G.; data curation, B.A.D. and R.-A.G.; writing—original draft preparation, B.A.D. and R.-A.G.; writing—review and editing, B.A.D. and R.-A.G.; visualization, B.A.D. and R.-A.G.; supervision, B.A.D.; project administration, B.A.D.; funding acquisition, B.A.D. All authors have read and agreed to the published version of the manuscript.

Funding: This paper was funded through the research project “Analyzing uncertainties with respect to the Forecast of the Evolution of the Economic Environment in the context of recent global socio-economic shocks”, within the Bucharest University of Economic Studies.

Data Availability Statement: The data presented in this study are available on request from the corresponding author.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

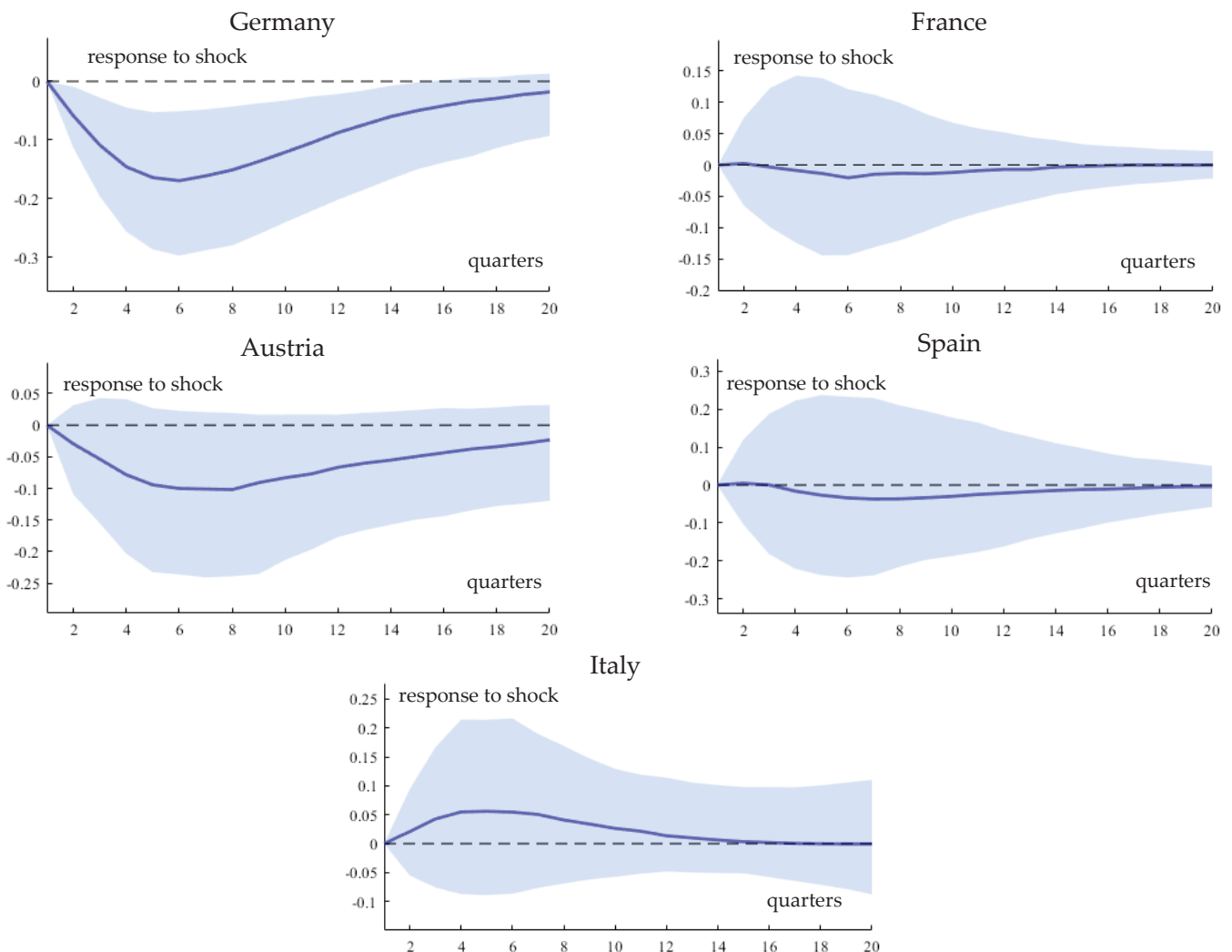


Figure A1. Dynamics of the economic cycle as a result of the shock from the level of loans granted to non-financial companies in the states of the central-western region of Europe. Note: the line represents the response of the economic cycle due to the shock, and the highlighted area represents the 95% confidence interval. Source of the data: own processing based on data provided by Eurostat and ECB.

Appendix B

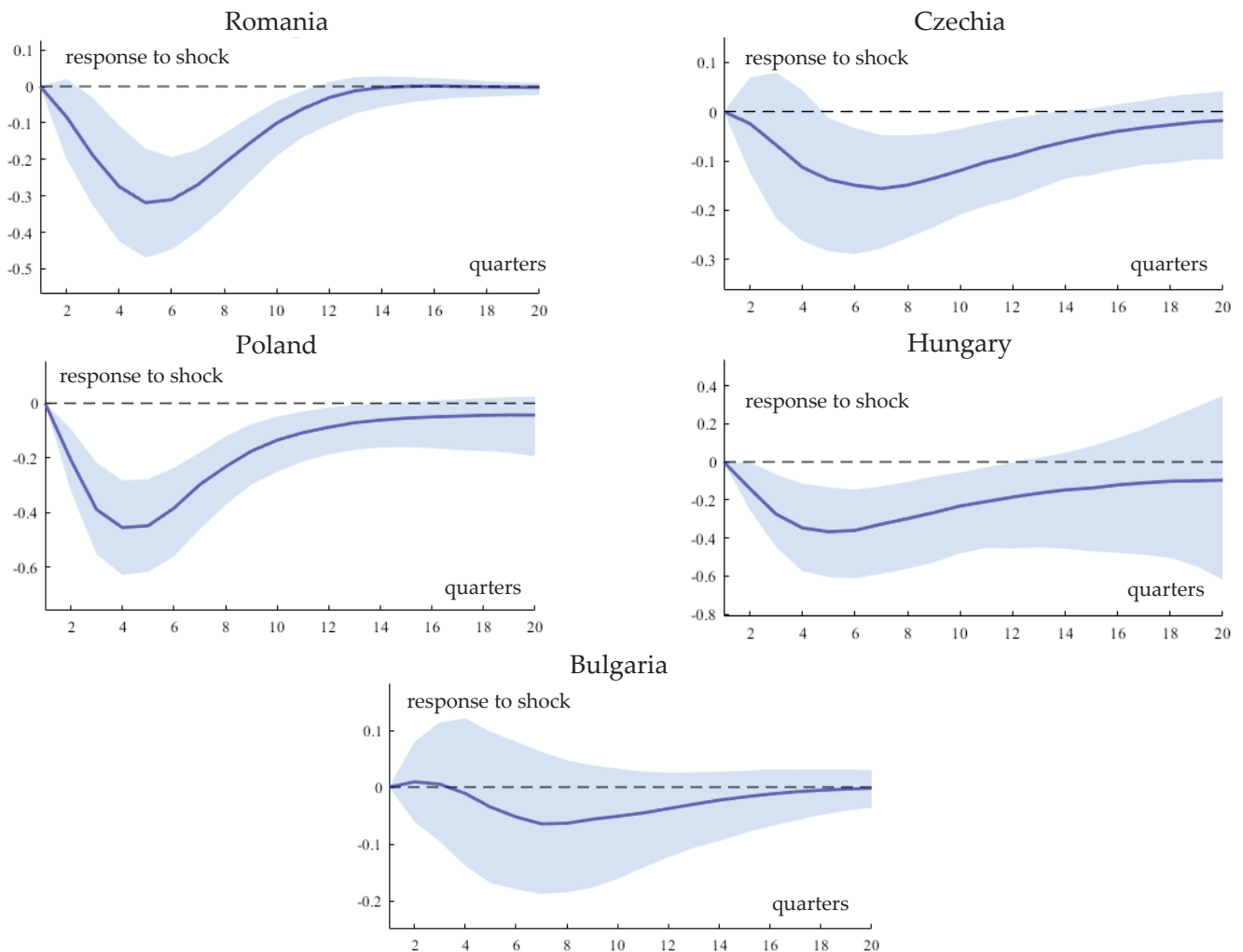


Figure A2. Dynamics of the economic cycle as a result of the shock at the level of credits granted to the population in the CEE states. Note: the line represents the response of the economic cycle due to the shock, and the highlighted area represents the 95% confidence interval. Source of the data: own processing based on data provided by Eurostat and ECB.

Appendix C

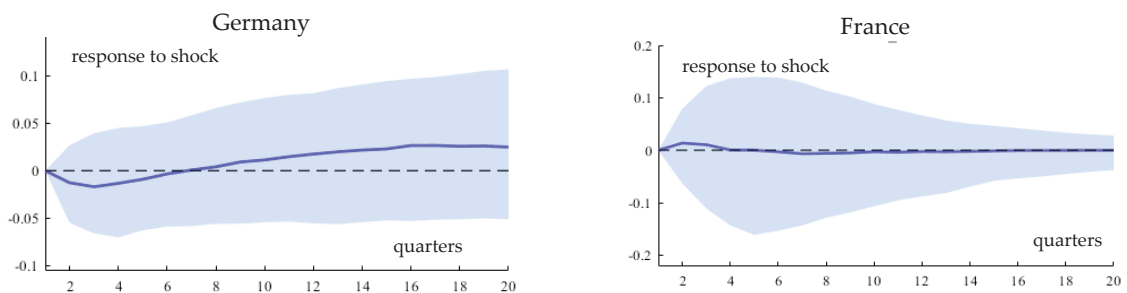


Figure A3. Cont.

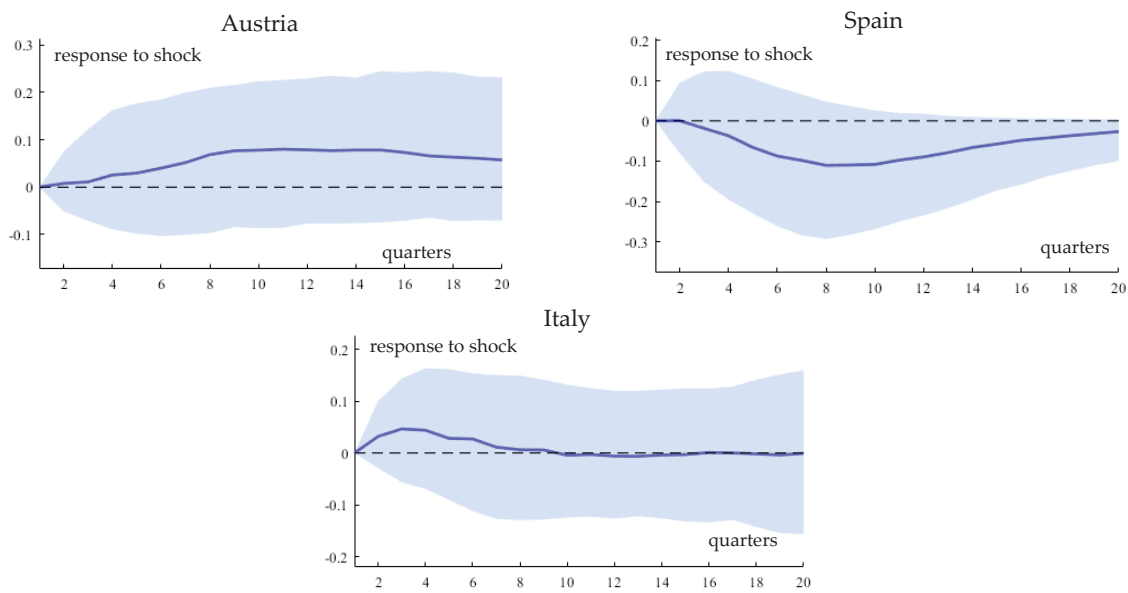


Figure A3. Dynamics of the economic cycle as a result of the shock on the level of credits granted to the population in the states of the central-western region of Europe. Note: the line represents the response of the economic cycle due to the shock, and the highlighted area represents the 95% confidence interval. Source of the data: own processing based on data provided by Eurostat and ECB.

Appendix D

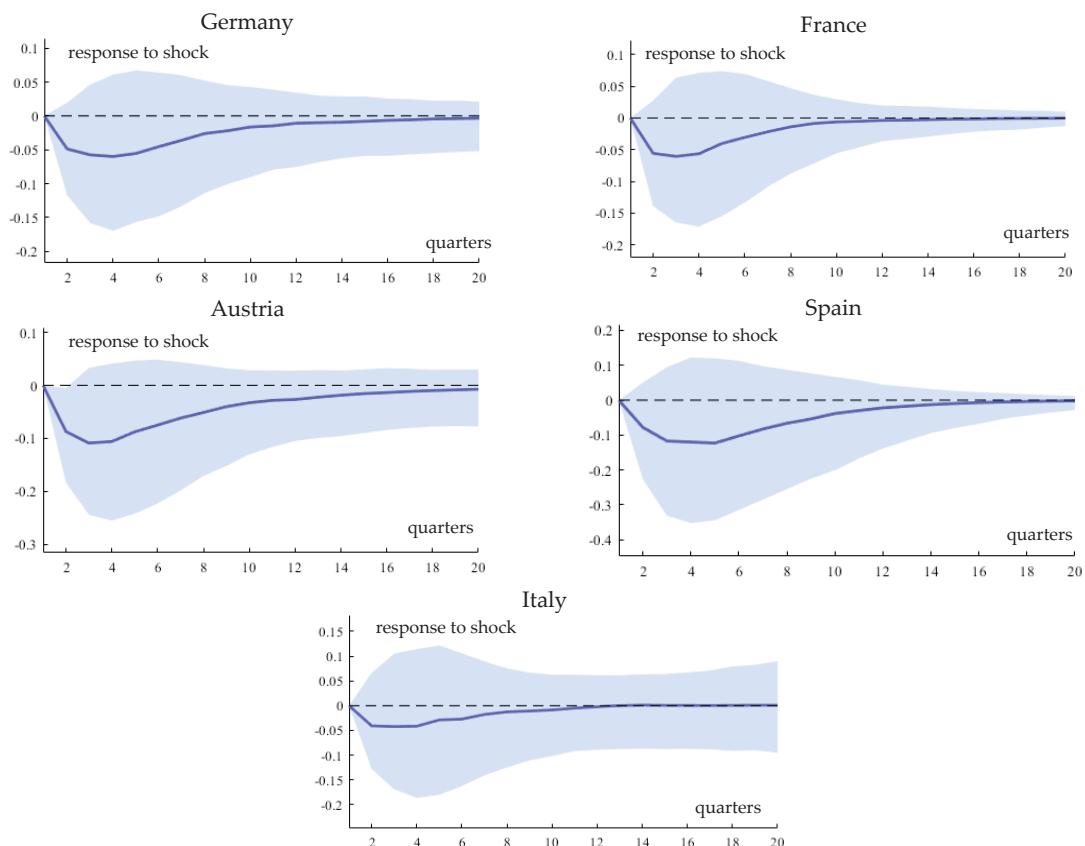


Figure A4. Dynamics of the economic cycle as a result of the shock at the CLIFS level in the states of the central-western region of Europe. Note: the line represents the response of the economic cycle due to the shock, and the highlighted area represents the 95% confidence interval. Source of the data: own processing based on data provided by Eurostat and ECB.

Appendix E

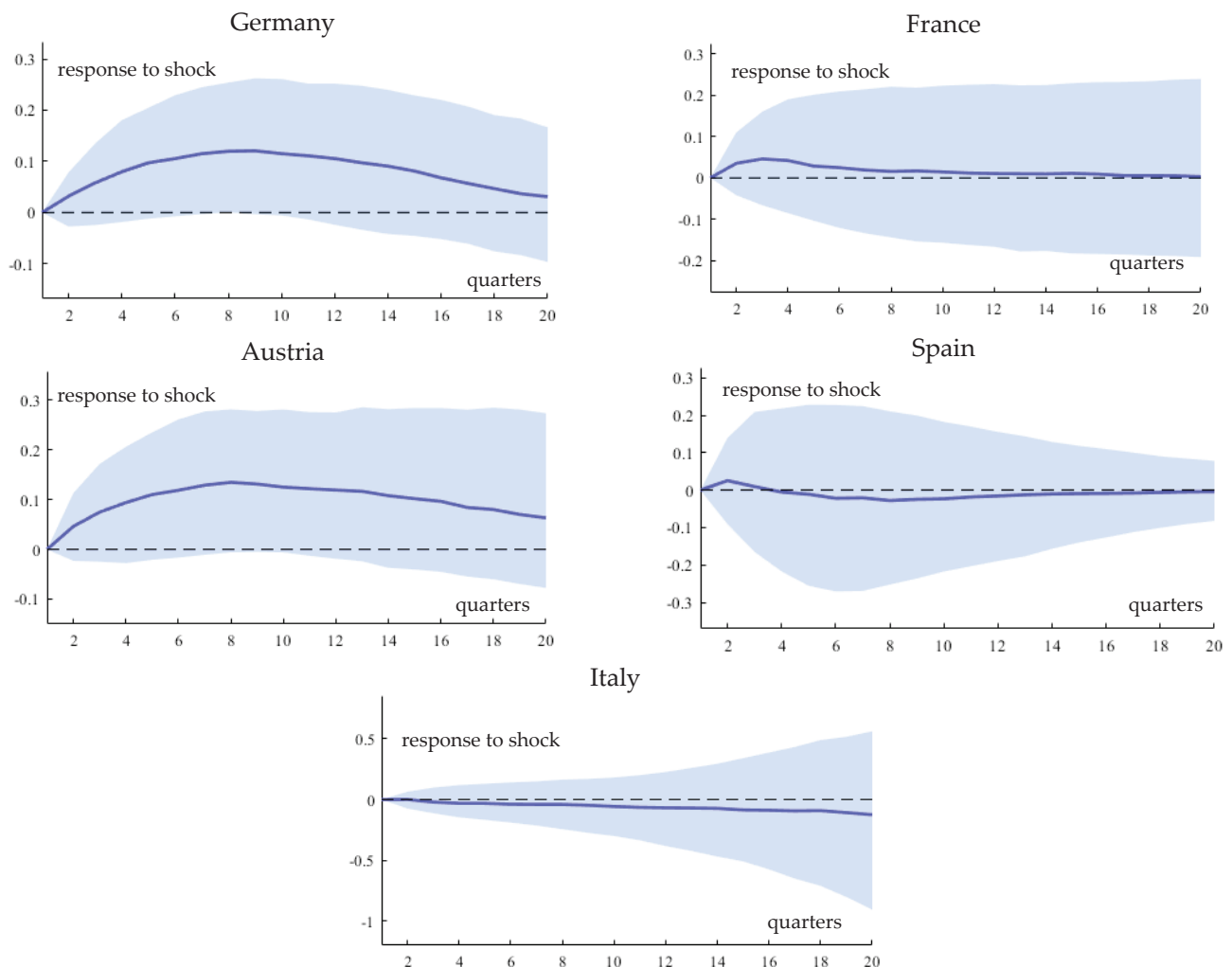


Figure A5. Dynamics of the economic cycle as a result of the real estate price shock in the states of the cCentral-wWestern region of Europe. Note: the line represents the response of the economic cycle due to the shock, and the highlighted area represents the 95% confidence interval. Source of the data: own processing based on data provided by Eurostat and ECB.

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Article

Determinants of Non-Performing Loans in a Small Island Economy of Fiji: Accounting for COVID-19, Bank-Type, and Globalisation

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Abstract: An increase in non-performing loans and bad debts in the banking sector can make banks vulnerable to a loss of confidence among customers and other banks and a banking collapse. The recent pandemic (COVID-19) and the evolving globalisation can affect bank operations, although the effects may depend on the type of banks and other bank-specific factors. In this paper, we revisit the topic on the determinants of non-performing loans of banks in a small island economy of Fiji over the period 2000 to 2022. We apply a fixed-effect method and consider seven banks (five commercial banks and two non-bank financial institutions). In our estimations, we examine the effect of bank-specific factors and control for the social and economic globalisation, the GFC, the COVID-19 pandemic, and bank-type effects, as well as the effect of the interaction between the bank type and the pandemic, as key contributions of the study. Overall, our results are consistent in terms of the effects noted from the bank-specific factors. From the extended model estimations, we note that COVID-19 had a more adverse effect on loan losses than the GFC, and the interaction between the bank type and COVID-19 indicates that non-banks were highly vulnerable to loan losses, whereas commercial banks exhibited greater preparedness. Economic globalisation reduces bank losses, whereas social globalisation exacerbates NPLs.

Keywords: bank profitability; institutions; globalisation; COVID-19; fixed-effect; island economy; South Pacific; Oceania; Fiji

1. Introduction

Investigating the impact of bank losses is an important issue for regulators, banks, and other key stakeholders, including shareholders. The level of non-performing loans (NPLs) can indicate the degree of stability in the banking system and the overall financial stability. Therefore, monitoring NPLs is in the interest of both the banks and the regulators. For instance, studies have noted that during the COVID-19 pandemic, job losses and economic contraction were evident, and banks faced higher non-performing loans (Kryzanowski et al. 2023; Berger and DeYoung 1997). Another important dimension that can create some degree of instability in the banking system is the role of non-bank financial institutions (cf. Pascual et al. 2023). Non-bank financial institutions (NBFIs) are highly interconnected with the global banking system and the real economy and hence can contribute to growing losses, which in turn can jeopardise the banking system and affect the whole economy (Cetorelli et al. 2023; Choudhary et al. 2023).

The banking sector in the Pacific remains a critical medium of channelling finance for economic activities. Moreover, the stability of a country's banking sector is necessary to foster economic growth and sustainable development (Chand et al. 2021; Kumar et al.

2018). However, one of the most significant challenges that financial institutions face is the rise in non-performing loans (NPLs). High NPLs can have adverse effects on both the banking system and the overall economy, as noted by recent studies (Loang et al. 2023). The level of NPLs can serve as an indicator of both a bank's low credit quality and the effectiveness of its risk management in handling its loan portfolio within the banking sector (Cortavarria-Checkley et al. 2000).

Moreover, high levels of NPLs can directly impact banks' profitability, as it reduces the income generated from interest payments (Ahiase et al. 2023; Gashi et al. 2022; Küçük 2022; Loang et al. 2023). Non-performing loans can signal the need for greater managerial attention and hence become the primary focus of a bank, which in turn can divert resources away from the pursuit of new and profitable activities (Cucinelli 2015; Khairi et al. 2021; Serrano 2021). Additionally, NPLs tie-up a bank's capital, thus limiting its ability to extend new loans to creditworthy borrowers (Constant and Ngomsi 2012; Foglia 2022; Khan et al. 2020). This, in turn, can stifle economic growth as businesses and individuals may struggle to access financing (Messai and Jouini 2013).

An increase in NPLs can diminish banks' investor confidence and affect the stability of the banking sector (Adeyemi 2011). Investors may become wary of such a bank and hence sell its stocks or bonds, which could lead to a decline in the bank's market value and potentially to a liquidity crisis (Abata 2014). In extreme cases, a bank with a high level of NPLs may face a loss of depositor trust, leading to a bank run and, ultimately, to bank failure (Adeyemi 2011; Curak et al. 2013).

Another important aspect is the different types of financial institutions that operate in the financial sector. Generally, although banks and non-bank financial institutions (NBFIs) may engage in deposit-taking and lending activities, they tend to have different features and purposes in the market system. The commercial banks tend to have a more conservative approach to lending and tend to adhere to stricter underwriting standards. As a result, they tend to have lower or manageable levels of non-performing loans compared to the NBFIs, which becomes evident especially in times of economic crisis. Moreover, commercial banks focus on traditional lending activities, such as mortgage loans, personal loans, and business loans. However, NBFIs have narrow revenue streams because they tend to focus on a specific type of loans, which can be more aligned to the national agenda (Pascual et al. 2023; Rahman et al. 2022; Duho et al. 2020; Cheng and Degryse 2010). In any case, the regulatory authorities and banks in general must monitor the level of NPLs to ensure sound operations. Bank regulators also set specific thresholds and guidelines for banks' non-performing assets. As such, both commercial banks and NBFIs are obligated to accurately classify and provision non-performing loans (NPLs). This ensures preparedness for potential losses and helps safeguard the stability of the financial system.

While recent studies on NPLs abound (Bayar 2019; Ozili 2019; Khan et al. 2020; Misman and Bhatti 2020; Fallanca et al. 2021; Karadima and Louri 2021; Phung et al. 2022; Golitsis et al. 2022; Fakhrunnas et al. 2022; Hakimi et al. 2022; El-Chaarani and Abraham 2022; Foglia 2022; Erdas and Ezanoglu 2022; Alnabulsi et al. 2022; Jubilee et al. 2022; Mdaghri 2022; Giammanco et al. 2022; Apergis 2022; Akhter 2023), they mainly examine the banking sector of developed, large, and developing and emerging economies. Notably, just a few studies have focused on small island countries (Kumar et al. 2018; Chand et al. 2021), and these are generally restrictive in terms of the model specification, sample, and scope.

Against this background, we focus on the banking sector of a small island economy of Fiji, with a relatively larger sample size (2000–2022). Although Fiji's economy is relatively small and the banking sector is less sophisticated compared to developed countries in the region, the sector has witnessed the collapse of a major bank some decades ago. In 1995, the state-owned bank—National Bank of Fiji (NBF)—collapsed, largely due to poor management and high losses (Siwatibau 1996; Chandra et al. 2004). It was observed that the NBF accumulated a significant sum of bad and doubtful debts, initially amounting to FJ\$90 million, which later surged to FJ\$220 million, approximately 8% of the country's GDP

(Lodhia and Burritt 2004). Since then, there have been no bank failures, although the sector noted episodes of rising non-performing loans (Chand et al. 2021).

Subsequently, investigating the determinants of NPLs in Fiji remains essential. In this study, we provide a more nuanced, up-to-date, and context-specific understanding of NPLs, which can benefit both policymakers and the academic community and contribute to Fiji's economic well-being. Identification of the factors could facilitate the implementation of preventive measures and targeted solutions.

It must be noted that the current socio-economic and geo-political climate, coupled with the recent pandemic of 2019, has put immense pressure on banks' ability to raise funds to support their operations or recover loans. Against this background, the study contributes to the literature on non-performing loans in a small island Pacific economy in the following ways. First, besides examining the effect of the global financial crisis of 2007–2008 (GFC), we account for the impact of the recent pandemic (COVID-19). Second, we account the bank-type effects, i.e., the effect of a commercial bank and the non-bank financial institutions. Third, we examine the role of globalisation, i.e., the social and economic globalisation. Finally, we investigate the interaction effects between bank types and COVID-19, to examine the degree of resilience exhibited by different bank types (commercial banks and non-bank financial institutions). Through our analyses, we have identified a set of crucial factors that plays a significant role in explaining the occurrence of non-performing loans in Fiji's financial sector. In addition to providing deeper insights on banks' stability through multiple extensions of the base model, our analyses show consistency and robustness of the results. The remainder of the paper is organised as follows: Section 2 draws on relevant theories and empirical studies. Section 3 presents data and methodology, and Section 4 presents the results. Section 5 concludes the paper.

2. Literature Review

NPLs are classified as bad loans. When a borrower is unlikely to repay a loan or the borrower has elapsed the agreed instalments for at least 90 days, this indicates that the loan is non-performing.¹ Non-performing loans entail cost to banks, and therefore, banks have a strong interest to minimise the level of bad loans. NPLs erode a bank's profitability by causing losses in their lending operations and necessitating increased provisions, which, in turn, diminishes the potential volume of future loans and accordingly banks' profits. More NPLs reduce banks earnings, weaken their financial position, and in cases where the situation is systemic, this can create an economy-wide catastrophe. NPLs can be an impediment to the development of the banking sector (Zhang et al. 2016), as more NPLs can potentially cause a collapse of the financial sector (Greenidge and Grosvenor 2010; Ghosh 2015).

It is well known in the literature that bank-specific and macroeconomic factors influence NPLs. In a study on banks in China over the period 2005–2014, Umar and Sun (2018) noted that factors, like the GDP, interest rate, inflation rate, foreign exchange rate, bank type, bank's risk-taking behaviour, ownership concentration, leverage, and credit quality are critical determinants of NPLs. Moreover, Kuzucu and Kuzucu (2019) examined the determinants of NPLs in emerging and advanced countries, both in the pre- and post GFC periods. They noted the finding that the GDP is negatively associated with NPLs in both countries in both periods; however, foreign direct investment and the exchange rate influenced the NPLs of banks in the post-GFC period and for banks in the emerging countries. Several studies confirm the negative association between the ROA and NPLs (Rachman et al. 2018; Kjosevski et al. 2019; Farooq et al. 2019). In Bayar's (2019) research on emerging countries, it was reported that macroeconomic indicators, such as GDP and inflation, bank-specific metrics, like the return on assets (ROA) and return of equity (ROE), regulatory capital, noninterest income, and global factors, like economic freedom, exhibit negative associations with NPLs. Additionally, the study revealed that unemployment, public debt, credit growth, lagged nonperforming loans, operational costs, and financial crises are factors that contribute to an increase in NPLs. Rachman et al.'s (2018) study on 36 commercial banks in Indonesia over the period 2008–2015 shows that the return on asset

(ROA) and credit growth are negatively associated with non-performing loans. Focusing on banks in Macedonia, Kjosevski et al. (2019) found that the ROA, growth of loans, and GDP reduce NPLs, whereas solvency and unemployment are positively associated with NPLs. Factors, like the capital adequacy ratio (CAR), were noted to have a negative effect on NPLs in India over the period 1996–2011 (Bardhan et al. 2019).

In a study conducted on banks in the Euro area during the period 2005–2017, Karadima and Louri (2020) observed that post-crisis consolidation accelerates the reduction in non-performing loans (NPLs), especially in peripheral countries. Furthermore, they note that competition and the presence of foreign banks reduce NPLs. Asiama et al. (2020) conducted an analysis using quarterly data spanning from 2000Q1 to 2018Q4 based on banks in Ghana. Their findings indicate a positive association between mobile money business operations and non-performing loans (NPLs). Tatarici et al.'s (2020) study on the European Economic countries over the period 2005–2017 shows that NPLs, as a ratio of total loans, increase with the deterioration of macroeconomic conditions, whereas government effectiveness reduces the NPL ratio. Similarly, Staehr and Uusküla (2020) show that economic growth, lower inflation, and lower debt are negatively associated with NPLs of banks in the EU countries.

In a more recent study on banks in Poland, Petkovski et al. (2021) noted that the ROA, growth of gross loans, economic growth, domestic credit to the private sector, public debt, and unemployment are significant determinants of NPLs. Žunić et al. (2021) noted that in Bosnia and Herzegovina, economic growth, loan loss provision, and COVID-19 were positively associated with the effect of NPLs. In the case of Tanzania, Pastory (2021) reports a host of factors positively associated with NPLs (effective tax rate, unemployment rate, inflation and lending rates, poor credit appraisal, insider lending, inadequate market information, and compromised integrity).

Kjosevski and Petkovski (2021) considered 21 commercial banks from the Baltic states over the period 2005–2016. They show that economic growth, public debt, inflation, and unemployment are positively associated with NPLs. Bank-specific factors, like equity to total assets, return on assets, return on equity, and the growth of gross loans, have an impact on the amount of NPLs. Moreover, considering banks in the Balkans, Krasniqi-Pervetica and Ahmeti (2022) found that economic growth and inflation have a negative effect, whereas government debt and unemployment have a positive effect, on NPLs.

Factors, like the bank size and competition, have a positive effect on NPLs in Nigeria (Bolarinwa and Akinlo 2022). In their 2022 analysis, Ben Bouheni et al. (2022) examined the fluctuations in NPLs across the economic cycle and the influence of past profitability within the largest Islamic banks in the United Kingdom and Turkey during 2010 to 2019. Their findings indicate a modest variation in NPLs, which correlates with an ascending ROA and a descending ROE. In Hajja's (2022) study examining the influence of bank capital on non-performing loans (NPLs) across 109 commercial banks in Malaysia, the analysis reveals threshold effects. It indicates that an initial increase in capital leads to a rise in NPLs up to a certain point. However, beyond that threshold, as additional capital accumulates, NPLs tend to decrease. In Küçük's (2022) analysis of monthly data in Turkey, it was demonstrated that rising interest rates and unemployment rates correlate with an increase in NPLs. Conversely, only escalations of deposit interest rates and the dollar exchange rate are associated with a decrease in NPLs.

Ofria and Mucciardi (2022) studied the effects of corruption and public debt on NPLs in European countries. They show that public debt and higher levels of institutional corruption exert upward pressure on NPLs. Syed et al. (2022) examined the impact of financial development on NPLs for 12 emerging economies over the period 1995–2020 and note that financial sector development and NPLs move together in the long run, and there is significant evidence of the asymmetric relationship. Akhter (2023) notes that NPLs of banks in Bangladesh are positively associated with loan loss provisions, equity-to-total assets, the capital adequacy ratio, net loans, return on equity, inflation, and economic growth. Saliba et al. (2023) analysed the impact of country risks (financial, economic, and political risks) on NPLs of banks in Brazil, Russia, India, China, and South Africa over the

period 2004–2020. The findings revealed that all three types of risks increase credit risk leading to more NPLs.

Background and Some Related Studies on Fiji's Banking Sector

Unlike other Pacific Island Countries, Fiji has a well-developed banking system regulated by the Reserve Bank of Fiji (RBF). The Reserve Bank oversees the monetary and banking system of Fiji, supervises currency issuance, enforces exchange controls, and offers various financial services to the government. It is responsible for maintaining the liquidity of trading banks through the implementation of the government's monetary policy. Alongside its role in shaping the credit landscape, the RBF oversees the foreign exchange regulations and oversees Fiji's global reserves.

Essentially, there are five commercial banks—Westpac Banking Corporation (WBC, established in 1901), Australia and New Zealand Banking Corporation Ltd. (ANZ, established in 1953), Bank of Baroda (BOB, established in 1961), Bank of the South Pacific (BSP, established in 1996), BRED Bank (BRED, established in 2012) (cf. Sharma et al. 2014), and Home Finance Corporation Ltd. (HFC, established in 2014), which was previously a non-bank financial institution. In its early days, HFC was a non-banking institution established in June of 1962 by the government of Fiji and the British Overseas Development Corporation (BODC), now known as the Commonwealth Development Corporation (CDC). It was subsequently incorporated as a local company under the name Fiji Development Company (FDC). Initially, the government of Fiji owned 33% of the bank's shares, and 67% of the shares were held by FDC. Later, in 1979, Fiji National Provident Fund (FNPF) became its third shareholder. By 1987, the Unit Trust of Fiji (UToF) joined as the fourth shareholder, with all four owners having equal shares by 1989. In 1995, the government of Fiji sold its shares to FNPF, making FNPF a major shareholder (50%), with management rights still intact with FDC. In 2002, FNPF bought FDC's share, hence having a 75% stake in the ownership. In 2014, HFC became a full-fledged bank. As of now, HFC is a locally owned bank, with 75% ownership by the Fiji National Provident Fund (FNPF) and the remaining 25% owned by the UToF. The other five banks are foreign-owned banks. The two non-bank institutions with saving and lending functions are Merchant Finance Ltd. (MFL, established in 1986) and Credit Corporation Ltd. (CFL, established in 1978).²

In Fiji, non-Bank financial institutions (NBFIs) comprise credit institutions, insurance companies, and the Fiji National Provident Fund (FNPF). Together, these NBFIs represent 63 percent of the total assets within the financial system.³ At present, three licensed credit institutions (LCIs) are operational: Merchant Finance Limited (MFL), Credit Corporation (Fiji) Limited (CCFL), and Kontiki Finance Limited (KFL).⁴ Alongside these licensed entities, there are non-licensed NBFIs, such as the Fiji Development Bank (FDB), Housing Authority (HA), Unit Trust of Fiji (UToF), and Fijian Holdings Unit Trust (FHUT). Additionally, Fiji hosts nine insurance companies. The licensed credit institutions deliver a diverse array of services. While some primarily finance the acquisition of machinery, equipment, and vehicles, others provide housing mortgage loans and various personal loans. The roles of licensed NBFIs are multifaceted. The FDB and HA focus on lending, whereas the UToF and FHUT function as investment vehicles for their unit holders. The insurance companies aim to safeguard policyholders against potential losses from uncertain events and offer alternative savings plans.⁵

A few studies have investigated different aspects of banking, such as bank stability (Chand et al. 2021), profitability (Gounder and Sharma 2012; Sharma and Gounder 2012), competition (Kumar and Patel 2014), and non-performing loans (Kumar et al. 2018).⁶ Kumar et al. (2018) considered annual data on bank-specific and macro-economic variables over the period 2000–2013 and found that the ROE, CAR, market share (measured based on the HHI), unemployment, and trend variables are negatively associated with NPLs, whereas NIM is positively associated with NPLs. In this study, we extend Kumar et al.'s (2018) study in terms of the latest available data size (2000–2022), controlling for non-bank financial institutions, the specific type of globalisation (social and economic globalisation), and the recent pandemic (COVID-19). During the pandemic, banks had to undertake measures to support existing customers and clients who were not able

to meet-up their loan obligations. Some critical measures included granting extensions on repayments, extending loans without additional fees, and options to repay interest only on the loan over a specified period.

3. Data

Hence, our dataset was extracted from multiple sources. Data on bank specific variables were extracted from the key disclosure statements published by banks to the Reserve Bank of Fiji (RBF 2023). The macroeconomic variables were obtained from the (World Bank 2023). The globalisation index was based on KOF globalisation index data (ETH-Zurich 2023). Specifically, we consider data based on two indices—economic and social (cf. Dreher 2006; Dreher et al. 2008). Our sample comprises seven financial institutions. Although there are six commercial banks, we take five commercial banks and two non-bank financial institutions (NBFIs), over the period 2000–2022.⁷ The two NBFIs are Credit Cooperation Fiji Limited (CCFL) and Merchant Finance Limited (MFL). Both institutions have lending and deposit functions; hence, similar to commercial banks, they are mandated by the RBF to furnish key disclosure statements. The five commercial banks are Australia and New Zealand Banking Group (ANZ), Westpac Banking Corporation (WBC), Bank of the South Pacific (BSP), Bank of Baroda (BOB), and Home Finance Corporation (HFC). The data used are a balanced panel sample covering the period from 2000 to 2022. Table A1 (Appendix A) reports a summary of the dependent and independent variables utilised in the model for estimation. The dependent variable is NPLs, which is a ratio of total bad debts to total loans (Khan et al. 2020; Küçük 2022; Kryzanowski et al. 2023). The descriptive statistics and correlation matrix for all banks (commercial banks and NBFIs) are presented in Table 1, and in Table 2, we present the statistics for NBFIs only.

Table 1. Descriptive statistics and correlation matrix (Commercial banks and NBFIs).

Descriptive statistics											
Variable Statistics	NPLs	BSIZE	NIM	ROA	INEF	CAR	HHI_LOAN	LTD	GDPG	EINDX	SINDX
Mean	0.01	12.96	0.06	0.03	0.29	19.04	2480.72	0.98	1.66	49.85	64.33
Median	0.01	13.11	0.04	0.02	0.25	16.55	2599.35	0.94	2.00	50.96	65.26
Maximum	0.08	15.02	0.56	0.09	0.67	49.77	2928.96	2.58	16.10	53.88	69.15
Minimum	0.00	10.64	0.02	−0.03	0.08	8.81	1780.24	0.00	−17.00	39.88	55.41
Std. Dev.	0.01	1.27	0.05	0.02	0.13	7.00	351.55	0.48	5.56	3.78	3.66
Skewness	2.75	−0.08	5.51	0.94	0.93	1.28	−0.64	0.46	−0.93	−1.40	−0.70
Kurtosis	14.18	1.72	50.49	4.01	2.96	4.94	2.10	4.14	7.73	3.93	2.76
Probability	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Observation	161	161	161	161	161	161	161	161	161	147	147
Correlation											
	NPLs	BSIZE	NIM	ROA	INEF	CAR	HHI_LOAN	LTD	GDPG	EINDX	SINDX
NPLs	1										
BSIZE	−0.4	1									
NIM	0.37	−0.58	1								
ROA	0.14	−0.41	0.68	1							
INEF	−0.15	−0.08	−0.15	−0.4	1						
CAR	0.38	−0.58	0.42	0.55	−0.11	1					
HHI_LOAN	−0.11	−0.34	0.2	0.14	0.01	−0.06	1				
LTD	0.28	−0.17	0.47	0.4	−0.28	0.21	0.2	1			
GDPG	−0.39	−0.06	−0.02	0.16	−0.15	−0.05	0.28	−0.01	1		
EINDX	−0.21	0.28	−0.01	0.22	0.07	0.19	0	0.16	0.17	1	
SINDX	−0.07	0.44	−0.15	0.04	0.09	0.21	−0.59	0	0.01	0.73	1

Notes: data for globalisation indexes are from 2000 to 2020, and for all other financial variables, the sample is from 2000 to 2022. Source: authors' computation using data compiled from different databases.

Table 2. Descriptive statistics and correlation matrix for NBFI.

Variable Statistics	Descriptive statistics										
	NPLs	BSIZE	NIM	ROA	INEFB	CAR	HHI_LOAN	LTD	GDPG	EINDX	SINDX
Mean	0.02	12.37	0.08	0.04	0.23	23.28	2480.72	1.15	1.66	49.85	64.33
Median	0.01	11.98	0.09	0.04	0.21	23.06	2599.35	1.13	2.00	50.96	65.26
Maximum	0.08	14.74	0.15	0.09	0.45	49.77	2928.96	2.04	16.10	53.88	69.15
Minimum	0.00	10.64	0.02	−0.03	0.14	9.38	1780.24	0.69	−17.00	39.88	55.41
Std. Dev.	0.02	1.30	0.04	0.02	0.07	8.15	353.02	0.26	5.58	3.78	3.66
Skewness	2.02	0.59	−0.17	−0.42	1.03	0.55	−0.64	0.60	−0.93	−1.40	−0.70
Kurtosis	8.40	1.88	1.83	4.03	3.63	3.20	2.10	3.41	7.73	3.93	2.76
Jarque-Bera Probability	130.68	7.63	4.25	5.04	13.45	3.58	7.03	4.66	74.33	53.12	12.35
Observation	69	69	69	69	69	69	69	69	69	63	63
	Correlation										
	NPLs	BSIZE	NIM	ROA	INEFB	CAR	HHI_LOAN	LTD	GDPG	EINDX	SINDX
NPLs	1										
BSIZE	−0.4	1									
NIM	0.37	−0.58	1								
ROA	0.14	−0.41	0.68	1							
INEFB	−0.15	−0.08	−0.15	−0.4	1						
CAR	0.38	−0.58	0.42	0.55	−0.11	1					
HHI_LOAN	−0.11	−0.34	0.2	0.14	0.01	−0.06	1				
LTD	0.28	−0.17	0.47	0.4	−0.28	0.21	0.2	1			
GDPG	−0.39	−0.06	−0.02	0.16	−0.15	−0.05	0.28	−0.01	1		
EINDX	−0.21	0.28	−0.01	0.22	0.07	0.19	0	0.16	0.17	1	
SINDX	−0.07	0.44	−0.15	0.04	0.09	0.21	−0.59	0	0.01	0.73	1

Notes: data for globalisation indexes are from 2000 to 2020, and for all other financial variables, the sample is from 2000 to 2022, extracted from RBF (2023). Source: authors' computation using data compiled from different databases.

The trends of key bank-specific factors are provided in Figures 3–8, A1 and A2 (see Appendix A). Figure A1 illustrates the return on assets (ROA). Notably, CREC (non-bank) has negative ROA values for the years 2000 and 2001, and WBC (commercial bank) displays a negative value in 2020. Figure A2 shows the ratio of operating expenses to revenue (measures of inefficiency). HFC (commercial bank) has the highest expenses-to-revenue ratio and CREC had the lowest ratio. In Figure 3, we note that the loan-to-deposit ratio of the commercial banks HFC and BSP are generally positive and high, while BOB exhibits the lowest ratio. In Figure 4, it is evident that NBFIs had the highest levels of the capital adequacy ratio. Both NBFIs (CREC and MFIN) maintained high levels of interest margins compared to the commercial banks (Figure 5). Furthermore, in Figure 6, we note that the two NBFIs were leading in terms of the non-performing loans, although we note a uniform increase in NPLs since 2019 for all banks. Notably, commercial banks' assets are larger than NBFIs' (Figure 7). Particularly, we note that ANZ is the largest bank based on assets, followed by BSP, WBC, HFC, and BOB. The size of ANZ and WBC have slightly decreased, although ANZ remains the largest bank in Fiji. BSP, which was relatively small in 2011, surpassed WBC in 2018, becoming the second largest bank in Fiji. It is interesting to note that both NBFIs (CREC and MFIN) have been relatively small, and their size remained generally constant size since 2000. From Figure 8, we note a marginal decline in the Herfindahl–Hirschman Index (HHI) by approximately 1.7% annually, which signals some level of competition in the banking sector.

4. Method

The model setup is an extension of Demirgüç-Kunt and Huizinga (1999). The general equation takes the following form:

$$NPL_{it} = \alpha + \underbrace{\beta_m X_m}_{\text{m-bank specific}} + \underbrace{\varphi_n K_n}_{\text{NBFI}} + \underbrace{\theta_p M_p}_{\text{Macroeconomic}} + \underbrace{\omega_q Z_q}_{\text{globalisation+structural}} + \varepsilon_{it} \quad (1)$$

whereby NPL denotes the amount of NPLs (bad debts) as a percentage of total volume of loans of bank i at time t ; β_m contains the set of coefficients of the bank-specific factors, X_m contains the set of a bank-specific factor m , φ_n comprises the coefficient of NBFI variables, θ_p contains the coefficients of the respective macroeconomic variables, ω_q contains the coefficients of globalisation and a structural variable (see Appendix A, Table A1 for variable definitions) and $\varepsilon \sim N(0, \sigma^2)$ is the error term. We specify our base mode as follows:

$$NPL_{it} = \alpha + \underbrace{\beta_1 BSIZE_{it} + \beta_2 NIM_{it} + \beta_3 ROA_{it} + \beta_4 INEF_{it} + \beta_5 CAR_{it} + \beta_6 HHI_{it} + \beta_7 LTD_{it}}_{X_m = \text{base model}} + v_{it} + \varepsilon_{it} \quad (2)$$

where $BSIZE$ = bank size, NIM = net interest margin, ROA = return on assets, $INEF$ = inefficiency measured based on the ratio of the operating expense to operating revenue, CAR = capital adequacy ratio, HHI = Herfindahl–Hirschman index, LTD = loan to deposit ratio, (see Appendix A, Table A1 for variable definitions), v_{it} = the unobserved (cross-section) firm-dependent error term, and ε_{it} = the idiosyncratic error term. The extended base model (2) also includes globalisation indexes, non-bank and commercial bank dummies, GFC, and the COVID-19 pandemic, and it can be specified as follows:

$$NPL_{it} = \alpha + \underbrace{\beta_1 BSIZE_{it} + \beta_2 NIM_{it} + \beta_3 ROA_{it} + \beta_4 INEF_{it} + \beta_5 CAR_{it} + \beta_6 HHI_{it} + \beta_7 LTD_{it}}_{X_m = \text{base model}} + \underbrace{\varphi_1 NBFI}_{K_n} + \underbrace{\theta_1 GDPP_t}_{M_p} + \underbrace{\omega_1 EINDEX_t + \omega_2 SINDEX_t + \omega_4 COVID + \omega_5 GFC_t}_{Z_q} + v_{it} + \varepsilon_{it} \quad (3)$$

Finally, we modify model (3) to incorporate the interaction between COVID-19 and a specific type of banks (i.e., commercial banks and non-bank financial institution, and bank-specific dummies).

To determine the appropriate regression technique to use, we conducted a Hausman test using the base model (Model 2) with our sample data spanning from 2000 to 2022. In the pooled OLS estimation, it is assumed that the regression coefficients are uniform across all firms, meaning that the regressors are non-stochastic, and errors are uncorrelated with the explanatory variables. This implies that $Cov(X_{it}, \varepsilon_{it}) = 0$, and the error term $\varepsilon_{it} \sim iid(0, \sigma_\varepsilon^2)$. To assess the appropriateness of choosing between pooled OLS and fixed-effect methods, we conducted a Wald test with the null hypothesis that the differences between the coefficients of the firm dummy variables are equal to zero (i.e., there is no firm-level heterogeneity). The choice of applying the pooled OLS is made by examining the F -statistic (and χ^2 -statistics) and the respective p -values. We report the results in Table A2 (See Appendix A). We note that $F = 14.447$ and $\chi^2 = 101.132$, with p -values of less than 0.01, respectively.⁸ The statistically significant p -values imply that banks are not homogeneous across the sample. Thus, there are banking characteristics that are not accounted for by the OLS model. Hence, we reject the null hypothesis in favour of the fixed-effect method (or random-effect method) to account for firm-level effects (unobserved heterogeneity $Cov(X_{it}, \varepsilon_{it}) \neq 0$). Additionally, the fixed-effect model assumes that the differences in the intercepts vary across groups or time periods. Rejecting the OLS estimation and determining the suitability of the fixed-effect against the random-effect method requires the execution of the Hausman test (Ali and Puah 2019; Chand et al. 2021; Theiri and Hadoussa 2023). In this case, the null hypothesis is that the covariance between

the explanatory variable and firm heterogeneity is zero, denoted as $Cov(X_{it}, v_{it}) = 0$, which would indicate support for the random-effect model. This decision requires examining the χ^2 -statistics and the respective p -value. A statistically significant p -value ($p < 0.01$) will reject the null at the 1% level, in support of applying the fixed-effect method. Upon conducting Hausman tests on the two base models (refer to Appendix A, Table A2, panel b), we observe $\chi^2 = 19.365$ and $\chi^2 = 27.748$, both with p -values below 0.01. Based on the results, we reject the random-effect method in support of the fixed-effect method at the 1% level of significance.⁹ Subsequently, we apply the fixed-effect method on the base model (Equation (2)), and then, we incorporate other variables (such as bank-types, COVID-19, globalisation, and pandemic and bank-type interactions).

5. Results and Discussion

5.1. Base Model (Model I–III)

The results of the fixed effects estimation are reported in Table 3 below. In model I, we estimated the bank-specific variables only and note that the R-squared is 0.43, implying that the base model could explain 43% of the relationship between the NPL and the associated explanatory factors. Starting with Model I, we observe that bank size, as measured based on total assets (BSIZE) and the ROA, are negative and significant. This suggests that as a bank's size or profitability increases, its non-performing loans tend to decrease. This result aligns with the argument that larger and more profitable banks typically possess greater resources and funds to effectively manage risk, implement robust credit assessment practices to either prevent or mitigate risk, and diversify their loan portfolios, thereby keeping their losses at relatively lower levels. (Ahmed et al. 2021; Akhter 2023; Yulianti et al. 2018; Alnabulsi et al. 2022). Furthermore, we note that the ratio of the operative expense to operating revenue (INEF) has a negative effect on the NPL. This confirms Kumar et al.'s (2018) finding, but here, the coefficient is not statistically significant at the conventional level (1–10 percent level of significance).

Moreover, we note that the net interest margin (NIM) and loan to deposit ratio (LTD) are positive, although they are not statistically significant. Nevertheless, the positive effects of the NIM and loan (relative to deposits) on losses can be due to the higher interest rates charged on loans, compared to those offered on deposits, and the greater uses of funds (loans) than the sources of funds (deposits) available. Which could potentially increase the risk of default and the possibility of losses (Adusei 2018; Ozili 2019; Silaban 2017; Nguyen 2012). Consistent results are also noted in Models II and III, where we control for NBFIs (with positive effect on NPL) in Model II and we control for commercial banks (with negative effect on NPL) in Model III. Although the effect of bank type is opposite, we note that in both cases, the coefficients are not statistically significant.

We note that the concentration ratio (HHI), a measure of the market concentration (a higher HHI indicates a more concentrated market), has a marginally positive impact and is significant in Model I; the opposite (negative impact and not significant) is true in Models II and III. The positive association implies that a higher HHI tends to lower competition and in turn disincentivises efficient and sound management practices based on lending. When we control for bank types, we note that the HHI exhibits a negligibly negative effect, which is statistically insignificant. Because of the negligible effect of the HHI on NPL (close to zero), we can conclude that the degree of competition does not necessarily influence the loan losses of Fijian banks. In this regard, trying to increase the market share is not a strategy for banks to minimise losses. Furthermore, we note that the capital adequacy requirement (CAR) has a positive effect on NPL, which is a statistically significant effect at the 1% level in all three models (Table 3). While an increase in CAR buffers the potential losses, this does not restrict banks from expanding their loan portfolio. Therefore, with higher capital adequacy requirements, on one hand, banks' safety-net increases; on the other hand, this increases confidence among banks to increase their lending activities, which can in turn increase the NPL. In Models II and III, we control for the bank-types, i.e., non-bank financial institutions (NBFIs) and commercial banks (COMBs), respectively.

As noted in both the models, the coefficient of NBFI is negative, and COMB is positive, although they are not statistically significant. Also, we note that controlling for bank-types per se (Models II-III) does not improve the adjusted R-squares (they remain around 42%).

Table 3. Fixed effects: the dependent variable is NPLs (base model).

Independent	Model I	Model II	Model III
Constant	0.096778 *** (0.028783)	0.105741 *** (0.031420)	0.102383 *** (0.029870)
BSIZE	−0.005197 *** (0.001700)	−0.005798 *** (0.001898)	−0.005798 *** (0.001898)
NIM	0.019831 (0.023378)	0.015984 (0.024022)	0.015984 (0.024022)
ROA	−0.005278 *** (0.069602)	−0.223431 *** (0.069765)	−0.223431 *** (0.069765)
INEF	−0.000373 (0.007466)	−0.000016 (0.007495)	−0.000016 (0.007495)
CAR	0.000667 *** (0.000202)	0.000681 *** (0.000203)	0.000681 *** (0.000203)
HHI_LOAN	−0.000013 *** (0.000006)	−0.000011 (0.000006)	−0.000011 (0.000006)
LTD	0.002705 (0.002007)	0.002502 (0.002030)	0.002502 (0.002030)
NBFI		−0.003357 (0.004679)	-
COMB			0.003357 (0.004679)
Adj- R^2	0.423784	0.421876	0.421876
F-stat	10.05182	9.339808	9.339808
DW-stat	1.553834	1.565126	1.565126
Observations	161	161	161

Notes: *** denotes a 1% level of statistical significance. Values in the parentheses (.) are standard errors. Source: authors' estimation.

5.2. Economic Growth, Bank Type, GFC, and COVID-19

Next, in models IV-IX (Table 4), we account for economic growth (GDPG), the bank type (i.e., NBFI or COMB), GFC, and the pandemic (COVID-19). Notably, the results with respect to bank types (Models V and VI) remain consistent with the results reported in Table 3. Interestingly, including GDPG, GFC, and COVID-19, we observe an improvement in the adjusted R-squares from 42% from the base model (Table 3) to 48% (Model IX). Also, the statistical significance, magnitudes, and the signs of the coefficients of BSIZE, NIM, ROA, INEF, CAR, HHI, and LTD, are consistent with the base model, further supporting the robustness of the results. Specifically, we note that economic growth or the increase in per capita GDP (GDPG) has a negative effect on the NPLs in all six estimations (see Models IV-IX). The negative coefficient implies that when the economy is growing, borrowers' ability to repay loans tends to improve, leading to fewer defaults or delayed payments. This might happen because during economic expansion, businesses and individuals have better financial prospects, the incomes of those already employed have a higher chance to grow, and there are more job opportunities and overall economic stability. Consequently, the favourable economic conditions make it more likely that borrowers are in a better position to take up new loans, refinance their loans, and regularly meet their loan repayment obligations—all of which supports the reduction in NPLs for banks (Akhter 2023; Krasniqi-Pervetica and Ahmeti 2022).

Table 4. Fixed effects: the dependent variable is NPLs (controlling for economic growth, bank type, the GFC, and Covid).

Independent	Model IV	Model V	Model VI	Model VII	Model VIII	Model IX
Constant	0.092893 *** (0.028125)	0.103366 *** (0.030654)	0.103366 *** (0.030654)	0.109772 *** (0.029660)	0.104475 *** (0.029001)	0.104475 *** (0.029001)
BSIZE	−0.005117 *** (0.001660)	−0.005821 *** (0.001851)	−0.005821 *** (0.001851)	−0.005906 *** (0.001713)	−0.006139 *** (0.001674)	−0.006139 *** (0.001674)
NIM	0.006708 (0.023267)	0.002018 (0.002918)	0.002018 (0.002918)	−0.001979 (0.023677)	−0.0004354 (0.023119)	−0.004354 (0.023119)
ROA	−0.155928 ** (0.007069)	−0.152845 ** (0.072220)	−0.152845 ** (0.072220)	−0.181442 ** (0.073167)	−0.167282 ** (0.071566)	−0.167282 ** (0.071566)
INEF	0.003293 (0.007397)	0.003761 (0.007423)	0.003761 (0.007423)	−0.000330 (0.007653)	−0.004603 (0.007614)	−0.004603 (0.007614)
CAR	0.000647 *** (0.000197)	0.000664 *** (0.000198)	0.000664 *** (0.000198)	0.000679 *** (0.000197)	0.000503 *** (0.000202)	0.000503 *** (0.000202)
HHI_LOAN	−0.000012 *** (0.000003)	−0.000012 *** (0.000003)	−0.000012 *** (0.000003)	−0.000013 *** (0.000003)	−0.000008 *** (0.000003)	−0.000008 *** (0.000003)
LTD	0.002382 (0.001962)	0.002140 (0.001983)	0.002140 (0.001983)	0.002968 (0.001980)	0.002770 (0.001933)	0.002770 (0.001933)
GDPG	−0.000383 *** (0.000133)	−0.000388 *** (0.000133)	−0.000388 *** (0.000133)	−0.000343 *** (0.000134)	0.000173 (0.000222)	0.000173 (0.000222)
NBFI		−0.003942 (0.004568)				
COMB			0.003942 (0.004568)			
GFC				0.004864 * (0.002864)		0.005128 * (0.001796)
COVID					0.017412 *** (0.005112)	0.014712 *** (0.005112)
Adj-R ²	0.451075	0.450115	0.450115	0.458070	0.483981	0.483981
F-stat	10.39136	9.731323	9.731323	10.01608	10.37915	10.37915
DW-stat	1.547243	1.561772	1.561772	1.578469	1.685662	1.685662
Observations	161	161	161	161	161	161

Notes: ***, **, and * denote a 1, 5, and 10% level of statistical significance. Values in the parentheses (.) are standard errors. Source: authors' estimation.

As noted from model VII, the impact of the GFC on NPL was positive, and it is statistically significant at the 10% level, implying that the global financial crisis increased the potential for loan losses and vulnerability in the banking sector. The result is quite intuitive because at least three of the large banks (ANZ, WBC, and BSP) have foreign ownership and hence are linked to developed country markets. Also, with global economic slowdown due to the GFC, business consolidation and closures could have had negative repercussions on high-end clients (i.e., large businesses and mortgage holders), thereby inflicting difficulty in their ability to meet loan repayments. As noted from Model VII, the effect of COVID-19 was positive and significant at the 1% level. We note that both the GFC and COVID-19 (Model IX) had positive and significant effects, although the effects from COVID-19 on loan losses were stronger than the effects induced by the GFC. One explanation for the greater impact of COVID-19 is its economy-wide effect, which was deeply and directly experienced by the entire country. In contrast, the Global Financial Crisis (GFC) may have had secondary effects owing to the remoteness of Fiji's banking sector and stronger connections with only a few sectors, primarily financial and real estate. On the contrary, as a consequence of the pandemic,

nationwide lockdowns significantly impacted virtually all business operations, irrespective of their size, as well as major sectors, like manufacturing and tourism. Notably, the pandemic ignited a widespread economic upheaval, leading to business closures, disruptions in supply chains, and reduced consumer spending. These disruptions, in turn, led to income losses for both businesses and individuals, affecting their capacity to meet financial obligations, including loan repayments. The positive effect of COVID-19 on NPLs is consistent with some recent studies (Žunić et al. 2021; Kryzanowski et al. 2023).

5.3. Social and Economic Globalisation

In Table 5 (Model X and XI), we include social (SINDEX) and economic (EINDEX) globalisation, together with the GFC and COVID-19. Moreover, the influence of the GFC and COVID-19 remain positive, although only the latter is statistically significant. In terms of the globalisation index, we note that SINDEX is positively, and EINDEX is negatively, associated with NPLs, implying that, *ceteris paribus*, social globalisation (example, information flows via internet and social media) increases loan losses, whereas economic globalisation reduces loan losses. The positive impact of SINDEX aligns with the argument that social globalisation, while promoting diversity and mutual understanding, can also expose economies to various social and economic practices (Chareonwongsak 2002). These practices may have a negative influence on business operations. The exposure to diverse cultural norms and consumer lifestyles can impact individual spending patterns and savings behaviour, potentially exacerbating a risk-taking attitude. For instance, individuals seeking loans or credit cards to enhance their lifestyles, facilitated by easy access to unsecured loans, may increase the likelihood of banks experiencing more NPLs.¹⁰ However, intuitively, an increase in economic globalisation implies an increasing trade volume, and this requires the greater engagement of financial institutions (banks) to facilitate transactions, which increase banks' revenue-generating potential. When countries engage in international trade and investment, they benefit from access to larger markets, technological advancements, and the potential to diversify their portfolios (Carr and Chen 2002)—all of which require banking and financial services. Moreover, an increasing trade volume contributes to economic growth, increasing job opportunities, and higher income levels, supporting loan repayments through technological advancement, and subsequently, lessens the likelihood of loan defaults.

5.4. Interaction Effect with COVID-19

The final set of estimations aims to gain further insights into how the pandemic affected losses based on the specific type of banks (see Table 6). We examined the effects of the GFC, COVID-19, and the interaction effect between the bank type and the pandemic on NPLs. Some interesting results are noted. The impact of the GFC remains positive (see Models XII–XV) as before, although it is not statistically significant. The effect of COVID-19 is still positive (as before) and significant in most of the models (Models XII, XIII, and XV). Moreover, the factors applied in the base model (Model I) remain generally consistent in terms of the magnitude, thereby further supporting the robustness of the results. Moreover, we note that accounting for the interaction effect also improved the adjusted R-square values, implying that extended models explain the relationship relatively better than the base model.

We note that the effect caused by the interaction between NBFIs and COVID-19 is positive (0.0216) and the interaction effect of COMBs and COVID-19 is negative (−0.0216), and they are both statistically significant (Models XII and XIII, respectively). Looking at the interaction of COVID-19 and specific banks within NBFIs (CREC, MFIN, and HFC¹¹) and COMBs (ANZ, BOB, BSP, and WBC), we note consistent results. Each specific NBFI interacting with COVID-19 exacerbated losses in the banking sector (Model XIV), whereas each commercial bank interacting with COVID-19 lowered the NPL in the banking sector (Model XV). These results indicate that non-banks were vulnerable to losses during the pandemic, whereas commercial banks were generally resilient and in fact could have had adequate measures in place to recover loan losses.

Table 5. Fixed effects: the dependent variable is NPLs (controlling for economic and social globalisation).

Independent	Model X	Model XI
Constant	0.033360 (0.031541)	0.022052 (0.002991)
BSIZE	−0.004768 ** (0.002401)	−0.004379 * (0.002379)
NIM	0.015740 (0.020790)	0.020206 (0.020445)
ROA	−0.195210 *** (0.066730)	−0.179862 *** (0.065448)
INEF	−0.003964 (0.007269)	−0.001950 (0.007062)
CAR	−0.000037 (0.000199)	−0.000075 (0.000197)
HHI_LOAN	0.000003 (0.000004)	0.000006 (0.000006)
LTD	0.001007 (0.001640)	0.000640 (0.001610)
GFC	0.002675 (0.002336)	-
COVID	0.019045 *** (0.003430)	0.019749 *** (0.003379)
SINDX	0.001028 * (0.000542)	0.001063 * (0.000542)
EINDX	−0.000644 * (0.000389)	−0.000655 * (0.000389)
Adj-R ²	0.546310	0.545225
F-stat	11.34153	11.93987
DW-stat	1.71587	1.692227
Observations	147	147

Notes: ***, **, and * denote a 1, 5, and 10% level of statistical significance level. The sample size is from 2000 to 2020, due to data constraints based on globalisation variables. Values in the parentheses (.) are standard errors. Source: authors' estimation.

Table 6. Fixed effects: the dependent variable is NPLs (controlling for the interaction effects of COVID with bank types).

Independent	Model XII	Model XIII	Model XIV	Model XV
Constant	0.078260 *** (0.028326)	0.078260 *** (0.028326)	0.077812 *** (0.028074)	0.080672 *** (0.028624)
BSIZE	−0.004954 *** (0.001610)	−0.004954 *** (0.001610)	−0.005092 *** (0.001600)	−0.005197 *** (0.001639)
NIM	−0.010280 (0.021972)	−0.010280 (0.021972)	−0.018838 (0.021635)	−0.016129 (0.022027)
ROA	−0.077149 (0.070245)	−0.077149 (0.070245)	−0.035627 (0.070199)	−0.055094 (0.071550)
INEF	0.006711 (0.007358)	0.006711 (0.007358)	0.013012 * (0.007503)	0.008699 (0.007382)
CAR	0.000530 *** (0.000187)	0.000530 *** (0.000187)	0.000439 ** (0.000187)	0.000520 *** (0.000191)

Table 6. Cont.

Independent	Model XII	Model XIII	Model XIV	Model XV
HHL_LOAN	−0.000006 ** (0.000002)	−0.000006 ** (0.000002)	−0.000006 ** (0.000002)	−0.000006 ** (0.000002)
LTD	0.002381 (0.001839)	0.002381 (0.001839)	0.002001 (0.001799)	0.001875 (0.001844)
GFC	0.003536 (0.002657)	0.003536 (0.002657)	0.003068 (0.002602)	0.003427 (0.002644)
COVID	0.006047 * (0.003165)	0.006047 * (0.003165)	0.003548 (0.003367)	0.028263 *** (0.004935)
NBFI*COVID	0.021575 *** (0.005393)			
COMB*COVID		−0.021575 *** (0.005393)		
CRECD*COVID			0.035778 *** (0.007278)	
MFINCD*COVID			0.014931 ** (0.006669)	
HFCD*COVID			0.012971 ** (0.006707)	−0.012122 (0.007730)
ANZD*COVID				−0.025606 *** (0.007730)
BOBD*COVID				−0.020043 *** (0.007575)
BSPD*COVID				−0.031793 *** (0.007809)
WBCD*COVID				0.020764 *** (0.007424)
Adj-R ²	0.533639	0.533639	0.555983	0.539284
F-stat	12.44263	12.44263	12.13035	10.36428
DW-stat	1.904056	1.904056	2.090153	1.971168
Observations	161	161	161	161

Notes: ***, **, and * denote a 1, 5, and 10% level of statistical significance. Values in the parentheses (.) are standard errors. * indicates interaction between two terms. The HFC bank transitioned into a full-fledged commercial bank since 2014. Source: authors' estimation.

6. Conclusions

In this study, we examine the determinants of non-performing loans of banks in Fiji. Based on the Wald-test and Hausman test, we apply the fixed-effect method of regression. While our base model follows Kumar et al.'s (2018) approach, we extend the model with specific bank types (non-banks and commercial banks), the COVID-19 pandemic, social and economic globalisation, and the interaction effects from bank types and the pandemic. In our analysis, we consider the seven banks (i.e., five commercial banks and two non-bank financial institutions) over the period 2000–2022 (see footnote 7).

The results presented in the extended models are consistent with the base model, which duly supports the robustness of the results. Additional insights are also generated from the extended models.¹² As our analysis emphasises, the pandemic exacerbated the potential for loan losses for all banks in Fiji. Moreover, the interactive effects reveal some distinct patterns across different bank types. Notably, commercial banks demonstrated significant resilience and preparedness in their efforts to effectively navigate the challenges posed by the pandemic on its losses. However, non-bank financial institutions seem to have been the hardest hit. The susceptibility of NBFIs to a high number of NPLs and their

subsequent vulnerability became more evident when we examined the interaction of bank types with the pandemic. Moreover, we noted that social globalisation tends to increase the possibility of bank losses, whereas economic globalisation support reduces the potential for losses.

By shedding light on the interplay of bank-specific factors, external factors, like globalisation (economic and social), and the disruptive impacts of the COVID-19 pandemic, this study is the first to provide in-depth insights into plausible determinants of non-performing loans, in a small island economy of Fiji. The results can be useful for managers and regulators in effectively managing NPLs and in strengthening their resilience to internal and global shocks. Overcoming data constraints, future studies could specifically examine the performance of NBFIs and incorporate a broader definition of the non-bank financial institutions to include pension funds (FNPF), development banks (FDB), trust funds (UTOF and FHUT), the housing authority of Fiji, and insurance companies. Moreover, since our study is at the bank-level and is country-specific, we are careful not to generalise the outcome to financial institutions that operate in large and/or developed countries. Nevertheless, at least for countries that are small, remote, and developing, our findings can offer insights into important factors viz. financial management of the banking sector. Accordingly, a comparative study can be undertaken on financial institutions in similar and different settings to gain further insights.

Author Contributions: Conceptualization, S.A.C. and R.R.K.; methodology, S.A.C. and R.R.K.; software, S.A.C. and R.R.K.; validation, S.A.C., R.R.K. and P.J.S.; formal analysis, S.A.C., R.R.K. and P.J.S.; investigation, S.A.C., R.R.K. and P.J.S.; resources, S.A.C., R.R.K. and P.J.S.; data curation, S.A.C. writing—original draft preparation, S.A.C., R.R.K. and P.J.S.; writing—review and editing, S.A.C., R.R.K. and P.J.S.; visualization, S.A.C., R.R.K. and P.J.S.; supervision, R.R.K.; project administration, R.R.K. All authors have read and agreed to the published version of the manuscript.

Funding: There was no external funding received for this project.

Data Availability Statement: All data is publicly available, and at the time of writing and publication, the data were accessible from the respective websites mentioned in the Data section of the paper.

Acknowledgments: All the authors sincerely thank the editors and the anonymous reviewers for their useful suggestions and recommendations; all remaining errors are ours. Peter J. Stauvermann sincerely acknowledges the financial support of the Changwon National University 2023–2024.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

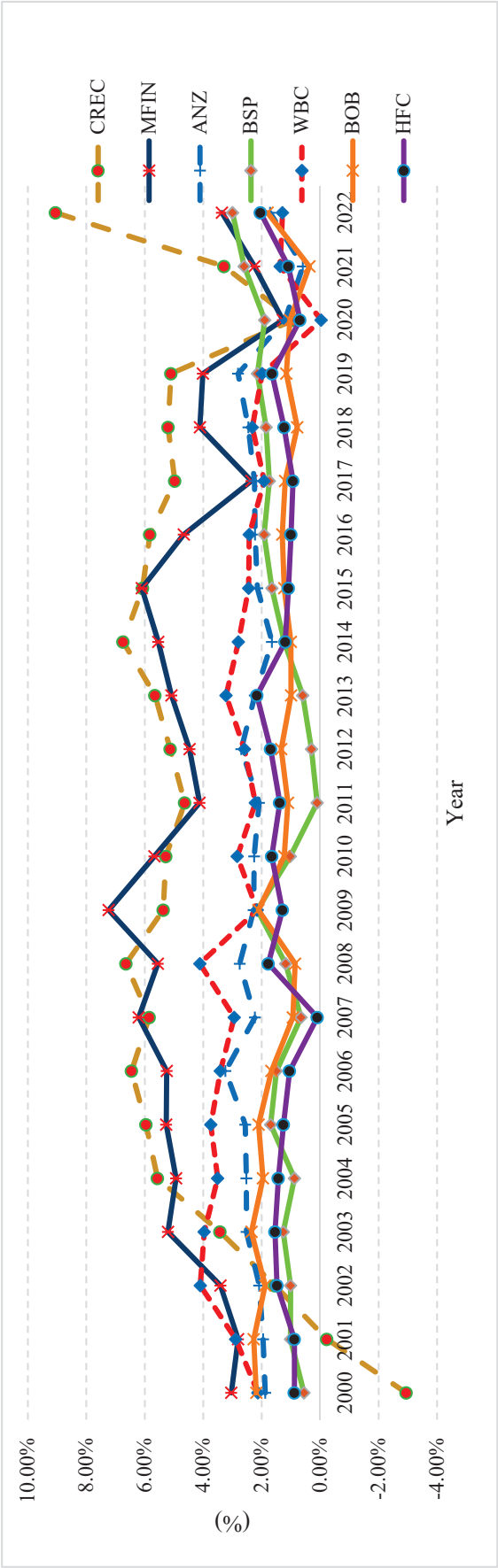


Figure A1. Return on asset. Source: authors' calculation with data from RBF (2023).

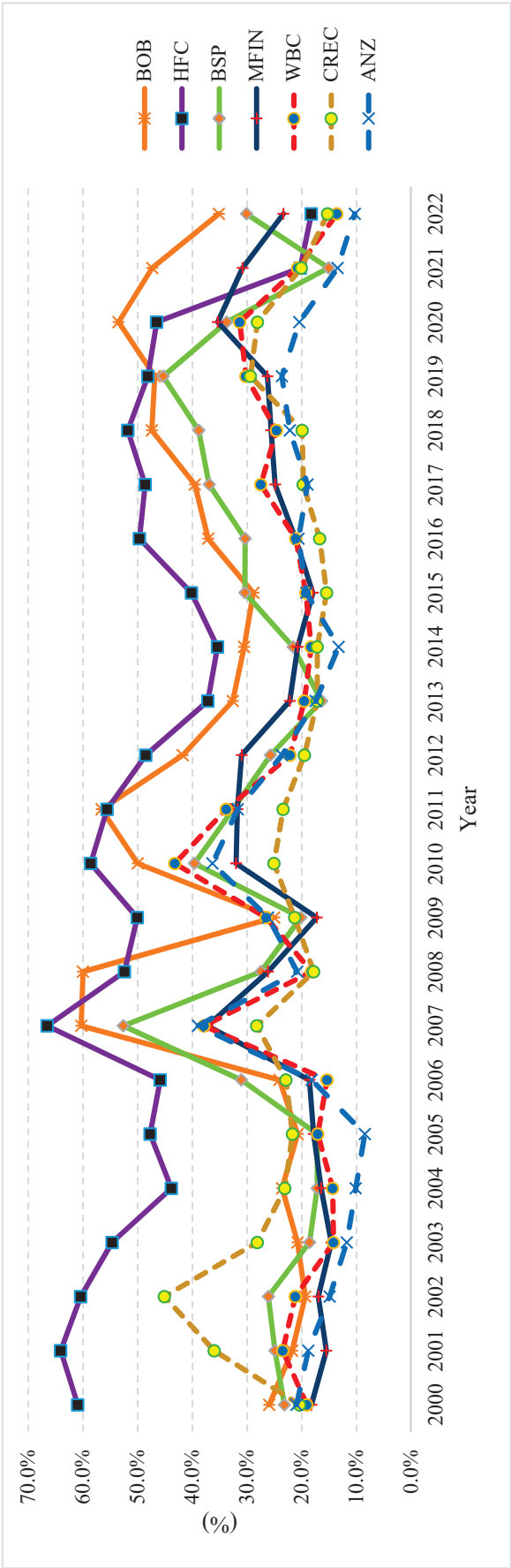


Figure A2. Expense to operating revenue. Source: authors' calculation with data from RBF (2023).

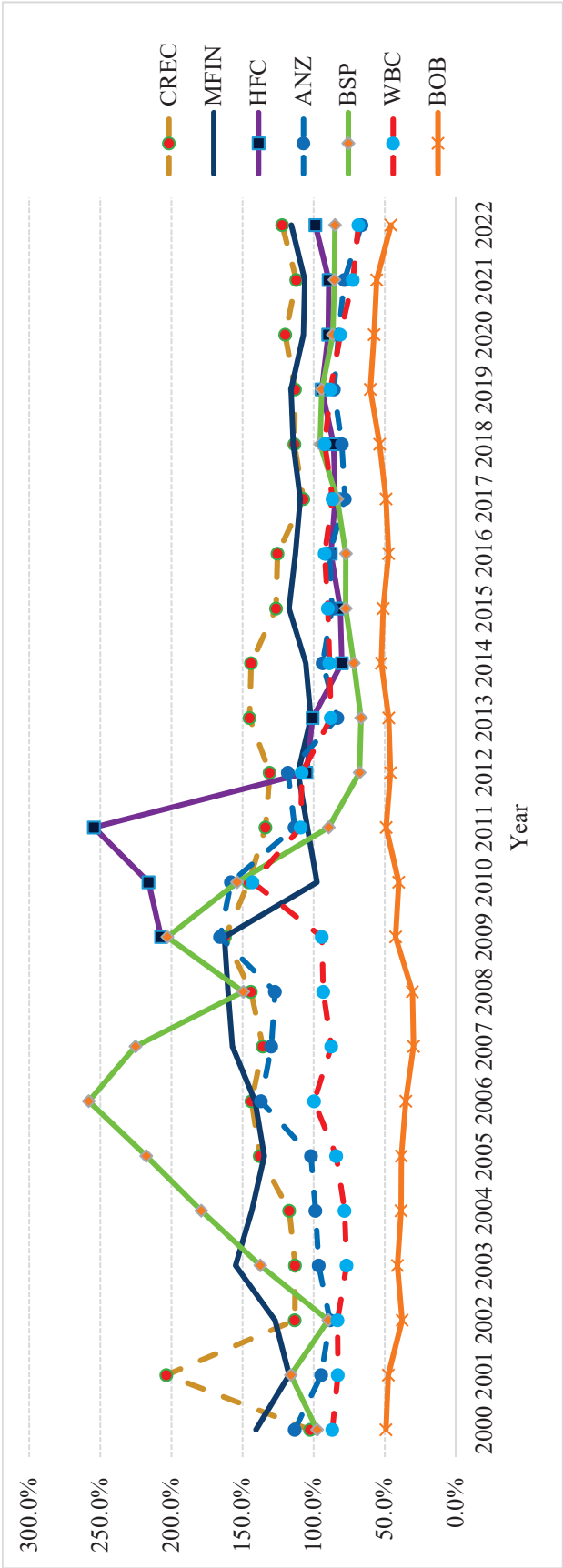


Figure 3. Loan-to-deposit ratio. Source: authors' calculation with data from RBF (2023).

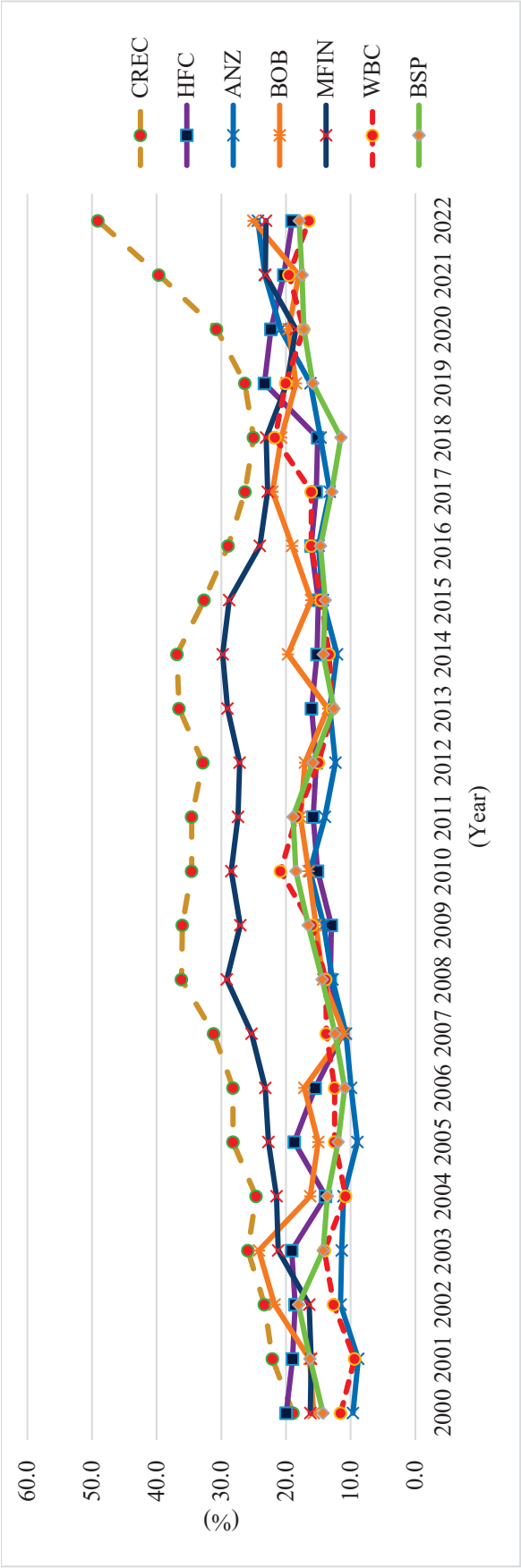


Figure 4. Capital adequacy ratio. Source: authors' calculation with data from RBF (2023).

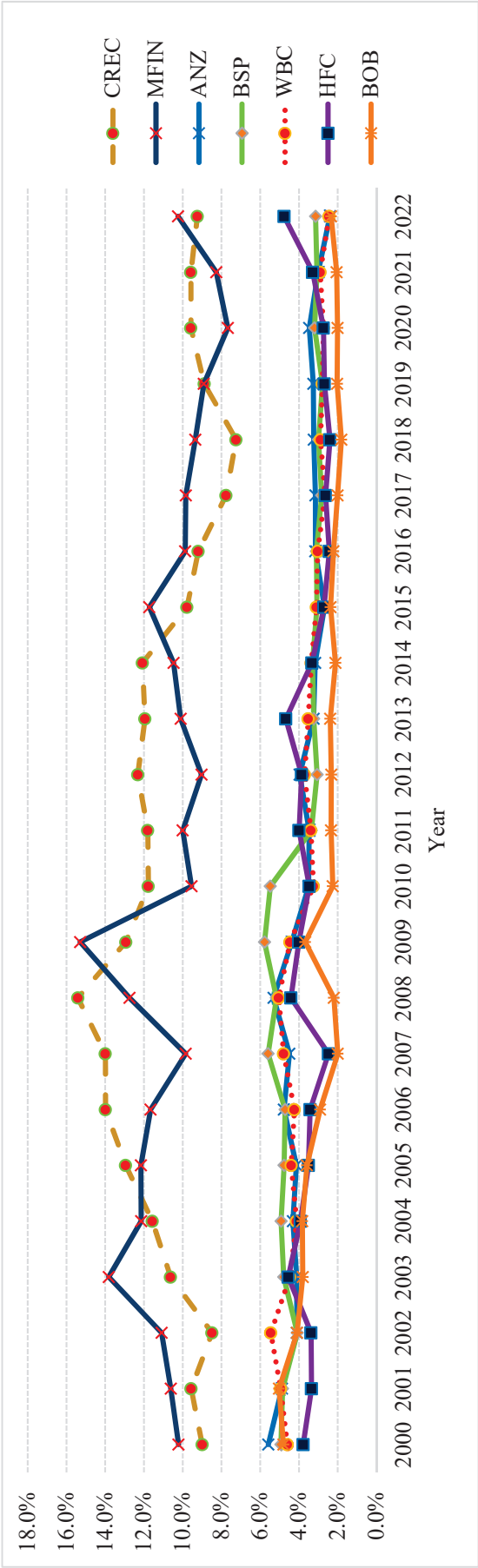


Figure 5. Net interest margin (%). Source: authors' calculation with data from RBF (2023).

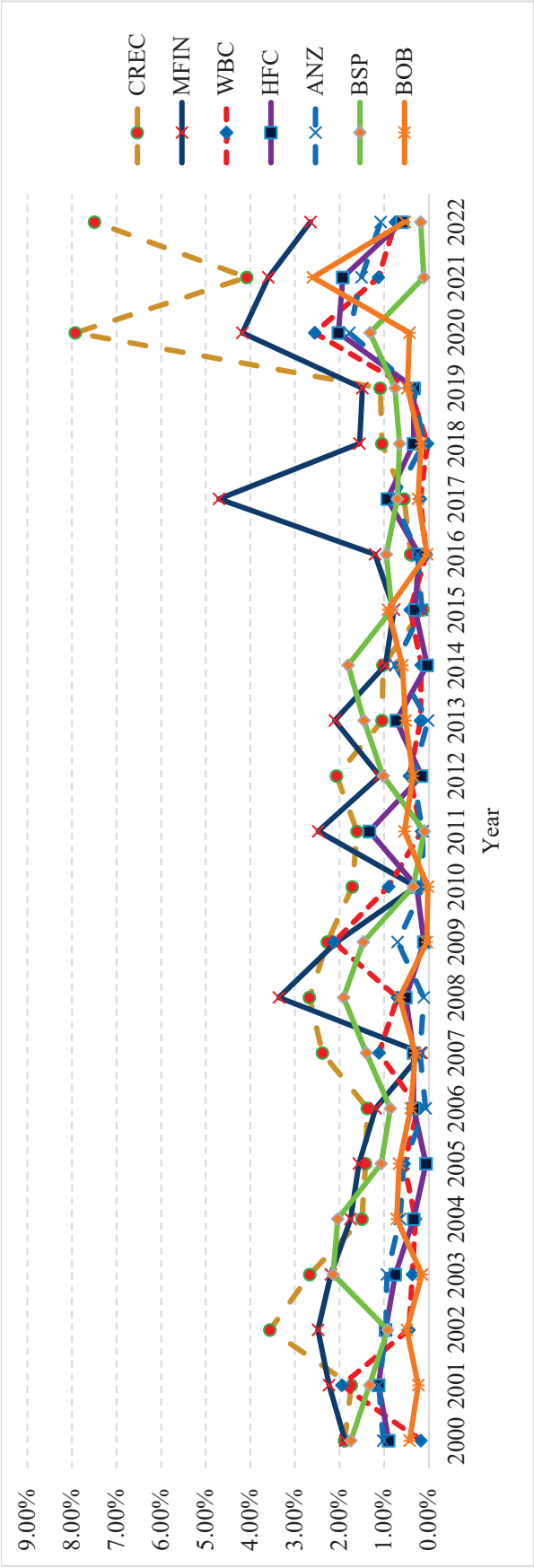


Figure 6. Non-performing loans (% of total loans). Source: authors’ calculation with data from RBF (2023).

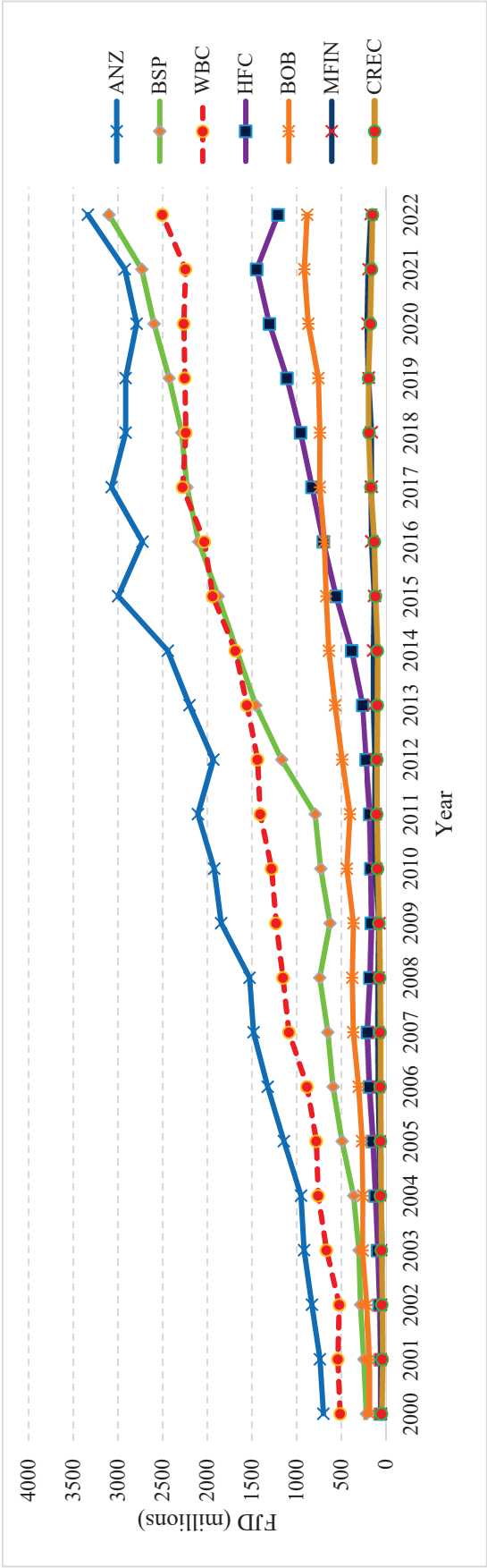


Figure 7. Bank assets (size). Source: authors' calculation with data from RBF (2023).

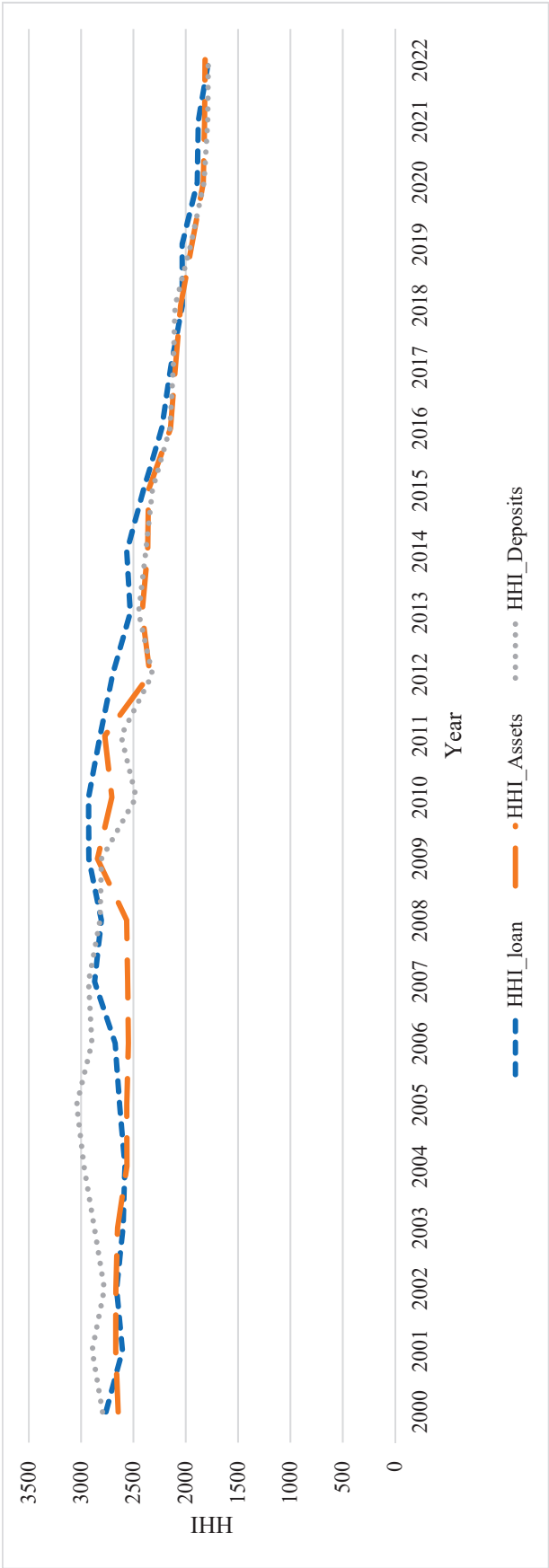


Figure 8. HHI based on loans, assets, and deposits. Source: authors' calculation with data from RBF (2023).

Table A1. Variable descriptions.

Variable	Definition	Symbol	Expected Sign	Source
Dependent Variable				
Non-performing loans	Bad debts/Total loans	NPLs	N/A	RBF
Independent/Control Variables				
Bank-Specific				
Bank size	Natural logarithm of total assets	SIZE	—	RBF
Net interest margin	(Interest income-interest expense)/total assets	NIM	—	RBF
Return on assets	Profit/total assets	ROA	—	RBF
Inefficiency ratio	Operating expenses/operating revenue	INEF	+	RBF
Capital adequacy ratio	Sum of tier capital and tier 2 capital divided by risk weighted assets	CAR	—	RBF
Concentration (HHI)	Herfindahl–Hirschman index based on loans	HHI_LOAN	—	RBF
Loan-to-deposit ratio	Total loans/total deposits	LTD	+	RBF
Non-bank financial institutions	1 = NBFI, otherwise 0	NBFI	?	RBF
Commercial banks	1 = Commercial bank, otherwise 0	COMBANK	?	RBF
Bank dummy				
ANZ	1 = ANZ, otherwise 0	ANZD	?	
BOB	1 = BOB, otherwise 0	BOBD	?	
BSP	1 = BSP, otherwise 0	BSPD	?	
CRC	1 = CREC, otherwise 0	CRCD	?	
HFC	1 = HFC, otherwise 0	HFCD	?	
MFIN	1 = MFIN, otherwise 0	MFIND	?	
WBC	1 = WBC, otherwise 0	WBCD	?	
Macroeconomic				
GDP	Annual percentage change in GDP based on local currency unit (FJD)	GDPP	+	World Bank (2023)
Globalisation				
Economic	Economic globalisation index	EINDX	?	KOF
Social	Political globalisation index	PINDX	?	KOF
Structural dummy				
COVID-19	2019–2020 were taken as dummy variables for COVID as these were the years where there was COVID	COVID	+	Authors
Global Financial Crisis	The financial crisis of 2007–2008 denoted by a dummy variable	GFC	+	Authors

Notes: RBF = Reserve Bank of Fiji (RBF 2023); WDI = World Development Indicators (World Bank 2023); N/A = not applicable. Each category of the globalisation index is measured on a scale of 1–100, where a higher value implies a greater level of globalisation; ‘+’ and ‘—’ indicate the signs based on a theoretical relationship, and ‘?’ = indicates that the sign can be + or —, hence based on the empirical results. Source: authors’ compilation

Table A2. Wald test and Hausman test for panel estimation.

(a) Wald Test				
Test Stat.		Value	d.f.	Prob.
F-stat.		14.447 *	(6, 153)	<0.0001
Chi-square		101.132 *	7	<0.0001
(b) Cross-section random (Hausman test)				
Base models		Chi-square	df	Prob.
Equation (A1): $NPL = f(C, BSIZE, NIM, ROA, INEF, CAR, LTD)$		19.365 †	6	0.0036
Equation (A2): $NPL = f(C, BSIZE, NIM, ROA, INEF, CAR, HHI\_LOAN)$		27.748 †	6	0.0001

Notes: * based on Wald-test, p -values imply the rejection of OLS at the 1% level in support of a fixed- or random-effect model; † based on Hausman test, the p -values imply the rejection of random effects, in support of fixed-effect regression. Source: authors' own computations using EViews 13.

Table A3. OLS: the dependent variable is NPLs (base model).

Independent Var.	Model I	Model II	Model III
Constant	0.058343 *** (0.020499)	0.051934 ** (0.025084)	0.053348 ** (0.023409)
BSIZE	−0.002631 *** (0.000962)	−0.002187 (0.001391)	−0.002187 (0.001391)
NIM	0.041126 * (0.023367)	0.043847 ** (0.024211)	0.043847 ** (0.024211)
ROA	−0.172920 *** (0.070262)	−0.178528 *** (0.071561)	−0.178528 *** (0.071561)
INEF	−0.003160 (0.070262)	−0.003546 (0.007228)	−0.003546 (0.007228)
CAR	0.000574 *** (0.000161)	0.000559 *** (0.000165)	0.000559 *** (0.000165)
HHI_LOAN	−0.000010 *** (0.001828)	−0.000010 *** (0.000003)	−0.000010 *** (0.000003)
LTD	0.005436 *** (0.001828)	0.005295 *** (0.001860)	0.005295 *** (0.001860)
NBFI	-	0.001414 (0.003173)	-
COMB	-	-	−0.001414 (0.003173)
Adj- R^2	0.370405	0.367090	0.367090
F-stat	14.447350	12.600060	12.600060
DW-stat	1.432011	1.426605	1.426605
Observations	161	161	161

Note: ***, **, and * denote a 1, 5, and 10% level of statistical significance. Values in the parentheses (.) are standard errors. Source: authors' estimation using EViews 13.

Table A4. OLS: the dependent variable is NPLs (controlling for economic growth, bank type, the GFC, and Covid).

Independent	Model IV	Model V	Model VI	Model VII	Model VIII	Model IX
Constant	0.053765 *** (0.020077)	0.051220 ** (0.022880)	0.051220 ** (0.022880)	0.060704 *** (0.021096)	0.051828 *** (0.019655)	0.059533 *** (0.020621)
BSIZE	−0.002513 *** (0.000940)	−0.002284 * (0.001359)	−0.002284 * (0.001359)	−0.002757 *** (0.000967)	−0.003075 *** (0.000941)	−0.003358 *** (0.000968)
NIM	0.027540 (0.023287)	0.029026 (0.024205)	0.029026 (0.024205)	0.022958 (0.023669)	0.024730 (0.022805)	0.019564 (0.023162)
ROA	−0.103087 (0.072668)	−0.152845 ** (0.072220)	−0.152845 ** (0.072220)	−0.117663 (0.073910)	−0.090805 (0.071233)	−0.106831 (0.072331)
INEF	0.000836 (0.007121)	0.000611 (0.007207)	0.000611 (0.007207)	−0.001243 (0.007380)	−0.002971 (0.007099)	−0.005364 (0.007356)
CAR	0.000549 *** (0.000158)	0.000542 *** (0.000198)	0.000542 *** (0.000198)	0.000550 *** (0.000157)	0.000424 *** (0.000161)	0.000423 *** (0.000160)
HHL_LOAN	0.0000009 *** (0.000002)	−0.000009 *** (0.000003)	−0.000009 *** (0.000003)	−0.000010 *** (0.000002)	−0.000005 * (0.000003)	−0.000006 ** (0.000003)
LTD	0.004944 *** (0.001791)	0.004924 *** (0.001822)	0.004924 *** (0.001822)	0.005405 *** (0.001831)	0.005013 *** (0.001753)	0.005471 *** (0.001790)
GDPG	−0.000403 *** (0.000138)	−0.000401 *** (0.000133)	−0.000401 *** (0.000133)	−0.000378 *** (0.000140)	0.000230 (0.000222)	0.000153 (0.000231)
NBFI	-	−0.000728 (0.003109)	-	-	-	-
COMB	-	-	−0.000728 (0.003109)	-	-	-
GFC	-	-	-	0.003152 (0.002956)	-	0.003516 (0.002891)
COVID	-	-	-	-	0.014800 *** (0.005302)	0.001508 *** (0.005298)
Adj-R ²	0.399793	0.396037	0.396037	0.400333	0.425468	0.427286
F-stat	14.32181	12.65745	12.65745	12.86833	14.16526	12.93714
DW-stat	1.423518	1.420422	1.420422	1.416154	1.506611	1.501339
Observations	161	161	161	161	161	161

Note: ***, **, and * denote a 1, 5, and 10% level of statistical significance. Values in the parentheses (.) are standard errors. Source: authors' estimation using EViews 13.

Table A5. OLS: the dependent variable is NPLs (controlling for economic and social globalisation).

Independent Var.	Model X	Model XI
Constant	0.026421 (0.028909)	0.017789 (0.027654)
BSIZE	−0.002768 *** (0.001088)	−0.0022657 ** (0.001083)
NIM	0.033852 (0.020478)	0.037405 * (0.020185)
ROA	−0.118644 * (0.068314)	−0.105948 (0.067188)
INEF	−0.006252 (0.007361)	−0.004518 (0.007164)

Table A5. *Cont.*

Independent Var.	Model X	Model XI
CAR	0.000239 (0.000176)	0.000220 (0.000175)
HHI_LOAN	0.000002 (0.000004)	0.000004 (0.000004)
LTD	0.005336 *** (0.001574)	0.004969 *** (0.001532)
GFC	0.002602 (0.002543)	-
COVID	0.018054 *** (0.003734)	0.018712 *** (0.003678)
SINDX	0.000879 (0.000562)	0.000930 * (0.000560)
EINDX	-0.001009 ** (0.000414)	-0.001011 ** (0.000414)
Adj-R ²	0.447563	0.447375
F-stat	11.75306	12.81936
DW-stat	1.484985	1.486485
Observations	147	147

Note: ***, **, and * denote a 1, 5, and 10% level of statistical significance. Values in the parentheses (.) are standard errors. Source: authors' estimation using EViews 13.

Table A6. OLS: the dependent variable is NPLs (controlling for the interaction effects of COVID with bank types).

Independent Var.	Model XII	Model XIII	Model XIV	Model XV
Constant	0.031068 (0.020284)	0.031068 (0.020284)	0.030729 (0.020146)	0.029320 (0.020840)
BSIZE	-0.002039 ** (0.000924)	-0.002039 ** (0.000924)	-0.002087 ** (0.000918)	-0.001984 ** (0.000948)
NIM	0.011345 (0.021787)	0.011345 (0.021787)	0.006751 (0.021743)	0.009236 (0.022015)
ROA	-0.017512 (0.069394)	-0.017512 (0.069394)	0.017422 (0.070912)	-0.000299 (0.070896)
INEF	0.006841 (0.007029)	0.006841 (0.007029)	0.010237 (0.007167)	0.008103 (0.007197)
CAR	0.000420 *** (0.000148)	0.000420 *** (0.000148)	0.000343 ** (0.000151)	0.000403 *** (0.000150)
HHI_LOAN	-0.000004 (0.000002)	-0.000004 (0.000002)	-0.000006 (0.000002)	-0.000004 (0.000002)
LTD	0.004288 *** (0.001693)	0.004288 *** (0.001693)	0.004110 ** (0.001684)	0.004201 *** (0.001708)
GFC	0.001928 (0.002707)	0.001928 (0.002707)	0.001553 (0.002693)	0.001757 (0.002731)
COVID	0.005921 * (0.003266)	0.006047 * (0.003165)	0.005390 (0.003494)	0.031334 *** (0.005096)
NBFI*COVID	0.024866 *** (0.005497)	-	-	-

Table A6. Cont.

Independent Var.	Model XII	Model XIII	Model XIV	Model XV
COMB*COVID	-	-0.024866 *** (0.005497)	-	-
CRECD*COVID	-	-	0.035455 *** (0.007486)	-
MFINCD*COVID	-	-	0.017770 *** (0.006856)	-
HFCDD*COVID	-	-	0.003422 (0.006602)	-0.022710 *** (0.007598)
ANZD*COVID	-	-	-	-0.025246 *** (0.007972)
BOBD*COVID	-	-	-	-0.025665 *** (0.007593)
BSPD*COVID	-	-	-	-0.032257 *** (0.007944)
WBCD*COVID	-	-	-	-0.020733 *** (0.007591)
Adj-R ²	0.494567	0.494567	0.502140	0.487988
F-stat	16.65601	16.65601	14.44796	11.89234
DW-stat	1.758679	1.758679	1.851695	1.776930
Observations	161	161	161	161

Notes: ***, **, and * denote a 1, 5, and 10% level of statistical significance. * indicates interaction between two terms. Values in the parentheses (.) are standard errors. Source: authors' estimation using EViews 13.

Appendix B

Table A7. Descriptive statistics and correlation matrix (six commercial banks and two NBFIs).

Descriptive statistics											
Variable Statistics	NPLs	BSIZE	NIM	ROA	INEF	CAR	HHI_LOAN	LTD	GDPG	EINDX	SINDX
Mean	0.01	13.42	0.04	0.02	1.09	48.97	2198.84	0.97	1.93	51.44	67.64
Median	0.01	13.58	0.03	0.02	0.58	18.33	2143.10	0.88	3.81	51.58	67.16
Maximum	0.08	15.02	0.12	0.14	38.40	1876.00	2698.07	8.09	16.10	53.59	69.15
Minimum	0.00	11.14	0.00	-0.08	0.31	11.51	1780.24	0.01	-17.00	48.52	66.53
Std. Dev.	0.01	1.18	0.03	0.03	4.04	208.60	297.96	0.80	7.78	1.59	0.99
Skewness	2.99	-0.30	1.17	0.41	9.11	8.05	0.26	7.99	-0.82	-0.31	0.38
Kurtosis	13.46	1.65	2.90	8.72	84.60	69.27	1.72	71.50	4.35	2.02	1.50
Probability	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Observation	88	88	88	88	88	88	88	88	88	72	72
Correlation											
	NPLs	BSIZE	NIM	ROA	INEF	CAR	HHI_LOAN	LTD	GDPG	EINDX	SINDX
NPLs	1										
BSIZE	-0.26	1									
NIM	0.42	-0.62	1								
ROA	0.02	-0.12	0.75	1							
INEF	0.02	-0.25	-0.19	-0.41	1						
CAR	0.05	-0.29	-0.11	-0.34	1.00	1					
HHI_LOAN	-0.25	-0.26	0.10	0.01	0.19	0.20	1				
LTD	0.13	-0.09	0.14	0.07	-0.12	-0.13	-0.18	1			
GDPG	-0.51	-0.12	0.04	0.14	0.01	0.01	0.56	-0.31	1		
EINDX	-0.38	-0.21	0.09	0.08	0.14	0.14	0.88	-0.21	0.64	1	
SINDX	0.09	0.21	-0.10	0.03	-0.14	-0.14	-0.78	0.03	-0.12	-0.74	1

Notes: data for globalisation indexes are from 2000 to 2020, and for all other variables, the sample is from 2000 to 2022; data for the BRED bank are from 2012 to 2022. Source: authors' computation using data compiled from different databases.

Table A8. Fixed effect: the dependent variable is NPLs (base model).

Independent Var.	Model I	Model II	Model III
Constant	0.050226 (0.098110)	−0.007693 (0.124417)	0.001337 (0.117526)
BSIZE	−0.000236 (0.006343)	0.003555 (0.008081)	0.003555 (0.008081)
NIM	0.113911 (0.183518)	0.117570 (0.184113)	0.117570 (0.184113)
ROA	−0.146427 * (0.082954)	−0.178253 * (0.093123)	−0.178253 * (0.093123)
INEF	0.000252 (0.000423)	0.000368 (0.000450)	0.000368 (0.000450)
CAR	0.000002 ** (0.000007)	0.000002 (0.000007)	0.000002 (0.000007)
HHI_LOAN	−0.000017 (0.000007)	−0.000001 * (0.000007)	−0.000001 * (0.000007)
LTD	0.000518 (0.001749)	0.000223 (0.001797)	0.000223 (0.001797)
NBFI	-	0.009030 (0.011872)	-
COMB	-	-	−0.009030 (0.011872)
Adj-R ²	0.319537	0.315586	0.315586
F-stat	3.918148	3.674399	3.674399
DW-stat	1.398449	1.375623	1.375623
Observations	88	88	88

Notes: ** and * denote a 5 and 10% level of statistical significance. Values in the parentheses (.) are standard errors. Data for the BRED bank are from 2012 to 2022. Source: authors' estimation using EViews 13.

Table A9. Fixed effect: the dependent variable is NPLs (controlling for economic growth, bank type, and Covid).

Independent	Model IV	Model V	Model VI	Model VII
Constant	0.089980 (0.099416)	0.060641 (0.130376)	0.064895 (0.122952)	0.047803 (0.095801)
BSIZE	−0.003017 (0.006456)	−0.001087 (0.008511)	−0.001087 (0.008511)	−0.001693 (0.006166)
NIM	0.096887 (0.181269)	0.099491 (0.182534)	0.099491 (0.182534)	0.005131 (0.175532)
ROA	−0.077367 (0.090901)	−0.095929 (0.105658)	−0.095929 (0.105658)	−0.068458 (0.086630)
INEF	0.000191 (0.000419)	0.000248 (0.000452)	0.000248 (0.000452)	0.000206 (0.000399)
CAR	0.000001 (0.000007)	0.000001 (0.000007)	0.000001 (0.000007)	−0.000003 (0.000007)
HHI_LOAN	−0.000018 *** (0.000007)	−0.000017 ** (0.000007)	−0.000017 ** (0.000007)	−0.000007 (0.000007)
LTD	−0.000251 (0.001781)	−0.000351 (0.001814)	−0.000351 (0.001814)	−0.000281 (0.001696)

Table A9. *Cont.*

Independent	Model IV	Model V	Model VI	Model VII
GDPG	−0.000325 (0.000186)	−0.000308 (0.000194)	−0.000308 (0.000194)	0.000328 (0.000287)
NBFI	-	0.004254 (0.012124)	-	-
COMB	-	-	−0.004254 (0.012124)	-
COVID	-	-	-	0.018432 *** (0.006370)
Adj- R^2	0.338039	0.329878	0.329878	0.399533
F-stat	3.961845	3.676689	3.676689	4.617951
DW-stat	1.381886	1.370285	1.370285	1.544449
Observations	88	88	88	88

Notes: ***, **, and * denote a 1, 5, and 10% level of statistical significance. Values in the parentheses (.) are standard errors. Data for the BRED bank are from 2012 to 2022. Source: authors' estimation using EViews 13.

Table A10. Fixed effect: the dependent variable is NPLs (with SINDX and EINDX).

Independent Var.	Model VIII
Constant	−0.358831 * (0.200225)
BSIZE	0.019394 *** (0.004475)
NIM	0.658651 *** (0.141892)
ROA	−0.661328 *** (0.094243)
INEF	0.007157 (0.004946)
CAR	−0.000384 (0.000284)
HHI_LOAN	0.000014 0.000008
LTD	−0.001161 (0.001126)
COVID	0.011977 ** (0.005545)
SINDX	0.001245 (0.001990)
EINDX	−0.000410 (0.001537)
Adj- R^2	0.718157
F-stat	11.64197
DW-stat	1.583276
Observations	72

Notes: ***, **, and * denote a 1, 5, and 10% level of statistical significance. Values in the parentheses (.) are standard errors. Data for the BRED bank are from 2012 to 2022. Source: authors' estimation using EViews 13.

Table A11. Fixed effect: the dependent variable is NPLs (with interaction effects of COVID with bank types).

Independent Var.	Model IX	Model X	Model XI	Model XII
Constant	0.087495 (0.087310)	0.087495 (0.087310)	0.147588 (0.092946)	0.147737 (0.099707)
BSIZE	−0.004220 (0.005693)	−0.004220 (0.005693)	−0.008152 (0.006073)	−0.007861 (0.006355)
NIM	0.106784 (0.166400)	0.106784 (0.005693)	0.002960 (0.168730)	0.136812 (0.185866)
ROA	−0.005639 (0.080199)	−0.005639 (0.080199)	0.046259 (0.081919)	0.033141 (0.083570)
INEF	0.000225 (0.000375)	0.000225 (0.000375)	0.0000059 (0.000377)	0.000516 (0.000763)
CAR	0.000001 (0.000006)	0.000001 (0.000006)	0.000004 (0.000006)	−0.0000028 (0.0000057)
HHI_LOAN	−0.000012 * (0.000006)	−0.000012 * (0.000006)	−0.000014 * (0.000006)	−0.000015 ** (0.000007)
LTD	0.000227 (0.001601)	0.000227 (0.001601)	0.000832 (0.001611)	−0.007599 (0.016899)
COVID	0.007121 * (0.004103)	0.029332 *** (0.006370)	0.005561 (0.004363)	0.030340 *** (0.006418)
NBFI*COVID	0.022212 *** (0.006917)	-	-	-
COMB*COVID	-	−0.022212 *** (0.006917)	-	-
CRECD*COVID	-	-	0.036040 *** (0.008994)	-
MFINCD*COVID	-	-	0.012892 (0.009141)	-
HFCD*COVID	-	-	0.011737 (0.009420)	−0.013306 (0.010284)
ANZD*COVID	-	-	-	−0.023651 ** (0.010169)
BOBD*COVID	-	-	-	−0.022381 ** (0.010020)
BRED*COVID	-	-	-	0.057969 (0.105880)
BSPD*COVID	-	-	-	−0.035771 *** (0.010200)
WBCD*COVID	-	-	-	−0.019712 * (0.010120)
Adj-R ²	0.466044	0.466044	0.491639	0.461386
F-stat	5.745933	5.745933	5.674340	4.548849
DW-stat	1.785511	1.785511	2.050825	1.905205
Observations	88	88	88	88

Notes: ***, **, and * denote a 1, 5, and 10% level of statistical significance. Values in the parentheses (.) are standard errors. * indicates interaction between two terms. Data for the BRED bank are from 2012 to 2022. Source: authors' estimation using EViews 13.

Notes

- ¹ <https://www.bankingsupervision.europa.eu/about/ssmexplained/html/npl.en.html>, accessed on 5 August 2023.
- ² Credit Corporation was established in 1978 and originated from Papua New Guinea and with operations in Fiji, Solomon Islands, and Vanuatu.
- ³ https://www.rbf.gov.fj/wp-content/uploads/2019/06/NA2005_03.pdf, accessed on 5 August 2023.
- ⁴ <https://www.trade.gov/country-commercial-guides/fiji-trade-financing>, accessed on 5 August 2023.
- ⁵ <https://www.parliament.gov.fj/wp-content/uploads/2022/05/Consolidated-Review-Report-of-the-Reserve-Bank-of-Fiji-Insurance-2019-and-2020-Annual-Reports.pdf>, accessed on 5 August 2023.
- ⁶ Additionally, other aspects, such as insurance companies (Kumar et al. 2022b) and the stock market analysis (Kumar et al. 2022a; Kumar and Stauvermann 2022), are important for a robust operation of the financial system.
- ⁷ We have excluded the BRED bank from the sample because of the small sample size (2012–2022). Including the BRED bank reduces the total sample in the panel for all other banks, which have data since 2000 and do not capture the effect of the GFC. Nevertheless, we include the estimations with the BRED bank in Appendix B (respective tables) for additional insights. We note that the results obtained are generally consistent with the main results.
- ⁸ We set the HFC bank as a reference, hence dropping its dummy to avoid the “dummy-trap”.
- ⁹ To avoid the problem where of the number of cross-sections is less than the number of coefficients, we dropped *HHI_LOAN* in the first case and then we included *HHI_LOAN* in the second case and dropped *LTD*. In both cases, the results consistently support the fixed-effect method.
- ¹⁰ Kumar (2014) noted that the demand and growth of second-hand cars have increased dramatically, surpassing the growth rate of per capita income. It is possible that most of these cars are financed though (unsecured) bank loans and can add to banks’ non-performing loans.
- ¹¹ Note that HFC was a non-bank until 2014.
- ¹² As an aside, we also provide OLS-based results (see Appendix A, Tables A3–A6), which are generally consistent with the results obtained from the fixed-effect estimation method.

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Article

Environmental Performance and a Nation's Growth: Does the Economic Status and Style of Governance of a Country Matter?

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Abstract: The literature abounds with studies on the impact of the growth of nations on the environment. However, studies on the financial materiality of environmental concerns are found less often. This study aims to determine the impact of environmental concerns on a nation's GDP per capita (GDPC). In addition, the influence of developed nations and democracy is also explored. The data for 106 countries and ten years (2011–2020) are procured from World Bank's official website. The countries with incomplete data for a balanced panel are not included. Panel data econometrics (quantile regression) is applied to analyze the data. Environmental concerns are measured with the help of environmental efficiency (EE) using data envelopment analysis (DEA). It is found that environmental efficiency (EE) negatively impacts the GDPC for low levels of GDPC. However, no association of EE with GDPC is witnessed in the case of high GDPC levels. In addition, developed nations positively moderate the EE's impact on the GDPC when the GDPC levels are high. Moreover, democratic nations negatively moderate the EE's impact on the GDPC when low GDPC levels exist. The main implication of the current study is that developed high GDPC countries could bear a significant chunk of the cost of EE. This way, the adverse impact of an increase in EE on the GDPC (by low GDPC countries) could be dodged, and by the efforts of developed high GDPC countries, EE could be increased significantly without adversely impacting their GDPC.

Keywords: environmental efficiency; GDP per capita; moderation; emerging economy; democracy

1. Introduction

A sustainable environment and a nation's growth and development are strongly intertwined (Muller 2014; Ward et al. 2016). It is illogical even to try to decouple them. However, how a sustainable environment and economic development are defined is relevant while exploring their mutual association. Morelli (2011) postulates that a sustainable environment maintains natural capital, including social and economic sustainability. The definition of a sustainable environment also overlaps with the context of economic sustainability. This study adopts this definition of a sustainable environment. One of the most essential aspects of a sustainable environment is the financial materiality of environmental improvement. The financial materiality of environmental performance concerns the financial viability of environmental improvements. It means that the environmental improvements obviously have some cost associated with them; however, the cost of environmental improvements results in much better financial viability in the economy, like in terms of GDP, and is a matter of concern (Schiehl and Kolahgar 2021). If a country works on boosting environmental efficiency then it benefits the economy in terms of financial materiality (GDP) (Baumüller

and Sopp 2022; Chiu 2022). Environmental efficiency is defined as the utilization of available resources to have minimum pollutant emissions. Hence, the resources infused to have a better environmental quality, should also be focused on cost cutting to financially benefit the economy (Zhang et al. 2021) rather than creating economic burden.

Feldman et al. (2016) quite explicitly present that economic development is expanding the capacities of societies through realising the full potential of individuals, firms, and communities. In the current study, the words growth and development are both used interchangeably, but they are used in the same context as defined by Feldman et al. (2016).

A country's primary focus area is always good economic development. Such development incorporates the growth of various components of society. In recent decades, it has also raised the concern that such developments are not being gained at the cost of environmental degradation. Therefore, researchers have given due importance to determining the developmental effects on the environment. However, very little attention has been given to finding whether environmental improvements can benefit the economic development of a country. There is an expansive literature on their (the environment and growth of nations) mutual association (Dinda 2004; Azevedo et al. 2018). However, the direction of the studies is usually from the nation's growth to environmental concerns. Studies, on topics ranging from environmental concerns to its impact on the growth of the nations, are pretty scarce. This situation becomes challenging when, in the literature, no association is found between the environment and the growth of the nations from either direction (Zilio and Recalde 2011).

There is an obvious question about environmental concerns' financial viability. There is scarcity in the literature regarding the financial materiality of environmental concerns. Studies are either limited to reporting sustainability and financial materiality (Schiehl and Kolahgar 2021) or the discussion is limited to a firm level (Albrecht and Greenwald 2014). The sustainable development goals (SDGs) (Sachs et al. 2019) do not group the two. The SDGs are 17 goals and 169 targets given by the United Nations, mainly focusing on social and environmental targets (Hák et al. 2016). They also include inclusive growth. However, they are not insufficiently grouped with the growth and development of the nations. This situation is one of the rudimentary questions of whether sustainability is financially viable. Though in a nascent stage, the growing clamour for double materiality is testimony to the fact that both the growth of nations and environmental concerns should be seen in totality (Baumüller and Sopp 2022; Chiu 2022). Moreover, the impact of the environment on a nations' growth also lacks pragmatism.

From the discussion above it is evident that there is a gap in the literature. Double-materiality-based studies do exist. However, they are inadequate in addressing such a large concept. Hence, the current study attempts to bridge the gap and provide a fresh perspective on the impact of environmental concerns on the growth and development of nations.

The identified problem can be studied in several ways, including using cross-sectional and time series data. However, due to their ability to capture more information and the richness of the outcome, we decided to use panel data to analyse the problem (Hsiao 1985; Hsiao 2005; Hsiao 2007). In addition, measuring the primary variables is also an issue of choice. We had several options to measure the environment and economic development of the nations. The use of different determinants of the environment is often seen in the literature (Del Río González 2009; Lee and Holden 1999). However, we decided to put a few determinants into estimating environmental efficiency using DEA, believing it to be a more effective (Song et al. 2012; Reinhard et al. 2000) measure of the variable (sustainable environment).

Similarly, growth and development are considered two things in the literature (Young et al. 2019). We decided to use GDP per capita (GDPC) as the proxy for the same, believing it to be a more effective and transparent measurement of the variable. Development is also considered more challenging to measure accurately than growth. Hence, we settle for growth (or GDPC).

Economic prosperity and the environment should complement, not compete with, each other. This lack of studies on the utility of environmental pursuits and economic prosperity is the current study's primary motivation, believing the two are well connected. The current study provides a few startling contributions which the authors have not observed in the literature. Environmental efficiency negatively impacts the GDPC when the GDPC is low and moderate. In addition, environmental efficiency does not influence the GDPC when the GDPC is in the highest quantile. In addition, developed economies positively influence (only when GDPC is high), and democracy negatively influences (only when GDPC is low) the already negative impact of the environmental efficiency of nations on the GDPC. The findings of the current study have path-breaking implications for policymakers to consider environmental efficiency critically for a nation's growth. Hence, they need to put in place some regulations to set it right.

The remaining paper is presented in six sections. The following section discusses a review of the relevant literature and the hypothesis formulation. The data and methodology are discussed in Section 3. The results are presented in Section 4. A discussion of the previous research on the topic, contribution, and its implications is presented in Section 5. The study is concluded in Section 6.

2. Literature Review

2.1. Theoretical Background

The utility of any endeavour must be probed if it can adversely affect a large section of fauna and flora. Environmental activism falls into that league. It is a pretty old phenomenon (Sguin et al. 1998). There is a never-ending debate on the utility of environmental pursuits and development (Dalton 2015). However, only recently has it been observed in the literature that environmental activism could be non-beneficial, digressed, and motivated by ulterior self-interests.

Moreover, such endeavours can cause more trouble than they can help the nations' overall betterment (Garavan 2007). In addition, activism with honest intentions can take an extremist view, which may be far from reality and create more trouble than helping the environment. Such situations are the reason for a drift in research toward the financial materiality of environmental concerns. Such an approach cannot be ignored entirely and may rest on a more realistic platform (Harper Ho 2019).

Financial materiality does talk about the utility of environmental concerns but misses out on the larger picture. Hence, a double materiality concept became popular to balance business and the environment (Chiu 2022). However, it seems to be more compromise than free will to care for both. Moreover, meeting both goals, simultaneously but divergent from each other, became a real challenge, especially during financial stress. Therefore, the SDGs (sustainable development goals) seem more plausible and measurable (Mensah 2019). However, the financial materiality of the SDGs is not researched well.

The betterment of nations/people is usually the goal of debates on the pragmatic perspective of environmental concerns. The authors do not observe any theory on that. Also, few studies are even found on the topic. However, abundant and varied versions of the EKC (Environment Kuznets Curve) theory are found in the literature (Kaika and Zervas 2013a). The EKC theory is on the impact of economic development on the environment, which is diametrically opposed to the current study (Kaika and Zervas 2013b). Moreover, this theory (EKC theory) also has its share of criticism (Chowdhury and Moran 2012; Weber and Weber 2020). Hence, the financial materiality of sustainability remains an unanswered question which needs a fresh empirical perspective.

2.2. Literature and Hypothesis Development

2.2.1. Association between Environmental Concerns and GDP Growth Rate of Nations

As discussed in the previous section, existing studies between environmental concerns and GDPC usually analyse from GDP growth rate to its environmental impact, not vice versa. Awan and Azam (2022) find an N-shaped Kuznets curve to defend the positive aspect of the EKC theory. However, no discussion of the environmental impact on the GDP growth rate or GDPC is witnessed. Muller (2014) proposes a correcting factor, GED (gross external damage), to adjust the GDP growth to incorporate environmental concerns. Hoff et al. (2021) also present an approach to incorporate environmental concerns in estimating GDP and call the revised version of GDP the green GDP. However, neither addresses the causal impact of environmental concerns on the GDP growth rate or GDPC.

The authors do not observe studies that address the environment's impact on the GDPC. However, a few studies are seen that address the concerns implicitly. Tran et al. (2022) explore the impact of energy consumption on the GDP growth rate of OECD countries using panel data cointegration and the Granger Cause Vector Error Correction model (VCM). They find the long- and short-run causality of energy consumption on the GDP growth rate provided GDP is below a threshold level. In addition, another study between energy consumption and GDP growth rate does not find any association between the two. They used data from 21 Latin and Caribbean countries from 1970 to 2007. They also use the Energy EKC theory and panel data cointegration to arrive at their findings of there being no association between them.

The above discussion demonstrates the lack of studies in the literature on the financial materiality of environmental concerns on the GDP growth rate of nations. In addition, whatever studies are present in the literature do not address the concerns fully. Hence, this situation needs further exploration using empirical analysis. Thus, the following hypothesis is framed in an alternative form to determine the causal impact of environmental concern on the GDPC:

H₁. *Environmental efficiency positively impacts the GDP per capita of nations.*

2.2.2. Developing versus Emerging Economy Regarding the Environment's Impact on the GDP Growth Rate

We do not find many studies on environmental concerns and GDP growth rates regarding developed and developing nations. Fakher and Abedi (2017) use data from developing economies from 1983 to 2013. They use an ARDL-based bounds cointegration test and find the significant and positive impact of the environmental performance index (EPI) on the growth of nations. However, a contrasting result is reported by Chowdhury and Islam (2017). They use data from BRICS (Brazil, Russia, China, India, and South Africa) for their analysis. They find an enormously significant but negative correlation between EPI and GDP growth rate. However, we do not observe any study comparing the developing versus developed economies regarding environmental concerns' impact on the growth of nations.

In addition, the criticisms of the EKC theory (Chowdhury and Moran 2012; Tiba and Frikha 2020), an extension of the EKC theory (Awan and Azam 2022), our analysis of contrasting evidence, and the lack of studies on the topic prompt us to empirically determine the influence of developed and developing nations on the impact of environmental concerns on the GDPC of nations. Thus, the following hypothesis is framed in an alternate form:

H₂. *The impact of environmental efficiency on the GDP growth rate is positively moderated by the developed economies compared to the emerging economies.*

2.2.3. Democracy versus Non-Democracy (Governance) Economy Regarding the Environment's Impact on the GDP Growth Rate

The existing literature on democracy and the environment is quite extensive. The studies can be divided into two broad sets. The first set of studies shows that high democracy indicators support reducing environmental degradation (Li and Reuveny 2006). On the contrary, the second set of studies finds contradictory evidence (Acheampong et al. 2022). Acheampong et al. (2022) find that a high level of democracy increases pollution. Furthermore, it is also seen that a high level of democracy negatively moderates the nations' growth rate to reduce pollution levels to curb environmental degradation.

The above discussion implies a contradiction in the literature. Furthermore, we do not find any study which determines the moderation of democracy on the impact of environmental concerns on the growth rate of nations. Hence, a fresh set of evidence is justified. Thus, the following hypothesis is framed in an alternate form to empirically determine the moderating impact of democracy on the environmental association on the growth rate of nations.

H₃. *The impact of environmental efficiency on the GDP growth rate is positively moderated by the democratic governance system compared to a non-democratic system.*

As evident from the literature discussed above, the research gap regarding how environmental concerns impact a nation's development exists. Hence, the current study is justified in attempting to fill the gap.

3. Data and Methodology

3.1. Data

This study has collected cross-country data from 106 countries for 2011–2020 (see Table A1 in Appendix A). In the beginning, there were 180 countries. However, the sample countries are reduced to 106. This is carried out after data filtration because authenticated data are unavailable for a balanced panel. A ten-year (2011–2020) sample period is considered, including the most recent data for providing fresh evidence with consistent outcomes. The sample period is also essential for investigation after the Global Financial Crisis of 2008. The quantitative data are sourced from the World Bank Economics and Environment database. The conceptual model of the study and the variables for which data are retrieved are discussed in Figure 1 and Table 1, respectively.

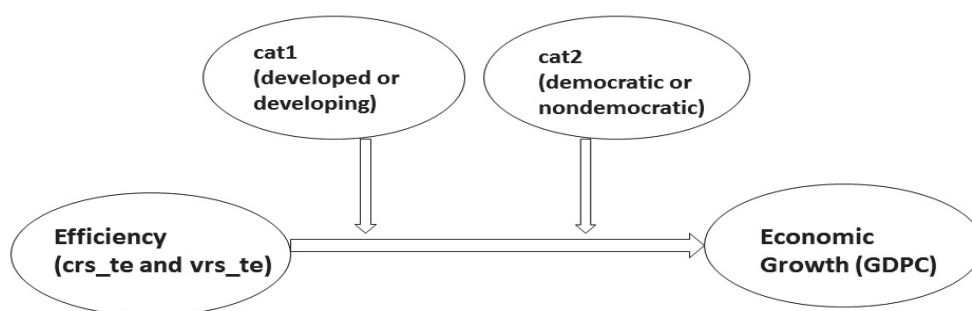


Figure 1. Conceptual model. Note: Efficiency is an independent variable, the Gross domestic product of countries (GDPC) represents economic growth as the dependent variable, and cat1 and cat2 represent the developed or developing and democratic and nondemocratic countries, respectively, as moderators of the study. Source: Author contribution.

Table 1. Variables.

Variable	Measurement	References
Economic Growth (GDPC)	‘GDPC’ is defined as the annual percentage growth rate of the “gross domestic product per capita” of a country. This is described by the World Bank’s data account. It represents the extent of a nation’s economic growth. Its unit is USD/population.	Aslam et al. (2021); Awan and Azam (2022)
Explanatory Variables		
Environmental efficiency (eec)	It is the environmental efficiency of a nation and is computed using Data Envelope Analysis (DEA) at a constant return to scale (CRS). Please see the detailed discussion in Section 4.4.	Zhang et al. (2021); Song et al. (2021)
Environmental efficiency (eev)	It is the environmental efficiency of a nation and is computed using Data Envelope Analysis (DEA) at a variable return to scale (VRS). Please see the detailed discussion in Section 4.4.	Zhang et al. (2021); Song et al. (2021)
Moderating Variables		
Category 1 (cat1)	It categorises the countries into developed or developing nations. Categorisation is based on World Bank categorisation. ‘1’ for developed country and ‘0’.	Maddison (1983); Sharma (2019)
Category 2 (cat2)	It categorises the countries into democratic or non-democratic nations. Categorisation is based on World Bank categorisation. ‘1’ for developed country and ‘0’.	Dyczkowska and Dyczkowski (2018); Al Khajeh (2018)
Control Variables		
Inflation (Inflation)	It is the rate of inflation in a country.	Goodhart and Pradhan (2020); Wafik and Tharwat (2022)
Energy intensity (EI)	It represents the energy intensity of a nation. It is defined as the consumption of energy in joules per USD.	Namahoro et al. (2021); Shakya et al. (2022)
Non-renewable energy consumption (NEC)	It is the share of non-renewable energy consumption out of total energy consumption in a country.	Namahoro et al. (2021); Shakya et al. (2022)
CO ₂ emission ^	It is a major cause of pollution. Therefore, it is taken as the undesirable output of DEA analysis to measure environmental efficiency. CO ₂ has a unit of measure of kilotonnes.	Kuo et al. (2014); Wu et al. (2013)

Note: cat1 and cat2 represent Category 1 and 2; the categorial variable signifies that developed and democratic countries are 1 and developing and nondemocratic nations are 0. ^ represents the output variable for DEA analysis to compute environmental efficiency. Source: Author compilation.

3.2. Methodology

The current paper uses panel data analysis (PDA) with countries as cross-sectional units and a ten-year time frame (2011–2020). The PDA models incorporate the features of both cross-section and time; hence, PDA gives unbiased results compared to typical cross-sectional or time-series analysis (Hsiao 2007; Baltagi 2008). Moreover, this study employs the Quantiles Regression Panel Data (QRPD) model (Powell 2010) because the dependent variable (GDPC) is not distributed normally (see Table 3). The QRPD model is also a better choice as it cannot significantly suffer from endogeneity issues (Kanoujiya et al. 2022; Wooldridge 2015). In the non-normal distribution of dependent variable data, QRPD models are a good fit model to find evidence at different quantiles as they give reliable results (Kanoujiya et al. 2022; Hettmansperger and McKean 2011; Asmare and Begashaw 2018). There are two base models (Models 1 and 2) developed to investigate the impact of environmental efficiency on economic development, each using eec (environmental efficiency at the constant return to scale [crs]) and eev (environmental efficiency at a variable return to scale [vrs]). Models 3 and 4 find the association between environmental efficiency and economic development under the interaction of developed and developing categories (cat 1). Moreover, Models 5 and 6 are developed to examine the environmental efficiency nexus with economic development under the interaction with democratic and non-democratic countries. The model specifications are given as follows:

$$GDPC_{it}(\tau) = \theta_1 EV_{it} + \theta_2 Inflation_{it} + \theta_3 EI_{it} + \theta_4 NEC_{it} \quad (1)$$

$$GDPC_{it}(\tau) = \theta_1 EV_{it} + \theta_2 cat1_{it} + \theta_3 INTR1_{it} \theta_2 Inflation_{it} + \theta_3 EI_{it} + \theta_4 NEC_{it} \quad (2)$$

$$GDPC_{it}(\tau) = \theta_1 EV_{it} + \theta_2 cat2_{it} + \theta_3 INTR2_{it} \theta_2 Inflation_{it} + \theta_3 EI_{it} + \theta_4 NEC_{it} \quad (3)$$

Equation (1) corresponds to Models 1 and 2. Models 3 and 4 are based on Equations (2) and (3), which correspond to Models 5 and 6, where GDPC is the dependent variable. The main exogenous variable (EV) is environmental efficiency, which has two proxies, eec (efficiency at crs) and eev (efficiency at vrs). Two categorical variables (cat1 and cat2) are also introduced as moderators in interaction models. ‘cat1’ is taken in Models 3 and 4 to categorise countries in developed or developing nations. ‘cat2’ is taken in Models 5 and 6 to categorise democratic or non-democratic nations. The interaction terms (INTR1 i.e., i_eec_cat1 or i_eev_cat1, and INTR2 i.e., i_eec_cat2 or i_eev_cat2). i_eec_cat1 (=eec*cat1) and i_eev_cat1 (=eev*cat1) are interaction terms in Models 3 and 4, respectively. i_eec_cat2 (=eec*cat2) and i_eev_cat2 (=eev*cat2) are interaction terms in Models 5 and 6, respectively. In addition, three control variables, Inflation, EI (energy intensity), and NEC (non-renewable energy consumption), are included in the models. The control variables are deployed to have a good fit model to determine the effect of EV on GDPC. ‘it’ as subscript indicates PDA where ‘i’ for cross-section (country) and ‘t’ is time (year).

3.3. Adoption of Quantile Regression

On the whole, earlier works analysing the relationship between development and environmental prospects are performed using parametric techniques. However, when the outcome variable is non-normal, there is evidence in the literature that the effect size may fluctuate with quantiles. Hence, regression analysis in quantiles gives more reliable evidence than classical regression analysis (Kanoujiya et al. 2022). This study’s dependent variable of interest (i.e., GDPC) is non-normally distributed. Section 5.2 contains an explanation of testing non-normality.

GDPC data are non-normal, as presented in Section 5.2. We, therefore, employ a quantile regression model to investigate the connection between economic development and environmental efficiency. Quantile regression was partly developed because non-parametric techniques have produced superior outcomes in empirical scenario analysis, as described in Asmare and Begashaw (2018) and Hettmansperger and McKean (2011), another factor that inspired its use. Moreover, the setting of quantiles is based on standard

quantiles available in other studies applying quantile regression (Kanoujiya et al. 2022; Asmare and Begashaw 2018; Hettmansperger and McKean 2011).

3.4. Variables

This study examines the relationship between environmental efficiency and economic development. The economic development of a nation is the dependent variable and is proxied by GDPC (Gross Domestic Product per Capita). The primary exogenous variable is environmental efficiency and is proxied by eec (at crs) and eev (at vrs). The environmental efficiency of a nation is measured using data envelope analysis (DEA). The following subsection discusses environmental efficiency assessment. 'cat1' and 'cat2' are two categorical variables used as a moderator in interaction models. 'cat1' differentiates the countries into developed or developing countries. 'cat2' categorises the countries into democratic or non-democracy. The control variables are also taken to obtain a good fit model to determine the sole effect of environmental efficiency on economic development. Inflation, EI, and NEC are control variables. Inflation is the price rise in goods and services in a country. The energy intensity is the consumption of energy in joules per USD. NEC is the share of non-renewable energy consumption out of the total energy. The control variables taken in the models are supposed to affect GDPC; hence, they are controlled.

3.5. Environmental Efficiency Assessment

This paper applies DEA analysis to measure the environmental efficiency of the sample countries. It is one of the most popular stochastic approaches to finding relative efficiency by analysing several inputs to obtain specific outputs (Thanassoulis 1993). DEA has several advantages of its application to find efficiency. As it is a non-parametric, it does not have the subjectivity of model specification. It automatically constructs the best-fit model; hence, no prior model specification is needed (Guo and Wu 2013; Li et al. 2013). Therefore, its implementation is relatively easy. A frontier efficiency is set to find relative efficiency (Bevilacqua and Braglia 2002). It should be noted that the DEA analysis required some criteria to be met before running the DEA program. Decision-Making Units [DMUs] (106 countries in this study) should be larger than five times the total number of inputs and outputs ($3 \times 5 = 15$ in this study) (Bevilacqua and Braglia 2002). Following Guo and Wu (2013) and Li et al. (2013), we use the DEA approach for its consistent output compared to other techniques.

Two inputs (i.e., the non-renewable energy consumption and energy intensity) are used for DEA. These inputs are crucial for environmental issues in a country and play a significant role in the economy. Environmental measures are generally undesirable; for instance, CO₂ emission should be less for better environmental quality. Hence, CO₂ emission is an undesirable output. An undesirable output needs to decrease. CO₂ is the major pollutant that causes environmental degradation. Therefore, we have solely taken this output variable. As per Kuo et al. (2014), Li et al. (2013), Wu et al. (2013), and Seiford and Zhu (2002), the inverse value of CO₂ emission (i.e., $f(\text{CO}_2) = 1/\text{CO}_2$) is taken to deal with the undesirable output in DEA. EE is assessed by employing DEA analysis as discussed using non-renewable energy consumption and energy intensity as inputs and CO₂ emissions as the undesirable output.

It should be noted that implementing the inverse value is a valid measure to resolve the issue of this undesirable output because the CO₂ emission of a country cannot be zero. As suggested by Kuo et al. (2014) and Seiford and Zhu (2002), for running the DEA program, DMUs are five times more extensive than the total number of inputs and outputs ($3 \times 5 = 15 < 106$). We have used two variants of DEA efficiency: (1) Constant return to Scale (CRS), assuming output changes with the same proportion as inputs change; and (2) Variable return to scale (VRS), assuming output does not change with the same proportion as inputs change (Kuo et al. 2014; Li et al. 2013).

4. Results

4.1. Descriptive Statistics

Table 2 demonstrates the descriptive statistics of the variables incorporated in the study. GDPC has a mean value of 1.336, which is closer to Max. It indicates that GDP per capita across the nations, on average, is at an adequate growth rate. The standard deviation (SD) is comparatively high, showing that the sample countries substantially vary in economic development. The environmental efficiency (eec) has a mean value of 0.502, which is about mid between Min and Max, showing an average level of environmental efficiency. However, the environmental efficiency (eev) has a mean value of 0.624 (slightly closer to Max). The average inflation is not alarming in the sample countries. However, the high SD of inflation implies variability. EI and NEC have mean values of 4.34 and 75.01, respectively. EI has its mean towards Min and NEC towards Max. Therefore, EI, on average, is low in the sample countries. However, its higher value of SD indicates high variations among the countries. However, the use of NEC is relatively high in the world. Its lower SD shows that countries have almost similar situations to NEC. The CO₂ emission is also high with high SD, indicating that nations highly vary in terms of CO₂ emissions

Table 2. Summary statistics.

Variable	Obs.	Mean	Std. Dev.	Min	Max
<i>DVs</i>					
GDPC	1060	1.332	4.326	−54.641	23.999
<i>EVs</i>					
<i>eec</i>	1060	0.502	0.212	0.156	1.000
<i>eev</i>	1060	0.624	0.186	0.251	1.000
<i>CVs</i>					
<i>Inflation</i>	1060	5.296	22.929	−19.146	558.56
<i>EI</i>	1060	4.349	22.751	0.22	15.56
<i>NEC</i>	1060	75.010	9.49	6.82	100.00
<i>CO₂ emission</i> ^	1060	380,864.6	1,258,963	110	10,707,220

Note: Min, Max, Obs., and Std. Dev. are minimum value, maximum value, number of observations, and standard deviation, respectively. DVs are dependent variables. EVs, MVs, and CVs are the explanatory, moderating, and control variables. EI is energy intensity. NEC is non-renewable energy consumption. Summary statistics are based on the data of whole sample period from 2011 to 2020 for 106 countries. ^ indicates output variable for DEA analysis. Source: Author compilation.

4.2. Normality and Multicollinearity

The Shapiro–Wilk test verifies the normality of data of the dependent variable (GDPC). Table 3 reports the results of the Shapiro–Wilk test. The significant *p*-value rejects the null of normalcy. Hence, the data of the GDPC are not normally distributed. Therefore, the QRPD model can be used between GDPC and environmental efficiency. The QRPD model is a suitable choice for analysis because it observes the relationship in different quantiles; hence, QRPD models can better deal with the non-normality of the dependent variable to obtain reliable results. Therefore, applying the QRPD is justifiable as the data meet all required conditions for its application.

Table 3. Normalcy check.

Variable	Obs	W	<i>p</i> -Value	H0: Data Normally Distributed	Outcome
GDPC	1070	0.882	0.000	Rejection of H0	Non-normal Data

Note: The Shapiro–Wilk W test was used to check the normality of data of the dependent variable. It has the null of normal distribution. Source: Author compilation.

Tables 4 and 5 present the results of the correlation matrix and VIF (variance inflation factor), respectively. Table 4 also shows that no significant correlation coefficient in the correlation matrix has a value greater than 0.80. The highest significant correlation coefficient

value is 0.620 in the opposite direction (negative). It is between *eev* and *NEC*. Therefore, the multicollinearity issue does not exist. Similarly, in Table 5, it is pretty evident that no VIF value is greater than 3. Hence, biasedness through multicollinearity does not exist (Shrestha 2020).

Table 4. Correlation matrix.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>GDP</i> (1)	1							
<i>eec</i> (2)	−0.011	1						
<i>eev</i> (3)	−0.009	−0.051	1					
<i>cat1</i> (4)	−0.001	−0.178 *	−0.120 *	1				
<i>cat2</i> (5)	0.062 *	0.169 *	0.184 *	0.051	1			
<i>Inflation</i> (6)	−0.078 *	−0.006	−0.009	−0.128 *	0.032	1		
<i>EI</i> (7)	0.037	−0.329 *	−0.427 *	−0.137 *	−0.090 *	0.169 *	1	
<i>NEC</i> (8)	−0.103 *	−0.619 *	−0.620 *	0.248 *	−0.117 *	−0.096 *	−0.199 *	1

Note: * signals *p*-value significance at 0.05. Source: Author compilation.

Table 5. Variance inflation factor.

Variable (DV: <i>GDP</i>)	<i>eec</i>	<i>cat1</i>	<i>cat2</i>	<i>EI</i>	<i>Inflation</i>	<i>NEC</i>	<i>eec*cat1</i>	<i>eec*cat2</i>
<i>VIF</i>	2.481	1.097	1.649	1.621	1.033	2.307	2.453	1.217
Variable (DV: <i>GDP</i>)	<i>eev</i>	<i>cat1</i>	<i>cat2</i>	<i>EI</i>	<i>Inflation</i>	<i>NEC</i>	<i>eev*cat1</i>	<i>eev*cat2</i>
<i>VIF</i>	1.543	1.085	1.037	2.191	1.044	2.886	1.040	1.150

Note: *VIF* is for the multicollinearity test. Values = or <3 indicates no issue of multicollinearity. Source: Author compilation.

4.3. Quantile Regression Results

Six models were developed in this study to determine the connection between *GDP* and countries' environmental efficiency. The first two models (Models 1 and 2) estimate the relationship using base variables (*eec* and *eev*). The following two models (Models 3 and 4) determine the relationship under the influence of the developed or developing category (*cat1*) of countries. The last two models (Models 5 and 6) estimate the relationship between *GDP* and efficiency under the influence of the democratic or non-democratic category (*cat2*) of countries. Table 6 reports the results of base models (Models 1 and 2). Table 7 presents the results of interaction models under *cat1* (Models 3 and 4). The results of interaction models under *cat2* (Models 5 and 6) are presented in Table 8.

In Table 6, the results of base models (Models 1 and 2) show that the coefficients of both proxies (*eec* and *eev*) of environmental efficiency are negative and significant at 5% significance. The '*eec*' and '*eev*' coefficients have values of −3.011 and −4.569, respectively, at the 25% quantile. It means that environmental efficiency has an inverse impact on a nation's economic development. At the 50% quantile, only '*eev*' is found to be negative and significant (with a value of −1.942) at a 5% significance. It, again, signifies that environmental efficiency is detrimental to economic growth. Environmental efficiency proxies (*eec* and *eev*) are insignificant at the 75% quantile. Hence, environmental efficiency does not significantly impact the nation's economic growth at higher quantiles. Furthermore, at the 25% quantile, only *EI* and *NEC* as control variables are found to be negative and significant at 1%. At the 50% and 75% quantiles, only *NEC* is significant and negative in both models. However, *EI* is found to be significant at a 10% significance level at the 75% quantile.

Table 6. Results of quantile regressions (with base variable).

		Model 1			Model 2		
		Coef.	Std. Err.	p	Coef.	Std. Err.	p
Quantile (25)	<i>eec/eev</i>	−3.011 **	1.221	0.013	−4.569 **	1.966	0.020
	<i>Inflation</i>	−0.017	0.056	0.752	−0.017	0.059	0.773
	<i>EI</i>	−0.217 *	0.081	0.008	−0.343 *	0.118	0.003
	<i>NEC</i>	−0.036 *	0.009	0.000	−0.046 *	0.012	0.000
Quantile (50)	<i>eec/eev</i>	−1.109	0.690	0.108	−1.942 **	0.970	0.045
	<i>Inflation</i>	−0.018	0.015	0.236	−0.018	0.019	0.364
	<i>EI</i>	−0.076	0.065	0.241	−0.113	0.076	0.138
	<i>NEC</i>	−0.023 *	0.006	0.000	−0.027 *	0.007	0.000
Quantile (75)	<i>eec/eev</i>	−1.257	0.839	0.134	−1.875	1.223	0.125
	<i>Inflation</i>	−0.005	0.012	0.665	−0.003	0.015	0.838
	<i>EI</i>	−0.110	0.071	0.124	−0.164 ***	0.087	0.060
	<i>NEC</i>	−0.030 *	0.008	0.000	−0.032 *	0.009	0.000

Note: *, **, and *** are for *p*-value is significant at 1%, 5%, and 10%. ‘*eec*’ and ‘*eev*’ are proxies for environmental efficiency at a constant return to scale (crs) and variable return to scale (vrs), respectively. ‘*eec*’ and ‘*eev*’ are the exogenous variables, respectively, in Model 1 and Model 2. Source: Author compilation.

Table 7. Results of quantile regressions (with interaction variable *cat1*).

		Model 3			Model 4		
		Coef.	Std. Err.	p	Coef.	Std. Err.	p
Quantile (25)	<i>eec/eev</i>	−4.008 *	1.438	0.005	−4.745 **	1.947	0.014
	<i>cat1</i>	−0.712	1.167	0.541	0.403	1.502	0.788
	<i>i_eec_cat1/i_eev_cat1</i>	0.137	2.575	0.957	−1.519	2.420	0.530
	<i>Inflation</i>	−0.017	0.063	0.780	−0.017	0.066	0.796
	<i>EI</i>	−0.283 *	0.089	0.001	−0.390 *	0.107	0.000
	<i>NEC</i>	−0.041 *	0.011	0.000	−0.049 *	0.012	0.000
Quantile (50)	<i>eec/eev</i>	−2.223 *	0.854	0.009	−2.301 ***	1.198	0.055
	<i>cat1</i>	−1.731 *	0.533	0.001	−1.526 **	0.764	0.046
	<i>i_eec_cat1/i_eev_cat1</i>	1.468	1.047	0.161	0.805	1.238	0.515
	<i>Inflation</i>	−0.018 *	0.003	0.000	−0.018 *	0.003	0.000
	<i>EI</i>	−0.090	0.058	0.120	−0.114	0.071	0.111
	<i>NEC</i>	−0.023 *	0.006	0.000	−0.024 *	0.007	0.002
Quantile (75)	<i>eec/eev</i>	−2.680 *	0.819	0.001	−3.647 *	1.075	0.000
	<i>cat1</i>	−3.332 *	0.593	0.000	−3.148 *	0.881	0.000
	<i>i_eec_cat1/i_eev_cat1</i>	3.881 *	1.521	0.010	2.702 ***	1.621	0.095
	<i>Inflation</i>	−0.022 *	0.003	0.000	−0.022 *	0.003	0.000
	<i>EI</i>	−0.057	0.066	0.381	−0.098	0.083	0.234
	<i>NEC</i>	−0.023 *	0.007	0.001	−0.029 *	0.008	0.000

Note: *, **, and *** are for *p*-value is significant at 1%, 5%, and 10%. ‘*eec*’ and ‘*eev*’ are proxies for environmental efficiency at a constant return to scale (crs) and variable return to scale (vrs), respectively. ‘*eec*’ and ‘*eev*’ are the exogenous variables, respectively, in Model 3 and Model 4. ‘*i_eec_cat1*’ and ‘*i_eev_cat1*’ are interaction terms in Model 3 and Model 4, respectively. Source: Author compilation.

Table 7 presents the results of the interaction models (Models 3 and 4) considering the moderating effect of *cat1* (developed or developing country). The coefficients of both proxies (*eec* and *eev*) are significant and negative with values of −4.008 and −4.745, respectively, at the 25% quantile. *cat1* is insignificant in both models. The interaction terms (*i_eec_cat1* and *i_eev_cat1*) are insignificant in both models. It implies that countries’ developing or developed status does not significantly affect the connection between GDPC and environmental efficiency at the 25% quantile. The control variables *EI* and *NEC* are found to be significant and negative in both models (Models 3 and 4). At the 50% quantile, similar results are estimated at the 25% quantile for *eec*, *eev*, and the interaction terms.

‘eec’ and ‘eev’ are significant and negative. The interaction terms are insignificant in both models. ‘cat1’ is found to be significant and negative. Inflation and NEC as control variables are found to be significant and negative. At the 75% quantile, similar results are estimated in the 50% quantile for eec, eev, inflation, and NEC. However, the interaction terms in Models 3 and 4 are significant and positive. It indicates that when countries are developed, environmental efficiency improves a nation’s economic growth (GDPC).

Table 8 reports the results of interaction models (Models 5 and 6) considering cat2 (democratic or non-democratic) as the moderating variable. Unlike earlier models, both the proxies, i.e., eec and eev, are insignificant at the 25% quantile. ‘cat2’ is found to be significant and positive in both models (Models 5 and 6). It implies that democratic countries have better GDPC than non-democratic countries at the 25% quantile. ‘i_eec_cat2’ is insignificant in Model 5. However, ‘i_eev_cat2’ is found to be significant and negative with a coefficient value of -4.902 . It indicates that environmental efficiency (eev) benefits GDPC in non-democratic countries. Both models have significant and negative EI and NEC (Models 5 and 6). Similar results are found at the 50% quantile as well. At the 75% quantile, only NEC is significant in Models 5 and 6. However, EI is significant and negative in Model 6. However, the rest of the variables in both models are insignificant.

Table 8. Results of quantile regressions (with interaction variable cat2).

		Model 5			Model 6		
		Coef.	Std. Err.	p	Coef.	Std. Err.	p
Quantile (25)	<i>eec/eev</i>	0.105	2.022	0.958	1.141	2.530	0.652
	<i>cat2</i>	2.361 **	0.973	0.015	3.818 *	1.420	0.007
	<i>i_eec_cat2/i_eev_cat2</i>	-2.702	1.824	0.138	-4.902 **	2.102	0.019
	<i>Inflation</i>	-0.017	0.049	0.723	-0.017	0.056	0.752
	<i>EI</i>	-0.178 **	0.069	0.011	-0.190 ***	0.108	0.080
	<i>NEC</i>	-0.024 **	0.010	0.018	-0.027 **	0.013	0.033
Quantile (50)	<i>eec/eev</i>	0.021	1.485	0.988	0.551	1.623	0.734
	<i>cat2</i>	1.427 **	0.673	0.034	2.363 *	0.855	0.005
	<i>i_eec_cat2/i_eev_cat2</i>	-1.125	1.377	0.414	-2.519 ***	1.405	0.073
	<i>Inflation</i>	-0.017 *	0.003	0.000	-0.018 *	0.005	0.002
	<i>EI</i>	-0.064	0.063	0.307	-0.085	0.072	0.237
	<i>NEC</i>	-0.016 *	0.006	0.009	-0.020 *	0.006	0.002
Quantile (75)	<i>eec/eev</i>	-0.353	2.060	0.863	-0.801	2.472	0.745
	<i>cat2</i>	1.240	0.889	0.163	1.732	1.184	0.143
	<i>i_eec_cat2/i_eev_cat2</i>	-0.891	1.911	0.640	-1.615	2.100	0.441
	<i>Inflation</i>	-0.001	0.028	0.972	-0.001	0.029	0.983
	<i>EI</i>	-0.085	0.072	0.234	-0.148 ***	0.089	0.098
	<i>NEC</i>	-0.027 *	0.008	0.000	-0.032 *	0.009	0.000

Note: *, **, and *** are for p -value is significant at 1%, 5%, and 10%. ‘eec’ and ‘eev’ are proxies for environmental efficiency at a constant return to scale (crs) and variable return to scale (vrs), respectively. ‘eec’ and ‘eev’ are the exogenous variables, respectively, in Model 3 and Model 4. ‘i_eec_cat1’ and ‘i_eev_cat1’ are interaction terms in Model 3 and Model 4, respectively. Source: Author compilation.

4.4. Results’ Robustness

The results’ robustness is essential to confirm reliable outcomes (Kanoujiya et al. 2022; Rastogi and Kanoujiya 2022). According to Kanoujiya et al. (2022), the multi-model approach is followed in this study. The results in the base models are pretty similar. It confirms the robustness of the base relationship. In addition, the results of the interaction models are also similar; hence, the outcomes are robust. The results’ robustness confirms the outcomes’ reliability in the current paper (Kanoujiya et al. 2022; Rastogi and Kanoujiya 2022).

5. Discussion

5.1. Hypotheses Testing Outcomes

The first hypothesis, that environmental efficiency (EE) positively impacts the GDPC, is rejected. The evidence provided in Table 6 does not support Hypothesis 1. This result

implies that EE's impact on GDPC significantly differs and depends upon GDPC levels. The EE significantly (negatively) impacts the GDPC when the GDPC is low. Moreover, for moderate levels of GDPC, the impact of EE on the GDPC is partially significant. However, for high GDPC, the EE does not impact GDPC.

The second hypothesis, that developed nations positively moderate the impact of EE on the GDPC, cannot be rejected. The results discussed in Table 7 highlight that developed nations positively moderate the impact of EE on the GDPC. This positive moderation by developed nations is significant only for high GDPC. The moderating impact of developed nations on the impact of EE on the GDPC is not significant for moderate and low GDPC.

The third hypothesis, that democratic governance positively influences the impact of EE on the GDPC, is rejected (Table 8). The moderating influence of democratic governance is negatively significant instead of positive (as expected). However, the significantly negative moderation is only valid for low and moderate levels of GDPC. This result implies that democratic governance with low GDPC will negatively impact EE on their already low GDPC.

5.2. Comparison with Earlier Studies on the Topic

The extant literature on the financial materiality of sustainability or ESG usually focuses on corporate and reporting purposes (Albrecht and Greenwald 2014; Schiehl and Kolahgar 2021). This situation is consistent even for the European-Union-based discussion on double materiality (Baumüller and Sopp 2022; Chiu 2022). The overlapping area in the literature and our findings is significant financial materiality. However, the nature might not be the same or may be unclear in the literature. This situation may exist because of their orientation towards reporting rather than determining EE's impact on GDPC.

Furthermore, our findings support the positive moderation by developed nations on the EE's impact on the GDPC. We could not observe any study on this. However, Fagher and Abedi (2017) find evidence of EE's positive impact on developing nations' GDP growth rate. Chowdhury and Islam (2017) report a negative association between the two using BRICS nations. However, none of the studies explores the moderating influence of developed nations on the EE's impact on the GDPC.

Similarly, we do not find any study where democracy moderates the EE's impact on the GDPC. However, studies on democracy and the environment are there. Their findings are also mixed. Some studies find that democracy reduces pollution (Li and Reuveny 2006; Winslow 2005). A few also report the negative or uncertain status of the impact of democracy on pollution (Acheampong et al. 2022). The current study reports the negative impact of democracy on the EE's impact on the GDPC (this is significant only for low or moderate GDPC nations), partially similar to Acheampong et al. (2022).

5.3. Contribution

The current study's findings of the environmental concerns' financial materiality are not so explicitly found in the literature. Environmental efficiency is rarely assessed in the existing literature and is considered an environmental factor. The current study has looked for this factor to examine its effect on economic development. The negative impact of environmental efficiency on the GDPC when the GDPC is low, and the insignificant impact when the GDPC is high, are novel and the main contributions of the current study. In addition, it is not found in any other study that developed nations reduce the negative association of EE on the GDPC when GDPC is high. Moreover, it is also not observed in the literature that democracy accentuates the negative impact of EE on the GDPC of nations when the GDPC is low. In toto, it is believed by the authors that all the findings are novel and significantly contribute to the extant knowledge on the topic.

5.4. Implications

The current study's findings debunk a few long-cherished illusions, and therefore carry some path-breaking implications for all the stakeholders. Above all, nations' long-

term environmental policies need a revisit based on the current study's findings. Firstly, it needs to be realised that environmental concerns hurt the GDPC under certain conditions. This negative impact of EE on GDPC is significant only for low GDPC nations. The same association is not significant for high GDPC nations. This situation implies that, if the policymakers want to protect the environment and simultaneously want the emerging nations to prosper unhindered, the nations with high GDPC should take the maximum burden of EE, not those with low GDPC.

Secondly, the positive moderation of developed nations on the EE's impact on GDPC for high GDPC nations reinforces the implication discussed in the first point. A developed nation with high GDPC nations would reduce the negative association of EE's on the GDPC. Thirdly, the negative moderation by democracy on EE's impact on the GDPC is significant for low GDPC nations. This finding implies that a democratic nation with a low GDPC would further deteriorate the negative impact of EE on the GDPC of such nations. This situation demands a two-pronged explanation. First, this result reinforces the implication discussed in the first point. Second, compared to democracy, a non-democratic nation would not be hurt further by EE's impact on the GDPC. This situation means a democratic nation with a low GDPC has much to worry about due to the negative implications of environmental concerns on the GDPC. The findings' practical implication is the financial unviability of environmental efficiency, indicating it is not always beneficial for a nation's growth. It might be due to the lower financial materiality of environmental quality. Hence, countries with higher GDPC (economic growth) should concentrate more on environmental performance than lower GDPC countries.

6. Conclusions

The current study is aimed at determining the impact of environmental efficiency (EE) on the gross domestic product per capita (GDPC). The study employs quantile regression to address the impact of EEs on GDPC regarding different levels of GDPC.

We find that an EE increase negatively impacts the GDPC for low GDPC nations. In addition, the negative impact of EE on the GDPC for low GDPC countries is further exacerbated if it is a democratic country. On the contrary, if the GDPC is high, EE has no negative impact on the GDPC. Moreover, for a highly GDPC-developed country, an increase in EE positively influences the GDPC of the country.

The current findings are significant as they address the disagreement between developed and emerging economies regarding environmental concerns. The differences between the two are regarding the issue of who will take the considerable burden to protect the environment. The findings are significant as their implications can change the course of action regarding the long-term policies on environmental protection for developed and developing nations.

One of the current study's limitations is the absence of data from the other counties that were not part of the sample. Additionally, this circumstance will be the focus of further study on the subject. We use GDPC as a measure to assess the growth and development of the nations. Some other tools or proxies can also be employed, such as standard of living, health parameters, and education, to assess the impact of environmental concerns on the nations. Such limitations also provide scope for future research on the topic.

Based on the current study's findings, the authors recommend rudimentary restructuring in the policy of environmental concerns so that the twin purpose of protecting the environment and the benefits for flora and fauna on the earth can also be ensured. Passing the buck to one another between nations will only attenuate all the excellent work carried out on the issue.

Author Contributions: Conceptualization, S.R. and J.K.; methodology, J.K.; software, P.T.; validation, S.R., J.K. and N.P.; formal analysis, J.K.; investigation, S.R.; resources, S.B.; data curation, A.D.; writing—original draft preparation, S.R.; writing—review and editing, J.K.; visualization, P.T.; supervision, S.R.; project administration, S.R.; funding acquisition, No funding. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: Data is unavailable due to privacy or ethical restrictions.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Sample countries.

Sr. No.	Country
1	Albania
2	United Arab Emirates
3	Argentina
4	Armenia
5	Australia
6	Austria
7	Azerbaijan
8	Belgium
9	Bangladesh
10	Bulgaria
11	Bahrain
12	Belarus
13	Bolivia
14	Brazil
15	Canada
16	Switzerland
17	Chile
18	China
19	Colombia
20	Costa Rica
21	Cuba
22	Cyprus
23	Czech Republic
24	Germany
25	Denmark
26	Dominican Republic
27	Algeria
28	Ecuador
29	Egypt, Arab Rep.
30	Spain
31	Estonia
32	Finland
33	Fiji
34	France
35	United Kingdom
36	Georgia
37	Greece
38	Guatemala
39	Hong Kong SAR, China
40	Honduras
41	Croatia
42	Hungary
43	Indonesia
44	India
45	Ireland
46	Iran, Islamic Rep.
47	Iceland
48	Israel
49	Italy

Table A1. *Cont.*

Sr. No.	Country
50	Jordan
51	Japan
52	Kazakhstan
53	Kyrgyz Republic
54	Cambodia
55	Korea, Rep.
56	Lao PDR
57	Sri Lanka
58	Lithuania
59	Luxembourg
60	Latvia
61	Macao SAR, China
62	Morocco
63	Moldova
64	Mexico
65	Malta
66	Mauritius
67	Nicaragua
68	Netherlands
69	Norway
70	Nepal
71	New Zealand
72	Oman
73	Panama
74	Peru
75	Philippines
76	Poland
77	Puerto Rico
78	Portugal
79	Paraguay
80	Romania
81	Russian Federation
82	Saudi Arabia
83	Singapore
84	Sierra Leone
85	El Salvador
86	Slovak Republic
87	Slovenia
88	Sweden
89	Eswatini
90	Sint Maarten (Dutch part)
91	Seychelles
92	Chad
93	Togo
94	Thailand
95	Tajikistan
96	Tunisia
97	Turkey
98	Uganda
99	Ukraine
100	Uruguay
101	United States
102	Uzbekistan
103	Venezuela, RB
104	Vanuatu
105	Samoa
106	Zimbabwe

Source: Author's selection and countries chosen from World Bank list.

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ISBN 978-3-7258-5494-3