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Sisira Colombage

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Guest Editor

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Contents

About the Editor

Sisira Colombage

Sisira Colombage, Ph.D., is an Associate Professor of Finance at Federation University Australia, whose expertise spans corporate finance, investments, sustainable finance, FinTech, and financial markets. He holds a Ph.D. in Finance from Kobe University, a Master of Business Administration (MBA) in Accounting Systems from Kobe University and a Master of Business Administration (MBA) in Finance from the University of Colombo, and a Bachelor of Business Administration from the University of Sri Jayewardenepura. Prof. Colombage is a member of several professional bodies, including the Certified Practising Accountants Australia (CPA) and the Financial Services Institute of Australasia (FINSIA).

His work on FinTech and digital banking explores the transformative impact of financial technology on traditional banking models. He investigates the nuances of digital payment systems, the application of blockchain technology in finance, the role of Artificial Intelligence (AI) in financial services, and the implications for consumer behaviour, market disruption, and regulatory frameworks. His insights help illuminate how technology is reshaping access to finance and financial intermediation globally.

Preface

The global shift toward sustainability demands financial innovation. This reprint provides essential research on the transformative impact of FinTech and ESG integration, offering timely insights for academics, investors, and policymakers navigating the future of responsible investment.

Sisira Colombage
Guest Editor

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Editorial

Editorial: Financial Technology (Fintech) and Sustainable Financing, 3rd Edition

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It is an honor to serve as the Guest Editor for this Special Issue, "Financial Technology (Fintech) and Sustainable Financing." This volume, which compiles 11 research papers, represents a significant contribution to a rapidly evolving and critical field.

The past few years have seen a remarkable convergence of financial innovation and the global sustainability agenda. We have witnessed the rise of Green Fintech, a rapidly expanding area that combines financial technology with environmental sustainability goals. This includes a wide range of innovations like platforms that facilitate the issuance of green bonds, applications that track and verify carbon emissions, and algorithmic tools that help investors assess the ESG (Environmental, Social, and Governance) performance of companies. By leveraging technologies such as blockchain and big data, Green Fintech can enhance the efficiency, transparency, and accessibility of sustainable financial activities, directly addressing the critical need to reallocate capital toward low-carbon and environmentally friendly solutions.

Concurrently, a holistic vision for economic growth is emerging through the blue economy, which focuses on the sustainable use of ocean resources. This concept goes beyond traditional maritime sectors like fishing and shipping to include new and innovative industries such as marine biotechnology, renewable ocean energy, and sustainable coastal tourism. It seeks to balance economic growth with environmental protection and social equity, acknowledging that the health of our oceans is intrinsically linked to global well-being. The financial mechanisms supporting this, such as "blue bonds" and "debt-for-nature swaps," are innovative instruments that direct capital towards ocean-positive projects.

Meanwhile, decentralized finance (DeFi) has challenged traditional financial models by enabling peer-to-peer transactions through smart contracts on a blockchain, without the need for intermediaries like banks. DeFi's potential for disintermediation, enhanced transparency, and greater efficiency is immense. Projects within this space are exploring how to tokenize real-world assets, create new credit systems, and build transparent, community-governed financial protocols. While still in its nascent stage, DeFi has the potential to reshape how capital is raised and allocated globally.

The rapid adoption of digital banking in emerging markets is a transformative phenomenon. Driven by high mobile phone penetration and a large unbanked or underbanked population, digital banking platforms are leapfrogging traditional brick-and-mortar financial infrastructure. This shift is not merely about convenience; it is a critical tool for achieving financial inclusion, providing millions with access to essential financial services like savings, credit, and insurance for the first time. For small business owners and individuals in remote areas, mobile financial services have created a direct pathway to the formal economy, fostering entrepreneurial activity and economic resilience.

Despite this progress, significant challenges remain. While overall digital banking adoption is increasing, there is a persistent digital divide based on factors like age, gender, and geographic location. The urban, young, and tech-savvy population often reaps the most benefits, while older, less digitally literate, or rural populations are left behind. Furthermore, issues of cybersecurity, data privacy, and a lack of clear regulatory frameworks create significant risks for both consumers and financial institutions.

Despite this rapid progress, a significant knowledge gap persists. The interdisciplinary nature of this field means that research often remains siloed, with sustainable finance scholars and fintech experts working in isolation. A critical need exists for research that explores the nexus of these two domains—understanding not just how to green finance, but how technology can be a scalable tool to achieve it. This Special Issue was conceived to bridge this gap. The papers within this volume collectively explore this convergence, addressing a range of topics from mobile financial services for sustainable agriculture to the role of crowdfunding in supporting green startups. By bringing these diverse perspectives together, this Special Issue serves as a foundational text that links technological innovation with tangible sustainability outcomes.

The work presented here is just the beginning. The next frontier of research lies in several key areas, particularly concerning the deeper integration and real-world impact of Green Fintech, the blue economy, and DeFi.

For Green Fintech and the blue economy, future research needs to move beyond conceptual frameworks and theoretical models to focus on empirical evidence. We need more data-driven studies that assess the actual impact of these technologies on achieving Sustainable Development Goals (SDGs), especially for SDG 13 (Climate Action) and SDG 14 (Life Below Water). For instance, research should investigate whether Green Fintech genuinely reduces carbon emissions and whether blue finance initiatives demonstrably improve marine ecosystem health. Additionally, scholars must explore the regulatory challenges and opportunities in these spaces, aiming to develop robust policy frameworks that can scale these innovations effectively while preventing greenwashing and ensuring accountability.

For DeFi, a central research challenge is reconciling its decentralized, often unregulated nature with the need for stability, consumer protection, and alignment with sustainable development. Future research should focus on how to build "permissioned" or "hybrid" DeFi models that can work alongside traditional financial systems and regulatory bodies to channel capital into sustainable projects. Another critical area is exploring how decentralized governance mechanisms, such as Decentralized Autonomous Organizations (DAOs), can be structured to make transparent and democratic decisions for environmental initiatives. Research is also needed to address the energy consumption of blockchain technology, with a focus on sustainable consensus mechanisms like Proof-of-Stake.

For digital Banking the work in this Special Issue serves as a springboard for a new and more nuanced research agenda. Future investigations should focus on several key areas. First, there is a pressing need for empirical studies on long-term impact. We must move beyond adoption rates to understand the actual, sustained effects of digital banking on poverty reduction, financial literacy, and gender equality in emerging markets. This research should employ longitudinal methodologies to track how digital financial services influence household welfare over time. Second, the role of governance and regulation requires much deeper scrutiny. Research should examine the effectiveness of different regulatory models, such as sandbox environments, in fostering innovation while protecting consumers. Researchers should also investigate how to create robust legal frameworks that address emerging risks like digital fraud, data breaches, and algorithmic bias, which could disproportionately affect vulnerable populations. A crucial area for future exploration is the behavioral and social dimensions of digital banking. This includes researching the factors that influence trust and acceptance among marginalized groups, exploring the role of financial literacy in technology adoption, and understanding how community-based social networks impact the spread and use of digital financial services. This will allow for the development of more inclusive and user-centric digital banking solutions that truly serve the entire population, bridging the gap between technological possibility and equitable reality.

Finally, a cross-cutting research theme is the social and ethical dimensions of all these technologies. How can we ensure that the benefits of Green Fintech and the blue economy are equitably distributed, preventing a new form of digital exclusion in developing economies? The papers in this issue lay the groundwork for a more cohesive and impactful research agenda. It is my sincere hope that this collection will not only serve as a valuable resource but also inspire the next generation of researchers to explore the exciting possibilities at the intersection of finance, technology, and sustainability.

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Article

Sustainable Investments in the Blue Economy: Leveraging Fintech and Adoption Theories

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Abstract: This study investigates the attributes influencing the adoption of fintech services for sustainable investment within the blue economy. Specifically, it integrates the Diffusion of Innovations (DOI) theory and the Technology Acceptance Model (TAM) to examine how the perceived relative advantages, compatibility, complexity, trialability, and observability of fintech services influence their perceived ease of use and perceived usefulness, and it explores their impact on the intention to adopt fintech services. Finally, the study assesses how the intention to adopt fintech services affects sustainable investment decisions in the blue economy. Data were collected from 224 stakeholders in the blue economy sectors in India during the summer of 2024 and analyzed using structural equation modeling with partial least squares (SEM-PLS). The results reveal which attributes significantly influence perceived ease of use and perceived usefulness. Additionally, perceived ease of use and perceived usefulness significantly influence the intention to adopt fintech services. The intention to adopt fintech services positively impacts sustainable investment decisions in the blue economy. This study provides a comprehensive framework for advancing fintech services that support sustainable investment decisions, thereby contributing to the growth of the blue economy.

Keywords: diffusion of innovation; technology acceptance model; fintech adoption; consumer behavior; blue economy

1. Introduction

The blue economy, which encompasses the sustainable utilization of ocean resources to foster economic growth, enhance livelihoods, and create jobs, has increasingly been recognized as an essential element of sustainable development. Despite this, sectors related to the ocean face considerable investment challenges due to high perceived risks, fragmented governance, financial inefficiencies, and insufficient transparency (Novaglio et al., 2024). These barriers obstruct the capacity to channel responsible investments into marine innovations, environmental stewardship, and community resilience. Addressing these constraints requires innovative financial mechanisms that can improve the flow, transparency, and accountability of investments in marine sectors.

Financial technology (fintech) provides a logical solution to these requirements. The application of digital tools such as mobile payments, blockchain, AI-driven analytics, and online lending enables fintech to improve the efficiency, traceability, and inclusiveness of financial systems (Boot et al., 2021; Bose & Srinivasan, 2024). In the realm of marine sustainability, fintech solutions play a crucial role in enhancing risk assessment, optimizing ESG compliance, and broadening access to funding—especially for smaller stakeholders and local communities (Wenhai et al., 2019). The potential of fintech in the blue economy is significant; however, its adoption is currently limited (Ha, 2024). This situation calls for a thorough examination of the factors that affect its uptake (Singh et al., 2020).

This research utilizes two theoretical frameworks to analyze these components: the Technology Acceptance Model (TAM) and the Diffusion of Innovations (DOI) theory. The TAM (Davis, 1989) highlights the significance of perceived usefulness and perceived ease of use as determinants of user adoption. The DOI theory, as articulated by Rogers in 1962 (Rogers, 1962) and revisited in 2003 (Rogers, 2003), delineates five key characteristics of innovation: relative advantage, compatibility, complexity, trialability, and observability, all of which significantly impact the adoption of new technologies. These models have been extensively applied in various technological fields, such as fintech, yet they remain insufficiently examined within the context of ESG-driven marine environments (Thottoli et al., 2024).

Earlier studies have enhanced these models by integrating factors such as trust and privacy (Tamasiga et al., 2022), or by merging them with behavioral frameworks like the Norm Activation Model (Ganjipour & Edrisi, 2023b). Nevertheless, the majority of research continues to concentrate on banking and consumer applications (Laidroo et al., 2021), neglecting the potential of ESG-oriented applications within the blue economy. This study aims to fill the identified gap by combining the DOI and TAM frameworks to analyze the impact of RA, COM, COMP, TR, and OBS on PU and PEU, which in turn affects the intention to adopt fintech services (IAFS). Additionally, we introduce the context-specific outcome variable—sustainable investment decisions in the blue economy (SIBE)—to examine whether adoption translates into responsible investment behavior aligned with the ESG principles.

India presents a compelling framework for examination, characterized by its vast coastal geography and the development of its digital infrastructure. The nation features a coastline that extends roughly 7500 km, with close to 30% of its population living in coastal areas. The contribution of ocean-based sectors, such as fisheries, marine tourism, and shipping, to the national GDP is approximately 4%, which translates to an estimated annual value of around USD 300 billion (KPMG, 2024). India encounters considerable challenges regarding marine sustainability, including overexploited fisheries, increasing coastal erosion, and pervasive plastic pollution. Strategic initiatives such as the Sagarmala Programme and the Blue Economy 2047 Vision have been introduced to tackle these challenges; however, ongoing deficiencies in systemic investment, inter-agency coordination, and environmental monitoring impede successful execution (Ministry of Shipping, GOI, Government of India, 2025). Simultaneously, India has positioned itself as a prominent player in the fintech sector, boasting an adoption rate of 87%, which significantly exceeds the global average of 67%. This trend is primarily fueled by the notable success of the Unified Payments Interface (UPI) (Capital Market, 2025).

Based on data collected in mid-2024 from 224 blue economy stakeholders in India, this study uses partial least squares structural equation modeling (PLS-SEM) to test the hypothesized relationships within the proposed model. This research contributes in three key ways. First, it applies an integrated TAM-DOI model to a novel context: sustainable fintech adoption in ocean-based investment sectors. Second, it introduces the construct of SIBE to capture ESG-driven decision-making in the blue economy. Third, it provides practical insights for fintech developers, sustainability investors, and policymakers aiming to enhance responsible capital flows in marine environments.

The remainder of this paper is organized as follows. Section 2 presents the theoretical foundations and the literature relevant to fintech adoption and sustainable investment in the blue economy. Section 3 outlines the research methodology, including the model specification, data collection, and analytical approach. Section 4 reports the empirical results based on structural equation modeling. Section 5 offers a critical discussion of the findings in light of the theoretical framework and contextual factors. Finally, Section 6 concludes the paper by summarizing the key contributions, policy implications, and directions for future research.

2. Grounding Theories and Literature Review

This section discusses the theoretical grounding of and literature on the adoption of fintech services, focusing on two key frameworks: the DOI theory and the TAM. These structures are combined to understand adoption behaviors, particularly regarding sustainable investment decisions in the blue economy.

2.1. Diffusion of Innovation Theory (DOI)

The Diffusion of Innovation (DOI) theory, formulated by Rogers (1962, 2003), offers a robust framework for analyzing the mechanisms by which new technologies and practices disseminate within a social system over time. It outlines five fundamental attributes that influence adoption behavior: relative advantage, compatibility, complexity, trialability, and observability. The relevance of these characteristics becomes apparent when examining the adoption of fintech services in intricate investment contexts like the blue economy.

Within the realm of financial technology, DOI has demonstrated its utility in elucidating user behavior and the adoption patterns of institutions (Taherdoost, 2018). Nonetheless, a significant portion of the literature utilizes the theory within general or commercial frameworks, neglecting to consider scenarios involving environmentally conscious investments. While prior studies acknowledge the importance of innovation, and attributes such as perceived benefit and ease of integration have been discussed (Jain et al., 2023), there is limited examination of these dimensions in a collective manner, or specifically within sustainability-focused domains.

Relative advantage denotes the extent to which fintech is viewed as a superior alternative to conventional systems, providing enhancements in efficiency, transparency, and cost-effectiveness (Hafner et al., 2020). Compatibility pertains to the degree to which fintech corresponds with established values, investment methodologies, and ESG requirements (Venkatesh et al., 2002). Conversely, complexity indicates the perceived challenges associated with utilizing fintech solutions, which can often hinder adoption when systems are not intuitively designed or when adequate user training is absent (Liu et al., 2024). Trialability refers to the degree to which fintech services can be evaluated on a restricted scale, aiding in the reduction in perceived risks and enhancing user familiarity (Park, 2024). Ultimately, observability relates to the clarity of advantages derived from fintech implementation, including enhanced ESG reporting or decision-making processes, which could strengthen trust and encourage adoption (Valizadeh et al., 2020).

While the model is widely applied, many current studies tend to concentrate on specific attributes, or do not adequately place them within the context of high-stakes, value-driven sectors such as sustainable investing. The limited scope of DOI restricts its ability to provide comprehensive explanations in areas that necessitate ethical, social, and environmental considerations. This study integrates all five innovation attributes to provide a thorough and contextually relevant understanding of fintech adoption within the blue economy.

2.2. Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM), introduced by Davis in 1989, is an adaptation of the Theory of Reasoned Action (TRA) formulated by Fishbein and Ajzen (1975), which aimed at providing a clearer understanding of user acceptance of technology. This model has garnered extensive empirical backing and continues to be a significant framework in information systems research, especially in analyzing the behavioral intention behind the adoption of technological innovations.

The TAM highlights two fundamental concepts: perceived usefulness (PU) and perceived ease of use (PEU). PU indicates the extent to which a user perceives that a technology will improve their performance, whereas PEU denotes the extent to which the user perceives that utilizing the technology will require minimal effort, according to Davis. Within the realm of fintech, PU is frequently linked to improved investment decision-making, increased efficiency, and better financial management (Sharma et al., 2024b). Users who recognize the utility of fintech services tend to cultivate positive attitudes and a greater likelihood of adopting these services (Shahzad et al., 2022). PEU influences the extent to which users perceive these tools as intuitive and accessible. A favorable view of ease of use can strengthen perceptions of usefulness, as users tend to concentrate on their financial goals rather than technological obstacles (Davis, 1993).

Although the TAM initially highlighted PU and PEU as key factors influencing user intention, recent studies have raised concerns about the adequacy of these two elements in fully understanding the intricacies of contemporary technology adoption. The evolution of digital technologies and the shifting expectations of users suggest that depending solely on PU and PEU could be restrictive (Venkatesh & Davis, 2000). In response, researchers have expanded the Technology Acceptance Model to include elements like trust, risk, and perceived value, especially in studies related to fintech adoption, where user behavior is shaped by both technological and contextual influences (Ganjipour & Edrisi, 2023a).

This research utilizes the Technology Acceptance Model to evaluate how perceived usefulness and perceived ease of use affect users' intentions to adopt fintech tools for sustainable investment. By integrating the TAM with DOI, we seek to offer a more thorough understanding of user decision-making, recognizing the impact of innovation characteristics and the specific contextual variables inherent to the blue economy.

2.3. Intention to Adopt Fintech Services (IAFS)

The intention to adopt fintech services (IAFS) denotes the readiness or strategy of individuals or organizations to initiate the use of financial technologies (Lee & Shin, 2018). This factor is a key indicator of real adoption behavior and functions as a primary outcome variable in both the Technology Acceptance Model (TAM) and the Diffusion of Innovation (DOI) framework.

Innovation adoption has been a significant focus in IT and organizational studies (Gosain, 2004). Researchers often differentiate between adoption, which refers to the decision made by individuals or organizations to utilize a new technology, and diffusion, which pertains to the wider dissemination of that technology within a social system (Wejnert, 2002). While both dimensions hold significance, the existing literature frequently emphasizes adoption, especially within the realm of fintech (Mahmud et al., 2022). Certain scholars contend that overlooking usage patterns or the wider diffusion process results in an inadequate understanding of innovation acceptance (Rupeika-Apoga & Wendt, 2022).

Recent studies have started to integrate various theoretical models to overcome these limitations and offer a more comprehensive understanding of adoption. For instance, Alam et al. (2018) integrated the DOI, TAM, and the Theory of Planned Behavior (TPB) to examine mobile banking in Malaysia, whereas Ganjipour and Edrisi (2023b) utilized the

Norm Activation Model (NAM) to analyze robotics adoption. In a similar vein, Jahangir and Zia-ul-Haq (2023) utilized a hybrid DOI–TAM–TPB framework in the context of digital marketplaces. These integrative approaches emphasize the importance of merging user-focused and innovation-focused viewpoints.

Nonetheless, these integrative studies have largely concentrated on traditional digital services, showing a restricted application in contexts that prioritize high-impact sustainability. The function of IAFS in facilitating sustainable investment via fintech, particularly within sectors such as the blue economy, is notably underexplored. Addressing this gap is crucial for understanding how financial technology can facilitate investment practices that prioritize environmental and social responsibility.

2.4. Sustainable Investment Decisions in the Blue Economy (SIBE)

The concept of sustainable investment decisions in the blue economy (SIBE), as outlined in this study, entails the strategic allocation of capital aimed at fostering the responsible utilization of ocean resources. This approach seeks to drive economic growth, enhance livelihoods, and maintain the integrity of ecosystems. The decisions integrate environmental, social, and governance (ESG) criteria to evaluate financial performance alongside non-financial impacts. SIBE holds significant importance in various sectors, including fisheries, renewable ocean energy, marine tourism, and marine biotechnology—fields where maintaining the ecological balance and ensuring long-term sustainability are essential.

While SIBE has not yet been fully defined in the literature, it is grounded in two well-established concepts: sustainable investment and the blue economy. Sustainable investment involves strategies that incorporate ESG factors into the selection and management of portfolios, with the objective of achieving beneficial societal results while maintaining long-term returns (Remer, 2023). The blue economy is characterized by the sustainable use of ocean resources, aimed at fostering economic development and generating employment, all while ensuring the protection of marine ecosystems (Selamoglu, 2021; Yousef, 2024).

Current research regarding the blue economy predominantly focuses on aspects of environmental safeguarding and economic robustness (Spalding, 2016), frequently emphasizing sector-specific issues like overfishing, pollution, and the enforcement of regulations. Nevertheless, there has been insufficient focus on the methods investors use to assess opportunities in this sector, as well as the technological and informational resources that could enhance the sustainability of financial decision-making. Various elements, including perceived environmental impact, policy frameworks, and sustainability risks, have been demonstrated to affect investment behavior (Narwal et al., 2024). However, the influence of technology, especially fintech, has not been thoroughly examined.

Recent studies indicate that advancements in technology have the potential to expedite sustainable transitions through enhanced data accessibility, increased transparency, and improved decision-making tools (Bharadwaj, 2021). However, there is a scarcity of research that specifically investigates the applicability of fintech adoption frameworks, such as the TAM and DOI, within sustainability-focused investment scenarios like the blue economy. Rahman et al. (2023) examined fintech diffusion with an emphasis solely on compatibility, neglecting other essential factors like observability and trialability. This limited scope restricts the capacity to extrapolate results or formulate thorough adoption strategies.

This study aims to address this gap by integrating the DOI and TAM. This analysis evaluates the interplay between the characteristics of innovation, as outlined in the Diffusion of Innovations theory, and the user perceptions derived from the Technology Acceptance Model in relation to their combined effect on the intention to adopt fintech solutions for sustainable investment.

2.5. Hypothesis Development

This study examines the adoption of fintech services for sustainable investments in the blue economy. To maintain clarity and avoid redundancy, the context of "fintech services for sustainable investments in the blue economy" is established at the outset and applies to all hypotheses discussed below.

Relative advantage (RA) bears similarities to the concept of perceived usefulness (G. C. Moore & Benbasat, 1991). While RA involves comparing a new solution to past solutions, perceived usefulness (PU) concerns the extent to which a user perceives the usage of a given solution to improve their work efficiency (Yeh & Teng, 2012). When users perceive significant advantages from fintech solutions, they are likely to find these tools useful for sustainable investments (Abdul-Rahim et al., 2022). Fintech solutions that provide more efficient, cheaper, and accessible opportunities to invest in securities are likely to be used by stakeholders, especially when these solutions are sustainable. Bureshaid (2021) supports this view, highlighting that fintech solutions that provide more efficient, cheaper, and accessible opportunities are likely to be adopted by bank consumers. Therefore, we hypothesize the following:

H1. *The perceived relative advantage (RA) is positively associated with their perceived usefulness (PU).*

In addition to influencing perceived usefulness, relative advantage may also impact perceptions of ease of use. Fintech solutions that offer clear efficiency gains—such as time savings or improved accessibility—may encourage users to invest effort in learning how to use them, thereby lowering perceived difficulty (Amnas et al., 2023; Dwianto et al., 2024). Over time, familiarity gained through perceived benefit can lead users to view the technology as easier to use. As prior work notes, a high perceived value may offset initial complexity and reduce resistance to use (Jha & Dangwal, 2024). Therefore, we hypothesize the following:

H2. *The perceived relative advantage (RA) is positively associated with their perceived ease of use (PEU).*

When fintech tools are more compatible with traditional systems and existing business models, it becomes easier for investors to understand and embrace these tools. This compatibility can include integration with existing systems for environmental reporting, or frameworks aimed at sustainable finance. When fintech solutions align with traditional approaches to investment management, they offer benefits such as better decision-making, growth efficiency, and more sustainable reporting (Dadabada, 2025). Bureshaid (2021) supports this view, highlighting that compatibility with existing systems and practices enhances PU. This alignment suggests that stakeholders will view fintech as valuable and beneficial for their goals in the blue economy. Therefore, we hypothesize the following:

H3. *The perceived compatibility (COM) is positively associated with their perceived usefulness (PU).*

Enhanced compatibility with the current systems and procedures makes the system easier to implement, since there is little need for additional training or redesigning other processes (Venkatesh et al., 2002). Accordingly, fintech solutions that can be easily incorporated into today's established best practices of blue economy investment vehicles are considered more user-friendly and hence receive more support. Fintech solutions for sustainable blue economy investments that are more compatible with existing practices are likely to be perceived as easier to use, potentially facilitating their adoption and integration into investment processes (Thiele & Gerber, 2017). Therefore, we hypothesize the following:

H4. *The perceived compatibility (COM) is positively associated with their perceived ease of use (PEU).*

When fintech solutions are perceived as overly complex, stakeholders may struggle to integrate them into existing systems or face steep learning curves, making the solutions appear burdensome rather than beneficial (Liu et al., 2024). High complexity can deter adoption by increasing the effort required to understand and apply the technology (Alamsyah et al., 2021). This perception undermines the solution's usefulness, as inefficiencies and operational barriers outweigh potential benefits. Prior studies confirm that increased complexity is associated with lower perceived usefulness (Wischnewski, 2020). Therefore, we hypothesize the following:

H5. *The perceived complexity (COMP) is negatively associated with their perceived usefulness (PU).*

This complexity also influences perceptions of ease of use. When users encounter systems that are difficult to navigate or require substantial learning, they are less likely to consider them user-friendly (Gregor & Benbasat, 1999). The added cognitive and procedural demands lower usability, which in turn reduces adoption likelihood. Prior findings emphasize the importance of simplicity in enhancing accessibility (Aysan & Bergigui, 2021). Thus, we hypothesize the following:

H6. *The perceived complexity (COMP) is negatively associated with their perceived ease of use (PEU).*

When users have the opportunity to test fintech solutions before committing to full adoption, they gain first-hand experience with the technology's features and benefits. This trial phase reduces perceived risk and enhances understanding of the tool's value, particularly in improving investment efficiency, operational workflows, and sustainability reporting (Roh et al., 2024). Direct interaction helps users form a clearer perception of the solution's practical advantages, strengthening beliefs about its utility (Abdul-Rahim et al., 2022). Therefore, we hypothesize the following:

H7. *The perceived trialability (TR) is positively associated with their perceived usefulness (PU).*

Trialability also contributes to ease of use by enabling users to explore a fintech system in a controlled or limited manner. This process allows them to understand how well the technology integrates with existing workflows and regulatory expectations in sustainable investment contexts. Exposure through experimentation reduces perceived complexity and fosters familiarity with the interface and functionality (Sanchez et al., 2020; Yoon et al., 2020). Thus, we hypothesize the following:

H8. *The perceived trialability (TR) is positively associated with their perceived ease of use (PEU).*

Perceived observability (OBS) is valuable in the adoption of new technologies, as it allows potential users to see the tangible benefits and successful outcomes of the innovation, thereby reducing uncertainty and increasing trust in the technology (Poorangi et al., 2013). The visible success of fintech solutions reassures potential users that the technology is practical and beneficial (Bakkabulindi, 2014). When the benefits of fintech solutions are easily observable, they reduce the perceived complexity, making the technology seem more accessible and less intimidating (Valizadeh et al., 2020). Therefore, we hypothesize the following:

H9. *The perceived observability (OBS) is positively associated with their perceived usefulness (PU).*

Beyond shaping perceptions of utility, observability can influence how users assess the ease of using fintech tools. When stakeholders can visibly track how fintech applications improve processes—such as enhancing efficiency or simplifying ESG compliance—they are more likely to perceive the technology as accessible and user-friendly (Park, 2024). In sustainability-oriented sectors like the blue economy, where transparency and performance visibility are essential, observability helps to demystify technological complexity (Rashidi et al., 2015; Valizadeh et al., 2020). Thus, we hypothesize the following:

H10. *The perceived observability (OBS) is positively associated with their perceived ease of use (PEU).*

When fintech solutions are easy to understand and navigate, users are more likely to feel comfortable using them, which enhances their perception of usefulness (Nizar et al., 2024). In the blue economy, where many users may lack prior exposure to sustainable finance platforms, the ease of use lowers entry barriers and reduces the cognitive load associated with complex investment decisions (Lun et al., 2024). By simplifying the user experience, fintech tools enable investors to concentrate on their financial and sustainability goals. This link between ease of use and perceived usefulness is well established in both the DOI and TAM frameworks, which emphasize that usability directly supports perceived value (Ahn & Park, 2023). Therefore, we hypothesize the following:

H11. *The perceived ease of use (PEU) is positively associated with their perceived usefulness (PU).*

Perceived usefulness is widely recognized as a key driver of behavioral intention to adopt new technologies. When users believe that fintech services improve investment performance, efficiency, or decision-making, their likelihood of adoption increases (Gupta et al., 2024). This relationship is foundational to the TAM, where usefulness has a direct effect on intention (Davis, 1989). Within the sustainability-oriented blue economy, where the stakes include both financial return and ecological outcomes, recognizing the utility of fintech solutions becomes even more critical for adoption. Thus, we hypothesize the following:

H12. *The perceived usefulness (PU) is positively associated with the intention to adopt fintech services (IAFS).*

When users perceive fintech solutions as easy to use, they are more likely to develop favorable attitudes toward their adoption—even before fully evaluating the benefits. A straightforward interface and intuitive user experience can reduce resistance and enhance trust, especially among stakeholders unfamiliar with digital investment tools. This direct effect of perceived ease of use on adoption intention is well supported in the technology acceptance literature (Davis, 1989; Shahzad et al., 2022). In the context of sustainable investing, ease of use becomes particularly important, as users must often engage with complex ESG-related data and tools (Jetzek, 2017). Therefore, we hypothesize the following:

H13. *The perceived ease of use (PEU) is positively associated with the intention to adopt fintech services (IAFS).*

Fintech services have significantly altered the financial landscape by enhancing access to information and expanding participation in investment markets. By utilizing data-driven platforms and sophisticated tools, fintech enables investors to make well-informed decisions, including those that align with sustainability objectives (Zhou et al., 2022). This heightened clarity allows for a more thorough evaluation of sustainable investment prospects. The straightforward and intuitive design of fintech platforms effectively reduces barriers to entry, thereby enhancing the accessibility of sustainable investing for a broader demographic (Gomber et al., 2017).

Alongside enhancements in processes, fintech firms provide cutting-edge financial products—like green bonds and ESG-linked instruments—that actively contribute to environmental initiatives (Lee & Shin, 2018). These tools integrate financial goals with sustainability results, especially in developing areas such as the blue economy. Additionally, fintech platforms frequently offer educational resources that improve the understanding of sustainable investment strategies (Dorfleitner et al., 2017), which particularly attracts younger investors who prioritize sustainability (Bollaert et al., 2021).

Personalization serves as a significant factor in driving outcomes. By utilizing big data and AI, fintech platforms are capable of providing customized investment recommendations that focus on both potential returns and environmental considerations (Jagtiani & Lemieux, 2019). Although previous research has examined the connection between fintech utilization and sustainable investment, there is a notable lack of focus on this interaction within the context of the blue economy.

This study investigates the extent to which the intention to adopt fintech services plays a significant role in influencing sustainable investment behavior within the blue economy. Consequently, we propose the following hypothesis:

H14. *The intention to adopt fintech services (IAFS) is positively associated with sustainable investment decisions in the blue economy (SIBE).*

The discussed theories and models are summarized in Figure 1, which illustrates the relationships between the DOI and TAM constructs and their impact on the IAFS and SIBE.

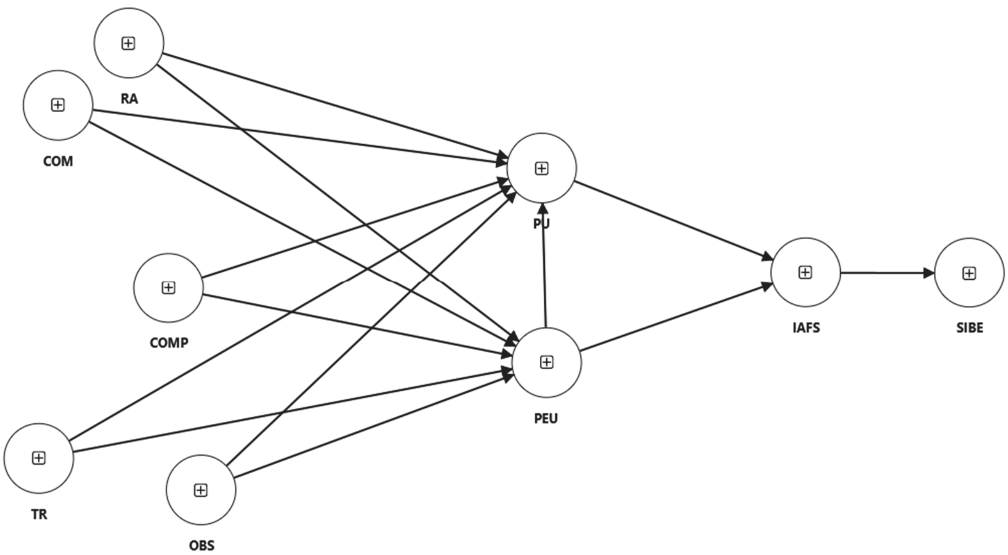

Figure 1. Conceptual model, where: RA: relative advantage, COM: compatibility, COMP: complexity, TR: trialability, OBS: observability; PEU: perceived ease of use; PU: perceived usefulness; IAFS: intention to adopt fintech services; SIBE: sustainable investment decisions in the blue economy. Source: authors' work.

3. Research Methods

To validate the model and develop hypotheses, a comprehensive questionnaire was designed as the primary data collection instrument. This method was selected for its capability to collect a large number of responses, capturing an extensive range of variables relevant to the research (Bergmann et al., 2016). The questionnaire facilitated the systematic and purposeful collection of quantitative data, which was essential for testing the anticipated hypotheses and ensuring the credibility and accuracy of the findings. The questionnaire was meticulously developed to encompass all aspects of the study. It was divided into two sections, each addressing different facets of the research. The first section focused on the hypotheses, incorporating items designed to measure the hypotheses proposed in the study. To ensure the validity of the questions, both internal and face validity tests were conducted. Internal validity was maintained by constructing items based on theoretical assertions of the factors. This involved a thorough review of the existing literature and theoretical frameworks relevant to the study. Each item in the questionnaire was carefully planned to align with the constructs being measured, ensuring that the questions accurately reflected the theoretical concepts. Face validity was established through consultations with a board of eight experts from both academia and industry. These professionals were nominated based on their extensive familiarity with and understanding of fintech, sustainable investments, and the blue economy. The panel included the following:

- Academic experts: four professors and researchers from leading universities in India and internationally, specializing in fintech, sustainable finance, and technology adoption models, with a focus on applications within the blue economy;
- Industry experts: four professionals from the fintech sector, including senior executives, product managers, and consultants with practical experience in fintech solutions and their implementation in sustainable investment contexts, particularly within the blue economy.

These experts reviewed the questionnaire to ensure that the items were clear, relevant, and comprehensive. Their feedback was instrumental in refining the questions to enhance their clarity and relevance to the study's objectives.

All items were measured using a seven-point Likert scale, ranging from 1 (strongly disagree) to 7 (strongly agree) (Jangir et al., 2022; Sharma et al., 2024a). This scale allowed for a nuanced quantitative analysis of the responses. The questionnaire included nine constructs and 45 measures, each representing a different aspect of the study's theoretical framework. A summary of the constructs and number of items is presented in Table 1, while the full list of measurement items, along with their references, is provided in Appendix A. Each statement in the questionnaire was accompanied by a scoring system, enabling detailed quantitative analysis. The data collection process was designed to be comprehensive and systematic, ensuring that all relevant variables were captured accurately.

Table 1. Summary of constructs and measurement items.

Construct	No. of Items	Key References
Relative Advantage	5	Al-Rahmi et al. (2021); Sin et al. (2016); Yoon et al. (2020)
Compatibility	5	Gomber et al. (2017); Thiele and Gerber (2017)
Complexity	5	Färe et al. (1994); Gai et al. (2017); Liu et al. (2024)
Trialability	5	Park (2024); Roh et al. (2024); Yoon et al. (2020)
Observability	5	Park (2024); Rashidi et al. (2015); Valizadeh et al. (2020)
Perceived Ease of Use	5	Hendrickson and Latta (1996); Kumar et al. (2025); Madi et al. (2024)

Table 1. *Cont*.

Construct	No. of Items	Key References
Perceived Usefulness	5	Dahleez et al. (2024); Kumar et al. (2025); Venkatesh and Davis (2000)
Intention to Adopt FinTech Services	5	Bajunaied et al. (2023); Senyo and Osabutey (2020)
Sustainable Investment Decisions in the Blue Economy	5	Colgan and Scorse (2020); Pace et al. (2023); Spalding (2016); Thompson (2022); Zhang (2023)

Note: The respondents were informed that the following questions were designed to understand their perspectives on fintech adoption for sustainable investments within the blue economy. They were asked to consider their experiences and intentions related to sustainable investments in marine resources, ocean energy, sustainable fisheries, and other blue economy sectors when responding to the questions.

To ensure the relevance of the sample, a pre-screening step was implemented to confirm that the respondents were suitable for the study. Potential participants were first asked the following qualifying question:

"Do you have experience in making investment decisions related to sustainable projects within the blue economy (e.g., marine resources, ocean energy, sustainable fisheries)?".

Only those who answered affirmatively were permitted to proceed with the full survey.

As no centralized database or official estimate exists for professionals engaged in blue economy-related investment decisions in India, the total population size remains unknown. Consequently, the study used non-probability convenience sampling, which is suitable for exploratory research involving hard-to-reach or undefined populations (Holden et al., 2015). While this limits the formal generalizability, it ensures practical relevance and access to knowledgeable participants.

The survey was distributed via a Google Form across various online professional and social platforms. Specific outreach was made to relevant LinkedIn networks, WhatsApp groups, and professional forums, targeting active individuals in sustainable finance, fintech, maritime industries, and the blue economy. While the questionnaire was distributed nationwide, particular attention was given to coastal regions such as Maharashtra, Kerala, Tamil Nadu, Gujarat, and Andhra Pradesh, where blue economy activities and fintech adoption are most prominent. Responses were also received from national-level professionals based in financial and administrative centers like Delhi and Bengaluru. The investigation link was shared during the summer of 2024 to maximize participation from professional investors engaged in sustainable investment decisions within the blue economy.

To define the least sample size required for this study, G*Power software version 3.1.9.7 (Kang, 2021) from Heinrich Heine University in Düsseldorf, Germany, was used. The calculation measured a projected effect size of 0.3 (medium), an anticipated statistical power level of 0.8, nine latent variables, a probability level of 0.05, and the number of predictors (Hu et al., 2021). This approach determined that a minimum sample size of 67 respondents was necessary to detect meaningful effects and provide reliable results. The final sample of 224 valid responses substantially exceeds this threshold, ensuring adequate statistical power for hypothesis testing.

To confirm the reliability and validity of the questionnaire, a pilot study was conducted with 35 respondents. Julious (2005) suggests a sample size of 12 per group as a rule of thumb for pilot studies; we opted for a larger sample size to improve the robustness of our findings. In social science research, pilot studies often use sample sizes ranging from 10 to 40 participants per group, depending on the study's complexity and objectives (Viechtbauer et al., 2015). Conducting the pilot study with 35 respondents allowed us to gather more comprehensive feedback and make more informed adjustments to the questionnaire, thereby improving its clarity and comprehensiveness. The pilot study yielded reasonable results, indicating that the questionnaire was both reliable and valid. Based on the feedback and results from the pilot study, minor adjustments were made to improve the clarity and comprehensiveness.

Following the pilot study, 400 questionnaires were distributed to managers and executives involved in sustainable investment decisions in the blue economy. Out of the 400 distributed questionnaires, we obtained the following results:

- A total of 224 responses were accurately completed and considered valid for analysis;
- A total of 124 responses were excluded due to incomplete or improperly completed questionnaires;
- A total of 52 questionnaires did not receive any response and were consequently excluded from the examination.

This study employed PLS-SEM to examine the data. PLS-SEM was chosen for its strength in managing complex models and its ability to deliver reliable estimates even with smaller sample sizes (J. Hair et al., 2017). This method allowed for the examination of the associations among latent variables and the testing of the proposed hypotheses. The analysis included several key steps:

- Factor analysis was conducted to validate the constructs and ensure that the items were loaded appropriately onto their respective factors. Factor analysis helped to confirm that the questionnaire items accurately represented the underlying theoretical constructs;
- Reliability analysis was completed to assess the internal consistency of the constructs. This analysis ensured that the items within each construct reliably measured the same fundamental concept, typically evaluated using Cronbach's alpha;
- Regression analysis was used to test the associations between the latent variables and validate the hypothetical model. This step involved inspecting the direct and indirect effects of the constructs on each other, thereby providing insights into the merits and direction of these relationships.

The additional section of the questionnaire aimed to gather demographic data about the respondents. This section comprised queries about the respondent's gender, age, income, organizational affiliation, and geographic region. Gathering demographic statistics was vital for understanding the background of the contributors.

4. Results

Authors should discuss the results and how they can be interpreted from the perspectives of previous studies and working hypotheses. The findings and their implications should be discussed in the broadest context possible. Future research directions may also be highlighted.

4.1. Sample Demographics

The demographic data collected in this study offers a comprehensive overview of the respondents' characteristics, which is crucial for understanding the context of the subsequent analyses. The data includes information on gender, age, and annual income, as summarized in Table 2.

The majority of respondents are male, accounting for 84.82% (190 respondents). Female respondents make up 15.18% (34 respondents). The age group with the maximum representation is 35–39 years, comprising 31.70% (71 respondents). The next largest age groups are 30–34 years (28.57%, 64 respondents) and 25–29 years (11.16%, 25 respondents). Respondents above 40 years make up 19.64% (44 respondents). The smallest age group is 20–24 years, constituting 8.93% (20 respondents). A significant majority of respondents (84.37%, 189 respondents) have an annual income of more than INR five lakhs. The remaining 15.63% (35 respondents) have an annual income of less than INR five lakhs.

Table 2. Demographic statistics.

Demographics	Respondents	%
Gender		
Male	190	84.82
Female	34	15.18
Age		
20–24	20	8.93
25–29	25	11.16
30–34	64	28.57
35–39	71	31.70
Above 40	44	19.64
Annual income (in INR)		
Less than five lakhs	35	15.63
More than five lakhs	189	84.37
Organizational affiliation		
Fintech companies	78	34.82
Maritime/Blue economy firms	61	27.23
Investment funds/Asset managers	43	19.20
Government/Regulatory bodies	24	10.71
Consulting/NGOs/Advisory firms	18	8.04
Geographic Region (States Represented)		
West Coast (Maharashtra, Goa, Gujarat)	60	26.79
East Coast (Tamil Nadu, Andhra Pradesh, Odisha)	50	22.32
South (Inland) (Karnataka, Telangana)	32	14.29
North (Delhi, Haryana, Punjab)	40	17.86
East and Northeast (West Bengal, Assam, Jharkhand)	22	9.82
Central India (Madhya Pradesh, Chhattisgarh)	20	8.93

The organizational affiliation of respondents spans several sectors. While respondents were not limited to blue economy organizations, all had confirmed experience with investment decisions in the context of blue economy sectors, confirmed through a pre-screening question. The largest group (34.82%, 78 respondents) worked in fintech companies, followed by those in maritime or blue economy-related firms (27.23%, 61 respondents), investment funds or asset managers (19.20%, 43 respondents), government or regulatory bodies (10.71%, 24 respondents), and consulting, NGO, or advisory firms (8.04%, 18 respondents).

Geographically, the sample includes respondents from both coastal and inland regions of India. The West Coast (Maharashtra, Goa, Gujarat) is represented by 26.79% of respondents, the East Coast (Tamil Nadu, Andhra Pradesh, Odisha) by 22.32%, and North India (Delhi, Haryana, Punjab) by 17.86%. Respondents from South India (inland) make up 14.29%, East and Northeast India 9.82%, and Central India 8.93%. This regional spread reflects the diversity of the professional investors engaged with the blue economy across India.

4.2. Structural Model and Discriminant Validity

In this section, we present the results of the SEM analysis, which tests the proposed hypotheses and examines the relationships between the constructs. The analysis includes the evaluation of R-square (R^2) and adjusted R-square values to determine the explanatory power of the model for each construct (see Table 3).

Table 3. R-square values.

Constructs	R-Square	R-Square Adjusted
PEU	0.622	0.613
PU	0.524	0.511
IAFS	0.559	0.555
SIBE	0.442	0.439

Table 4 shows the predictive power of four constructs—PEU, PU, IAFS, and SIBE—in sustainable investment decisions in the blue economy. The PEU construct has the highest R-square value (0.622), explaining 62.2% of its variance, indicating that it is a primary predictor in the model. IAFS follows, with an R-square of 0.559, showing a substantial impact, with 55.9% of its variance explained. PU has an R-square of 0.524, meaning 52.4% of its variance is accounted for, suggesting a significant influence. SIBE has the lowest R-square at 0.442, with 44.2% of its variance explained, indicating a moderate effect (Yuniarti, 2022).

Table 4. Construct reliability and validity.

Constructs	Coding	Factor Loadings	Cronbach's	Alpha rhoA	Composite	Reliability AVE
Relative Advantage	RA	0.392 0.893 0.924 0.899 0.654	0.812	0.858	0.878	0.608
Compatibility	COM	0.645 0.742 0.830 0.814 0.780	0.820	0.827	0.875	0.585
Complexity	COMP	0.774 0.766 0.804 0.839 0.784	0.854	0.861	0.895	0.630
Trialability	TR	0.882 0.878 0.880 0.890 0.899	0.931	0.934	0.948	0.785
Observability	OBS	0.904 0.917 0.922 0.914 0.898	0.949	0.949	0.961	0.830
Perceived Ease of Use	PEU	0.778 0.804 0.795 0.813 0.793	0.859	0.865	0.897	0.635

Table 4. *Cont*.

Constructs	Coding	Factor Loadings	Cronbach's	Alpha rhoA	Composite	Reliability AVE
Perceived Usefulness	PU	0.813 0.830 0.848 0.774 0.762	0.867	0.868	0.903	0.650
Intention to Adopt FinTech Services	IAFS	0.768 0.806 0.782 0.762 0.721	0.827	0.828	0.878	0.590
Sustainable Investment Decisions in the Blue Economy	SIBE	0.875 0.915 0.900 0.925	0.877	0.885	0.918	0.699

Source: Created using PLS-SEM.

Table 4 shows the construct reliability and validity of various factors that impact fintech adoption and sustainable investment decisions.

The Cronbach's alpha values are all above 0.70, indicating solid internal consistency, with particularly high values for Trialability (0.931) and Observability (0.949). Composite reliability scores also exceed the 0.70 threshold (Pokhrel & K.C., 2024), demonstrating consistent measurement across items, with Trialability and Observability again showing high reliability (0.948 and 0.961, respectively). The Average Variance Extracted (AVE) values for all constructs surpass the 0.50 threshold, indicating good convergent validity, as seen with the high AVE scores for Observability (0.830), Trialability (0.785), and Sustainable Investment Decisions in the Blue Economy (0.699). These metrics collectively confirm that the constructs are reliable and valid for evaluating sustainable investment decisions in the blue economy (Baudry et al., 2024; Cheung et al., 2024).

Table 5 shows the discriminant validity using the HTMT ratio matrix and HTMT criterion; values below 0.85 indicate good discriminant validity, ensuring that each construct measures a unique impression (Henseler, 2017).

Table 5. Discriminant validity.

Heterotrait–Monotrait Ratio Matrix	RA	COM	COMP	TR	OBS	PEU	PU	IAFS
COM	0.625							
COMP	0.514	0.473						
TR	0.416	0.627	0.345					
OBS	0.442	0.677	0.428	0.434				
PEU	0.808	0.570	0.358	0.500	0.640			
PU	0.737	0.718	0.372	0.468	0.503	0.660		
IAFS	0.561	0.666	0.461	0.539	0.747	0.711	0.815	
SIBE	0.426	0.658	0.308	0.430	0.802	0.635	0.584	0.766

Source: Created using PLS-SEM.

COM and COMP have a low correlation (HTMT = 0.473), while PU and RA show a moderate association (HTMT = 0.737), both within acceptable limits. TR and OBS demonstrate a low correlation (HTMT = 0.434), indicating clear differentiation. PEU exhibits moderate correlations with RA (HTMT = 0.808) and IAFS (HTMT = 0.711), both of which are within acceptable bounds. Additionally, SIBE has moderate HTMT values with OBS (HTMT = 0.802) and IAFS (HTMT = 0.766), confirming acceptable levels of construct distinction. Overall, these HTMT values affirm the constructs' distinctiveness, supporting the model's discriminant validity (Montiel et al., 2021).

Table 6 shows the Fornell–Larcker criterion values, confirming discriminant validity by comparing the square basis of the AVE for each construct (crosswise) with correlations between constructs (Putra et al., 2021).

Table 6. Fornell–Larcker criterion.

Constructs	RA	COM	COMP	TR	OBS	PEU	PU	IAFS	SIBE
RA	0.765								
COM	0.410	0.794							
COMP	0.565	0.398	0.768						
TR	0.550	0.313	0.486	0.886					
OBS	0.600	0.395	0.683	0.410	0.911				
PEU	0.489	0.322	0.623	0.446	0.584	0.797			
PU	0.598	0.331	0.706	0.424	0.457	0.603	0.806		
IAFS	0.469	0.416	0.450	0.346	0.384	0.695	0.608	0.780	
SIBE	0.560	0.274	0.665	0.387	0.731	0.549	0.514	0.341	0.836

Source: Created using PLS-SEM.

For each construct, the square root of the AVE (on-diagonal values) is compared with inter-construct correlations (off-diagonal values). Discriminant validity is confirmed if a construct's AVE square root is higher than its correlations with other constructs (Henseler et al., 2015). For instance, RA has a diagonal value of 0.765, which exceeds its correlations with COM at 0.410 and COMP at 0.565, indicating distinctiveness. Similarly, COM has a diagonal value of 0.794, which exceeds its correlations with COMP at 0.398 and TR at 0.313. Each construct's AVE square root surpasses all inter-construct correlations, confirming strong discriminant validity across the model.

Given the use of self-reported structured questionnaires as the primary data collection method, there is an inherent risk of common method bias (CMB), which could threaten the validity of the results. To mitigate this risk and assess the potential impact of CMB, we employed the full collinearity assessment approach proposed by Kock (2015). This approach involves evaluating the variance inflation factor (VIF) values for all latent constructs in the model. According to this method, VIF values exceeding the threshold of 3.3 may indicate problematic collinearity and potential CMB. As shown in Table 7, all latent constructs in our study had VIF values well below this critical value, ranging from 2.18 to 2.94. These results suggest that common method bias is unlikely to compromise the validity of the findings in this study.

In addition to examining path significance and R^2 values, we assessed effect sizes (f^2) and predictive relevance (Q^2), in accordance with J. F. Hair et al. (2019). The f^2 statistic evaluates the contribution of each exogenous construct to the explained variance (R^2) of its corresponding endogenous construct. As per Cohen (1988), f^2 values of 0.02, 0.15, and 0.35 indicate small, medium, and large effects, respectively. Notably, relative advantage had a large effect on perceived usefulness, and perceived usefulness showed a strong effect on intention to adopt fintech services. Other constructs exhibited small-to-moderate effects, reinforcing their relevance in the model.

Table 7. Full collinearity VIFs for latent constructs.

Latent Construct	VIF
Relative Advantage (RA)	2.45
Compatibility (COM)	2.31
Complexity (COMP)	2.67
Trialability (TR)	2.18
Observability (OB)	2.49
Perceived Ease of Use (PEU)	2.83
Perceived Usefulness (PU)	2.71
Intention to Adopt Fintech Services (IAFS)	2.94
Sustainable Investment Decisions in the Blue Economy (SIBE)	2.56

Predictive relevance was assessed using the Q^2 value generated via the blindfolding procedure. Q^2 values above zero indicate that the model has predictive capability. Following J. Hair and Alamer (2022), values of 0.02, 0.15, and 0.35 reflect weak, moderate, and strong predictive power. In our model, key endogenous constructs such as PU, PEU, and SIBE recorded Q^2 values substantially above 0.35, demonstrating strong predictive relevance.

4.3. Hypothesis Testing Results

Table 8 shows the results of hypothesis testing, highlighting the relationships between variables affecting the IAFS and sustainable investment decisions in the blue economy. The study highlights significant and non-significant relationships based on path coefficients (β), *p*-values, and statistical significance.

Table 8. Summary of hypothesis testing results.

Hypothesis	Path Coefficient (β)	Sample Mean (M)	Standard Deviation (STDEV)	T Statistic	*p*-Value	Significance
H1: RA -> PU	0.283	0.284	0.097	2.913	0.004 ***	Yes
H2: RA -> PEU	0.557	0.559	0.064	8.715	0.000 ***	Yes
H3: COM -> PU	0.334	0.340	0.089	3.772	0.000 ***	Yes
H4: COM -> PEU	−0.041	−0.035	0.073	0.569	0.569	No
H5: COMP -> PU	−0.010	−0.003	0.074	0.141	0.888	No
H6: COMP -> PEU	−0.086	−0.083	0.051	1.689	0.091	No
H7: TR -> PU	0.044	0.040	0.087	0.508	0.611	No
H8: TR -> PEU	0.153	0.150	0.067	2.280	0.023 **	Yes
H9: OBS -> PU	0.003	0.000	0.094	0.032	0.974	No
H10: OBS -> PEU	0.367	0.361	0.064	5.759	0.000 ***	Yes
H11: PEU -> PU	0.225	0.222	0.097	2.324	0.020 **	Yes
H12: PU -> IAFS	0.519	0.519	0.060	8.582	0.000 ***	Yes
H13: PEU -> IAFS	0.310	0.311	0.068	4.553	0.000 ***	Yes
H14: IAFS -> SIBE	0.665	0.667	0.042	15.693	0.000 ***	Yes

Source: Authors' calculation. Note(s): Path Coefficient (significance levels: $p < 0.01$ is denoted by **; $p < 0.001$ is denoted by ***.); β—Path Coefficient; STDEV—Standard Deviation; and M—Sample Mean.

The study presents findings in Table 8, indicating that the perceived relative advantage has a significant positive effect on perceived usefulness (H1: β = 0.283, *p* = 0.004 ***). This suggests that when users perceive significant advantages from fintech solutions, they are likely to find these tools useful for sustainable investments. Furthermore, the perceived relative advantage significantly influences perceived ease of use (H2: β = 0.557, *p* = 0.000 ***), indicating that if fintech tools provide clear advantages in terms of efficiency and effectiveness, users may find these solutions easier to use. Similarly, compatibility has a significant positive impact on perceived usefulness (H3: β = 0.334, p = 0.000 ***), implying that when fintech solutions align well with users' existing values and practices, they are perceived as more useful. However, compatibility does not significantly influence perceived ease of use (H4: β = −0.041, p = 0.569), suggesting that even if fintech services align with users' needs, they may still appear complex. Regarding complexity, hypothesis H5 indicates that it does not significantly affect perceived usefulness (H5: β = −0.010, p = 0.888), but that complexity does not significantly affect perceived ease of use either (H6: β = −0.086, p = 0.091). This suggests that complexity does not have a strong impact on how easy users find fintech solutions to use. Hypotheses H7 and H8 examine the role of trialability. H7 shows that trialability does not significantly affect perceived usefulness (H7: β = 0.044, p = 0.611), indicating that the ability to try fintech solutions does not necessarily enhance their perceived usefulness. However, H8 shows the significant positive effect of trialability on perceived ease of use (H8: β = 0.153, p = 0.023 **), suggesting that the ability to experiment with fintech solutions makes them easier to use. Although observability does not significantly impact perceived usefulness (H9: β = 0.003, p = 0.974), it has a significant positive effect on perceived ease of use (H10: β = 0.367, p = 0.000 ***). This suggests that when the benefits of fintech solutions are easily observable, they are perceived as easier to use.

Further analysis in H11 demonstrates that the perceived ease of use significantly influences perceived usefulness (H11: β = 0.225, p = 0.020 **).

Similarly, perceived usefulness has a significant effect on the intention to adopt fintech services (H12: β = 0.519, p = 0.000 ***), indicating that when users find fintech solutions useful, they are more likely to adopt them. The analysis of hypothesis H13 indicates that ease of use is an important factor influencing the adoption of fintech services. Specifically, H13 shows a beta coefficient of 0.310 and a p-value of 0.000 ***. Similarly, H14 also finds a significant relationship (H14: β = 0.665, p = 0.000 ***). This indicates that IAFS plays an important role in leading to sustainable investment decisions in the blue economy.

Figure 2 shows the structural model showcasing the relationships among various constructs influencing fintech adoption and sustainable investment decisions in the blue economy.

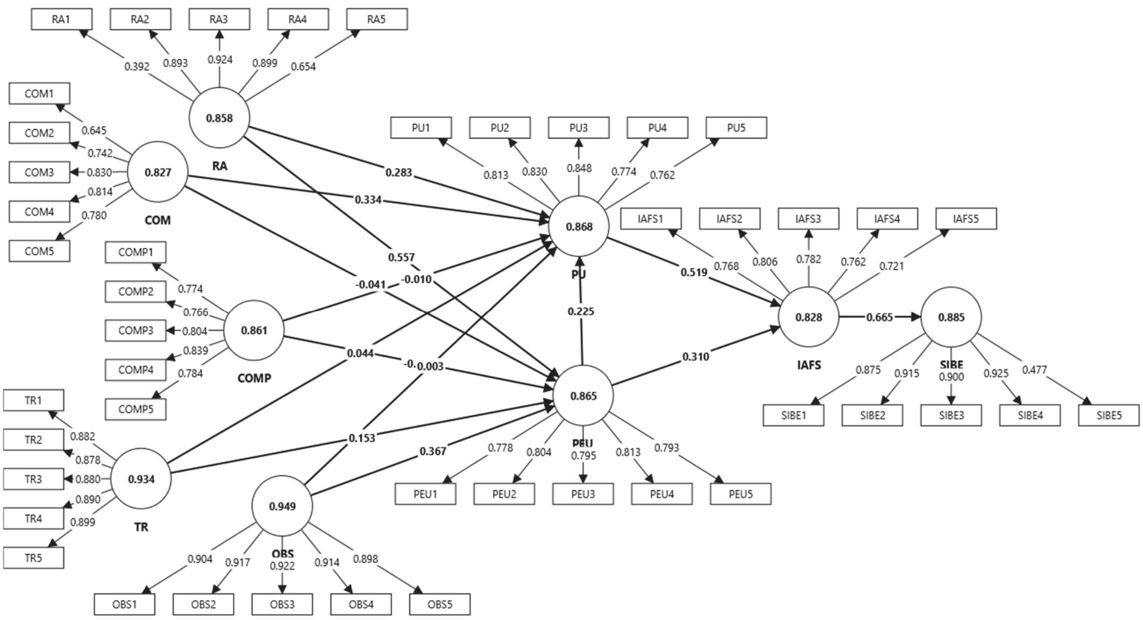

Figure 2. Structural model of fintech adoption and sustainable investment decisions in the blue economy, where: RA: relative advantage, COM: compatibility, COMP: complexity, TR: trialability, OBS: observability; PEU: perceived ease of use; PU: perceived usefulness; IAFS: intention to adopt fintech services; SIBE: sustainable investment decisions in the blue economy. Source: Created using Smart PLS-SEM.

5. Discussion

This study provides important insights into the factors influencing fintech adoption for sustainable investment within India's blue economy. By integrating constructs from the Diffusion of Innovations (DOI) theory and the Technology Acceptance Model (TAM), we analyze how specific characteristics shape user behavior in a context marked by resource constraints, limited digital literacy, and localized investment cultures.

Relative advantage significantly influences both perceived usefulness (PU) and perceived ease of use (PEU). The DOI theory posits that when users perceive a new technology as offering substantial benefits over the existing solutions, adoption becomes more likely. In our study, participants included coastal entrepreneurs, small-scale fishers, and sustainable investors—groups often underserved by traditional finance. For them, fintech platforms represent tangible improvements: easier access to credit, better data analytics for marine resource management, and streamlined payment systems. These direct, practical benefits not only reinforce fintech's usefulness, but also make it appear more approachable. This supports prior work (e.g., M. Moore et al., 2016; Yeh & Teng, 2012) and aligns with Abdul-Rahim et al. (2022), who emphasize efficiency and accessibility as key adoption drivers. However, in our sample, the significant impact on the PEU may be uniquely strong due to low baseline digital expectations; even modestly intuitive platforms may be viewed as "easy to use" in contrast to previous informal or manual systems.

Compatibility significantly impacts PU, but not the PEU. The DOI theory suggests that innovations congruent with existing values and practices are perceived as more beneficial. Our participants often rely on traditional community-led financial systems and sustainability-oriented goals. Fintech solutions that support cooperative lending, integrate ESG metrics, or provide transparent reporting are seen as aligning well with their existing financial philosophies; hence, they are perceived as useful. Yet, compatibility does not significantly influence ease of use, contrasting with Bureshaid (2021). This discrepancy may stem from a contextual disconnect: while users appreciate the alignment with their values, many still face infrastructural or educational barriers that limit ease of use. This nuance underscores the importance of considering external variables in the TAM—even compatible tools may seem difficult without appropriate training or support structures.

Complexity does not significantly affect PU or the PEU. This diverges from studies such as Grover et al. (2019) and Liu et al. (2024), which argue that complexity hinders both perceptions. However, our sample reveals a different reality. For stakeholders in India's blue economy, especially those managing environmental risks and financial exclusion, functionality outweighs interface simplicity. In line with task-technology fit theory, users may overlook technological difficulty if the system delivers critical outcomes—such as mobile loan access or traceable investment for sustainable aquaculture. Moreover, being mostly "late adopters" per the DOI categories, our participants may judge complexity not in absolute terms, but relative to traditional alternatives, which are often slower or more opaque.

Trialability significantly influences the PEU, but not PU. The opportunity to experiment with fintech solutions helps to reduce apprehension and improve user familiarity, echoing Yoon et al. (2020) and Park (2024). In many blue economy communities, early exposure happens through NGO-led workshops or informal peer demonstrations. However, trialability does not significantly increase PU, which contrasts with Abdul-Rahim et al. (2022). This may be because trial experiences often do not capture the full utility of fintech for long-term sustainable investment, or because users focus on interface rather than strategic impact during early trials.

Observability similarly affects the PEU, but not PU. As Valizadeh et al. (2020) suggest, seeing peers successfully use fintech improves one's own confidence in their ability to use it. In our fieldwork, participants often relied on word-of-mouth endorsements or visible success stories from nearby communities. Yet, the visibility of benefits does not automatically translate into perceived usefulness. This may be due to the localized and socially embedded investment mindset in the blue economy: seeing results does not necessarily equate to perceived long-term value unless those results align with one's own goals or environmental priorities.

The PEU significantly influences PU, reinforcing the TAM's core assumption. Tools that are easier to navigate allow users to focus on goals—like sustainable marine investment—rather than system mechanics. This effect may be amplified in the blue economy context, where technical self-efficacy is often low, and users derive value from any reduction in friction.

Both PU and the PEU significantly influence the intention to adopt fintech services (IAFS), as predicted by the TAM. In this context, user-friendly, outcome-oriented platforms are more likely to be embraced by stakeholders who view fintech as a bridge to greater sustainability and inclusivity. Gupta et al. (2024) support this relationship. Notably, participants in our study often referenced environmental stewardship as a motivation for investing, highlighting a convergence between fintech functionality and sustainability goals.

Finally, IAFS significantly impacts sustainable investment behavior in the blue economy (SIBE). This confirms that fintech adoption intentions are a critical gateway to actual behavior change. Zhou et al. (2022) support this, noting that fintech tools empower users through data, access, and simplified processes. In the Indian context, government-backed programs like Sagarmala and PMMSY have increased awareness of blue economy opportunities, but adoption depends on ease of access—where fintech plays a pivotal role.

Some of our findings diverge from the existing literature, which may be explained by the distinctive characteristics of our sample and the Indian blue economy context—such as informal financial systems, collective decision-making processes, and varied levels of digital literacy. These contextual differences underscore the importance of applying the TAM and DOI not as static models, but as flexible frameworks responsive to local realities. Importantly, the study's implications extend beyond academic theory and stakeholder strategy, directly aligning with several of the United Nations Sustainable Development Goals (SDGs)—notably SDG 14 (Life Below Water), SDG 9 (Industry, Innovation, and Infrastructure), and SDG 13 (Climate Action). By facilitating more transparent, accessible, and sustainability-oriented financial systems, fintech adoption in the blue economy can serve as a practical instrument in advancing global sustainability and inclusive development targets.

6. Conclusions

This study investigated the key factors influencing the adoption of fintech services for sustainable investment within the blue economy by integrating the Diffusion of Innovations (DOI) theory and the Technology Acceptance Model (TAM). The findings confirmed that the perceived usefulness and ease of use are central to driving adoption intentions, which in turn significantly impacts sustainable investment behavior. While relative advantage, compatibility, trialability, and observability showed varying effects on these perceptions, complexity did not emerge as a significant barrier. These insights provide a foundation for understanding how digital financial tools can be effectively leveraged to support sustainability goals in marine-based economic sectors.

6.1. Theoretical Implications

This study provides a comprehensive framework for understanding how fintech adoption influences sustainable investment decisions in the blue economy (SIBE). By integrating the DOI theory and the TAM, the research demonstrates the applicability of these models in a context that has received limited theoretical attention. Importantly, the findings also highlight how the influence of key constructs may vary when applied in settings such as the Indian blue economy, where informal financial systems, sustainability priorities, and digital access constraints shape user behavior.

Specifically, the study reveals that complexity does not significantly influence either perceived usefulness (PU) or the perceived ease of use (PEU), suggesting that users may overlook technological challenges if the tools contribute meaningfully to sustainability and efficiency. This underscores the need to interpret TAM constructs with sensitivity to context—where perceived value may outweigh technical barriers.

The significant effect of compatibility on PU—but not on the PEU—also supports the idea that alignment with users' values and investment goals can drive adoption, even when ease of use is not guaranteed. This reinforces prior findings, but also suggests that in mission-driven domains such as sustainable marine investment, value congruence may matter more than interface simplicity.

The observed effects of trialability and observability on the PEU, but not on PU, further refine existing theory. While these factors reduce the perceived effort required to use fintech solutions, they may not fully convey long-term strategic benefits, especially in complex or high-stakes investment contexts. This highlights a potential gap in how short-term engagement translates into long-term adoption, and calls for future research on how fintech trials and demonstrations are designed and perceived.

6.2. Practical Implications

Fintech companies can draw on these findings to design solutions that clearly demonstrate operational advantages and align with existing investment behaviors. These developers should focus on compatibility with localized financial practices, especially in coastal and rural regions. Furthermore, offering trial opportunities and showcasing successful case studies can improve ease of use and encourage adoption. Interface simplicity and local language support could also mitigate perceived challenges in digital literacy.

Maritime and blue economy firms—such as those in fisheries, aquaculture, and ocean-based infrastructure—can leverage fintech tools to improve traceability, financial access, and operational efficiency. However, as the findings show, compatibility with existing workflows and systems is key to increasing perceived usefulness. Fintech solutions that support cooperative lending, marine asset tracking, or sustainability-linked finance may see higher adoption rates when they build on familiar community investment patterns.

The investment funds and asset managers involved in sustainable finance are encouraged by the strong relationship between PU, PEU, and intention to adopt. This reinforces the need for scalable, transparent, and ESG-aligned fintech platforms that can facilitate capital flows into blue economy ventures. As strategic enablers, these actors can promote the best practices in fintech adoption and direct attention toward impact-driven innovations.

Government and regulatory bodies can support adoption by creating enabling environments that improve accessibility while fostering innovation. Given that complexity was not a significant barrier in this study, regulators may focus less on simplification and more on making the benefits of fintech solutions more visible and trusted. This includes integrating fintech into development programs, establishing regulatory sandboxes, or incentivizing adoption in sustainability-critical sectors.

Consulting firms, NGOs, and advisory organizations working at the interface of technology and sustainability are well positioned to drive grassroots engagement. The importance of trialability and observability in shaping ease of use suggests that community demonstrations, capacity-building programs, and peer-led training can play a central role in fintech uptake, especially among informal or small-scale stakeholders.

Across the various geographic regions represented in the study—including India's coastal states and inland economic centers—stakeholder needs and digital readiness levels vary. In high-activity coastal zones, fintech applications are likely to be directly embedded in fisheries, logistics, and marine investment. In northern, inland, and central regions, fintech may play a more supporting role in funding or data provision. This geographical diversity reinforces the importance of adaptable, context-sensitive fintech design and deployment strategies.

6.3. Study Limitations and Future Research

This study has several limitations that should be acknowledged. First, the research employed a cross-sectional design, capturing data at a single point in time. While this approach provides valuable insights, it does not account for changes in perceptions and behaviors over time. Longitudinal studies could offer a more comprehensive understanding of how fintech adoption and sustainable investment behaviors evolve within the blue economy. Second, the study relies on self-reported data, which may be subject to biases such as social desirability or recall bias. Participants might have provided responses they perceived as favorable rather than their true opinions. Future studies could incorporate objective measures or triangulate data sources to mitigate these biases. Third, the research primarily focused on constructs such as PU, PEU, IAFS, and SIBE. While these are critical factors, other relevant variables, such as cultural influences, regulatory environments, and technological infrastructure, were not explored in depth. Future research could expand the scope to include these additional factors.

Additionally, exploring the role of fintech in supporting the United Nations Sustainable Development Goals (SDGs) related to the blue economy could provide a deeper understanding of how fintech solutions can drive sustainable development. Research could focus on how fintech platforms facilitate environmentally friendly investments, improve resource management, and contribute to the conservation and sustainable use of ocean resources.

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Appendix A

Table A1. Measurement items.

Constructs	Statements
Relative Advantage (Al-Rahmi et al., 2021; Sin et al., 2016; Yoon et al., 2020)	Fintech services offer significant advantages over traditional investment methods.
	Using fintech platforms saves me time in managing my investments.
	Fintech tools provide better insights into market trends than other methods.
	Fintech services enhance the overall efficiency of my investment activities.
	The benefits of fintech services outweigh those of traditional investment methods.
Compatibility (Gomber et al., 2017; Thiele & Gerber, 2017)	Fintech services fit well with my existing investment strategies.
	The fintech platforms I use are compatible with my financial goals.
	Fintech services integrate seamlessly into my current investment processes.
	Fintech services align with my investment preferences and habits.
	The use of fintech services complements my overall financial planning.
Complexity (Färe et al., 1994; Gai et al., 2017; Liu et al., 2024)	Fintech platforms seem too complex for my investment needs.
	It is difficult to understand how to use fintech solutions effectively.
	Fintech tools require significant effort to operate efficiently.
	The complexity of fintech services hinders my ability to use them.
	I find it challenging to navigate fintech platforms.
Trialability (Park, 2024; Roh et al., 2024; Yoon et al., 2020)	I had the opportunity to try out fintech services before fully adopting them.
	Fintech services allow me to experiment with different features before committing to them.
	The ability to try fintech solutions before adoption increased my confidence in using them.
	Trial periods for fintech services help me understand their benefits.
	I value the option to test fintech services before making a full commitment.
Observability (Park, 2024; Rashidi et al., 2015; Valizadeh et al., 2020; Yoon et al., 2020)	The benefits of using fintech services are clear and visible in my investment outcomes.
	The success of fintech platforms is evident from their performance in sustainable investments.
	Fintech services provide visible improvements to my investment strategies.
	I can easily observe the positive impact of fintech services on my investments.
	The results of using fintech services are apparent and measurable.
Perceived Ease of Use (Hendrickson & Latta, 1996; Kumar et al., 2025; Madi et al., 2024)	I find the fintech solution easy to use for sustainable investment decisions.
	My interaction with the fintech platform is strong and reasonable.
	I believe I can quickly learn how to use fintech tools for investments.
	The user interface of the fintech platform is intuitive.
	Fintech services are user-friendly and straightforward.
Perceived Usefulness (Dahleez et al., 2024; Kumar et al., 2025; Venkatesh & Davis, 2000)	Fintech tools improve my efficiency in making sustainable investment decisions.
	Using fintech platforms enhances the quality of my investment analysis.
	The fintech platform enables me to manage my investments more effectively.
	Fintech services provide valuable insights that aid my investment decisions.
	The usefulness of fintech tools positively impacts my investment performance.

Table A1. *Cont.*

Constructs	Statements
Intention to Adopt Fintech Services (Bajunaied et al., 2023; Senyo & Osabutey, 2020)	I plan to adopt fintech services for sustainable investments.
	I intend to utilize fintech services for handling my financial transactions in the future.
	I am considering using fintech services to improve my investment strategies.
	I intend to integrate fintech services into my regular financial activities.
	I am likely to recommend fintech services to others for investment purposes.
Sustainable Investment Decisions in the Blue economy (Colgan & Scorse, 2020; Pace et al., 2023; Spalding, 2016; Thompson, 2022; Zhang, 2023)	I make investment decisions that consider the sustainability of the blue economy.
	My investment choices are influenced by the potential environmental impact of my actions.
	I prioritize investments that support the conservation and sustainable use of ocean resources.
	I focus on sustainable financial decisions that contribute to the growth of the blue economy.
	Fintech services help me make more informed sustainable investment decisions.

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What Is Green Fintech?

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Abstract: This paper addresses the definitional ambiguity surrounding the term "green fintech" and its distinction from related concepts such as green finance and sustainable finance. We argue that the lack of clarity impedes accountability and facilitates greenwashing. To resolve this, we develop a conceptual framework grounded in a six-step "litmus test" that specifies the necessary conditions for an initiative to qualify as green fintech. These include demonstrable environmental objectives, the application of innovative financial technologies, and regulatory alignment. The test functions as a diagnostic tool, enhancing verifiability and reducing the risk of misrepresentation. We illustrate its practical use and integrate the Dynamic Integrated Model of Climate and the Economy (DICE) to support the analysis. Green fintech is defined as the implementation of green climate objectives through the medium of financial technology. This contribution provides both definitional precision and a means to assess the credibility of green fintech initiatives, offering clarity in an increasingly complex and contested area of sustainable finance.

Keywords: green fintech; sustainability; digital finance; climate change; blockchain

1. Introduction

This paper addresses the definitional and evaluative ambiguity surrounding the term "green fintech". While the term is increasingly invoked in academic, regulatory, and market discourse, its scope and meaning remain unclear. Green fintech is often conflated with broader categories such as "green finance" or "sustainable finance". This occurs despite significant differences in technological foundation, operational mechanisms, and intended outcomes. This paper offers a precise definition of green fintech and proposes a six-step litmus test to evaluate whether initiatives that self-identify as such satisfy the environmental, technological, and regulatory criteria needed to support sustainability claims.

Financial technology ("fintech") encompasses a wide array of innovations, including blockchain, mobile banking, algorithmic credit scoring, and digital platforms for trading or investment (Broby, 2021). These technologies have transformed the efficiency, accessibility, and transparency of financial services. In environmental contexts, this transformation is increasingly viewed as an enabler of sustainability (Marín-Rodríguez et al., 2024). Green fintech, as the term suggests, encompasses the integration of these digital tools into environmentally focused finance. However, the lack of consensus undermines its conceptual clarity and exposes it to potential misuse.

In the academic literature, we found two explicit definitions. Kwong et al. (2023) describe green fintech as the synergy between financial technology and green finance, aimed at promoting environmental sustainability through innovative financial solutions. They also highlight the need for a better definition. Similarly, Kabaklarlı (2022) defines green fintech as the application of emerging financial services, such as big data, AI, and blockchain, to support environmental goals, particularly emphasizing its role in addressing the ecological footprint of digital finance.

In support of the scholarly framing, we reviewed twenty publicly available definitions of green fintech sourced from government organizations, top web searches, and non-governmental organizations. Our definition emerges from a synthesis of these sources and the key peer-reviewed articles (see Appendix A).

This follows an interpretive content analysis approach. It ensures conceptual breadth and institutional credibility. The comparative analysis of these sources allowed us to identify recurring dimensions that informed the structured definition we now propose:

Definition 1. *Green fintech is the implementation of climate objectives through the medium of financial technology. Utilizing the internet, it involves the integration of technology into finance for the allocation, oversight, and deployment of capital based on green criteria. It enhances the efficiency, accessibility, and scalability of sustainable financial activities, and conforms to regulatory or audit-based verification mechanisms.*

This definition contributes to measurable environmental outcomes. It also avoids the word innovation as many of the technologies are now well established. To operationalize the definition, we introduce a litmus test in Section 4. This test serves as a diagnostic framework to distinguish between legitimate fintech solutions and those that engage in greenwashing. This is the practice of making misleading or unverifiable environmental claims to benefit from market or regulatory incentives.

Greenwashing has become increasingly prevalent as investors, regulators, and the public demand greater accountability in the transition to a low-carbon economy. The term refers to the misrepresentation of financial products or technologies as environmentally beneficial without credible evidence. In the context of green fintech, greenwashing can occur when digital platforms, carbon token systems, or AI-driven ESG tools claim environmental benefits that are neither measurable nor aligned with verified standards. Without defined criteria, green fintech risks becoming a rhetorical device rather than a meaningful classification. Addressing this requires definitional rigor and a systematic evaluative tool.

The proposed framework is grounded in foundational theories from finance, sustainability, and innovation studies. From a financial perspective, the framework builds on capital allocation theory, which holds that financial markets channel resources based on risk-adjusted returns and informational efficiency. In this context, green fintech mechanisms such as ESG scoring or carbon tracking serve to reduce information asymmetries around environmental performance (Healy & Palepu, 2001). From the sustainability literature, the framework draws on the theory of environmental externalities and the role of finance in internalizing social costs through pricing mechanisms (Pigou, 1920; Stiglitz, 1989; Othman, 2025). The objective is to ensure that fintech contributes to allocative efficiency not only in financial returns but also in environmental outcomes.

The motivation for this study is both conceptual and practical. On the one hand, financial systems are increasingly expected to contribute to global climate goals, such as those outlined in the Paris Agreement. On the other, the rapid evolution of fintech has outpaced the development of sustainable governance and assurance mechanisms. As noted by Muganyi et al. (2022), empirical evidence on the relationship between fintech and environmental or developmental outcomes remains limited. While technologies such as blockchain and AI offer clear operational efficiencies, their environmental impact is contingent on how they are used. For example, Kakar et al. (2025) suggest that fintech tools can support biodiversity financing, but, without definitional and methodological consistency, such claims are difficult to assess.

The paper contributes to both definitional clarity and evaluative practice in the green fintech domain. It addresses a gap between high-level sustainability taxonomies and the specific characteristics of fintech applications. While regulatory and academic efforts have articulated broad environmental standards, they often lack operational tools for assessing whether digitally enabled finance initiatives meet these criteria. The litmus test presented here formalizes this process by linking definitional clarity with diagnostic assessment. The intended users of the framework include regulators, ESG auditors, fintech developers, and institutional investors.

The paper therefore fills a gap in the literature by (1) clarifying the meaning of green fintech, (2) proposing a litmus test for evaluation, and (3) demonstrating the test through a comparative analysis of two real-world cases. One is a regulated tokenized green bond issued by the Hong Kong government; the other is the Klima Protocol (formerly KlimaDAO), a decentralized platform that tokenizes carbon credits (supposedly without clear environmental verification).[1]

2. Conceptual Foundations

Green fintech arises from the imperative to align financial systems with environmental objectives. Scientific consensus confirms that global warming is accelerating due to anthropogenic greenhouse gas (GHG) emissions (L. Wang et al., 2023; Wiedmann & Minx, 2008). Addressing this challenge requires systemic reallocation of capital towards low-carbon solutions (Qin et al., 2024). Green fintech offer tools to support this transition by enabling quantification, verification, and accountability in environmental performance. A widely used operational metric, in this respect, is the carbon footprint. This attributes GHG emissions to firms and can be stated by enterprise value. This enables comparative assessments of environmental efficiency across firms and sectors. The formula can be represented as

$$\text{Carbon Footprint} = \sum W_i \left(\frac{\text{GHG emissions}}{\text{EVIC}} \right)$$

Technologies such as blockchain can support the credibility of such measures by providing immutable, transparent records of emission data and financial transactions. In this regard, green fintech serves as a mechanism for establishing trust in sustainability-linked finance initiatives. It not only enables more accurate measurement but also supports accountability by linking fintech usage to verifiable environmental outcomes.

Institutional actors have increasingly acknowledged the potential of finance in addressing environmental risks. According to the Green Finance Institute, approximately USD 1.1 trillion has already been allocated to low-carbon energy, with an annual USD 1.7 trillion investment needed to meet the net-zero goals by 2050 (Holmes, 2023). The UN Task Force on Digital Financing of the Sustainable Development Goals similarly highlights the importance of leveraging digital infrastructure to mobilize climate-aligned capital.[2] However, definitional ambiguity remains a significant barrier. As noted by Berensmann and Lindenberg (2016), the lack of standardized terminology and criteria allows unverified claims to be made, thereby creating the conditions for what we earlier defined as greenwashing.

Figure 1 outlines a conceptual framework that synthesizes green finance, financial technology, and ethical alignment into a coherent definition of green fintech. Beyond serving as definitional anchors, these three pillars interact in ways that reinforce the transformative potential of green fintech. Green finance defines the objective, ethical alignment provides the normative rationale, and financial technology represents the operational mechanism through which environmental outcomes are pursued. In this respect, green finance provides the environmental targets and metrics that fintech tools operationalize, such as through algorithmic scoring of ESG risks or the tokenization of carbon credits. Financial technology enables scalability and accessibility, making green products viable for retail and institutional segments alike. Ethical alignment, often overlooked in early-stage innovation, ensures these solutions do not compromise transparency or integrity, particularly in contexts where data privacy and regulatory arbitrage can undermine trust. Together, the framework captures how green fintech is not merely the digitalization of sustainable finance. Rather, it is an integrated system that promotes environmental outcomes and risks through verifiable, efficient, and ethically governed technological innovation (Mandić et al., 2025).

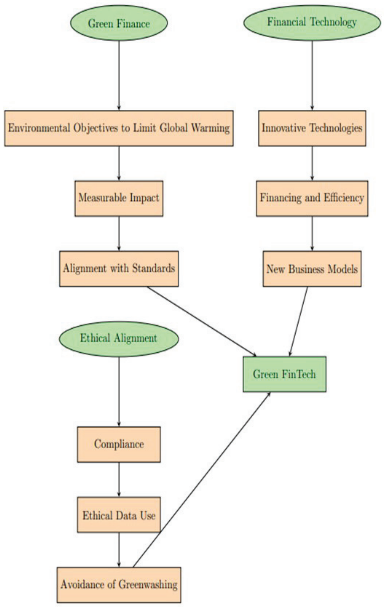

Figure 1. Defining green fintech. The figure illustrates the three core dimensions that form the foundation of green fintech: green finance, financial technology, and ethical alignment. Each dimension is further broken down into key sub-processes. Green finance emphasizes environmental objectives, measurable impact, and alignment with global standards. Financial technology focuses on the use of innovative technologies, improving financing efficiency, and the creation of new business models. Ethical alignment covers regulatory compliance, avoiding greenwashing, and ensuring ethical data use. The integration of these processes culminates in a clear and verifiable definition of green fintech, as represented by the final box.

We argue that greenwashing undermines both market credibility and environmental impact. As introduced in the preceding section, we define greenwashing in the context of green fintech as the strategic misrepresentation of products or services as environmentally sustainable without verifiable evidence of their environmental impact. This risk is particularly acute in fintech contexts, where innovation often outpaces regulatory oversight and where environmental claims may lack auditability. To address this challenge, we formulate the following hypothesis:

H1: *The lack of standardized definitional frameworks contributes significantly to greenwashing in green fintech products and/or services.*

To examine this, we propose a six-step evaluative framework to classify fintech initiatives based on their alignment with environmental outcomes, technological innovation, and regulatory standards. As shown in later sections, this framework allows for the systematic assessment of both compliance and credibility. While green fintech encompasses innovations such as tokenized green bonds, decentralized ESG scoring, and real-time carbon tracking, the legitimacy of these approaches depends on the whole picture: in other words, how they are governed, verified, and implemented. The resultant litmus test operationalizes this evaluative logic.

3. Literature Review

We structure our review around the three core dimensions of the proposed framework. First, environmental impact is grounded in the sustainability finance literature and green finance metrics (Alsedrah, 2024; Q. Li et al., 2022). Second, technological innovation draws on digital finance and fintech applications to ESG objectives (Shi & Yang, 2025). Third, regulatory alignment builds on evolving sustainable finance taxonomies and green finance standards across jurisdictions. These pillars provide the theoretical basis for each corresponding step in the litmus test.

While the green finance literature provides ample discussion on ESG instruments and fintech innovation, no existing study to our knowledge integrates a structured evaluative framework grounded in definitional precision. Most research treats fintech and green finance separately or assumes inherent synergies, thus neglecting critical criteria for credibility and governance.

The academic literature on green finance and green fintech is growing rapidly yet remains conceptually fragmented (Puschmann & Khmarskyi, 2024). The existing studies address sustainability-aligned investment, digital transformation in finance, and the growing market for green bonds and ESG-labeled funds. However, no one to our knowledge has provided a unified definition of green fintech, or a method for evaluating whether fintech applications meet substantive environmental objectives. This lack of definitional clarity leads to the interchangeability of terms such as "green finance", "sustainable fintech", and "ESG innovation" despite their differing theoretical and operational scopes (Berensmann & Lindenberg, 2019; Georgeson et al., 2017).

As shown in Table 1, the current literature on green fintech demonstrates thematic clustering around ESG integration, tokenized finance, and regulatory dimensions yet lacks consistent verification standards, evaluative taxonomies, and fintech-specific benchmarks.

Table 1. Summary of thematic gaps in the green fintech literature.

Theme	What Is Known	What Is Missing
ESG integration in fintech	Common use in platforms	No verification standards
Green finance via tokens	Blockchain examples abound	No evaluative taxonomy
Regulatory dimensions	Taxonomies vary	No fintech-focused benchmarks

S. Wang et al. (2025) support the view that definitional ambiguity enables greenwashing. As Berensmann and Lindenberg (2016) observe, vague taxonomies allow institutions to make sustainability claims that are unsubstantiated or unverifiable. Moreover, studies often describe the potential of digital technologies in supporting environmental goals (Puschmann et al., 2020). That said, they often treat these tools as inherently beneficial without critically assessing their actual application or effectiveness.

A key strand of the literature focuses on the mobilization of capital for the green transition. Kemp and Never (2017) characterize this transition as the phased deployment of low-carbon technologies supported by long-term financial strategies. Green financial instruments, particularly green bonds and Socially Responsible Investment (SRI) funds, are widely used to allocate resources toward sustainable investments (Bhutta et al., 2022; Kempf & Osthoff, 2008). However, questions remain about the true environmental performance of such instruments. For instance, Nitsche and Schröder (2018) raise concerns that many SRI-labeled funds fail to meet the impact claims on which they are marketed.

To assess the environmental effectiveness of such financial mechanisms, the literature increasingly draws on Integrated Assessment Models (IAMs) (Gopal & Pitts, 2025). IAMs provide a systematic framework for evaluating the economic and environmental trade-offs of climate-aligned investments. Among these, the Dynamic Integrated Model of Climate and the Economy (DICE) developed by Nordhaus (2018) is one of the most widely used. The DICE quantifies climate damages over time by linking GHG emissions with projected temperature increases and economic losses. This is represented as

$$\text{Cost of Climate Change} = \sum_t \left(\frac{D_t}{(1+r)^t} \right)$$

where D_t represents estimated economic damages at time t, and r is the discount rate.

IAMs, and particularly the DICE, support analysis of whether green fintech can achieve meaningful reductions in emissions (Daah et al., 2024). The model's estimation of the social cost of carbon provides a quantitative basis for pricing emissions in traded markets, ensuring alignment between digital innovation and environmental performance. That said, despite their analytical promise, IAMs are largely absent from the empirical green fintech literature. Most studies remain qualitative or descriptive. As a result, there is little evidence on how fintech applications influence climate outcomes beyond narrative claims. This is a critical gap, particularly in light of growing interest in tokenized green bonds, decentralized ESG platforms, and algorithmic sustainability rankings.

Beyond modeling, the literature also explores institutional mechanisms that support the financing of green innovation. Public–Private Partnerships (PPPs), for instance, are highlighted as a key vehicle for green fintech development. Sun et al. (2021) and Kościelniak and Górka (2016) suggest that PPPs can leverage private innovation and capital while maintaining public oversight. Fintech tools, such as blockchain for fund traceability or AI for risk assessment, enhance the governance of PPP-led sustainability projects.

Impact investing also features prominently in the literature. Barber et al. (2021) note that financial technologies enable more granular screening of ESG criteria, allowing capital to be directed toward businesses with verifiable sustainability outcomes. However, much like SRI funds, the degree to which these investments avoid greenwashing remains uncertain without structured evaluative tools. Green fintech can be used to enable this approach.

The literature also has a strong strand focused on enhancing transparency and accountability (Rerung et al., 2024). Artificial intelligence, blockchain, and other financial technologies are playing an increasingly important role in the drive toward a green future. They offer new ways to track, verify, and report on environmental data, making it easier to align their operations with sustainability goals. By improving the integrity of environmental data and increasing stakeholder trust, these technologies are reshaping finance.

AI can analyze large datasets quickly and accurately, identifying trends and patterns that are not immediately apparent. This capability, according to Mohammed et al. (2024), is particularly useful in promoting eco-friendly investments and avoiding greenwashing, as well as for monitoring environmental metrics, such as carbon emissions, water usage, and energy efficiency (Zhong et al., 2024; Yang & Broby, 2020). Through AI-powered algorithms, companies can track their environmental impact in real time, allowing for more immediate corrective actions and greater accountability. Additionally, as observed by Bhatti et al. (2023), AI can assist in reducing carbon emissions: for example, in the use of predictive modeling to help firms understand the long-term consequences of their actions on the environment, which supports better decision-making for sustainable investments.

As highlighted by Bouafia et al. (2024), blockchain, with its decentralized and immutable ledger, offers a powerful tool for increasing transparency. Adigun et al. (2024) provide a good overview on how it can be used to enhance carbon markets with fintech. It ensures that environmental data, such as carbon offsets or green bonds, are recorded and verified without tampering. Blockchain can also streamline the process of verifying corporate claims about sustainability as it creates a trusted shared record that all stakeholders can access. For instance, companies can use blockchain to certify that their supply chains are free of environmentally harmful practices, such as deforestation or excessive resource extraction, enhancing accountability across the entire production process.

Egger and Keuschnigg (2015) also suggest that innovations can be applied to more traditional financial technologies for green purposes. In a fintech context, this includes innovations in digital banking services. Many green fintech applications rely on tracking environmental impacts, like carbon footprints. However, ambiguity surrounds the use of customer data, particularly in terms of transparency, privacy, and ethical considerations. Defining the appropriate balance between data use and green goals remains an unresolved issue.

Other fintech applications, such as green bonds (see Section 4.2.1) and tokenized carbon credits (see Section 4.2.2), enable financing of environmental projects and/or carbon mitigation (Tao et al., 2022). They provide both investors and regulators with greater confidence in how resources are being allocated. Reza-Gharehbagh et al. (2022) suggest that digital platforms can be used to aggregate and analyze data on green investments. This allows for more rigorous scrutiny, ensuring that companies are held to account for their environmental commitments.

Regulatory uncertainty further complicates the landscape of green fintech (Andreeva et al., 2018). Regulations for green finance and fintech vary significantly across jurisdictions, meaning that what qualifies as green fintech in one region might not be recognized as such elsewhere. Additionally, emerging regulations, like the EU's Green Taxonomy, may not be harmonized globally (O'Reilly et al., 2024), This creates challenges for fintech companies navigating this space. There is also an inherent tension between financial innovation and environmental goals. The ambiguity here lies in whether green fintech should prioritize financial returns or environmental impact, and how these dual objectives can be balanced within regulation.

There are economic trade-offs that contribute to the ambiguity of green fintech. Some fintech companies focus on financial inclusion for underserved communities (Liu et al., 2022). These initiatives do not always align with strict environmental sustainability goals, so there is an outstanding question as to whether they are classified as green fintech or simply fintech. Because of this, balancing financial inclusion within the definition presents challenges. These ambiguities need to be resolved, possibly by empirical research. This supports the need to establish a clearer framework for defining green fintech.

A core rationale underpinning our definition of green fintech is its functional contribution to climate mitigation. Unlike broader categories such as ESG investing or sustainable finance, green fintech, as conceptualized in this paper, requires the demonstrable use of financial technologies to support verifiable environmental outcomes. This distinction is essential to avoiding definitional ambiguity and reducing the risk of greenwashing in climate-aligned financial initiatives. In this respect, green fintech offers a suite of tools for quantifying, disclosing, and tracking environmental impact. These tools enable investors, regulators, and institutions to align capital flows with climate objectives in ways that are both transparent and scalable. Importantly, they help to translate sustainability pledges into measurable outcomes.

One key area of application is the measurement of greenhouse gas (GHG) emissions (M. Li et al., 2025). Metrics such as carbon intensity, carbon footprint, and owned GHG emissions allow stakeholders to assess carbon efficiency relative to financial performance. For example, the owned GHG emission metric quantifies the direct emissions for which a firm is responsible, normalized by its revenue. This provides an indicator of environmental impact per unit of economic output, facilitating both cross-company comparison and longitudinal tracking. The formula is as follows:

$$\text{Owned GHG emissions} = \sum W_i \left(\frac{\text{GHG Emissions}}{\text{Revenue}} \right)$$

where

- W_i is the weighting factor for each company.
- GHG emissions refers to the total greenhouse gas emissions of the company.
- Revenue is the total revenue generated by the company.

They suggest that carbon intensity can be measured through an index method. Again, green fintech can assist with this. This metric compares GHG emissions to financial metrics such as "enterprise value including cash" (EVIC) and corporate sales. These measure emissions relative to a company's operational or financial scale. The formulae are

$$\text{Carbon intensity (EVIC)} = \sum W_i \left(\frac{\text{GHG emissions}}{\text{EVIC}} \right)$$

$$\text{Carbon intensity (Sales)} = \sum W_i \left(\frac{\text{GHG emissions}}{\text{Sales}} \right)$$

where

- W_i is the weighting factor for each company.
- EVIC stands for enterprise value including cash.
- Sales refers to the total sales revenue of the company.

Green fintech platforms that incorporate such metrics into their design, through dashboards, automated ESG scoring, or real-time emission monitoring, are particularly useful. They deliver measurable objectives, data-driven impact, and transparency. However, for these tools to contribute meaningfully to climate mitigation, they must also be embedded in regulatory-compliant structures and supported by verifiable third-party reporting. The literature identifies a wide range of digital solutions, including ESG analytics and green lending platforms. Yet, it offers limited insight into the definitional boundaries or evaluative standards that would allow stakeholders to differentiate between credible green fintech initiatives and superficial applications.

In summary, the literature suggests that the presence of financial technology alone is insufficient to establish environmental credibility. Platforms that track emissions or promote sustainability claims, yet lack verifiable methodologies or integration into regulatory and investment decisions, risk functioning as superficial compliance mechanisms. This reinforces the central premise of this paper that the legitimacy of green fintech hinges not merely on the definition. A meaningful framework, such as the one we propose, must therefore link environmental metrics to specific financial technologies within a structure that ensures transparency, auditability, and accountability. Only under such conditions can green fintech function as a credible instrument of climate-aligned finance. Otherwise, it becomes a technologically enhanced extension of conventional finance and potentially subject to greenwashing.

4. Conceptual Framework

To address the ambiguities surrounding the term green fintech, we now present our proposed conceptual framework. This is grounded in diagnostic logic across three foundational dimensions: (1) environmental impact, (2) financial technology innovation, and (3) regulatory alignment.

The methodology employed is conceptual and diagnostic. It aims not to test causal relationships but to construct and apply an evaluative approach for determining whether fintech-labeled initiatives credibly meet the threshold for being classified as green fintech. The resultant litmus test translates the conceptual foundation into a series of criteria that can be applied to real-world cases.

The first dimension, "environmental impact", requires that any green fintech solution demonstrate a tangible and measurable contribution to environmental objectives. These may include emission reduction, energy efficiency improvements, or resource optimization. The contribution must be traceable through standardized metrics, such as carbon savings, GHG intensity, or climate-adjusted return measures. Crucially, these outcomes should align with global frameworks such as the Paris Agreement or the UN Sustainable Development Goals (SDGs), ensuring definitional coherence across jurisdictions.

The second dimension, "technology-driven innovation", focuses on the nature of the financial technology employed. Qualifying initiatives must embed innovative digital tools, such as blockchain, AI, or internet of things (IoT). Innovation is not limited to infrastructure but includes the deployment of new business models such as tokenized bonds, decentralized carbon markets, or ESG-integrated platforms for impact investing. These features distinguish green fintech from traditional green finance by expanding the capacity of the financial system to mobilize and verify capital flows toward sustainable outcomes.

The third dimension, "regulatory and ethical alignment", requires compliance with both financial and environmental governance standards. This includes conformity with reporting obligations, auditability by third parties, and transparency in sustainability claims. To mitigate greenwashing, fintech products must undergo independent verification or certification of their environmental performance. Additionally, given the data-driven nature of many green fintech applications, solutions must respect data protection regulations and uphold ethical standards in the use of consumer or transaction-level data.

Together, these three dimensions form the basis of the litmus test presented in the next section. Figure 2 summarizes the framework's conceptual logic, illustrating how definitional clarity is constructed from the integration of environmental, technological, and regulatory subcomponents. The litmus test translates this framework into operational criteria that enable the classification and evaluation of green fintech initiatives in empirical settings.

4.1. The Litmus Test

We now present the step-by-step litmus test that we suggest can help to determine whether a financial technology qualifies as green fintech. Our process ensures that the solution is not merely labeled as "green" but methodically meets the criteria for environmental sustainability, technological innovation, and regulatory compliance.

The litmus test we propose serves a dual purpose. Conceptually, it functions as a classification mechanism for identifying legitimate green fintech initiatives. Analytically, it allows us to evaluate whether the absence of standardized definitions correlates with an increased risk of greenwashing. In this way, the framework also provides a means to assess the validity of our hypothesis.

By applying the litmus test to contrasting cases, namely a well-documented standardized tokenized green bond and a less clearly defined decentralized carbon platform, we illustrate how definitional clarity affects the credibility and verifiability of green claims. This comparative approach underscores the operational relevance of definitional precision in mitigating the risk of greenwashing.

The test assesses whether the technology contributes to measurable environmental outcomes, such as reducing carbon emissions or improving energy efficiency. It also ensures that leveraging innovative financial technologies is captured. Additionally, it ensures the solution that green fintech companies adhere to relevant regulatory frameworks and ethical data usage standards.

The litmus test is presented in Figure 2. It is structured into six key steps: defining measurable environmental objectives, ensuring technology-driven innovation, verifying data-driven environmental impact, assessing regulatory compliance, confirming ethical data handling, and evaluating for greenwashing risks. Each step serves as a checkpoint to validate the legitimacy and sustainability of the financial technology under review. The steps themselves are as follows:

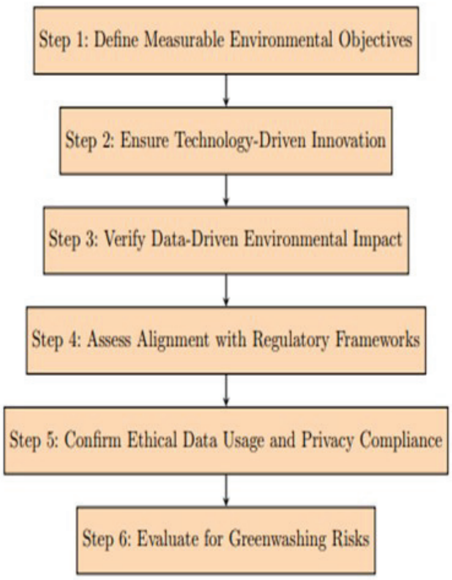

Figure 2. A six-step litmus test. This figure illustrates a method of evaluating green fintech solutions, ensuring that financial technologies meet criteria for environmental sustainability, technological innovation, regulatory compliance, and ethical data use while mitigating greenwashing risks.

1. Define measurable environmental objectives, whereby the key question to address is whether the financial technology aims to achieve specific and measurable environmental outcomes. The solution must target concrete environmental goals, such as reducing carbon emissions, increasing renewable energy usage, or improving resource efficiency. These objectives should align with global standards, such as those outlined in the Paris Agreement or the UN Sustainable Development Goals (SDGs). The test for this step involves determining whether there are clear metrics, such as carbon savings or energy efficiency improvements—that can be tracked and verified.
2. Ensure technology-driven innovation, where the question is whether the solution leverages innovative financial technologies. The technology involved must enhance transparency, efficiency, or accessibility in the financing of green projects or the management of green investments. Examples of such technologies include blockchain, which can provide immutability, AI for ESG reporting, or digital platforms for tracking carbon footprints. To pass this step, the solution must show measurable improvement in existing financial systems, such as by enabling peer-to-peer energy trading or crowdfunding for sustainable projects.
3. Verify data-driven environmental impact, which involves assessing whether the environmental impact of the solution is measurable and verifiable through data. The technology should be capable of producing data-driven outcomes that demonstrate real contributions to sustainability. Quantifiable metrics, such as carbon footprint tracking, energy savings, or emission reductions, should be used to verify the environmental

impact. The test for this step is whether the solution can provide data-supported evidence that is independently verifiable.

4. Assess alignment with policy structure, where the financial technology solution is examined for compliance with relevant financial and environmental regulations. The solution must adhere to both financial and regulatory standards, including reporting and disclosure requirements. Regulatory compliance ensures that the solution can be audited or certified by third parties. To pass this step, the solution must meet the necessary standards for financial and environmental compliance, and it must be certifiable or auditable by regulatory bodies.
5. Confirm ethical data usage and privacy compliance, addressing whether the solution handles data in an ethical and secure manner. Any use of consumer data, such as carbon footprint tracking, must comply with data privacy regulations, including the General Data Protection Regulation (GDPR). Ethical data usage is critical for building trust and ensuring transparency. The test for this step is whether the solution has clear protocols for data privacy and security, and whether it aligns with data protection laws.
6. Evaluate greenwashing risks, focusing on determining whether the claims of environmental impact can be independently verified to avoid greenwashing. The solution must provide clear and verifiable evidence of its environmental impact, which should be supported by independent certification when necessary. The test for this step is whether third-party certification or auditing is in place to validate the claims made by the technology.

We believe this litmus test ensures that any financial technology solution aiming to be classified as green fintech meets high standards of environmental sustainability, technological innovation, and compliance. By adhering to these steps, stakeholders can ensure that such solutions genuinely contribute to sustainability goals and avoid the risks of greenwashing.

To support future empirical validation, we propose a preliminary scoring rubric detailed in Table 2. This rubric applies a 0–2 scale across each of the six evaluative dimensions. A cumulative threshold of 10 or more (out of a maximum of 12) may serve as a provisional benchmark for classifying an initiative as credible green fintech, subject to independent verification. Each of the six dimensions of the litmus test can be evaluated on a 0–2 scale:

- 0 = Absent or Not Evident: No meaningful demonstration of the criterion.
- 1 = Partial or Ambiguous Evidence: Criterion is addressed but lacks clarity, rigor, or independent validation.
- 2 = Fully Satisfied: Clear documented evidence supports full alignment with the criterion.

Table 2. Suggested rubric for scoring green fintech initiatives against the litmus test.

Criterion	Description	Score (0–2)
1. Environmental Objectives	Specific measurable goals aligned with recognized climate standards	
2. Technological Innovation	Use of fintech tools that demonstrably enhance sustainability performance	
3. Data-Driven Impact	Verifiable, quantifiable metrics of environmental benefit	
4. Regulatory Compliance	Adherence to relevant financial and environmental governance frameworks	
5. Ethical Data Use	Compliance with data protection norms and transparent usage protocols	
6. Greenwashing Risk Mitigation	Use of third-party verification or audit-based assurances	

A total score of 10 or higher (out of 12) suggests a high alignment with green fintech classification standards. Subsequent research should test the rubric using case-based scoring exercises and stakeholder interviews. Methodologies such as the Delphi method proposed by Okoli and Pawlowski (2004) could provide construct validity and enhance framework robustness. The rubric also enables future extension through weighting schemes or regional regulatory adaptation.

We define thresholds for acceptability indicators for each dimension as follows: In the context of environmental objectives, ‘sufficient’ denotes the presence of clearly stated measurable targets (such as emissions saved per dollar invested, or contribution to a recognized climate goal) that can be traced to external verification or statutory standards (e.g., ICMA Green Bond Principles). In terms of technological innovation, ‘sufficient’ reflects the application of digital tools (such as blockchain, smart contracts, or AI) that enable enhanced transparency, data integrity, or automated verification, as evidenced in official technical documentation. Similar thresholds apply across the remaining dimensions, with scores of ‘2’ indicating that the initiative meets established standards or best practices, ‘1’ representing partial or ambiguous evidence, and ‘0’ denoting absence. These thresholds and indicators are applied consistently across the case studies, providing an objective and reproducible basis for evaluation.

While the litmus test offers a structured conceptual framework, it has not yet undergone empirical validation through stakeholder engagement, field piloting, or statistical reliability testing. This limitation is acknowledged. The framework is intended as a first-order diagnostic tool, grounded in normative and regulatory reasoning. However, its practical utility must be assessed through subsequent empirical work.

To formalize the evaluation process and enhance its transparency, we now express it as a structured formula. Each initiative is assessed across six dimensions, with each dimension receiving a score $s_i \in \{0, 1, 2\}$, where 0 denotes an absent criterion, 1 denotes partial evidence, and 2 denotes full evidence. The total “green fintech” score, $S_{\text{Green Fintech}}$, is defined as

$$S_{\text{Green Fintech}} = \sum_{i=1}^{6} s_i$$

where the six dimensions are

1. s_1: Environmental Objectives (measurable climate or sustainability outcomes).
2. s_2: Technological Innovation (integration of digital technologies such as blockchain or AI).
3. s_3: Data-Driven Impact (availability of verifiable metrics for environmental benefits).
4. s_4: Regulatory Compliance (conformance with relevant financial and environmental standards).
5. s_5: Ethical Data Use (alignment with data privacy and ethical usage standards).
6. s_6: Greenwashing Risk Mitigation (third-party verification and auditability).

An initiative is classified as credible green fintech if and only if

$$S_{\text{Green Fintech}} \geq 10$$

This formalization allows for transparency, reproducibility, and comparability across cases. By anchoring the assessment in a defined scale and making the supporting evidence explicit (Appendix B), the approach ensures that the evaluative logic can be traced, audited, and replicated across different green fintech initiatives.

The limitation of this approach is that there is some degree of subjective evaluation in the quantitative scoring. While the litmus test offers a classification framework for practitioners and regulators, the DICE supports ex ante evaluation of fintech initiatives by quantifying environmental and economic trade-offs. Used in tandem, they provide a holistic means of evaluating both the legitimacy and effectiveness of green fintech solutions

In summary, the litmus test establishes a structured means of evaluating definitional adequacy in green fintech. The six steps not only provide guidance for practitioners and policymakers but also operationalize our conceptual framework. By assessing whether initiatives satisfy all criteria, we can identify where definitional gaps persist. In this way, the framework serves as both a diagnostic and classificatory tool. It allows users to examine whether the absence of standardization is indeed associated with a heightened risk of greenwashing.

4.2. Testing the Litmus Test for Greenwashing Risk

This section evaluates the hypothesis by applying the litmus test to two contrasting cases: the Hong Kong Special Administrative Region's (HKSAR) tokenized green bond issuance and the Klima Protocol, a decentralized blockchain-based carbon credit platform. The comparative analysis illustrates how definitional rigor, regulatory adoption, and verifiability reduce the risk of greenwashing in green fintech initiatives.

The two cases were selected based on a purposive sampling strategy. The first, Hong Kong's tokenized green bond, represents a regulated state-sponsored instrument that publicly claims compliance with global green finance standards. The second, the Klima Protocol, was chosen due to its decentralized structure and minimal formal oversight. This contrast allows the framework to be tested across institutional extremes.

In presenting this comparison, we demonstrate that the successful application of the litmus test depends not only on regulatory frameworks and measurable goals but also on the availability of technological infrastructure. Table 3 maps core digital technologies to specific steps in the evaluative process. This illustrates the role of technology in supporting verifiability, innovation, and greenwashing mitigation.

The first case pertains to green bonds. These are often positioned as exemplary instruments of sustainable finance. However, the increasing integration of fintech into these instruments introduces a risk. Digital labeling may obscure weak environmental performance behind technological novelty. The Hong Kong tokenized green bond provides a high-profile test of whether digital issuance mechanisms enhance or merely mask environmental accountability.

In contrast, the second case, the Klima Protocol, claims to democratize carbon markets through decentralized finance. That said, its operational structure raises questions about credit quality, verification, and regulatory oversight.

Table 3. Digital technologies supporting the litmus test.

Technology	Function in Green Fintech	Linked Litmus Step (s)
Blockchain	Adds transparency and auditability.	Step 2: Innovation Step 6: Greenwashing
AI and Big Data	Automates ESG scoring and impact analysis.	Step 3: Impact Verification
Smart Contracts	Links financing to green milestones.	Step 2: Innovation Step 6: Greenwashing Step 3: Impact Verification
Open Data	Enables standard ESG reporting.	Step 4: Regulation Step 6: Greenwashing
Audit Tools	Checks ESG compliance.	Step 3: Impact Verification Step 5: Data Ethics
Rating Algorithms	Scores green performance.	Step 3: Impact Verification Step 6: Greenwashing

4.2.1. Hong Kong Tokenized Green Bond

In February 2023, the HKSAR Government issued a tokenized green bond under its green bond program.[3] A second issuance followed in 2024, valued at HKD 6 billion and denominated in four currencies.[4] Issued in a digitally native format, the bond was fully integrated with blockchain infrastructure for tokenization, settlement, and disclosure.

We apply the litmus test as follows:

1. Measurable Environmental Objectives: The bond finances projects aligned with quantified decarbonization goals, including renewable energy and efficiency initiatives.
2. Technology-Driven Innovation: Blockchain is used for tokenization, digital settlement, and documentation—representing a substantive innovation in green bond infrastructure.
3. Data-Driven Environmental Impact: Investors have access to real-time allocation reports and verified impact metrics, improving environmental transparency.
4. Regulatory Alignment: The issuance complies with both local and international green finance frameworks, including the ICMA Green Bond Principles and the Climate Bond Taxonomy.
5. Ethical Data Use and Privacy Compliance: The blockchain system ensures secure, auditable, and transparent data usage without compromising user confidentiality.
6. Greenwashing Mitigation: The use of third-party verification, immutable documentation, and international standards minimizes the risk of misrepresentation.

This case satisfies all six litmus test criteria. It demonstrates how definitional precision, technological verifiability, and alignment with regulatory norms can jointly mitigate greenwashing risk. The case supports our hypothesis by showing that initiatives grounded in established frameworks and metrics are less prone to sustainability misrepresentation.

4.2.2. Klima Protocol

The Klima Protocol is a decentralized autonomous organization that issues a token backed by tokenized carbon credits.[5] The platform claims to deepen carbon markets by creating on-chain incentives to lock up verified emission offsets. However, it operates without regulatory supervision and has faced scrutiny regarding the legitimacy of the credits it uses, many of which are drawn from outdated or low-quality offset registries.

We apply the litmus test as follows:

1. Measurable Environmental Objectives: The platform lacks clear independently defined environmental targets. Its impact is derived from the financial manipulation of existing credits rather than new emission reductions.
2. Technology-Driven Innovation: The Klima Protocol uses smart contracts, treasury management, and decentralized governance—clearly qualifying as fintech-driven.
3. Data-Driven Environmental Impact: There is limited evidence of verifiable environmental improvements. Carbon credits are pooled and reissued without robust disclosure of provenance or additionality.
4. Regulatory Alignment: The project operates entirely outside regulated financial or environmental markets and does not align with recognized taxonomies or standards.
5. Ethical Data Use and Privacy Compliance: Governance is anonymous and decentralized. There is no evidence of formal compliance with data governance standards.
6. Greenwashing Mitigation: Due to speculative token dynamics and unverified environmental claims, the platform has high exposure to greenwashing risk.

Unlike the Hong Kong case, the Klima Protocol is non-compliant with most of the litmus test criteria. It demonstrates how fintech platforms can exploit sustainability narratives without satisfying regulatory, environmental, or evidentiary standards. This contrast provides a counter case for our hypothesis where initiatives that lack standardized definitions and verification mechanisms are more likely to result in greenwashing.

4.2.3. Comparative Evaluation

Table 4 presents a comparative analysis. This reinforces the central claim of the paper, namely that definitional rigor, verifiability, and alignment with recognized standards are essential in distinguishing credible green fintech initiatives from those that merely adopt the label. The Hong Kong bond issuance is compliant with all six steps of the litmus test, demonstrating its status as a legitimate green fintech innovation. The Klima Protocol, by contrast, is non-compliant with most criteria, illustrating how the absence of precision can lead to unsubstantiated environmental claims.

Table 4. Comparison of two fintech initiatives using the litmus test.

Litmus Test Step	HK Green Bond	Klima Protocol
1. Environmental Goals	Carbon targets; metrics disclosed.	No targets; uses credits.
2. Technological Innovation	Blockchain for settlement.	DAO with tokens.
3. Data and Impact	Verified outcomes; transparent.	Poor data; no checks.
4. Regulation	Follows green standards.	Unregulated.
5. Data Ethics	Regulated use.	Anonymous; no safeguards.
6. Greenwashing Risk	Certified; low-risk.	High-risk; unverifiable.

Together, these cases demonstrate that the litmus test is not only conceptually robust but also practically useful as a tool to identify greenwashing in fintech products. Thus, the analysis offers empirical support for our hypothesis and reinforces the value of applying structured evaluation to emerging sustainability-focused technologies in finance.

4.3. Applying the Litmus Test

We apply the proposed litmus test to the Hong Kong tokenized green bond and the Klima Protocol. This allows an empirical illustration of how the framework operates across its six dimensions. Each dimension is scored from 0 to 2, yielding a total potential score of 12. The results, presented in Table 5, draw on publicly available documents listed in Appendix B.

This application demonstrates the framework's discriminating ability. The HKSAR tokenized green bond satisfies all the dimensions, yielding the maximum score (12) and aligning with recognized green finance standards. The Klima Protocol, by contrast, scores only 3, reflecting its lack of formal environmental metrics, verification processes, and regulatory alignment despite its technological innovation. These results underscore the utility of the litmus test in differentiating credible green fintech instruments from those prone to greenwashing. Importantly, these scores are illustrative, based on publicly available data listed in Appendix B, and intended as a foundation for future empirical testing and calibration.

Table 5. Comparative evaluation of the HKSAR tokenized green bond and the Klima Protocol using the six-step litmus test (sources listed in Appendix B).

Dimension	HKSAR Tokenized Green Bond	Score	Klima Protocol	Score
Environmental Objectives	Clear emission reduction and climate-aligned financing objectives	2	No independently defined environmental objectives but has tokenized credit pooling	1
Technological Innovation	Tokenization and blockchain settlement fully implemented	2	Smart contract and DAO structure present	2
Data-Driven Impact	Verified outcomes available via allocation and impact metrics	2	Limited verification; no robust data or external audits	0
Regulatory Compliance	Follows ICMA Green Bond Principles and Climate Bonds Taxonomy	2	No formal regulation or alignment with global green finance taxonomies	0
Ethical Data Use	Operates within HKMA and ICMA frameworks, supporting secure and auditable data handling	2	Anonymous, decentralized governance with no formal data privacy or disclosure policies	0
Greenwashing Risk	Certified program and external verification mitigate risk	2	High risk due to opaque credit provenance and lack of external audits	0
Total Score		12		3

5. Discussion

The two presented cases highlight the importance of definitional clarity and evaluative mechanisms in shaping credible green fintech initiatives. In this discussion, we extend these arguments by considering how the current applications of financial technology address, or fail to address, the identified gaps in sustainability measurement, standardization, and access.

A significant limitation in green fintech is the uneven alignment between innovation and regulation. While fintech platforms offer promising tools for environmental accountability—such as real-time carbon tracking, smart contracts, and automated ESG scoring—there is limited consistency in how these tools are governed. For example, few jurisdictions mandate uniform disclosure or third-party verification for sustainability claims made by fintech products. This regulatory gap enables greenwashing as fintech solutions often operate outside the taxonomies used in traditional sustainable finance.

The technologies themselves are evolving rapidly. Blockchain, artificial intelligence (AI), and big data analytics support traceability, automate ESG reporting, and enable more granular assessments of environmental impact. These tools expand the potential for evidence-based climate finance. However, the extent to which they are used systematically, and in ways that align with global standards such as the EU Green Taxonomy or the Paris Agreement, remains under-examined.

The accessibility of green fintech is another underexplored issue. While technologies such as crowdfunding and decentralized platforms increase investor participation, they also raise concerns about the quality and verifiability of claims. Lower barriers to entry may democratize finance but also amplify the risk of poorly defined or weakly monitored initiatives gaining traction. The litmus test proposed in this paper could be extended to assess not only institutional offerings but also retail-oriented platforms where regulation is less mature.

Additionally, green fintech raises important distributional questions. Most green fintech tools are designed around high-quality data, digital infrastructure, and technical expertise, features that are unevenly distributed across jurisdictions and populations. As such, there is a risk that the benefits of green fintech will remain concentrated in advanced economies, reinforcing global disparities in access to sustainable capital. Research into digital exclusion, interoperability, and cross-border standardization is essential to address these asymmetries.

The integration of economic modeling, such as the DICE, offers a promising pathway for linking fintech innovation with rigorous environmental valuation. Yet, the current fintech platforms rarely draw on such models in a systematic way. Future applications could embed dynamic carbon pricing, the social cost of carbon adjustments, or climate risk projections into fintech product design, thereby enhancing the alignment between financial innovation and climate objectives.

The litmus test proposed in this paper offers a structured basis for addressing inconsistencies in the classification and verification of green fintech initiatives. From a policy perspective, several implications follow.

First, there is a strong case for integrating structured evaluative criteria into existing regulatory taxonomies. Institutions such as the European Commission, the ASEAN Taxonomy Board, and national fintech regulators could incorporate criteria aligned with the six-step test into sustainable finance classification frameworks. This would help to ensure that digital financial products claiming environmental benefits are assessed on a consistent and transparent basis, thereby reducing definitional fragmentation and regulatory arbitrage.

Second, mandatory disclosure of verifiability metrics should be a condition for accessing sustainability-linked incentives or regulatory relief. Green fintech initiatives should be required to report on measurable environmental impacts, including methodologies for carbon reduction estimates, third-party verification mechanisms, and alignment with recognized benchmarks. Without such disclosures, fintech products risk functioning as self-declared green instruments, undermining market credibility and public trust.

Third, the development of ESG audit standards tailored to fintech applications should be prioritized. The existing ESG audit frameworks are generally designed for traditional financial institutions and do not account for the specific risks associated with decentralized platforms, automated scoring tools, or blockchain-based asset issuance. A dedicated fintech ESG audit regime could help to evaluate the environmental claims of algorithm-driven or tokenized systems, particularly those operating outside conventional reporting frameworks.

These regulatory measures, if adopted, would help to ensure that green fintech evolves in a direction that supports environmental integrity, policy alignment, and market accountability. They also offer a pathway for operationalizing the evaluative framework proposed in this study.

In sum, while green fintech introduces tools that can improve environmental transparency and extend sustainable finance, its credibility depends on consistent definitions, verifiable outcomes, and inclusive design. Addressing the gaps in regulatory compliance, access, and modeling integration is necessary if green fintech is to move from a promising concept to a credible instrument in the climate transition.

5.1. Ethical Foundations and the Role of Verifiability

Ethical alignment is a foundational dimension in the proposed framework for evaluating green fintech, yet it remains underdeveloped in both practice and policy. While digital financial innovations often emphasize technological efficiency, the legitimacy of sustainability claims depends equally on their verifiability and ethical coherence. This includes not only compliance with regulatory standards but also a normative commitment to transparency, accountability, and public trust.

The importance of verifiability in ESG disclosures has been highlighted in the work of Hart and Zingales (2017) who argue that firms should pursue shareholder welfare, broadly conceived, rather than simply maximizing market value. In their view, where externalities such as climate change are present and where regulation is incomplete, corporate behavior should reflect societal preferences. Unverified or misleading claims about environmental impact undermine this form of legitimacy, particularly when made by financial platforms that benefit from regulatory ambiguity.

Similarly, Bénabou and Tirole (2010) critique the prevalence of reputational signaling in corporate social responsibility (CSR) and ESG communications. They caution that, without credible enforcement or disclosure requirements, such claims risk becoming what they term "cheap talk"—symbolic gestures that lack substantive commitment. In the context of green fintech, this concern is amplified by the use of opaque algorithms, decentralized governance structures, and tokenized asset offerings, many of which lack third-party certification or audit trails.

Addressing these concerns requires more than regulatory compliance. It requires a systematic commitment to ethical data use, verifiable environmental performance, and institutional accountability. This paper's litmus test operationalizes these principles by making verifiability a necessary criterion for classifying a financial technology as "green fintech". It distinguishes between technological enhancement and ethical legitimacy, recognizing that innovation alone does not guarantee alignment with sustainability objectives.

Without structured ethical safeguards, fintech solutions risk reinforcing superficial compliance or opportunistic branding. To prevent this, policymakers should embed normative standards for transparency, auditability, and independent verification into ESG frameworks, particularly as they relate to digital finance. Ethical alignment, properly defined, is not peripheral but central to the credibility of green fintech.

5.2. Limitations and Future Directions

While the litmus test is grounded in clearly defined constructs, it has not yet been empirically field-tested or validated through structured stakeholder engagement. This represents an important limitation of the current study. The framework's utility in regulatory, investment, or auditing contexts remains theoretical and requires practical application pilots with green fintech providers, third-party verifiers, and relevant supervisory authorities.

We have suggested that definitional ambiguity contributes to greenwashing risk. That said, we did not empirically test this relationship through matched controls or quantifiable misrepresentation outcomes. The findings are therefore illustrative. Future studies could compare initiatives with and without formal definitions across metrics such as regulatory sanction, ESG rating volatility, or investor disputes to examine this relationship systematically.

6. Conclusions

This paper addresses the definitional ambiguity surrounding the term green fintech and proposes a structured means to evaluate whether financial technologies labeled as green genuinely contribute to environmental sustainability. It provides a precise definition: green fintech is the implementation of climate objectives through the medium of financial technology. This definition emphasizes measurable environmental outcomes, technological innovation, and regulatory compliance that conform to regulatory or audit-based standards.

The core contribution lies in clarifying how green fintech differs from adjacent categories such as green finance, and in proposing a six-step litmus test that can be used to assess definitional rigor, reduce misrepresentation, and strengthen verifiability. By applying the framework to contrasting real-world cases, we illustrate both the risks of definitional ambiguity and the potential for structured criteria to support regulatory alignment and investor confidence.

The framework's diagnostic structure enables future empirical work and provides a basis for policy tools, such as classification systems or ESG assurance protocols tailored to fintech. However, as acknowledged, the framework requires further validation, including scoring calibration and stakeholder engagement. Addressing this will be essential for its integration into regulatory practice. In sum, this study offers both a conceptual clarification and a testable evaluative method, with the aim of supporting more transparent and accountable green fintech innovation.

Looking forward, the development of interoperable taxonomies and mandatory disclosure standards remains essential. Policymakers need to design regulatory frameworks that link innovation to demonstrable climate outcomes. Integrating climate risk models such as the DICE into financial assessment and strengthening ESG reporting practices can improve the credibility of reporting. Regulatory bodies and international standard-setting organizations should consider integrating evaluative tools such as the litmus test into guidance on fintech innovation.

We conclude by pointing out that technology alone does not deliver sustainability. Its effectiveness depends on the institutional context in which it operates. By grounding the green fintech definition in measurable environmental evidence and applying systematic evaluative criteria, technology can contribute meaningfully to a low-carbon transition and support a more transparent, accountable financial system.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
AML	Anti-Money Laundering
ASIC	Australian Securities and Investments Commission
CBDC	Central Bank Digital Currency
DAO	Decentralized Autonomous Organization
DICE	Dynamic Integrated Model of Climate and the Economy
DLT	Distributed Ledger Technology
ESG	Environmental, Social, and Governance
EVIC	Enterprise Value Including Cash
EU	European Union
FCA	Financial Conduct Authority (UK)
FSCA	Financial Sector Conduct Authority (South Africa)
GHG	Greenhouse Gas
HKMA	Hong Kong Monetary Authority
IAM	Integrated Assessment Model
ICMA	International Capital Market Association
IoT	Internet of Things
MAS	Monetary Authority of Singapore
MDPI	Multidisciplinary Digital Publishing Institute
PPP	Public–Private Partnership
SDGs	Sustainable Development Goals
SRI	Socially Responsible Investment
UN	United Nations

Appendix A

Table A1. Selected institutional definitions of green fintech.

Source	Definition
Monetary Authority of Singapore (MAS)	Green fintech refers to the application of financial technology to support and promote environmental sustainability.
FSCA, South Africa	Green fintech is the combination of fintech solutions and environmental sustainability goals.
Green Finance Platform	Tech-enabled innovations applied to any financial processes and products promoting environmental sustainability.
EU Sustainable Finance Platform	Green fintech encompasses digital technologies that contribute to environmental objectives aligned with EU taxonomy.
Hong Kong Monetary Authority (HKMA)	Use of technology to enhance the development and delivery of green and sustainable financial products and services.
People's Bank of China (PBoC)	Leverages fintech to support green credit, green bonds, and environmental information disclosure.
Bank of England	Technological innovations in financial services that support the transition to a low-carbon economy.
U.S. Department of the Treasury	Fintech that facilitates investment in sustainable projects and enhances climate-related disclosures.
Financial Conduct Authority (FCA), UK	Technology to improve access to sustainable financial products and services.
Australian Securities and Investments Commission (ASIC)	Innovative technologies that promote sustainable financial services and products.
Juniper Research	Technology that enables sustainable financial services via payments, monitoring, and ESG reporting.
Softjourn	Embeds sustainability into the fintech sector through green-oriented initiatives.
DashDevs	The fusion of fintech and environmental sustainability goals.
Oxford Corporation	Uses blockchain, AI, and big data for transparent and sustainable investments.
Green Digital Finance Alliance	Digital finance that facilitates green investments and behavioral change.
European University Institute (EUI)	Uses platforms to match investors with environment-friendly companies.
Credgenics	Applies fintech including AI and mobile banking to promote sustainable development.
ScoreMe Solutions	Blockchain and AI are used to create environmentally focused financial solutions.
Smallbiztechnology.com	Applies fintech to address environmental challenges through responsible finance.
Green Fintech News	Innovations in fintech that drive green investments, ESG tools, and carbon markets.

Appendix B. Source Documents for Case Studies

Initiative	Document and Link	Description
HKSAR Tokenized Green Bond	HKSAR Press Release: https://www.info.gov.hk/gia/general/202302/16/P2023021600466.htm, (accessed on 22 June 2025)	Official announcement and terms of the HKSAR Government tokenized green bond issued in February 2023.
HKSAR Tokenized Green Bond	HKMA Project Evergreen Report: https://www.hkma.gov.hk/eng/news-and-media/insight/2024/11/20241128/, (accessed on 22 June 2025)	Technical and operational details of the tokenized green bond initiative.
HKSAR Tokenized Green Bond	ICMA Quarterly Report: https://www.icmagroup.org/assets/documents/Regulatory/Quarterly_Reports/Articles/ICMA-Quarterly-Report-article-Hong-Kong-tokenised-green-bonds-April-2024-100624.pdf, (accessed on 22 June 2025)	Analysis of HKSAR multi-currency tokenized green bond program.
Klima Protocol	Klima White Paper v1.43: https://whitepaper.klimaprotocol.com/, (accessed on 22 June 2025)	Technical and governance framework for KlimaDAO.
Klima Protocol	Klima Documentation Portal: https://docs.klimadao.finance/, (accessed on 22 June 2025)	Technical specifications, governance structures, and carbon credit mechanics.

Notes

1 https://app.klimadao.finance/, (accessed on 22 June 2025).
2 https://www.un.org/en/digital-financing-taskforce, (accessed on 22 June 2025).
3 https://www.hkma.gov.hk/eng/news-and-media/press-releases/2023/02/20230216-3/, (accessed on 22 June 2025).
4 https://www.hkma.gov.hk/eng/news-and-media/press-releases/2024/02/20240207-6/, (accessed on 22 June 2025).
5 The assessment of Klima Protocol in this paper is based on publicly available information and reflects an analytical application of the proposed framework. It does not constitute a legal or financial judgment of the organization, nor does it imply misconduct. The evaluation is offered solely for illustrative and academic purposes.

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Exploring Antecedents of Rural Users' Continuance of Use Intention Toward Mobile Financial Services in Bangladesh: Deployment of Expectation Confirmation Model

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Abstract: Numerous studies have focused on the phases of technology adoption or acceptance, while little consideration has been given to rural users' intentions to continue using the technology. Emphasizing this reality, the study has investigated the antecedents that exert ascendancy on rural communities' inclination to continue using mobile financial services. This paper conceived the theoretical model based on the expectation confirmation model. Participants in this study were 400 Bangladeshi rural users who were continuously using mobile financial services. For the sake of data analysis, utilizing a structural equation modeling approach, R version 4.4.1 software was deployed. The robust findings show that users' satisfaction with mobile financial services was significantly influenced by perceived value, perceived risk, perceived cost, government support, and perceived trust. Furthermore, satisfaction demonstrated a substantial and positive influence on the continuance of use intention. Theoretically, the study expands on ECM by adapting the concept to the technological and socioeconomic realities of rural Bangladeshi users, developing digital financial inclusion by investigating the crucial antecedents of satisfaction toward continuance of use intention through evaluation. Practically, service providers may yield strategies to increase the users' satisfaction, which will escalate continuous use intention.

Keywords: mobile financial services; mobile banking; financial technology; expectation confirmation model; expectation confirmation theory

1. Introduction

Mobile financial services (MFS) make it simpler and more favorable for users to govern financial operations on a large scale from any location by settling real-time online transactions (Uddin & Nasrin, 2023). MFS is now the simplest and most practical way for Bangladesh's underbanked and lower-income populations to access financial services due to the growing digitalization of the financial service industries, the rise in mobile device users, and the accessibility of networks and internet connectivity (Bangladesh Bank, 2022). By facilitating financial transactions, MFS has transformed the lives of Bangladeshis, especially those who are economically underprivileged (Al Amin et al., 2023). Again, quality and well-being are crucial to financial inclusion because quality ensures that financial products and services meet customers' needs and preferences and that product development takes these needs into account (Roa, 2015), and that well-being reflects the tangible impact that financial services have on consumers' lives. Consequently, since better quality engages users and increases satisfaction, it can be claimed that quality closes the gap between access to financial services and their actual use. Probably due to these causes, MFS have expanded to nearly every region of the nation within a short span of time, focusing on low-income and unbanked individuals.

Dutch Bangla Bank Limited introduced MFS in Bangladesh for the first time on 31 March 2011. Following the bank-led model, thirteen MFS providers in Bangladesh function for remittance inbound, cash-in and cash-out transactions, utility charges, government payments, business payments, and other purposes (Hassan et al., 2022). Bangladesh has achieved notable progress in promoting financial inclusion and granting affordable financial services to all classes of people, including the underprivileged and poorer rural communities. With 20% of females and 45% of males among its entire population, Bangladesh leads Asian nations in mobile money account ownership, as stated in "State of the Industry Report on Mobile Money 2023". Instead, Bangladesh is far from African nations' penetration rate of financial inclusion. Africa leads other continents with 906 million registered MFS account ownership and 942 billion transaction value, compared to the global total of 1.7 billion registered accounts and 1.4 trillion transaction values (GSMA, 2024). Nevertheless, by the end of October 2024, there were 1,544,573.2 million MFS transactions and 234.25 million registered MFS users overall. Of these, only 87.20 million were active, or 35.94% of all registered users (Bangladesh Bank, 2024). This scenario shows a state of deterioration in more extended use of MFS due to different factors. Surprisingly, according to the report on Socio-Economic and Demographic Survey 2023, the Rangpur division, consisting of eight districts, has the highest number of MFS accounts among the eight divisions, with 28.10% of its population utilizing these services, (out of this the majority 67.45% resides in rural areas) and it remains the poorest division of Bangladesh (Bangladesh Bureau of Statistics, 2024).

The future development of MFS platforms in developing nations like Bangladesh profoundly relies on overall government support. Public institutions help to ensure MFS technology's availability and excellent trustworthy service for rural users. More government support for the MFS industry would lead to increased confidence in the sector, resulting in better user satisfaction. External institutional support from the government may bring pivotal dimensions to ECM, which details how such support affects MFS user satisfaction for sustained service engagement. The ECM does not address how users perceive the risks affecting their satisfaction after system adoption. The development of frameworks through the incorporation of perceived risk may provide an understanding of how user concerns affect MFS continuance behavior. The issue becomes relevant in rural areas, since these populations often display low online competence while demonstrating limited technological confidence. The perceived cost is regarded as a precursor to the development of satisfaction concerning MFS. Individuals residing in rural regions undergo significant financial obstacles that necessitate cost assessment for their service utilization. Adding perceived cost analysis to the ECM improves its practical usefulness, particularly when financial constraints determine technology user experiences. The MFS platform trust perceived by users consists of their trust in service provider competence and platform security, which leads to satisfaction. The ECM framework would gain additional value from perceived trust because rural users require the MFS platform trust to feel comfortable and maintain their presence in such environments. Though prior research identified different factors that influenced the continuous usage of MFS, hardly any study specifically focused on the reality of rural regions (Ikhsan et al., 2023; Saima et al., 2024). Thus, it is necessary to assess principal antecedents affecting users' satisfaction toward continuance of use in rural communities. To fill the research gap, this study has developed a unique model by incorporating institutional trust and affordability concern within the ECM model in rural contexts and tried to identify influential factors that contribute to continuous usage. Therefore, this study comprises two objectives:

I. To explore the significant determinants of satisfaction in a rural MFS context;
II. To investigate the impact of satisfaction on the continuance of the use of MFS.

Theoretically, the extension of ECM will improve its applicability by including socio-economic and contextual elements that affect rural users' satisfaction towards continuance of use intention. ECM often ignores external variables like trust, risk, and cost, especially in rural areas with poor infrastructure, financial literacy, digital adoption, and financial restraints. By adding these antecedents, the study will expand ECM beyond urban or technologically sophisticated environments to better explain MFS users' continuing intention in undeveloped countries. Practically, this extension of the ECM model will enable service providers to customize their offers and ensure that government policies fit users' preferences, promoting increased engagement and sustained adoption of MFS in rural regions.

2. Literature Review

In the contemporary world, the typology of MFS comprises three leading forms: mobile banking, mobile payments, and mobile money (Gbongli et al., 2020; Gupta & Dhingra, 2022). For this study, these terms are considered as MFS. MFS is the denomination that explains the caterer's services to its clients via mobile devices or personal digital help (Naruetharadhol et al., 2021). It can also refer to a product or service offered by a bank or a microfinance institute (bank-led model) or mobile network operator (nonbank-led model) for conducting financial and nonfinancial transactions using a mobile device, namely a mobile phone, smartphone, or tablet (Shaikh & Karjaluoto, 2015). In technology adoption, users' strong impulse to utilize a newly invented technology is based on their views about it, which determines whether or not they embrace it (Davis, 1986). While technologically enabled financial innovation offers enhanced convenience, it is not the only facet of the narrative. This provides a unique opportunity to incorporate more citizens into a sustainable framework by granting them quality access to financial services, such as payments and transfers, credit, savings, asset management, and insurance (De Mariz, 2022). The creation of positive beliefs is apparent, which in turn fosters adoption. In case of the creation of a negative belief due to riskiness, lack of trust, high cost, and inertia, a reverse result may take place. Post-adoption experience is necessary for developing a response regarding satisfaction towards technology usage. Users' responses to the discrepancies between their preconceived notions and the actual effective functioning of the service after using it are known as satisfaction (Tse & Wilton, 1988). It is a psychological result of users' responses to MFS about their anticipated emotions (Gupta et al., 2020). Hence, a user is likely to be satisfied when actual functioning reaches or outperforms their expectations, and they are likely to be dissatisfied if the accurate functioning falls short of their expectations (Oliver, 1980). Thus, after experiencing technology, if users identify that the outcomes reach the expected level, satisfaction advances progressively afterwards. Continuing to use intention is a measure of a user's perceived willingness to use MFS over a stretched period (Uddin & Nasrin, 2023). Over time, users' emotions, feelings, realizations, choices, and willingness may change along with the technology. But, for users, satisfaction is a pivotal determinant of MFS's continued use intention (Franque et al., 2020). While dissatisfied users are more inclined to rethink the current relationship and search for comparatively better alternatives, satisfied users are more supposed to fortify the association with a specific service caterer (Al Amin et al., 2023). Thus, it can be said that satisfaction yields continuance of the intention to use MFS.

In a study on mobile banking users in a single Indonesian province, Rokhimah and Suhermin (2024) showed that satisfaction, customer experience, perceived usefulness, and confirmation all had meaningful yielding on users' intentions to continue using MFS. It was discovered that the security component increased user satisfaction by moderating the connection between perceived usefulness and satisfaction. This research fails to clarify if the security pertains to MFS users' data safety or transaction safety. External elements such as economic and social changes and regulatory events remain unconsidered regarding MFS continuance intentions. This research uses cross-sectional data, so it cannot establish direct cause-effect relationships between the analyzed variables.

By deploying a purposive sampling technique to collect data from 455 suburban Bangladeshi people, the study of Al Amin et al. (2023) conducted quantitative research. The research revealed that information, service, and system quality are important determinants of satisfaction and continuance intention toward MFS. The research data were collected during the COVID-19 pandemic, so the observed behavioral patterns might not reflect typical occurrences in normal conditions. Thus, expansive external applications of these outcomes are challenging to achieve. All data obtained from a single group of respondents exposes the research to the impact of common method variance.

Using a quantitative research methodology, Akter et al. (2023) recognized that fintech literacy influences user satisfaction and continuous use intention of MFS. Additionally, it acknowledged that user satisfaction mediated the connection between fintech literacy and sustainable intention to use. The study focused exclusively on bKash account holders and collected data from 200 responders by deploying purposive sampling in the Khulna area of Bangladesh. The research analysis depends heavily on limited urban student self-reports, thus creating potential biases that restrict the extension of findings to broader age demographics. No result is provided regarding monitoring how MFS users use the platform beyond its initial testing phase in real-world settings.

Rabaa'i and ALMaati (2021) extended the ECM to explore users' post-adoption behavior towards mobile banking services in Kuwait. This quantitative research used convenience and quota sampling to collect data from 303 respondents. The findings revealed that effort expectancy, satisfaction, perceived trust, performance expectancy, and self-efficacy influence users' continuance intention. Performance expectancy and confirmation were found to have the highest impact on satisfaction, while perceived trust was a crucial determinant for users' willingness to continue using mobile banking. The research examined users from a country with advanced technology infrastructure and tech-forward citizens, this might not reflect the user experience in other nations without similar technological practices. A demographic which is primarily knowledgeable about mobile technology and the age bias affects the generalization of the study due to the predominance of respondents under forty years old.

Following the examination of data derived from 529 participants, a quantitative investigation elucidated the determinants that affect the sustained utilization of MFS within the context of Bangladesh. User satisfaction exhibited a considerable influence on the intention to continue usage when juxtaposed with perceived usefulness. Expectation confirmation was found to exert an indirect effect on the intention to continuous use. Moreover, perceived self-efficacy and perceived credibility emerged as significant predictors of both satisfaction and the intention to continue usage (Saima et al., 2024). The study dedicates its analysis to the COVID-19 pandemic effects that restricted its research findings from general application beyond pandemics or outside cultural environments. Other noteworthy variables affecting continuance intention that could be relevant in Bangladesh's situation, such as cost rationality and trust issues, remain outside the scope of the study despite its inclusion of ECM and Health Belief Model (HBM) key variables. This research omits an analysis of MFS usage intention patterns between demographic populations (including gender, age, and income level).

Expectation Confirmation Theory (ECM)

Extending on Expectation Confirmation Theory (ECT), Anol Bhattacherjee presented the ECM in 2001. ECT was initially employed in marketing to examine user satisfaction and decision-making processes. It was derived from social psychology and consumer research (Oliver, 1980). ECM mainly focused on the post-use or post-acceptance aspects to explain usage continuance. Where congruence between expected and actual performance is known as confirmation (Bhattacherjee, 2001), satisfaction gleams the degree of expectation corresponding to experience and perceived usefulness. Perceived usefulness shows the cognitive belief of users (Kang & Lee, 2010). ECM depicts a noteworthy positive association between satisfaction and continued usage. The initial expectations and confirmation or disconfirmation of those anticipations following the initial engagement represent two critical antecedents to the satisfaction construct. Expectations serve as a foundational reference point, an anchor for subsequent evaluations of the system's performance (Shukla et al., 2023). ECM is one of the well-known models used in numerous studies to compare the link between user satisfaction and continuance of use (Al Amin et al., 2023). Despite having a strong theoretical foundation, when ECM comes to understanding post-adoption dynamics, it has been proven to be economical (Gupta et al., 2020).

Previous research used the ECM framework, concentrating on typical banking services considering urban and suburban realities in different contexts. Even these researchers ignored the rural users' MFS-using sensibilities. Therefore, there is a rarity of research focusing on rural communities. To fill this research gap, the study employed the interplay of dominant variables like perceived value, perceived cost, perceived risk, government support, perceived trust, and satisfaction in explaining rural users' continuance of use intention towards MFS. Figure 1 shows research on the model.

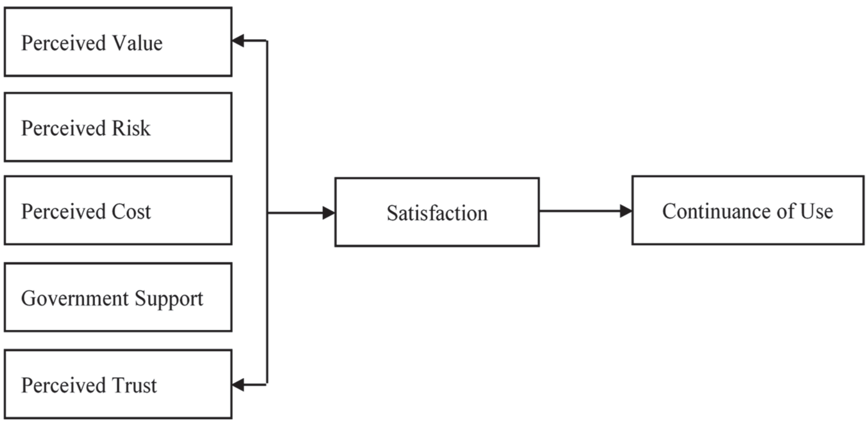

Figure 1. Research Model.

3. Hypothesis Developments

The research framework has been developed based on ECM. Since Bangladesh is a developing country, attention ought to be paid to the development, flourishing, and widespread use of MFS so that a more significant amount of the population may benefit from financial services with a minimum of effort, cost, risk, and assistance from the government, especially those without banking facilities and dwelling in rural communities. Considering these issues, this research adds variables to measure satisfaction, leading to the continuance of the use of MFS.

3.1. Perceived Value

The higher perceived value indicates an increased desire to adopt MFS since users' sense of value is a pivotal driver of adoption intention (Kim et al., 2007). The users' overall judgment of the usefulness of MFS, based on perceptions of what is sacrificed (costs) versus what is gained (benefits), is known as the perceived value in the setting of MFS (Rivière & Mencarelli, 2012). It shows a trade-off between the advantages of using the service and the costs incurred in obtaining and utilizing it (Ye et al., 2014). This trade-off is cognitive, which depends on the context and needs of individual users. If functional, economic, and social benefits are more significant than monetary, time, and psychological costs, then a perceived value for them would be created, which leads to satisfaction. Furthermore, a significant positive connection between perceived value and corresponding user satisfaction with mobile banking services offered by banks was evident (Arifin et al., 2019; Sriwidadi & Prabowo, 2023). Rural Bangladeshis rely on MFS technology because it provides value where traditional banking services are limited. MFS consumers evaluate healthy suppliers based on how well they provide convenient financial access and rapid, secure transfers. Users are more satisfied and keep using MFS when they sense its worth. Thus, it is rational to put forth the assumption:

H1: *Perceived value positively influences satisfaction toward the continuance of the use of MFS.*

3.2. Perceived Risk

Risk is the users' arbitrary anticipation of losing something to achieve an expected objective (Pavlou, 2001). Since the users vest sensorial personal and financial information to the MFS platform, any perceived risk can undermine their confidence and corresponding satisfaction. Moreover, risk is considered an extra metric when implementing technology-based financial services (Ravichandra, 2016). So, perceived risk is an obstacle and can be regarded as a key factor in confining users' satisfaction regarding MFS. It is essential to foster a positive view of the MFS platform's security since safe users will likely exhibit greater satisfaction and a stronger desire to continue with MFS (Ikhsan et al., 2023). Non-urban users generally lack digital financial experience, making MFS seem risky for money loss, security breaches, and system failures. Risks may make users unsatisfied with MFS because security concerns restrict them from using the services. Risk perception negatively impacts satisfaction and usage intention. Once again, perceived risk negatively influenced mobile banking usage satisfaction (Winata et al., 2024). Hence, the following supposition is put forth.

H2: *Perceived risk significantly negatively impacts satisfaction toward the continuance of the use of MFS.*

3.3. Perceived Cost

The perceived cost refers to users' assessment of monetary and non-monetary expenses associated with using MFS, such as transaction fees, data costs, and the opportunity cost of time spent on the service (Hazra & Priyo, 2021). Customers need to pay MFS providers different prices based on the various types of services they offer. If consumers realize these costs are significantly higher, cognitive disharmony may arise from the poorer rural residents. Higher perceived costs may deteriorate the level of satisfaction since users evaluate services using a value equation that compares perceived costs and benefits (Gong & Jiang, 2023). Users residing in rural Bangladesh have restricted financial capabilities may encounter financial barriers to MFS because they must cover expenses linked to transaction fees. MFS users who deem the costs higher than the benefits will be less satisfied and less likely to use. To improve user satisfaction, MFS must be cost effective. Moreover, a study on mobile banking reveals that cost significantly lowers user satisfaction (Jahan & Shahria, 2022). Thus, we assume the succeeding postulation.

H3: *Perceived cost significantly negatively influences satisfaction toward the continuance of use of MFS.*

3.4. Government Support

Virtual and actual worlds were simultaneously formed by the quick spread of sophisticated digital technology, but oddly, both dimensions also impact one another. Considering this issue, governments must play a significant role in preparing businesses, citizens, and agencies for the difficulties posed by the digital change in the economy brought about by digitalization and digital technology (Pesha & Shramko, 2020). The MFS platform demands government assistance where infrastructure is lacking; suitable regulations are necessary to enhance security and reliability and taking the initiative is necessary to establish a suitable pricing policy for a user-friendly environment. These issues ultimately lead to stronger satisfaction and a greater likelihood of continued use. Furthermore, the government of Bangladesh has expectations of the MFS sector and is responsible for overseeing and regulating it, and it has specific expectations from this industry. Among these expectations, upholding industry standards for MFS comes first (Sultana, 2023). Balaskas et al. (2024) revealed that government support had no significant relation with Fintech adoption. A study by Rahman et al. (2020) observed that government support in the form of policy initiatives and infrastructural improvements positively influenced satisfaction in MFS among rural populations. So, succeeding speculation is proposed.

H4: *Government support positively influences satisfaction toward the continuance of the use of MFS.*

3.5. Perceived Trust

Trust in MFS indicates that the user feels secure, relying on the organization's competence, honesty, and fame that caters to the services (Khan & Chaipoopirutana, 2020). Dass and Pal (2011) revealed that underbanked rural populations choose trustworthy channels when executing financial transactions. Complexity concerning trust consists of trust in technology and the financial service provided. As a result, building trust in MFS remains one of the pivotal challenges to guarantee that the rural underbanked are satisfied with the services offered. Nowadays, banks strongly emphasize developing excellent relationships to achieve users' trust. Users will be less hesitant if they believe in MFS providers. Moreover, user satisfaction is positively and significantly impacted by trust, which acts as a mediating factor, and as an independent variable, it indirectly affects users' satisfaction in the MFS industry (Rouf et al., 2024). Trust perception signifies that a service provider exhibits reliability, integrity, and professional competence. Users must place their trust in MFS service providers when disclosing their financial resources and personal information, as trust is a crucial safety safeguard. Individuals in rural regions necessitate fundamental trust in financial services due to their apprehension about digital platforms. In Bangladesh, diminished digital trust enables customer perceptions of service provider reputation, together with security protocols and user feedback, to shape trust development. Elevated trust in MFS will result in user satisfaction and retention of the service. According to (Geebren et al., 2021), trust significantly improves users' satisfaction when looking into the device to enhance users' satisfaction in mobile banking. Therefore, we projected succeeding postulation.

H5: *Perceived trust significantly influences satisfaction toward the continuance of the use of MFS.*

3.6. Satisfaction

Satisfaction refers to the degree of fulfillment from a service's attributes or the service offering a pleasant stance of fulfillment associated with using it (Oliver, 1980). Regarding non-government profit-seeking banking in Bangladesh, users' satisfaction plays a critical role in deciding whether users choose to remain with the service provider or switch to another one (Saha & Ali, 2024). Users may evaluate experiences according to their realization and may perceive varying satisfaction from the same service encounter due to different factors. Empirical research on MFS showed that satisfied users presumptively continue using the service in the future (Goel et al., 2022). Saima et al., 2024 confirm an affirmative association between the existing users' satisfaction and continuance of use. On the other hand, ECM designates satisfaction as a crucial determinant of continuous use intention. Users are inclined to persist in utilizing a service when they encounter satisfaction, as their positive emotions cultivate favorable anticipation for future use. Satisfaction leads to favorable behavioral intentions, particularly continuous usage, as users wish to preserve the beneficial benefits of their experiences (Bhattacherjee, 2001). Moreover, rural Bangladesh users' satisfaction with MFS platforms based on user friendliness, price, and stability leads them to form enduring connections with MFS. The satisfaction that users experience generates a continuous feedback process that makes them stay connected to the service because of its value. Utilizing the mentioned arguments, we assume the following:

H6: *Satisfaction positively influences the continuance of the use of MFS.*

4. Methodology

The research adheres to positivist principles and adopts a quantitative method focusing on determinants of satisfaction toward continuous use of MFS.

4.1. Research Context

To examine hypotheses, primary data have been collected from eight northern districts of Bangladesh: Gaibandha, Rangpur, Dinajpur, Nilphamari, Kurigram, Lalmonirhat, Thakurgaon, and Panchagarh during November–December 2024 to assess users' satisfaction with the continuance of use of MFS. Respondents from three villages of each district were selected randomly, and these villages were situated 5–12 km away from any formal financial institution. Much literature on MFS focused only on urban dwellers (Uddin & Nasrin, 2023; Akter et al., 2023; Balaskas et al., 2024), representing a scarcity of literature on rural realities. This scarcity and higher growth of MFS due to fewer or no traditional banking facilities are the reasons for choosing rural areas. The abovementioned areas are considered appropriate for this study.

4.2. Questionnaire Design

A structured questionnaire was created for a survey, with a 5-point Likert scale (1 being strongly disagreed and 5 being strongly agreed) in the first section for gathering demographic data and the second part for measurement-related data to guarantee validity. Measurement items were assimilated from diverse previous studies to develop a questionnaire. Five items were acquired from Yan et al. (2021) and Xie et al. (2021) to assess perceived value. Five items were endorsed by Arifin et al. (2019), Gbongli et al. (2020), and Rahman (2021) to measure perceived risk. Five measurement items of perceived cost were adapted from Gbongli et al. (2020) and Rahman (2021). Four items were derived from Balaskas et al. (2024) to evaluate government support. Five measures originated from Hassan et al. (2022) to assess perceived trust. Five items adapted from Arifin et al. (2019) and Rabaa'i and ALMaati (2021) evaluated the satisfaction construct. Finally, the continuance of use was assessed with the help of four items that originated from Arifin et al. (2019). The questionnaire was developed using English first and subsequently back-translated into Bengali because individuals in rural areas prefer to speak Bengali. Before starting the survey, the questionnaire was pretested by four university professors, experts in this field, and 25 university students. Additionally, to determine the optimal phrasing, relevance, applicability, and efficacy of the questionnaire, an experimental test was carried out on a sample of 40 respondents, and subsequently, it was modified with minor changes in a few words and items.

4.3. Sampling and Data Collection

The research uses random sampling to eliminate bias and improve generalizability by giving every participant an equal chance of being selected. This method ensures a diverse and representative sample of rural MFS users, which is essential for understanding satisfaction factors across demographics. Random sampling eliminates researcher bias and ensures unbiased selection. This randomness ensures that the sample closely resembles the larger population of rural Bangladeshi MFS users, improving data reliability. At the very beginning, people were asked whether they use MFS, and by asking this preliminary screening question, favorable response showers were selected as respondents. Each respondent had been using at least one MFS among thirteen service providers and was 18 years old or above. To collect data, a team of four local surveyors visited outhouses, agricultural farms, tea stalls, grocery shops, and marketplaces where village people used to gather. The surveyors also randomly visited a few educational institutions situated in rural areas. Structured paper-based questionnaires were supplied to a total of 425 respondents. A total of 400 usable responses were obtained, more than 385 as prescribed by Cochran (1977) for unknown populations. The sample size comprises 35.75% female and 64.25% male responders. Among the vocations, agriculturists had the highest opinion, with 29% of respondents. Rangpur is the most impoverished division, including four riverine districts with a notably low literacy rate. Consequently, the primary school level constitutes the largest percentage of the sample size at 30.25%, followed by individuals with no formal education at 26.25%.

4.4. Analysis and Findings

After reviewing, 400 responses were prepared for analysis, and unfinished responses from respondents were rejected from the data. “R version 4.4.1 (2024-06-14), Race for Your Life” software was used in our study to measure the constructs that support the research model. Structural equation modeling (SEM), which applies statistical techniques to evaluate and measure associations between many variables concurrently, was then used to calculate the associations between the variables. “Python 3.12.3” package was used only for the depiction of the measurement model. Using a two-fold analytical technique, as advocated by (Anderson & Gerbing, 1988), the measurement model was assessed at the very beginning just after the test of common method variance; the structural model was examined then. Measurement model analysis consists of validity, construct reliability, and assessment of corresponding indicators. After assessing these, multicollinearity, the path coefficient and t-statistics associated with the structural model, effict size, standard errors and confidence intervals and model fit indices are evaluated.

5. Results

5.1. Common Method Variance (CMV)

The study aims to identify Common Method Bias (CMB) at the outset of the analysis to ascertain whether the observed relationships among variables are affected by the measurement method rather than the underlying constructs. The likelihood of CMV involves assessing both dependent and independent variables derived from the perceptions of a singular group of respondents. Both exploratory and confirmatory methodologies were utilized to mitigate the risk of standard method bias (CMB). The current study employs a Confirmatory Factor Analysis (CFA)-based Likelihood Ratio Test (LRT) as a supplementary method to Harman's Single-Factor Test for evaluating CMB. The study performed the single factor test without rotation, utilizing exploratory principal component analysis (PCA). The initial factor represented 19% of the total variance (total variance explained = 33%), falling short of the widely recognized threshold of 50%, indicating that CMB is improbable to present a significant risk. CFA evaluated a single-factor model against the proposed multi-factor model utilizing LRT. The theoretical multi-factor model exhibited a markedly superior fit ($\Delta\chi^2 = 1301.8$, $\Delta df = 21$, $p < 0.01$), offering additional evidence against considerable CMV (Podsakoff et al., 2003).

5.2. Measurement Model

5.2.1. Convergent Validity

Measurement model evaluation is required to ensure convergent validity by using factor loadings, composite reliability (CR), and average variance extracted (AVE). All loadings' values of items surpassed 0.70; AVE values went beyond 0.50 significantly, and CR values exceeded generally recognized 0.70 criteria, validating the convergent validity of measures (Hair et al., 2017), as seen in Table 1.

Table 1. Measurement Model Evaluation.

Constructs	Items	Loadings	CR	AVE
Perceived Value (PV)	PV1: The usefulness of MFS platform is much helping me compared to the effort needed.	0.75		
	PV2: In terms of time consumption, using MFS is more beneficial.	0.74		
	PV3: Using MFS delivers value for me compared to fees or costs that need to be paid.	0.74		
	PV4: Because of many proportional benefits, employing MFS is financially viable.	0.77		
	PV5: Overall, the MFS platform offers decent value.	0.81	0.8443	0.58
Perceived Risk (PR)	PR1: There is little chance of fraud while using MFS.	0.77		
	PR2: Hacking (OTP, Password) of an MFS account is not very likely.	0.76		
	PR3: There is little chance of bad transactions because of network issues.	0.73		
	PR4: Using MFS transactions is not riskier than using regular transaction techniques (Cash, card).	0.79		
	PR5: MFS safeguards my privacy and transactions.	0.76	0.8427	0.60

Table 1. *Cont.*

Constructs	Items	Loadings	CR	AVE
Perceived Cost (PC)	PC1: The MFS cash-out charge is minimal.	0.74		
	PC2: The MFS balance transfer charge is minimal.	0.74		
	PC3: Merchant payment and pay bill charges are minimal while using MFS.	0.75		
	PC4: There is no hidden charge while using MFS.	0.73		
	PC5: Compared to banking transaction costs, MFS is less expensive.	0.77	0.8398	0.56
Government Support (GS)	GS1: The government has approved the usage of MFS in Bangladesh.	0.73		
	GS2: The government is actively putting in place the infrastructure needed to make MFS use easier.	0.80		
	GS3: The government has passed laws and regulations that benefit MFS.	0.76		
	GS4: The government must provide financial and legal support for MFS to be used effectively.	0.72	0.7960	0.57
Perceived Trust (PT)	PT1: The MFS system is reliable.	0.75		
	PT2: The MFS system is safe.	0.79		
	PT3: Through the MFS channel, service is guaranteed.	0.80		
	PT4: The MFS channel's technological and legal support protects me from issues.	0.75		
	PT5: I do believe MFS is trustworthy.	0.77	0.8551	0.60
Satisfaction (SAT)	SAT1: I am pleased that I am utilizing the MFS.	0.80		
	SAT2: My MFS usage experience was satisfactory.	0.79		
	SAT3: MFS has allowed me to make personal financial decisions with only a few clicks.	0.84		
	SAT4: I made the proper choice to use MFS.	0.81		
	SAT5: I was satisfied with MFS overall.	0.85	0.8857	0.67
Continuance of Use (COU)	COU1: Using MFS has become a daily requirement for many people.	0.84		
	COU2: I got used to using MFS.	0.88		
	COU3: I am unable to stop using MFS.	0.85		
	COU4: I plan to keep using MFS since those around me are growing dependent on it.	0.85	0.8838	0.73

Notes: CR, composite reliability; AVE, average variance extracted.

5.2.2. Discriminant Validity

To evaluate discriminant validity, the Fornell–Larcker criterion is applied. According to Hair et al. (2017), the correlation between each construct and every other construct in the model must be less than the square root of each construct's Average Variance Extracted (AVE). For every construct, the square root of AVE is represented by a diagonal value. These values indicate the extent of variance independently elucidated by each construct. Latent correlations between constructs are represented by off-diagonal values, which show how each pair of constructs is related to the others. The square root of AVE (diagonal) for every construct is higher than its highest correlation (off-diagonal) with any other construct. Refer to Table 2.

Table 2. Fornell–Larcker Matrix.

	PV	**PR**	**PC**	**GS**	**PT**
PV	0.762	0.015	0.034	0.067	−0.021
PR	0.015	0.765	−0.034	−0.034	−0.010
PC	0.034	−0.034	0.746	0.006	0.039
GS	0.067	−0.034	0.006	0.755	0.055
PT	−0.021	−0.010	0.039	0.055	0.774

Notes: PV, perceived value; PR, perceived risk; PC, perceived cost; GS, government support; PT, perceived trust.

All constructs in the model satisfy the Fornell–Larcker criterion for discriminant validity. This signifies that each construct is separate and assesses a unique concept within the model, thereby reinforcing the model's discriminant validity. Refer to Table 3.

Table 3. Fornell–Larcker Criterion Validation Results.

Construct	$\sqrt{\textbf{AVE}}$	**Max Correlation with Others**	**Passes FL?**
PV	0.762	0.067 (with GS)	Yes
PR	0.765	0.034 (with PV)	Yes
PC	0.746	0.039 (with PT)	Yes
GS	0.755	0.067 (with PV)	Yes
PT	0.774	0.055 (with GS)	Yes

Notes: PV, perceived value; PR, perceived risk; PC, perceived cost; GS, government support; PT, perceived trust; FL, Fornell–Larcker Criterion.

5.3. Structural Model

5.3.1. Multicollinearity

Multicollinearity can confuse predictors, distorting their relationships. Data relationships make each independent variable hard to interpret. It can also lead to inaccurate assessments of independent–dependent relationships (Fox, 2015). The Kaiser–Meyer–Olkin (KMO) test assessed multicollinearity in the dataset before estimating the structural model. The overall KMO value of 0.86 is praiseworthy according to the scale. The dataset is suitable for factor analysis or SEM. The items have measures of sampling adequacy (MSA) values between 0.75 and 0.93, above the acceptable threshold of 0.50 (Williams et al., 2010). This shows that each variable contributes adequately to factor structure and has no severe multicollinearity. The MSA values are in Table 4.

Table 4. Kaiser–Meyer–Olkin (KMO) Test.

Variable Group	Items	MSA Range	Interpretation
PR (Perceived Risk)	PR1, PR2, PR3, PR4, PR5	0.77–0.86	All items have an acceptable sampling adequacy; PR4 has the lowest value but is still acceptable.
PC (Perceived Cost)	PC1, PC2, PC3, PC4, PC5	0.80–0.83	All items show good sampling adequacy, indicating suitability for analysis.
GS (Government Support)	GS1, GS2, GS3, GS4	0.75–0.83	Acceptable values, though GS1 and GS3 are on the lower end.
PT (Perceived Trust)	PT1, PT2, PT3, PT4, PT5	0.86–0.89	High sampling adequacy, suitable for factor analysis.
PV (Perceived Value)	PV1, PV2, PV3, PV4, PV5	0.82–0.85	Good sampling adequacy across all items.
SAT (Satisfaction)	SAT1, SAT2, SAT3, SAT4, SAT5	0.90–0.93	Excellent sampling adequacy, indicating a very strong factor structure.
COU (Continuance of Use)	COU1, COU2, COU3, COU4	0.88–0.93	Excellent sampling adequacy across all items.

Notes: MSA, measure of sampling adequacy.

5.3.2. Hypothesis Testing

The current research used data from a sample of 400 respondents to examine the path coefficients and their accompanying t-statistics to evaluate the structural model, as suggested by (Wetzels et al., 2009). To account for specific impact inside the structural model, path coefficients should be more than 0.10 (Rabaa'i & ALMaati, 2021). According to (Henseler et al., 2015), it must be significant at 0.05 or above. R^2 values for endogenous constructs were also used to evaluate the model's explanatory capacity. The study demonstrated that perceived trust (PT) exerted the most substantial positive influence on satisfaction (SAT) ($\beta = 0.497$, $t = 10.94$, $p < 0.01$) compared to other variables. Perceived value (PV) ($\beta = 0.210$, $t = 3.96$, $p < 0.01$) has a positive and moderate effect on satisfaction, although not as noticeable as perceived trust. The impact of government support (GS) on satisfaction was positive ($\beta = 0.202$, $t = 3.68$, $p < 0.01$). This moderate relationship signifies a weak influence on satisfaction, closely resembling perceived value. The perceived cost (PC) somewhat lowered satisfaction ($\beta = -0.100$, $t = -1.86$, $p = 0.06$). This result is marginally significant, with a p-value slightly exceeding the 0.05 threshold yet remaining significant at the 0.10 level. Of all the variables, the weakest correlation exists between perceived cost and satisfaction. Satisfaction was negatively impacted by perceived risk (PR) ($\beta = -0.154$, $t = -2.99$, $p < 0.01$). Despite being one of the weaker relationships in this model, this effect is still statistically significant ($p < 0.01$). Satisfaction showed substantial and favorable effects on continuance of use intention (COU) ($\beta = 0.70$, $t = 20.78$, $p < 0.01$). The model explained 37.40% of the variance in satisfaction and 48.90% in continuance of use intention. Furthermore, the cross-validated redundancy values of 0.891 for satisfaction and 0.904 for continuance of use intention, which is more prominent than zero as advocated by (Hair et al., 2017), indicate strong anticipating pertinence of the model for these constructs (Table 5 and Figure 2). The results demonstrate the model's capacity to explain a significant proportion of variance in key outcomes, thereby supporting its robustness and predictive validity.

Table 5. Path Coefficient, t Statistics and Hypothesis Testing.

Relations			Path Coefficient	*t*-Statistics	*p*-Value	Decision	Q^2	R^2
SAT	~	PV	0.210128	3.95632 **	<0.01	Supported		
SAT	~	PR	−0.153807	−2.9862 **	<0.01	Supported		
SAT	~	PC	−0.100052	−1.85556 *	0.06	Supported	0.8913348	0.3738413
SAT	~	GS	0.201831	3.6769 **	<0.01	Supported		
SAT	~	PT	0.496830	10.9392 **	<0.01	Supported		
COU	~	SAT	0.699662	20.784 **	<0.01	Supported	0.9038131	0.4895269

Notes: * *p*-value < 0.10; ** *p*-value < 0.01.

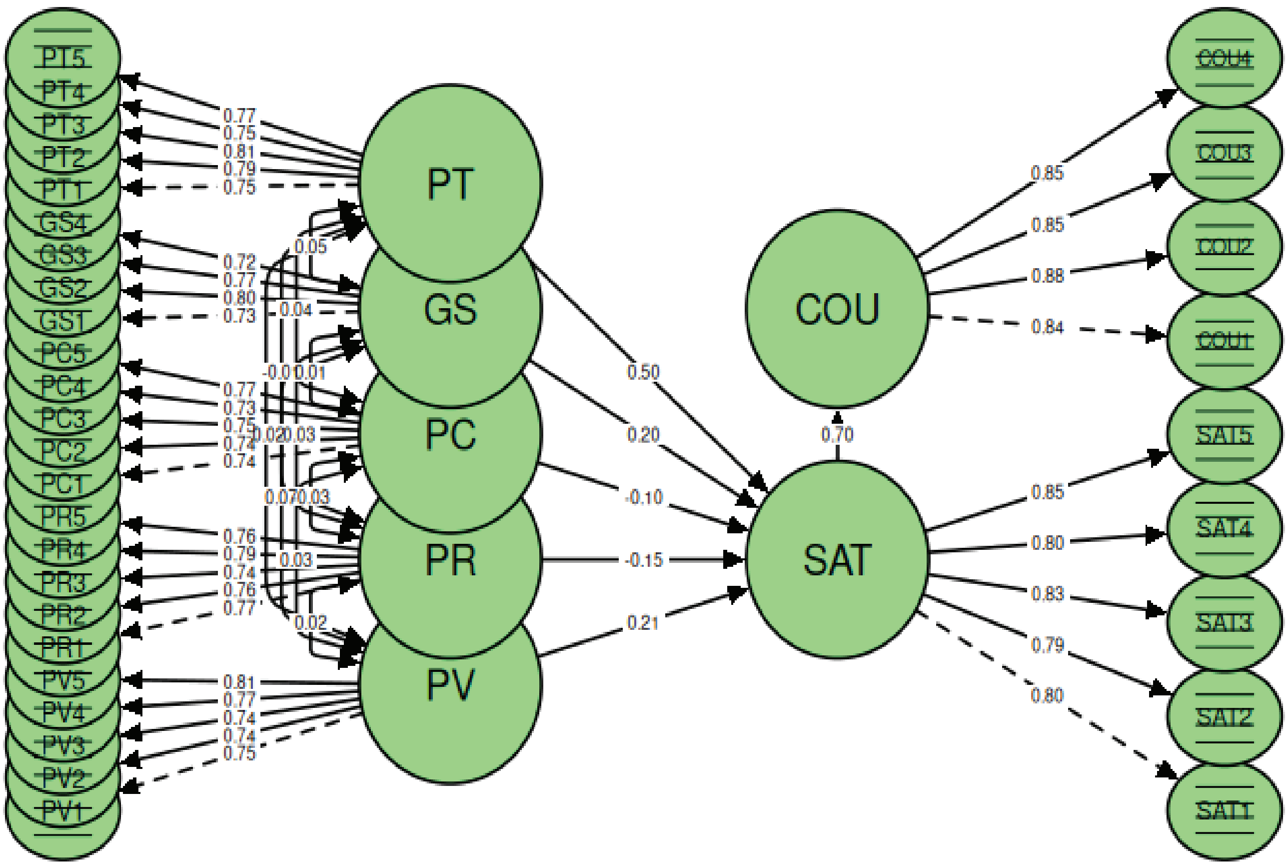

Figure 2. The Measurement Model.

5.3.3. Effect Size, Standard Errors, and Confidence Intervals

The analysis indicates that perceived trust and continuance of use exert the most significant influence on satisfaction, with effect sizes of 0.74 and 0.53, respectively. Perceived value and government support exhibit medium effect sizes of 0.21 and 0.20, respectively, whereas perceived risk and perceived cost demonstrate small yet statistically significant effects with effect sizes of −0.16 and −0.11. Table 6 shows the analysis results.

Table 6. Effect Size and Confidence Intervals for Relationships Between Satisfaction and Other Variables.

Directions	Estimate	SE	Confidence Interval		Standardized Estimate	p Value	Effect Size
			Lower Limit	Upper Limit			
SAT ~ PV	0.22	0.06	0.11	0.34	0.21	<0.01	Medium Effect
SAT ~ PR	−0.16	0.05	−0.26	−0.05	−0.15	<0.01	Small Effect
SAT ~ PC	−0.11	0.06	−0.22	0.01	−0.10	0.06	Small Effect
SAT ~ GS	0.22	0.06	0.10	0.34	0.20	<0.01	Medium Effect
SAT ~ PT	0.53	0.06	0.42	0.64	0.50	<0.01	Large Effect
COU ~ SAT	0.74	0.05	0.65	0.83	0.70	<0.01	Large Effect

Notes: PV, perceived value; PR, perceived risk; PC, perceived cost; GS, government support; PT, perceived trust; COU, continuance of use; SE, standard errors.

5.3.4. Model Fit Indices

The Comparative Fit Index (CFI) is valued at 1.00. This signifies an optimal model fit. The CFI values span from 0 to 1, with values exceeding 0.95 typically considered excellent (Bentler, 1990). The Root Mean Square Error of Approximation (RMSEA) is 0.00. An RMSEA of 0.00 indicates an ideal close fit to the data. Values under 0.05 are deemed excellent, while those below 0.08 are acceptable (Browne & Cudeck, 1992). The Standardized Root Mean Square Residual (SRMR) is 0.04. This quantifies the mean standardized residuals. Values under 0.08 are deemed acceptable, while those below 0.05 are regarded as excellent. A value of 0.04 signifies an adequate fit (Hu & Bentler, 1999). Collectively, these indices affirm that the model's fit is exemplary, offering substantial evidence that the model accurately depicts the data. Consequently, the model may be deemed dependable for subsequent analysis and interpretation.

6. Discussion

The research intended to provide a further understanding of the vital determinants that may predict MFS users' continuance of use intention in rural Bangladesh. The ECM served as a basis for the research, which was explained with additional elements such as perceived value, perceived risk, perceived cost, government support, and perceived trust. Model fit indices, predictive relevance, construct validity, and construct reliability were all attained. Furthermore, conceptual model predictive power was supported by statistical results in explaining substantial variance in satisfaction (R^2 = 0.3738413) and continuance of use (R^2 = 0.4895269). These values were within the highly satisfactory level, which surpassed all the suggested standards in this respect, such as 30% (Kline, 2016). The conceptual model used in our research to clarify users' intention to continue use was recognized and deep-rooted in the results, and the results demonstrate the model's capacity to describe an extensive proportion of variance in key outcomes, thereby supporting its robustness and predictive validity.

According to the study, perceived trust exhibited the most potent positive effect on satisfaction. A similar result was found in studies by (Geebren et al., 2021; Rouf et al., 2024). MFS is easier to access in rural Bangladesh due to mobile phone use. Mobile operators have a good reputation and history. Communication reliability may have made people trust mobile technologies like MFS. After implementing transparency, data security, and consumer protection regulations, Bangladesh has promoted financial inclusion in rural areas without banking facilities. MFS platforms gain trust from government endorsement. Moreover, MFS integrated security features like PIN codes, biometric verification, and transaction notifications to boost user confidence and safety. Ability, compassion, and integrity—all trustworthy factors regarded by service providers—influence MFS use. Consequently, convenience, established mobile networks, favorable government regulations, improved security protocols, community impact, and the economic advantages of financial inclusion foster greater perceived trust in MFS among rural Bangladeshis.

It was shown that satisfaction was positively and significantly impacted by perceived value. This important result was supported in previous studies (Arifin et al., 2019; Sriwidadi & Prabowo, 2023). The findings indicate that rural consumers regard MFS as efficiently addressing their financial requirements, including seamless money transfers, bill payments, and access to financial services, hence enhancing their perceived utility of the service. Furthermore, those with restricted technical proficiency like uncomplicated services that necessitate less effort to utilize, resulting in enhanced happiness. These factors collectively influence the perceived value of MFS among rural users. When users recognize significant value in these services, their satisfaction increases, hence enhancing their intention to persist in utilizing MFS.

Government support positively influenced satisfaction in line with prior studies (Rahman et al., 2020). The government has established a regulatory framework in collaboration with financial institutions and MFS providers to ensure compliance with operational and legal standards in MFS. This builds users' confidence and so raises their level of satisfaction. In order to encourage financial inclusion, the Bangladeshi government has also started many projects including the development of MFS platform, which enables rural people to obtain financial services without visiting bank branches. This phenomenon fosters a supportive ecosystem in which rural users feel secure, valued, and empowered to utilize MFS, resulting in increased satisfaction and sustained usage.

The perceived cost also negatively affected satisfaction marginally, which is consistent with the findings of (Jahan & Shahria, 2022). Rural users might not be fully aware of MFS's financial costs or fees. Because they are more focused on the perceived benefits (such as convenience, accessibility, and safety), the costs might not seem significant in comparison due to fewer service alternatives. Moreover, limited access to alternative financial services (like banks, other financial institutions or physical cash handling) makes MFS more attractive. Even though there are costs involved, the overall value of the service outweighs the dissatisfaction caused by those costs, leading to a marginal negative impact. Regardless, banks can reduce costs by introducing bundled services and packages and waiving transaction fees for specific demographics, making this service more lucrative.

Perceived risk negatively influences satisfaction, indicating that increased concerns about risk decrease satisfaction, as evident in previous studies (Arifin et al., 2019; Winata et al., 2024). Insecurity about MFS accounts' money and information, unexpected hacking, and fraud lower rural users' satisfaction with MFS. Cybercrime has made users wary of sharing personal information online, especially for financial transactions. Users fear breaches, fraud, and identity theft of their personal and financial data. These security issues lower satisfaction, albeit not significantly, due to infrequent occurrence along with lower cultural acceptance in rural areas. MFS providers should guarantee transaction security, multi-factor authentication, encryption, and real-time fraud detection, as well as compensate fraud victims. A solid customer care system should include phone, chat, and email for user complaints. The government should act to ensure MFS follows local laws.

Furthermore, satisfaction demonstrated a substantial and positive influence on the continuance of use intention. Prior studies portrayed similar results (Goel et al., 2022; Al Amin et al., 2023; Saima et al., 2024). This result shows that perceived value, perceived cost, government support, perceived risk, and perceived trust directly influenced satisfaction, and satisfaction influenced continuance of use. It also indicates that when users are more satisfied using perceived value, government support, and perceived trust, they are significantly more likely to continue using it.

7. Conclusions and Implications

In light of the theoretical structure, the study built on the prevailing knowledge of MFS and assessed distinguishable factors foretelling users' satisfaction toward the continued use of these services. Regarding the researcher's knowledge, this study is one of the earliest approaches that experimentally examined the applicability of ECM, considering the context of rural dwellers' MFS usage. The current research has deployed the ECM by incorporating elements significant to MFS. Beyond what was suggested in the original ECM, this study examined the ways in which users' satisfaction was impacted by perceived value, perceived risk, perceived cost, government support, and perceived trust. The association between satisfaction and continued intention to use MFS was also evaluated.

A unique addition to the literature, government support helps to enable satisfaction with the continuance of MFS use intention. This paper highlights the role of governmental regulations, infrastructure, and support in augmenting the credibility and reliability of MFS offerings. This necessitates government engagement in ECM, which had been minimized in prior applications of ECM. The study sets forth crucial antecedents, including perceived cost and perceived risk, to the ECM framework. Although ECM traditionally focusses on the congruence between user expectations and performance, the inclusion of these new factors elucidates the obstacles rural users encounter in adopting and sustaining the use of MFS. This contribution enhances the comprehension of how external variables influence users' satisfaction regarding continuance intention in rural and financially constrained contexts. The research highlights trust as a crucial element influencing satisfaction regarding continuance intention, particularly among rural MFS users. This study enhances existing research on trust in technology by demonstrating how trust in the MFS provider, platform security, and transparency influence user engagement in disadvantaged regions. This understanding enhances the perception of trust in the continued utilization of technology in developing countries. The research establishes that satisfaction is crucial for the intention to continue usage. Satisfaction, consequently, exerts a significant and positive influence on this. This underscores the essential role of satisfaction in maintaining the engagement of rural users with MFS over time.

Thus, the study addresses rural Bangladeshi users, who have been under-represented in MFS research, filling a gap in the literature. Most studies have focused on urban or semi-urban users, ignoring rural issues like low digital literacy, financial constraints, and limited banking access. It sheds light on how rural users view and use MFS platforms in this study. This theoretical expansion makes the model more robust and relevant to understanding MFS usage dynamics in developing countries. The study offers practical insights for service caterers and policymakers to improve user satisfaction and promote ongoing usage. By emphasizing trust-building initiatives, augmenting governmental support, reducing perceived costs, and mitigating perceived risks, service providers can formulate strategies that more effectively address the needs of rural users. This enhances ECM by emphasizing the significance of service design that addresses local socio-economic issues.

Limitations and Future Research

The current research on MFS utilization in rural Bangladesh provides valuable knowledge about user persistence but needs to acknowledge certain limitations. The research limitations specify the study boundaries while providing directions for additional academic work that investigates MFS usage complexity in rural settings. The research includes several limitations and possible directions for future work, which are presented in the following detail.

First, the research was conducted in rural northern areas of Bangladesh, consisting of eight districts. Because of insufficient time and cost, the study surveyed only 400 randomly chosen respondents, and thus, these findings alone may not be generalized to comprehensive MFS continuance of use intention. Therefore, it would be rational to conduct future studies and increase the sample size to test this model extensively to make it more generalizable.

Second, this study concentrated on Bangladeshi mobile banking service users. Bangladesh is a developing nation with inadequate technological infrastructure, and the people living in its rural areas are not technology-friendly compared to nationals of different developing countries. Future research should examine the suggested paradigm in other nations with distinct technological, cultural, and economic characteristics.

Third, the research extends ECM through analysis of variables which affect rural users including perceived trust factors and cost elements and risk evaluations and government support initiatives. The research design did not consider several factors like cultural elements (such as social influence, social attitude toward technology, peer network) and psychological characteristics (such as risk aversion, perceived behavioral control, personal pride or independence) that determine rural users' MFS usage behavior. Knowledge about rural users' MFS interaction requires an extensive analysis of social-cultural factors together with psychological characteristics impacting financial system trust, digital literacy and familial behavior patterns. The explanatory power of the ECM can be strengthened through added external factors in these conditions.

Fourth, this cross-sectional study cannot show how users' continuous intention to utilize MFS changes over time. Future research should undertake a longitudinal empirical analysis to understand how temporal changes (such as shift in financial stress and economic condition, changes in digital literacy and technological adoption, impact of external events) impact users' continuous intention to utilize MFS.

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The Role of Project Description in the Success of Sustainable Crowdfunding Projects

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Abstract: Crowdfunding nowadays has become a significant source of financing for all those entrepreneurs who require funds to start their operations, specifically for social ventures. Furthermore, determining what factors decide whether a project will successfully raise funds is a very relevant question. Past literature has examined various factors that influence fundraising success. Of these factors, information efficiency is the determinant of successful fundraising due to precise project descriptions and effective message delivery. Despite this fact, few studies have investigated how such project descriptions affect the success of crowdfunding campaigns, specifically sustainable projects. The present study tries to fill this gap by examining the relation between the length and readability of the crowdfunding project descriptions and the success rate for sustainable projects in a reward-based model. For the analysis, data were obtained from Kickstarter, the largest crowdfunding platform in the world, with a sample of 12,613 projects, employing a multiple logistic regression model. The results show that the word count and readability of the project descriptions are positively related to crowdfunding success. Furthermore, the analysis shows that using more words related to SDG keywords results in positive fundraising. Such insights reflect that good project descriptions are important for crowdfunding success and, on the theoretical level, provide practical value for project owners.

Keywords: crowdfunding; crowdfunding success; information description; text readability; sustainable crowdfunding; SDG

1. Introduction

Social entrepreneurship is a creative way to address significant social challenges, but it often faces the hurdle of limited access to funding (Böckel et al., 2021). Social entrepreneurs frequently find it challenging to obtain financing from traditional sources like banks (Calic & Mosakowski, 2016; Hörisch & Tenner, 2020). Consequently, crowdfunding has become an important source of finance, offering an alternative path toward sustainable development (Calic & Mosakowski, 2016). It involves the founder soliciting small amounts of finances from many people over the Internet, bypassing traditional financial intermediaries (Mollick, 2014).

At present, it is expected that the global crowdfunding industry will have a compound annual growth rate (CAGR) of 15.86% for the years from 2022 to 2027 (Ndumbaro et al., 2023). By 2027, it is expected that the market will grow by USD 264.09 billion (Ndumbaro et al., 2023). As reported by Technavio (2022), the several factors contributing to this market growth include the use of social media as an effective and low-cost marketing tool, with comparatively more accessible funding compared to traditional funding channels, and a growing consumer base. However, within this broad market, more than 80% of crowdfunding campaigns have failed to gain 20% of their desired funding (Forbes & Schaefer, 2017), with only 45% of projects reaching their desired financial targets (Mollick, 2014). As a result, research into the factors behind successful fundraising has become a key area of research interest (Shneor & Vik, 2020).

Regarding the factors that determine the effectiveness of sustainable crowdfunding projects, a significant amount of academic literature investigates the contribution that the sustainability focus of such projects makes to their overall success (Hörisch & Tenner, 2020). An increasing body of literature focuses on communication, attributing to it the dynamism and innovativeness of sustainable crowdfunding campaigns; it is a factor highlighted by researchers in the field (Vismara, 2019).

Success in crowdfunding is mainly about communication; a well-articulated project description can effectively influence the decisions of potential supporters (Shneor & Vik, 2020). In the case of green crowdfunding, the project description is crucial because it directs them toward the relevant audience and helps secure the much-needed funds. Such clarity enables the intended investors to fully understand the project's essence through a clear and unbiased presentation of its aim, aspirations, and expected outcomes. In the case of green initiatives, there is an evident rise in interest in the social and environmental implications of such projects—an area that is quite appealing to green investors who are willing to sacrifice short-term financial gains in the name of long-run sustainable returns (Lu et al., 2022).

In addition, a carefully constructed project description strengthens the legitimacy of the initiative by providing details on the administrative procedures and resource management strategies implemented, thereby promoting transparency and accountability. It alleviates any suspicions that potential donors may have by explaining the expected projects aimed at promoting sustainability, the potential risks involved, and the significant milestones necessary for the project's success. It therefore presents the project description logically and compellingly and effectively sets a strong ground for potential donors, hence maximizing the success rate in the fundraising campaign (Liu et al., 2024).

According to Chan et al. (2021), project descriptions serve as stories that can reduce information gaps and establish trust among the backers. Although much significance has been attached to communication, very little, if any, research has documented the role of project descriptions in the success of sustainable crowdfunding campaigns (Zhou et al., 2018). This knowledge gap calls for further research. The present research investigates how project description details influence crowdfunding campaigns' success. Data are analyzed from Kickstarter, which is currently the most popular crowdfunding platform in the world. The current research seeks to explore the specifications in project descriptions according to two main dimensions: readability and length. The first dimension relates to the amount of information delivered, and the second relates to the quality of the information delivered. The study generally hypothesizes a positive relationship between the quality of the project descriptions, the length thereof, and the respective crowdfunding success rates thereof. The study further shows that the greater the dominance in project descriptions by sustainability-related keywords the better the correlation with higher crowdfunding success rates. The findings have important implications for policy in enhancing the quality of project descriptions as a tool for enhancing the financing capacity of various projects. First, the study promotes changes in the length of project descriptions. Second, the use of informal and concise language may increase the readability of sustainable projects for investors, and hence the success of the projects. Finally, a focus on sustainability may allow easy access to capital for a greater variety of projects, and an increased frequency in sustainability-related keywords may greatly enhance fundraising success. The recommendations are geared towards financial sustainability in the crowdfunding sector and the creation of new sustainable businesses.

This paper is organized as follows: Section 2 reviews related literature concerning the impact of project description and sustainability in crowdfunding. Section 3 describes the sample and the methodology of the study. Section 4 discusses empirical results. Finally, Section 5 concludes with recommendations for future research.

2. Literature Review

2.1. Overview of Crowdfunding and Sustainability

Crowdfunding has three essential elements: people, projects, and online platforms (Jovanović, 2019). The people looking for financial support are called entrepreneurs or creators, and they present their projects to potential supporters. Those who provide financial support are called backers or "the crowd". Depending on the crowdfunding model, these backers can act as agents, shareholders, or donors. People contribute with varied motivations, such as interest, enjoyment, curiosity, and altruism, which often make projects with social or environmental advantages much more attractive than other forms of funding (Forbes & Schaefer, 2017).

One of the crowdfunding essentials is a platform in the middle that links fund seekers to their prospective investors (Burkett, 2011). It provides essentials such as project presentation, fund management, communication enabling, information exchange, and operation management. The first ever platform for crowdfunding was ArtistShare, launched in 2001 to support artists seeking funds to finance a project in music (Deng et al., 2022). Since then, crowdfunding has been a developed means for entrepreneurs to secure funds for their projects.

Entrepreneurs often turn to crowdfunding to gain more money or cushion their financial base in business. Under microfinance, different kinds of crowdfunding appear to be preferred by entrepreneurs based on needs (Younkin & Kashkooli, 2016). The most common ones are donation-based, equity-based, lending-based, and reward-based crowdfunding, each offering contributors some specific advantages (Jovanović, 2019).

Donation-based crowdfunding primarily serves charitable or social initiatives. In this framework, individuals provide financial contributions without anticipating reciprocal benefits. Conversely, reward-based crowdfunding has gained significant popularity, wherein supporters receive a tangible reward in exchange for their contributions (Belleflamme et al., 2014; Jovanović, 2019).

Equity crowdfunding, also called crowd investing, allows people to purchase company shares; so, in exchange for their financial contribution, it will give them a small ownership interest. Lending crowdfunding, or peer-to-peer lending, involves a direct loan from investors, not banks. Repayment of these lenders carries interest (Hörisch & Tenner, 2020).

These types of crowdfunding mostly function through online platforms, making them easy to access and participate in from anywhere.

Specifically, two general models of reward-based crowdfunding are discussed: patronage and the pre-purchase/pre-order model (Tomczak & Brem, 2013). In the patronage model, the supporters contribute money and receive a gift or product in return (Tomczak & Brem, 2013). On the other hand, the pre-purchase model is when some contributors agree to buy the product before it is built at a discount (Tomczak & Brem, 2013). People back such campaigns not just because they share similar values but because they come with incentives. These incentives can take the shape of gifts or samples of the product. On a less material level, it can be a matter of getting their name in the movie's credits or having input in developing the product. Entrepreneurs perceive these backers as early loyal customers by offering them decent pricing or special perks, effectively pre-selling products to these early customers. For example, transmitting funds to projects takes the 'all-or-nothing' model in which the money is only issued to projects that meet the projected financial goals. On the other hand, websites like IndieGogo and GoFundMe revolve around the 'keep-it-all' model: the project initiators get to keep the money despite the probability of meeting the stipulated goals. Therefore, this paper addresses one of the foremost crowdfunding websites in the world, which applies the 'all-or-nothing' model, known as Kickstarter (Allison et al., 2015; Colombo et al., 2015; Tomczak & Brem, 2013).

Crowdfunding is mainly used to finance new and innovative ideas (Lehner & Nicholls, 2017); however, it enables entrepreneurs to achieve other big goals. Companies like Coca-Cola, Motorola, and Procter & Gamble use this tool to validate their market studies by attaining genuine feedback and customer transactions (Liang et al., 2020). Crowdfunding campaigns are often advertised through social and traditional advertising, which significantly creates interest and excitement about new projects, particularly in their early stages (Brown et al., 2017; Hörisch, 2018). In addition, it is a method of market testing through which entrepreneurs can determine consumer desire for their products and further develop their product or service based on consumer response (Zhang & Tian, 2021). It carries financial risks, but there is potential to earn money and get exposure and for creators to learn (Forbes & Schaefer, 2017). Crowdfunding sites make money from successful projects using fees taken on transactions and through enhanced reputation in the field. Therefore, knowledge concerning factors influencing a successful crowdfunding campaign can support the participants in achieving their goals (Deng et al., 2022).

Crowdfunding is a necessary channel through which considerable funds are raised for initiatives for sustainability. It allows both individual and institutional investors to contribute to the financing of projects for the conservation of the environment and the development of local populations. The literature shows that scholarly investigation in the field is in the initial stages; however, it is rapidly developing and investigating the role played by crowdfunding in searching for sustainable development from multiple dimensions (Böckel et al., 2021).

Studies have recognized several key components that influence the effectiveness of crowdfunding campaigns for sustainability (Böckel et al., 2021; Gai et al., 2025). The determinants underlying such a phenomenon include the degree to which a specific initiative aligns with sustainable development goals, its effectiveness in addressing environmental and social impacts, and the extent to which such initiatives are supported by institutional trust. For instance, an analysis of 771 campaigns on platforms for crowdfunding in Italy between the years 2014 and 2021 found that campaigns with a focus on sustainability posted better performances, with such a finding supported through assessment from the economic sector and investor views with regard to environmental, social, and governance aspects (Gai et al., 2025).

In the last few years, there has been a remarkable surge in the platforms for crowdfunding sustainability projects, with unique features that improve the efficacy of their functioning. Such platforms address specific challenges in financing sustainability projects, including high transaction costs and the need for effective governance structures. Using blockchain technology, they create secure setups intended to discourage possible fraud and ensure high transparency levels. Theoretical conceptual frameworks put forward by scholars validate the viability of the use of blockchain-based decentralized co-governance structures in crowdfunding and thereby promote the use of a three-level community model in maintaining the integrity and fairness in the distribution of value (B. Chen et al., 2023).

Crowdfunding is a vital platform for raising funds for sustainability initiatives while building a dedicated following of supporters of positive environmental and social impacts.

The success of the projects largely depends on numerous factors, including the extent to which the projects align with sustainability goals, the efficiency of the communication channels used, and the legitimacy of the project organizers. With the growth of the industry, the use of innovative technologies such as blockchain is expected to enhance the efficiency and effectiveness of crowdfunding projects aimed at sustainability (Gai et al., 2025).

2.2. Factors Influencing Fundraising Success in Crowdfunding

Thus, crowdfunding has grown popular in recent years. However, not all campaigns are eventually successful in completing their funding. For example, the largest crowdfunding platform in the world, Kickstarter, posts a success rate on fully funded projects at only 37.44 percent on the current website version (Shneor & Vik, 2020). Indeed, Shneor and Vik (2020), in a review paper of 88 journal articles published from 2010 to 2017, outlined three levels of success-affecting factors in crowdfunding based on these articles: macro (built on country, culture, and geography), mezzo (industry, sector, and distribution channel), and micro (people, organizations, and specific projects). Even more importantly, a large proportion of the variables brought in their study are classified on a micro-level, indicating 85% of all factors considered. This shows that most current literature emphasizes the elements related to the campaign, the entrepreneur, or the participating businesses. Extensive research focuses on the campaign level, the dimensions of which encompass media content and campaign duration, as well as the financial goals of the campaign (Shneor & Vik, 2020). These are often called non-numeric project-related data components (Cumming et al., 2020). Prior studies provide evidence that, generally, lofty funding targets lead to lower chances of success, and setting a longer duration for the campaign does not always result in a higher amount of money collected (Adamska-Mieruszewska et al., 2021). Moreover, more important in this sense will be the factor of effective communication in the campaign materials (Adamska-Mieruszewska et al., 2021). Beyond the main content of the project, Wang et al. (2018) insist that characteristics like the size of the comments, comment rating, response length, and the time lapse before responding are all positively correlated with fundraiser success.

Generally, projects with higher quality thresholds tend to attract higher levels of sponsorship (Hörisch & Tenner, 2020). As Deng et al. (2022) observe, the qualitative data state the popularity or value of projects since the platform or the backers influence the existing project.

Another important area under investigation is the level of fundraising, which includes issues related to the creators, entrepreneurs, or organizations involved in the process. The existing literature explores dimensions such as the reputation and credibility of these actors or institutions, their experience in crowdfunding, the difference between group and solo fundraisers, geographic distance, gender, human, and social capital, amongst others (Deng et al., 2022; Shneor & Vik, 2020).

The specific characteristics of fundraisers, including creativity, readiness, and enthusiasm, may hugely influence the effectiveness of the fund-gathering initiative outcome (Deng et al., 2022).

2.3. Role of Project Descriptions in Crowdfunding

In crowdfunding, the way a project is presented is of utmost importance. It is the primary way to attract potential supporters, and proper project articulation makes them perceive it better and be willing to support a project (Adamska-Mieruszewska et al., 2021; Liang et al., 2020). From empirical studies, some writers think that the choice of vocabulary or images is one of the keys to success in this area (Scheaf et al., 2018). A project description is fundamental because it provides most of the information about the project, as Zhou et al. (2018) had not conducted much research on his work.

The project description fulfills two important roles for potential investors and those launching projects. Investors rely on this information to understand the project and decide on potential financial support (Zhou et al., 2018). As crowdfunding occurs on digital platforms, project creators must produce high-interest descriptions. Emergent projects typically start in the early stages, offering some new technology services or undertaking partial activities. In a reward-based crowdfunding context, supporters financially back 'products' that do not yet exist, and they are now reliant on simply descriptive information. On the other hand, equity crowdfunding schemes focus on creating financial returns, and supporters in reward-based schemes invest in certain products or services. Therefore, how creators present their propositions is fundamental.

In communication, project descriptions are essential for disseminating persuasive information and facilitating decision-making and problem-solving processes (Adamska-Mieruszewska et al., 2021). Scholars have investigated the influence of the complexity and clarity of these descriptions on their effectiveness within crowdfunding platforms. In their study, Adamska-Mieruszewska et al. (2021) examined more than 2800 projects hosted on a prominent Polish platform, revealing that the descriptions' extent and comprehensibility significantly influence fundraising results. Recently, Lagazio and Querci (2018) explored one of the Italian platforms and found that texts over 500 words raise the likelihood of achieving funding goals by 13% more than texts of under 200 words. Koch and Siering (2015) argue that there exists an increased level of detail related to a campaign's success; thus, it also prevents information asymmetries that might lead to misinterpretation between creators and potential backers. Moy et al. (2018) found a U-shaped relationship between text length and funding success, suggesting an optimal length and that overly long descriptions could overwhelm prospective backers. Then, Liang et al. (2020) found an inverted U relationship for the number of words used in 7207 Kickstarter projects.

2.4. Sustainability in Crowdfunding

According to Ortas et al. (2013), research concludes that one of the most significant challenges to securing sustainable businesses is inadequate available capital, with more people finding that crowdfunding has become increasingly popular to make up for this lack. It is a way of raising small amounts of money from several people via the Internet to fund those with innovative ideas and business start-ups. Crowdfunding has become increasingly significant for initiators of projects and enterprises in raising the necessary funds for starting up. Social entrepreneurs often cannot mobilize the usual sources of capital and thus consider crowdfunding a more feasible option (Testa et al., 2019). Addressing systemic injustice and unsustainability is the main focus of these entrepreneurs, who seek to recognize and change these into totally new and sustainable alternatives based on responsibility towards society and time (Rosati & Faria, 2019). For this, social or sustainable entrepreneurs use the principle of the 'triple bottom line'—where the focus is on economic, environmental, and social aspects of sustainability, instead of a focus primarily addressed to an economic aspect—in their practice (Belz & Binder, 2017; Maehle, 2020). Crowdfunding has proven to be effective in social or environmental projects for sustainable development as a source of income for such projects (Jovanović, 2019). Recently, several platforms specifically oriented towards sustainable initiatives have surfaced (e.g., Kiva and GreenCrowd), while numerous well-known crowdfunding platforms include a substantial array of sustainable projects (Maehle, 2020).

Crowdfunding has increasingly become vital for entrepreneurs with an emphasis on sustainability; however, a discussion persists regarding the effectiveness of this focus in aiding projects in securing funding. Some researchers, such as Chan et al. (2021), argue that pursuing sustainability sends messages that could influence the rationale behind supporters' decisions to back a project. The research supports this view, indicating that core terms related to sustainability generally led to more donations and higher involvement levels, as noted by Vismara (2019). At the same time, Hörisch and Tenner (2020) pointed out that projects with an environmental focus usually result in difficulties in achieving their fundraising goals. This fact suggests that an environmental appeal can reduce the ability to raise funds. Calic and Mosakowski (2016) researched technology and movie campaigns; they established that an environmental and social focus only positively benefits technology projects, while in film projects, a social focus is rather beneficial.

According to Parhankangas and Renko (2017), traditional entrepreneurs typically know precisely what their audiences expect of them and, hence, take strong cues from the product and the movie quality indicators to supplant these expectations. Secondly, social entrepreneurs often confront more ambiguous expectations and hence need to enable mechanisms that communicate effectively and quickly build trust, according to Y. S. Chen and Chang (2012). Third, Parhankangas and Renko (2017) conducted a study based on 656 Kickstarter projects and concluded that the relatable use of linguistic style boosts success for social campaigns but not commercial ones.

Research on crowdfunding and sustainability is growing, as reflected in the increasing number of articles published yearly. As shown by Böckel et al. (2021), this work identifies that a sustainability-oriented campaign requires more strategies than a regular crowdfunding campaign. This will be necessary to underline the sustainable characteristics of the projects and their respective value for supporters and society and to match the expectations set by supporters. The project description gives an avenue for project owners to interact with supporters. Researchers, such as Liang et al. (2020), have found evidence that a comprehensive project description is generally associated with higher chances of success,. However, very few prior studies have investigated the role of project descriptions in determining the success of sustainability-related crowdfunding campaigns. This research indicates that more information about the project eliminates misunderstandings and builds trust among backers, as suggested by Macht (2014), thus ultimately securing more significant financial support; this is even more the case in sustainable crowdfunding projects because of their distinctive nature. Therefore, this thesis considers the following hypothesis:

Hypothesis 1 (H1). *The length of the crowdfunding project description is associated with the success of sustainable crowdfunding projects under a reward-based model.*

The contribution of this present study to the extant literature is that while quantity and quality are important in crowdfunding campaigns, readability must also be considered for successful fundraising. In other words, readability means how easily people can grasp the project description, and it is considered crucial for effective communication by governments, businesses, and organizations (Zhou et al., 2018). In finance, readability has generally been considered a key factor of persuasion in different contexts, such as annual reports, according to Adamska-Mieruszewska et al. (2021). Nevertheless, some studies are inconsistent regarding the readability and success of projects. Skillful writers could draft complex descriptions that build trust with potential backers, according to Zhou et al. (2018). On the other hand, Xu and Zhang (2018) found that using simpler language increases community engagement in crowdfunding updates, which also increases the likelihood of success in funding. Based on these, the research proposes:

Hypothesis 2 (H2). *The readability of a crowdfunding project description is related to the success of sustainable crowdfunding projects in the reward-based model.*

3. Methodology

3.1. Analytical Approach and Data Source

This study investigates the association between length and readability in crowdfunding project descriptions and their outcomes for sustainability in crowdfunding projects. In this quantitative research, a dataset found on Kaggle is used. It merges two secondary datasets, one containing comprehensive data on Kickstarter projects and another containing project description data. Kickstarter is the primary case because of its popularity and widespread application in crowdfunding research. It combines 14,337 projects from October 2009 to February 2017, purely in the technology category; hence, it is representative. The dependent variable is fundraising success, defined as the meeting of one's financial goal; thus, it is a binary variable taking a value of 0-failure or 1-success. The independent variables, therefore, are project description length in words and readability, measured through the Gunning Fog Index. The Gunning Fog Index was introduced by Robert Gunning in 1952 (Gunning, 1952) and has been used by other researchers to measure readability (Adamska-Mieruszewska et al., 2021; Liang et al., 2020; Zhou et al., 2018; F. Li, 2008). This formula calculates how easy or hard it is to understand a text based on sentence length and word complexity. The readability formula accounts for the number of complex words containing more than three syllables and sentence length. The higher the score, the harder the material is to read. This research explores those features of project descriptions that determine crowdfunding success, focusing on sustainability-related projects.

To be more specific, the formula for the Gunning Fog Index is shown below.

$$\text{The Gunning Fox Index } = \left[\frac{\text{words}}{\text{sentences}} + 100 \times \frac{\text{complex words}}{\text{words}}\right] \times 0.4$$

The reading ease is usually best in a Gunning Fog Index of between 12 and 14. The reading is difficult if the Gunning Fog Index is between 14 and 18. When the Gunning Fog Index exceeds 18, the text is unreadable. According to F. Li (2008), when the index is below 12 and above 10, the readability of the text is sufficient. A higher Gunning Fog Index value corresponds to lesser readability, and thus, readability makes use of the negative form of the Gunning Fog Index, as seen by Zhou et al. (2018):

$$\text{Readability} = -\left[\frac{\text{words}}{\text{sentences}} + 100 \times \frac{\text{complex words}}{\text{words}}\right] \times 0.4$$

This study controls for funding goals, project duration, and launch year to capture any other variables behind this effect. Funding goal controls, as lower goals, are easier to attain. Duration is the time in days a project is open to funding, and shorter durations are more likely to be successful—launch year controls for time effects. Controls allow for the impact that description length and readability have on crowdfunding success in isolation. The variables and their measures are provided in Table 1.

Table 1. Variables and their measures.

Variables	Measures
Dependent Variable	
Crowdfunding Success	The value of successful fundraising is 1, otherwise it is 0
Independent Variable	
Length	Number of words in project description
Readability	The negative value of Gunning Fox Index
Control Variable	
Goal	The financial amount the projects aim to reach (US dollars)
Duration	The number of days that a project accepts funds from backers
Year	The year when the projects were launched

The current study quantifies the sustainability orientation of a project by proposing a keyword-based measurement using SDGs. It lists 17 SDG goals and counts the number of relevant keywords present in the descriptions of a project. It is quantified by a new variable, SDG kw count, where the higher counts suggest the higher sustainability orientation of a project. Projects with no SDG keywords will be less sustainable, and their SDGs_kw_count will be marked as zero. This variable is used to measure the sustainability aspect of each project. Table 2 presents the 17 sustainable development goals (SDGs).

Table 2. Seventeen sustainable development goals (SDGs); source: United Nations (2015).

SDGs Goal	
1. No Poverty	10. Reduced Inequalities
2. Zero Hunger	11. Sustainable Cities and Communities
3. Good Health and Well-being	12. Responsible Consumption and Production
4. Quality Education	13. Climate Change
5. Gender Equality	14. Life Below Water
6. Clean Water and Sanitation	15. Life on Land
7. Affordable and Clean Energy	16. Peace, Justice, and Strong Institutions
8. Decent Work and Economic Growth	17. Partnerships for the Goals
9. Industry, Innovation and Infrastructure	

The paper further analyzes the average basket value and compares crowdfunding and e-commerce for reward-based and donation-based models. Many crowdfunding project owners wish to "pre-sell" products or services, like e-commerce. E-commerce merchants seek to increase the average basket value to increase overall sales. This, too, translates into crowdfunding, and the authors review how pivotal the average basket value is in crowdfunding success. This additional determinant accounts for the financial behavior of backers in crowdfunding projects.

3.2. Data Analysis and Model

The data gathered are coded and entered into the Jupyter Notebook (version 6.5.2), the Python-integrated development environment (Python version 3.10.9). Because the dependent variable of this research is a binary variable, several logistic regression models are constructed to examine the effect of project descriptions on fundraising success.

Other primary variables that could also affect project success, such as goal, duration, and year, are held constant to examine what degree of influence the independent variables have. Below is one logistic regression model presented in the study:

$$\begin{aligned} &logit(Fundrasing\ Success) \\ &= \beta_0 + \beta_1 length + \beta_2 readability + \beta_3 goal \\ &+ \beta_4 duration + \beta_5 year + \beta_6 SDGs\_kw\_count \\ &+ \beta_7 avg\_basket\_value + \epsilon \end{aligned}$$

where the control variables are goal, duration, and year.

3.3. Validity of the Research

The external validity is very high because the Kickstarter data utilized represent crowdfunding websites. Ecological validity dominates because the data tracked the behavior of actual customers in the real world. Measurement validity is also enhanced by using word count and the Gunning Fog Index to measure project description readability and length. However, the study has internal validity limitations in the sense that it does not control for confounding variables like project category or creator reputation, which are bound to influence crowdfunding success. These flaws could reduce the internal validity of the research.

3.4. Reliability of the Research

The Kaggle data are publicly available; thus, the research process is very easily reproducible, enhancing reliability. The operational definitions and data analysis procedures are made explicit, ensuring that the findings from this study will be consistent with those of whoever is conducting the research. Overall, this research is very reliable.

4. Empirical Results

4.1. Descriptive Results

The descriptive statistics analysis results are reported in Table 3: means, standard deviation, maximum, and minimum. The project description length in our sample varies between 105 words and 4921 words, with an average of 676.16 words SD = 558.11. The readability of the project is −11.87 on average SD = 4.31, which is very readable, as Zhou et al. (2018) suggested. Additionally, the sample projects have an average funding goal of USD 85,006.1, SD = 1,247,912, which is comparatively larger compared to other studies such as those of (Liang et al., 2020; Zhou et al., 2018). The mean of the SDG keywords in this dataset is 2.75 (SD = 3.26), and the median number is 2, indicating that more than 50% of projects contain only 2, 1, or 0 SDG keywords in the project descriptions.

Table 3. Descriptive statistics.

Variable	Min	1st Q	Medium	Mean	3rd Q	Max	Std Deviation
length	105	276	508	676.16	902	4921	558.11
readability	−155.82	−15.4	−13.49	−11.87	−11.31	−5.36	4.31
goal	1	5000	18,000	85,066.1	50,000	100,000,000	1,247,912
duration	1	30	30	34.78	40	60	11.07
year	2009	2014	2015	2014.66	2016	2017	1.23
SDGs_kw_count	0	1	2	2.75	4	40	3.26
average_basket_value	0	13	49.81	103.49	115.41	4408.68	197.43

Although the highest number of SDG keywords is 40, crowdfunding projects with several SDG keywords are not common. Finally, the average basket value is USD 103.49 (SD = 197.43), ranging from USD 0 to 4408.68.

Of the 12,613 Kickstarter projects, 8754, or 69.4%, failed to achieve their goal amount, and 3859, or 30.6%, succeeded in achieving their goal. Successful projects totaled more than 3.4 billion, pledged by more than 2.85 million backers, and unsuccessful projects totaled more than 2.7 billion, pledged by 228 thousand backers. Also, Table 4 shows that the average basket value of each backer in the successful projects is well above that of the failed projects, at USD 164.62 and USD 76.55, respectively.

Table 4. Status of projects by goal, backers, amount pledged, and average basket value.

Status of Projects	Count of Projects	Average of the Amount of Goal	Sum of Backers	Sum of the Amount of Pledged	Average Basket Value
Fail	8754 (69.4%)	110,468.78	228,089	27,484,671.63	76.55
Success	3859 (30.6%)	27,441.03	2,857,294	345,281,520.2	164.62
Total	12,613	85,066.10	3,085,383	372,766,191.8	103.49

Regarding the variables addressed by this research, the performance of these variables from failed projects to successful projects is demonstrated in Table 5. From the table, the average project description length of the successful projects is longer than that of the failed projects, with 876.06 and 588.05, respectively, and a word count of nearly 300 words. As far as readability is concerned, there is not much difference. The projects' readability in the successful projects is slightly lower than in the failed projects: −13.60 and −14.20, respectively. In other words, the project descriptions of the successful projects were more readable than those of the failed projects. Regarding SDG-related keywords, successful projects generally have more keywords related to SDGs, but not by much. The results of the further research are represented in the following section.

Table 5. Status of projects by length, readability, and SDGs_kw_count.

Status of Projects	Average of Length	Average of Readability	Average of SDGs_kw_count
Fail	588.05	−14.20	2.51
Success	876.06	−13.60	3.32
Total	676.17	−14.01	2.76

The study identified that 9760 projects, making up 77.4% of the dataset, focus on sustainability, while 2853 projects, or 22.6%, do not. According to Table 6, the average funding goal for sustainable projects is nearly 80,000, which is lower than the goal set by non-sustainable projects. In terms of funding, sustainable projects have amassed over 3.4 billion in pledges, while non-sustainable ones have gathered just over 243 million. Sustainable projects tend to attract more backers, with an average of over 286 supporters, compared to only 100 for non-sustainable projects. Furthermore, the average pledge amount per supporter is higher for sustainable projects, at 116.21, whereas it stands at 59.99 for projects lacking a sustainability focus.

Table 6. Sustainable orientation by goal, backers, amount pledged, and average basket value.

Sustainable Orientation	Count of Projects	Average of the Amount Goal	Average of Backers	Sum of the Amount Pledged	Average Basket Value
No	2853 (22.6%)	104,401.64	100.90	24,378,654.51	59.99
Yes	9760 (77.4%)	79,414.02	286.63	3,483,875,373.3	116.21
Total	12,613	85,066.10	244.62	3,727,661,918.8	103.49

The study examined how long and readable the project descriptions were for sustainability- and non-sustainability-focused projects, as shown in Table 7. On average, the descriptions for sustainability-focused projects are longer, with 773.82 words, while those without a sustainability focus have 342.12 words. However, the readability score is slightly lower for sustainability-focused projects at −14.15, compared to −13.56 for those without a sustainability focus. This suggests that descriptions for sustainable projects are slightly more difficult to read than those without a sustainability orientation.

Table 7. Sustainable orientation by length and readability.

Sustainable Orientation	Average of Length	Average of Readability
No	342.12	−13.56
Yes	773.82	−14.15
Total	676.17	−14.01

The research tallies projects associated with each sustainable development goal (SDG); the findings are detailed in Table 8. The authors used a keyword list from Institut Teknologi Sepuluh Nopember, published in 2021, to develop a sustainability indicator; this list includes specific terms for all 17 SDGs. Some terms apply to several goals, resulting in overlaps. The authors refined the list by eliminating general terms like “wood”, “lake”, and “water” to focus on projects that truly align with sustainability objectives. In Table 8, it is clear that most sustainable development goals have more than 1000 projects. However, goal no.6, which is about clean water and sanitation, only has 349 projects, and goal no.17, dealing with partnerships for the goals, has just 21 projects. The goal with the highest number of projects is goal no.12, Responsible Consumption and Production, with 3949 projects. Next in line is goal no.7, which focuses on affordable and clean energy, with 3815 projects. Both goals are tied to environmental sustainability, aiming to cut down on plastic waste and reduce carbon dioxide emissions.

Table 8. The number of projects regarding each sustainable development goal.

SDGs Goal	Number of Projects Related
1. No Poverty	2533
2. Zero Hunger	2532
3. Good Health and Well-being	2794
4. Quality Education	1824
5. Gender Equality	1043
6. Clean Water and Sanitation	349
7. Affordable and Clean Energy	3815
8. Decent Work and Economic Growth	810
9. Industry, Innovation and Infrastructure	1083
10. Reduced Inequalities	1383
11. Sustainable Cities and Communities	1370
12. Responsible Consumption and Production	3949
13. Climate Change	1092
14. Life Below Water	1087
15. Life on Land	1859
16. Peace, Justice, and Strong Institutions	1306
17. Partnerships for the Goals	21

The authors sort projects by the number of unique sustainable development goal (SDG) keywords to see how using sustainable keywords in project descriptions affects crowdfunding success. Each keyword is only counted once, no matter how often it appears. The projects are divided into five categories:

- Group A: Projects with more than 20 different SDG keywords.
- Group B: Projects with 6 to 19 SDG keywords.
- Group C: Projects with three to five SDG keywords.
- Group D: Projects with one or two SDG keywords.
- Group E: Projects with no SDG keywords.

The criteria for these groups and the number of projects in each are detailed in Table 9.

Table 9. The standard of SDG keywords ranking and the corresponding number of projects.

SDGs Keywords Ranking	Number of SDGs Keywords	Count of Projects
A	≥ 20	47 (0.37%)
B	$6-19$	1728 (13.7%)
C	$3-5$	3250 (25.7%)
D	$1-2$	4735 (37.5%)
E	0	2853 (22.6%)
Total		12,613

After categorizing the projects, the authors analyzed the length of project descriptions, how easy they are to read, and the average pledge per supporter for each category.

Figure 1 reveals that descriptions with more sustainable development goal (SDG) keywords generally have more words. Projects rated A for having many SDG keywords have descriptions averaging 2062.09 words. B-rated projects, with fewer keywords, average 1252.69 words. Projects with no SDG keywords are rated E and have much shorter descriptions, averaging 342.166 words.

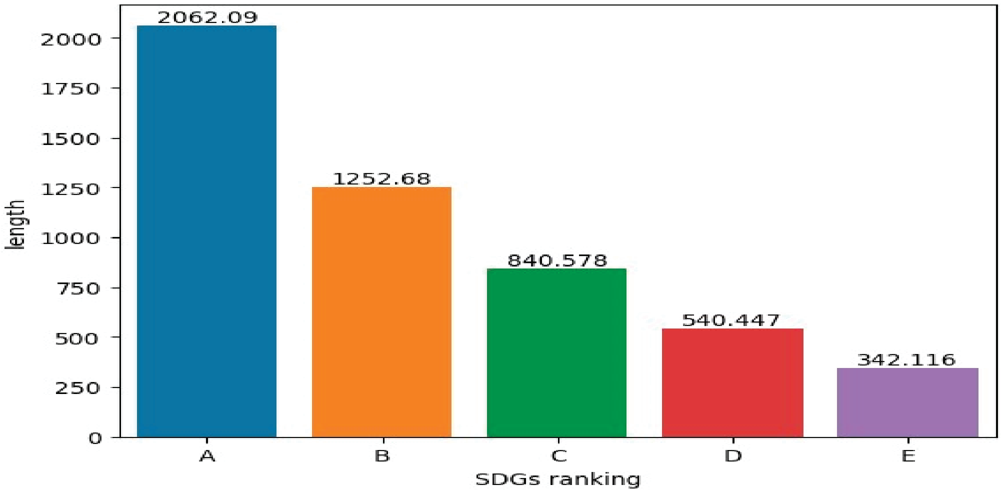

Figure 1. Length of project descriptions by the ranking of SDG keywords.

When looking at readability, scores change with different SDG keyword rankings. Projects that rank higher with these keywords usually have lower readability scores. This makes their descriptions harder for potential supporters to understand. Research suggests a good Gunning Fog Index score is between 10 and 14 (Liang et al., 2020; Zhou et al., 2018). This means that keywords for projects ranked A in SDGs are not as easy to read. Figure 2 shows how these readability scores are spread based on SDG keyword rankings.

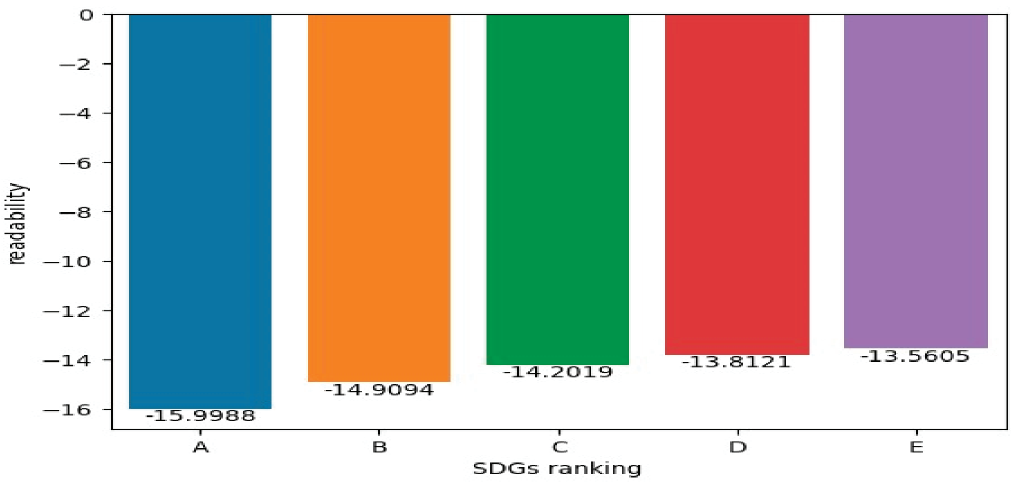

Figure 2. Readability of project descriptions by the ranking of SDG keywords.

Projects that receive an A ranking for sustainable development goal (SDG) keywords usually have longer and harder-to-read descriptions. This is likely because of the nature of sustainable crowdfunding projects. First, sustainability is a new and changing idea for many people, as Battilana and Lee (2014) mentioned. Because of this, project creators need to use many words and provide a detailed background to clearly explain their plans and the solutions they offer through crowdfunding. Also, sustainable concepts linked to SDG keywords are believed to often include technical terms with many syllables, making the text more challenging to read and understand.

There is a noticeable pattern in how much money people spend on projects linked to specific sustainable development goals (SDGs). Projects with SDG keywords ranked in category A receive about USD 146.469 from each supporter, while those in category B obtain around USD 153.903. On the other hand, projects with keywords ranked in category E receive significantly less, with each backer contributing only about USD 60 on average. This information is depicted in Figure 3.

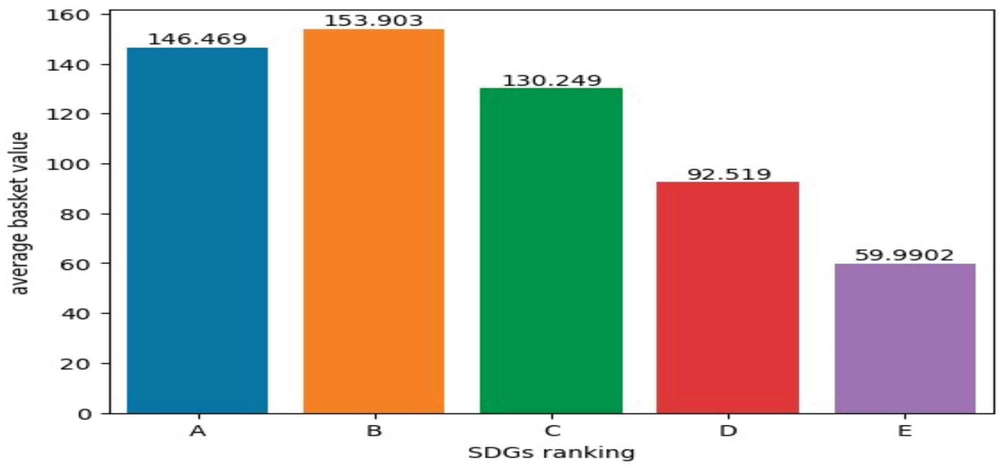

Figure 3. Average basket value by the ranking of SDG keywords.

4.2. Logistic Regression Analysis

Because the outcome is either 0 or 1, logistic regression analysis was used. For this study, we developed eight models. Model 1 contains only the basic factors we wanted to control for and the outcome. To examine each idea independently, the authors added a new factor to Models 2 through 8. Model 8 is the most comprehensive, including all factors. The analysis results are presented in Table 10, which includes 12,613 observations.

The study labeled as H1 explores how the length of project descriptions influences the success of sustainable crowdfunding campaigns. In Table 10, it is shown that longer descriptions have a positive effect on crowdfunding success, as seen in both single and multiple logistic regression models. Specifically, from Model 2 to Model 8, there is a noticeable positive link between the length of the description and success in raising funds. The coefficient, which is 1.0080 with a *p*-value of less than 0.001, suggests that for every 1% increase in the description's length, the chances of successfully raising funds increase by 1.0080 times. These findings support the H1 hypothesis, indicating that longer project descriptions are likely to improve the outcomes of crowdfunding efforts focused on sustainability.

This finding matches what other studies have discovered. Research by Zhou et al. (2018) and Adamska-Mieruszewska et al. (2021) and her team in 2021 showed that having longer project descriptions can make crowdfunding efforts more successful. This idea supports the belief that because sustainability is a relatively new concept for many people, entrepreneurs must work harder to clearly explain their projects to potential supporters (Petruzzelli et al., 2019). By sharing more detailed information about their projects, owners can lessen the uncertainty potential backers might feel and boost their confidence and willingness to support the projects.

Research indicates that the length of project descriptions impacts crowdfunding success in a more complex, upside-down U-shaped way because too much information can overwhelm potential backers. Studies by Liang et al. (2020) back this up. Liang's research suggests that when a description goes beyond 2013 words, it may hinder success. This highlights the importance of finding the correct word count, as going over this range can reduce effectiveness. The relationship between the length of a project description and its success on crowdfunding platforms is not straightforward, as more words do not always lead to better outcomes.

Table 10. Regression analysis results on the success of sustainable crowdfunding (12,613 observations).

Variables	Model 1 Controls Only	Model 2 Words_Count	Model 3 Reada-Bility	Model 4 SDGs_kw_Count	Model 5 Average_Basket_Value	Model 6 Length, Reada-Bility	Model 7 Length, Readability, SDGs_kw_Count	Model 8 All Variables
Controls								
log(Goal)	−0.2936 ***	−0.4592 ***	−0.2894 ***	−0.3645 ***	−0.4153 ***	−0.4549 ***	−0.4606 ***	−0.5613 ***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Duration	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Main effects								
log(length)			1.1260 ***			1.1329 ***	1.0729 ***	1.0080 ***
			(0.000)			(0.000)	(0.000)	(0.000)
Readability			0.0337 ***			0.0446 ***	0.0487 ***	0.0512 ***
			(0.000)			(0.000)	(0.000)	(0.000)
log(SDGs_kw_count)				0.5569 ***			0.1110 ***	0.0945 ***
				(0.000)			(0.001)	(0.004)
average_basket_value					0.0041 ***			0.0034 ***
					(0.000)			(0.000)
constant	1.4699 ***	−3.8900 ***	1.9094 ***	1.7417 ***	2.1824 ***	−3.3420 ***	−2.9416 ***	−1.9368 ***
Model Summary								
Pseudo R-square	0.05492	0.1468	0.05718	0.08351	0.1151	0.1496	0.1504	0.1911

*** $p \leq 0.01$.

The research identified as H2 explores how making project descriptions easier to read influences the success of sustainable crowdfunding. According to Table 10, both straightforward and detailed statistical evaluations show a positive connection between readability and crowdfunding success. In Model 3, an increase in readability (with a coefficient of 0.0037 and a *p*-value less than 0.001) is linked to better outcomes. Similarly, in Model 8, a 1% boost in readability raises the chances of successful fundraising by 0.0487, with a *p*-value below 0.001. This evidence supports H2, demonstrating that improved readability significantly enhances the likelihood of crowdfunding success.

This study's logistic regression findings contrast with those of earlier research. Previous studies by Liang et al. (2020) and Zhou et al. (2018) suggested that readability does not significantly boost fundraising success. However, this study agrees with Adamska-Mieruszewska et al. (2021), indicating that when descriptions are easier to read, potential supporters can understand them better, reducing misunderstandings and improving the likelihood of project success. In general, supporters favor project descriptions that are clear and easy to follow. There are three main reasons for this. Firstly, sustainable crowdfunding projects are relatively new and constantly changing (Battilana & Lee, 2014); so, potential backers often look for simple explanations to comprehend these new concepts.

Additionally, these projects must communicate clearly to convey their value, which might not be immediately apparent (Parhankangas & Renko, 2017). Secondly, clearer descriptions help minimize confusion and build trust between supporters and projects, making people more inclined to donate. Thirdly, in reward-based crowdfunding, where supporters usually give small amounts, overly detailed and complex descriptions can be discouraging (Adamska-Mieruszewska et al., 2021). Supporters generally do not want to invest too much time deciphering complicated information, especially when they feel their small contributions do not warrant such an effort.

The study investigates factors such as SDGs_kw_count and average_basket_value, which positively affect crowdfunding success. SDGs_kw_count has a coefficient of 0.0945, and average_basket_value has a coefficient of 0.0034, with both showing significance at $p < 0.001$. This indicates that these factors boost the likelihood of a crowdfunding project succeeding.

SDGs_kw_count refers to the number of sustainability-related keywords used in a project's description. The research finds that projects focusing more on sustainability by including these keywords are more likely to meet their financial goals. This finding is consistent with earlier research, all of which concludes that a sustainable approach improves crowdfunding outcomes (Calic & Mosakowski, 2016; Hörisch & Tenner, 2020; Lam & Law, 2016; Vismara, 2019).

The study further explores the influence of sustainability on crowdfunding success. It reveals that for every 1% increase in SDG-related keywords in project descriptions, the odds of successful fundraising rise by 0.0945. Therefore, highlighting sustainability in project descriptions significantly enhances the chances of reaching financial targets.

The average amount each supporter donates to a crowdfunding campaign, known as the average basket value, plays a crucial role in determining the success of the fundraising effort. A positive link exists between the amount each backer contributes and the likelihood of the project meeting its funding goals. Specifically, for every 1% increase in the average donation, the chances of successfully raising funds improve by 0.0034. This relationship is backed by strong evidence, with a coefficient of 0.0034 and a *p*-value of less than 0.001, highlighting its statistical significance. Essentially, the slight increase in contributions from each supporter enhances the project's chances of reaching its financial objectives.

4.3. Evaluation of Predicting Performance

This study compares how well the new model (Model 8) predicts against the popular model (Model 1), which relies on the basic control factors mentioned earlier. The researchers divided the data, using 80% to train the logistic regression model and 20% to test its predictions. They assessed prediction accuracy and included the F-measure, which evaluates prediction and recall accuracy for a more balanced performance view. This approach is supported by Lipton et al. (2014) and Novaković et al. (2017). Detailed results are provided in Table 11.

Table 11. Performance measures.

	Model 1 Mainstream Model	Model 8 Proposed Model
Accuracy	70.60%	75.90%
F-measure	17.41%	49.58%

This study looks at how well a new model (Model 8) predicts outcomes compared to a commonly used model (Model 1), which only considers certain control factors discussed earlier. As shown in Table 11, the new model achieves a prediction accuracy of 75.90% and an F-measure of 49.58%. In contrast, the common model has a prediction accuracy of 70.60% and an F-measure of 17.41%. A higher F-measure, as noted by Y. Li and Chen (2018), means the model is better. This suggests that the new model is more effective at predicting funding success.

To evaluate predicting models, we often look at accuracy and the F-measure. Another useful tool is the receiver operation characteristic (ROC) curve, which visually shows how well predictions are classified as positive or negative. It helps identify the best decision threshold for optimal results (Bradley, 1997; Nahm, 2022). We also use the area under the ROC curve (AUC) as a metric. The AUC gives a score from 0 to 1, with 1 indicating perfect model performance.

Figure 4 displays the ROC curves for Model 8, Model 1, and a baseline, illustrating each model's ability to predict outcomes such as fundraising success. Model 8's curve is more pronounced and closer to the top left corner than Model 1's. This indicates that Model 8 achieves a higher true positive rate and a lower false positive rate, making it more effective for predicting outcomes. This advantage is valuable for people launching projects, as it helps them assess and adjust their projects to improve funding success before starting (Zhou et al., 2018).

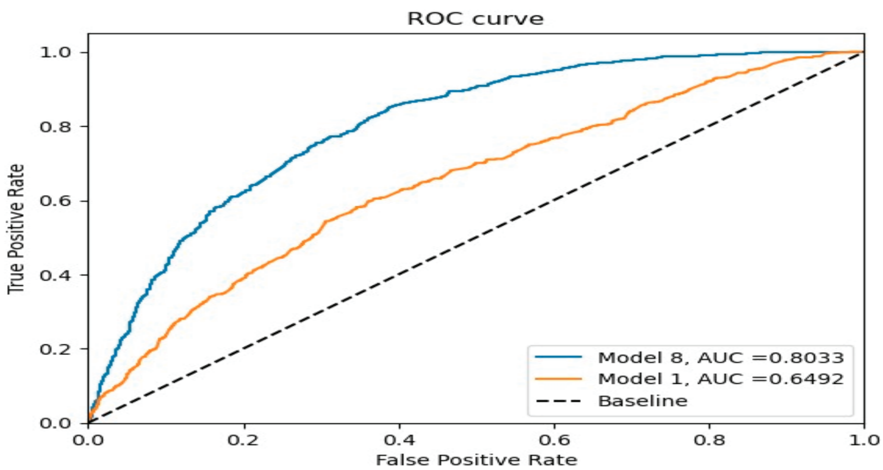

Figure 4. The ROC curves of baseline, Model 1, and Model 8.

Moreover, Model 8 boasts a higher AUC value of 0.8033 than Model 1's 0.6492, signifying greater accuracy. The larger area under Model 8's curve suggests it is positioned closer to the left side of the graph in Figure 4, underscoring its superior performance relative to Model 1.

5. Conclusions

Interest in crowdfunding is growing, but the success rate on the top platform is still below 50%. This has led to a lot of research into what makes crowdfunding work. It is easier for entrepreneurs with sustainable business ideas to access crowdfunding than traditional fundraising, making it a popular choice for eco-friendly businesses looking for money. Because of this, the topic of sustainable crowdfunding and what influences its success has captured the attention of many scholars. This study explores how the quantity and quality of project descriptions can affect the outcomes of sustainable crowdfunding efforts.

This study looks at the length and readability of project descriptions. Length shows how much text there is, while readability shows how easy it is to understand. The authors had two main ideas. The first idea is that the length of a crowdfunding project description might affect sustainable projects' success in a reward-based model. The second idea is that readability might influence the same model's success. To test these ideas, the study uses data from Kickstarter, covering 12,613 projects. The researcher uses multiple logistic regression models to examine the link between these variables and project success. The study shows that the length and readability of project descriptions significantly impact crowdfunding success. This backs up our first two ideas. For the first idea, having more words in project descriptions boosts the chances of sustainable crowdfunding success (with a coefficient of 1.0080 and a p-value of less than 0.001). More words help share more information, reduce gaps in understanding, and provide better explanations about sustainable crowdfunding. For the second idea, project descriptions that are easier to read are linked to better fundraising results (with a coefficient of 0.0487 and a p-value of less than 0.001). This finding agrees with some earlier studies, like the one by Adamska-Mieruszewska et al. (2021), but it differs from others, such as those by Liang et al. (2020) and Zhou et al. (2018).

The literature highlights the importance of a strong narrative in the success of crowdfunding campaigns for promoting sustainability. It is clear from the literature that narratives have the capacity to engage and inform possible donors; hence, when such narratives are carefully designed to highlight the social or environmental benefits linked with the project, they greatly increase the possibility of raising the necessary funds (Adamska-Mieruszewska et al., 2021; Mollick, 2014). Additionally, clear and concise statements on the distribution of funds, backed by detailed examinations of the long-term implications involved with the respective projects, have been linked to a greater success rate in obtaining funds for these projects (Ryu, 2024). Recent studies on this issue have proven that projects most in line with the United Nations' sustainable development goals have a better ability to attract greater interest from respective donors, thus promoting greater confidence and popularity among the general public (Kim et al., 2021).

On the other hand, empirical studies show that crowdfunding campaign narratives are not always the decisive determinants of the success of sustainable crowdfunding campaigns. For instance, Liang et al. (2020) showed that perceived novelty of the campaign, project leader credibility, and social network presence are more important determinants of campaign success than the narrative. Similarly, Zhou et al. (2018) argue that a project description can provide necessary information to potential funders; however, it does not guarantee fundraising success, especially when external market conditions and other factors, such as the economic well-being of the target market, are likely to have a greater impact. Such claims suggest that while project descriptions are of significant value, they are not the sole determinants of crowdfunding success under different situations.

This research demonstrates that better readability increases a project's chances of success. Project descriptions should use informal or simple language to clarify the information for potential backers. This clarity helps supporters understand and view the project positively, which boosts the likelihood of crowdfunding success. In conclusion, this study highlights that having longer, more readable project descriptions is key to reaching funding goals.

The study looks at how focusing on sustainability impacts the success of crowdfunding projects. Not many have examined this connection. Including more keywords related to sustainable development goals (SDGs) in project descriptions improves crowdfunding success. This underscores the vital role of sustainability in these projects.

Despite its worthwhile contribution, the study exhibits a few limitations that might offer directions for future research. First, and as mentioned, four crowdfunding models exist: donation-based, reward-based, equity-based, and lending-based. This research focuses specifically on the reward-based crowdfunding model, utilizing data exclusively from Kickstarter. While Kickstarter defines itself as the largest crowdfunding website in the world, such a claim necessarily limits the generalizability of the findings. Second, the selection of studies is limited to the technological sector, thereby introducing potential biases. Future research may explore crowdfunding efforts across models or websites that prioritize environmentally friendly causes, such as Kiva and GreenCrowd.

Third, this research only examines the textual aspects of project descriptions. However, visual aspects, including images and videos, are essential elements of these descriptions. Visual media are often considered more effective communication tools than text because they involve more than one sensory system in content processing (Scheinbaum et al., 2017). The researcher cannot access this kind of data in the dataset due to technical limitations.

Finally, this research does not claim authority with regard to the individual characteristics of supporters, such as age, gender, income, experience with crowdfunding, or interest in specific categories, all of which may influence their decision making. Future studies may further elaborate on the matters covered in this work.

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Drivers and Barriers of Mobile Payment Adoption Among MSMEs: Insights from Indonesia

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Abstract: Mobile payment systems have rapidly expanded globally, especially in developing countries like Thailand, Malaysia, and Indonesia. Technological advances, public acceptance, and increased adoption during the COVID-19 pandemic drive this growth. Mobile payments involve key stakeholders: technology providers, end-users, government regulators, and merchants, each contributing to the adoption ecosystem. Users prefer mobile payments for their speed and convenience over traditional cash transactions. This study explores the driver and barrier factors influencing mobile payment QR adoption among merchants, particularly from the MSME perspective, using existing frameworks based on previous research adapted to MSME conditions. Conducted in Indonesia with 418 MSME business respondents, this study employs a quantitative, cross-sectional methodology with a 95% confidence level and an SEM analysis. The findings reveal that perceived ease of use does not significantly impact perceived experience, while perceived usefulness does. Perceived risk, convenience, experience, and word-of-mouth learning statistically significantly influence merchants' intention to use mobile payments. However, customer engagement, cost, trust, and complexity appear less influential. Overall, this research advances understanding of the key factors affecting merchants' adoption of mobile payment and provides insights relevant to MSME economic growth.

Keywords: merchant intentions; business intermediaries; moderation; mediation; micro–small–medium enterprises (MSMEs)

1. Introduction

Mobile payment (MP) is a means of payment that utilizes information technology that is currently popular (R. Liu et al., 2021; The global payments report, 2021). An MP has different characteristics from manual payments. MP involves integration with banks and other digital wallets (Lou et al., 2017). Mobile payment (MP) involves at least four stakeholders: technology providers, end-users, governments, and merchants (Lou et al., 2017). Each party has a role, including technology providers providing application services that allow users to conduct transactions with their mobile devices. End-users are users who use mobile payments (MPs) as a means of payment. The government acts as a regulator that oversees and ensures no legal violations in the transaction process.

In comparison, merchants are partners of technology providers in receiving transactions. The main reason users choose to use mobile payment (MP) is that it is faster and more practical because there is no need to go to a bank or an ATM to obtain cash (Au & Kauffman, 2008; Cheng et al., 2021; Dahlberg et al., 2015). Even the largest accounting institution in the world, based in the Netherlands, KPMG, predicts that mobile payment

(MP) will change world civilization (Hallsworth et al., 2019). The COVID-19 pandemic has also significantly increased the use of mobile payment (MP).

According to scholars, mobile payment (MP) can increase the efficiency and effectiveness of transactions, the use of mobile payments (MPs) can also increase consumer reach, so it is hoped that it will encourage the development of MSMEs. The studies conducted by Mahakittikun, Lu, and Eiriz (Eiriz et al., 2019; Lu, 2019; Mahakittikun et al., 2020) confirm that the use of technology allows small companies to access the market and has the possibility to increase transaction growth. Therefore, governments in many countries are pushing to create integrated payment systems, including Indonesia. In Indonesia itself, many studies related to mobile payment (MP) have been carried out but are limited to end-users as objects.

Recent studies highlight the increasing role of digital payment adoption in emerging markets and its impact on MSME digital transformation. Research by the Cambridge Centre for Alternative Finance [CCAF] (2025) and ADBI underscores how digital finance providers enhance MSME access to credit, improving business performance in emerging economies (Cambridge Centre for Alternative Finance [CCAF], 2025). Furthermore, ODI Global Advisory, in their report, underlines how digital payments contribute to micro and small enterprises' economic empowerment and competitiveness (ODI Global Advisory, 2024). Moreover, digital orientation and innovation significantly drive MSME growth, with studies confirming that a strong digital strategy improves firm performance in emerging markets (Egala et al., 2024). However, digital transformation remains gradual and unequal as firms encounter barriers such as infrastructure limitations and digital literacy gaps (Marolt et al., 2025). These insights emphasize the need for policy interventions and fintech innovations to bridge the digital divide and accelerate MSMEs' adoption of digital payments.

Furthermore, MSMEs play a significant role in most economies, especially in developing countries (Kumar et al., 2019). More than 90% of businesses and 50% of workforces come from MSMEs. These data illustrate how massive the MSME economy is. MSMEs are one part of intermediary businesses, which provide digital payment services (Musyaffi et al., 2021). On the other hand, China, India, and Indonesia occupy the top-ranking positions regarding the number of unbanked populations, and the majority are in rural areas (Wang et al., 2021). This phenomenon opens considerable opportunities for MP stakeholders to increase profits. In Indonesia, MSMEs are predicted to employ 97% of the workforce, contributing 60.3% of the country's GDP, and makeup 14.4% of its exports in 2021 (ASEAN Investment Report, 2022).

Almost every country has a QR MP payment channel. For example, the Thai QR is used in Thailand as a means of payment directly connected to a bank account. The Quick Response Indonesian Standard (QRIS) is used in Indonesia. The QRIS is a QR code developed by the joint regulator of the Indonesian Payment Systems Association (ASPI), which aims to streamline digital payment systems securely, encourage government efficiency, and accelerate digital financial inclusion (Dahlberg et al., 2015). Meanwhile, DuitNow is a payment channel issued by the Malaysian government. Singapore introduced SQQR in 2018 to combine multiple payment QR codes into a single label and aims to simplify QR code-based mobile payment (MP) for consumers and merchants. In India, the QR Payment channel is called Bharat QR.

More than 96% of the industries in Indonesia are MSMEs, and from that, only less than 20% are already using information technology or digitizing. Meanwhile, 51% of the MSMEs in Singapore have enacted a digital transformation (Rouillard, 2008). Thailand is an ASEAN country with the highest level of digitization of MSMEs, around 71% (Bezhovski, 2016), while in Vietnam, 43% of MSMEs have utilized information technology to support their business, including mobile payment (MP) (Yakean, 2020). In Indonesia, the use of QRIS is very low compared to debit card use in transactions.

This fact is a challenge for MSMEs in developing countries, especially in Indonesia, because compared to other countries in the ASEAN Region, the level of digitization of the MSMEs in Indonesia is still very low. It is necessary to conduct research related to the factors that influence the use of MP QR by merchants, especially the MSMEs in developing countries, to increase the penetration of the use of MP QR.

Mobile payment (MP) research has been widely carried out and developed in both developed and developing countries. However, more research has been conducted to determine factors related to end-users, such as intention to use (World Bank, n.d.; World Bank Group Support for Small and Medium Enterprises A Synthesis of Evaluative Findings, 2019), the influence of gender (Mishra et al., 2022), age (Lee et al., 2019), experience with MP (World Bank Group Support for Small and Medium Enterprises A Synthesis of Evaluative Findings, 2019), and trust (Lee et al., 2019; Liébana-Cabanillas & Lara-Rubio, 2017; Mishra et al., 2022). Although the implementation of MP QR continues to grow and it is known that the effect of implementing it significantly helps increase value for merchants, especially MSMEs, research on MP QR in MSMEs is still rarely carried out; researchers focus on acceptance factors from end-users.

This study proposes factors and confirms the new models that can measure acceptance technologies of MP QR for merchants. The proposed factors in this study will refer to the frameworks and models that have been previously confirmed, such as Technology Acceptance models (TAM) (Davis, 1986; Mallat & Tuunainen, 2008), the Extended TAM (Pal et al., 2019), the Unified Theory of Acceptance and Use of Technology (UTAUT) (Ponte & Bonazzi, 2021), Theory Reason Action (TRA) (Venkatesh & Bala, 2008), the Theory of Planned Behaviors (TPB) (Pal et al., 2019), and a qualitative study from Mallat (2007), which will be adapted and developed with the conditions of MSMEs.

2. Literature Review

2.1. Mobile Payment with QR

According to the Global Payment Report, the penetration rate of mobile payment worldwide has increased yearly (The global payments report, 2021). In China, the country with the largest population using mobile payments, more than 87% of the population uses mobile payment as a means of payment. Meanwhile, a sharp increase in the use of mobile payments occurred in South Korea, wherein in 2019, 36% of the population used mobile payments, while in 2021, this increased to 45% and it became the country with the second-highest use of mobile payments. Then, it was followed by the US, with 43% of the population using mobile payments (The global payments report, 2021).

The most widely used types of mobile payment are NFC and QR codes (R. Liu et al., 2021). Two payment methods using QR codes that are commonly used are customers who scan a merchant's QR code (Lou et al., 2017), which is called autonomous payment, and a merchant who scans a QR code of customers, also called dependent payment.

Mobile payment has four main stakeholders (Au & Kauffman, 2008): governments, financial service providers, end-users, and merchants. Each stakeholder has a different role in the mobile payment ecosystem (Dahlberg et al., 2015). Customers and merchants can be categorized as users. Financial service providers provide infrastructures such as databases, processors, servers, and QR generators (Kumar et al., 2019). Users must provide a mobile phone with a camera to scan a QR code or receive proof of payment.

The mobile payment process using a QR Code starts with the customer selecting products and services and then scanning the QR code of the merchant. After that, the customer is asked to verify the account. If successful, the transaction is immediately transferred from the user to the merchant's account (Musyaffi et al., 2021). This process is fast and allows for transactions without contact between the end-users and merchants (Wang et al., 2021). Mobile payment using QR gives customers more privacy (Bezhovski, 2016; Rouillard, 2008). Besides that, by scanning QR codes, users can easily retrieve all the related data needed for transactions. The use of mobile payments will increase along with the increase in smartphones and information technology.

2.2. Micro–Small–Medium Enterprises

One important part of intermediary businesses in the mobile payment ecosystem are micro–small–medium enterprises (MSMEs). According to the World Bank, MSMEs are businesses with no more than 300 employees and total assets/total annual sales between USD 3 million and USD 15 million (World Bank Group Support for Small and Medium Enterprises A Synthesis of Evaluative Findings, 2019). MSMEs are the primary industry in every country, especially in developing countries. However, on average, MSMEs have limited capital and have difficulty accessing capital loans (World Bank, n.d.). One of the causes of MSMEs difficulty accessing capital loans is the absence of financial records or transaction books. This is helpful as evidence that the business being run can grow. Information technology is expected to help MSMEs to develop their businesses. Based on the number of employees and their capital, MSMEs can be grouped. The clustering of MSME is shown in Table 1: MSME Clusters (World Bank Group Support for Small and Medium Enterprises A Synthesis of Evaluative Findings, 2019).

Table 1. MSME Clusters.

Indicator	**Micro–Small–Medium Enterprise Definition**		
	Employees (No.)	**Total Assets ($)**	**Annual Sales ($)**
Micro	<10	<100,000	100,000
Small	10–49	100,000–3,000,000	100,000–3,000,000
Medium	50–300	3,000,000–15,000,000	3,000,000–15,000,000

2.3. Influencing Factor from a Merchants Perspective

The implementation of new technologies, such as the MP QR code, can proceed and be well received if stakeholders understand their role and know the benefits that will be obtained. The difficulty level of implementation can be tolerated (Mishra et al., 2022). The factors that influence end-users and merchants are also different.

Various studies have been conducted to try to uncover these factors. Lee revealed that network externalities, trust, and brand value affect retailer satisfaction. In comparison, the higher the retailer satisfaction with MP, the higher the interest in using it (Lee et al., 2019). Liébana-Cabanillas and Lara-Rubio (2017), in their research, propose five factors that influence interest in using MP. The five factors are the number of workers, income from merchants, experience using the old model, usability, and considerable advantages (Liébana-Cabanillas & Lara-Rubio, 2017). Meanwhile, Lisana (2021) argues that self-efficacy, social influence, trust, network externalities, and uncertainty avoidance are major variables influencing mobile payment adoption in Indonesia (Lisana, 2021). In addition, Mallat and Tuunainen (2008), stated that merchants expect the use of mobile payments to reduce costs and facilitate sales, including both services and products to consumers (Mallat & Tuunainen, 2008). Furthermore, customer engagement was proposed by Hepola et al. (2020), who stated that customer interaction has quite a beneficial effect on intention to use (Hepola et al., 2020).

Most articles have sought to build constructs based on existing technology adoption frameworks to develop a research model to capture mobile payment end-user and merchant behavior. This study attempts to build a construct based on the established technology adoption frameworks to develop a new theoretical framework tailored to the context of MSME mobile payment adoption in Indonesia. The established theories like the Technology Acceptance Model (TAM) (Davis, 1986; Pal et al., 2019), Unified Theory of Acceptance and Use of Technology (UTAUT) (Ponte & Bonazzi, 2021; Venkatesh & Bala, 2008), Theory of Reason Action (TRA) (A. Hasan & Gupta, 2020; Martin et al., 1975), Theory of Planned Behavior (TPB) (Ajzen, 1991; A. Hasan & Gupta, 2020), and Diffusion of Innovation Theory (DOI) (E. Rogers, 1983) are described in Table 2.

Table 2. Basic theory.

Basic Theory	Factors/Variables	References
TAM	Perceived usefulness, perceived ease of use, and intention to operate with usage behavior	A. Hasan and Gupta (2020); Davis (1986, 1989)
UTAUT/UTAUT 2	Relation between performance expectancy, effort expectancy, facilitating conditions, the perceived risk with behavioral intention	Ponte and Bonazzi (2021); Venkatesh et al. (2003)
TRA	Behavioral beliefs, attitude, normative beliefs, subjective norm, behavioral intention, actual use	Ajzen (1991); A. Hasan and Gupta (2020)
TPB	Attitude, subjective norm, perceived behavioral control, intention, behavior.	Ajzen (1991); A. Hasan and Gupta (2020)
DOI	Relative advantages, compatibility, complexity, trialability, observability	Pal et al. (2019, 2021); E. Rogers (1983)

3. The Hypothesis

Both drivers and barriers influence mobile payment adoption among MSMEs. Drivers include perceived usefulness and ease of use, as mobile payments offer speed and efficiency (Davis, 1989; Venkatesh et al., 2003). Word-of-mouth learning encourages adoption, as MSMEs rely on peer recommendations (Banerjee & Fudenberg, 2004). Additionally, customer engagement and perceived convenience motivate businesses to adopt mobile payments to enhance customer experience (Mallat & Tuunainen, 2008). Moreover, barriers include perceived cost, as transaction fees may burden small businesses (Y. Liu et al., 2019). Trust and security concerns also hinder adoption due to fears of fraud and data breaches (Farivar et al., 2017; Gefen, 2000). Lastly, complexity and a lack of digital literacy make it harder for some MSMEs to adopt mobile payments (Anatan, 2023). Identifying these factors helps in designing better strategies to increase adoption. Based on this, we can see that groups became drivers and barriers. The drivers in this research are perceived ease of use, perceived usefulness, word-of-mouth learning, customer engagement, perceived convenience, and perceived experience. Furthermore, the barriers are perceived cost, trust and security, risk, and complexity.

3.1. Perceived Ease of Use

Davis (1986) proposed the Theory Acceptance Model (TAM) which became the theoretical basis of this research. The TAM states that perceived ease of use and usefulness are independent factors determining attitudes towards using a technology (Davis, 1986). Consistent with Venkatesh and Davis (2000), it contends that attitudes on the use of information technology can be influenced by perceived ease of use, which is a significant issue (Venkatesh & Davis, 2000). Thus, Venkatesh assumes someone will use an application if the application is easy to use and learn. According to Sinha and Singh (2022), ease of use refers to how simple it is to utilize a technology (Sinha & Singh, 2022). Additionally, the measurement of a technology's usability depends on user expectations regarding the efficiency and utility of specific tasks when utilizing a technology (Sinha & Singh, 2022). The technology under consideration may include mobile payment, mobile commerce, and related technologies. According to Lisana (2021), one of the elements determining the success of implementing mobile payments in Indonesia will be if the form of mobile payment is intended to be easy to use and follows standard regulations. In Indonesia, the simplicity of use for a new technology is a significant feature (Lisana, 2021). Moreover, Liébana-Cabanillas et al. (2021), and Puriwat and Tripopsakul (2021) stated that when technology is simple to use and effortless, customers have a positive experience (Liébana-Cabanillas et al., 2021; Puriwat & Tripopsakul, 2021). Based on the opinions and findings of several researchers above, this encourages the formulation of the following hypothesis:

Hypothesis 1. *Perceived ease of use has a significant, positive, direct effect on perceived experience in MP usage.*

3.2. Perceived Usefulness

Davis (1989) has defined perceived ease of use as the extent to which a person believes that using the system will support and improve their work performance (Davis, 1989). Davis assumes that a person will use an application if the application helps him to complete the job better. Furthermore, Venkatesh analyzed usage predictions based on a comparison model including moderators in his study toward a unified view. Based on this study, perceived usefulness has a direct effect on interest in use (Venkatesh et al., 2003). Still, based on Venkatesh et al. (2003), perceived usefulness is the degree to which someone believes that using technology can improve and help their work. The more people believe that using technology will make their work easier, the greater the increase in the number of people using technology. Sinha and Singh (2022) confirmed that usefulness has a significant direct impact on perceived experience. Research involving technology acceptance analyses, which included usefulness as one of the variables, has been widely carried out in Indonesia. For example, the research conducted by Limantara et al. (2021), Lisana (2021), involves usefulness as one of the factors that influence the use of technology (Limantara et al., 2021; Lisana, 2021; Rahardja et al., 2020). Therefore, according to Qalati et al. (2021), in the merchant context, the usefulness of a service may be considered important if it increases value and provides the best experience for the retailer (Qalati et al., 2021). In the MP studies conducted by Khan et al. (2021), Talwar et al. (2021), and Mishra et al. (2022), factors such as usefulness and convenience were found to be relevant to improving merchant experience and behavioral intentions (Khan et al., 2021; Mishra et al., 2022; Talwar et al., 2021). Therefore, we propose the following:

Hypothesis 2. *Perceived usefulness has a significant, positive, direct effect on perceived experience in MP usage.*

3.3. Perceived Experience

Merchants have increasingly embraced digital payment services, prioritized high-quality products, and focused on perceived experience. Perceived experience encompasses the benefits and overall satisfaction derived from the features and effectiveness of a product or service (Jiang & Stylos, 2021). It plays a crucial role in evaluating technology performance and popularity, influencing merchants' intentions and decisions to adopt payment technologies (Talwar et al., 2021). During the COVID-19 pandemic, mobile payment systems (MPSs) helped merchants address challenges in supplier payments, credit facilities, and physical transactions, enhancing their perceived experience. Research shows that perceived experience directly impacts merchants' behavioral intentions and the adoption of technology, aligning with their business goals and improving efficiency (Chowdhury & Sarkar, 2003; Jiang & Stylos, 2021). To support adoption, payment companies must address merchants' desires and challenges, recognizing the critical role of perceived experience in shaping behavioral intentions.

Hypothesis 3. *Perceived experience has a significant, positive, direct effect on a merchant's intention to use.*

3.4. Word of Mouth Learning

A merchant's decision-making process is influenced by word-of-mouth communication, which is an informal statement about a product's features and benefits. An existing user may communicate this way to a new user, sharing his or her experience with the service. According to recent research, customers' recommendations for goods and services are influenced by their perceptions of the quality of those goods and services, which in turn affects their intentions to utilize them. Despite the proliferation of commercial communication channels, word-of-mouth recommendations remain one of the most trustworthy methods to choose products or services (83% of us say we trust recommendations from people we know).

Hypothesis 4. *Word-of-mouth learning has a significant, positive, direct effect on a merchant's intention to use.*

Hypothesis 5. *Perceived experience mediates the relation between word-of-mouth learning and a merchant's intention to use.*

Hypothesis 6. *Perceived experience moderates the relationship between word-of-mouth learning and a merchant's intention to use.*

In Hypothesis 5, perceived experience acts as a mediator, meaning it helps to explain how or why word-of-mouth learning influences merchants' intention to use mobile payments. In this case, word-of-mouth learning affects a merchant's perception of the experience, influencing their intention to adopt the technology. The effect of word-of-mouth learning on intention occurs indirectly through perceived experience. Meanwhile, in Hypothesis 6, perceived experience is proposed as a moderator, which affects the strength or direction of the relationship between word-of-mouth learning and intention to use. That is, the influence of word-of-mouth learning on intention may be stronger or weaker depending on the perceived experience level.

According to prior research, it is indicated that perceived experience serves a crucial role in both mediating and moderating the relationship between word-of-mouth learning and its outcomes. This suggests that an individual's prior experiences can significantly influence how they interpret and react to information shared through word-of-mouth interactions (Sinha & Singh, 2022). So, in this study, we want to know the relationship between them from the perspective of Indonesian merchants.

3.5. Perceived Cost

Cost refers to the monetary implications that arise when users use mobile payment applications. The cost structure of the technology has a substantial impact on users (Venkatesh et al., 2003). The banking system in Indonesia still charges transaction fees for every interbank transaction and top ups on digital wallets. This is predicted to influence the interest of

MSMEs and the public in using mobile payments as the main means of payment. Perceived cost is one of the many factors that affect Micro, Small, and Medium-Sized Enterprise (MSME)s' adoption of mobile payment systems. The perceived cost negatively affects the intention to use mobile payment systems. High perceived costs can deter users from adopting mobile payment solutions, as they may view these costs as a barrier to entry or continued use (Al-Saedi et al., 2020; Y. Liu et al., 2019; Schmidthuber et al., 2020).

Costs that arise can be in the form of investment fees, subscriptions, balance top-ups, transfers, internet, etc. Costs incurred can be borne by consumers as end users or merchants. Investment costs are costs that may arise when a merchant intends to provide mobile payment services as a payment medium. In Indonesia, several mobile payment financial service providers charge fees to top-up balances, and inter-bank transfers are also subject to quite high rates for each transaction.

Hypothesis 7. *Perceived cost has a significant, positive, direct effect on a merchant's intention to use.*

3.6. Perceived Trust

The degree of trust is impacted by the danger and inadequate security of information systems. Trust refers to an individual's psychological state based on positive expectancy toward others' behaviors or intentions. Trust has been studied as an important predictor of a user's behaviors in social commerce (Farivar et al., 2017). Trust has been extensively studied in the information system literature, and it is considered an essential element in purchasing transactions, especially in the environments in which risk elements exist. Therefore, we consider trust as the driver of social commerce use which can motivate users to purchase from a social commerce website (Farivar et al., 2017).

In line with Handarkho's, Shi's, and Farivar's research, this study places trust as a factor influencing intention to use. In the use of technology, trust is an important factor that must be held by users (Farivar et al., 2017; Handarkho, 2021; Shi & Chow, 2015). If a user has trust, they will use it safely and comfortably, so that the intention to use it also increases. By having trust for social commerce websites and the other users on them, a customer will accept the credibility of the information provided by the company who owns that site and the other users that engage in it (Shi & Chow, 2015). The combination of trusts established by the two sources above will develop a customer's positive perception, which will influence their intention to engage with and use social commerce sites (Handarkho, 2021). Based on that study, we propose the following:

Hypothesis 8. *Perceived trust has a significant, positive, direct effect on a merchant's intention to use.*

3.7. Perceived Convenience

According to previous research, convenience is a major aspect. Consumers prefer to utilize mobile payment to save time and effort when making purchases (Boden et al., 2020; Pal et al., 2021; Shankar & Behl, 2021). Convenience refers to the degree of usefulness a technology offers. Convenience consists of various dimensions of benefits that can be felt by users, such as faster transactions and simpler payments, to support practicality (Pal et al., 2021). Offline transactions require consumers to spend time, effort, and money, whereas mobile payment allows users to execute transactions at any time and from any location. As a result, transactional convenience, attentiveness, customer service, and transactions all have a big impact on the consumer's mobile payment experience (Shankar & Behl, 2021).

In Indonesia, convenience is something that is desired: to achieve a certain level of comfort, people are willing to pay more. The research of Hadiyan et al. (2021) revealed that when users feel comfortable using a technology, they will use and recommend it more often (Hadiyan et al., 2021).

Mobile payments offer convenience by eliminating the need to carry cash and coins or provide exact change for purchases (Mallat & Tuunainen, 2008). Furthermore, convenience in general can increase the willingness of customers to pay. So, the more comfortable it is to use mobile payments, the more willing a customer will be to pay, thus the merchant has the opportunity to increase revenue. Adoption of technology implies an acceptance of and familiarity with it, which raises the feeling of convenience (Boden et al., 2020).

Hypothesis 9. *Perceived convenience has a significant, positive, direct effect on a merchant's intention to use.*

3.8. Customer Engagement

Customer engagement is an interaction or communication relationship carried out by a company or producer with customers. Customer engagement can be seen as a multi-dimensional concept consisting of emotional, cognitive, and behavioral aspects (Rather & Hollebeek, 2021). In the context of merchants, customer engagement is important because good relationships and the best service to customers will drive customers to continue shopping and if merchants have strong engagement with customers, they will be satisfied with the services provided and will increase loyalty. Kumar and Pansari (2016) define customer engagement as a mechanism for adding customer value to merchants, either directly or indirectly (Kumar & Pansari, 2016). Meanwhile, Hepola et al. (2020) discovered that customer interaction had a considerable beneficial effect on intention to use (Hepola et al., 2020). In this study, customer engagement is seen from the point of view of the business owner of an MSME.

Hypothesis 10. *Customer engagement has a significant, positive, direct effect on a merchant's intention to use.*

3.9. Complexity

Complexity is one of the significant inhibiting factors in the use of mobile payments (Mallat & Tuunainen, 2008). Seventy percent of the MSME players in Indonesia have completed at least high school, while the country's MSME actors still have comparatively low levels of education. This has an impact on MSME participants' ability to solve problems, and complexity will make it challenging for MSMEs to accept mobile payment applications.

Mobile applications are more widely used by educated people, the younger generations, who are accustomed to using other information technologies, and people who find it easy to learn new things. Complexity becomes an obstacle because economic transactions can be carried out by all groups, whether they are using technology or not. New users are concerned about the usability of mobile payment applications and view usability as an important factor influencing user adoption. As a modern payment technology, mobile payment should be easy to use and simple (Mallat & Tuunainen, 2008). Furthermore, the MSME actors in Indonesia are predominantly parents and those with a low education. Based on a survey by the Faculty of Economics and Business, at the University of Indonesia, as many as 61% of MSME managers are over 40 years old and as many as 83% have high school as their highest education level. In recent research, complexity is also considered a predictor of intention to use mobile payments.

Hypothesis 11. *Complexity has a significant, positive, direct effect on merchants' intention to use.*

3.10. Perceived Risk

In comparison to developed nations, Indonesia still maintains relatively low security standards. Numerous instances of unsuccessful transactions, data theft, and even money theft from consumer accounts have occurred.

As cybercrimes are on the rise, mobile payment transactions pose a risk to your finances and data (Pal et al., 2021). Risk is a component that many researchers include and address in their research, as opposed to convenience. They use the UTAUT theory as a foundational theory, similar to Ponte and Bonazi's investigation. Numerous changes were made, such as excluding social influence because it was shown to be insufficiently influential and adding the perceived risk variable to understand how much influence these risk factors have on the intention to use and find out whether the use of technology is safer (Ponte & Bonazzi, 2021). The risks can be differentiated based on the losses that may be experienced, such as financial, privacy, security, and performance risks (Pal et al., 2021). Financial risks can occur, such as failed transfers, wrong transfers, and theft. Some cases that often occur are crimes involving changing the payment barcode code, so that the user is not aware that he has transferred money to the wrong account. By linking mobile payments with a bank account, the possible losses will be greater when compared to cash transactions (Zhou, 2015).

Hypothesis 12. *Perceived risk has a significant, positive, direct effect on a merchant's intention to use.*

3.11. Merchant Intention to Use

Intention to use is the extent to which consumers are likely to use and engage in social commerce. Intention to use and usage behavior in the TAM are factors that refer to a user's habitual interest in using information technology; meanwhile, intention to use can affect usage behavior (Venkatesh & Davis, 2000). Intention to use in the context of technology describes a user's interest in starting to use it and their desire to use it again. In this study, merchant intention to use is a mediating factor, because it links other factors rather than modifying their effect on actual use.

Hypothesis 13. *Merchant's intention to use has a significant, positive, direct effect on actual use.*

3.12. Actual Use

Actual use was proposed by Davis in the Technology Acceptance Model. Davis distinguishes between desire to use and actual use. Meanwhile, Venkatesh with his UTAUT tries to confirm the factors that influence intention to use and then, influence use behavior either directly or indirectly (Venkatesh et al., 2003). Studies on actual use continue to grow; for example, Pal et al. found that there is still a gap between intention to use and actual usage (Pal et al., 2019) and there is still has chance for further research. Liu also mentions actual use (C. H. Liu et al., 2022); he researched the impact of using mobile payments on shopping intentions and usage behavior. The results show that intention to use has a significant and positive effect on usage behavior. However, recent research indicates that utilization determines how much of an impact IT adoption has on corporate performance (Au & Kauffman, 2008).

4. Proposed Model

After comprehensively discussing previous research and the factors involved, the researcher developed a theoretical model for further measurements. The proposed model incorporates key constructs such as perceived risk, convenience, and behavioral intention, adapted from established information systems' adoption theories. The eight exogenous variables include perceived word-of-mouth learning, perceived cost, perceived trust, perceived convenience, customer engagement, complexity, perceived risk, and perceived experience. In addition to acting as an exogenous variable, perceived experience acts as a mediator and moderator for the word-of-mouth learning variable. Moreover, there are two antecedent variables: perceived ease of use and usefulness. We also have one intervening variable, intention to use, and one dependent variable, actual use.

Hence, the researcher would like to present the conceptual model of this study as follows:

Each of the 13 causal relationships shown in Figure 1 are associated with a research hypothesis, which is based on previous research which has been discussed in the previous sub-section.

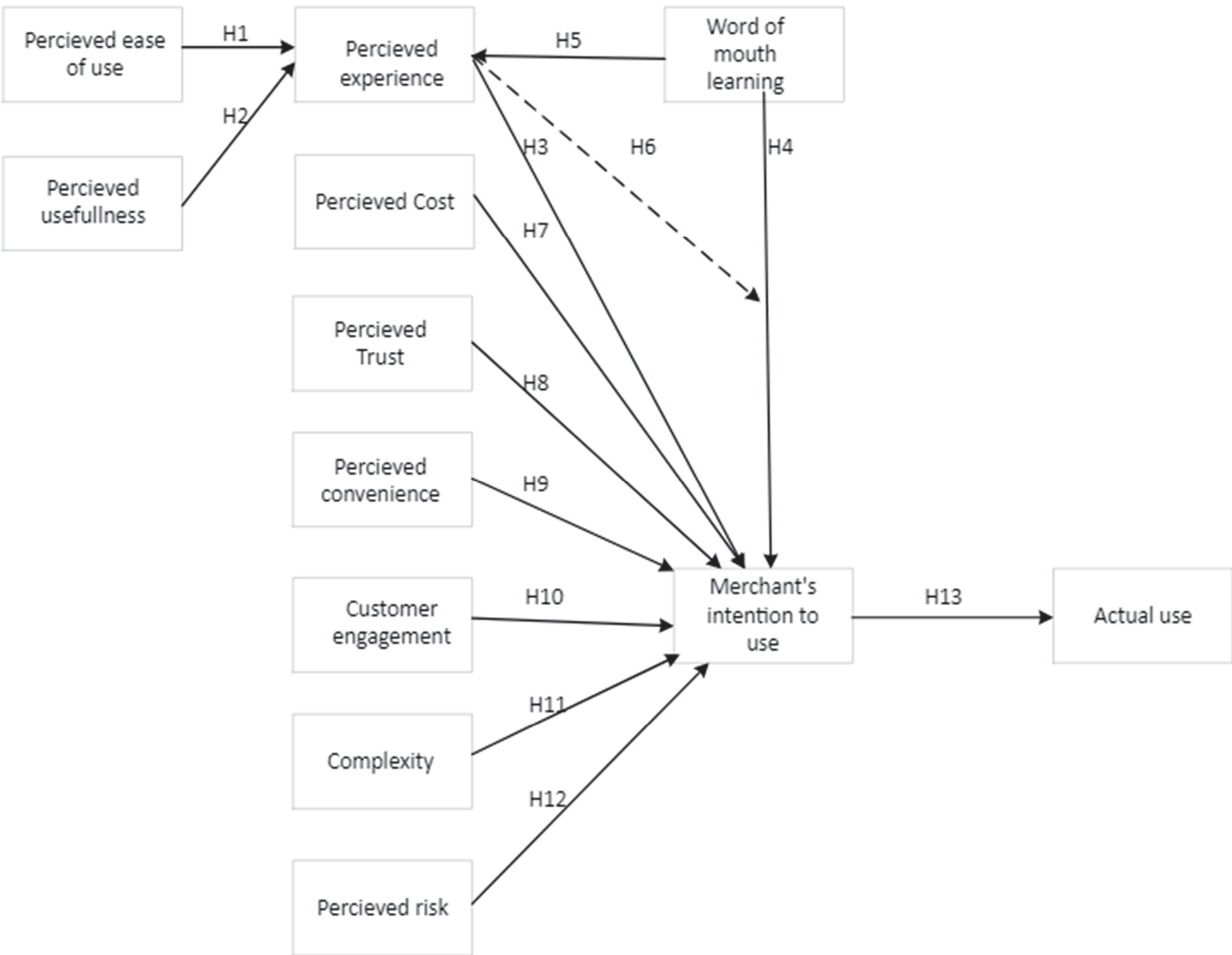

Figure 1. Theoretical model.

5. Research Methodology

The research employs structural equation modeling (SEM) with a 95% confidence level, utilizing AMOS 21 for a SEM analysis and SPSS 22 for data processing. This approach includes a factor loading analysis and a confirmatory analysis (CFA) to systematically organize, process, and validate the data. By using this method, this study ensures that all variables and constructs are accurately measured and properly aligned, enhancing the reliability of the findings.

5.1. Sample and Data Collection

The target population of this research includes business owners and decision-makers whose businesses meet the criteria of MSMEs and who are 18 years of age or older. The questionnaire was derived from the existing research and carefully translated into Indonesian to maintain accuracy and preserve the original meaning. To further translation accuracy, a back-translation method was applied. Additionally, a pilot test with ten responders was conducted to improve the instruments' clarity, validity, and reliability.

For a population exceeding 100.000, a minimum sample size of 400 is required to achieve a 5% margin of error at a 95% confidence level (Hair et al., 2014; Kline, 2016). Eligible respondents were provided with a self-administered questionnaire in person or online.

The data used to test the research model were collected through questionnaire responses, with each item measured on a five-point Likert scale (1 = strongly disagree to 5 = strongly agree). To minimize semantic issues, the questionnaire was refined based on input from three experts in acceptance models and digital transformation. The questionnaire was then presented in a pretest to ten MSME actors and changed based on their feedback to ensure validity. Indicators and measurement instruments are shown in Table 3.

Table 3. Indicators and measuring instruments.

Variable (Symbol)	Indicator	Measuring Instrument	Adopted From
Perceived ease of use	PEOU1	Mobile payment services are easy to use	Shin et al. (2014)
	PEOU2	Mobile payment transactions save my time and efforts	
	PEOU3	Mobile payment service looks very convenient to me	
Perceived usefulness	PUSE1	Mobile payment service is very useful for performing daily transactions	Shin et al. (2014)
	PUSE2	I can access mobile payment services anytime and anywhere	
Perceived experience	PEXP1	Mobile payment service improves my business experience.	Shanmugam et al. (2016)
	PEXP2	The more I use the app the more I become experienced with it	
	PEXP3	Mobile payment allows me to receive all relevant information related to my business.	
Word of mouth learning	WOML1	I read online consumer reviews and feedback about mobile payment services.	Lee and Hong (2019)
	WOML2	I read recommendations from consumers about mobile payment services	
Perceived cost	COST1	My daily transaction expenses will be reduced using mobile payments.	Zhou (2011)
	COST2	Mobile payment service reduces the cost of processing consumer payments	
Perceived trust	TRUS1	I trust mobile payment service secures my consumer personal and financial data	Liébana-Cabanillas and Lara-Rubio (2017)
	TRUS2	I trust mobile payment service is secure from fraud	

Table 3. *Cont.*

Variable (Symbol)	Indicator	Measuring Instrument	Adopted From
Perceived convenience	PCON1	Mobile payment is convenient for me to engage in receiving and making payments	Shin et al. (2014)
	PCON2	I feel that mobile payment is convenient for me to pay for	
Customer engagement	CENG1	My customers feel satisfied and happy to be able to pay using mobile payment	Han et al. (2016)
	CENG2	My customers feel very positive when they use mobile payment methods to pay	
	CENG3	My customers (will) feel well served by providing various types of payment alternatives	
Complexity	COMP1	By using mobile payment my job in making financial reports becomes easier	Shin et al. (2014)
	COMP2	Transaction times are faster if you use mobile payment because you don't have to bother looking for change	
Perceived risk	RISK1	The decision to carry out banking transactions via mobile payments has high profit potential	Han et al. (2016)
	RISK2	The decision to carry out banking transactions via mobile payments is a very positive situation	
Merchant intention to use	INTN1	I have a plan to use mobile payment services for my business	Shin et al. (2014); Sinha and Singh (2022)
	INTN2	I intend to increase my usage of mobile payment services for consumer service	
Actual use	ACUS1	On average per month, I use mobile payment apps	(Park et al., 2010); Han et al. (2016)
	ACUS2	On a monthly basis, my overall frequency of using mobile payment apps is:	

5.2. Data Preparation and Analysis

A total of 418 responses from the target population were collected for this study. The measurements model was evaluated based on convergent validity and discriminant validity to ensure the reliability and accuracy of the constructs. Convergent validity was assessed using three criteria: factor loadings, average variance extracted (AVE), and composite reliability (CR). It measures the extent to which indicators of a specific construct share a high proportion of common variance. Discriminant validity is crucial for establishing construct validity, preventing multicollinearity, defining clear conceptual boundaries, and improving the accuracy of the theoretical model.

For convergent validity, standardized loading estimates should be 0.5 or higher, ideally 0.7 or higher (Hair et al., 2014). The extracted variance should be 0.5 or higher, and the coefficient alpha for construct reliability should be 0.7 or greater (George & Mallery, 2019), although values between 0.6 and 0.7 can be acceptable (Dash & Paul, 2021). They also recommended that the variance extracted estimates for two factors should be more than the square of the correlation between them to provide evidence of discriminant validity for the total scale.

AVE measures how well a set of items converges to represent a construct, while CR evaluates the internal consistency of those items. In other words, AVE assesses how well a set of items converges to measure a construct, and CR checks the internal consistency of those items. In addition to convergent validity, discriminant validity is essential for ensuring construct validity, preventing multicollinearity, defining clear conceptual boundaries, and improving theoretical model accuracy. To assess discriminant validity, we apply the Fornell–Larcker criterion (Fornell & Larcker, 1981), which compares the correlation between constructs with the square root of their AVE. For discriminant validity to be established, the square root of a construct's AVE must be greater than its correlation with the other constructs. This confirms that a construct shares more variance with its indicators than the other constructs.

6. Result

The construct validity (discriminant and convergent) of the measures of the 12 latent variables from the theoretical models was examined using a principal component factor analysis (Hair et al., 2014). The results derived from the evaluation of the factor loadings of the indicators in relation to their corresponding variables, as well as among the variables themselves, are presented in Table 4. The factor loading values indicated in the table are above the recommended threshold of 0.5, which is commonly accepted for the measurement of factor loadings. We evaluated Composite Reliability (CR), and Average Variance Extracted (AVE) to assess validity further. All constructs have CR and AVE values that are higher than the minimal cutoffs of 0.7 for CR and 0.5 for AVE, except for the COST which had a CR value 0.677. Although slightly below the ideal threshold, it can still be acceptable (Dash & Paul, 2021). We retained the COST variable due to its theoretical and practical significance in understanding merchant decision-making (Bhimani, 2021; E. F. Hasan et al., 2025; James et al., 2025). Overall, the result of the factor loadings, average variance extracted (AVE), and composite reliability (CR) confirm that the survey items consistently and dependently align with their respective constructs, and each construct explains at least 50% of the variation in its indicators, supporting the measurement model's reliability and validity.

Table 4. Factor loading analysis and value of CR and AVE.

Factor	Indicator Relation			Estimate	CR	AVE
Perceived usefulness (PUSE)	PUSE2	←	PUSE	0.787	0.802	0.670
	PUSE1	←	PUSE	0.849		
Perceived ease of use (PEOU)	PEOU3	←	PEOU	0.895	0.928	0.812
	PEOU2	←	PEOU	0.899		
	PEOU1	←	PEOU	0.909		
Perceived convenience (PCON)	PCON2	←	PCON	0.846	0.870	0.770
	PCON1	←	PCON	0.908		
Customer engagement (CENG)	CENG3	←	CENG	0.78	0.876	0.702
	CENG2	←	CENG	0.842		
	CENG1	←	CENG	0.888		
Cost (COST)	COST2	←	COST	0.812	0.677	0.517
	COST1	←	COST	0.612		

Table 4. *Cont.*

Factor	Indicator Relation			Estimate	CR	AVE
Trust (TRUS)	TRUS2	←	TRUS	0.826	0.863	0.760
	TRUS1	←	TRUS	0.915		
Merchant intention to use (INTN)	INTN2	←	INTN	0.861	0.816	0.690
	INTN1	←	INTN	0.799		
Complexity (COMP)	COMP2	←	COMP	0.751	0.755	0.607
	COMP1	←	COMP	0.806		
Perceived risk (RISK)	RISK2	←	RISK	0.748	0.700	0.539
	RISK1	←	RISK	0.72		
Perceived experience (PEXP)	PEXP3	←	PEXP	0.754	0.834	0.626
	PEXP2	←	PEXP	0.8		
	PEXP1	←	PEXP	0.819		
Actual usage (ACTU)	ACTU2	←	ACTU	0.907	0.900	0.818
	ACTU1	←	ACTU	0.902		
Word-of-mouth learning (WOML)	WOML2	←	WOML	0.842	0.834	0.716
	WOML1	←	WOML	0.85		

Table 5 shows the result of the discriminant validity measurement. The values along the diagonal represent the square roots of the AVE (Average Variance Extracted) for each construct, and they are all greater than the corresponding inter-construct correlations. This confirms that each construct is different from the others, thus indicating acceptable discriminant validity based on the Fornell–Larcker criteria.

Table 5. Correlation matrix and discriminant validity assessment.

	CR	AVE	PEOU	WOML	TRUS	PUSE	PEXP	INTN	PCON	CENG	RISK	ACTU	COST	COMP
PEOU	0.928	0.812	**0.901**											
WOML	0.834	0.716	0.581 **	**0.846**										
TRUS	0.863	0.760	0.649 **	0.531 **	**0.872**									
PUSE	0.802	0.670	0.788 **	0.579 **	0.644 **	**0.819**								
PEXP	0.834	0.626	0.730 **	0.593 **	0.559 **	0.740 **	**0.791**							
INTN	0.816	0.690	0.729 **	0.657 **	0.682 **	0.752 **	0.723 **	**0.831**						
PCON	0.870	0.770	0.782 **	0.604 **	0.626 **	0.791 **	0.696 **	0.741 **	**0.878**					
CENG	0.876	0.702	0.711 **	0.572 **	0.548 **	0.646 **	0.639 **	0.684 **	0.723 **	**0.838**				
RISK	0.700	0.539	0.659 **	0.587 **	0.597 **	0.638 **	0.622 **	0.712 **	0.658 **	0.650 **	**0.734**			
ACTU	0.900	0.818	0.653 **	0.496 **	0.478 **	0.561 **	0.577 **	0.668 **	0.633 **	0.558 **	0.622 **	**0.905**		
COST	0.677	0.517	0.302 **	0.311 **	0.242 **	0.305 **	0.352 **	0.270 **	0.325 **	0.264 **	0.260 **	0.167 **	**0.719**	
COMP	0.755	0.607	0.684 **	0.555 **	0.458 **	0.675 **	0.642 **	0.605 **	0.711 **	0.653 **	0.570 **	0.571 **	0.335 **	**0.779**

** Correlation is significant at the 0.01 level (2-tailed). Bold value: the value of AVE square roots.

The results in Table 6 indicate that hypotheses H1, H6, H7, H8, H10, and H11 are not supported, as their *p*-values exceed 0.05. In contrast, hypotheses H2, H3, H4, H5, H9, H12, and H13 are statistically significant, with *p*-values below the 0.05 threshold, demonstrating a strong relationship consistent with the theoretical framework. These findings partially validate the proposed model, identifying the areas requiring further investigation and refinement. Table 6 presents the detailed hypothesis testing results.

Table 6. The hypotheses testing results, and the Direct, and Indirect effect analysis.

Relations	*Direct Effect*	*Status*
Perceived ease of use → Perceived experience (H1)	0.327 NS	Rejected
Perceived usefulness → Perceived experience (H2)	0.07 ***	Accepted
Perceived experience → Merchant Intention to use (H3)	0.15 ***	Accepted
Word of mouth learning → Merchant Intention to use (H4)	0.066 *	Accepted
Word of mouth learning → Perceived experience	0.001 ***	Accepted
Word of mouth learning_Perceived experience → Merchant Intention to use (H6)	0.362 NS	Rejected
Perceived cost → Merchant Intention to use (H7)	0.614 NS	Rejected
Perceived trust → Merchant Intention to use (H8)	0.392 NS	Rejected
Perceived convenience → Merchant Intention to use (H9)	0.049 ***	Accepted
Customer engagement → Merchant Intention to use (H10)	0.661 NS	Rejected
Complexity → Merchant Intention to use (H11)	0.535 NS	Rejected
Perceived risk → Merchant Intention to use (H12)	0.027 ***	Accepted
Merchant Intention to use → Actual Use (H13)	0.002 ***	Accepted
Relations	**Indirect Effect**	**Status**
Perceived experience → Merchant Intention to use → Actual Use	0.014 ***	Accepted
Word of mouth learning → Merchant Intention to use → Actual Use	0.021 *	Accepted
Perceived cost → Merchant Intention to use → Actual Use	0.589 NS	Rejected
Perceived trust → Merchant Intention to use → Actual Use	0.381 NS	Rejected
Perceived convenience → Merchant Intention to use → Actual Use	0.049 ***	Accepted
Customer engagement → Merchant Intention to use → Actual Use	0.654 NS	Rejected
Complexity → Merchant Intention to use → Actual Use	0.532 NS	Rejected
Perceived risk → Merchant Intention to use → Actual Use	0.028 ***	Accepted
Word of mouth learning → Perceived experience → Merchant Intention to use → Actual Use (H5)	0.021 ***	Accepted
Perceived ease of use → Perceived experience → Merchant Intention to use	0.245 NS	Rejected
Perceived usefulness → Perceived experience → Merchant Intention to use	0.017 ***	Accepted
Perceived ease of use → Perceived experience → Merchant Intention to use → Actual Use	0.237 NS	Rejected
Perceived usefulness → Perceived experience → Merchant Intention to use → Actual Use	0.017 ***	Accepted

Note(s): The indirect effect was calculated using the heuristic method by Cohen et al. (2002).

The values in Table 6 were presented in the following form: unstandardized effect followed by statistical significance presented by *, ***, or NS which refers to 0.05, 0.001, or Not Significant, respectively. In addition, the goodness of fit indicators of the models meet the minimum criteria of statistical values. The indicators of goodness of fit can be seen in Table 7.

Table 7. Fit indices for the models.

Model Fit Statistics	Result	Value Recommended
Root Mean Square Error of Approximation (RMSEA)	0.047	<0.05/Good fit
Comparative Fit Index (CFI)	0.968	>0.9/Good fit
Tucker–Lewis Index (TLI)	0.958	>0.90/Good fit
Standardized Root Mean Square Residual (SRMR)	0.026	<0.08/Good fit
AGFI	0.879	>0.80/fit
Goodness-of-Fit Index (GFI)	0.914	>0.9/Good fit
χ/df (Normed Chi-square, NC) where df is the degrees of freedom	1.903	<3/Good fit

7. Discussions and Implications

The results highlight both supported and unsupported hypotheses, offering a clearer understanding of the factors influencing mobile payment usage. Notably, perceived ease of use directly affects perceived experience, which is rejected (H1). This result contrasts with the findings in previous research (Liébana-Cabanillas et al., 2021; Puriwat & Tripopsakul, 2021; Sinha & Singh, 2022), which reported a significant relationship between these constructs. One of the potential explanations for this difference is the current study context, which focuses on MSME students in Indonesia. These users may prioritize practical business outcomes, such as cost-effectiveness, customer reach, and transaction reliability, over perceived system simplicity. In this context, ease of use may not significantly affect their overall experience, especially if combined with factors like trust, perception of utility, or security services. More specifically, various levels of digital literacy among MSME owners can reduce their perception of the ease of use of a system, making this concept more important for their adoption experience. This finding indicates that while ease of use is essential, it does not singularly shape users' experiences, as individual preferences, expectations, and product features also play a significant role. Conversely, the positive impact of perceived usefulness on perceived experience was strongly supported (H2), aligning with previous research by Sinha, Puriwat, and Liebana-Cabanillas showcasing the critical importance of perceived value in shaping user experiences.

In addition, the significant influence of perceived experience (H3), word-of-mouth learning (H4), convenience (H9), and perceived risk (H12) on mobile payment adoption and actual usage was validated. Hence, these results highlight the critical role of these constructs in shaping user behavior and adoption decisions and align with prior studies (Boden et al., 2020; Jiang & Stylos, 2021; Pal et al., 2021; Ponte & Bonazzi, 2021; Sinha & Singh, 2022; Talwar et al., 2021). Additionally, the mediation analysis reveals that perceived experience mediates the relationship between word-of-mouth learning and intention to use, offering more profound insights into the indirect factors driving adoption. However, in this study, factors such as perceived cost (H7), trust (H8), customer engagement (H10), and complexity (H11) did not directly affect mobile payment adoption, likely due to the specific priorities and context of MSMEs. Business owners tend to focus on functionality and perceived benefits, such as usefulness, rather than concerns about cost and trust. In the context of Indonesian MSMEs, these factors may be less influential due to several contextual reasons, including limited digital literacy, the prioritization of business practicality over system features, and a reliance on peer recommendations over system characteristics. Additionally, trust may not be a significant barrier because, in Indonesia, there is no other system, so the community and MSME communities continue to use the mobile payment system even though trust issues exist. Government initiatives and technology provider policies may have further mitigated trust-related uncertainties, making it less of a deciding factor for adoption. Meanwhile, intention to use (H13) has a positive, direct effect relationship with actual usage. This result is consistent with previous studies by C. H. Liu et al. (2022) and Pal et al. (2019).

Similarly, perceived cost might not hinder the adoption of mobile payments in the MSME sector; since, they may also view the long-term benefits, such as increased sales, customer convenience, and easy handling with cashless payments, as outweighing the costs. Customer engagement may play a more indirect role, as MSMEs could adopt mobile payments primarily for operational efficiency rather than because of direct customer interaction. Moreover, complexity may not be a significant barrier, especially for business owners with less technology experience, but who are already familiar with digital payment systems. Training programs and fintech education could further reduce usability concerns, making perceived complexity less of an issue. The findings indicate that other factors, such as perceived usefulness, word-of-mouth learning, and perceived experience, strongly influence the adoption of mobile payments among MSMEs. This result suggests that MSMEs prioritize the practicality and benefits of mobile payments over the potential challenges related to cost, trust, or complexity.

7.1. Theoretical Implications

This study extends prior research by integrating multiple theoretical perspectives (TAM, UTAUT, and TPB) to develop a new theoretical framework tailored to MSME mobile payment adoption. By combining key factors from the proven theories in previous studies, this research offers a novel approach to explaining the factors influencing adoption behavior. Moreover, this study highlights the mediating role of merchants' intention to use, showing how perceived usefulness, perceived risk, and word-of-mouth learning collectively shape actual adoption, in contrast with the previous studies that focused on individual constructs. Furthermore, the findings challenge the conventional assumption that perceived cost and trust directly influence adoption, suggesting that financial literacy and regulatory interventions may moderate their impact. This study also extends prior research by examining the indirect pathways through which user perceptions translate into adoption behavior, providing a more nuanced understanding of the decision-making process. These insights enrich theoretical discussions on digital payment adoption and serve as a foundation for future research exploring the evolving role of fintech solutions in MSME digital transformation.

7.2. Practical Implications

The findings of this study offer insights for fintech companies as technology providers and governments as policymakers to enhance mobile payment adoption among MSMEs. The results highlight the critical role of perceived usefulness, perceived experience, word-of-mouth learning, and perceived risk in shaping mobile payment adoption, while factors such as perceived cost, trust, customer engagement, and complexity were found to be insignificant. Table 8 provides the following actionable implications:

Table 8. Practical implications.

Key Findings	Implications for Technology Providers	Actionable Steps for Technology Providers	Implications for Government	Actionable Steps for Governments
Perceived usefulness and experience strongly influence mobile payment adoption.	Improve mobile payment platforms by enhancing user-friendly interfaces and seamless transactions.	- Design intuitive navigation and simple workflows. - Implement automated payment reminders and transaction insights. - Offer personalized features to improve perceived usefulness.	Support MSMEs with education on the benefits of mobile payments.	- Integrate digital payment education into financial literacy programs. - Provide training on how mobile payments improve business efficiency.
Word-of-mouth learning significantly affects adoption.	Leverage referral programs, community engagement, and user testimonials to drive adoption.	- Implement user referral incentives. - Organize peer-led training sessions for MSMEs. - Promote successful adoption stories through case studies.	Foster peer-learning networks among MSMEs.	- Partner with MSME associations to facilitate knowledge sharing. - Develop regional mentoring programs for digital adoption.

Table 8. *Cont.*

Key Findings	Implications for Technology Providers	Actionable Steps for Technology Providers	Implications for Government	Actionable Steps for Governments
Perceived risk affects mobile payment adoption.	Strengthen fraud detection, dispute resolution, and transparency.	- Enhance real-time fraud monitoring and alerts.	Enforce stronger cybersecurity regulations and consumer protection.	- Implement stricter fraud protection laws.
		- Improve customer support for faster dispute resolution.		- Establish government-backed complaint resolution systems.
		- Publicize security certifications and compliance measures.		- Conduct public awareness campaigns on cybersecurity.
Perceived cost, trust, customer engagement, and complexity were not significant.	Continue simplifying pricing models and enhancing customer support.	- Introduce tiered pricing structures for MSMEs.	Improve MSME access to digital infrastructure and payment integration.	- Provide incentives for digital infrastructure expansion.
		- Offer cost-effective transaction plans and fee reductions.		- Ensure clear, standardized regulations for mobile payment integration.
		- Maintain transparent communication on pricing and service policies.		- Support fintech–MSME partnerships to streamline adoption.

8. Conclusions

This study provides insights into the factors influencing mobile payment adoption among MSMEs by integrating multiple theoretical perspectives. The findings confirm the significant roles of perceived usefulness, perceived risk, word-of-mouth learning, and merchants' intention to use in shaping actual adoption behavior. Additionally, this study highlights the mediating effect of intention to use, demonstrating its role as a key mechanism through which various factors influence adoption decisions.

Interestingly, perceived cost, trust, customer engagement, and complexity did not directly affect adoption, suggesting that these factors may be more context-dependent and influenced by external conditions such as financial literacy and regulatory interventions. These findings challenge existing assumptions and underscore the need for further exploration into moderating effects and contextual variations.

The theoretical contributions of this research lie in its integration of the TAM, DOI, Trust Theory, and other proven theories, offering a more comprehensive understanding of mobile payment adoption dynamics. The findings provide actionable recommendations for technology providers, fintech companies, and governments as policymakers to enhance MSME adoption, such as improving financial literacy programs, ensuring secure and cost-effective payment systems, and leveraging word-of-mouth promotion strategies.

Future research could explore how cognitive biases, heuristics, and bounded rationality influence mobile payment adoption decisions, particularly among MSMEs with limited technological knowledge or regions with weaker FinTech regulations. Understanding these behavioral aspects may also shed light on the significance of perceived cost, trust, customer engagement, and complexity in different adoption contexts. Additionally, examining the moderating effects of financial literacy and regulatory interventions could provide deeper insights into how knowledge and policy frameworks shape MSME adoption behavior. Moreover, future studies should incorporate additional contextual and moderating factors to refine the theoretical framework further, ensuring a more nuanced understanding of adoption dynamics. A mixed-methods approach, integrating qualitative and quantitative perspectives, would offer a more comprehensive view, capturing statistical trends and deeper behavioral motivations. By bridging these perspectives, future research can enhance the applicability of mobile payment adoption models across diverse MSME environments.

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Article

Exploring the Asymmetric Multifractal Dynamics of DeFi Markets

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Abstract: The rapid growth of decentralized finance (DeFi) has revolutionized the global financial landscape, providing decentralized alternatives to traditional financial services. This study investigates the asymmetric multifractal behavior of nine DeFi markets—AAVE, Pancake Swap (CAKE), Compound (COMP), Curve Finance (CRV), Maker DAO (MKR), Synthetix (SNX), Sushi Swap (SUSHI), UniSwap (UNis), and Yearn Finance (YFI)—using Asymmetrical Multifractal Detrended Fluctuation Analysis (A-MFDA). The use of generalized Hurst exponents, Rényi exponents, and singularity spectrum functions revealed that DeFi markets exhibit multifractal behaviors. The analysis uncovered clear differences between uptrend and downtrend fluctuation functions, highlighting asymmetric multifractal behavior. The asymmetry intensity was analyzed through excess differences in uptrend and downtrend generalized Hurst exponents. AAVE, COMP, SNX, UNis, SUSHI, and MKR exhibit negative asymmetry, with stronger correlations during negative trends. CAKE shifts from positive to negative asymmetry, showing sensitivity to both trends. CRV is more volatile in negative trends, while YFI consistently displays positive asymmetry across market fluctuations. The results also reveal that long-term correlations and heavy-tailed distributions contribute to the multifractality of DeFi assets. This study highlights the need for dynamic risk management in DeFi markets, urging investors to adopt adaptive strategies for volatile assets and prepare for sudden price fluctuations to safeguard investments.

Keywords: DeFi markets; multifractality; asymmetry; generalized Hurst exponent; Rényi exponent; singularity spectrum

1. Introduction

The rapid expansion of decentralized finance (DeFi) has transformed the global financial landscape, offering decentralized alternatives to traditional banking services. DeFi protocols have gained significant traction, attracting both institutional investors and retail participants. These assets provide unprecedented opportunities for individuals to engage in banking activities without intermediaries, but they also bring substantial complexity and volatility, which present new challenges for market participants.

DeFi markets, characterized by decentralized financial assets and protocols, exhibit highly volatile and non-linear behavior due to their nascent and evolving nature. The rapid development and absence of centralized regulation lead to a level of unpredictability that is not typically present in traditional financial markets. Furthermore, DeFi assets are prone to extreme price swings, driven by market sentiment, technological changes, liquidity shocks, and regulatory announcements, all of which make capturing their behavior challenging.

Traditional financial models, such as GARCH and simple Hurst exponent analysis, are effective in analyzing certain aspects of financial volatility and persistence. However, these models often assume symmetrical market behavior and linear relationships, failing to account for the multifaceted and complex dynamics that arise in DeFi markets. Specifically, GARCH models are focused on volatility clustering and mean-reverting behavior, while simple Hurst exponent analysis measures long-term memory without addressing the multifractal nature of the underlying price series.

DeFi markets not only exhibit significant volatility but also display asymmetric responses during different market phases, such as bull and bear markets. This directional asymmetry—where market participants react differently during rising and falling price trends—is a crucial feature of DeFi assets that traditional models struggle to capture. The asymmetry often leads to differences in market dynamics during uptrends compared to downtrends, which can have important implications for risk management and investment strategies.

DeFi markets, being decentralized, pose unique challenges for investors and risk managers, particularly regarding volatility management and adapting to asymmetric market responses. Factors such as speculative trading, technological risks, regulatory uncertainty, and macroeconomic events drive sharp price swings. DeFi's 24/7 global trading and unpredictable reactions during crises, like the COVID-19 pandemic, further complicate risk management. Investors and risk managers must develop advanced models, including real-time data analysis and stress testing, to account for extreme price movements and liquidity constraints, adjusting portfolios dynamically to navigate the complex DeFi landscape.

The use of Asymmetric Multifractal Detrended Fluctuation Analysis (A-MFDA) is thus particularly well suited to address these challenges. A-MFDA not only captures the multifractal properties of price fluctuations, which are indicative of the varying levels of volatility and complexity across different time scales, but it also identifies the asymmetry in the scaling laws governing price dynamics in different market phases. This provides a more holistic and accurate understanding of DeFi markets, enabling researchers and investors to better grasp the intricacies of their risk–return profiles.

Moreover, A-MFDA's ability to detect both long-range correlations and non-linear relationships offers significant advantages over traditional models, making it more effective in explaining the persistence of volatility and the impact of extreme events. By incorporating A-MFDA, this study can reveal how DeFi markets respond differently to upward and downward price movements, highlighting the need for dynamic and adaptive risk management strategies tailored to the unique characteristics of these assets.

Previous research has focused on multifractal dynamics in traditional markets, but studies on decentralized finance (DeFi) markets remain limited. Most existing research uses linear methods that do not fully capture the non-linear and multifractal nature of DeFi, especially during asymmetric market movements. This study addresses this gap by applying Asymmetrical Multifractal Detrended Fluctuation Analysis (A-MFDA) to DeFi markets, offering new insights into the multifractal and asymmetric properties of these assets, with implications for investment strategies and risk management.

Despite their promising potential, DeFi markets are characterized by highly complex, non-linear price behaviors marked by unpredictable fluctuations and volatility. Unlike traditional financial markets, DeFi markets exhibit multifractal dynamics, meaning that price movements show varying degrees of persistence or anti-persistence across different time scales. This complexity calls for more advanced analytical methods that go beyond traditional linear models. Specifically, understanding the asymmetric behavior of DeFi markets—

where market dynamics differ significantly during uptrends and downtrends—becomes essential for effective risk management and forecasting.

The scientific problem addressed in this study lies in the need to accurately capture and analyze the multifractal and asymmetric behaviors of DeFi assets. Traditional financial models fail to adequately account for the non-linear nature of these markets, particularly when multifractality and asymmetry are present. This study aims to explore the asymmetric multifractal behavior of nine prominent DeFi assets through Asymmetrical Multifractal Detrended Fluctuation Analysis (A-MFDA).

This study reveals that DeFi assets exhibit multifractal behavior, with distinct asymmetry patterns across market trends. AAVE, COMP, and MKR show stronger negative asymmetry, while CAKE transitions from positive to negative. YFI maintains positive asymmetry, and CRV shows greater volatility in negative trends.

By examining how DeFi assets behave differently during upward and downward price movements, this research will offer deeper insights into their underlying drivers and provide valuable information for risk management, helping investors and traders navigate the complex and volatile nature of DeFi markets.

The remainder of this paper is structured as follows: Section 2 presents a review of the literature on the application of asymmetric and multifractal analysis to financial markets. Section 3 outlines the materials and methods. Section 4 presents and discusses the results. Finally, Section 5 concludes the paper by summarizing the findings, highlighting practical implications.

2. Literature Review

The application of Multifractal Detrended Fluctuation Analysis (MF-DFA) and its extended form, Asymmetric Multifractal Detrended Fluctuation Analysis (A-MFDFA), in financial markets has evolved significantly over time. For instance, one of the earliest studies by Norouzzadeh and Rahmani (2006) applied MF-DFA to analyze the Iranian rial to US dollar exchange rate, revealing significant multifractality due to fat-tailed distributions and non-linear temporal correlations. Subsequently, Benbachir and El Alaoui (2011) contributed by examining the Moroccan stock market, identifying more complex multifractal behavior in the MASI index compared to the MADEX index, which was among the pioneering works in the North African context.

In addition, Caraiani (2012) investigated the daily returns of European stock indices, highlighting fluctuations in the global Hurst exponent over time, an indicator of multifractal spectrum changes in European markets. Following this, Cao et al. (2013) applied A-MFDFA to analyze asymmetric multifractal scaling behaviors in the Chinese stock market. They found stronger multifractality during uptrends, with long-range correlations playing a dominant role, whereas fat-tailed distributions were found to drive multifractality in downtrends. That same year, Lu et al. (2013) analyzed the Chinese stock index futures market and concluded that long-term correlations and fat-tailed distributions were the primary sources of multifractality.

Moving forward, Rui et al. (2015) studied major stock indices from Europe, America, and Asia, confirming the universal presence of multifractal properties across global markets. Moreover, a couple of years later, Minhyuk et al. (2017) introduced a trend-based approach to detect asymmetric multifractality in US stock indices, demonstrating stronger multifractal asymmetry during financial crises.

Mensi et al. (2019) explored asymmetric multifractality in Bitcoin and Ethereum, showing that inefficiencies were more pronounced in Bitcoin compared to Ethereum, with asymmetry more evident in cryptocurrency markets. Furthermore, Faheem et al. (2020) focused on stock indices from nine emerging Asian economies, showing more pronounced multifractality in markets with stronger long-term dependencies, especially in India and Malaysia. Additionally, Şahin and Hongzhuan (2020) examined Bitcoin's and gold's return and volatility, finding higher multifractality and persistence in Bitcoin compared to gold, thus highlighting the difference between cryptocurrencies and traditional assets.

Also, Mensi et al. (2020) investigated the impact of the COVID-19 pandemic on the gold and oil markets, discovering stronger asymmetry in multifractality during downside trends for Brent oil and upside trends for gold. This was followed by Naeem et al. (2021), who analyzed bond markets during the COVID-19 crisis and found that green bonds were more efficient than traditional ones, particularly during the pandemic.

Naeem et al. (2022) examined the asymmetric price efficiency of regional ESG markets before and during the COVID-19 pandemic, showing a decline in market efficiency, particularly outside of Europe. Concurrently, Zhuang and Wei (2022) studied green finance markets, conventional equity indices, and crude oil, revealing strong multifractality and significant asymmetry in green finance indices compared to conventional assets. Moreover, Kakinaka and Umeno (2022) explored the impact of COVID-19 on cryptocurrency markets, finding stronger multifractality and inefficiencies in the short term for several major cryptocurrencies.

Datta (2023) investigated multifractality in exchange rates, specifically USD, GBP, EUR, and JPY against the INR. The study revealed that the USD and JPY exhibited multifractal features due to fat-tailed distributions, while GBP and EUR displayed multifractality driven by long-term correlations and fat-tailed distributions. In the same year, Naeem et al. (2023) focused on inefficiencies in petroleum markets, finding more pronounced inefficiencies during downward trends, with the natural gas market being the most efficient. Likewise, Khurshid et al. (2023) studied asymmetric multifractality in renewable and technological asset prices, particularly in Chinese markets during the pandemic, confirming increased inefficiencies in green energy prices.

In addition, Ghosh et al. (2023) explored the dynamics of NFTs and DeFi assets, which had gained investor interest despite their niche status. They analyzed these assets during the COVID-19 pandemic, constructing a multivariate framework incorporating technical indicators, macroeconomic factors, media hype, and pandemic sentiment. Techniques like ISOMAP, UMAP, GBR, and RF were used for predictive analysis, showing strong performance in forecasting asset prices during financial distress. Using Explainable AI (XAI), they found that daily price movements were largely driven by historical trends, offering insights into predictive modeling under uncertain financial conditions.

Moreover, Chaudhary and Pinna (2022) evaluated the market risk of DeFi lending protocols using a multi-asset agent-based model. The model simulated users exposed to price-driven liquidation risks, showing that the systemic risk of the protocol remained minimal, even during periods of stress. Following this, Imran et al. (2023) explored the dynamic connectedness between DeFi assets and sector stock markets during the COVID-19 pandemic crisis. They applied the TVP-VAR model to assess connectedness and the DCC-GARCH model to compute optimal weights and hedge ratios for equity portfolios of the DeFi assets sector.

Ngo (2024) investigated the time-varying and asymmetric relationships between decentralized finance (DeFi) and Central and Eastern European (CEE) stock returns, focusing on the COVID-19 pandemic and the Russo-Ukrainian conflict. Using the multivariate DECO-GARCH model and cross-quantilogram framework, the study revealed a positive equicorrelation between DeFi and CEE stock market returns, with DeFi having a stronger influence during the pandemic and conflict. A cross-quantilogram analysis showed that CEE stock markets were less dependent on DeFi at longer lag lengths, highlighting DeFi's diversification benefits for long-term investments. The research provided new insights into dependence structures, aiding investor decision-making and trading strategies. Similarly, Charifzadeh et al. (2024) examined the impact of the Terra-Luna collapse in 2022 on volatility correlations between digital assets (such as Bitcoin, Ether, and a DeFi index) and conventional US assets (stocks, bonds, oil, gold, and the dollar index). Using a DCC-GARCH model and data from January to May 2022, they found increased volatility but no clear evidence of heightened correlations during the collapse. Bitcoin was confirmed as a diversifier with oil and a hedge against the US dollar, while gold was observed to be an unreliable hedge during the event. The findings offer practical insights for investors, institutions, and regulators into risk management and portfolio diversification in times of market stress.

Benbachir (2024) extended the analysis to six major African stock markets, identifying persistent multifractality due to long-term correlations and heavy-tailed distributions across these markets. At the same time, Mensi et al. (2024) examined decentralized finance (DeFi) assets such as BAT, LINK, MKR, and SNX using A-MFDFA, revealing more pronounced inefficiencies during upward trends before the pandemic, which reversed during the crisis. Additionally, Opryshko (2024) applied MF-DFA to Bitcoin price series, revealing higher volatility and a multifractal spectrum during shorter time intervals, indicating more predictability in longer intervals. Furthermore, Wątorek et al. (2024) analyzed decentralized cryptocurrency markets such as Uniswap, finding multifractality despite lower liquidity compared to centralized exchanges, with large fluctuations contributing to this behavior.

Finally, Meng and Khan (2024) studied Bitcoin, Ripple, and Ethereum during the COVID-19 pandemic, finding stronger multifractality in Bitcoin and Ripple during downward trends and in Ethereum during upward trends, suggesting better market efficiency in bullish periods.

Overall, these studies contribute significantly to the understanding of market inefficiency, multifractality, and asymmetry across various asset classes during turbulent periods. In line with previous research, the current study aims to investigate the asymmetric multifractal behavior of nine DeFi markets using the Asymmetrical Multifractal Detrended Fluctuation Analysis (A-MFDA) method.

3. Materials and Methods

3.1. Data

This study focuses on nine major DeFi assets: AAVE, Pancake Swap (CAKE), Compound (COMP), Curve Finance (CRV), Marker DAO (MKR), Synthetix (SNX), Sushi Swap (SUSHI), UniSwap (UNis), and Yearn Finance (YFI).

These nine DeFi assets were selected based on their prominence within the decentralized finance (DeFi) ecosystem. These assets consistently rank among the top DeFi tokens in terms of the Total Value Locked (TVL) and liquidity, which are key indicators of their influence, utility, and adoption. These metrics were chosen as they reflect the market share, stability, and usage of these assets within DeFi markets. Additionally, these assets span various sectors of DeFi (lending, decentralized exchanges, stablecoin trading, and synthetic assets), ensuring that the study captures a comprehensive overview of the ecosystem.

AAVE is one of the most prominent DeFi lending protocols, with a TVL of over USD 4 billion as of December 2024. AAVE's large liquidity pool makes it a central player in DeFi lending markets. Uniswap is the leading decentralized exchange (DEX) protocol with a TVL of around USD 3.5 billion. Its automated market maker (AMM) model has revolutionized decentralized trading by providing liquidity pools for token swaps. It consistently ranks among the highest in daily trading volume, often exceeding USD 1 billion. Curve Finance specializes in stablecoin trading and is renowned for its low slippage, attracting liquidity providers. With a TVL of approximately USD 4.7 billion, Curve has become a cornerstone for stablecoin liquidity, offering efficient swaps for stable assets. MakerDAO governs DAI stablecoin, one of the most widely used decentralized stablecoins in the market. MakerDAO has a TVL of about USD 4.5 billion, and its protocol facilitates the collateralized lending that maintains DAI's stability. This makes it a crucial element in decentralized finance. Compound is another major DeFi protocol specializing in lending and borrowing with a TVL of about USD 3.8 billion. It enables users to earn interest on deposits and borrow assets through collateralized loans. Like AAVE, Compound is a leader in decentralized lending markets. SushiSwap is a decentralized exchange and liquidity pool platform with a TVL of around USD 650 million. While initially a fork of Uniswap, SushiSwap has expanded its ecosystem to offer additional DeFi features, including staking and yield farming. Operating on the Binance Smart Chain, Pancake Swap is a leading decentralized exchange and yield farming protocol with a TVL of USD 1.2 billion. It provides efficient trading with low fees, which has attracted significant liquidity, especially from users seeking alternatives to Ethereum-based platforms. Synthetix allows the creation and trading of synthetic assets, enabling exposure to various real-world assets in a decentralized manner. It has a TVL of USD 850 million and offers a unique approach to decentralized trading by facilitating synthetic assets such as commodities and indices. Yearn Finance is an automated yield aggregator that maximizes returns for users by automatically shifting funds between different DeFi protocols. Yearn has a TVL of approximately USD 600 million and plays a significant role in yield farming strategies within the DeFi space.

Table 1 presents the periods studied for the nine DeFi assets based on their creation dates and data availability. These sample periods encompass both bull and bear market conditions, making them appropriate for the objectives of our analysis. All data were sourced from the website www.investing.com.

Table 1. The study periods of the 9 DeFi assets.

DeFi	Period
AAVE	16 January 2018–1 December 2024
CAKE	20 February 2021–1 December 2024
COMP	18 August 2020–1 December 2024
CRV	8 February 2021–1 December 2024
MKR	4 January 2019–1 December 2024
SNX	8 February 2021–1 December 2024
SUSHI	16 December 2020–1 December 2024
UNis	6 November 2020–1 December 2024
YFI	6 November 2020–1 December 2024

The primary focus of our study is on asymmetric autocorrelations within each individual asset. We examined the internal dynamics of each DeFi asset—specifically, how changes in trends within a given asset impact its own behavior over time. This means that we investigated the temporal dependencies and trend reversals of each asset in isolation without considering interactions or correlations between different assets. Since each asset was analyzed independently in terms of its own asymmetric autocorrelation patterns, the varying start dates across assets do not affect the validity of the analysis. In other words, the analysis was self-contained within each asset's time series, and there was no dependency between assets that could introduce bias or inconsistencies due to their different starting points. Therefore, the temporal structure and trends of each asset were considered separately, ensuring that the results remain unaffected by the differences in sample periods.

Daily prices were then converted into logarithmic returns, $r_t = ln(P_t) - ln(P_{t-1})$, where P_t denotes the index price and ln corresponds to the natural logarithm.

3.2. Methodology

3.2.1. Description of A-MFDA

Asymmetrical Multifractal Detrended Fluctuation Analysis (A-MFDA) was introduced by Cao et al. (2013) as an extension of the Multifractal Detrended Fluctuation Analysis (MF-DFA) method (Kantelhardt et al., 2002), specifically designed to address the asymmetric nature of time series. In many real-world systems, such as financial markets, upward and downward fluctuations often exhibit different scaling properties.

We begin the description with a simplified overview of Asymmetric Multifractal Detrended Fluctuation Analysis (A-MFDFA). A-MFDFA is a tool used to analyze complex time series data that exhibit multifractality (different patterns at various time scales) and asymmetry (unequal behavior between positive and negative trends). It is particularly useful in fields like finance, where markets show non-linear and irregular behavior.

The key concepts of the A-MFDFA are as follows:

- Multifractality: The data show complex patterns that change depending on the scale being looked at. It is like zooming in or out of a picture and seeing different details at each level.
- Asymmetry: In real-world data, upward and downward trends do not always behave the same way. For example, stock prices might increase slowly but drop suddenly. A-MFDFA helps capture this uneven behavior.
- Detrending: A-MFDFA removes overall trends in the data (like long-term growth) so that it can focus on the patterns and fluctuations that remain.

The steps of A-MFDFA can be summarized as follows:

- Remove Trends: The method removes any long-term trends from the data to avoid distortion.
- Look at Fluctuations: It then breaks the data into segments and examines the fluctuations at different scales to identify any multifractal behavior.
- Capture Asymmetry: order overall fluctuation functions It analyzes how different the positive trends (upward movements) are from the negative trends (downward movements) in the data.

The A-MFDA process can be outlined in five key steps.

Let $x = (x(k))_{1 \leq k \leq N}$ be a time series, where N is the length of the series. The series is assumed to have compact supports, meaning that $x(k) = 0$ for only a negligible fraction of k.

Step 1: In this step, the profile $X = (X(i))_{1 \leq i \leq N}$ is determined for the series x as follows:

$$X(i) = \sum_{k=1}^{N} (x(k) - \overline{x}) \tag{1}$$

where $\overline{x}$ is the mean of x.

Step 2: For each time scale s, the series x and its profile X are divided into $N_s = Int(N/s)$ non-overlapping sub-time series of the same length s, where $Int(.)$ gives the integer part of a real number. Based on the recommendations of Peng et al. (1994), $5 \leq s \leq N/4$ is traditionally selected. Since N is generally not a multiple of s, a short part at the end of the two series may be neglected. To incorporate all of the ignored parts, the same procedure is repeated starting from the end of the two series. Thus, we obtain $2N_s$ intervals $I_{v,s} = (I_{v,s}(j))_{1 \leq j \leq s}$ defined by

$$I_{v,s}(j) = (v - 1)s + j \tag{2}$$

for $v = 1, 2, \cdots, N_s$ and

$$I_{v,s}(j) = (N - v - N_s)s + j \tag{3}$$

for $v = N_s + 1, \cdots, 2N_s$.

We denote by $X_{v,s}$ and $x_{v,s}$, the vth sub-time series corresponding to X and x:

$$\begin{aligned} X_{v,s}(j) &= X((v-1)s + j) \\ x_{v,s}(j) &= x((v-1)s + j) \end{aligned} \tag{4}$$

for $v = 1, \cdots, N_s$, and

$$\begin{aligned} X_{v,s}(j) &= X((N - v - N_s)s + j) \\ x_{v,s}(j) &= x((N - v - N_s)s + j) \end{aligned} \tag{5}$$

for $v = N_s + 1, \cdots, 2N_s$.

Step 3: For each time scale s and for each segment $v = 1, 2, \cdots, 2N_s$, the local trend $\widetilde{X}_{v,s}$ is measured by performing degree-2 polynomial least-square regressions of $X_{v,s}$ on $I_{v,s}$:

$$\widetilde{X}_{v,s}(j) = \alpha_0^{v,s} + \alpha_1^{v,s}.j + \alpha_2^{v,s}.j^2 \tag{6}$$

Simultaneously, the local linear least-squares fit $\widetilde{x}_{v,s}$ is measured by performing a linear least-square regression of $x_{v,s}$ on $I_{v,s}$:

$$\widetilde{x}_{v,s}(j) = a^{v,s} + b^{v,s}.j \tag{7}$$

The linear fit $\widetilde{x}_{v,s}(j)$ is used only to discriminate via slope $b^{v,s}$ whether the trend of the sub-time series $x_{v,s}$ is positive (uptrend) or negative (downtrend).

The detrended covariances $f^2(v,s)$ are then calculated as follows:

$$f^2(v,s) = \frac{1}{s}\sum_{j=1}^{s}\Big(X((v-1)s + j) - \widetilde{X}_{v,s}(j)\Big)^2 \tag{8}$$

for $v = 1, 2, \cdots, N_s$, and

$$f^2(v,s) = \frac{1}{s}\sum_{i=1}^{s}\Big(X((N - v - N_s)s + j) - \widetilde{X}_{v,s}(j)\Big)^2 \tag{9}$$

for $v = N_s + 1, \cdots, 2N_s$.

Step 4:

➢ The qth order overall fluctuation functions $F_q(s)$ are determined as follows:

For each s and for a given order q, the qth order overall fluctuation function $F_q(s)$ is defined (Kantelhardt et al., 2002) as an average of the covariances over all segments by

$$F_q(s) = \left[\frac{1}{2N_S}\sum_{v=1}^{2N_S}\Big(f^2(v,s)\Big)^{\frac{q}{2}}\right]^{\frac{1}{q}} \tag{10}$$

for $q \neq 0$, and

$$F_0(s) = exp\left[\frac{1}{4N_S}\sum_{\text{v}=1}^{2N_S} ln\Big(f^2(v,s)\Big)\right] \tag{11}$$

for $q = 0$.

➢ The qth order uptrend and downtrend fluctuation functions $F_q^+(s)$ and $F_q^-(s)$ are determined as follows:

For each s and for a given order q, the qth order uptrend $F_q^+(s)$ and the qth order downtrend $F_q^-(s)$ fluctuation functions are obtained by averaging the covariances $f^2(v,s)$ over all segments v when the sign of the slope $b^{v,s}$ is strictly positive or negative, respectively:

$$F_q^+(s) = \left[\frac{1}{M^+}\sum_{v=1}^{2N_S}\frac{1+sign(b^{v,s})}{2}\left(f^2(v,s)\right)^{\frac{q}{2}}\right]^{\frac{1}{q}} \tag{12}$$

$$F_q^-(s) = \left[\frac{1}{M^-}\sum_{v=1}^{2N_S}\frac{1-sign(b^{v,s})}{2}\left(f^2(v,s)\right)^{\frac{q}{2}}\right]^{\frac{1}{q}} \tag{13}$$

for $q \neq 0$, and

$$F_0^+(s) = exp\left[\frac{1}{2M^+}\sum_{\text{v}=1}^{2N_S}\frac{1+sign(b^{v,s})}{2}ln\left(f^2(v,s)\right)\right] \tag{14}$$

$$F_0^-(s) = exp\left[\frac{1}{2M^-}\sum_{\text{v}=1}^{2N_S}\frac{1-sign(b^{v,s})}{2}ln\left(f^2(v,s)\right)\right] \tag{15}$$

for $q = 0$, where $M^+ = \sum_{\text{v}=1}^{2N_S}\frac{1+sign(b^{v,s})}{2}$ and $M^- = \sum_{\text{v}=1}^{2N_S}\frac{1-sign(b^{v,s})}{2}$ represent the number of sub-time series $x_{v,s}$ with positive and negative trends, respectively. We assume $b^{v,s} \neq 0$ for all $v = 1, 2, \cdots, 2N_s$, such that $M^+ + M^- = 2N_s$.

Step 5: The scaling behavior of the fluctuations is determined.

If the time series x exhibits an asymmetric long-term correlation according to a power law, such as fractal properties, the fluctuation functions $F_q(s)$, $F_q^+(s)$, and $F_q^-(s)$ will behave, for sufficiently large values of s, according to the following power law scaling laws:

$$F_q(s) \sim s^{H(q)} \quad F_q^+(s) \sim s^{H^+(q)} \quad F_q^-(s) \sim s^{H^-(q)} \tag{16}$$

where $H(q)$, $H^+(q)$, and $H^-(q)$ are called the overall generalized Hurst exponent, the uptrend generalized Hurst exponent, and the downtrend generalized Hurst exponent, respectively.

To estimate $H(q)$, $H^+(q)$, and $H^-(q)$ for different values of q, the log–log linear Ordinary Least Squares regression of the time series $H(q)$, $H^+(q)$, and $H^-(q)$ is performed on $F_q(s)$, $F_q^+(s)$, and $F_q^-(s)$, respectively.

When $H(q)$ depends on q, the time series x is multifractal; otherwise, it is monofractal. In the case of $q = 2$, the exponent $H(2)$ is interpreted in the same manner as the Hurst exponent. Furthermore, $H(q)$ is a decreasing function, and the multifractal intensity can be measured by

$$\Delta H = \Delta H_{Max} - H_{Min} = H(q_{min}) - H(q_{max}) \tag{17}$$

The larger ΔH is, the stronger the degree of multifractality of x will be.

It is well known that $H(q)$ is directly related to the multifractal scaling exponent $\tau(q)$, commonly known as the Rényi exponent:

$$\tau(q) = q.H(q) - 1 \tag{18}$$

If $\tau(q)$ increases nonlinearly with q, the time series x is multifractal. Otherwise, if $\tau(q)$ is a linear function of q, then the time series x is monofractal.

Another interesting way to characterize the multifractality is to use the singularity spectrum $f(\alpha)$ of the Hölder exponent α. It is well known that the singularity spectrum $f(\alpha)$ is related to the Rényi exponent $\tau(q)$ through the Legendre transform:

$$\begin{cases} \alpha = \tau'(q) \\ f(\alpha) = q.\alpha - \tau(q) \end{cases} \tag{19}$$

where $\tau'(q)$ is the derivative of the function $\tau(q)$.

When x is multifractal, then $f(\alpha)$ presents a concave bell-shaped curve.

The richness of the multifractality can be determined by the width of the spectrum:

$$\Delta\alpha = \alpha_{max} - \alpha_{min} \tag{20}$$

The wider the spectrum, the richer the multifractal behavior of x.

By analogy, the uptrend Rényi exponent $\tau^{+}(q)$, the downtrend Rényi exponent $\tau^{\pm}(q)$, the uptrend singularity spectrum $f^{+}(\alpha)$, and the downtrend singularity spectrum $f^{-}(\alpha)$ can be defined when the time series x has a different trend.

The analysis of the asymmetry of the multifractal correlations results from the comparison of $H^{+}(q)$ and $H^{-}(q)$. If $H^{+}(q) = H^{-}(q)$, the multifractal correlation of x is symmetric. Conversely, if $H^{+}(q) \neq H^{-}(q)$, the multifractal correlation of x is asymmetric, meaning that the correlation is different when the trending of x is positive than when it is negative. The asymmetric degree can be measured by

$$\Delta H^{\pm}(q) = H^{+}(q) - H^{-}(q) \tag{21}$$

The larger the magnitude of $\Delta H^{\pm}(q)$, the more pronounced the asymmetry of the correlation when x experiences different trends. The sign of $\Delta H^{\pm}(q)$ indicates the dependence on the trending of x. If $\Delta H^{\pm}(q) = 0$, the multifractal correlation is symmetric for different trends of x. If $\Delta H^{\pm}(q) > 0$, this indicates that the correlation is stronger during positive trends in the time series x compared to negative trends. Conversely, if $\Delta H^{\pm}(q) < 0$, the correlation is weaker during positive trends than during negative trends in x.

3.2.2. DCCA Cross-Correlation Coefficient Method

To quantitatively evaluate the cross-correlations between two non-stationary time series, Zebende (2011) introduced the DCCA cross-correlation coefficient. This approach builds on the DCCA method developed by Podobnik and Stanley (2008), as well as the DFA method introduced by Peng et al. (1994).

Let $x = (x(k))_{1 \leq k \leq N}$ and $y = (y(k))_{1 \leq k \leq N}$ represent two time series of length N. Both series are assumed to have compact support, meaning that $x(k) = 0$ and $y(k) = 0$ for only an insignificant portion of the values of k. The profiles $= (X(i))_{1 \leq i \leq N}$ and $Y = (Y(i))_{1 \leq i \leq N}$ for the time series x and y are computed as follows:

$$X(i) = \sum_{k=1}^{N} (x(k) - \overline{x}) \quad Y(i) = \sum_{k=1}^{N} (y(k) - \overline{y}) \tag{22}$$

Here, $\overline{x}$ and $\overline{y}$ represent the average values of the series X and Y, respectively.

For a given time scale s, the profiles X and Y are partitioned into $N_S = Int(N/s)$ segments, each with a length of s, where $Int(.)$ denotes the integer part of a real number. A total of $2N_S$ segments are generated.

In each segment, the data are fitted to a local trend using the Ordinary Least Squares (OLS) method. The fitting polynomials for the profiles X and Y in the v-th segment are denoted as $p^{m}_{X,v}(i)$ and $p^{m}_{Y,v}(i)$:

$$p^{m}_{X,v}(i) = \alpha^{v}_{0} + \alpha^{v}_{1}.i + \cdots + \alpha^{v}_{m}.i^{m} \tag{23}$$

$$p^{m}_{Y,v}(i) = \beta^{v}_{0} + \beta^{v}_{1}.i + \cdots + \beta^{v}_{m}.i^{m} \tag{24}$$

Then, the detrended covariances $f_X^2(v,s)$, $f_Y^2(v,s)$, and $f_{X,Y}^2(v,s)$ are computed for all time scales s and for each segment v, where $1 \leq v \leq 2Ns$:

$$f_X^2(v,s) = \frac{1}{s}\sum_{i=1}^{s}\left(X((v-1)s+i) - p_{X,v}^m(i)\right)^2 \tag{25}$$

$$f_Y^2(v,s) = \frac{1}{s}\sum_{i=1}^{s}\left(Y((v-1)s+i) - p_{Y,v}^m(i)\right)^2 \tag{26}$$

$$f_{XY}^2(v,s) = \frac{1}{s}\sum_{i=1}^{s}\left|X((v-1)s+i) - p_{X,v}^m(i)\right|.\left|Y((v-1)s+i) - p_{Y,v}^m(i)\right| \tag{27}$$

for $1 \leq v \leq Ns$, and

$$f_X^2(v,s) = \frac{1}{s}\sum_{i=1}^{s}\left(X(((N-v-Ns)s+i)) - p_{X,v}^m(i)\right)^2 \tag{28}$$

$$f_Y^2(v,s) = \frac{1}{s}\sum_{i=1}^{s}\left(Y(((N-v-Ns)s+i)) - p_{Y,v}^m(i)\right)^2 \tag{29}$$

$$f_{XY}^2(v,s) = \frac{1}{s}\sum_{i=1}^{s}\left|X((N-v-N_S)s+i) - p_{X,v}^m(i)\right|.\left|Y((N-v-N_S)s+i) - p_{Y,v}^m(i)\right| \tag{30}$$

for $Ns+1 \leq v \leq 2Ns$.

Finally, the covariances are averaged over all segments to obtain the DFA variance fluctuation functions $F_{DFA-X}^2(s)$ and $F_{DFA-Y}^2(s)$, along with the DCCA covariance fluctuation function $F_{DCCA}^2(s)$, defined as follows:

$$F_{DFA-X}^2(s) = \frac{1}{2Ns}\sum_{v=1}^{2Ns} f_X^2(v,s) \tag{31}$$

$$F_{DFA-Y}^2(s) = \frac{1}{2Ns}\sum_{v=1}^{2Ns} f_Y^2(v,s) \tag{32}$$

$$F_{DCCA}^2(s) = \frac{1}{2Ns}\sum_{v=1}^{2Ns} f_{XY}^2(v,s) \tag{33}$$

The DCCA cross-correlation coefficient $\rho_{DCCA}(s)$ is deduced by

$$\rho_{DCCA}(s) = \frac{F_{DCCA}^2(s)}{\sqrt{F_{DFA-X}^2(s)} \times \sqrt{F_{DFA-Y}^2(s)}} \tag{34}$$

The DCCA cross-correlation coefficient $\rho_{DCCA}(s)$ serves as an effective metric, exhibiting properties similar to the conventional correlation coefficient. This dimensionless value ranges from -1 to 1. A coefficient of $\rho_{DCCA}(s) = 0$ indicates no cross-correlation between the two time series. A value within the range $-1 < \rho_{DCCA}(s) < 0$ reflects anti-persistent cross-correlation, while $0 < \rho_{DCCA}(s) \leq 1$ denotes persistent cross-correlation. A perfect anti-persistent correlation is represented by $\rho_{DCCA}(s) = -1$, while $\rho_{DCCA}(s) = 1$ indicates perfect persistent cross-correlation.

3.2.3. Sources of Multifractality

Kantelhardt et al. (2002) identified two primary sources of multifractality in a time series: long-term temporal correlations and heavy-tailed distributions. To determine how each source contributes to the overall multifractality, two transformations on the original series are applied, namely the shuffling (random permutation) and the surrogation (phase randomization).

In the literature, there are various techniques for surrogation: Inverse Fast Fourier Transform (IFFT) (Proakis & Dimitris, 1996), Iterated Algorithm (iAAFT) (Schreiber & Schmitz, 1996), and the Statically Transformed Autoregressive Process (STAP) (Kugiumtzis, 2002). In this study, the Inverse Fast Fourier Transform (IFFT) method was applied. Two shuffling techniques, "randperm" and "randi", were employed.

The code used for the analysis in this study was custom written in MATLAB R2023a. We developed our own scripts specifically for this research, ensuring that the methodology aligns precisely with the objectives of the study. This is mentioned in the Materials and Methods Section.

4. Results

4.1. Analysis of Cross-Correlations Between DeFi Assets

In this section, the DCCA cross-correlation coefficients are computed between the nine assets. Figure 1 presents the DCCA cross-correlation coefficient $\rho_{DCCA}(s)$ plotted against variable s for all 36 asset pairs.

As we can see in Figure 1, the DCCA cross-correlation coefficient $\rho_{DCCA}(s)$ for all nine pairs of DeFi assets falls within the range of $0 < \rho_{DCCA}(s) < 1$. This indicates that there is a positive and persistent cross-correlation between the nine DeFi assets. This persistence suggests that these correlations are stable and lasting rather than random or short-lived.

Additionally, for most pairs, the DCCA cross-correlation coefficients are greater than 0.5, indicating a strong and persistent positive relationship between these assets. When one asset in the pair moves in a certain direction, the other tends to move in the same direction, with a relatively high level of consistency. However, for the pairs involving MakerDAO, the coefficients are slightly less than 0.5. This suggests a weaker positive correlation between MakerDAO and the other DeFi assets. The relationship between MakerDAO and the other DeFi assets is less consistent, meaning the price movements of MakerDAO are less strongly aligned with those of the other assets in the group. This may be due to several factors. Firstly, MakerDAO's distinct use case as a stablecoin platform (issuing Dai) differs from other more speculative DeFi sectors like lending or decentralized exchanges. Secondly, the stable nature of Dai, pegged to fiat currencies, results in less volatility compared to other assets that fluctuate more with market trends. Additionally, MakerDAO's lower risk profile attracts different investor behavior, leading to smaller price changes during market fluctuations.

Figure 1. DCCA cross-correlation coefficient $\rho_{DCCA}(s)$ for all pairs of DeFi assets.

4.2. Multi-Scale Behavior of Overall Fluctuation Functions

The overall fluctuation functions $F_q(s)$ are derived with $s \in S = [20 : 10 : 100, 200 : 50 : 400]$ $q \in [-45 : 5 : -5, -2.1 : 0.1 : -0.1, 0.1 : 0.1 : 2.1, 5 : 5 : 45]$. Figure 2 shows $Log(F_q(s))$ with respect $Log(s)$.

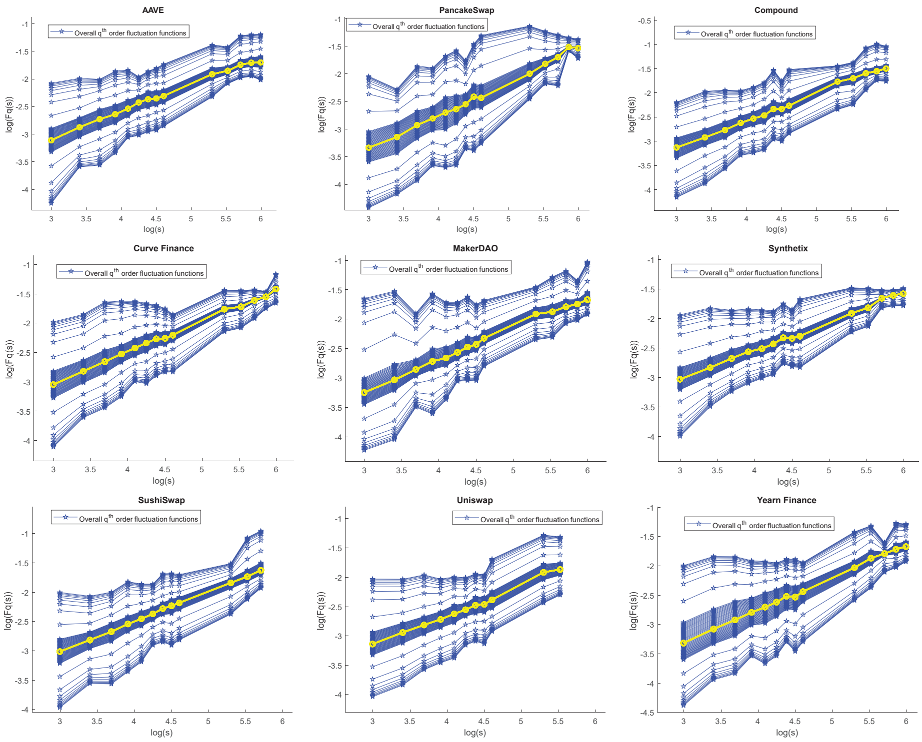


Figure 2. $Log(F_q(s))$ vs. $Log(s)$ for the 9 DeFi assets. The yellow plot corresponds to $q = 0$.

Figure 2 presents the double logarithmic plot of $Log(F_q(s))$ versus $Log(s)$, where $Log(F_q(s))$ represents the fluctuation function for different moments q, and s denotes the window size. The plot illustrates the relationship between these variables over varying time scales. A linear trend in this log–log plot indicates the presence of scaling behavior, with the slope corresponding to the generalized Hurst exponent $H(q)$. The different values of q capture the behavior of small and large fluctuations, helping to reveal the multifractal characteristics of the data. Specific trends, such as deviations from linearity or differences between positive and negative q values, will be highlighted and discussed in the context of multifractality.

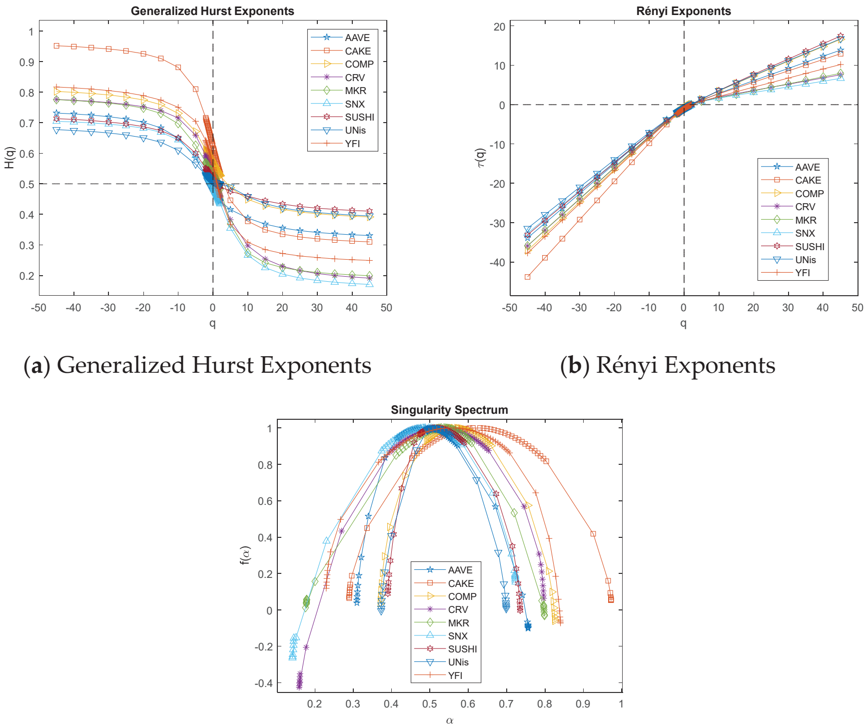
For each value of q, the plot exhibits a straight line, indicating power law scaling, which is a hallmark of multifractal systems.

By regressing $Log(F_q(s))$ on $Log(s)$, the overall generalized Hurst exponent $H(q)$ is derived:

$$Log(F_q(s)) \approx H(q).Log(s) \tag{35}$$

4.3. Multifractality and Persistence of DeFi Markets

The multifractal and persistence characteristics of DeFi markets are analyzed using $H(q)$, $\tau(q)$, and $f(\alpha)$. Figure 3 presents the results as q varies from -45 to 45.



(**a**) Generalized Hurst Exponents (**b**) Rényi Exponents

(**c**) Singularity Spectrum

Figure 3. $H(q)$, $\tau(q)$, and $f(\alpha)$ values of the 9 DeFi assets.

Figure 3 illustrates the multifractal analysis of the nine DeFi assets, showing three essential multifractal characteristics: (a) the generalized Hurst exponent $H(q)$, (b) the scaling exponent $\tau(q)$, and (c) the singularity spectrum $f(\alpha)$.

(a) The generalized Hurst exponent $H(q)$: This plot shows how the Hurst exponent varies for different moments q. The shape of the curve reflects the presence of multifractality, where a decreasing $H(q)$ with increasing q indicates multifractal behavior. Each curve for the DeFi assets demonstrates how the fluctuations scale across different time windows.

(b) The scaling exponent $\tau(q)$: The plot of $\tau(q)$ versus q depicts the scaling behavior of the moment functions. A linear $\tau(q)$ would suggest monofractality, while non-linear behavior signals multifractality, highlighting the DeFi assets' complexity in volatility patterns.

(c) The singularity spectrum $f(\alpha)$: The $f(\alpha)$ plot represents the distribution of singularities (or scaling exponents α) in the data. The width of the spectrum indicates the strength of multifractality, with a broader spectrum corresponding to more significant multifractal behavior. The position and peak of the $f(\alpha)$ curve offer insights into the dominant fluctuations within each asset.

Figure 3 shows that the nine DeFi assets revealed a multifractal nature, as shown by the non-linear behavior of $H(q)$ and $\tau(q)$, and the inverted parabolic shapes of $f(\alpha)$. The varying correlations imply that risk and volatility are not uniform over time, requiring forecasting, investment, and advanced risk management strategies.

Furthermore, for small negative values of q, $H(q) > 0.5$, which indicates persistent behavior in all of the correlations. This suggests that the correlations tend to remain stable over short periods, meaning that past trends are more likely to continue soon. This persistence can be useful for short-term trading strategies, where patterns are more predictable. Conversely, for large positive values of q, $H(q) < 0.5$, indicating anti-persistent behavior in the correlations at shorter timescales. This implies higher volatility and more rapid shifts in trends, requiring traders to adjust their strategies quickly.

To measure the multifractal intensity, the metrics ΔH and $\Delta\alpha$ are used. The results are presented in Table 2 in decreasing order for ΔH and $\Delta\alpha$.

Table 2. Intensity of multifractality of the 9 DeFi assets based on ΔH and $\Delta\alpha$.

Range	DeFi	ΔH	$\Delta\alpha$
1	CAKE	0.641	0.683
2	CRV	0.584	0.637
3	MKR	0.575	0.623
4	YFI	0.567	0.610
5	SNX	0.534	0.582
6	COMP	0.410	0.455
7	AAVE	0.401	0.447
8	UNis	0.380	0.425
9	SUSHI	0.332	0.377

Table 2 shows that both metrics yield the same ranking for the multifractal intensity among the DeFi assets.

Assets such as CAKE, CRV, MKR, and YFI, with $0.567 < \Delta H < 0.641$ and $0.610 < \Delta\alpha < 0.683$, exhibit significant multifractality. The high multifractality of these assets means their price movements are less predictable using linear models. Investors dealing with these assets may need more advanced risk management strategies.

Assets like SNX, with $\Delta H = 0.534$ and $\Delta\alpha = 0.582$, show moderate multifractality. SNX is somewhat less volatile and less dynamic. A balanced approach using both traditional and advanced models could be effective.

COMP, AAVE, UNIS, and SUSHI exhibit lower multifractality with $0.332 < \Delta H < 0.410$ and $0.377 < \Delta\alpha < 0.455$. These assets are less likely to exhibit extreme volatility and thus could be better suited for conservative investors seeking lower risk exposure.

4.4. Analysis of Asymmetry Using Fluctuation Functions (q = 2)

Figure 4 presents the log–log plots of the overall $F_2(s)$, uptrend $F_2^+(s)$, and downtrend $F_2^-(s)$ fluctuation functions versus s under different DeFi market conditions.

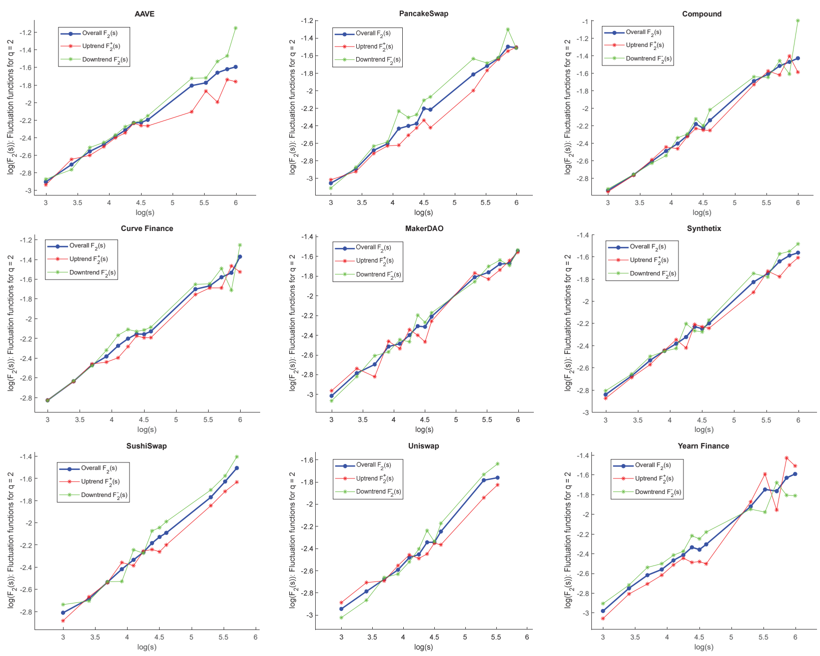


Figure 4. Log–log plots of $F_2(s)$, $F_2^+(s)$, and $F_2^-(s)$ vs. s for the 9 DeFi assets.

Figure 4 presents the log–log plots of the overall fluctuation function $F_2(s)$, as well as the uptrend fluctuation function $F_2^+(s)$ and the downtrend fluctuation function $F_2^-(s)$, for different DeFi market conditions. The x-axis represents the window size s, and the y-axis shows the magnitude of the fluctuation function. This analysis reveals how multifractal properties change during uptrend and downtrend market conditions across the selected DeFi assets.

The overall fluctuation function $F_2(s)$: This represents the general scaling behavior of fluctuations in DeFi markets across different time scales. A straight line on the log–log plot indicates a power law relationship, and deviations in slope suggest multifractal behavior.

The uptrend fluctuation function $F_2^+(s)$: This captures the scaling properties during periods of market growth. A comparison of this curve with the downtrend function indicates asymmetry in market dynamics between rising and falling markets.

The downtrend fluctuation function $F_2^-(s)$: This shows the scaling behavior during market declines, highlighting how negative trends differ from positive ones in terms of volatility and scaling properties.

The slopes of these curves offer insights into the market's long-range correlations and the degree of persistence or anti-persistence in price movements under different conditions.

Figure 4 shows a clear distinction in the behaviors of $F_2^+(s)$ and $F_2^-(s)$ across all timescales, indicating the presence of asymmetry in the multifractal correlations of all nine DeFi assets.

To more precisely quantify this asymmetric behavior, the metric $\Delta log(F_2^{\pm}(s)) = log(F_2^+(s)) - log(F_2^-(s))$ is used. The results are shown in Figure 5.

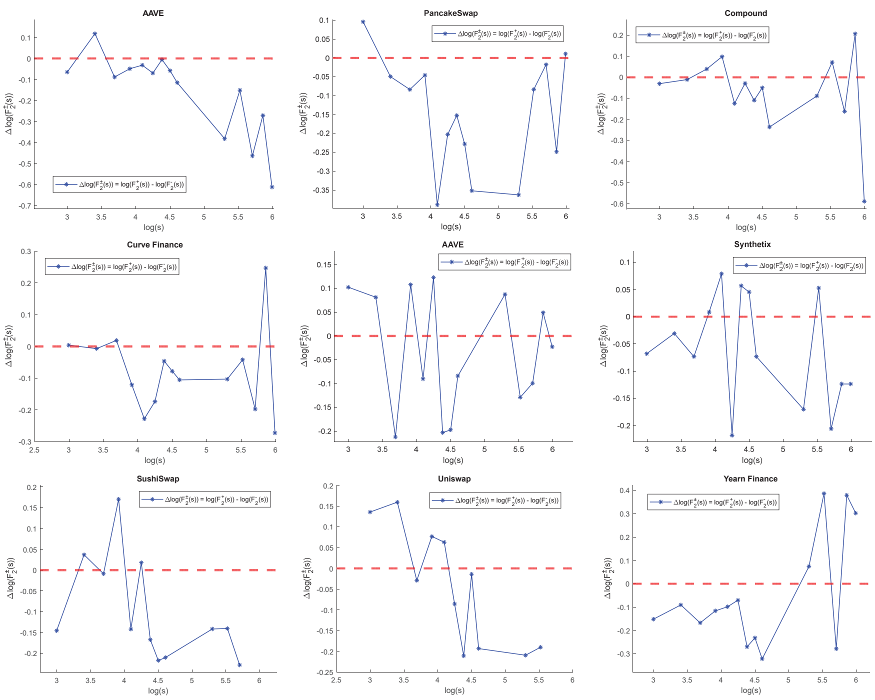


Figure 5. Differences in fluctuations between uptrend $F_2^+(s)$ and downtrend $F_2^-(s)$.

Figure 5 illustrates the difference in fluctuations between the uptrend $F_2^+(s)$ and downtrend $F_2^-(s)$ fluctuation functions across different time scales s for the selected DeFi assets. The x-axis represents the time scale s (on a log scale), and the y-axis shows the magnitude of the difference between the uptrend and downtrend fluctuation functions $\Delta log(F_2^{\pm}(s)) = F_2^+(s) - F_2^-(s)$.

Positive values indicate that fluctuations are more pronounced during uptrends, while negative values suggest larger fluctuations during downtrends.

Difference in fluctuation functions $\Delta log\left(F_2^{\pm}(s)\right)$: This represents the asymmetry in volatility between market uptrends and downtrends. This plot highlights how the scaling behavior and market volatility differ during positive versus negative trends, offering insights into the asymmetric behavior of DeFi markets.

Time scale analysis: The plot shows how the magnitude of the difference $\Delta log\left(F_2^{\pm}(s)\right)$ varies over different window sizes s, indicating whether asymmetry is more pronounced at shorter or longer time scales.

Figure 5 demonstrates that for most timescales, $\Delta log\left(F_2^{\pm}(s)\right) \neq 0$, suggesting that the multifractal correlations of the DeFi assets are asymmetric. The fluctuation differences reveal large amplitude variations around zero, reinforcing the existence of asymmetry over various time scales.

4.5. Analysis of Asymmetry Intensity Using Generalized Hurst Exponents

Figure 6 illustrates the overall, uptrend, and downtrend generalized exponents for all nine DeFi assets when $q \in [-45, 45]$.

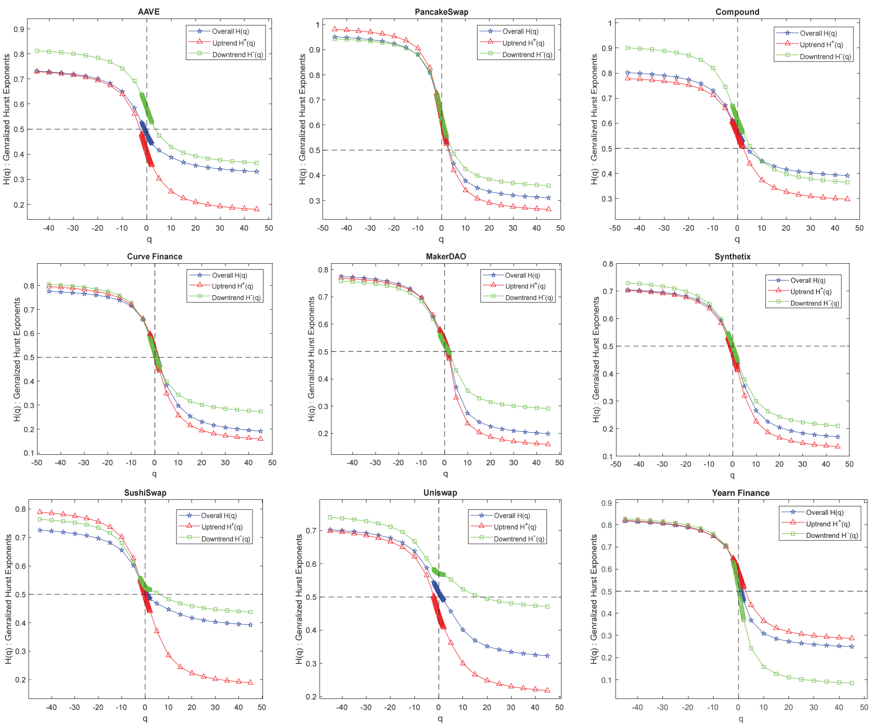


Figure 6. Plots of the overall, uptrend, and downtrend generalized Hurst exponents. The x-axis represents the time scale s, while the y-axis indicates the Hurst exponent values for different q values. Differences between uptrend and downtrend exponents reveal asymmetries in market behavior, highlighting the multifractal structure under different market conditions.

For all nine DeFi assets, $H^+(q)$ and $H^-(q)$ decrease non-linearly as $q \in [-45, 45]$. This indicates that the correlations exhibit multifractal characteristics for the nine assets during both upward and downward trend markets.

Furthermore, Figure 6 reveals that $H^+(q)$ and $H^-(q)$ exhibit distinct behavior, surrounding the overall generalized Hurst exponent $H(q)$ as $q \in [-45, 45]$. This suggests that the correlations differ under upward and downward trend markets. Consequently, the multifractal correlations are asymmetric.

To quantify the degree of asymmetry, the excess differences, $\Delta H^{\pm}(q) = H^+(q) - H^-(q)$, are measured. Figure 7 shows the results.

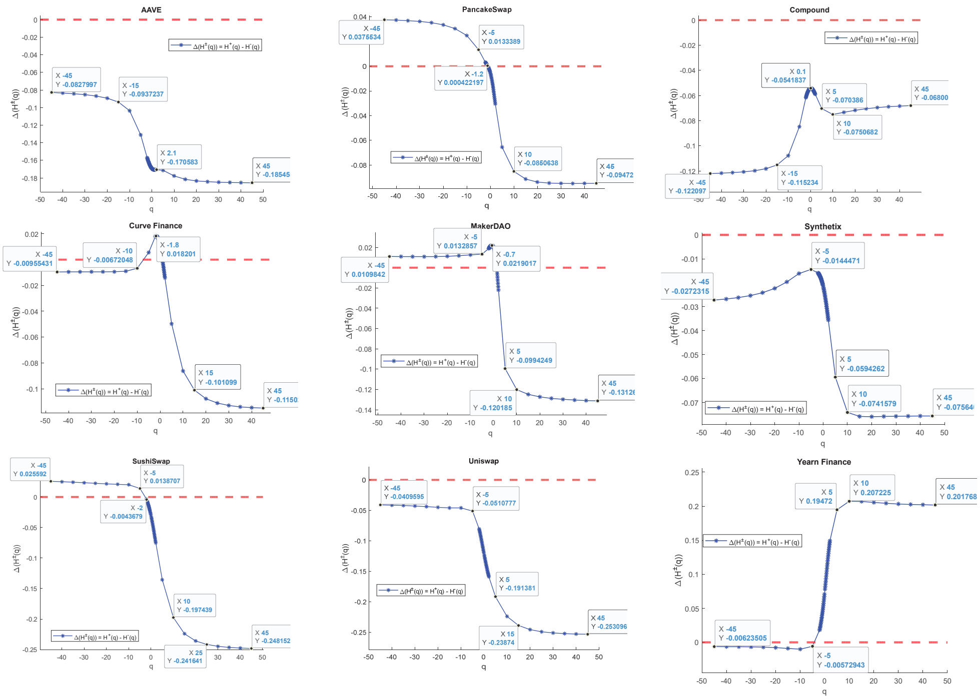


Figure 7. Excess differences in asymmetric degrees for the 9 DeFi assets. The y-axis represents the degree of asymmetry in market fluctuations, with positive values indicating stronger asymmetry in uptrend movements and negative values showing stronger downtrend asymmetry. The figure highlights significant variations across assets, suggesting differences in their susceptibility to market conditions.

$\Delta H^{\pm}(q)$ is nonzero for all DeFi assets, across most values of fluctuation orders, indicating that the multifractal correlations are asymmetric when markets have various trends. As shown in Figure 7, $\Delta H^{\pm}(q)$ for the AAVE DeFi asset remains consistently negative across all fluctuation orders, indicating that $H^{-}(q)$ is greater than $H^{+}(q)$. This suggests that AAVE exhibits asymmetrical multifractal correlations, with negative trends generating stronger multifractal correlations. Specifically, $\Delta H^{\pm}(q)$ gradually decreases from -0.0827 to -0.0937 as $q \in [-45, -15]$, then undergoes a sharp decline to -0.171 when q reaches 2.1 before further decreasing to -0.185, where it stabilizes. In absolute value, $\Delta H^{\pm}(q)$ increases from 0.0827 to 0.185 as $q \in [-45, 45]$, suggesting that the asymmetry intensifies with stronger multifractal correlations observed during downward trends. This suggests that negative fluctuations in the AAVE market generate more pronounced and persistent correlations over time, which could have important implications for risk management and trading strategies. The increasing intensity of the asymmetry implies that AAVE may become more volatile and unpredictable under negative market conditions. For investors and traders, this means that AAVE may present higher risks during periods of decline, necessitating more cautious strategies in bearish market conditions.

For Pancake Swap, $\Delta H^{\pm}(q)$ starts off positive and decreases from 0.0376 to 0.00042 (near zero: at symmetry) as $q \in [-45, -1.2]$. In this range, $H^{+}(q)$ is greater than $H^{-}(q)$, suggesting that the Pancake exhibits asymmetrical multifractal correlations, with positive trends generating stronger multifractal correlations, but the asymmetry decreases as q rises. From $q = -1.2$, $\Delta H^{\pm}(q)$ becomes negative and continues to decrease, reaching -0.0947, where it stabilizes. In absolute value, $\Delta H^{\pm}(q)$ increases from 0.0376 to 0.0947 as $q \in [-45, 45]$, suggesting that the asymmetry intensifies with stronger multifractal correlations observed during downward trends. From $q = -1.2$ onwards, $\Delta H^{\pm}(q)$ becomes negative and continues to decrease, reaching -0.0947, where it stabilizes. This behavior indicates that Pancake Swap's market dynamics are highly sensitive to both positive and negative price movements, with the asset displaying stronger multifractal characteristics during downturns. Investors should consider the varying strength of correlations across different time scales when developing strategies, particularly as the market transitions from positive to negative trends. Risk management strategies may need to be adjusted to account for the intensified multifractal correlations during downward trends.

Figure 7 shows that $\Delta H^{\pm}(q)$ for the Compound asset remains consistently negative across all fluctuation orders, indicating that $H^{-}(q)$ is greater than $H^{+}(q)$. This suggests that Compound exhibits asymmetrical multifractal correlations, with negative trends generating stronger multifractal correlations. Specifically, $\Delta H^{\pm}(q)$ increases from -0.122 to -0.0542 as $q \in [-45, 0.1]$, indicating a reduction in asymmetry. Then, $\Delta H^{\pm}(q)$ decreases to -0.075 as q reaches 10, before gradually increasing again to -0.068, where it stabilizes. The consistently negative $\Delta H^{\pm}(q)$ across all fluctuation orders indicates that negative trends result in stronger multifractal correlations compared to positive trends. This could imply that the Compound market reacts more strongly during downturns than during upward movements, which can influence risk management and trading strategies.

For the Curve Finance asset, $\Delta H^{\pm}(q)$ gradually increases from -0.0096 to -0.0067 as $q \in [-45, -10]$, remaining negative but close to zero (near symmetry). As q further increases, $\Delta H^{\pm}(q)$ becomes positive and rises to 0.0182 at $q = 1.8$, signaling a growing asymmetry, with positive trends producing stronger multifractal correlations than negative trends. This could imply that during periods of growth or positive momentum, the asset is more stable or predictable, allowing for potentially higher returns and more reliable forecasting. Afterward, $\Delta H^{\pm}(q)$ decreases sharply to -0.101 at $q = 15$ and continues to decrease gradually until stabilizing at -0.115. This pattern suggests an increase in asymmetry, with negative trends generating stronger multifractal correlations. This points to greater volatility and potential risk during market declines.

For the MarkerDAO asset, $\Delta H^{\pm}(q)$ increases gradually from 0.011 to 0.0219 as $q \in [-45, -0.7]$, remaining positive but relatively close to zero (near symmetry). Then, $\Delta H^{\pm}(q)$ crosses the symmetry axis and decreases sharply to -0.120 at $q = 10$ and decreases gradually to -0.131, where it stabilizes. When $q \in [10, 45]$, $H^{-}(q)$ is greater than $H^{+}(q)$, suggesting that Compound exhibits asymmetrical multifractal correlations, with negative trends generating stronger multifractal correlations. This suggests more stability, offering opportunities for short positions or hedging in bearish conditions.

Figure 7 shows that $\Delta H^{\pm}(q)$ for the Synthetix asset remains consistently negative across all fluctuation orders, indicating that $H^{-}(q)$ is greater than $H^{+}(q)$. This suggests that the Synthetix asset exhibits asymmetrical multifractal correlations, with negative trends generating stronger multifractal correlations. Specifically, $\Delta H^{\pm}(q)$ increases from -0.0272 to -0.0144 as $q \in [-45, -5]$. Then, it experiences a sharp decline to -0.0742 at $q = 10$ and continues to decrease to -0.0756, where it stabilizes. In absolute value, $\Delta H^{\pm}(q)$ increases from 0.0827 to 0.185 as $q \in [-5, 45]$, indicating that the asymmetry intensifies, with stronger correlations observed during downward trends. As the asymmetry intensifies, investors may need to adjust their risk management strategies to account for the stronger correlations in negative trends.

For the Sushi Swap asset, $\Delta H^{\pm}(q)$ starts off positive and decreases from 0.0256 to 0.0139 as $q \in [-45, -5]$. In this range, $H^{+}(q)$ is greater than $H^{-}(q)$, indicating that Sushi Swap exhibits asymmetrical multifractal correlations, with positive trends generating stronger correlations. This could present opportunities for strategies that capitalize on upward movements. However, the asymmetry diminishes as q rises. At $q = -2$, $\Delta H^{\pm}(q)$ crosses the symmetry axis and decreases sharply to -0.197 at $q = 10$, continuing to decrease to -0.248, where it stabilizes. In absolute value, $\Delta H^{\pm}(q)$ increases from 0.197 to 0.248 as $q \in [10, 45]$, suggesting that the asymmetry intensifies, with stronger correlations observed during downward trends. This indicates that investors might need to adjust their strategies, focusing more on risk management or short-selling tactics as the market turns bearish.

Figure 7 shows that $\Delta H^{\pm}(q)$ for the Uniswap asset remains consistently negative across all fluctuation orders. This suggests that Uniswap exhibits asymmetrical multifractal correlations, with negative trends generating stronger correlations. Specifically, $\Delta H^{\pm}(q)$ gradually decreases from -0.041 to -0.051 as $q \in [-45, -5]$, then undergoes a sharp decline to -0.239 when q reaches 15, before further decreasing to -0.253, where it stabilizes. In absolute value, $\Delta H^{\pm}(q)$ increases from 0.041 to 0.253 as $q \in [-45, 45]$, suggesting that the asymmetry intensifies, with stronger multifractal correlations observed during downward trends. The intensification of asymmetry indicates that downward movements are more pronounced, highlighting potential risks for investors during bearish phases. More cautious strategies focusing on risk mitigation or even short-selling opportunities are needed.

For the Yearn Finance asset, $\Delta H^{\pm}(q)$ starts with a value close to 0 as $q \in [-45, -5]$. It then rises sharply above the symmetry axis, reaching 0.195 at $q = 5$, and stabilizes at 0.202. From $q = 5$ to 45, the asymmetry strengthens, with stronger correlations observed during upward trends. As the asymmetry increases, investors may benefit from leveraging bullish trends. This could guide strategies that capitalize on positive momentum.

4.6. Source of Multifractality for the Nine DeFi Assets

In this section, shuffling and surrogation transformations are performed on original series of the nine DeFi assets. Two shuffling techniques, namely "randperm" and "randi", are employed. For surrogation, the Inverse Fast Fourier Transform (IFFT) method is applied.

Figure 8 illustrates the generalized Hurst exponent $H(q)$ for the original, the surrogate, and the two shuffled series of the nine DeFi assets.

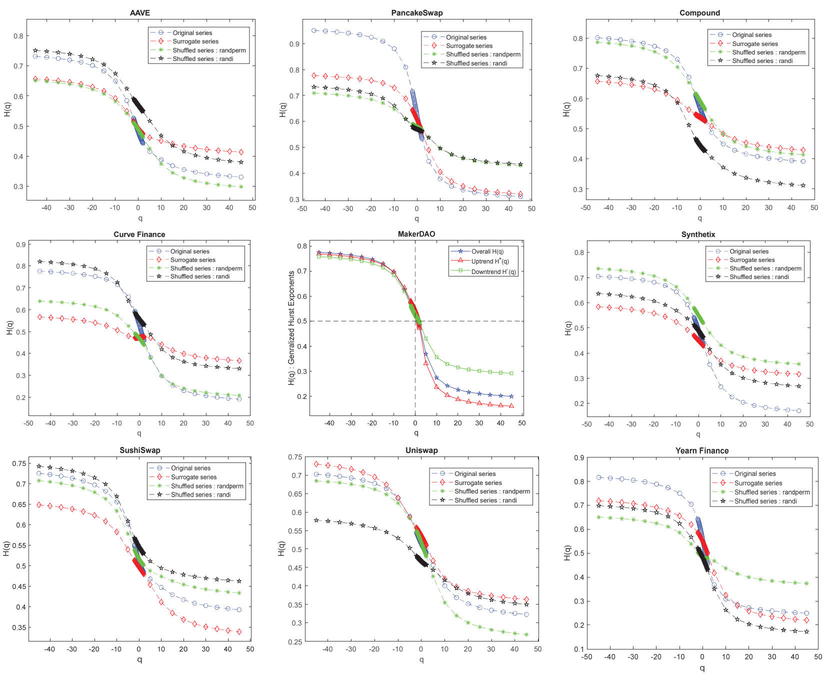


Figure 8. Plots of $H(q)$ vs. q for the original, surrogate, and shuffled series for the 9 DeFi assets. The figure compares the generalized Hurst exponent $H(q)$ across three types of series: the original (unmodified) series, surrogate data (generated to preserve the statistical properties), and shuffled series (randomly permuted data). Deviations between the original and surrogate or shuffled series indicate the presence of multifractality and non-linear dependence, suggesting significant market structure. Differences in the curves across assets provide insights into their market behavior and the robustness of the multifractal analysis.

As shown in Figure 8, all curves of the generalized Hurst exponent $H(q)$ for the original, surrogate, and two shuffled series decrease non-linearly, indicating that these series exhibit multifractal behavior. To compare the degrees of multifractality of the four series, the values of $\Delta H = H(q_{min}) - H(q_{max})$ are calculated.

The MF-DFA program was run 100 times for the nine DeFi assets, and each time, the ΔH of the original series was consistently greater than the ΔH of the surrogate and the two shuffled series. Table 3 presents the results.

Table 3. Degrees of multifractality of original, surrogate, and shuffled series based on ΔH.

Index	ΔH=$H(q_{min})$−$H(q_{max})$			
	Original	**Surrogate**	**Shuffled—Randperm**	**Shuffled—Randi**
AAVE	0.401	0.243	0.353	0.371
CAKE	0.641	0.457	0.279	0.299
COMP	0.410	0.228	0.373	0.365
CRV	0.584	0.199	0.431	0.489
MKR	0.575	0.457	0.382	0.440
SNX	0.534	0.268	0.379	0.367
SUSHI	0.332	0.309	0.274	0.280
UNis	0.380	0.366	0.416	0.228
YFI	0.567	0.498	0.277	0.526

The results indicate that $\Delta H_{Originate} > \Delta H_{Surrogate}$ and $\Delta H_{Originate} > \Delta H_{Shuffled}$ for the nine DeFi assets. This indicates that the multifractality of the nine DeFi assets has been diminished by both the surrogate and shuffled series. It can be concluded that both long-term correlations and heavy-tailed distributions contribute to the multifractal behavior of the nine DeFi assets.

These findings are confirmed by the following analysis. Figure 9 illustrates the singularity spectrums $f(\alpha)$ for the original, the surrogate, and the two shuffled series of the nine DeFi assets.

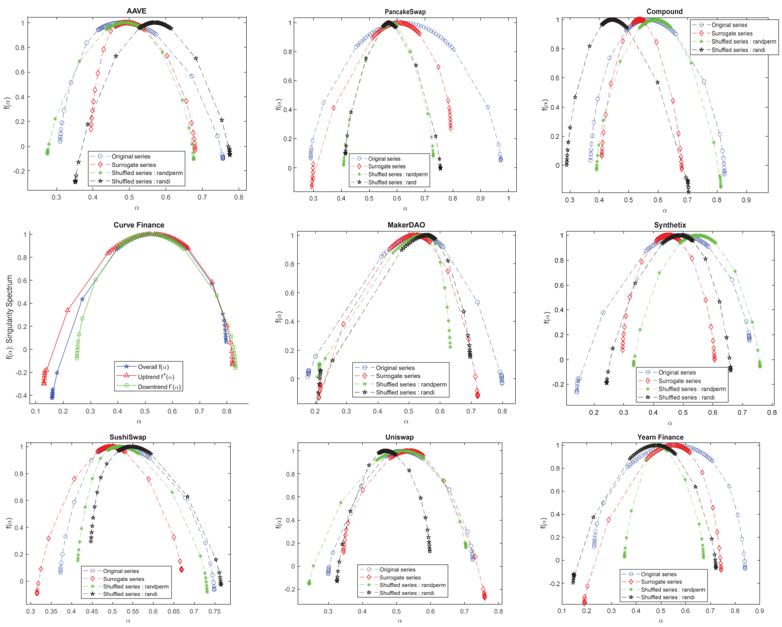


Figure 9. Plots of $f(\alpha)$ vs. α for the original, surrogate, and shuffled series for the 9 DeFi assets. The singularity spectrum illustrates the multifractal nature of each asset's price series. A wider spectrum indicates a more multifractal nature. Deviations between the original and surrogate or shuffled series suggest that the observed multifractality is not solely due to random fluctuations, highlighting the inherent complexity of the DeFi markets.

To compare the degrees of multifractality of the nine DeFi assets, the values of $\Delta\alpha = \alpha_{max} - \alpha_{min}$ are calculated. The MF-DFA program was run 100 times for the nine DeFi assets, and the results are presented in Table 4.

Table 4. Degrees of multifractality of original, surrogate, and shuffled series based on $\Delta\alpha$.

Index	$\Delta\alpha{=}\alpha_{max}{-}\alpha_{min}$ Original	Surrogate	Shuffled—Randperm	Shuffled—Randi
AAVE	0.447	0.285	0.401	0.424
CAKE	0.683	0.500	0.322	0.341
COMP	0.455	0.272	0.422	0.415
CRV	0.637	0.248	0.477	0.546
MKR	0.623	0.509	0.426	0.493
SNX	0.582	0.310	0.426	0.418
SUSHI	0.377	0.354	0.317	0.318
UNis	0.425	0.414	0.461	0.273
YFI	0.610	0.554	0.320	0.578

Table 4 shows that $\Delta\alpha_{orginale} > \Delta\alpha_{Surrogate}$ and $\Delta\alpha_{orginale} > \Delta H_{shuffled}$ for the nine DeFi assets, indicating that the multifractality has been reduced by both the surrogate series and the two shuffled series across the nine DeFi assets.

The practical implications of these findings suggest that the multifractal nature of the nine DeFi assets is significantly influenced by long-term correlations and heavy-tailed distributions. For investors and traders, this implies that the nine DeFi assets may exhibit predictable long-term behaviors, especially in terms of trend persistence, and that price movements could be more sensitive to sudden, extreme events (tail risks) than traditional assets. Therefore, understanding and managing the risk associated with extreme market movements is essential for developing risk management strategies.

4.7. Discussion

In this section, the results of this study are compared to those of previous studies, highlighting both similarities and differences.

The findings of this study on the multifractality, asymmetry, and sources of multifractality in the nine decentralized finance (DeFi) assets align with prior studies on traditional financial markets and cryptocurrencies. Our results are consistent with the results of Norouzzadeh and Rahmani (2006) and Lu et al. (2013), who identified long-term correlations and fat-tailed distributions as key contributors to multifractality. However, our findings suggest that DeFi assets tend to exhibit higher multifractal dimensions, which may be attributed to the greater volatility and speculative nature of these markets.

This study reveals significant asymmetry in the behavior of DeFi assets, particularly during downward price movements, aligning with the findings obtained by Mensi et al. (2020) and Zhuang and Wei (2022). The increased asymmetry in DeFi markets, similar to cryptocurrency markets studied by Kakinaka and Umeno (2022), is driven by exaggerated reactions to negative shocks, often exacerbated by external market factors such as liquidity crises.

The sources of multifractality identified in our study—long-range correlations and fat-tailed distributions—mirror those found in both traditional and cryptocurrency markets. These factors, highlighted by Faheem et al. (2020) and Mensi et al. (2022), are amplified in DeFi due to the speculative nature of the market and the susceptibility of DeFi assets to extreme price events. These dynamics are reflected in the significant price fluctuations observed in DeFi tokens like YFI and CAKE, which exhibit strong long-range correlations and fat-tailed distributions, similar to the findings of Minhyuk et al. (2017) and Mensi et al. (2019) in traditional markets and cryptocurrencies.

In summary, our results indicate that while DeFi markets share common multifractal characteristics with traditional markets and cryptocurrencies, they exhibit stronger multifractality and asymmetry due to their heightened volatility and speculative behavior. These findings contribute to the understanding of DeFi as a unique asset class with both shared features and distinct traits compared to traditional financial markets.

5. Conclusions

This study aimed to explore the asymmetric multifractal behavior of nine DeFi markets (AAVE, Pancake Swap, Compound, Curve Finance, Maker DAO, Synthetix, Sushi Swap, UniSwap, and Yearn Finance). The focus was on assessing the degree of multifractality, identifying underlying drivers, and analyzing market asymmetry. Asymmetrical Multifractal Detrended Fluctuation Analysis (A-MFDA) was employed for this study.

The study began by examining the multi-scale behavior of fluctuation functions across time scales. The results reveal power law scaling, a hallmark of multifractal systems, indicating the presence of multifractality in the data.

Next, multifractal and persistence characteristics were analyzed using generalized Hurst exponents, Rényi exponents, and singularity spectrum functions. The analysis showed varying correlations over time scales. The DeFi markets exhibited both persistence and anti-persistence behaviors, suggesting stable short-term trends as well as rapid reversals, which require adaptive trading strategies. Among the assets, CAKE, CRV, MKR, and YFI displayed high multifractality, signaling complex and unpredictable price behaviors that demand advanced forecasting techniques. In contrast, assets like SNX showed moderate multifractality, indicating somewhat less volatility, while COMP, AAVE, UNIS, and SUSHI exhibited lower multifractality, suggesting more stable and predictable price movements suitable for conservative investors.

Additionally, the analysis of uptrend and downtrend fluctuation functions revealed distinct differences, indicating asymmetric multifractal correlations across all nine DeFi assets.

The asymmetry intensity was further quantified by examining the excess differences between the uptrend and downtrend generalized Hurst exponents. The nine DeFi assets exhibit distinct asymmetrical behaviors. AAVE, Compound, Synthetix, Uniswap, SushiSwap, and MakerDAO show negative asymmetry, where negative trends result in stronger multifractal correlations. Pancake Swap starts with positive asymmetry but transitions to negative as q increases, indicating sensitivity to both positive and negative trends. Curve Finance initially shows near symmetry but becomes more volatile during negative trends. Yearn Finance stands out with positive asymmetry. Overall, most assets are more sensitive to negative trends, necessitating risk management strategies focused on mitigating volatility, while Yearn Finance offers opportunities in bullish market conditions.

Finally, the source of multifractality was investigated using shuffling and surrogation transformations. The results show that long-term correlations and heavy-tailed distributions significantly influence the multifractal behavior of the nine DeFi assets. This emphasizes the need for advanced forecasting and risk management strategies in DeFi markets.

The findings emphasize the need for advanced risk management strategies that account for the multifractality and asymmetry of DeFi assets. Traditional linear models are insufficient for forecasting price movements in these markets. Consequently, risk management must be dynamic, with strategies like hedging, short-selling, or diversification, particularly in downturns where correlations tend to be stronger and more persistent.

This study also highlights the varying degrees of multifractality across different DeFi assets, suggesting that more volatile assets require sophisticated forecasting models and adaptive trading strategies, while more stable assets may be more suitable for conservative investors using traditional methods. The identification of market asymmetry—where negative trends cause greater volatility—further underscores the need for cautious approaches during bearish markets. Additionally, this study reveals that DeFi assets are highly sensitive to extreme events, making it essential for market participants to prepare for sudden price swings.

Our study provides implications for both theory and practice. From a theoretical perspective, the discovery of power law scaling in DeFi markets contributes significantly to advancing the understanding of market behavior in decentralized finance. This reinforces the notion that these markets exhibit complex, non-linear dynamics, akin to those observed in traditional financial markets, yet with additional nuances due to their decentralized nature. Practically, this insight underscores the importance of employing advanced analytical tools like multifractal analysis to capture the intricate price fluctuations in DeFi assets, which are often missed by traditional linear models. As such, this study provides a foundational framework for improving investment strategies as it suggests the need for adaptive models that can account for the varying degrees of multifractality across different assets. Furthermore, this has profound implications for risk management approaches, suggesting the importance of dynamic and robust methods that can handle the complexity and volatility inherent in DeFi markets.

This study connects to broader trends by addressing the increasing relevance of decentralized finance (DeFi) in the global financial landscape. The observed power law scaling and multifractal behavior can be contextualized within broader trends in financial markets, especially when compared to traditional asset classes like stocks and commodities. While traditional markets often assume linear or weakly non-linear dynamics, decentralized markets like DeFi exhibit strong non-linear relationships that challenge conventional theories of market behavior. This aligns with existing research that highlights the fractal nature of financial time series, but it also extends this knowledge by identifying how multifractal behaviors specifically manifest in decentralized and digitally native markets. The findings contribute to the growing body of literature suggesting that DeFi markets could be modeled more effectively with multifractal tools, offering a more nuanced understanding of asset interactions in these emerging financial ecosystems.

The novelty of this study lies in its application of Asymmetrical Multifractal Detrended Fluctuation Analysis (A-MFDA) to DeFi assets. By incorporating asymmetric multifractality, this study provides a fresh perspective on the behaviors of these assets, highlighting market interdependencies, non-linear relationships, and asymmetric correlations. These aspects, which were previously underexplored in the context of DeFi, offer unique insights into how different assets within the ecosystem are interconnected and how they behave under varying market conditions. This approach, which differentiates between uptrends and downtrends, captures the asymmetric nature of market fluctuations that are pivotal for designing more effective forecasting models and trading strategies.

This study opens several avenues for future research. First, extending the methodology to other decentralized markets, including those beyond DeFi, could provide valuable insights into the multifractal nature of cryptocurrency markets as a whole. A further exploration of how various factors, such as network effects, tokenomics, and governance structures, influence the multifractal behavior of DeFi assets would also be beneficial. Additionally, integrating machine learning techniques with multifractal analysis could help enhance the forecasting power of these models, making them even more applicable to real-world trading scenarios. Finally, future studies could delve into the implications of multifractal behavior for market efficiency and the role of liquidity in shaping the fractal dynamics of DeFi markets.

This study provides the following policy recommendations:

(a) Enhance Regulatory Oversight: Policymakers should focus on creating a regulatory framework tailored to the unique characteristics of DeFi markets. This includes establishing guidelines for transparency, auditing smart contracts, and managing risks related to volatility and liquidity. Proper oversight could mitigate systemic risks and enhance market confidence.
(b) Implement Measures for Market Stability: Given the high volatility and asymmetry observed in DeFi markets, policymakers should encourage the development of mechanisms like decentralized insurance and liquidity pools that can stabilize market conditions during periods of extreme fluctuations. These can act as safety nets for market participants.
(c) Encourage Disclosure and Transparency: To improve market efficiency, regulators should mandate real-time disclosure of information on transactions, token holdings, and governance decisions in DeFi platforms. This would reduce information asymmetry, making markets more transparent and accessible for all participants.
(d) Support Education and Risk Awareness: Policymakers can promote educational programs to raise awareness among investors about the risks associated with DeFi investments, including asymmetry and multifractality. Empowering participants with knowledge will foster a more resilient and informed market.

We also offer several investment recommendations:

(a) Adopt Dynamic Risk Management Strategies: Investors should implement adaptive risk management strategies to account for the asymmetric multifractal behavior in DeFi markets. This includes regularly rebalancing portfolios to respond to changing market conditions and volatility spikes in assets such as AAVE, COMP, and YFI.
(b) Focus on Diversification: Given the differing asymmetry across DeFi markets, investors are advised to diversify their portfolios by holding assets that exhibit varying levels of positive and negative asymmetry. For instance, combining assets like YFI (which shows consistent positive asymmetry) with assets that show negative asymmetry can help reduce risk exposure.
(c) Use Hedging Instruments: Considering the multifractal characteristics and long-term correlations of DeFi assets, investors can use hedging strategies to protect their portfolios during periods of market downturns. Instruments like options and futures on major DeFi tokens can help mitigate risks from price drops.
(d) Monitor Market Trends Closely: Since DeFi markets exhibit volatility clustering and trend sensitivity, investors should adopt a proactive approach by monitoring both positive and negative market trends. Employing real-time data analytics and machine learning models to detect early warning signals can help in mitigating potential losses during high-volatility periods.

In conclusion, this study introduces the innovative application of Asymmetrical Multifractal Detrended Fluctuation Analysis to DeFi markets, providing valuable insights into their complex, non-linear dynamics. By identifying asymmetric multifractal behavior and its underlying drivers, the study offers a more accurate understanding of DeFi market fluctuations. Furthermore, it emphasizes the importance of advanced risk management strategies tailored to the unique characteristics of DeFi assets, contributing to more effective forecasting and investment strategies in these rapidly evolving markets.

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K.A. and M.B.; resources, S.B., K.A. and M.B.; data curation, S.B., K.A. and M.B.; writing—original draft preparation S.B.; writing—review and editing, S.B., K.A. and M.B.; visualization, S.B., K.A. and M.B.; supervision, S.B.; project administration, S.B. All authors have read and agreed to the published version of the manuscript.

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Abbreviations

The following abbreviations are used in this manuscript:

DeFi	Decentralized Finance
AAVE	AAVE Token
CAKE	Pancake Swap
COMP	Compound
CRV	Curve Finance
MKR	Maker DAO
SNX	Synthetix
SUSHI	Sushi Swap
UNis	UniSwap
YFI	Yearn Finance
A-MFDA	Asymmetrical Multifractal Detrended Fluctuation Analysis

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Trends in the Literature About the Adoption of Digital Banking in Emerging Economies: A Bibliometric Analysis

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Abstract: This study examines the trends in the literature about adopting digital banking in emerging economies. It is based on the concepts of digital transformation and technological adoption, which significantly impact the development of the banking industry. A quantitative approach was used through a bibliometric analysis using data from Scopus to achieve the objective. The search equation allowed 118 publications to be extracted and analyzed. The results show that digital banking in emerging countries is a growing field of research that has driven the introduction of new information technologies. The perceived usefulness of digital banking is a key factor in promoting its adoption in the market. Attributes such as security and trust were identified as affecting the level of user satisfaction. Most studies are based on technological adoption, where perceived risk, usefulness, and ease of use are key to understanding the intention to use these technologies. Some countries' concerns about financial inclusion, cyber security, and trust in financial technology are evident. While digital banking has the potential to increase the coverage of financial services, there are concerns about cybersecurity risks and user data protection.

Keywords: digital banking; technological adoption; emerging economies; bibliometric analysis

1. Introduction

Information technologies have transformed the competitive dynamics of industries worldwide and how value is delivered to the customer. The banking sector is no exception. Technological advances have generated significant transformations in the financial system (Rahi et al. 2021). The growth of these technologies has been exponential and has had considerable effects on this sector (Shaikh et al. 2020). The introduction of new business models in the financial sector in fintech format has generated contributions to the development of the operation of banking establishments and has also generated competitive pressures in the industry. According to (Phan et al. 2020), fintech companies are likely to trigger a substitution effect, and banks will probably have to divest part of their business activity. This is not a minor concern for participants in the banking industry; since 2008, global fintech activity has been growing, and customers now have multiple alternatives to receive personalized and secure banking experiences (Wewege et al. 2020).

Banks have developed strategies to boost business by adopting new technologies. Innovations in financial products and services, such as real-time payments, online lending, or financial services through mobile platforms, have experienced explosive growth (Allen et al. 2022). Internet-based e-banking has become an alternative channel that offers convenience to the user, facilitating 24-hour service delivery anywhere through a digital banking website (Rahi et al. 2021). Banks have evidenced the potentiality of digital channels, resulting in increased mobile and online banking platforms, with solutions for Internet and smartphone users (Wewege et al. 2020). Banks have also developed new models of electronic, e-financing, and cell phone financing (Shaikh et al. 2020). These technologies allow bank customers to pay their commercial bills, make online purchases, transfer funds, and generate bank statements through a website (Rahi et al. 2021).

Banks spend more money on IT investments than other sectors (Kitsios et al. 2021; Scott et al. 2017). Digital transformation empowers new banking establishments to offer new service channels through technology platforms and points of service and enables them to reduce operating costs (Kitsios et al. 2021). However, although the benefits of new information technologies bring opportunities, they also represent challenges for the banking business (Miskam et al. 2019). Digitization involves substantial costs. Therefore, it may not be financially viable or compromise the bank's stability due to increased technical and regulatory risk (Khattak et al. 2023). Managers should systematically evaluate these investments because they could commit funds that can be used to finance other strategic activities.

Some studies show the effect of information technologies on bank profitability. For example, (Le and Ngo 2020) pointed out that IT-based products can improve bank profitability. (Del Gaudio et al. 2020) also found evidence of a positive relationship between bank profitability and the adoption of information and communication technologies, ICT. The authors stressed the importance of the diffusion of these technologies. Therefore, strong government policies are required to safeguard the security of user data, as well as measures that favor open platforms and encourage innovation processes. Some countries have developed government programs and initiatives, including the possibility of financing fintech companies; however, only in some countries have these technologies been accompanied by a regulatory framework (Tsindeliani et al. 2021).

Therefore, this study aims to examine the trends in the literature about digital banking in emerging countries through a bibliometric analysis. In this way, it seeks to provide an overview of the factors that best characterize the academic production in this field of knowledge. This bibliometric analysis contributes to identifying the main trends in the literature about the adoption of digital banking in emerging countries. To this end, it analyzes the prevalent topics over time using thematic mapping. In addition, characterization of the main countries, institutions, authors, and academic collaboration networks with the greatest impact is carried out. This study contributes to identifying the influence of research centers on developing cooperation strategies, formulating public research policies, and new projects based on the contributions of the main experts or referents in the area. The context of analysis is emerging economies, considering that these countries experience lower levels of financial inclusion than advanced economies (Finkelstein-Shapiro et al. 2022).

In addition, fintech companies have made an important contribution to closing this gap since their business model, leveraged on digital technologies, makes it possible to provide financial services to individuals and companies that cannot participate in the traditional financial system (Finkelstein-Shapiro et al. 2022). For this purpose, the number of publications, the geographical nodes of greatest academic production, the impact of the authors, thematic areas, and knowledge networks are analyzed. This study is relevant due to the increase in publications related to digital transformation in the banking sector, such as digital banking, mobile banking, open banking, digital payments, and digital wallets, among other products. Therefore, a bibliometric analysis helps to address this gap in the academic literature as it allows the grouping of fragmented knowledge from different domains according to their similarity and relatedness (Ren et al. 2020).

This study generates a significant contribution to researchers interested in recognizing trends and knowledge gaps related to the adoption of digital banking. In addition, higher education institutions and governments can take advantage of the results of this study to identify critical areas of research that can impact strategic sectors of countries with emerging economies and on which projects can be linked and funds can be allocated efficiently. Along these lines, (Garg et al. 2023) stated that bibliometric studies help to identify knowledge gaps, examine the research conducted in some countries on a given topic, and identify those countries that need to be studied. These studies also provide valuable information on the current state of knowledge and provide directions for future research (Dissanayake et al. 2023). In addition, bibliometric studies apply statistical techniques that can be used to identify key topics in a field of knowledge, examine their influence, and recognize emerging areas (Parker et al. 2023).

This study differs from previous studies, which have characterized the academic literature on technologies and innovation in the financial industry based on bibliometric data. Unlike (Dissanayake et al. 2023), who addressed the concept of fintech in a general way, in this study, the object of analysis is specific since it is literature related to the adoption of digital banking in emerging countries. These technologies can have a significant impact on areas such as inclusion and financial literacy, which are necessary for the development of emerging economies. A study along these lines was developed by Aziz et al. (2021). However, the authors focused on analyzing patterns of publications, authors, geographic affiliation, and topics, while this study identifies specific thematic trends that may constitute future lines of research. On the other hand, although (Tuli 2023) studied the obstacles that impede the adoption of digital banking technologies in emerging economies, the author focused his analysis on the Asian context.

The paper is organized as follows. First, the theoretical foundation related to information technologies in the banking sector is addressed. A conceptual analysis of digital banking and its theoretical and empirical approaches is made. Secondly, the methodological strategy for data collection and bibliometric analysis is presented. A search equation was developed to collect publications that address digital banking in the context of emerging economies. A sample of 123 documents published from 1992 to 2023 was obtained. A bibliometric analysis was performed by mapping knowledge, considering the evolution of academic productivity, the main research centers on the subject, authors, and publications with the highest impact, and co-occurrence networks allow the dimensioning of this domain. Thirdly, an analysis and discussion of the results are proposed to identify patterns and trends related to the object of study. Finally, the conclusions are presented.

2. Theoretical Foundation

2.1. The Digital Transformation of the Banking Business

Digital transformation is a process of integration of technologies and digital solutions in companies which has driven the development of applications to facilitate user operations, in addition to making transactions between the parties involved faster, more efficient, and more secure. In the banking sector, this transformation can be documented in initiatives such as those of the Bank of Scotland (Loyds Banking Group n.d.), which in 1959 became the first bank in the United Kingdom to use a computer to process its accounts centrally. By 1985, before the Internet was available, it was the first institution to offer its customers electronic banking services from home. All they needed was a television screen and a telephone connection. (Wewege et al. 2020) reported that Stanford Federal Credit Union in the United States became the first online bank in 1994. Currently, 80% of U.S. banks offer their customers the possibility of online banking (Napoletano and Whiteman 2021), which has contributed to a significant reduction in the number of physical branches around the world (Wewege et al. 2020).

The integration of technologies into the different activities of the banking business has been consolidated as a transformation process that has significantly impacted the industry. According to (Khattak et al. 2023), this digital transformation process will affect commercial banks internally and externally. External digital transformation implies that non-banking firms can offer digital services such as traditional banking. Internal digital transformation relates to the adoption of advanced technologies. These technologies include artificial intelligence, blockchain, big data, cloud computing technology, etc. These technologies are driving innovation in the banking sector, to the extent that they offer opportunities to facilitate customer transactions, product customization, and security in service delivery.

Although digital transformation considerably impacts the banking sector, strong regulation is required to ensure customer security, transaction integrity, and personal data protection. According to (Tsindeliani et al. 2021), government intervention in the banking sector is necessary at all stages given the inevitable digitalization. Currently, many cases of unauthorized companies offering financial services related to financial technology startups have been reported (Balyuk and Davydenko 2023). Considering the above, the lack of regulation on digital transformation is a cause for concern in the financial sector, as it has considerable implications for the system's stability. These technologies should reduce the possibility of illegal activities seeping into the system, and governments have a key role to define and enforce consumer protection regulations (Demirguc-Kunt et al. 2021).

2.2. Digital Banking and Its Modalities

According to Sharma (2017), digital banking involves leveraging technology to offer banking products and adopting the latest technologies at all functional levels and across all service delivery platforms. According to Ananda et al. (2020), factors such as easy access to the Internet, the increased number of online users, cost efficiency, convenience, and cost-effectiveness have encouraged greater adoption of e-banking. A digital bank offers similar benefits to a physical branch. Digital banking is not just about mobile platforms or online transactions; it can be applied in other functional areas of the bank. The online or mobile platform is only the interface of the platform. There are hundreds of banking functions such as risk management, treasury, product development, etc., that take place at the trading desk and the settlement desk. All these activities are also susceptible to digitization. Recently, some technological trends have been consolidated in the banking industry:

- Mobile banking or m-banking: Allows 24-hour remote access to finances on a mobile device such as a smartphone or tablet (Sorbet 2022). Through mobile devices, a broad suite of services can be accessed to enable individuals to manage money.
- Open banking: It has been considered the platform of the retail banking industry. The essence of open banking is to recognize the right of banking customers to share their transactional data with authorized third parties (O'Leary et al. 2021). This model is a vector to drive the transformation of the banking industry into an open platform model, as has happened in industries such as telecommunications.
- Cloud-based banking or cloud banking: Refers to the implementation and management of banking infrastructure to control cloud-based core banking operations and financial services without dedicated physical servers (Shatalova and Huseynov 2021). Cloud technology is a model that provides on-demand access to a box of configurable resources that can be rapidly provisioned, scaled, and released with minimal operational costs by contacting the provider.

2.3. Impact of Digital Technologies on Banking Business Performance

At the theoretical level, few studies have proposed a model or approach to explain the performance of the banking business in terms of digital technologies since most studies focus on analyzing technology adoption or the impact of digital solutions in specific areas. However, some works have identified some theoretical approaches that contribute to explaining the impact of these technologies on the performance of these businesses. For example, (Zhu and Jin 2023) referred to the theory of externalities, which explains how digital transformation can reduce the negative externalities caused by banks. Another perspective that explains this impact is the theory of technological innovation, which explains how digital technology has promoted innovation in commercial banks and how this leads to significantly reduced costs, improves efficiency in information gathering, supports decision making, and improves operations management (Zhu and Jin 2023). In contrast, (Le and Pham 2022) mentioned that, based on the theory of efficiency and cost, the acquisition of technology does not increase the efficiency of the banking business, since it is necessary for banks to be able to comprehensively combine the system of technical and social factors within the organization.

Some studies explain the performance of the banking business from an empirical point of view. According to (Koroleva and Kudryavtseva 2020), three approaches to the economic efficiency of banking organizations are identified in the academic literature. The first is based on financial reporting, characterized by flexibility, but does not allow a probabilistic evaluation of the results. The second method is inquiry with experts, which, according to the authors, is the most applicable for performance analysis but faces the problem of subjectivity in the evaluation. In addition, there is a recent trend towards econometric models, which, despite difficulties in their construction, tend to be more objective and help identify dependency relationships in the variables and analyze long-term trends. The authors consider that regression models are a reasonable alternative for evaluating the performance of digital banks because they allow for estimating the impact of variables on profitability measures.

(Koroleva and Kudryavtseva 2020) found a positive impact of digital banking features on the performance of Russian banks, using ROA as an endogenous variable. Specifically, a positive and statistically significant relationship was evident when relating the number of users and online banking transactions to the performance variable. (Scott et al. 2017) found a positive effect of the adoption of financial technologies such as SWIFT on banks' performance, measured in terms of profit margin. However, some papers have found evidence that contrasts with these findings. (Nguyen-Thi-Huong et al. 2023) observed a negative impact of the digital transformation process on performance measures such as ROA and ROE. The authors explained this result as being due to the significant investment represented by technology adoption, the business results of which cannot be seen immediately. Meanwhile, (Phan et al. 2020) analyzed the effect of fintech growth on banking business performance. The authors used panel data of 41 banks and analyzed the effect on different financial performance measures such as return on assets (ROA), return on equity (ROE), net interest income to asset ratio (NIM), and return on income earning assets (YEA). The results revealed a negative impact on all performance measures.

3. Materials and Methods

A bibliometric study was carried out with a quantitative approach and longitudinal design. An analysis was carried out based on numerical data, which are susceptible to statistical analysis. In addition, the publications under study date from 1992 to 2023. Therefore, bibliometric data of works up to 31 years old are addressed. In this way, it is possible to analyze the evolution of this field of knowledge over time, which allows for a deeper understanding of the characteristics of bibliographic production (Forliano et al. 2021). With the above, the aim was to have objective and quantifiable information on the impact, evolution, and degree of dissemination of research related to digital banking in emerging countries.

According to (Donthu et al. 2021), scholars apply bibliometric analysis to discover emerging trends in areas of study, collaboration patterns, and research components that allow for exploring the intellectual structure of a specific domain of literature. In addition, bibliometric studies contribute to mapping large volumes of scientific literature, allowing the application of rigorous techniques that guarantee the quality of the information and the results generated (Nobanee et al. 2021). In business research, bibliometric studies have gained considerable popularity as they allow for handling large volumes of scientific data and produce a high research impact (Donthu et al. 2021).

This study maps the bibliographic production related to digital banking in emerging countries. To this end, a search equation was constructed to address the two main categories of analysis, as shown in Table 1. To compile an important bibliometric database, terms related to each category were identified based on the titles, abstracts, and keywords. The database chosen to conduct this study was Scopus, a source of quality and reliability for bibliographic extraction, with wide coverage for collecting information and easy access to data (Herrera-Franco et al. 2020).

Table 1. Analysis categories.

Category	Related Term [1]
Digital Banking	Digital Bank, Online Bank, Internet Bank, Electronic Bank, Virtual Bank, E-bank
Emerging Economy	Emerging Economy, Developing Economy, Emerging Market

[1] The information query was based on the terms corresponding to each category.

Once the study categories and query terms were defined, the search equation was developed. Then, publications corresponding to the intersection of digital banking and emerging economies could be identified. Scopus was consulted and 128 documents were obtained; however, a filter was applied for the year of publication to exclude those corresponding to 2024. This is the year this study was conducted, so not all published studies would be available for bibliometric analysis. The search equation was defined as shown in Table 2, allowing 118 publications to be obtained to conduct the study.

Table 2. Search equation.

Database	Search Equation
Scopus	(TITLE-ABS-KEY ((“digital bank*” OR “online bank*” OR “internet bank*” OR “electronic bank*” OR “virtual bank*” OR e-banking)) AND TITLE-ABS-KEY ((“emerging econom*” OR “developing econom*” OR “emerging market*”))) AND PUBYEAR > 1991 AND PUBYEAR < 2024

Note: The Boolean AND and OR indicators and the reserved symbols * and “” were used to construct the search equation.

To conduct this bibliometric study in a structured manner, a protocol for consultation, purification, systematization, and presentation of the results of the bibliometric analysis was developed. This procedural framework for conducting studies of this nature is usually applied in different jobs in the field of management (Farooq 2022; Forliano et al. 2021; Nobanee et al. 2021; Herrera-Franco et al. 2020). For this study, the protocol proposed by (Donthu et al. 2021), who systematized some recommendations for carrying out this analysis in a logical order, as shown in Figure 1, was taken as a reference.

In the execution stage of the bibliometric analysis and report of findings presented in Figure 1, the VOSviewer tool was used to report the co-occurrence, bibliographic coupling, and citation maps. Although there are other computer programs to carry out this type of analysis, VOSviewer focuses on graphical representation, which helps to easily evaluate and interpret the bibliometric maps (Herrera-Franco et al. 2020). In this way, it is possible to carry out data analysis (Donthu et al. 2021) without implying that it is a technically deficient tool. This tool usually produces better results when dealing with medium to large datasets (van Eck and Waltman 2010; Kirby 2023). The metadata analyzed in this study are mainly the references cited in the documents that make up the sample. Based on these data, bibliographic linkage and citation networks were prepared in VOSviewer. To complement the results provided by this software, the Bibliometrix library in the R (version 1.6.19) statistical package was used, which includes some useful applications for identifying trends, such as thematic maps and the analysis of production over time.

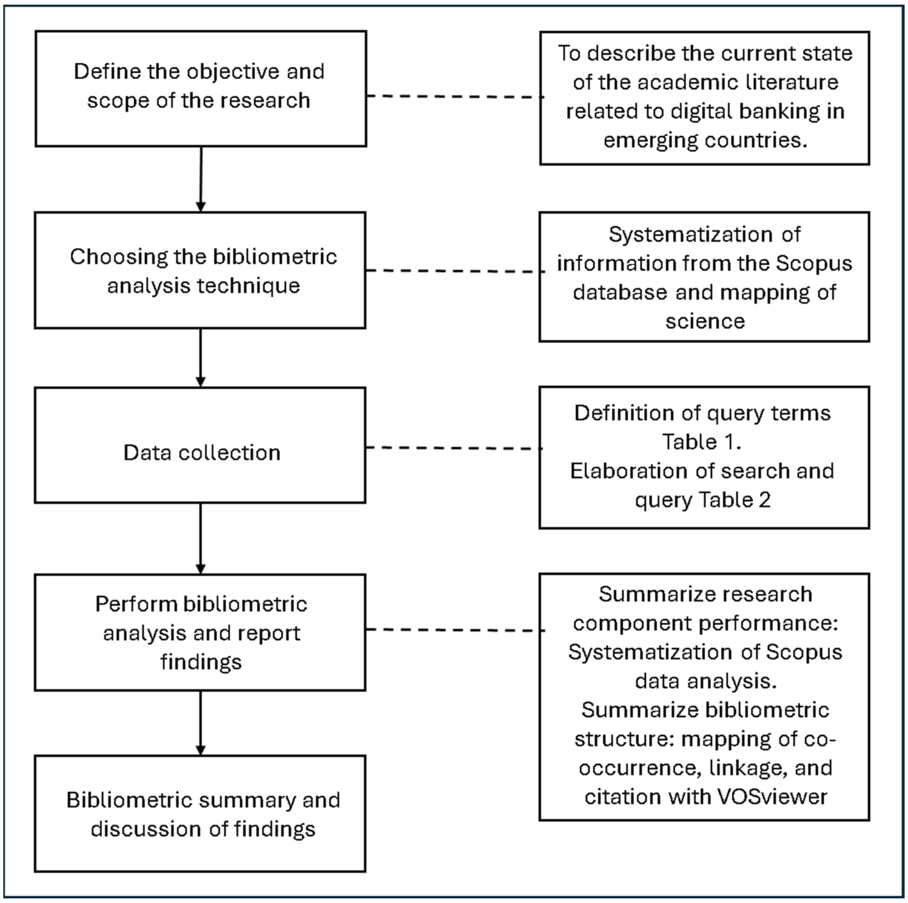

Figure 1. Bibliometric analysis protocol. ***Note***: Based on (Donthu et al. 2021).

4. Results

First, an analysis of the publications generated annually was carried out, as shown in Figure 2. This analysis made it possible to show the attention that the academic community pays to a certain domain of knowledge. In this way, it is possible to identify temporal trends and periods in which an increase or decrease in the number of publications is evident. In addition, this analysis can help to determine the periods in which a given research topic has received more attention from researchers.

As with other types of firms, banks face the threats of ever-changing technological disruption. To counter these threats, digitization of banking services has become indispensable. This can be evidenced by the academic productivity in digital banking in 2020–2023, setting a growth trend in related research. According to Figure 2, the field of digital banking research and its adoption has received increased attention from the academic community.

At least four thematic clusters can be identified in the literature reviewed: information and communication technologies, trade and consumption, banking and finance, and economics and development. Figure 2 also shows an accelerated increase in publications on electronic commerce and consumption and banking and finance. This can be explained by the development of new mobile technologies, which were consolidated in the first two decades of this century. New operating systems such as Android and iOS have boosted the development and adoption of mobile applications (Adlatina 2011) as they offer the possibility of accessing advanced functions such as intuitive interfaces and integration capabilities.

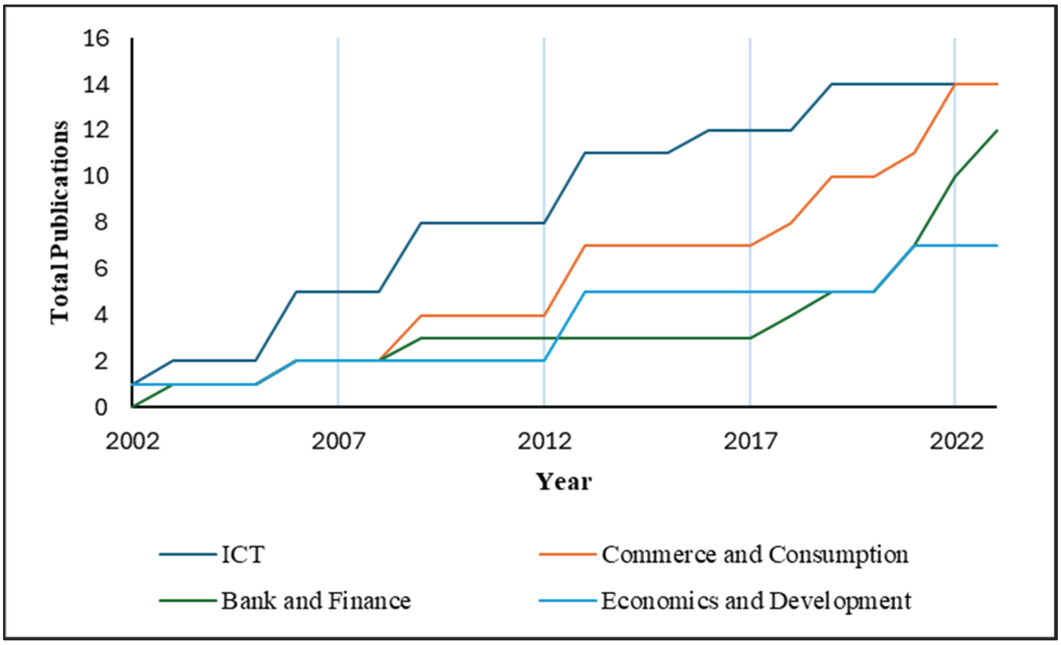

Figure 2. Analysis of thematic trends. ***Note***: Based on data from Scopus, prepared with Bibliometrix software (version 4.3.0) and edited in Microsoft Excel.

Since 2017, there has been an increase in the number of publications on banking and finance, which can be explained by a consolidation of the structure of digital payment systems, an increase in venture capital investments to finance these solutions, and the development of new technologies in the financial industry such as cryptocurrencies and smart contracts. (Crame and Bodie 1996) already anticipated that new information technologies would bring about lower processing costs, a reduction in geographical boundaries, and the application of government regulations that would affect competition in the financial industry.

This dynamic represents serious challenges for traditional banking and has contributed to the emergence of new problems that have encouraged the development of studies related to cybersecurity and the regulation of financial technology. Another issue that is the subject of analysis in recent research has to do with financial inclusion and the impact that these technologies have on the problems inherent in emerging countries. This contrasts with older studies, which were focused on addressing problems such as the adoption of these technologies, which were studied for their potential capacity (Barnes and Corbitt 2003).

Figure 2 does not show the prevalence and trend of papers published between 1992 and 2001 because only two papers associated with that period were retrieved. The first, published by (Martinsons 1992), is a case study of an electronic banking system called HEXAGON, which was developed by the Hongkong Bank. The adoption of this technology enabled the bank to reduce costs, improve the quality of customer service, facilitate access to the bank's services, and position itself in the global market. Secondly, (Polatoglu and Ekin 2001) anticipated a fact that is particularly relevant today, namely that a bank without an advanced technological infrastructure could see its market share compromised vis-à-vis other banks and non-bank competitors (fintech).

To contextualize the object of study, an analysis was performed considering the thematic areas in which a greater number of publications have been produced. In this way, active areas of research, emerging trends, and disciplines from which the problem is addressed can be identified. In addition, this information can be useful for identifying emerging fields of research that deepen and broaden the perspectives that enrich the object of study.

Figure 3 shows the main areas of research in terms of the number of publications related to the object of study. The areas where publications are most prevalent are Business, Management, and Accounting, followed by Economics, Econometrics, and Finance in second position. These two areas represent 57% of the total number of publications. Other areas that stand out are Computer Science and Social Sciences. This analysis indicates that the most relevant areas in this field are related to business and economics. However, there are a significant number of publications in journals related to information technologies and social sciences.

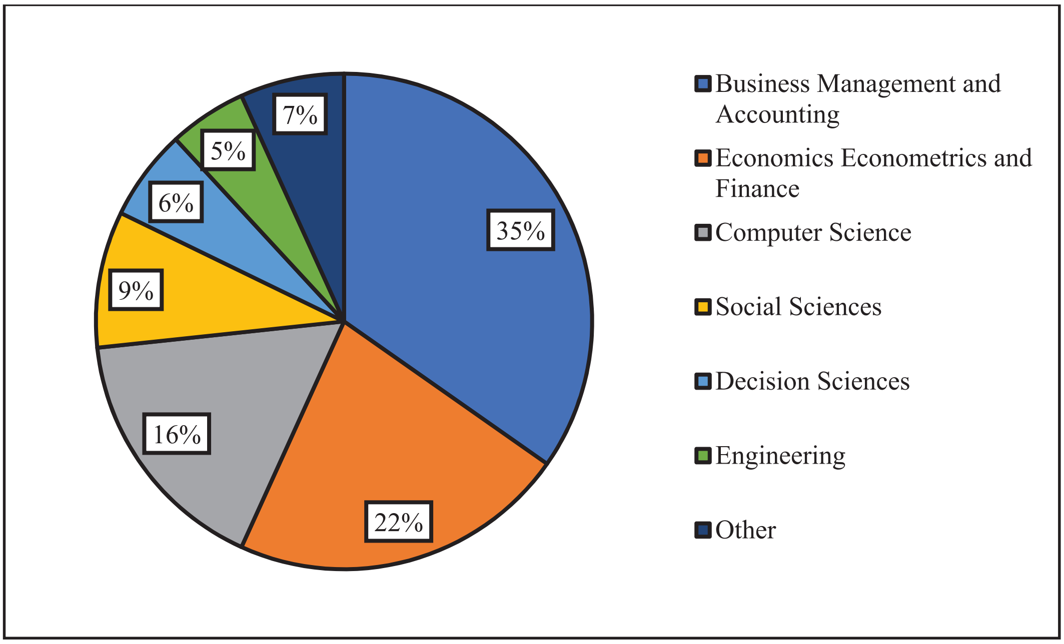

Figure 3. Thematic areas. ***Note***: Based on data from Scopus.

Another relevant factor for evaluating the potential for generating international collaboration networks is the origin of publications. Identifying the regions or countries in which scientific content is produced helps to detect geographic trends in scientific production and the geographic centers that are leading the generation of new knowledge. Some studies show that there are factors that differentiate productivity between countries, such as the use of cutting-edge technologies to conduct studies and differences in affinity concerning thematic areas. Figure 4 presents a characterization of the level of academic productivity in different countries worldwide. India is a country with a significant prevalence of academic papers.

The construction of research networks is a factor that affects the level of productivity and the quality of research products. (Uwizeye et al. 2022) found that improved networks and collaborations contribute to creating a research environment conducive to increasing researcher productivity. In this sense, identifying the authors who generate the greatest contributions to the knowledge domain can enhance the impact of publications as this information makes it easier for researchers to identify potential collaborators or experts in a field, from whom they can obtain relevant information on the research problems addressed. This encourages the exchange of ideas and facilitates the construction of knowledge based on the main contributions of research.

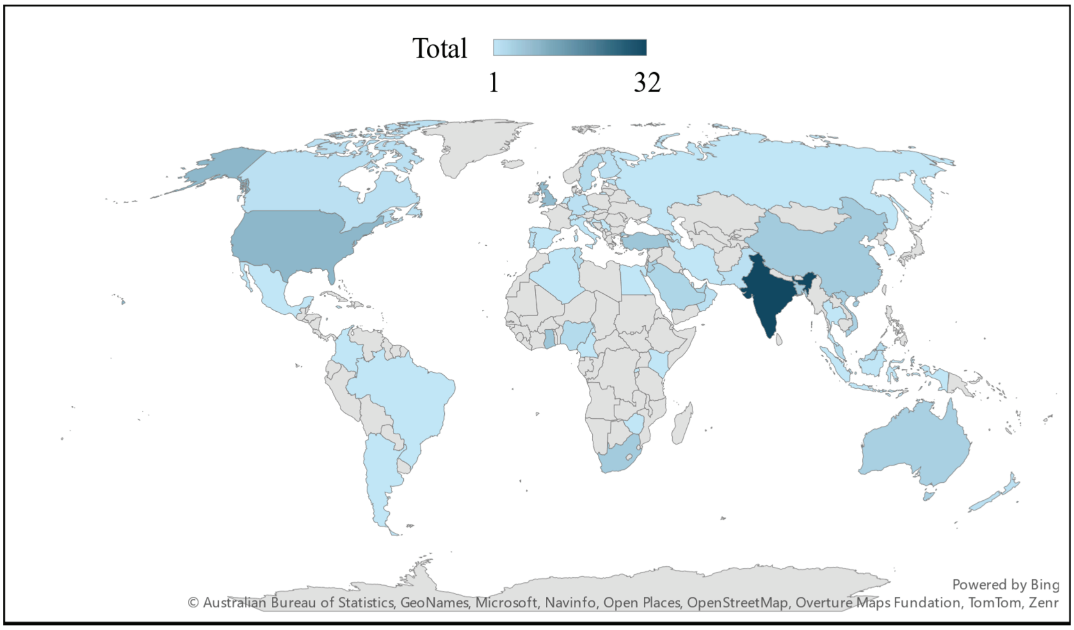

Figure 4. Productivity by region. ***Note***: A choropleth map was prepared in Microsoft Excel based on data from Scopus to differentiate the countries with the highest level of productivity. Higher intensity of the blue color indicates higher productivity.

Table 3 presents the top five authors in terms of academic production in the field and the impact of the publications. The h-index measures influence, which quantifies bibliometric productivity based on the authors' publication history. It is measured based on the distribution of citations received by a researcher's total number of publications. The results show that a significant number of contributions have come from authors located in Tunisia and Sweden. This result shows that authors from advanced economies, such as Sweden, also show a growing interest in analyzing the phenomenon of digital banking adoption in emerging economies. According to the h-index, the author with the highest impact is Aymen Ben Rejeb, who has generated three publications related to this domain in emerging countries.

Table 3. Productivity and impact by authors.

Author Name	Country	Number of Publications	H-Index
Aymen Ben Rejeb	Tunisia	3	9
Daniel Nilsson	Sweden	3	4
Adel Boughrara	Tunisia	2	7
Kent Eriksson	Sweden	2	20
Ankan Shahriar Islam	Bangladesh	2	1

The frequency of keywords provides information on the main topics covered in publications, which allows researchers to understand the focus of the studies. In addition, this analysis allows the discovery of connections and relationships between concepts, topics, and fields of study, which contributes to identifying critical points and research trends (Liu and Prajapati 2022).

As shown in Figure 5, some clusters of emerging themes in the academic literature were identified using a network graph based on a thematic map. For its construction, Keywords Plus were considered, which are words that are not directly selected by the authors but are automatically generated from the titles and references cited in each article. The Bibliometrix Leiden clustering algorithm was used. The literature provides evidence that this algorithm produces better connected clusters, in contrast with the Louvain algorithm, which is used in extension; see (Traag et al. 2019).

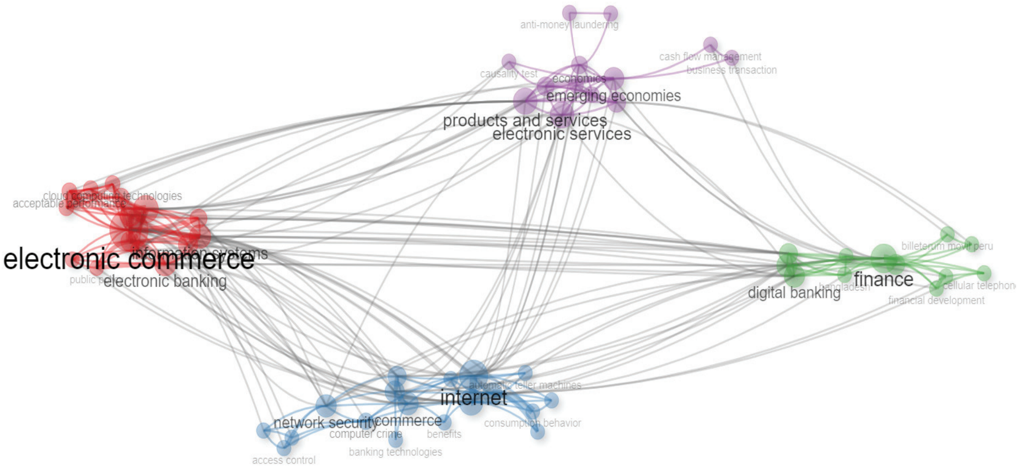

Figure 5. Thematic map. ***Note***: Based on Scopus data and prepared with Bibliometrix.

The results of this analysis confirmed the four clusters reported in the thematic trend analysis in Figure 1. In short, the following thematic clusters are identified in Figure 5:

1. E-commerce: Connects issues such as electronic banking, cloud computing, information systems, and performance.
2. Internet: Addresses issues such as network security, access control, ATMs, banking technologies, and criminal computing.
3. Finance: Includes aspects such as digital banking, financial development, cellular telephony, and mobile wallets.
4. Emerging Economies: Considers issues related to the economy, products and services, electronic services, and anti-money laundering.

Although specific themes can be identified in the conceptual framework of the literature reviewed, there are strong linkages that make the categories overlap. For example, cash flow management and business transactions belong to the emerging economies cluster, but they have a direct connection to the finance cluster. Electronic products and services are linked to the Internet and e-commerce. Network security has a direct link to e-commerce. In this sense, despite the algorithm's effort to separate the contents into thematic clusters, there is an underlying construct that brings these dimensions together, which is related to the digitization of banking services in the context of technological innovation.

This analysis makes it possible to describe the mutual relationships in a citation network. According to (Rousseau et al. 2018), bibliographic coupling depends on the number of items that the reference lists of the documents under analysis have in common; therefore, the strength of this relationship is determined by the intersection elements in these lists. Figure 6 shows the collaboration networks between the main countries. The first group identified was India, the United States, Turkey, and Jordan. Another group of countries with important links around this research topic was also observed, including the United Kingdom, South Africa, Ghana, China, Australia, Vietnam, and Bangladesh.

Recurrent citation analysis indicates the impact or popularity of a given study. By elaborating a citation network, a graph is obtained where the nodes represent the individual publications, and the edges are the relationships between them. Closely related publications can be grouped into clusters, as shown in Figure 7, from which important topics can be identified (Nguyen et al. 2019).

Some aspects should be considered when interpreting the results of a citation analysis (Nguyen et al. 2019). For example, it is advisable to identify the year of publication since older publications are more regularly cited. On the other hand, some research topics may be more popular than others, which favors their citation to the detriment of other topics that could be related to emerging fields.

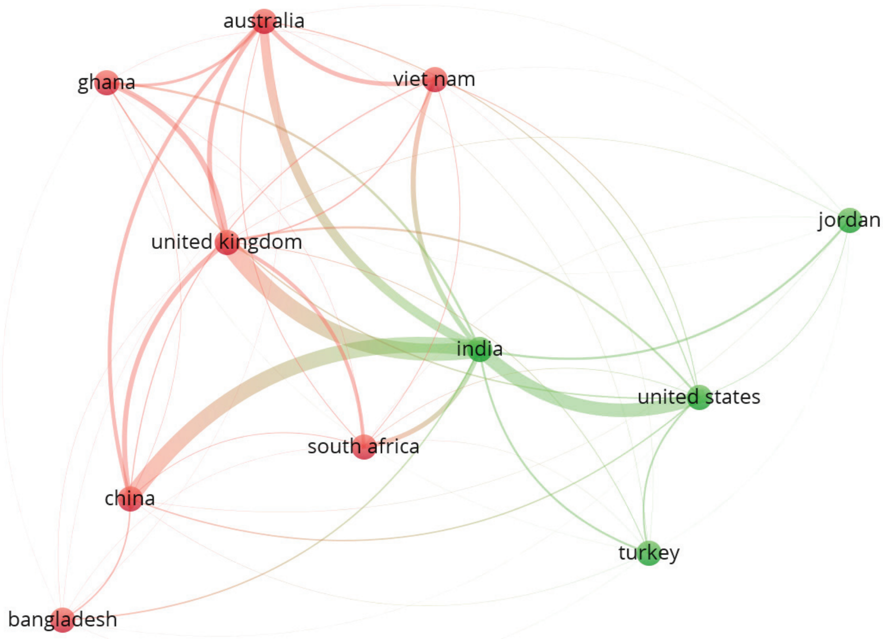

Figure 6. Bibliographic linkage map. ***Note***: Based on Scopus data and elaborated with VOSviewer.

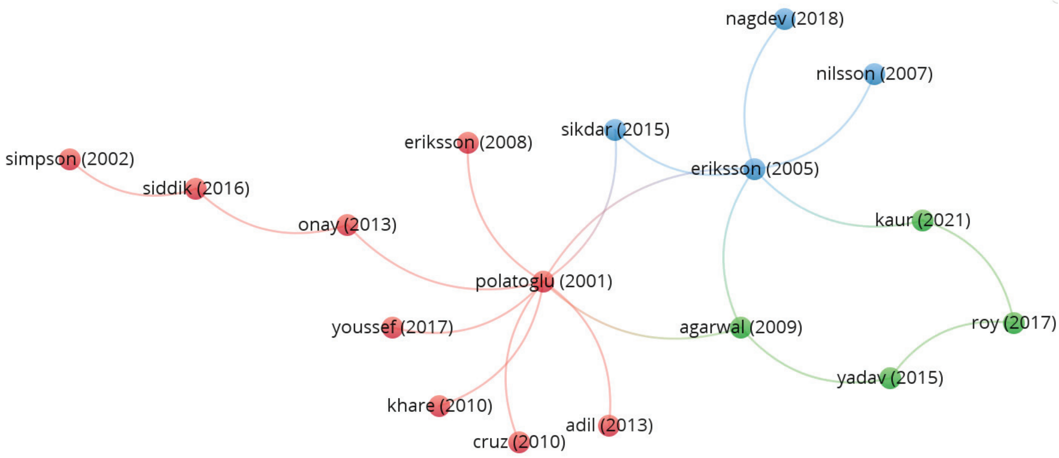

Figure 7. Map of documents citation. ***Note***: Based on Scopus data and elaborated with VOSviewer (Polatoglu and Ekin 2001; Simpson 2002; Eriksson et al. 2005, 2008; Nilsson 2007; Agarwal et al. 2009; Cruz et al. 2010; Khare et al. 2010; Adil 2013; Onay and Ozsoz 2013; Yadav et al. 2015; Sikdar and Makkad 2015; Siddik et al. 2016; Youssef et al. 2017; Roy et al. 2017; Nagved and Rajesh 2018; Kaur et al. 2021).

Figure 7 shows the citation map of documents, where three groups of authors with a citation relationship between research studies can be observed. (Polatoglu and Ekin 2001) stand out for their level of centrality in the network. They conducted an exploratory study on consumer acceptance of online banking services. This study has become a benchmark for the development of subsequent publications related to the adoption of digital banking. In the green cluster, the study by (Agarwal et al. 2009) stands out, in which the determinants affecting customer perception, attitude, and satisfaction concerning online banking are analyzed. In the blue cluster is the work of (Eriksson et al. 2005), which addresses the technological acceptance of Internet banking in Estonia, an emerging economy in Eastern Europe.

Table 3 shows the authors with the most publications in this field. Among them, Daniel Nilsson and Kent Eriksson stand out and have developed some studies on the acceptance of digital banking and financial innovations in the context of developed countries such as Sweden and Estonia. The authors can also be identified in Figure 7, where Eriksson's central position stands out. A surprising finding is that both authors reference the work of (Polatoglu and Ekin 2001), who analyzed the acceptance of Internet banking in the emerging economy of Turkey. This shows that studies contextualized in emerging economies are also a reference for research carried out in developed economies; therefore, they contribute to local knowledge and enrich the international academic panorama.

Ben Rejeb and Boughrara, on the other hand, developed their studies in the context of emerging economies. These authors are not identified in Figure 7, which shows that, despite having generated contributions in the field of research, their studies do not yet occupy a central place in the citation network. Although these studies address the problems of emerging economies, their focus is oriented toward the role played by stock markets. This explains their absence in the network in Figure 7, since this identifies studies that closely relate to technological adoption and innovation in the banking sector. For his part, the works of Shahriar Islam address specific issues related to banking technologies such as smartphone applications, electronic banking, and cybersecurity problems in the context of Bangladesh. Although the author deals with issues related to the digitalization of banking and the problems of emerging countries, his work focuses on characterizing these technologies and their functionalities, rather than on identifying the factors that influence their adoption.

5. Discussion

The results show an increase in the number of publications related to digital banking in emerging countries. Particularly noteworthy are the studies that approach this topic of research from the perspective of technological adoption. This is explained by the fact that even though electronic banking offers multiple benefits, experience has shown that its adoption rate is very low in developing countries compared to advanced economies (Demirguc-Kunt et al. 2021; Guerra-Leal et al. 2023). However, online banking has experienced an increase in popularity as it provides customers with a quick and easy transactional avenue (Abdou 2023). In this regard, online banking may favor the development of new business models in the industry, which may produce improvements in terms of operational efficiency as well as competitive pressures on banks operating under the traditional model.

As mentioned in the objective of this study, trends in the literature on the adoption of digital banking in emerging economies have been examined. The results allow us to divide the body of academic literature into four categories. The first, commerce and consumption, studies the factors that influence the acceptance of these technologies and allow us to understand the risks associated with their use. The second, information and communication technologies (ICT), analyzes the problems related to ICT such as security networks, authentication mechanisms, access control, and ATMs. The third, banking and finance, shows a broad group of studies that address specific services that banks and financial institutions can offer, such as mobile banking and digital wallets. The fourth is economics and development, which refers to financial inclusion, collaborative financing models, literacy, and the prevention of criminal activities, among others.

In this regard, there has been a significant increase in studies dealing with issues related to trade and consumption and the use of financial technologies, as illustrated in Figure 2. Most of these studies base their contributions on theories related to the intention to adopt technology, particularly on the basis of consumption. Another prevalent approach to theoretically support the results is the construct of perceived risk, which is related to the subjective assessment that a person can make about possible harms or drawbacks with the use of financial technologies (Yadav et al. 2015). Table 4 shows a characterization of the theoretical bases that support the 17 publications systematized in this bibliometric study, identified in Figure 7.

Table 4. Theoretical foundation.

Authors	Category	Theoretical Basis	Country
(Agarwal et al. 2009), (Eriksson et al. 2008), (Eriksson et al. 2005), (Kaur et al. 2021), (Sikdar and Makkad 2015), (Youssef et al. 2017), (Nagved and Rajesh 2018)	Technology Adoption	Innovation Adoption, Theory Technology Acceptance Model, Theory of Planned Behavior, The Unified Theory of Acceptance and Use of Technology (UTAUT), Expectation Confirmation Theory	India, Estonia Saudi Arabia
(Cruz et al. 2010), (Khare et al. 2010), (Adil 2013)	Perceived Quality	Customer Experience Management Relationship Marketing	Portugal and Spain, India
(Roy et al. 2017), (Yadav et al. 2015)	Perceived Risk	Technology Acceptance Model Theory of Planned Behavior	India
(Siddik et al. 2016), (Simpson 2002), (Onay and Ozsoz 2013)	Performance	e-Banking Concept	Bangladesh, Turkey, Emerging Economies
(Nilsson 2007), (Polatoglu and Ekin 2001)	Other	Cross-cultural Characteristics Innovation Adoption Theory	Sweden, Turkey

Note: The theoretical foundation that supports the 17 publications systematized in this bibliometric study is identified in Figure 7.

Technology adoption is a dimension widely discussed in the literature addressed in this analysis. There is evidence in the literature suggesting the perceived ability of technology to improve performance and reduce the effort required to adopt new technologies (Kaur et al. 2021). The perceived quality of Internet banking services is defined in terms of availability, information content, financial security, convenience, and personalization (Cruz et al. 2010). Some aspects considered are efficiency in the handling of accounts, the attitude of service personnel, frequency of errors, compliance with instructions, or data entry errors (Khare et al. 2010). Perceived risk influences customer trust, and this in turn affects the valuation of Internet banking for transactions (Roy et al. 2017). Other studies have found evidence of a positive relationship between e-banking adoption and performance measures such as accounting profitability (Siddik et al. 2016). However, the cost structure and risks play in favor of developed economies, as opposed to their emerging counterparts (Simpson 2002). Finally, there is another group of studies that address particular issues such as the demographic characteristics of e-banking users (Nilsson 2007) and factors affecting satisfaction such as reliability, security, and privacy (Polatoglu and Ekin 2001).

Table 4 confirms the central position of India, presented in Figures 4 and 6, concerning studies addressing the phenomenon of digital banking adoption in the context of emerging economies. According to (Agarwal et al. 2009), India offers great commercial opportunities for banks as a consequence of the economic liberalization policies adopted by the governments since 1990 and the increase in the flow of foreign direct investment. However, Indian banks need to understand that it is not enough to invest heavily in technology; it is important to get most customers to adopt it for electronic transactions (Kaur et al. 2021). (Nagved and Rajesh 2018) stated that the Indian banking industry has developed different Internet banking digital transformation initiatives that include features such as personalization, a broad view of customer relationships, and cross-channel integration. However, the perception of risk associated with Internet banking prevails among Indian users (Roy et al. 2017), so banking managers should strive to make a more robust and secure digital banking platform (Yadav et al. 2015). This phenomenon, observed in the Indian context, is also applicable to other emerging economy settings. Therefore, the studies conducted in this country provide a valuable benchmark for future research in other regions.

A striking fact that can be observed in Table 4 is that although the object of analysis of this study is focused on emerging countries, some papers identified in the co-authorship network were developed in the context of developed economies. A review of these papers revealed some relevant findings. For example, the study by (Polatoglu and Ekin 2001), who analyzed the acceptance of Internet banking services in Turkey (an emerging economy), occupies a central position in the network and is cited in papers contextualized in developed countries. For example, (Eriksson et al. 2008) studied the acceptance of Internet banking technology in Estonia (Polatoglu and Ekin 2001), explaining that the perceived attributes of this technology are more important than the characteristics of the innovators in predicting adoption. (Cruz et al. 2010) analyzed the impact of perceived quality on satisfaction and enjoyment of these technologies in the European context (Portugal and Spain). These publications also refer to (Polatoglu and Ekin 2001) to support the idea that the typical Internet banking user is a relatively young man.

This bibliometric analysis has identified some studies that stand out in digital banking. For example, (Polatoglu and Ekin 2001) conducted a study where factors that may affect the adoption of an innovation or a product include complexity, perceived risk, and relative advantage. Organizational factors such as marketing efforts are also analyzed. In turn, (Agarwal et al. 2009) studied the factors determining user satisfaction in digital banking. It was observed that security and trust are factors that affect their level of satisfaction. Other studies suggest that a well-designed and user-friendly Internet bank cannot be used if it is not perceived as useful (Eriksson et al. 2005). Therefore, the perceived usefulness of Internet banking is a key factor in promoting customer usage.

Meanwhile, (Guerra-Leal et al. 2023) addressed the benefits in terms of financial inclusion that can be achieved through digital banking. The findings showed that the adoption of products such as an online bank account can be influenced by gender. Women were found to be more excluded than men, demonstrating a gender gap in access to digital banking accounts. Region is another factor that may have an impact on the adoption of digital banking; in more developed regions, the population uses a wide variety of digital banking services. The dimensions of technology adoption also affect the adoption of digital banking, as demonstrated in (Bellahcene and Latreche 2023). This study showed that perceived ease of use and perceived usefulness affect digital banking adoption in Algeria.

The findings of some studies show that digital banking is a key factor in boosting financial inclusion in emerging countries. However, efforts are needed to bring these technological benefits to regions with less access to Internet infrastructure. In addition, governments need to adopt policies that facilitate access to digital banking for populations that have traditionally been excluded from the system. For their part, banks face the challenge of developing solutions that better meet the expectations of their users. In that sense, the technology itself is not the added value of the digital banking model. The value depends on how these platforms facilitate and address key customer needs. Trust and security are essential factors from the users' perspective; therefore, it is imperative to adopt systems that safeguard financial consumer information and ensure the integrity of transactions made over the Internet.

In general terms, the bibliometric data show that digital banking in emerging countries is a growing field of research which has been encouraged by the introduction of new information technologies such as artificial intelligence, big data, and cloud computing. Although the most prevalent subject area is business and economics, there are studies related to the fields of computer science and social sciences. The bibliometric data show considerable contributions from emerging economies, where India stands out. Some of the research topics developed in this country relate to user satisfaction and perceived quality of use. For example, (Agarwal et al. 2009) showed that responsiveness is a key predictor of customer satisfaction. Other important contributions have come from countries in Asia, as is the case of (Khattak et al. 2023), who observed that diversification of the banking business improves profitability. In this context, financial technologies can be considered as a great opportunity for diversification.

6. Conclusions

This study conducted a bibliometric analysis of the development of digital banking in emerging economies. A conceptual framework related to digital banking has been presented and a bibliometric data collection strategy has been proposed. The publications included in the sample correspond to academic documents obtained from the Scopus database, for which a search equation was applied that included terms related to digital banking and emerging countries, allowing to obtain 118 publications. The results show a significant growth in this field of study, mainly during the last few years in which it can be observed that the adoption of technologies related to data analysis and automation has generated significant contributions in the banking industry. There are a significant number of publications that address the subject from the perspective of technological adoption. The findings of these studies point to critical factors that favor the adoption of technologies by financial consumers, particularly the trust and security of transactional channels and the ease and timeliness of these solutions.

The results reveal four trendsetting categories in this field of knowledge. The first is commerce and consumption, considering problematic issues such as quality and perceived risk (Adil 2013; Cruz et al. 2010; Khare et al. 2010; Roy et al. 2017; Yadav et al. 2015). The second, ICT, focuses on the provision of specific financial services, such as mobile banking, electronic payments, and digital wallets (Agarwal et al. 2009; Eriksson et al. 2005; Eriksson et al. 2008; Kaur et al. 2021; Youssef et al. 2017). The third, banking and finance, is related to the benefits and challenges of digital technologies, such as network security, criminal activities, and access control (Nagved and Rajesh 2018; Onay and Ozsoz 2013; Simpson 2002; Siddik et al. 2016). The fourth, economics and development, analyzes the impact of digital banking on economic and social development in emerging economies (Nilsson 2007; Polatoglu and Ekin 2001; Sikdar and Makkad 2015). Although nuances can be found in these clusters, some elements tend to cut across many studies, such as challenges related to technological adoption and innovation diffusion. An important compendium of papers focuses on issues related to consumption, while others focus their analysis on the performance of banks and the impact of these technologies on society.

These findings suggest that marketers may find an opportunity in this field of knowledge since digital banking technologies favor the processes of personalization of the bank's offered value and customer communication. Similarly, bank managers may find opportunities to develop a competitive advantage supported by digital technologies perceived as valuable to the target market. The development of the digital banking ecosystem also represents an opportunity for technology developers, as there is an increasing demand for mobile applications, online platforms, data analysis tools, and security systems aimed at providing a better customer experience. Finally, public policymakers and those in charge of developing social programs can study these technologies to help with the implementation of projects related to financial inclusion programs and the development of a solid regulatory framework that prevents fraud, inhibits criminal activities, and protects data privacy.

In this study, the prominent role of India in this field of knowledge became evident. A significant compendium of academic literature originating in this country was observed. These publications constitute a reference to be considered by academics and professionals interested in this domain of knowledge. Geographic complexity and cultural diversity mean that a significant part of the population in India does not have access to financial products and services. Digital technologies play a key role in addressing this problem since they make it possible to bring the banking portfolio to the most remote regions of the country. These technologies are also a catalyst for economic growth in the country by facilitating electronic transactions, automating access to many banking services, and reducing banks' operational costs. However, these benefits are accompanied by challenges that need to be addressed, such as gaps in access to the Internet or electronic devices, lack of financial and digital education, and cybersecurity and data protection issues. These characteristics are present in other emerging economies, so it is worth having a reference with the aim of developing comparative studies and adapting analysis models to the particular needs of the countries.

This study has some limitations. First, only research articles published in the Scopus database were considered. Other sources of information could be considered in subsequent studies to expand the sample size and, thus, the spectrum of bibliometric elements that allow for characterizing the domain. The information input to conduct this work comprised publications and visual representations of the bibliometric networks. However, today it is possible to take advantage of data analysis technologies to obtain information that can broaden the scope of bibliometric studies. For example, further studies could apply thematic analysis techniques or deepen the longitudinal analysis through a spectrograph of references. Some strategies for literature analysis can also contribute to understanding the results, such as systematic reviews or meta-analyses. Furthermore, there are clear opportunities to develop empirical work to analyze the degree of adoption of digital banking in emerging countries and the factors that promote it.

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Article

Determinants of Digital Payment Adoption Among Generation Z: An Empirical Study

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Abstract: The main goal of the current paper is to investigate the factors that influence Millennials' adoption of digital payments among Generation Z by analyzing the potential effects of perceived convenience, perceived cost, perceived security, perceived convenience, innovativeness, and social influence on the adoption of digital payments. A total of 258 individuals in Malaysia were asked to complete a questionnaire to gather statistics. To assess the research model and test the hypotheses, structural equation modeling with partial least squares (SEM-PLS) was utilized. Smart PLS path analysis results revealed that perceived convenience, perceived security, perceived cost social influence, and innovativeness were positively significant determinants of digital payment adoption. This study offers fresh theoretical perspectives for identifying potential adoption barriers that need to be addressed. Concerns about privacy and security, a lack of information or comprehension, and aversion to change are all prevalent challenges among Millennials. Recognizing these limitations allows service providers to incorporate measures such as better security features, educational campaigns, and user-friendly interfaces to alleviate these concerns and boost adoption.

Keywords: digital payment; mobile payment; Generation Z; perceived convenience; perceived cost; social influence; innovativeness

1. Introduction

In this age of innovation, the advancement of information technology has opened the way for big data analytics. Various data streams can now be efficiently synchronized owing to APIs and Social, Mobile, Analytics, and Cloud (SMAC) technologies (Gallego-García et al. 2022). Several platforms have been merged into a single network to provide digital financial services in order to facilitate normal business transactions. Adopting innovation and embracing digital transformation to improve financial institutions' overall performance is critical for their survival (Shuhaiber et al. 2023; Gruenhagen and Parker 2020). The channels that deliver financial and banking products and services are now more dependable and user-friendly as a result of the use of new technology and the digital transformation of business processes (Melo et al. 2023; Alsmadi et al. 2023a).

According to Ernst & Young's "Global FinTech Adoption Index 2019" survey, 64% of people in 27 selected countries used fintech services in 2019. This proportion represents the number of people who are actively using the internet. It is important to note that, according to Ernst & Young LLP (2016), this percentage was 87% for China, 71% for Great Britain, 64% for Switzerland, and 46% for the United States. Banerjee and Pradhan (2022) point out that people of different ages and demographic backgrounds adopt new technologies at varying rates. This study focuses on Millennials, also called Generation Y, which includes people who were born between 1980 and 1995. Among the generational cohorts that are actively reshaping the landscape of conventional financial institutions today are Generation Y and Generation Z (also known as iGen, born 1996–2010) (Liu et al. 2023).

Since its emergence, fintech has altered the global financial framework and the everyday economic behaviors of people. In view of the readiness and capabilities of ICT companies to offer safe and user-friendly financial alternatives, it is no surprise that non-financial enterprises have begun to encroach on the finance market (Cham et al. 2018). In a similar case, BNM has introduced the Financial Technology Regulatory Sandbox Framework, which requires fintech companies to comply with a number of conditions to ensure all the financial services and products provided are legally compliant with relevant statutes (Badran 2023; El-Bermawy 2022; Hjij 2023; Raza et al. 2021).

As outlined in the paper written by Pertiwi and Purwanto (2021), Millennials are more likely than other age groups to access fintech services. For instance, in Western Europe, 65.6% of Millennials utilized fintech services, as compared to 53.2% of the other age groups. In Central Europe, the difference in fintech services adoption between Millennials and older generations was smaller but still significant at 9.5%. Similarly, the report by Ernst & Young in 2017 indicated that the Fintech Adoption Index for the Millennial generation was 48% and 59% within the United States. In Poland, this proportion for the Millennial generation was approximately 75% in the year 2019 (Alsmadi et al. 2020).

Digital payment adoption research that focuses on perceived convenience and perceived security is still limited. Most studies currently concentrate on technological and economic facets, with only a small amount of effort devoted to security (Holub and Johnson 2018). Al-Okaily et al. (2023c) indicated that the technical characteristics, user interaction, and trust are the main themes of recent literature on digital payment adoption and that the unsaturated research themes are mainly in the areas of user interaction and behavior (including acceptance and trust).

Even though prior studies have examined the acceptance and adoption of digital payment globally (e.g., Al-Okaily 2023, 2024), only a few studies have tried to discuss digital payment acceptance and adoption in the Jordanian context. Therefore, according to the best of our knowledge based on a comprehensive literature review, the current study is among the first empirical studies examining the potential impact of perceived cost, social influence, and innovativeness on digital payment adoption in the Jordanian context, particularly among Generation Z. Based on the foregoing arguments, the purpose of this research is to create a unified research paradigm for experimentally investigating the possible influence of perceived convenience, perceived security, perceived cost, social influence, and innovativeness on digital payment adoption among Millennials.

The remainder of this paper is structured as follows: Section 2 introduces the research background and examines related literature with the research hypotheses. Section 3 explains the methodology and data collection. Section 4 presents the results of data analysis and hypothesis testing. Section 5 discusses the findings and key research implications. Lastly, Section 6 wraps up the paper with research limitations and ideas for future research.

2. Theoretical Background and Hypothesis Development

The Technology Acceptance Model (TAM) is central to understanding how perceived ease of use and perceived usefulness drive the adoption of digital payments, as users are more likely to adopt technologies they find convenient and beneficial (Raza et al. 2017). Similarly, the Unified Theory of Acceptance and Use of Technology (UTAUT) expands on TAM by incorporating social influence, recognizing the critical role of peer recommendations and social pressure in shaping adoption behaviors (Joa and Magsamen-Conrad 2022). The Diffusion of Innovations Theory further explains how individuals' innovativeness influences their propensity to embrace digital payments, suggesting that early adopters lead the way in the diffusion of new technologies (Singh et al. 2018). Lastly, Social Influence Theory highlights the impact of social networks and peer interactions, where users are more inclined to adopt digital payments if they observe others using and endorsing these systems (Alsmadi et al. 2023b; Wei et al. 2021).

2.1. Perceived Convenience and Digital Payment Adoption

Perceived convenience refers to the subjective evaluation of the consumer regarding the ease of use, smoothness, and comfort of a particular product, service, or system. It incorporates the user's view of the offering's ease of use, accessibility, and other impressions, such as effortlessness, flexibility, integration, reliability, and support (Lee and Kim 2020). Perceived convenience results from previous experiences as well as expectations and the context within which the product or service in question is used (Chang et al. 2013). It plays an important role in customer behavior; consumers are relatively more likely to adopt, use, and be satisfied with technologies perceived to be easy. The reason for this is that more businesses and organizations are trying to ensure increased convenience for customers, to improve customer experience, satisfaction, and loyalty, thereby gaining a competitive edge in the market (Faguet 2023; Dong et al. 2017).

The relationship between perceived convenience and the adoption of digital payments has been tested in a number of studies on consumer behavior and technology acceptance (Acheampong et al. 2017; Lai and Liew 2021). Perceived convenience is referred to as the 'ease of use' of a particular technology or service. This concept includes the ease of conducting transactions, the availability of funds, and overall user accessibility, with regard to digital payments (Al-Qudah et al. 2022; Singh and Rana 2017).

As the findings indicate, perceived convenience has a positive impact on the adoption of a certain form of digital payment. It is noted that consumers are more likely to adopt and use a payment method they find easy to use (Al-Okaily et al. 2024d, 2024c, 2024b). The convenience factor encompasses, among other things, ease of installation, transaction execution time, diversity of payment methods, safety, and integration with existing technologies (Al-Qudah et al. 2022; Sarkar 2019; Ming-Yen Teoh et al. 2013).

Moreover, several studies have shown that ease of use or perceived convenience is an important determinant of customers' tendency to adopt mobile payments. In this regard, Najdawi and Said (2021) identified perceived ease of use and convenience as important factors that influenced customers' intention to adopt mobile payment systems. In a similar vein, Khiong et al. (2022) found that the adoption of e-payment systems was significantly increased by perceived convenience. Additionally, the availability of a range of mobile devices and the development of simple interfaces for payment systems have enhanced the perceived convenience of the service. The growing use of digital wallets, contactless payments, and biometric identification techniques adds to the convenience factor (Wardana et al. 2022; Pandey 2022; George and Sunny 2023). As a result, it might suggest the following:

H1: *Perceived convenience significantly impacts digital payment adoption.*

2.2. Perceived Security and Digital Payment Adoption

Perceived security, according to Salisbury et al. (2001), refers to an individual's subjective sense of safety, protection, or trust in a certain product, service, or system. It describes interactions with a service, taking into account the number of threats, weaknesses, and protections, which the consumer applied to the service (Aloulou et al. 2024; Hasan et al. 2023; Al-Okaily et al. 2023a). Perceived security depends on the perceived effectiveness or reliability of security measures, how the information is treated, privacy protection, and, most importantly, the perceived level of the provider/system. It consists of security technical aspects, such as encryption and authentication, together with non-technical, psychological components related to the user's experience of security (Hartono et al. 2014).

According to Alkhowaiter (2020), security perception is the most crucial factor that determines customers' willingness to adopt digital payment systems. In cases of financial information and transactional activities, perceived security can be explained as an individual's subjective opinion based on the overall situation when utilizing various digital payment systems (Alazmi and Alemtairy 2024; Hidayanto et al. 2015; Siagian et al. 2022). Confidence in adopting new digital payment systems is also influenced by perceived security, which is defined as the level at which a consumer trusts or feels a payment system is secure. Protection against fraud, data encryption, authentication measures, and trust in the system as a whole are some of the factors that foster perceived security (Al-Okaily et al. 2022; Al-Sartawi et al. 2022; Zhang et al. 2019).

Perceived security is an influential factor that determines customers' intentions to use digital payment systems. Hanafi and Toolib (2020) and Hamzah (2023) demonstrated that perceived security accelerated customers' intention to adopt mobile payment services. Similarly, Singh and Rana (2017) emphasized perceived security's importance in e-payment system acceptance. Sophisticated security solutions, such as two-factor authentication, tokenization, or secure payment gateways, facilitate consumers' perception of security and address concerns over their financial data. Consumers' confidence in a digital payment system, however, can be damaged by reports of data breaches, identity theft, or fraud. Digital signatures have been cited as potential solutions to these issues. As a result, it might suggest the following:

H2: *Perceived security significantly impacts digital payment adoption.*

2.3. Perceived Cost and Digital Payment Adoption

Perceived cost is defined as the personal evaluation of the costs, risks, and other trade-offs that one must make to purchase, use, or maintain a product, service, or system (Cheung et al. 2015). It consists of several cost components in the user's mind, including, but not limited to, money, time, effort, mental or emotional cost, and other significant resources. Target market personal financial status, preferences, and expectations from a particular product/service offering affect perceived costs, which vary from person to person. According to Zainab et al. (2017), the perceived cost of the desired benefit is very important in making a final decision, as it seems logical to balance the expected benefit with the potential cost. It includes not only the initial price but also all peripheral costs such as maintenance, upgrade, and subscription (Alzoubi et al. 2022; Al-Sartawi et al. 2023; Al-Gasaymeh et al. 2023; Alhawamdeh et al. 2023). To retain and win over consumers, businesses and organizations have to deal with the perceived cost issues seriously. By offering competitive prices, making value the selling point, and minimizing perceived costs, companies can enhance customer satisfaction levels, improve adoption rates, and build enduring relationships with their clients (Hansen 2005).

The link between perceived cost and digital wallet penetration has always been a critical aspect influencing consumers' decisions to adopt and use any form of digital wallet (Ranjith et al. 2021). Perceived cost has been defined by Ligon et al. (2019) as the individual's mental image of the monetary costs incurred in the use of electronic payment systems—transaction fees, service fees, additional fees, etc. Liu and Tu (2021) have reported that perceived cost is one of the primary components affecting consumer adoption of the various types of digital payment (Liu and Tu 2021). Users are more likely to adopt and use electronic payment systems for business transactions when they perceive them to be reasonably priced. Elements such as transaction costs, promotional discounts or rewards, and branding, to mention a few, all contribute to the perceived costs of a digital payment system (Alkhaldi et al. 2024; Al-Okaily and Al-Okaily 2024). The perception of cost and the level of acceptance and use of digital payments have been the focus of a significant number of studies. As a result, it might suggest the following:

H3: *Perceived cost significantly impacts digital payment adoption.*

2.4. Social Influence and Digital Payment Adoption

Social influence is defined as the processes by which one or more individuals influence, persuade, or direct the thoughts, opinions, attitudes, beliefs, or actions of other individuals or groups of people. It is connected with the effect that social presence, rules, conviction, and anticipation have upon an individual, shaping and guiding their choices. There are various ways in which group dynamics can influence individuals, including direct interactions, observations, group conformity, and exposure through mass media and significant others (Lutfi et al. 2022).

Social influence can stem from wanting to fit in, being curious, or the presence of someone in authority (Sirola et al. 2021). The process is employed by people attempting to change the opinions or behavior of others through their ideas, arguments, or advice. Its reach extends to consumer behavior, public opinion, social customs, and social trends (Tunçgenç et al. 2021). An understanding of the relationship between social impact and the adoption of new technology, in this case digital payment systems, is critical in knowing consumers' decision-making with respect to the adoption and usage of the technology (Koenig-Lewis et al. 2015). Social influence refers to the effect of social interactions, opinions, and recommendations of peers, family, colleagues, and other important persons or groups on an individual's conduct (Susanto et al. 2022).

Various studies have sought to explain the impact of social forces on customers' usage of digital payments. For instance, Xena and Rahadi (2019) explored social interaction as a substantial attribute affecting the intention of mobile payment users. Similarly, many studies have confirmed the social impact on digital payment adoption. A study by Nguyen and Huynh (2017) confirmed that social influence variables had a significantly positive impact on customers' intention or adoption of payment resources. Therefore, it may suggest the following:

H4: *Social influence significantly impacts digital payment adoption.*

2.5. Innovativeness and Digital Payment Adoption

Innovativeness can be described as the tendency of an individual to accept or adopt new changes or shifts in ideas, technologies, products, or activities. It shows the willingness to engage in creative actions such as problem-solving, seeking alternatives, and being flexible (Yu et al. 2020).

According to Michal and Szymon, Yukari, and others, innovativeness includes behavioral, cognitive, and psychological characteristics that shape a person's willingness to accept new ideas (Yen et al. 2020). Essentially, innovativeness is defined by imagination, creative thinking, willingness to take chances, and the desire to explore new things. Innovative individuals tend to be active in the pursuit of new ideas, products, and processes, and in the application of new ideas. They are driven to grow and change or challenge the way things are regularly done (Ardi et al. 2020).

To begin with, understanding the relationship between innovativeness and the use of digital payments can reveal why people are willing to adopt and use such systems. Innovativeness represents one's openness to new technologies and ideas (Patil et al. 2019). Researchers have stated that the level of innovativeness within an individual is linked to their digital payment adoption (Patil et al. 2020). Users who are more innovative will be the first adopters of digital payments, driving technological advancements. Innovativeness is associated with broad personality characteristics such as openness to experience, risk-taking behavior, and curiosity (Singh et al. 2020). Thus it may imply the following:

H5: *Innovativeness significantly impacts digital payment adoption.*

Based on the gaps in the literature, the research model (Figure 1) of this study proposes that perceived convenience, perceived security, perceived cost, social influence, and innovativeness are key determinants of digital payment adoption among Millennials. These proposed relationships and related hypotheses are discussed below.

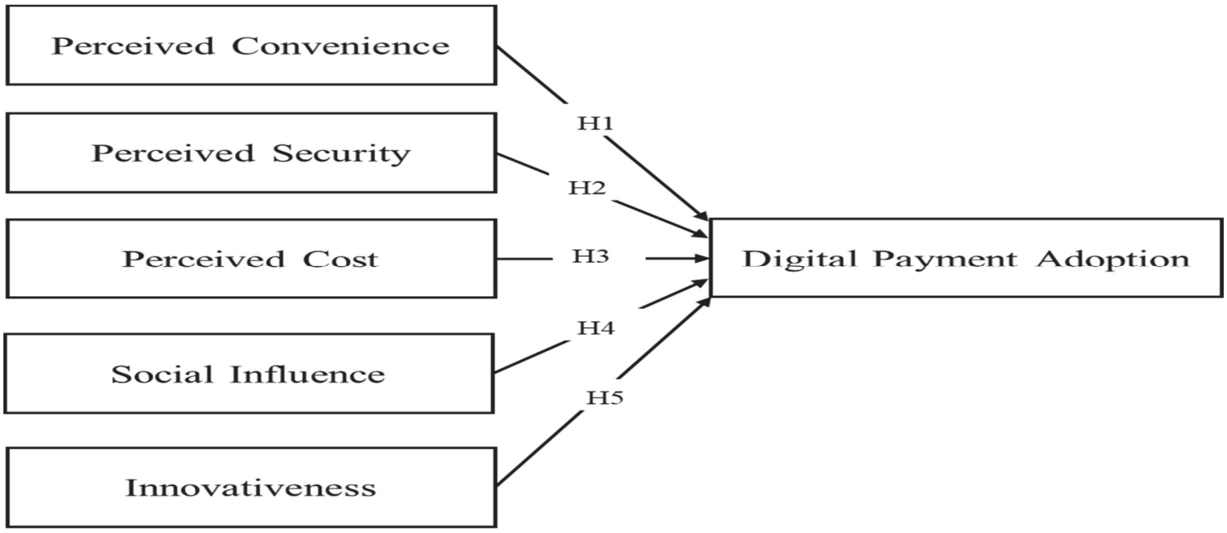

Figure 1. The research model.

3. Research Methodology

3.1. Measures

This research study specifically focused on the evaluation of the relationship between perceived convenience, perceived security, perceived cost, social influence, and innovativeness in digital payment adoption among Millennials in Malaysia, a developing country. To achieve the specific objectives of this study, a quantitative approach was used in order to statistically test the various hypotheses associated with the relationships among the research variables.

The data-gathering instrument, a questionnaire, was constructed based on the relevant literature. The survey questionnaire included demographic and descriptive questions such as gender, age, major, and prior experience. Following this, the survey included the research items (manifest variables) to measure the latent variables. In total, 34 items were listed in the survey. The survey items used a 5-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree). A cover letter and a consent form were included at the beginning of the questionnaire, outlining the scope of the study and its nature, the participants' willingness to participate, the confidentiality of the information obtained, and other ethical considerations. Table 1 and Appendix A. display the survey items and sourcesfor all variables.

Table 1. The source of the measures for all variables.

Variables	Number of Items	Source
Digital Payment Adoption	4	Widayani et al. (2022).
Innovativeness	3	Shoham et al. (2012).
Perceived Convenience	3	Lin (2016).
Perceived Cost	3	García-Fernández et al. (2018).
Perceived Security	3	Tahar et al. (2020).
Social Influence	3	Dekkers et al. (2019).

3.2. Data Collection Procedure

This study adopted a quantitative research design with an online survey to test the formulated hypotheses, as shown in the suggested model, which aligns with previous studies (Al-Okaily et al. 2024b; 2023b; Qatawneh et al. 2024). For convenience and flexibility, this method focused on respondents aged 18 to 35 years who had experience with digital payment. They were recruited through Facebook, LinkedIn, Instagram, email, and WhatsApp invitations. To select respondents, the current study used a filter question to ensure that only those with digital payment experience were included. In total, there were 258 responses, which required attention before analysis, as each survey question was compulsory. This stage of the research lasted 2 months, from mid-April 2023 to early July 2023.

For data analysis, SPSS software version 28 was employed to show the demographic profile of the sample, as displayed in Table 2, while factor analysis and structural equation testing were performed using the PLS regression algorithm software, SmartPLS. The following sections present the results of the data analysis.

Table 2. Demographic characteristics of the respondents.

Demographic Variable	Category
Gender	Male: 57.8% (149 respondents), Female: 42.2% (109 respondents)
Age Group	18–25: 60% (155 respondents), 26–35: 40% (103 respondents)
Major	Business: 45% (116 respondents), IT: 35% (90 respondents), Others: 20% (52 respondents)
Prior Experience	Yes: 70% (181 respondents), No: 30% (77 respondents)
Current Usage	Yes: 80% (206 respondents), No: 20% (52 respondents)

4. Research Findings

The sections that follow illustrate the descriptive analysis of the research items and the demographic profile. Then, the SEM-PLS method is described, and its application in testing the hypotheses is explained.

4.1. Descriptive Analysis

Preliminary descriptive statistics established the profile of the sampled respondents. Variables such as gender, age, major, prior and present usage of one payment method or another, and trust scores of respondents were all estimated using SPSS software version 28 and were subsequently evaluated. For example, 57.8% of the respondents were male, while 42.2% were female. In order to analyze the relationships between the research items and the latent variables explaining them, SEM-PLS analysis was conducted, as outlined in the next section.

4.2. SEM-PLS Analysis

The SEMPLS includes two phases: (1) the measurement (outer) model, which assesses the validity and reliability of the latent variables and the items, and (2) the structural model, which performs multivariate analysis and tests the structural model's hypotheses using T-statistics and *p*-values (Hair et al. 2017). The next follow-up displays step-by-step processes and the outputs of the two phases, aided by SmartPLS 4.0. The next sections present the steps and outcomes of the PLS.

4.3. Results of the PLS Measurement Model

The primary loading occurs between active constructs and the question. Latent variables should be higher than manifest (or vice versa), so it could be 0.6, constituting an appropriate acceptable threshold for research validity. Average variance extracted (AVE) estimates and coefficient of alpha values were used. Except for Perceived Value, which stands at 0.52, all AVE scores also exceed the 0.5 cut-off (the highest being 9.89 for Optimism), demonstrating external valid structures. In relation to the internal consistency, reliability coefficients were relatively high (0.831 for Fin Literacy and 0.945 for Perceived

Value). Hair et al. (2017) conducted the research where the highest alpha cut-off of 0.7 was also set, and all estimates of the coefficient were 0.70 or more. This supports the reliability of the research. Other evaluations of validity are summarized in Table 3.

Table 3. Constructs' validity and reliability estimates.

Variables	Cronbach's Alpha	Composite Reliability (rho_a)	Average Variance Extracted (AVE)
Digital Payment Adoption (DPA)	0.71	0.719	0.531
Innovativeness (INV)	0.85	0.856	0.768
Perceived Convenience (PCE)	0.887	0.888	0.816
Perceived Cost (PCT)	0.776	0.778	0.69
Perceived Security (PS)	0.713	0.719	0.603
Social Influence (SI)	0.71	0.712	0.588

Discriminant validity of latent variables can be evaluated using the Fornell–Larcker criterion, which has been devised by Hair et al. (2017) in their paper. This criterion confirms a valid construct to be dissertatively valid when the square root of the AVE positive score of every structure is lesser than the multi-correlations of this structure with the rest. As shown in Table 4, values on the diagonal are higher than the intercorrelations below, indicating that all latent variables meet discriminant validity.

Table 4. Discriminant validity and constructs' intercorrelations.

Variables	DPA	INV	PCE	PCT	PS	IS
DPA	0.865					
INV	0.441	0.943				
PCE	0.465	0.756	0.721			
PCT	0.278	−0.035	0.18	0.792		
PS	0.388	0.746	0.71	−0.033	0.861	
IS	0.33	0.211	0.681	0.423	0.399	0.812

4.4. PLS Structural Model Findings

Discriminating links between latent variables (constructs) at the inner SEM-PLS level will likewise be evaluated in the course of this study. More particularly, the findings of the structural model align with the findings in the original samples of the linear regression such as Beta values, T-statistics, and *p*-values of path coefficients (Hair et al. 2017). Consequently, all hypotheses are confirmed under these levels of significance at 0.05, as *p*-values are lower than the cut-off point of 0.05 for all paths. Table 5 displays the significance level retentions of all paths.

Table 5. Hypothesis results and path significance.

Hypotheses	Original Sample	T Values	*p* Values	Results
INV → DPA	0.158	2.558	0.011	Supported
PCE → DPA	0.149	2.524	0.012	Supported
PCT → DPA	0.232	3.912	0.000	Supported
PS → DPA	0.294	5.299	0.000	Supported
SI → DPA	0.130	1.992	0.021	Supported

Figure 2 depicts the research model, which was evaluated and verified in SmartPLS 4.0. The SEM-PLS model displays item loadings, beta values, and R-squared values for each study construct.

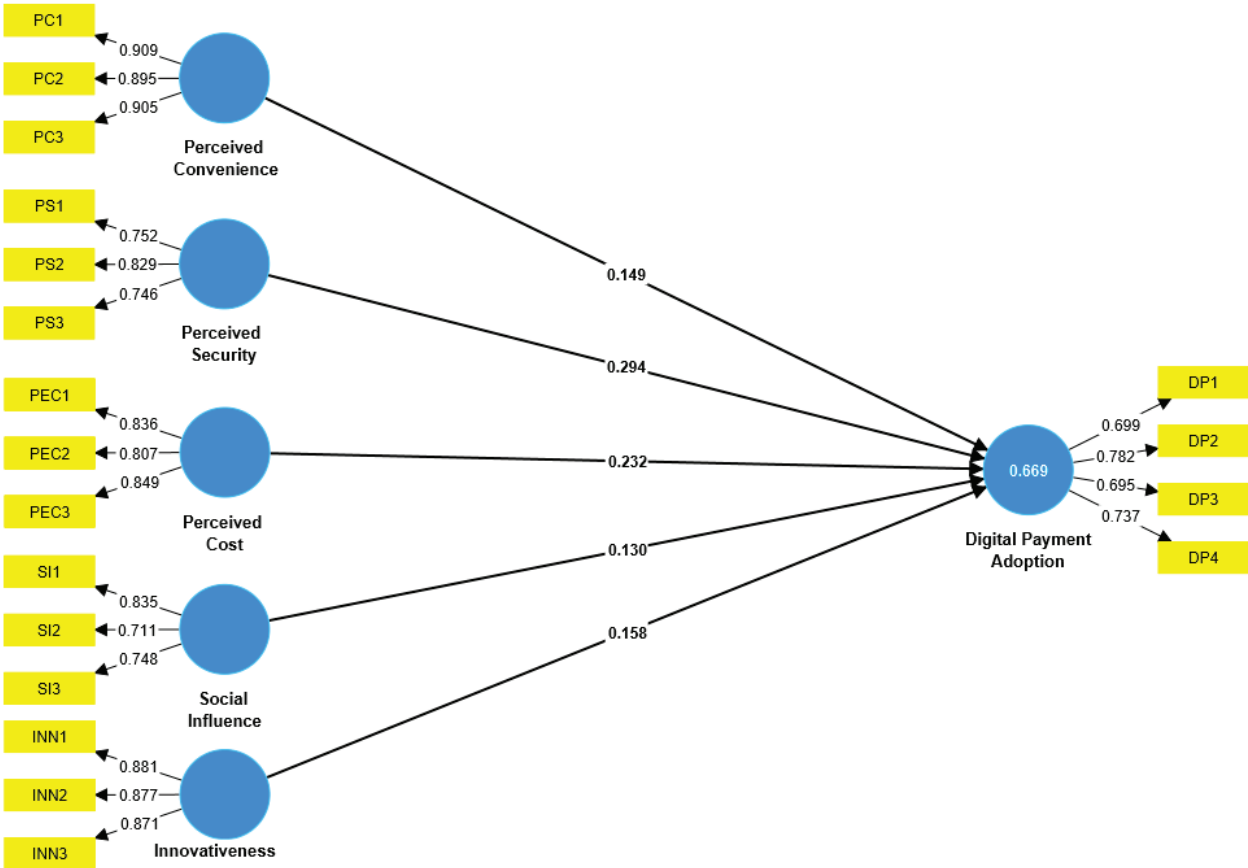

Figure 2. Validated SEM-PLS model.

In order to investigate the predictive proportion of the endogenous construct from the exogenous constructs, the coefficient of determination (R^2) was screened. As a result, the R^2 of digital payment adoption was found to be 0.669, which means digital payment adoption could be explained by 66.9% of other exogenous constructs; this value is considered moderate and acceptable (Hair et al. 2017).

5. Discussion

From the results of the path analysis, it was found that digital payment adoption is positively influenced by innovativeness. These results are in agreement with studies conducted earlier, which confirmed that user engagement in e-transactions is enhanced by increased innovative ability (Patil et al. 2020; Senali et al. 2022). They also echo previous studies supporting the claim that positive attitudes toward digital payment usage stem from innovation (Tang et al. 2021). Empirical studies on 'applications of blockchain' and 'digital payment adoption' have made it clear that innovativeness plays a supportive role in the relationship between consumer adoption and trust (Patil et al. 2020). In addition, the aforementioned findings are congruent with other recent sources suggesting that greater security, through encryption, tokenization, and biometrics, enhances confidence in digital transactions (Abu Hashish and Hassounah 2023; Alshammry 2023; Alghamdi 2024; Chauhan et al. 2022). It was apparent in a survey that 42% of consumers considered security as the most important in the uptake of digital payment. By establishing trust and providing assurances regarding financial data security, security innovations promote digital payment system adoption (Al-Omoush et al. 2020).

These findings agreed with previous research which stated that the perception of convenience has a positive impact on attitudes toward digital payment systems (Treiblmaier et al. 2006; Ajmera and Bhatt 2020). Some studies done before regarding the level of digital payment adoption have also substantiated the convenience with time-saving and raised efficiency (Al-Shahrani 2023; AlMutairi 2024). These findings are in conformity with the studies that indicate that digital payment enrolments allow users to access the services and make transactions on a 24 h basis. They use their cell phone, tablets, or laptops to make payments anytime and anywhere. Such facilities help to eliminate the geographical and time barriers associated with physically moving to a place like a bank to make payments or use traditional cash. The benefits of being able to make a payment anywhere at any time encourage people to use electronic payments (Najib and Fahma 2020; Liébana-Cabanillas et al. 2020).

The results suggest that the perceived cost acts in a beneficial manner in terms of the level of adoption of digital payments. This is in agreement with other researchers who pointed out the relevance of perceived cost for the adoption of digital payments (Singh and Rana 2017). Using digital payment systems often proves more cost-efficient than traditional payment methods (Yadav 2017). Digital payments significantly reduce the need for physical cash, thereby reducing the risk of loss or theft (Alahmed et al. 2023; Al-Saedi et al. 2020). Moreover, digital payments reduce time and cost by streamlining transactions, reducing the need for human involvement and paperwork (Singh et al. 2020; Al-Omoush et al. 2020).

The findings of this study indicate that security perception boosts the potential for accepting digital payment systems. This finding echoes the previous studies which have established that security availability accounts for an important factor while making value-related requirements when embracing digital payment mechanisms (Nuryyev et al. 2021). It was therefore found that people who feel more secure are actually more prone to the acceptance of innovative technologies (Teo et al. 2020; Widyanto et al. 2022). However, the majority of clients of digital payment systems have a reason to feel secure because providers of the services have come up with ways in which consumer rights will be enhanced; for example, reviewing disputes and chargebacks (Alshemmari 2024; Betar and Murtaza 2023; Elgedawy 2024; Dehghan and Haghighi 2015). Such steps reassure customers that their funds are secure during electronic transactions. Negative perceptions of security risks can deter acceptance of such technologies (Alghusin et al. 2020; Al-Okaily et al. 2024a).

Finally, this study established that social factors have a positive effect on ease of use of digital payments. This finding is consistent with the findings of earlier studies which suggested that there are human factors that determine whether or not one adopts digital payment options (Singh et al. 2020; Alrashdan 2023; Alsayed 2023; AlMarri and Elayah 2024; Kumari and Lodha 2021). Researchers have established that social influence mechanisms, including word-of-mouth promotion, social network participation, or peer preference, can have favorable results on the use of digital payment mechanisms. When an individual views others engaging and succeeding in the use of digital payments, the perceived risks tend to diminish, trust is enhanced, and social endorsement is present which motivates individuals to engage in the use of digital payment mechanisms (Oyelami et al. 2020; Hoo et al. 2021). Indeed, a number of reports have sufficiently utilized concepts of highly social levels of information and perception to explain the levels of use of digital payment methods. These studies emphasize that if the individual is exposed to greater social influence in the form of higher numbers of people using and promoting different forms of digital payments, there is an increased probability of his/her adoption (Kumari and Lodha 2021). Social influence to a high degree can foster social endorsement, enabling people to trust electronic payment mechanisms. Also, social influence is enhanced when important people or reference groups promote and encourage the use of digital payments (Alhaimer 2024; Almarashdeh et al. 2021). Consequently, social influence is markedly high and serves to reinforce attitudes and behaviors towards the adoption of digital payment technologies (Lu and Kosim 2024; Yang et al. 2021; Singh et al. 2020).

6. Theoretical and Practical Contributions

The implications of this study, grounded in the Technology Acceptance Model (TAM), offer important insights for digital payment providers. The findings suggest that perceived convenience and perceived security—core components of TAM—are crucial in influencing Generation Z's adoption of digital payment systems. Providers can enhance adoption by improving user-friendly interfaces and implementing robust security measures. Since perceived ease of use significantly affects adoption decisions, simplifying the payment process through intuitive design will make digital payments more accessible to users. Moreover, perceived usefulness, another TAM factor, can be enhanced by emphasizing the practical benefits, such as time savings and ease of transactions. Marketing strategies should highlight these aspects to attract more users. The study also underscores the importance of addressing social influence, as positive peer reviews and recommendations can further promote adoption.

The theoretical contributions lead to a number of implications. First, they inform politicians and service providers on the concerns that affect the Millennials in the use of digital payment systems. With these drivers in mind, they are able to formulate policies and initiatives meant to facilitate and foster adoption and, subsequently, help realize a cashless economy. Second, theoretical contributions assist in recognizing potential barriers to adoption that need to be overcome. Common concerns include privacy and security, absence of knowledge or understanding, and resistance to change among younger generations, such as Millennials. This understanding enables service providers to adopt measures such as enhanced security features, educational campaigns, or simpler user interfaces, which will address these concerns and encourage adoption. Finally, the theoretical contributions allow readers to gain a deeper understanding of the impact of the adoption of new payment systems by Millennials. In this regard, it is believed that digitized payments would assist in promoting economic growth, lowering transaction fees, and enhancing financial inclusion. There is a need to comprehend the factors behind adoption in order to harness the benefits and promote an inclusive and effective financial encompassing.

Understanding the factors that promote the adoption of digital payments by Millennials has significant practical implications. These implications can be utilized by the service providers and policymakers in redrawing their plans and practices. First of all, they should focus on appealing to the needs of Millennials' interests and lifestyles by offering fast, easy, and appropriate images of digital payment forms. Adoption rates might be significantly improved through quick, simple, and engaging experiences. Second, to make the privacy and security concerns an issue of the past, trust and security have to be established first. In order to build trust and reduce anxiety, the following strategies may be helpful: the introduction of robust security systems, data transparency, and informing users about safety measures concerning the use of digital payments. Furthermore, social features, social endorsement, and user content may enhance the acceptability of digital payment methods among Millennials and stimulate the word-of-mouth effect. Finally, strong messaging, education, and awareness through advertisements, videos, and interactions with customer service can further build confidence in digital payment platforms. Considering these outcomes, practitioners may efficiently meet Millennials' needs, overcome barriers, and create a scenario that promotes the extensive usage of this segment's digital payment methods. Providers of services will not only be able to increase their clientele and the volume of operations performed by them but they will also contribute to the wider development of a cashless economy and enable the Millennium generation who value the flexibility and effectiveness in their money-related activities.

7. Limitations and Future Research Directions

While research on the factors influencing digital payment adoption among Millennials has yielded significant insights, several limitations should be addressed. For starters, most research has concentrated on individual-level characteristics, potentially overlooking wider contextual impacts such as cultural, sociological, and economic implications. Future studies might look at the influence of these contextual variables on the adoption behavior of Millennials. Second, the bulk of research has relied on self-reported data, which may be biased and prone to social desirability effects. To gain a better understanding of adoption behavior, future studies might use objective metrics or experimental methods. Finally, because technology is continuously evolving, future studies should investigate the influence of emerging payment technologies, such as cryptocurrencies or biometric payment systems, on Millennial adoption behavior and their consequences for the financial ecosystem.

Future studies should look at the long-term effects of Millennials' digital payment use. This involves researching the effect on financial behaviors, spending habits, and general financial well-being. Understanding generational trends in digital payment acceptance, as well as the distinctions between Millennials and subsequent generations, will also give significant insights for future service providers and legislators. Exploring adoption patterns in different geographical locations and cultural situations would also contribute to a more thorough understanding of the factors of Millennial digital payment uptake. We may continue to enhance our understanding of digital payment uptake and its consequences for the Millennial generation and beyond by addressing these constraints and following these research topics.

8. Conclusions

The adoption of digital payments among Generation Z is not uniform, as the participants have different motivations and societal factors at play. For this reason, this research sought to determine the factors that are responsible for the acceptance of digital payment systems by Generation Z, who are proficient in technology and are always connected to the internet. The findings of this research indicate that several factors affect the usage of digital payments by Generation Z. To begin with, Generation Z is highly focused on convenience; therefore, digital payment systems are quick and easy to operate. They appreciate the fact that transactions can be completed within seconds on a phone or any other handheld digital device.

Generation Z has been known to be cautious when it comes to risky ventures, to the extent that it affects their acceptance of digital payment modes and digital wallets. Such members of society are likely to be more trusting of organizations that follow the necessary protocols regarding safety and privacy and inform their customers about these protocols. Cost, however, is also a significant factor when encouraging them to try out the different modes of payment. Companies interested in such a demographic can use such cost advantages to influence the purchasing patterns of the younger Generation Z members.

Additionally, social aspects enhance Generation Z's perspective regarding the use of digital payments. As per the opinion survey results, their friends, social networks, and activities concerning the processes of digitalization influence the members of this generation. People often use cashless payment systems only when they perceive that cashless payment systems have a massive proliferation or are regarded as a norm. Another aspect that needs explanation is the degree of novelty associated with cashless payment systems. Technology is developing, and Gen Z is the first generation to accept new technologies much faster than previous generations. They are attracted to modern and progressive systems of payment that have interesting features and functionalities. It is the young people of Generation Z who are likely to notice new digital payment systems and want to use them.

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Appendix A. Survey Items

1. Perceived Convenience
   - Digital payments make transactions more convenient than traditional methods.
   - I can complete payments quickly with digital payment systems.
   - Digital payments are accessible and easy to use at any time.
2. Perceived Security
   - I trust that my personal information is secure when using digital payments.
   - Digital payment systems ensure the safety of my financial data.
   - I feel safe conducting transactions through digital payment platforms.
3. Perceived Cost
   - The cost of using digital payments is reasonable.
   - I believe digital payments reduce overall transaction costs.
   - I am satisfied with the fees charged for digital payments.
4. Social Influence
   - People important to me think I should use digital payments.
   - I use digital payments because my peers do.
   - I feel encouraged by others to adopt digital payment methods.
5. Innovativeness
   - I am open to trying new digital payment technologies.
   - I am usually among the first to adopt new digital payment methods.
   - I like using advanced technologies, such as digital payments, for financial transactions.
6. Digital Payment Adoption
   - I frequently use digital payment systems for my transactions.
   - I prefer digital payments over traditional payment methods.
   - I will continue using digital payments in the future.
   - I recommend using digital payment systems to others.

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Article

Estimation of Optimal Hedge Ratio: A Wild Bootstrap Approach

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Abstract: This paper proposes a new approach to estimating the minimum variance hedge ratio (MVHR) based on the wild bootstrap and evaluates the approach using a spectrum of conservative to aggressive alternative hedging strategies associated with the percentiles of the MVHR's bootstrap distribution. This approach is suggested to be more informative and effective relative to the conventional method of hedging solely based on a single-point estimate. Furthermore, the percentile-based MVHRs are robust to influential outliers, non-normality, and unknown forms of heteroskedasticity. The bootstrap percentile-based hedging strategies' effectiveness is compared with those from the naïve method and the asymmetric DCC-GARCH model for a range of financial assets and commodities. The bootstrap percentile-based hedging technique is identified to outperform its alternatives in terms of hedging effectiveness, downside risk, and return variability, suggesting its superiority to other methods in both the literature and in practice.

Keywords: minimum variance hedge ratio; wild bootstrap; DCC-GARCH; hedging effectiveness; heteroskedasticity; stochastic dominance

JEL Classification: C58; G13

1. Introduction

The optimal hedge ratio (or the minimum variance hedge ratio; MVHR) is widely adopted in financial risk management by both academics and practitioners. Derivative instruments, such as futures contracts, are crucial to a diversified portfolio in controlling and reducing the risk associated with unfavorable price changes. Since the first establishment of the futures market as part of the Chicago Mercantile Exchange in 1975, many studies on estimating the optimal hedge ratio and evaluating its effectiveness have been published (Chen et al. 2003; Chen et al. 2014; Wang et al. 2015; Markopoulou et al. 2016; Park and Shi 2017; Chen et al. 2021). By taking a position guided by the MVHR, an investor can effectively hedge the risk associated with price changes of an underlying asset. Ederington (1979) presents the earliest empirical study of the optimal hedge ratio as a means of risk minimization.

While the conventional method of estimating the MVHR is based on the ordinary least-squares (OLS) technique due to its simplicity and easy implementation, a number of new alternatives have been proposed in the literature, including the vector error-correction (VEC) model (Kroner and Sultan 1993; Li 2010), the generalized autoregressive conditional heteroskedasticity (GARCH) model (Caporin et al. 2014; Chang et al. 2013; Hsu et al. 2008; Ku et al. 2007; Lien et al. 2002; Park and Jei 2010), the Markov regime-switching method (Alizadeh and Nomikos 2004; Chen and Tsay 2011; Lee 2009, 2010; Lee and Yoder 2011; Su and Wu 2014), and the quantile regression method (Lien et al. 2016; Shrestha et al. 2018). These new methods are designed to overcome the shortcomings of the OLS-based method under non-normality and heteroskedasticity, which are the salient features of financial data. However, whether these new methods provide superior hedging over the OLS-based method has not been fully confirmed, in terms of hedging effectiveness and variance reduction. A number of studies find evidence that the OLS-based method does outperform these newly proposed methods: see, for instance, Lien (2009) and Lien and Shrestha (2008). As Maharaj et al. (2008) and Moosa (2017) recently pointed out, there is no evidence that econometric sophistication, in terms of elaborate model specification and superior estimation method, has boosted hedging effectiveness. Wang et al. (2015) provide an interesting finding that the naïve strategy[1] is hardly outperformed by an advanced model under the minimum variance framework. This can be partly explained by estimation error and model misspecification considerations, as a small change in data quality and model specification can cause a complicated model to fail.

A notable feature of previous studies is that they rely solely on the point estimators for the optimal hedge ratio. A point estimator produces a single number as an estimate of the unknown population value. Although it may represent the most likely value from a sampling or predictive distribution, it carries no information about the degree of intrinsic uncertainty associated with estimation or prediction. As Chatfield (1993) points out in the forecasting context, an interval estimator is more informative by offering a range of possible alternatives or contingencies with a prescribed level of confidence. More importantly, Kim and Robinson (2019) demonstrate that hypothesis testing based on the interval estimator provides significantly improved inferential outcomes than those based on a single-point estimate. For this reason, one may justifiably argue that risk analysis based solely on a point estimate of the MVHR is of limited usefulness. By presenting an interval—or the percentiles within—for the optimal hedge ratio, a researcher or investor is able to conduct better-informed hedging and a more detailed risk analysis, taking full account of the degree of estimation uncertainty. Moreover, they can consider a range of possible scenarios based on a group of alternative MVHR values. For example, a number of hedging strategies within a 95% confidence interval for the optimal hedge ratio (e.g., the 25th, 50th, and 75th percentiles) can be considered.

In this paper, we contribute to the literature by proposing a new method of hedging based on the interval estimation of the MVHR. As it is OLS-based in nature, our proposal does not represent an econometric sophistication; instead, it relies on a non-parametric method of interval estimation. While it is possible to construct an OLS-based interval or percentile estimator for the optimal hedge ratio using a normal approximation, such estimators are likely to show undesirable properties in the presence of strong non-normality and heteroskedasticity in financial data (see, for example, Kim 2006). For example, an interval estimator based on a normal distribution is always symmetric around the value of the optimal hedge ratio, fails to capture the high degree of volatility of financial data, and may be subject to the effects of influential outliers. For this reason, we propose the wild bootstrap method (Davidson and Flachaire 2008) to estimate a confidence interval or percentiles for the optimal hedge ratio. The wild bootstrap is a non-parametric method of approximating the sampling distribution of a statistic based on data resampling. It is well known that a superior alternative should be provided to the conventional normal approximation when the data show unknown forms of (conditional) heteroskedasticity (Kim 2006). This paper conducts extensive empirical analyses to evaluate the hedging effectiveness based on the wild bootstrap percentiles, in comparison with the strategies based on the dynamic conditional correlation (DCC-GARCH) model with an asymmetric specification and the naïve method. Furthermore, we consider two alternative wild bootstrap procedures, i.e., one based on resampling the residuals of a regression, and the other resampling the pairs of observations. Our paper presents an innovative but simple non-parametric approach, which is different from the semi-parametric quantile regression methods used by Lien et al. (2016) and Shrestha et al. (2018). Their estimated quantile hedge ratios are based on the pairwise spot–futures quantiles independently. The hedging effectiveness is thus defined for an effective estimation of the hedge ratio for a given quantile. The major drawbacks of the quantile regression method are the complicated estimation methods required and the potential problem of quantile crossing (Waldmann 2018).

Using daily spot and futures price indices of multiple assets from 1980 to 2020 with a dynamic out-of-sample analysis framework, we find that the hedging strategies based on percentiles of the optimal hedge ratio's bootstrap confidence interval outperform those based on the naïve hedge and the DCC-GARCH model in terms of hedging effectiveness, downside risk, and hedged return variability. Note that these percentiles are within the inter-quartile range of the bootstrap distribution, which is highly likely to cover the true value of the optimal hedge ratio. In addition, they have the desirable property of not being affected by possible extreme values. It is also found that the optimal hedging based on the pairs' bootstrap is marginally better than that based on the residual bootstrap. Our findings hold when we perform robustness checks with stochastic dominance tests and various estimation windows. To the best of our knowledge, this approach is not yet examined in the literature. This paper is organized as follows. Section 2 presents a brief literature review. Section 3 provides the methodological details. Section 4 presents the data details and Section 5 presents the empirical results. Finally, Section 6 concludes the paper.

2. Literature Review

Chen et al. (2003) conducted a survey of different optimization functions and techniques to estimate an optimal hedge ratio. They conclude that, in general, there is no particular optimal hedge ratio that is significantly superior to the alternatives. According to Chen et al. (2014), numerous studies have been conducted to provide a solution to the risk-minimizing function of the MVHR. Nonetheless, the conclusion of which estimation method has the best hedging effectiveness remains a mixed opinion based on an out-of-sample evaluation basis. It is suggested that the major cause of these mixed results is the estimation error (Lien and Shrestha 2008).

From the in-sample analysis, the VEC hedging model with the GARCH error structure employed in Kroner and Sultan's work (1993) is reported to be the best currency hedging strategy based on 4.5 percent and 1.5 percent variance reduction compared to the naïve and OLS models, respectively. With regard to currency hedging, Ku et al. (2007) documented that the estimation of hedge ratios using the dynamic conditional correlation (DCC–GARCH) model can reduce 0.14 percent of the variation in the unhedged portfolio relative to the constant OLS model. This is reported as the second-most-effective strategy, followed by the VEC and constant conditional correlation (CCC-GARCH) models. Park and Jei (2010), upon evaluating the hedging effectiveness for corn and soybean spot and futures prices, conclude that the incorporation of asymmetry and flexible distribution specification in the DCC-GARCH model cannot yield a better hedge outcome compared to the OLS hedge ratio, since the variance reduction benefits are relatively small. This finding is consistent with the study of Lien et al. (2002), which compares the CCC-GARCH and constant OLS approaches to hedging a spot position with different corresponding futures indices on currency, commodities, and equity securities. They also agree on similar hedging benefits among the models. In an effort to document the effect of the Euro sovereign debt crisis on currency hedging, Caporin et al. (2014) conclude that static OLS estimates for hedging strategy were appropriate during the calm (non-crisis) period and after the European Central Bank intervened. However, the authors assert that the exponential weighted moving average filter technique outperforms several other multivariate GARCH models and the static OLS model in terms of hedging effectiveness in the aftermath of the failure of the Lehman Brothers in 2008.

By using the Markov regime-switching (MRS) model, Alizadeh and Nomikos (2004) report a new technique for estimating the hedge ratio, which depends on prevailing market conditions and is also free from the non-trivial persistence effect of the distant past volatilities in the GARCH models. Although MRS ratios outperform the others as indicated in the in-sample analysis, the results from the out-of-sample analysis are mixed. In particular, the MRS ratios provide better variance reduction for the FTSE 100 hedge, but not for the S&P 500 index in comparison with the GARCH and constant OLS hedging estimates. Following this stream, Lee and Yoder (2011) and Su and Wu (2014) combine the MRS with the GARCH models (BEKK and DCC, respectively) to allow the parameters to vary over time and be state-dependent. Thus, the optimal hedge ratio is estimated from the conditional second moments of the spot and futures series that are dependent on the market states. They find better in-sample performance with the new approach, but only marginal dominance in the out-of-sample analysis in comparison to the benchmark strategies based on no hedging and the constant OLS hedge ratio. The variance reductions for hedging nickel and corn in Lee and Yoder (2011), and the S&P 500 and Nikkei 225 indices in Su and Wu (2014), are reported to be within the 0 to 2% range. Park and Shi (2017) demonstrate an innovative approach to estimating the MVHR by the MRS with trading pressures in the energy and metal commodity markets. However, the reported out-of-sample results for individual commodities do not show a significant improvement of their model over a simpler one such as the OLS or the naïve hedge in terms of variance and downside risk reduction.

In the aforementioned studies, the evidence that the alternative techniques for the MVHR estimation outperform the OLS approach has been modest in the out-of-sample analysis. This raises a question regarding the effective predictability of the proposed models, and the superiority of their time-varying properties as opposed to the static OLS model for estimating the optimal hedge ratio. Based on similar concerns, Lee and Yoder (2011) implement the statistical testing of forecasting superiority of the best model over a given benchmark, for instance, regime switching–GARCH compared to the traditional GARCH and the constant OLS models. They report that the tests for forecasting superiority among these methods are not statistically significant via White's method for data-snooping reality check (White 2000). Notably, by using model confidence set tests for various econometric models, Wang et al. (2015) found that there is no outstanding model clearly outperforming the naïve strategy. However, the naïve hedge is significantly outperformed by the OLS-based hedge for some futures markets when the model parameters are known to a hedger ex ante.

Generally, the most popular methodology employed in recent studies are the GARCH-class models, which are able to capture dynamic relationships between the spots and futures, while the constant approaches, such as the static OLS model or the naïve strategy, fail to capture such relationships. The rationale for employing the GARCH models is the fact that high volatility in one period tends to have persistent effects in the following periods. However, convergence is also a typical problem in estimating the GARCH models. Additionally, Brooks et al. (2011) conclude that the multivariate GARCH models at best have provided a very modest enhancement for hedging effectiveness in an out-of-sample analysis. This assertion can be re-examined by reviewing reported tables of variance reduction and hedging effectiveness by employing various methods against a specific benchmark in many studies within the related literature. The reported differences in hedging improvement among the models are minor and the estimated hedge ratios appear to be slightly different. Thus far, the main disadvantage of the OLS method is that it fails in capturing the time-varying nature of the relationship among financial time series. Furthermore, the OLS assumptions are normality and constant variance of financial returns for statistical inference. Despite these shortcomings, the OLS-based MVHR is still utilized universally by financial professionals due to its computational efficiency and simplicity. As mentioned earlier, past studies rely exclusively on the point estimates of the MVHR generated from the alternative models. They report empirical results on the hedging effectiveness that are often mixed and inconclusive. This is possibly due to the above fact that the degree of uncertainty associated with the optimal hedging ratio estimation is not reflected in their evaluation. In this paper, we propose the adoption of percentile-based optimal hedging using the wild bootstrap method. The hedging strategy is based on the simple OLS regression and conducted in a time-varying framework using rolling sub-sample windows. The wild bootstrap provides estimation and statistical inference for the MVHR robust to non-normality and heteroskedasticity issues.

3. Methodology

In this section, we present the methodological details, including the wild bootstrap methods and the asymmetric DCC-GARCH model for the optimal hedge ratio. The measures for the hedging effectiveness are also discussed.

3.1. Background

The hedge ratio can be interpreted as a dollar amount in futures contracts taken by an investor or a hedger to protect against the risk of any loss from holding every one dollar in the spot market. Particularly for hedging purposes, the position in a futures contract should be opposite to the position in the spot market. Price changes in the spot and futures positions constitute the hedged return, which can be expressed as

$$R_h = R_S - \beta\, R_F \tag{1}$$

where R_h is a vector of the hedged portfolio's returns; R_S is a vector of spot returns of a risky asset; R_F is a vector of futures contract returns of the risky asset; β is the hedge ratio reflecting the size of futures contracts that needs to be entered into for the purpose of hedging the risk of USD 1 in the spot market. Note that each vector of the above returns has a length of T, which denotes the sample size.

The variance of the hedged return in (1) is as follows:

$$Var(R_h) = Var(R_S) - 2\beta\, Cov(R_S,\ R_F) + \beta^2 Var(\ R_F) \tag{2}$$

To minimize the variance of the hedged return in (2), a hedge is established using futures contracts with a size determined by the optimal hedge ratio, which is the so-called MVHR and is given by

$$\beta = \frac{Cov(R_S,\ R_F)}{Var(\ R_F)} \tag{3}$$

The conventional approach uses the estimate of β based on the regression of the form

$$R_S = c + \beta\, R_F + \varepsilon \tag{4}$$

The OLS estimator for β in (4) is expressed as

$$\hat{\beta} = \left(R_F'\, R_F\right)^{-1} R_F' R_S \tag{5}$$

where the sign $'$ refers to the transpose of the corresponding vector.

3.2. Hedging with Wild Bootstrap Percentiles

Efron (1979) proposed a bootstrap method for approximating the sampling distribution of a statistic in a non-parametric way by repeated resampling of the observed data. However, the true data-generating process (DGP) of the observed data cannot accurately be imitated in the bootstrap DGP if the form of heteroskedasticity is unknown. The wild bootstrap (Liu 1988; Mammen 1993) is a bootstrap method designed for data with unknown forms of heteroskedasticity, which have been shown to be asymptotically valid (Cribari-Neto and Lima 2009; Cribari-Neto et al. 2007; Davidson and Flachaire 2008; Flachaire 2005).

We contribute to the related literature by estimating distributions of the MVHR with the wild bootstrap, which is a non-parametric method and does not require prior assumptions for the heteroskedasticity and normality in the disturbance term of Equation (4). We thus examine percentiles within a confidence interval, which covers the true value of the MVHR with a prescribed level of confidence. By constructing the confidence interval and its percentiles for the MVHR, the degree of estimation uncertainty is explicitly presented. Firstly, the wild bootstrap based on residual resampling is considered, and it is employed in conjunction with the heteroskedasticity-consistent covariance matrix estimator (HCCME), as proposed in Flachaire (2005), Davidson and Flachaire (2008), and Cribari-Neto and Lima (2009). Additionally, we employ the wild bootstrap based on resampling the pairs of observations. The former bootstrap method assumes that R_F in regression (4) is exogenous and uncorrelated with the disturbance term, while the latter assumes that it is random. The pairs' bootstrapping process considers the potential endogeneity problem, when both R_S and R_F are likely to be driven by the same market shocks. The two wild bootstrap methods are proposed as alternatives for the percentile-based hedging strategy.

The wild bootstrap based on residual resampling can be described as follows:

Step 1: Estimate the optimal hedge ratio $\hat{\beta}$ given in (5) for the regression (4).
Step 2: Draw a bootstrap sample (R^*_{Si}, R_{Fi}) based on $\hat{\beta}$ for each ith observation from 1 to T:

$$R^*_{Si} = \hat{\beta}\ R_{Fi} + t^*_i \hat{\varepsilon}_i / (1 - h_i)$$

where R^*_{Si} is resampled data of the spot returns, t^*_i is a independent random variable with zero mean and unit variance, and $\hat{\varepsilon}_i / (1 - h_i)$ is the transformed residual from the regression (4) robust to heteroskedasticity[2].
Step 3: Compute the new estimate of the hedge ratio $\hat{\beta}^*$ with the bootstrap sample (R^*_{Si}, R_{Fi}) (for i = 1, . . ., T) following the regression (4).
Step 4: Repeat Steps 2 and 3 many times, say B, to form the bootstrap distribution of $\{\hat{\beta}^*(i)\}_{i=1}^{B}$ for $\hat{\beta}$.
Step 5: The $(1 - \alpha)100\%$ wild bootstrapping confidence interval is constructed with the lower limit and upper limits representing the 0.5α percentile and $(1 - 0.5\alpha)$ percentile, respectively, of the bootstrap distribution $\{\hat{\beta}^*(i)\}_{i=1}^{B}$. The percentiles within the confidence interval can be estimated in a similar way. The number of bootstrap iterations B is set at 1000.

The wild bootstrap based on resampling the pairs is identical to the above-mentioned procedure, except in Steps 2 and 3, where resampling and estimations are conducted as $(R^*_{Si},\ R^*_{Fi}) = (t^* R_{Si}, t^* R_{Fi})$; and $\hat{\beta}^*$ is the OLS estimator from R^*_{Si}, R^*_{Fi} (for i = 1, . . ., T).

Considering $X^*_t = t_i{}^* X_i$ and $Y^*_t = t_i{}^* Y_i$, where X and Y are random variables, the variance and covariance of resampled data X^* and Y^*, conditional on X and Y, respectively, can effectively replicate those of X and Y. That is,

$$Var\ (X^*_i / X_i) = X^2_i; Var\ (Y^*_i / Y_i) = Y^2_i; Cov(X^*_i, Y^*_i / X_i, Y_i) = X_i Y_i$$

A choice should be made for the distribution for t^*_i. In this paper, we use Mammen's (1993) two-point distribution:

$$t^*_i = \begin{cases} -\frac{\sqrt{5}-1}{2} with\ probability\ p = \frac{\sqrt{5}+1}{2\sqrt{5}} \\ \frac{\sqrt{5}+1}{2} with\ probability (1 - p) \end{cases}$$

which is well known for giving higher-order refinements.

In this study, we construct the 95% confidence interval of the MVHR, paying attention to the 10th, 25th, 50th, 75th, and 90th percentiles. Hedging strategies are then produced based on the percentile hedge ratios. A hedged position based on an upper percentile may be regarded as an aggressive strategy, whereas that based on a lower percentile may be considered a conservative one. The 50th percentile (median) hedging position may be regarded as a neutral strategy. We argue that these percentile-based hedging strategies effectively provide different scenarios under different market conditions, since the interval will be tighter in normal times, but wider under turbulent market conditions. As a result, these hedging strategies are much more informative than the one based on a single-point estimate of the hedge ratio to seek protection against the hedged return fluctuations.

3.3. Hedging Based on the DCC-GARCH

As an alternative to the wild bootstrap, we use the bivariate DCC-GARCH(1,1) model developed by Engle (2002), which is widely used in the prior literature. The model has been popular due to its superiority to the OLS approach in considering time-varying conditional variance and covariance of the spot and futures returns. Notably, there is strong evidence in the previous literature that past volatilities have leverage effects on financial asset returns (Black 1976; Christie 1982); in particular, the effect is observed to be larger for the aggregate market index returns (Tauchen et al. 1996; Andersen et al. 2001). On this basis, the methods of Glosten et al. (1993) and Park and Jei (2010) are followed to employ an asymmetric version of the DCC-GARCH(1,1) model. The objective is to capture asymmetry in the volatility specification of the asset returns in estimating the dynamic relationship between the spot and futures returns. This model is defined as follows:

$$R_{S,t} = \mu_S + \varepsilon_{S,t}$$

$$R_{F,t} = \mu_F + \varepsilon_{F,t}$$

$$\begin{bmatrix} \varepsilon_{S,t} \\ \varepsilon_{F,t} \end{bmatrix} / \Omega_{t-1} \sim N(0,\ H_t)$$

$$H_t = D_t \Gamma_t D_t$$

$$D_t = diag\left\{ h_{SS,t}^{\frac{1}{2}},\ h_{FF,t}^{\frac{1}{2}} \right\}$$

$$h_{ii,t} = c_i + a_i \varepsilon_{i,t-1}^2 + b_i h_{ii,t-1} + d_i I_{t-1} \varepsilon_{i,t-1}^2,\ i = S, F$$

$$\Gamma_t = (diag\{Q_t\})^{-\frac{1}{2}} Q_t (diag\{Q_t\})^{-\frac{1}{2}}$$

$$Q_t = (1 - \delta_1 - \delta_2)\overline{Q} - \delta_3 \overline{S} + \delta_1 u_{t-1} u_{t-1} + \delta_2 Q_{t-1} + \delta_3 s_{t-1} s_{t-1} \tag{6}$$

where H_t is the dynamic conditional covariance matrix. $u_{i,t} = (u_{S,t},\ u_{F,t})$ is the vector of standardized residuals of the spot and futures returns. Q_t is the dynamic conditional correlation. $\overline{Q} = T^{-1}\sum_{t-1}^{T} u_t u'_t$ is the unconditional variance matrix of u_t. I_t is the indicator of the leverage effect of the past volatility on asset return, $I_t = 1$ when $\varepsilon_t < 0$ and otherwise 0. $s_t = I_t \odot u_t$ measures the asymmetric effect of the shocks on the dynamic conditional correlation and $\odot$ is the element-by-element product operator and $\overline{S} = T^{-1}\sum_{t-1}^{T} s_t s'_t$. Hence, the time-varying hedge ratio $\hat{\beta}_t$ can be calculated based on the conditional covariance matrix from the asymmetric DCC-GARCH(1,1) model, as follows:

$$\hat{\beta}_t = \frac{\hat{h}_{SF,t+1}}{\hat{h}_{FF,t+1}} \tag{7}$$

3.4. Computational Details and Evaluation of Hedging Strategies

To conduct the hedging with time-varying estimators, we adopt the rolling sub-sample window of a 1-year trading period[3] for both the wild bootstrap and the DCC-GARCH(1,1) model. From each sub-sample window, one-step ahead prediction from the DCC-GARCH(1,1) model is generated along with the wild bootstrap percentiles. To compare the predictive ability of the alternative strategies, the hedged portfolios are constructed by combining the long position in the spot market and the short position in the futures market from all windows. These hedging strategies are evaluated in terms of variance reduction, downside risk, and the overall riskiness feature of the hedged return distributions.

Conventionally, the hedging effectiveness of the strategies is measured by the percentage decrease in the return volatility of the hedged portfolio relative to that of the unhedged portfolio. An optimal hedging strategy under the minimum variance framework is expected to have a relatively stable hedge ratio and provide the largest variance reduction from the unhedged position, which is the purely long position in the spot market in this study. The hedging effectiveness (*HE*) is given by

$$HE = \frac{Var(U) - Var(H)}{Var(U)} \tag{8}$$

where *Var*(*U*) and *Var*(*H*) denote variances in the unhedged return and hedged return, respectively. Here, the semi-variance (SV) is used to capture the average squared deviation of the observations below the mean of the hedged returns. It can be written as follows:

$$SV = \frac{\sum_{i=1}^{m} \left(X_i - \overline{X}\right)^2}{m-1} \tag{9}$$

where m is the number of hedged return observations X_i below the average $\overline{X}$. By comparing the SV values across the proposed hedging strategies, a strategy that may potentially expose an investor to higher downside risks or substantial losses can be identified. It provides information regarding which of the available strategies is safer in situations of adverse market conditions or situations of high volatility in market movements. In addition to these measures, the inter-quartile range (difference between the 3rd and 1st quartiles) and 95% range (difference between the 97.5th and 2.5th percentiles) of the hedged return distributions are compared.

As a robustness check, we perform stochastic dominance (SD) tests to compare the overall riskiness feature of the hedged return distributions among the alternative strategies. The first and the second orders of SD tests have been widely applied in economics and finance studies (Chang et al. 2015; Liu 2016). SD testing does not require a prior assumption but considers higher moments of the data distribution. In line with the objective of financial risk managers, SD test is employed to detect which hedging strategy produces the least volatile returns. Let us consider two different hedging strategies with $F_A(z)$ and $F_B(z)$ as cumulative distribution functions (CDFs) where it is desirable to maximize z, denoting the value of the hedged return. The first-order test of SD is defined as $F_A(z) \leq F_B(z)$ for all z. That is, the CDFs of the strategy B's hedged returns is to the right of that of strategy A. In this case, strategy B is said to first-order stochastically dominate strategy A or $B \geq_1 A$. This dominance order means strategy B always produces a higher average return with lower risk than strategy A. The second order is defined as $B \geq_2 A$ if $\int_{min}^{z} [F_B(z) - F_A(z)]dz \geq 0$ for all z. The $min_B(z) \geq min_A(z)$ is the necessary condition for B $\geq_2$ A, which indicates that the F_A has a thicker left tail than F_B and thus shifts to the left of F_B. When strategy B is said to second-order stochastically dominate strategy A, it is implied that strategy B involves less risk than strategy A. Therefore, strategy B is more attractive to the financial risk managers and the hedgers. When there are no CDFs stochastically dominating another, the relationship is said to be inconclusive.

We employ the statistical test for SD proposed by Barrett and Donald (2003). The authors based their study on the Kolmogorov–Smirnov-type tests to compare all points of the objects, which are multiple integrals of the objects' underlying distribution, to produce statistical inference for a degree of stochastic dominance. For brevity, interested readers can refer to Barrett and Donald's paper (Barrett and Donald 2003) for more information. Using the p-values simulated from the bootstrap method suggested by the authors, we test the hypotheses of stochastic dominance at the first order and the second order, respectively, for any pair of the included hedging strategies.

4. Data Details

Hedging effectiveness is evaluated for a wide range of assets, including both developed and developing equity markets (S&P 500 index, MSCI Emerging Markets index), the US 10-year government bond index, the currency (US dollar index[4]), and various commodities (S&P gold spot price index, WTI crude oil mid-price, S&P corn spot price index, and soybean and nickel price indices in US dollars). The futures contracts employed for hedging instruments are continuous settlement price indices available from DataStream[5]. The data range from 1980 to 2020, although some assets have different starting values due to data availability, covering the periods of a number of economic and financial crises. Descriptive statistics for the spot and futures' log-returns of each asset are presented in panel A of Table 1. The mean and variance properties of the return series are typical of financial returns. The Lagrange multiplier test for the ARCH effect indicates the presence of conditional heteroskedasticity, which justifies the use of a dynamic strategy to reduce the price risk exposure in the spot market, such as the rolling OLS and DCC-GARCH models. The Jarque–Bera test for non-normality indicates the existence of non-normal returns. Panel B of Table 2 shows that the estimated OLS residuals in Equation (4) are non-normally distributed, serially correlated, and heteroskedastic at the 1% significance level for the entire period of study. The strong evidence of heteroskedasticity and non-normality justifies the use of the wild bootstrap. For all assets, the Pearson correlations among the spot and futures returns indicate a strong linear association. In untabulated results, we find that the spot and futures of all included assets are co-integrated using the Johansen's testing procedure (Johansen 1991). Figure **??** presents the time plots of the return of the different financial assets and their futures. The futures price indices appear to be more sensitive and volatile relative to changes in the spot price indices. The price reaction in most of the futures markets, except for nickel, is stronger than in the spot market, as shown by the sharper spikes in the return plots. This suggests that an incoherent strategy involving futures transactions may result in higher risks than expected.

Table 1. Panel A—Descriptive statistics for the asset returns.

	S&P 500		Emerging Markets		BOND	
	SPOT	FUTURES	SPOT	FUTURES	SPOT	FUTURES
Mean	0.035 ***	0.035 ***	0.0256 *	0.029	0.0071	0.0164
Variance	1.265 ***	1.4626 ***	0.6799 ***	1.1316 ***	0.2111 ***	0.1601 ***
Skewness	−1.1993	−2.0849	−0.6037	−0.4749	0.0022	0.0439
Kurtosis	27.4245	72.4538	5.2391	4.0391	3.4813	4.0891
J-B test	323,194 ***	2,246,131 ***	3826.4 ***	2279 ***	5165.5 ***	7129.9 ***
ARCH test	1255.3 ***	985.37 ***	766.1 ***	616.63 ***	739.07 ***	880.7 ***
Pearson Correlation	0.96 ***		0.94 ***		0.94 ***	
	USD		GOLD		OIL	
	SPOT	FUTURES	SPOT	FUTURES	SPOT	FUTURES
Mean	−0.0033	−0.0034	0.0101	0.0113	0.0081	0.0082
Variance	0.2585 ***	0.2861 ***	1.2993 ***	1.3455 ***	7.2838 ***	6.2511 ***
Skewness	−0.0366	−0.0083	−0.1336	−0.174	−2.2866	−1.2686
Kurtosis	2.1446	2.0817	7.3637	8.5646	71.7029	29.2159
J-B test	1784.2 ***	1679.3 ***	24,521 ***	33,182 ***	2,149,206 ***	358,049 ***
ARCH test	234.01 ***	217.65 ***	1174.3 ***	1289.4 ***	1018.5 ***	1403.8 ***
Pearson Correlation	0.97 ***		0.99 ***		0.87 ***	

Table 1. *Cont.*

	CORN		SOYBEAN		NICKEL	
	SPOT	FUTURES	SPOT	FUTURES	SPOT	FUTURES
Mean	0.006	0.006	0.0176	0.0174	0.0192	0.0183
Variance	2.1298 ***	2.4919 ***	3.153 ***	3.0904 ***	4.486 ***	4.4166 ***
Skewness	−0.0209	−0.7041	−0.2081	−1.2622	−0.1337	−0.1333
Kurtosis	3.0253	14.8187	5.4233	15.3669	4.0583	4.0288
J-B test	4134.2 ***	100,069 ***	4921 ***	40,338 ***	4968.6 ***	4896.8 ***
ARCH test	1167.84 ***	1261.52 ***	430.57 ***	85.418 ***	736.01 ***	754.28 ***
Pearson Correlation	0.90 ***		0.82 ***		0.98 ***	

Note: Asset returns are presented in percentage terms. J-B test is the Jarque–Bera normality test for the asset returns' distribution with the test statistic following the χ^2 distribution. The ARCH test is the Lagrange multiplier test for conditional heteroskedasticity up to 24 lags. * and *** denote the statistical significance at the 10% and 1% levels, respectively.

Table 2. Panel B—Normality test, autocorrelation, and heteroskedasticity tests for residuals.

	J-B Test	**Box Test**	**ARCH Test**
S&P 500	1,939,712 ***	1437.8 ***	3164.6 ***
EMERGING MARKETS	6283.7 ***	277.38 ***	429.31 ***
BOND	532,811 ***	501.67 ***	693.74 ***
USD	332,852 ***	1002.5 ***	765.13 ***
GOLD	21,932,902 ***	1231.8 ***	2652.7 ***
OIL	9,463,902 ***	1153.1 ***	1546.1 ***
CORN	26,471,382 ***	1115.1 ***	154.2 ***
SOYBEAN	271,734 ***	216.95 ***	575 ***
NICKEL	4,258,932 ***	1397.5 ***	2540.9 ***

Note: Residuals are the estimated values of ε in Equation (4) for the entire period of study. J-B test is the Jarque–Bera normality test with the test statistic following the χ^2 distribution. The Box test is the Ljung–Box Q test for serial correlation up to 24 lags. The ARCH test is the Lagrange multiplier test for conditional heteroskedasticity up to 24 lags. *** denote the statistical significance at the 1% levels, respectively.

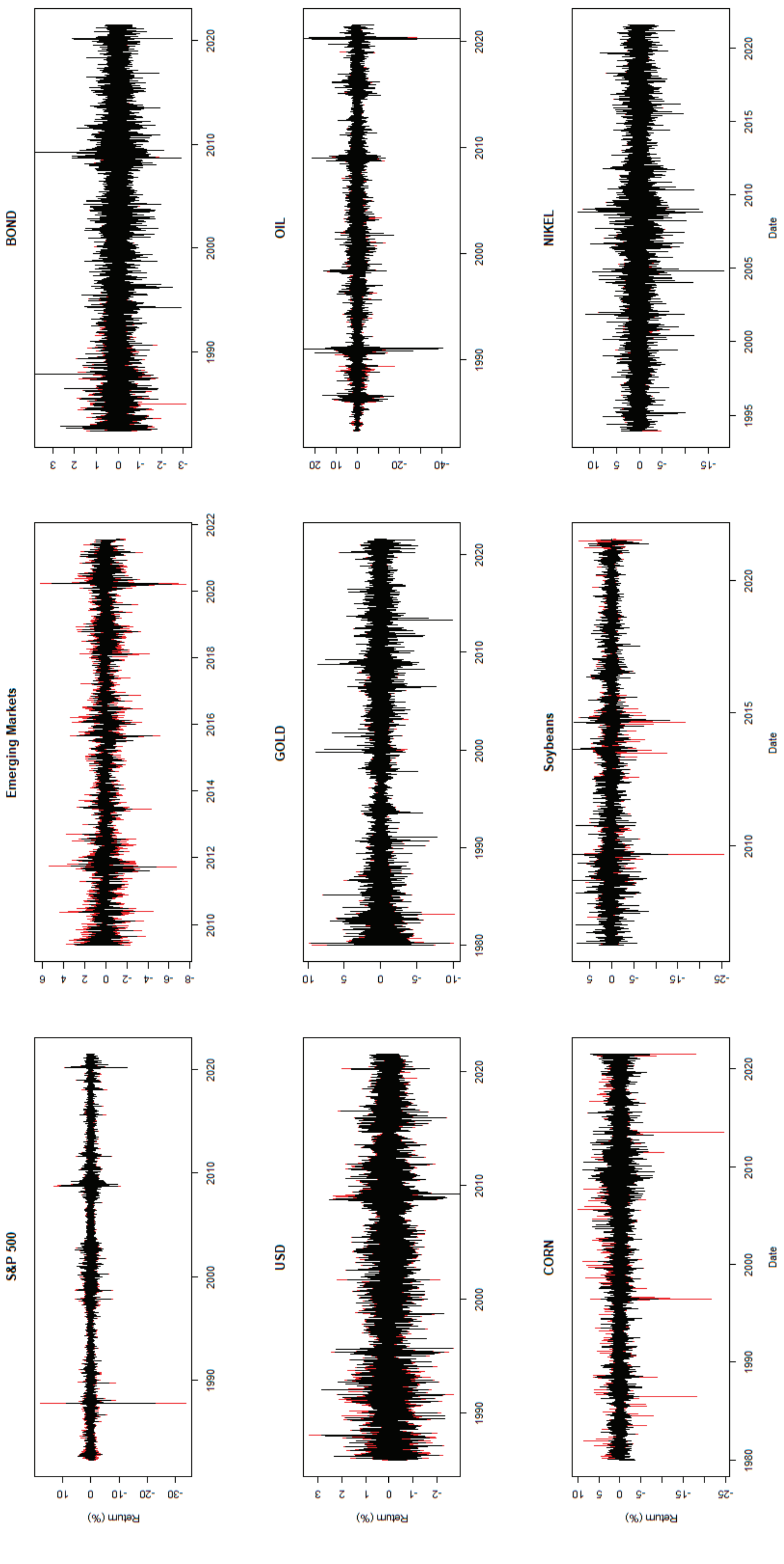

Figure 1. Spot and futures return plots. Note: Continuous changes in the spot and futures markets are demonstrated in black and red, respectively.

5. Empirical Results

5.1. Optimal Hedge Ratio Estimates

The time-varying MVHRs are shown in Figures 2–10 for the included assets[6]. These MVHRs are generated using a moving sub-sample window of a 1-year trading period. In each figure, the bootstrap percentile-based MVHRs, using the pairs bootstrap, are reported in the top panel, while those based on the residual resampling procedure appear in the middle panel. These plots present the 95% confidence interval band within which are used for percentile-based hedging strategies. The DCC-GARCH-based MVHRs are presented in the bottom panel of the figures. As a conventional hedge, the naïve strategy is also indicated by the horizontal line at a hedge ratio of 1 in each panel for comparison.

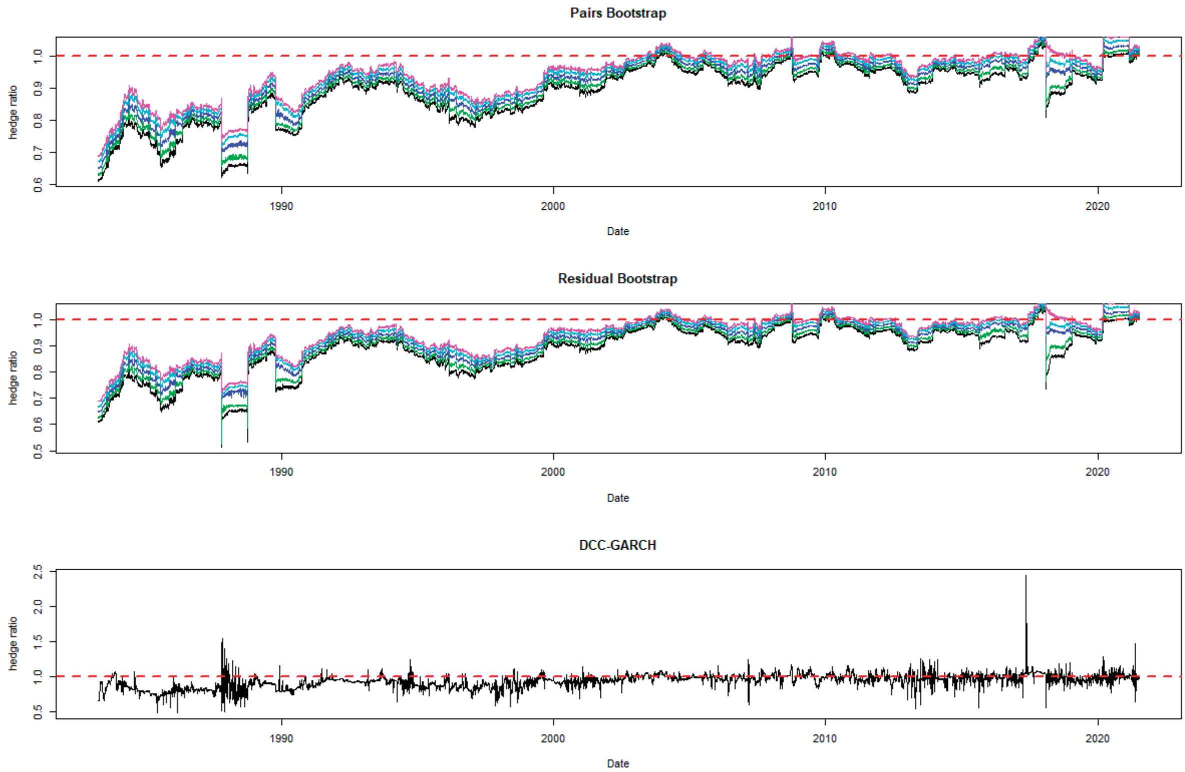

Figure 2. Optimal hedge ratios for S&P 500 index: one-year period rolling sub-sample window.

A noticeable feature in the figures is the stability of the bootstrap percentile-based MVHRs, in comparison with the DCC-GARCH counterparts. The latter are considerably more volatile, especially during the turbulent economic and financial market periods. Obviously, significant swings are observed in the time-varying DCC-GARCH-based MVHRs across the assets. The high volatility of the MVHRs based on the DCC-GARCH is also documented in previous studies (Park and Jei 2010; Chang et al. 2013; Caporin et al. 2014). From the figures, it is worth noting that changes in the MVHR using the DCC-GARCH strategy are well outside the bootstrap confidence bands. The bootstrap percentile-based MVHRs are stable, mostly well above 0 and less than 1, except for the Bond security. In contrast, the DCC-GARCH hedge ratios move erratically and are sometimes negative and even greater than 2. The observed large volatility of the DCC-GARCH-based MVHRs is probably due to the highly parametric nature and the assumed persistence effect of past shocks of the GARCH model.

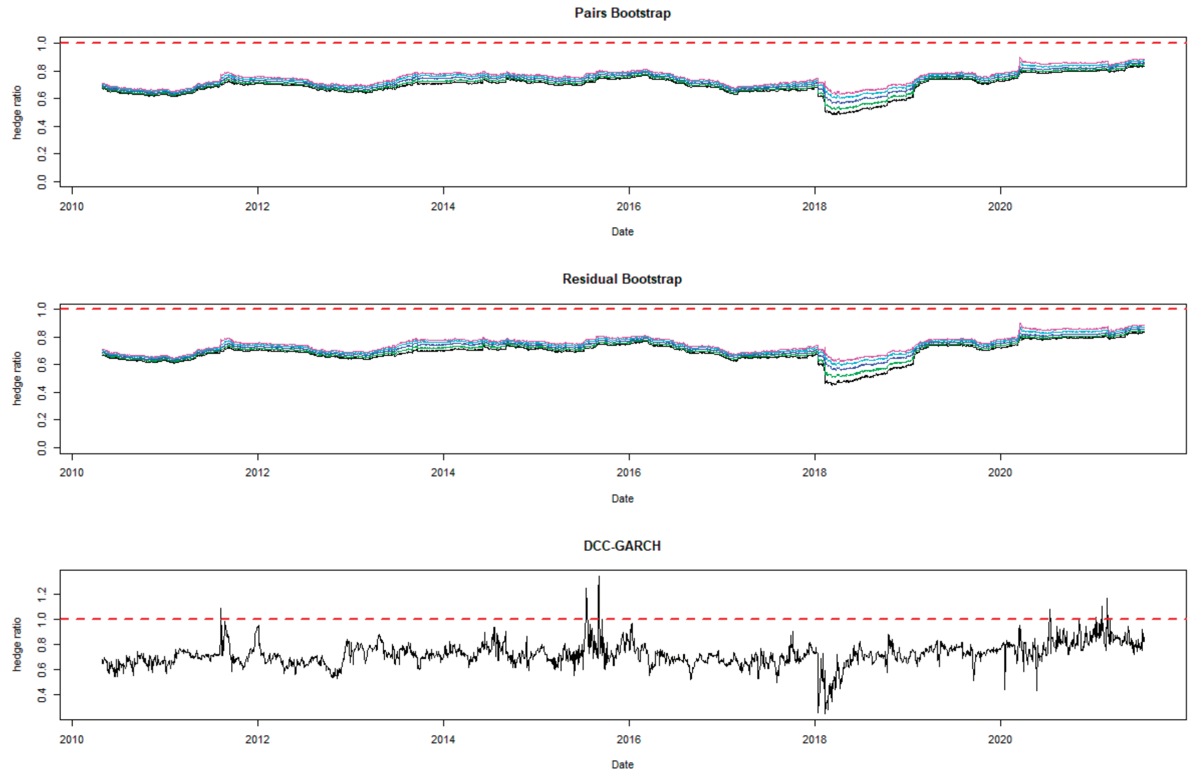

Figure 3. Hedge ratio plots for Emerging Markets index: one-year period rolling sub-sample window. Note: The plots for bootstrap present the 95% confidence band for the optimal hedge ratio. The red horizontal line indicates the hedge ratio of 1.

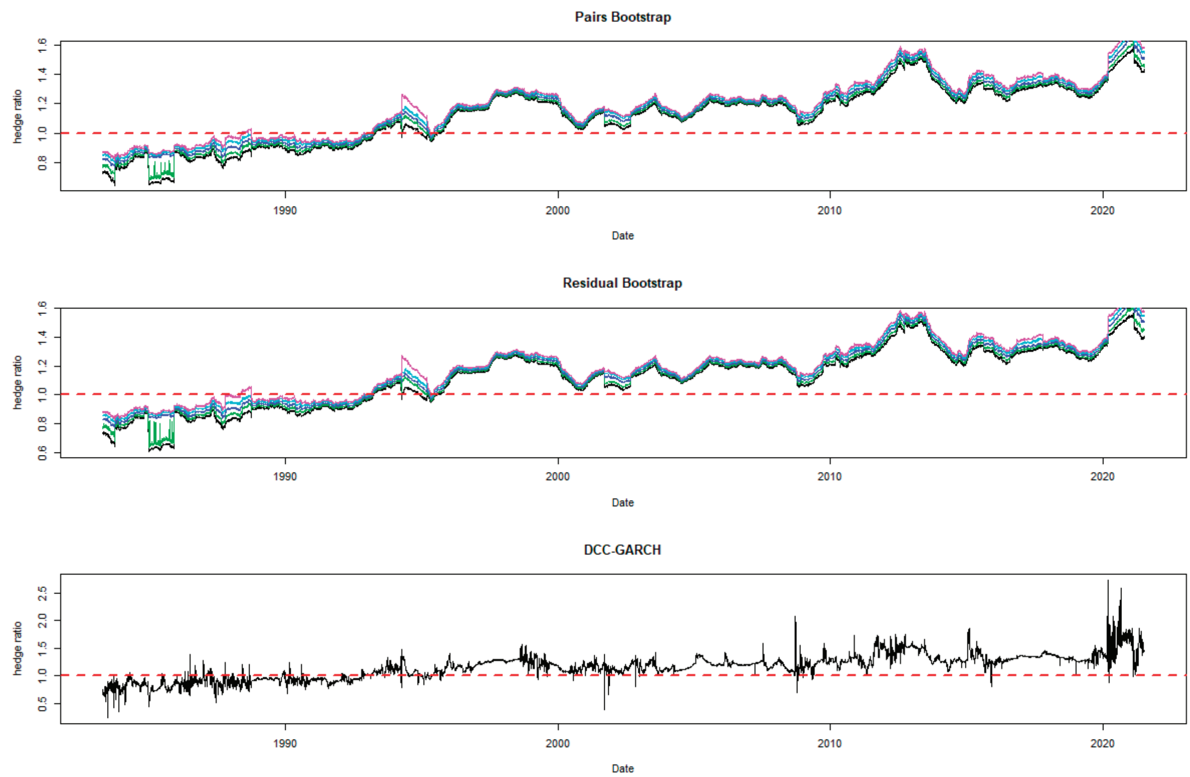

Figure 4. Hedge ratio plots for BOND: one-year period rolling sub-sample window.

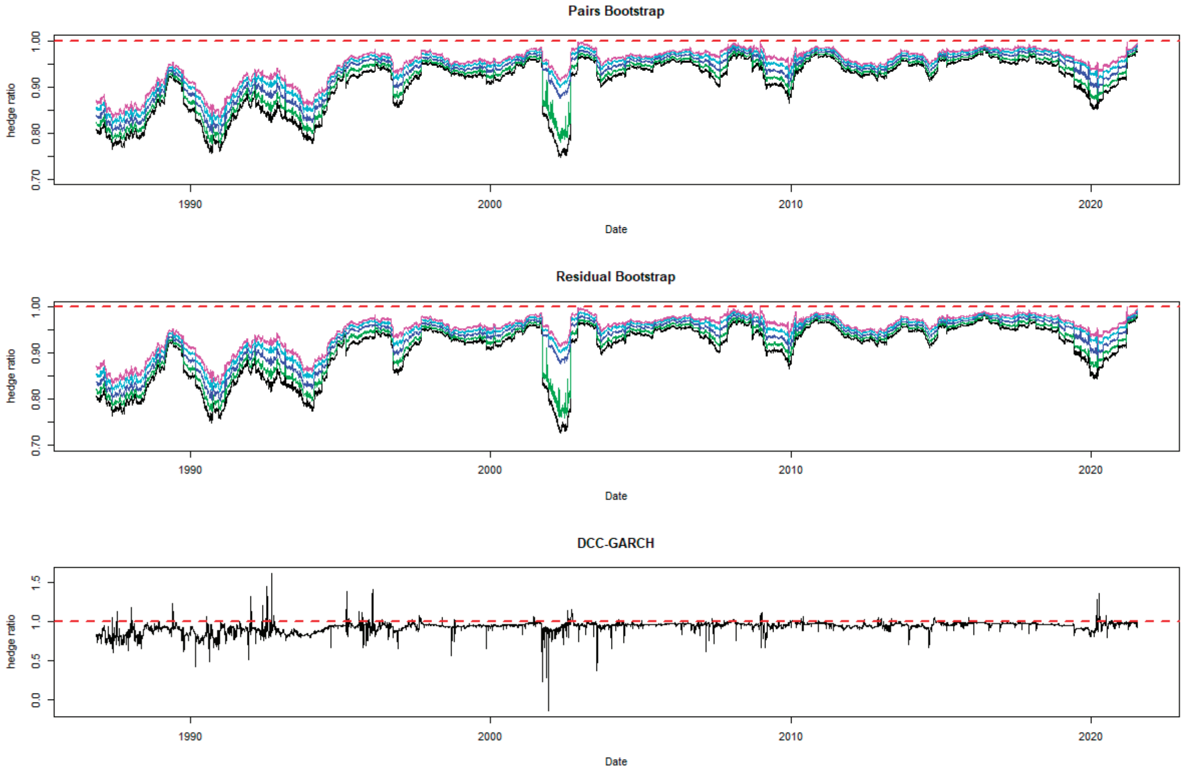

Figure 5. Hedge ratio plots for the US dollar index: one-year period rolling sub-sample window. Note: The plots for bootstrap present the 95% confidence band for the optimal hedge ratio. The red horizontal line indicates the hedge ratio of 1.

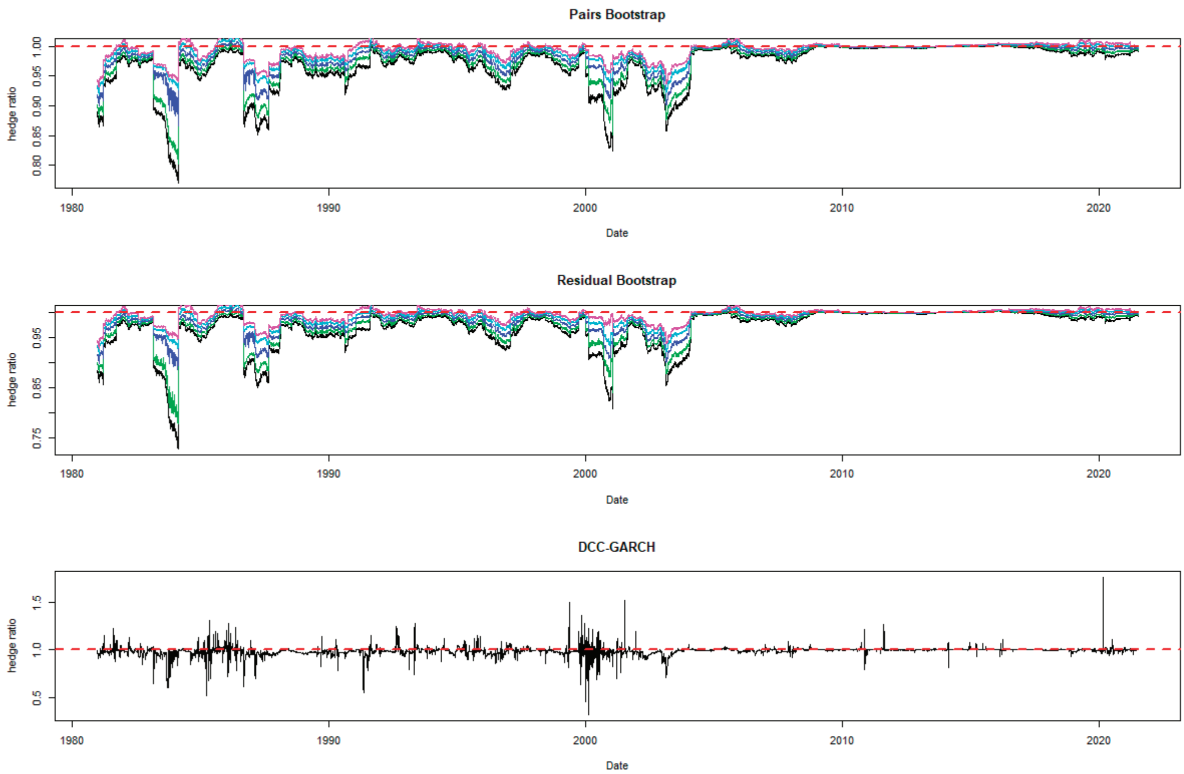

Figure 6. Hedge ratio plots for GOLD: one-year period rolling sub-sample window.

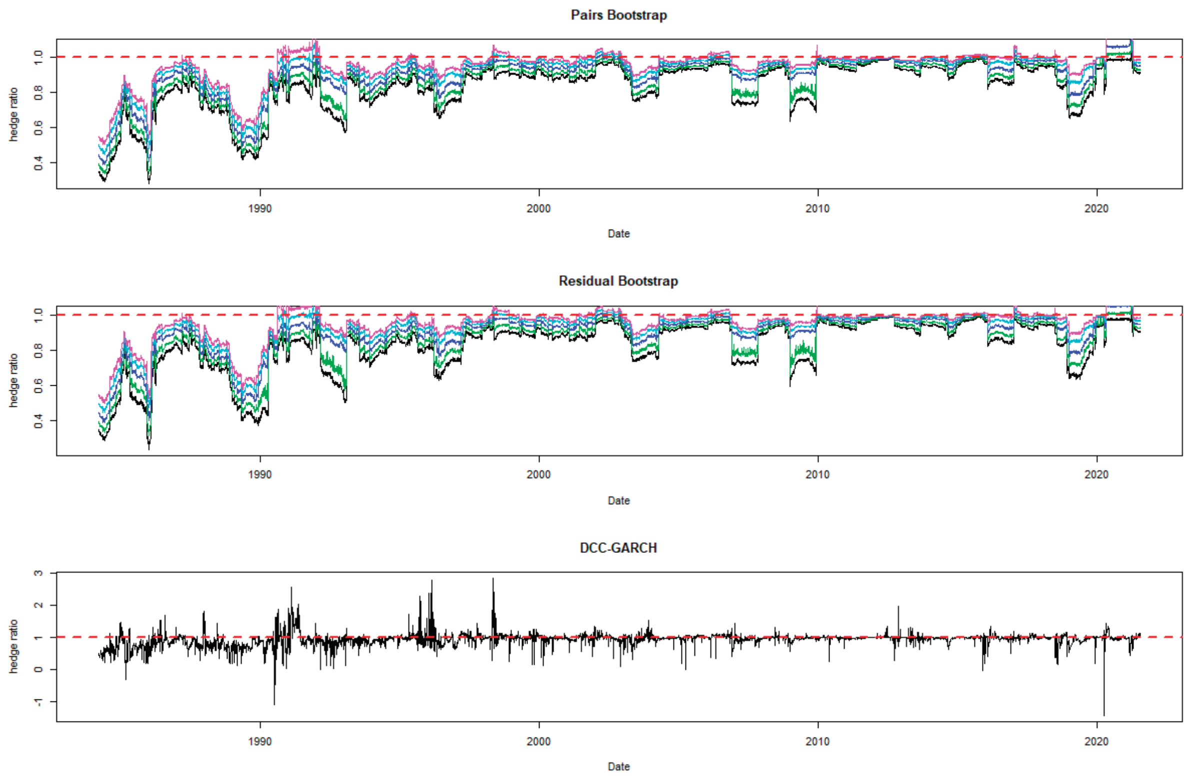

Figure 7. Hedge ratio plots for OIL: one-year period rolling sub-sample window. Note: The plots for bootstrap present the 95% confidence band for the optimal hedge ratio. The red horizontal line indicates the hedge ratio of 1.

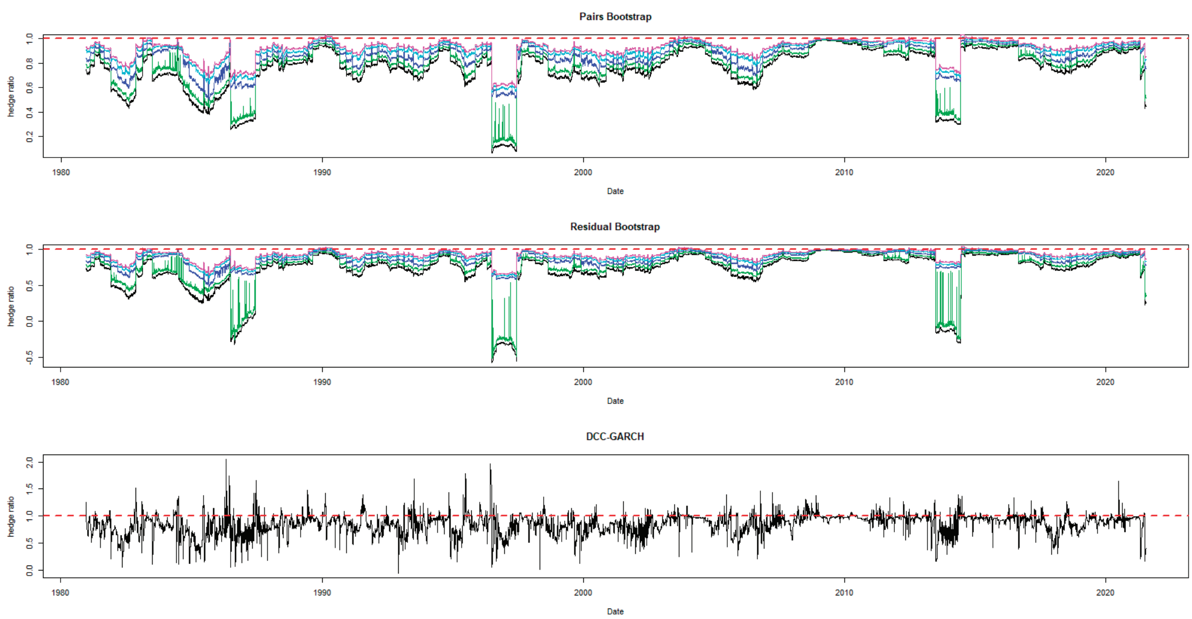

Figure 8. Hedge ratio plots for CORN: one-year period rolling sub-sample window.

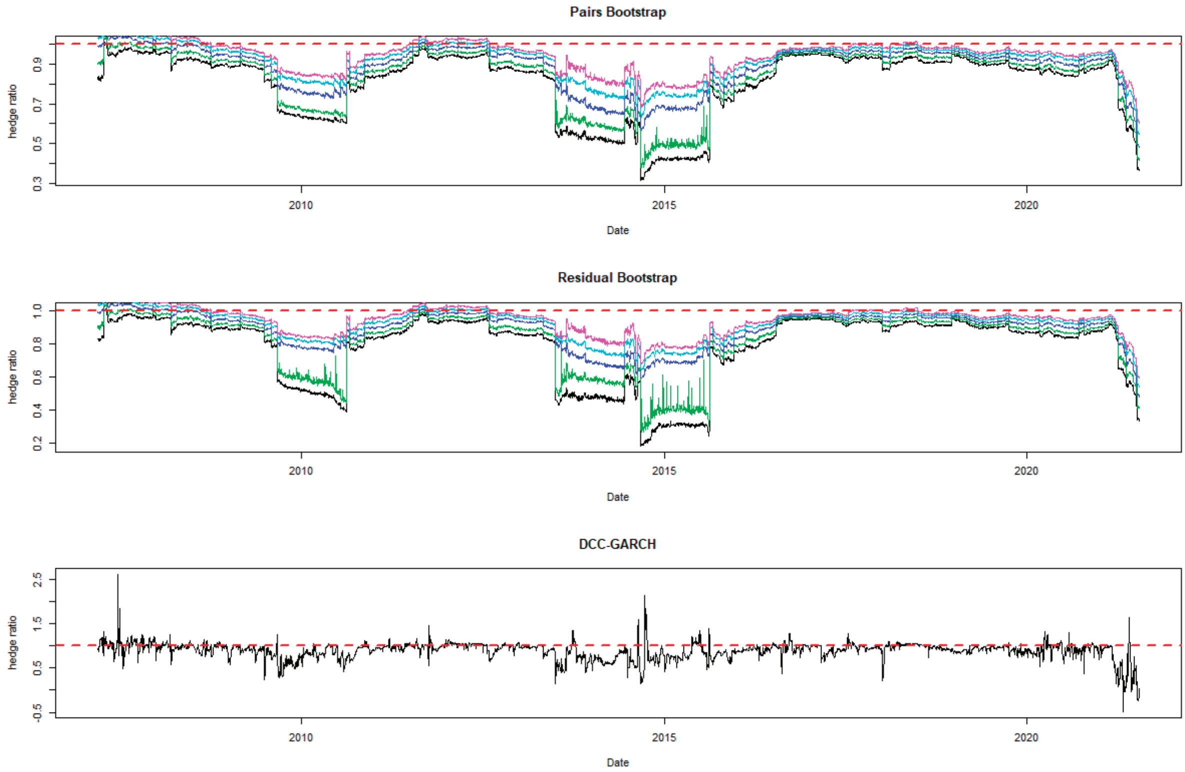

Figure 9. Hedge ratio plots for SOYBEAN: one-year period rolling sub-sample window. Note: The plots for bootstrap present the 95% confidence band for the optimal hedge ratio. The red horizontal line indicates the hedge ratio of 1.

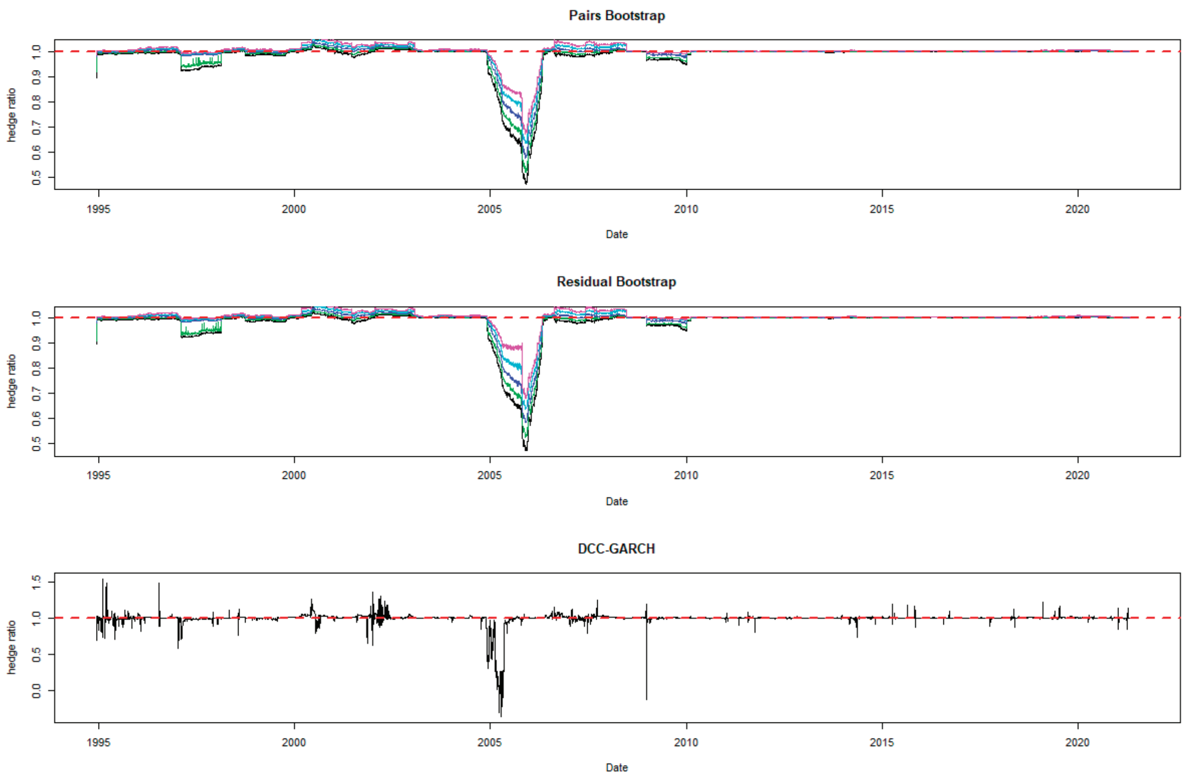

Figure 10. Hedge ratio plots for NICKEL: one-year period rolling sub-sample window. Note: The plots for bootstrap present the 95% confidence band for the optimal hedge ratio. The red horizontal line indicates the hedge ratio of 1.

Another advantage of presenting the 95% wild bootstrap confidence band is that the hedger can conduct a test for statistical significance (see Kim and Robinson 2019). For example, if the confidence band does not cover the value of 1, we cannot accept the null hypothesis that the MVHR is equal to one, at the 5% level of significance. This suggests that the MVHR is statistically different from the naïve hedge ratio. Our empirical results show that, for most of the assets, the MVHR is statistically different from 1 frequently over time at the 5% level of significance. For the US dollar and the Emerging Markets indexes, the naïve strategy has never been optimal over the entire study period at the 5% level of significance, since the 95% wild bootstrap confidence bands do not cover 1. However, the wild bootstrap confidence bands of the MVHR for gold and nickel have become tighter and increasingly convergent to 1 after 2010. The two alternative bootstrap confidence intervals appear to show a similar pattern over time, but the one based on the pairs bootstrap is slightly more stable overall. Comparing the width of the bootstrap confidence band, the time-varying degree of uncertainty associated can be assessed. A wider band indicates a higher degree of uncertainty in estimation. It is likely that the width changes depending on the prevailing market conditions that drive the degree of risk. We observe tighter confidence interval bands of MVHRs for the financial assets such as equities and bonds than the commodities (excluding nickel) and the US dollar. Particularly, the confidence interval plots of the MVHRs for gold, oil, corn and soybean show a high degree of estimation risk. This may be explained by more complicated fundamentals affecting most of the commodities' spot and futures markets (Wu et al. 2011), especially the global supply and demand (Ai et al. 2006; Groen and Pesenti 2010; Gorton et al. 2013), effects of US dollar strength (Akram 2009), speculative activities (Park and Shi 2017), and active positions of hedge funds in both commodity and equity futures markets (Gorton et al. 2013; Büyükşahin and Robe 2014).

High degrees of estimation uncertainty of the MVHR for most of the included assets obviously appear in some common periods: 1987–1988 (effect of Black Monday), 1992–1993 (European Currency crisis), 1997–1998 (Asian Financial crisis), 2001–2003 (Dot-com bubble which triggered a sharp fall in the US dollar index), 2007–2010 (the US Subprime Housing crisis and the subsequent Global Financial crisis), and the recent health-induced crisis during 2019–2020. These turbulent episodes have influenced not only the US market but also impacted the global financial markets. However, gold appears to be an exception among the analyzed asset classes, and especially during and after the crisis starting in 2007. This may represent the popularity of gold as a safe haven asset, as discussed and investigated by Nguyen and Liu (2017).

5.2. Comparing the Hedging Effectiveness and the Robustness Checks

A hedged portfolio is constructed by taking a combined position in spot and futures returns of an asset in order to minimize the exposed risk in the physical market, using the MVHRs obtained from the alternative methods. The hedged returns in percentage are calculated daily.

We refer to the values of SV, HE, IQ, and the 95% range in Table 3 to infer downside risk, variance reduction and the variability in the hedged returns across the included assets. We first compare the hedging effectiveness between the bootstrap percentile-based methods with the naïve strategy. The bootstrap percentile-based strategies outperform the naïve hedge for most of the assets, excluding gold, oil, and nickel where similar hedging effectiveness are found. Noticeably, the naïve strategy performs worst for hedging the Emerging Markets risk. Overall, the variance reduction associated with the naïve hedge is around 1–12% lower than that for the wild bootstrap percentile-based hedge across the asset markets.

Table 3. Statistics for the hedged portfolio returns and hedging effectiveness.

S&P 500	Mean	Variance	SV	HE	IQ	95% Range
Unhedged	0.0336	1.2636	1.1794		0.9469	4.3848
Naïve	0	0.0976	0.3148	92.28%	0.2288	1.0864
DCC	0.0039	0.0868	0.2975	93.13%	0.2299	1.0730
Resid10th	0.0052	0.0747	0.2757	94.09%	0.2350	1.0836
Resid25th	0.0047	0.0734	0.2723	94.19%	0.2314	1.0548
Resid50th	0.0036	0.0748	0.2778	94.08%	0.2276	1.0334
Resid75th	0.0031	0.0754	0.2790	94.03%	0.2271	1.0291
Resid90th	0.0026	0.0765	0.2808	93.95%	0.2276	1.0256
Pair10th	0.0047	0.0751	0.2791	94.06%	0.2342	1.0775
Pair25th	0.0043	0.0741	0.2760	94.14%	0.2310	1.0551
Pair50th	0.0037	0.0740	0.2755	94.14%	0.2274	1.0348
Pair75th	0.0032	0.0745	0.2764	94.10%	0.2269	1.0260
Pair90th	0.0027	0.0755	0.2782	94.03%	0.2269	1.0243
EMERGING	Mean	Variance	SV	HE	IQ	95% range
Unhedged	0.0184	0.6626	0.8782		0.8454	3.2273
Naïve	−0.0001	0.1480	0.3637	77.66%	0.3966	1.5015
DCC	0.0049	0.0733	0.2728	88.94%	0.2887	1.0673
Resid10th	0.0045	0.0724	0.2768	89.07%	0.2970	1.0455
Resid25th	0.0044	0.0709	0.2730	89.30%	0.2903	1.0390
Resid50th	0.0043	0.0701	0.2696	89.42%	0.2908	1.0426
Resid75th	0.0041	0.0702	0.2693	89.41%	0.2898	1.0411
Resid90th	0.0040	0.0711	0.2684	89.27%	0.2904	1.0552
Pair10th	0.0045	0.0719	0.2760	89.15%	0.2971	1.0358
Pair25th	0.0044	0.0708	0.2726	89.31%	0.2901	1.0392
Pair50th	0.0043	0.0701	0.2697	89.42%	0.2910	1.0414
Pair75th	0.0042	0.0702	0.2695	89.41%	0.2895	1.0361
Pair90th	0.0039	0.0710	0.2684	89.28%	0.2912	1.0522
BOND	Mean	Variance	SV	HE	IQ	95% range
Unhedged	0.0056	0.2064	0.4534		0.5087	1.8519
Naïve	−0.0090	0.0245	0.1581	88.13%	0.1412	0.6057
DCC	−0.0096	0.0193	0.1400	90.65%	0.1045	0.5289
Resid10th	−0.0094	0.0193	0.1382	90.65%	0.1074	0.5378
Resid25th	−0.0097	0.0189	0.1368	90.84%	0.1054	0.5344
Resid50th	−0.0101	0.0184	0.1351	91.09%	0.1043	0.5246
Resid75th	−0.0103	0.0184	0.1355	91.09%	0.1035	0.5171
Resid90th	−0.0105	0.0186	0.1363	90.99%	0.1040	0.5182
Pair10th	−0.0095	0.0191	0.1378	90.75%	0.1074	0.5335
Pair25th	−0.0097	0.0188	0.1364	90.89%	0.1057	0.5320
Pair50th	−0.0101	0.0184	0.1352	91.09%	0.1044	0.5251
Pair75th	−0.0103	0.0184	0.1356	91.09%	0.1033	0.5186
Pair90th	−0.0105	0.0185	0.1362	91.04%	0.1042	0.5184
USD	Mean	Variance	SV	HE	IQ	95% range
Unhedged	−0.0018	0.2549	0.5166		0.5517	2.0872
Naïve	0	0.0166	0.1383	93.49%	0.0539	0.5393
DCC	−0.0010	0.0149	0.1377	94.15%	0.0568	0.5087
Resid10th	−0.0005	0.0152	0.1340	94.04%	0.0614	0.5105
Resid25th	−0.0005	0.0149	0.1335	94.15%	0.0586	0.5098
Resid50th	−0.0004	0.0147	0.1330	94.23%	0.0556	0.4982
Resid75th	−0.0003	0.0147	0.1334	94.23%	0.0535	0.4966
Resid90th	−0.0003	0.0148	0.1340	94.19%	0.0529	0.5028
Pair10th	−0.0005	0.0151	0.1339	94.08%	0.0613	0.5084
Pair25th	−0.0005	0.0149	0.1332	94.15%	0.0586	0.5081
Pair50th	−0.0004	0.0147	0.1330	94.23%	0.0557	0.4969
Pair75th	−0.0003	0.0147	0.1334	94.23%	0.0536	0.4977
Pair90th	−0.0003	0.0148	0.1338	94.19%	0.0531	0.5020

Table 3. *Cont.*

GOLD	Mean	Variance	SV	HE	IQ	95% range
Unhedged	0.0099	1.1599	1.0815		0.9389	4.4309
Naïve	−0.0009	0.0237	0.2560	97.96%	0.0223	0.4043
DCC	−0.0006	0.0261	0.2236	97.75%	0.0308	0.4492
Resid10th	−0.0011	0.0247	0.2250	97.87%	0.0339	0.4789
Resid25th	−0.0011	0.0240	0.2282	97.93%	0.0315	0.4517
Resid50th	−0.0010	0.0235	0.2328	97.97%	0.0283	0.4197
Resid75th	−0.0010	0.0234	0.2376	97.98%	0.0265	0.4093
Resid90th	−0.0010	0.0235	0.2379	97.97%	0.0258	0.4059
Pair10th	−0.0010	0.0245	0.2241	97.89%	0.0339	0.4743
Pair25th	−0.0010	0.0239	0.2279	97.94%	0.0312	0.4475
Pair50th	−0.0010	0.0235	0.2333	97.97%	0.0283	0.4208
Pair75th	−0.0010	0.0234	0.2377	97.98%	0.0266	0.4096
Pair90th	−0.0010	0.0235	0.2382	97.97%	0.0260	0.4058

OIL	Mean	Variance	SV	HE	IQ	95% range
Unhedged	0.0079	7.4613	2.8111		2.2300	9.7561
Naïve	0	1.8557	1.6861	75.13%	0.0730	3.9421
DCC	−0.0029	2.1846	1.5424	70.72%	0.2155	4.2929
Resid10th	0.0003	1.9294	1.4405	74.14%	0.3541	4.2156
Resid25th	−0.0002	1.8729	1.4639	74.90%	0.2909	4.0347
Resid50th	−0.0015	1.8249	1.4464	75.54%	0.2248	3.8982
Resid75th	−0.0050	1.8364	1.5016	75.39%	0.1819	3.9523
Resid90th	−0.0061	1.8679	1.5424	74.97%	0.1528	4.0073
Pair10th	−0.0002	1.9219	1.4996	74.24%	0.3474	4.1064
Pair25th	−0.0006	1.8630	1.4610	75.03%	0.2873	4.0370
Pair50th	−0.0016	1.8227	1.4437	75.57%	0.2263	3.8952
Pair75th	−0.0035	1.8212	1.4804	75.59%	0.1792	3.9072
Pair90th	−0.0045	1.8398	1.5148	75.34%	0.1530	3.9574

CORN	Mean	Variance	SV	HE	IQ	95% range
Unhedged	0.0038	2.1491	1.4207		1.5102	6.1754
Naïve	0	0.4993	0.7173	76.77%	0.0042	1.7181
DCC	−0.0022	0.4823	0.7255	77.56%	0.2464	2.1768
Resid10th	−0.0069	0.6079	0.8125	71.71%	0.3679	2.9273
Resid25th	−0.0060	0.5782	0.7891	73.10%	0.3093	2.7801
Resid50th	−0.0012	0.4536	0.6716	78.89%	0.2136	1.8796
Resid75th	−0.0013	0.4615	0.6817	78.53%	0.1641	1.7830
Resid90th	−0.0013	0.4699	0.6928	78.14%	0.1336	1.7441
Pair10th	−0.0036	0.4870	0.7107	77.34%	0.3457	2.4456
Pair25th	−0.0036	0.4789	0.7030	77.72%	0.2962	2.3239
Pair50th	−0.0017	0.4534	0.6745	78.90%	0.2168	1.9288
Pair75th	−0.0018	0.4620	0.6852	78.50%	0.1621	1.8273
Pair90th	−0.0018	0.4691	0.6956	78.17%	0.1311	1.7817

SOYBEAN	Mean	Variance	SV	HE	IQ	95% range
Unhedged	0.0155	3.1518	1.7304		1.7331	7.4145
Naïve	0.0021	1.1470	0.9109	63.61%	0.1308	3.7792
DCC	−0.0011	1.0919	1.0180	65.36%	0.2542	3.7704
Resid10th	−0.0017	1.0829	1.0525	65.64%	0.3742	3.9539
Resid25th	−0.0017	1.0520	1.0283	66.62%	0.3183	3.7859
Resid50th	−0.0006	1.0056	0.9821	68.09%	0.2409	3.5367
Resid75th	−0.0007	1.0245	0.9763	67.49%	0.1870	3.6052
Resid90th	−0.0005	1.0475	0.9733	66.77%	0.1489	3.6449
Pair10th	−0.0013	1.0321	1.0231	67.25%	0.3590	3.7438
Pair25th	−0.0009	1.0213	1.0073	67.60%	0.3085	3.6931
Pair50th	−0.0005	1.0078	0.9846	68.02%	0.2447	3.5657
Pair75th	−0.0005	1.0256	0.9747	67.46%	0.1898	3.6315
Pair90th	−0.0006	1.0480	0.9720	66.75%	0.1501	3.6661

Table 3. *Cont.*

NICKEL	Mean	Variance	SV	HE	IQ	95% range
Unhedged	0.0115	4.5584	2.0992		2.3105	8.5971
Naïve	0.0001	0.1727	0.4684	96.21%	0.0296	0.6895
DCC	0.0007	0.1354	0.4047	97.03%	0.0352	0.8080
Resid10th	0.0011	0.1758	0.4392	96.14%	0.0388	0.9508
Resid25th	0.0009	0.1743	0.4428	96.18%	0.0364	0.9208
Resid50th	0.0009	0.1735	0.4527	96.19%	0.0347	0.8941
Resid75th	0.0010	0.1729	0.4547	96.21%	0.0348	0.8680
Resid90th	0.0011	0.1733	0.4523	96.20%	0.0358	0.8097
Pair10th	0.0011	0.1757	0.4389	96.15%	0.0388	0.9442
Pair25th	0.0009	0.1742	0.4429	96.18%	0.0365	0.9212
Pair50th	0.0009	0.1733	0.4522	96.20%	0.0346	0.8921
Pair75th	0.0009	0.1730	0.4557	96.20%	0.0348	0.8728
Pair90th	0.0009	0.1731	0.4541	96.20%	0.0360	0.8413

Note: SV: semi-variance given in (8); HE: hedging effectiveness given in (7). IQ: inter-quartile range; 95% range: difference between 97.5th and 2.5th percentiles. Pair#th represents the confidence interval percentile at 10th, 25th, 50th, 75th, and 90th of the hedge ratio distribution using the pairs bootstrap method. Resid#th represents the confidence interval percentile at 10th, 25th, 50th, 75th, and 90th of the hedge ratio distribution using the residual bootstrap method.

We proceed to comparing the hedging performance between the wild bootstrap approach and the DCC-GARCH model. The bootstrap percentile-based strategies show better hedging effectiveness in terms of higher variance reduction and lower downside risk for the S&P 500, Emerging Markets, oil, soybeans, and corn. The DCC-GARCH strategy shows the worst performance for hedging the oil price risk but appear to be a better model for hedging the price risk of nickel. Compared to the DCC-GARCH model, the bootstrap percentile-based strategies provide around 0.5–5% higher variance reduction with lower downside risks indicated by SV across the assets.

In general, the bootstrap percentile-based hedge ratios, especially at the 25th, 50th, and 75th percentiles of the bootstrap distribution[7], which may be regarded as the defensive, neutral, and aggressive strategies, respectively, provide better hedging effectiveness. As for the point estimator, the 50th percentile (the median of the bootstrap distribution) may be preferred to the OLS-based optimal hedge ratio, since it is not influenced by extreme observations or outliers. Furthermore, the variance reduction in the hedged portfolio returns using the pairs bootstrap method is marginally higher than the residual bootstrap method, especially for corn.

To check the robustness of the superior performance of the wild bootstrap methods, we employ the statistical tests of SD as described in Section 3 for all pairs of the hedging strategies and across the asset markets. Particularly, we test for both first-order and second-order dominance relationships. We desire to test which of the hedging strategies yield a return distribution with larger benefit and lower risk. Table 4 summarizes the outcomes of the SD tests. We find statistical evidence of stochastic dominance for S&P 500 and Emerging Markets hedges but inconclusive results for the other assets. This means the alternative hedging approaches yield similar benefits with overlapping risk–return distributions, and thus the naïve strategy is still plausible given its simplicity and stability (Wang et al. 2015). However, we find that the wild bootstrap methods are second-order dominant over the naïve strategy for the included equity markets. Particularly, at least there is one percentile in the bootstrap confidence interval of the MVHR having a lower tail risk of the hedge distribution for the S&P 500 and Emerging Markets indices compared to the naïve. On the other hand, we find stochastic dominance of the bootstrap percentile-based hedging over the DCC-GARCH model only for the S&P 500 index at the 10th and 25th percentiles. Similarly, the wild bootstrap methods appear to provide a safer hedge with lower left-tail risk in hedged returns than the DCC-GARCH model.

Table 4. Statistical dominance test of the hedged return distributions among the hedging strategies.

Panel A: Hedging for S&P 500								
Dominance	Naïve	DCC	Pair10th	Pair25th	Pair50th	Pair75th	Pair90th	
Naïve								
DCC	Inconclusive							
Pair10th	Pair10th $\geq_2$ Naïve	Pair10th $\geq_2$ DCC						
Pair25th	Pair25th $\geq_2$ Naïve	Pair25th $\geq_2$ DCC	Inconclusive					
Pair50th	Pair50th $\geq_2$ Naïve	Inconclusive	Inconclusive	Inconclusive				
Pair75th	Pair75th $\geq_2$ Naïve	Inconclusive	Inconclusive	Inconclusive	Inconclusive			
Pair90th	Pair90th $\geq_2$ Naïve	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive		
Dominance	Naïve	DCC	Resid10th	Resid20th	Resid50th	Resid75th	**Resid90th**	
Naïve								
DCC	Inconclusive							
Resid10th	Resid10th $\geq_2$ Naïve	Resid10th $\geq_2$ DCC						
Resid25th	Resid25th $\geq_2$ Naïve	Resid25th $\geq_2$ DCC	Inconclusive					
Resid50th	Resid50th $\geq_2$ Naïve	Inconclusive	Inconclusive	Inconclusive				
Resid75th	Resid75th $\geq_2$ Naïve	Inconclusive	Inconclusive	Inconclusive	Inconclusive			
Resid90th	Resid90th $\geq_2$ Naïve	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Resid75th $\geq_2$ Resid90th		
Panel B: Hedging for Emerging Markets								
Dominance	Naïve	DCC	Pair10th	Pair25th	Pair50th	Pair75th	Pair90th	
Naïve								
DCC	Inconclusive							
Pair10th	Inconclusive	Inconclusive						
Pair25th	Inconclusive	Inconclusive	Inconclusive					
Pair50th	Inconclusive	Inconclusive	Inconclusive	Inconclusive				
Pair75th	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive			
Pair90th	Pair90th $\geq_2$ Naïve	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive		
Dominance	Naïve	DCC	Resid10th	Resid20th	Resid50th	Resid75th	Resid90th	
Naïve								
DCC	Inconclusive							
Resid10th	Inconclusive	Inconclusive						
Resid25th	Inconclusive	Inconclusive	Inconclusive					
Resid50th	Inconclusive	Inconclusive	Inconclusive	Inconclusive				
Resid75th	Resid75th $\geq_2$ Naïve	Inconclusive	Inconclusive	Inconclusive	Inconclusive			
Resid90th	Resid90th $\geq_2$ Naïve	Inconclusive	Inconclusive	Inconclusive	Inconclusive	Inconclusive		

Note: The stochastic dominance test outcomes are based on the comparison between the bootstrapped p-value (see Barrett and Donald 2003) and the significance level of 5%. Pair#th represents the confidence interval percentile at 10th, 25th, 50th, 75th, and 90th of the hedge ratio distribution using the pairs bootstrap method. Resid#th represents the confidence interval percentile at 10th, 25th, 50th, 75th, and 90th of the hedge ratio distribution using the residual bootstrap method.

To further check the sensitivity of our findings to the data quality and the estimation windows, the rolling window is reduced to the 6-month period and then increased to the 2-year period. We repeat our estimation and testing procedures and our findings generally hold. When the information is reduced for the model estimation, the wild bootstrap methods are still stochastically second-order dominant over the DCC-GARCH model for the two equity markets, indicating a lower risk of big losses. However, the bootstrap approach's superiority over the naïve strategy does hold for the case of hedging the Emerging Markets index only. When the estimation window is doubled, the dominance of our proposed bootstrap approach still holds in hedging both equity indices. Compared to the wild bootstrap hedging strategy based on resampling the residuals of the regression model, it is noted that the one based on resampling the pairs of observations provides a safer hedged return distribution with lower left-tail risk in five out of nine assets. This suggests that the endogeneity issue in the estimation of the optimal hedge ratio may play a role, since the spot and futures returns are both possibly affected by the same shocks.

6. Conclusions

The paper proposes a new method of hedging based on the percentiles of the MVHR's bootstrap distribution. The proposed method is simple since it is OLS-based but provides a range of possible hedging strategies within the 95% confidence interval for the optimal hedge ratio. In line with Kim and Robinson (2019), it is more informative than the conventional hedging based on a single-point estimate, since the interval hedging strategy provides a hedger with a clear sense of estimation uncertainty and a range of alternative strategies, with a prescribed level of confidence. In order to estimate the percentiles of the MVHR distribution, the wild bootstrap (the one based on residual resampling and the other based on pairs resampling) is employed. This method is non-parametric for approximating the sampling distribution of a statistic based on repeated data resampling. The wild bootstrap percentiles exhibit a range of desirable features: firstly, being robust to influential outliers; and secondly, robust to non-normality and unknown forms of heteroskedasticity[8]. These hedging strategies are then compared to those based on the naïve method and the DCC-GARCH model with an asymmetric specification, adopting 250-day rolling sub-sample windows.

Hedging effectiveness among the alternative approaches is evaluated for a range of assets using the daily spot and futures prices from 1980. The estimation uncertainty of the MVHR is exhibited by varying width of the wild bootstrap confidence intervals during the historical turbulent periods of financial and commodity market activity. The DCC-GARCH hedge ratios are found to fluctuate in a highly volatile manner due to the specification issue, in comparison with the bootstrap percentile-based alternatives. The high volatility of the DCC-GARCH estimates adversely impact the hedging position and increase the uncertainty in hedging.

Overall, the hedging strategies based on the wild bootstrap percentiles[9] are found to outperform those based on the DCC-GARCH model and the naïve hedge in terms of the hedging effectiveness, downside risk, and hedged return variability at least for hedging the equity market price risks. Our results are robust to stochastic dominance tests using bootstrap simulations and using different estimation windows. In particular, hedging strategies based on the central percentiles (the 25th, 50th, and 75th) demonstrate desirable hedging performance. The two alternative bootstrap methods perform similarly in hedging effectiveness, but the one based on resampling the pairs of observations provides a safer hedged return distribution with a lower risk of big losses. This may indicate the importance of the endogeneity issue in estimation, which is widely neglected in previous studies. While the conventional hedging methods rely solely on the point estimate of the MVHR, this paper represents the first study that proposes hedging based on the confidence interval or percentile estimation. The latter is associated with a richer information content across a range of alternative hedging strategies, which can lead to safer and more informed risk management.

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Notes

1 The naïve strategy is static with a hedge ratio of 1, taking a hedging position in a futures contract equal to the exact exposure in the spot market.

2 h_i is the ith diagonal element of the orthogonal projection matrix $\mathrm{H} = \mathrm{R_F}\left(\mathrm{R}'_\mathrm{F}\mathrm{R_F}\right)^{-1}\mathrm{R}'_\mathrm{F}$ (see Long and Ervin 2000).

3 The length of the time window is constructed for rebalancing needs of a portfolio for every 12 months when the portfolio manager can revise their hedging position based on the time-varying spot–futures relationship. Choosing the time window length also facilitates the convergence issue of the rolling DCC-GARCH model.

4 The US dollar index, which has existed since 1973, is a geometrically weighted average of a basket of six currencies against the US dollar, i.e., British pound, Canadian dollar, the Euro, Japanese yen, Swedish krona, and Swiss franc. Since the US dollar is freely floated against all other foreign currencies, the Federal Reserve Bank initiated the measure of the US dollar index to provide an external bilateral trade-weighted average of the US dollar.

5 The continuous futures indices are a perpetual series of futures prices, volumes, and open interest derived from individual futures contracts. They start at the nearest contract month, which forms the first price values for the continuous series until either the contract reaches its expiry date or until the first business day of the notional contract month, whichever is sooner. At this point, prices from the next trading contract month are taken. No adjustment for price differentials is made. Thomson Reuters DataStream provides the methodology.

6 Estimation of the MVHRs based on the proposed methods is processed in R. Interested readers can find the R codes by clicking on the linked Online Appendix.

7 As suggested by an anonymous referee, interested readers and practitioners are encouraged to try different percentiles other than the ones used in this paper to find the most suitable hedging position. It is subject to underlying assets, market conditions, estimation uncertainty, confidence level, and computing resources.

8 An alternative solution to the consequential effects of the outliers or leverage points is the robust regression technique (Knez and Ready 1997; Martin and Xia 2022). However, our wild bootstrap approach is more informative and effective by estimating a confidence interval of the optimal hedge ratio for various time windows and offering a range of possible alternatives based on the estimated percentiles.

9 Maximum entropy bootstrap ("meboot") is a powerful alternative bootstrap method to deal with endogeneity issue in the relationship between non-stationary spot and futures return data (Zanjani et al. 2021).

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Adaptive Conformal Inference for Computing Market Risk Measures: An Analysis with Four Thousand Crypto-Assets

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Abstract: This paper investigates the estimation of the value at risk (VaR) across various probability levels for the log-returns of a comprehensive dataset comprising four thousand crypto-assets. Employing four recently introduced adaptive conformal inference (ACI) algorithms, we aim to provide robust uncertainty estimates crucial for effective risk management in financial markets. We contrast the performance of these ACI algorithms with that of traditional benchmark models, including GARCH models and daily range models. Despite the substantial volatility observed in the majority of crypto-assets, our findings indicate that ACI algorithms exhibit notable efficacy. In contrast, daily range models, and to a lesser extent, GARCH models, encounter challenges related to numerical convergence issues and structural breaks. Among the ACI algorithms, Fully Adaptive Conformal Inference (FACI) and Scale-Free Online Gradient Descent (SF-OGD) stand out for their ability to provide precise VaR estimates across all quantiles examined. Conversely, Aggregated Adaptive Conformal Inference (AgACI) and Strongly Adaptive Online Conformal Prediction (SAOCP) demonstrate proficiency in estimating VaR for extreme quantiles but tend to be overly conservative for higher probability levels. These conclusions withstand robustness checks encompassing the market capitalization of crypto-assets, time-series size, and different forecasting methods for asset log-returns. This study underscores the promise of ACI algorithms in enhancing risk assessment practices in the context of volatile and dynamic crypto-asset markets.

Keywords: value at risk (VaR); adaptive conformal inference (ACI); Aggregated Adaptive Conformal Inference (AgACI); Fully Adaptive Conformal Inference (FACI); Scale-Free Online Gradient Descent (SF-OGD); Strongly Adaptive Online Conformal Prediction (SAOCP); GARCH; daily range; risk management

1. Introduction

In the realm of predictive modeling and decision making, accurately quantifying uncertainty is as crucial as making accurate predictions themselves. This need for robust uncertainty estimation becomes particularly pronounced in high-stakes scenarios, where the consequences of erroneous decisions can be significant. One widely accepted approach for quantifying uncertainty is through the utilization of prediction sets, which associate each prediction with a range of potential outcomes, thereby providing a measure of the model's confidence in its predictions.

Conformal inference, introduced by Vovk et al. (2005) and Shafer and Vovk (2008), offers a powerful framework for enhancing predictive models by constructing valid prediction sets with coverage guarantees. Unlike traditional methods that rely heavily on specific assumptions about data distributions, conformal prediction imposes minimal assumptions, primarily requiring exchangeability of the data; see Angelopoulos and Bates (2023) for a recent survey. However, in many real-world scenarios, such as time-series data or instances of distributional shift, the assumption of exchangeability may not hold, necessitating the development of adaptive techniques to handle such complexities.

Recent advancements in conformal inference have led to the emergence of adaptive conformal inference (ACI) algorithms, designed explicitly to address scenarios where data arrive sequentially, without assuming exchangeability. These algorithms dynamically adjust the width of prediction intervals in response to observed data, thereby providing adaptive and accurate uncertainty quantification. Notably, ACI algorithms have been shown to be effective in various domains, including financial forecasting, epidemiology, and image classification.

Motivated by the success of ACI algorithms in handling sequential data, we turn our attention to the task of forecasting the value at risk (VaR) using adaptive conformal inference techniques. The VaR, a measure of the maximum potential loss that an investment portfolio may face over a specified time horizon, is of paramount importance in risk management across financial institutions and investment firms. Moreover, Emmer et al. (2015) and Kratz et al. (2018) showed that the expected shortfall (ES)[1] can be backtested through the approximation of several VaR estimates computed at different probability levels using a multinomial test. Accurate risk estimation is critical for ensuring financial stability and making informed investment decisions.

In this paper, we explore an innovative application of adaptive conformal inference (ACI) methods, traditionally employed for generating prediction intervals in machine learning, to the domain of financial risk management, specifically for estimating value-at-risk (VaR) measures. While ACI methods have been predominantly used to construct robust confidence intervals around mean predictions, we adapt these methods to provide precise point estimates for tail quantiles. This adaptation leverages the ability of ACI to dynamically adjust prediction intervals based on the observed data, which is particularly useful in capturing the extreme quantiles necessary for accurate VaR estimation.

The conventional use of ACI methods involves creating prediction intervals for a given mean prediction model, adjusting the interval widths based on whether recent predictions have been included or excluded within these intervals. This adaptive mechanism ensures that the prediction intervals remain reliable over time, even as the underlying data distribution shifts. In our work, we repurpose this adaptive mechanism to estimate the quantiles of the prediction errors, which are then combined with point forecasts from a simple mean prediction model. This approach allows us to accurately predict the tail quantiles, which correspond to the VaR measures. By clearly delineating this novel application of ACI methods, we provide a fresh perspective on how these techniques can be utilized beyond their traditional scope. Our main interest lies not in constructing prediction intervals around mean forecasts, but in obtaining accurate point estimates for tail quantiles directly. This focus on quantile estimation for VaR calculation is crucial for effective financial risk management, where understanding the behavior of extreme values is more relevant than the central tendency. Thus, our work bridges the gap between robust prediction interval methodologies and the specific needs of financial risk estimation, offering a valuable contribution to the field.

Specifically, we explore the application of various ACI algorithms, including Aggregated ACI by Zaffran et al. (2022), Fully Adaptive Conformal Inference by Gibbs and Candès (2022), Scale-Free Online Gradient Descent by Bhatnagar et al. (2023), and Strongly Adaptive Online Conformal Prediction by Bhatnagar et al. (2023), in the context of VaR prediction. These algorithms offer different approaches to adaptively adjusting prediction intervals, thereby catering to diverse modeling requirements and data characteristics.

The primary objectives in this study are twofold. First, we aim to conduct a comprehensive empirical evaluation to assess the performance and applicability of the proposed ACI algorithms in VaR prediction tasks, to evaluate whether these methodologies can ensure accurate and reliable estimation of uncertainty in financial risk assessment. Secondly, we perform a wide range of robustness checks to verify that the results for the baseline case also hold in different settings. Therefore, we perform a series of checks considering the market capitalization of crypto-assets, time-series size, and different forecasting methods for asset log-returns.

In the rapidly evolving landscape of cryptocurrencies, understanding risk measures is crucial for both investors and regulators. Previous empirical works have often focused on the most capitalized cryptocurrencies, such as Bitcoin and Ethereum, due to their high liquidity and significant market impact. However, the cryptocurrency market is highly diverse, encompassing assets with varying degrees of liquidity, capitalization, and investor profiles. It is for this reason that this paper aims to address this diversity by analyzing a comprehensive dataset of 4000 cryptocurrencies. This broad scope allows us to capture a wide range of market behaviors and dynamics, providing a more holistic view of risk measures across the entire cryptocurrency spectrum. By including assets with different characteristics, we can derive more robust and generalizable conclusions about the effectiveness of adaptive conformal inference (ACI) methods for computing market risk measures.

The remainder of this paper is organized as follows. In Section 2, we review the literature devoted to adaptive conformal inference algorithms, while Section 3 presents a description of the ACI algorithms under consideration, highlighting their key features and theoretical properties. Subsequently, in Section 4, we conduct extensive empirical evaluations with four thousand crypto-assets to compare the performance of these algorithms in VaR forecasting tasks, together with robustness checks. Finally, Section 5 summarizes our findings and outlines directions for future research in this domain.

2. Literature Review

Conformal inference (CI), originally proposed by Vovk et al. (1999) and Vovk et al. (2005), has emerged as a versatile framework for constructing prediction intervals around point predictions, facilitating robust uncertainty quantification across various domains (Angelopoulos and Bates 2023). It has garnered significant attention for its utility in uncertainty quantification in regression and classification tasks; see Papadopoulos (2008), Lei et al. (2013), Lei and Wasserman (2014), Vovk et al. (2018), Romano et al. (2019, 2020), Cauchois et al. (2021), and Barber et al. (2021) for several examples and detailed discussions.

However, traditional CI methods operate under the assumption of data exchangeability, wherein the joint distribution of observations remains invariant to their order. However, real-world datasets often deviate from this assumption, particularly in scenarios involving temporal dependence, such as time-series data; see Gibbs and Candès (2021, 2022), Zaffran et al. (2022), and Bhatnagar et al. (2023). In this regard, several extensions of conformal prediction techniques have addressed challenges related to distribution shift, employing methods such as reweighting and distributionally robust optimization to maintain approximately valid coverage; see Tibshirani et al. (2019), Podkopaev and Ramdas (2021), Yang et al. (2022), and Barber et al. (2023).

A recent line of research within the CI framework focuses on adaptive conformal inference (ACI) algorithms, designed to handle non-exchangeable data by dynamically adjusting prediction intervals based on observed data (Gibbs and Candès 2021). The original ACI algorithm introduces a learning rate parameter to control the rate of adaptation, with subsequent research exploring meta-algorithms to optimize this parameter. Notable ACI algorithms include the Aggregated ACI by Zaffran et al. (2022), the Fully Adaptive Conformal Inference by Gibbs and Candès (2022), the Scale-Free Online Gradient Descent by Bhatnagar et al. (2023), and the Strongly Adaptive Online Conformal Prediction by Bhatnagar et al. (2023).

Alternative lines of research have also started to explore the application of conformal prediction to time-series data by using randomization, ensembles, and other meta-algorithms to produce valid prediction sets (Chernozhukov et al. 2018; Sousa et al. 2022; Xu and Xie 2021). Other approaches include simply using vanilla conformal prediction for time series without theoretical guarantees or resorting to weaker notions of exchangeability; see Dashevskiy and Luo (2008), Wisniewski et al. (2020), Stankeviciute et al. (2021), and Kath and Ziel (2021). To keep track of the latest developments in conformal prediction, the reader may want to see the *Awesome Conformal Prediction* repository by Manokhin (2024).

Overall, the literature on adaptive conformal inference algorithms underscores their significance in addressing the complexities of non-exchangeable data, offering the most promising avenues for robust uncertainty quantification in diverse application domains. It is for these reasons that we will use these methodologies to compute robust market risk measures with crypto-assets.

We remark that Wisniewski et al. (2020) and Kath and Ziel (2021) are the only authors who employed (vanilla) conformal prediction to generate prediction intervals and rigorously tested their validity using unconditional and conditional coverage tests. However, their primary focus was on obtaining valid prediction intervals rather than on the tails of the distribution, which are critical for financial risk management. Wisniewski et al. (2020) evaluated their models using 19 different confidence levels, ranging from 5% to 95%, while Kath and Ziel (2021) focused on 50% and 90% prediction intervals. Despite their thorough examination, the quantiles they considered do not align with the requirements of financial risk management. Regulatory frameworks such as the Basel II agreement mandate the use of value at risk (VaR) at the 1% probability level, while Basel III suggests using expected shortfall at the 2.5% probability level. The higher quantiles examined by Wisniewski et al. (2020) and Kath and Ziel (2021) are less relevant for these purposes. Moreover, both studies revealed that although several models passed the unconditional coverage tests, almost none succeeded in the conditional coverage tests across all significance levels (see table 2 in both papers). Such results highlight the limitations of existing models in providing reliable risk measures that are crucial for serious risk management applications. In contrast to these prior works, our study pioneers the application of ACI methods specifically for estimating tail quantiles relevant to financial risk management and that are robust to distributional shifts. By focusing on quantile estimation for VaR, we address a critical gap in the literature. Our approach not only leverages the adaptive nature of ACI to dynamically adjust prediction intervals but also repurposes these intervals to provide precise point estimates for the tail quantiles. This innovative use of ACI methods extends their applicability beyond traditional prediction interval construction, offering significant benefits for the accurate estimation of risk measures. To our knowledge, this alternative use of ACI for direct quantile estimation in the context of financial risk management has not been explicitly considered in the previous literature. Thus, our work not only builds on the previous studies of Wisniewski et al. (2020) and Kath and Ziel (2021) but also introduces a novel application that enhances the toolkit available for risk managers.

3. Materials and Methods

The aim of this study is to compare the performance of four ACI algorithms with traditional volatility models for daily data, such as GARCH models and daily range models, in computing the value at risk (VaR) at various probability levels for a large set of crypto-assets. Additionally, this comparison indirectly assesses the quality of the models' expected shortfall (ES), as proposed by Kratz et al. (2018). The ES represents the average of the worst p losses, where p is the percentile of the returns distribution. Although Gneiting (2011) demonstrated that the ES lacks a mathematical property known as elicitability and cannot be directly backtested, Emmer et al. (2015) showed that the ES becomes elicitable when conditioned on the VaR and can be backtested by approximating multiple VaR levels. This concept was further refined by Kratz et al. (2018), who introduced a multinomial test of VaR violations across multiple levels as a means of backtesting the ES.

Before presenting the outcomes of our extensive empirical evaluations, we first discuss the general structure of adaptive conformal inference, the four specific ACI algorithms used in our analysis, the benchmark volatility models for daily data, and backtesting procedures for market risk measures.

3.1. Adaptive Conformal Inference: The General Structure

We delve into an online learning scenario where we have a sequential stream of crypto-assets' log-returns $(y_t)_{t \geq 1}$, one at a time; see Cesa-Bianchi and Lugosi (2006) for a detailed discussion of online learning theory. Supposing that $\alpha \in (0,1)$ is our desired empirical coverage of prediction intervals, our objective is to produce, at each time step t, a prediction interval for the upcoming log-return y_t. This interval is generated using an interval construction function denoted as $\hat{C}_t$, that takes a parameter $\theta_t \in \mathbb{R}$ and produces a closed prediction interval $[l_t, u_t]$. It is essential that the interval construction function be nested, so that if $\theta' > \theta$, then $\hat{C}_t(\theta)$ must be a subset of $\hat{C}_t(\theta')$, thus indicating wider prediction intervals for larger values of θ. $\hat{C}_t(\theta)$ is indexed by t to highlight its potential dependence on other information available at each time point, such as a point prediction $\hat{\mu}_t$. In addition, let $r_t = \inf\{\theta \in \mathbb{R} : \mathbb{I}(y_t \in \hat{C}_t(\theta))\}$ be the radius at time t, i.e., the smallest θ ensuring that the prediction interval covers the log-return y_t, and $\mathbb{I}(\cdot)$ be the indicator function. A critical assumption used for the theoretical analysis of several ACI algorithms is the boundedness of these radii, so there exists a constant $D > 0$ such that $r_t < D$ for all t.

A straightforward approach to build prediction intervals involves directly employing the parameter θ_t to determine the interval width. Given the point prediction $\hat{\mu}_t$ at each time t, we can create a symmetric prediction interval around this point estimate as $\hat{C}_t(\theta_t) = [\hat{\mu}_t - \theta_t, \hat{\mu} + \theta_t]$. This method is known as the *linear interval constructor* and, in this setup, the radius is given by the absolute residual $r_t = |\hat{\mu}_t - y_t|$. The original work on adaptive conformal inference (ACI) by Gibbs and Candès (2021) proposed constructing intervals based on past observed residuals. Assume we have a function S, known as a "nonconformity score", where a common choice is given by the absolute residual $S(\mu, y) = |\mu - y|$. Moreover, if we denote with $s_t = S(\hat{\mu}_t, y_t)$ the nonconformity score of the t-th log-return, then the *quantile interval constructor* is formulated as follows:

$$\hat{C}_t(\theta_t) = [\hat{\mu}_t - \text{Quantile}(\theta, \{s_1, \ldots, s_{t-1}\}), \hat{\mu}_t + \text{Quantile}(\theta, \{s_1, \ldots, s_{t-1}\})],$$

where $\text{Quantile}(\theta, M)$ is the empirical θ-quantile of the elements in set M. It is easy to verify that $\hat{C}_t$ is nested within θ_t because the quantile function is non-decreasing in θ. The linear interval constructor is used with Scale-Free Online Gradient Descent by Bhatnagar et al. (2023) and Strongly Adaptive Online Conformal Prediction by Bhatnagar et al. (2023), whereas the quantile interval constructor is used with Aggregated ACI by Zaffran et al. (2022) and Fully Adaptive Conformal Inference by Gibbs and Candès (2022).

In this framework, the lower quantile l_t of the interval constructor $\hat{C}_t(\theta_t)$ corresponds to the 1-day-ahead value at risk (VaR) at the probability level $p = (1-\alpha)/2$, denoted as $VaR_{t,p}$. Conversely, the upper quantile u_t of the interval constructor $\hat{C}_t(\theta_t)$ corresponds to the 1-day-ahead value at risk (VaR) at the probability level $1 - p = 1 - (1-\alpha)/2$, denoted as $VaR_{t,1-p}$.

In general, the ACI algorithms' interactions with the data and the computations of losses follow a similar pattern, which is repeated sequentially for each time step $t = 1, \ldots, T$:

- Predict θ_t and build the prediction interval $\hat{C}_t(\theta_t)$;
- Observe the true outcome y_t and compute the radius r_t;
- Verify whether y_t is not included in the prediction interval, $err_t := \mathbb{I}[y_t \notin \hat{C}_t(\theta_t)]$;
- Compute the so-called pinball loss $L^\alpha(\theta_t, r_t)$, defined as follows:

$$L^\alpha(\theta_t, r_t) = \begin{cases} \alpha(\theta_t - r_t), & \theta_t \geq r_t \\ (1-\alpha)(r_t - \theta_t), & \theta_t < r_t \end{cases}$$

This iterative process forms the foundation of the theoretical framework of online learning, from which theoretical results are then derived for each ACI algorithm.

The original adaptive conformal inference (ACI) algorithm proposed by Gibbs and Candès (2021) dynamically adjusts the width of prediction intervals based on observed data. Their algorithm is outlined in pseudo-code format in Appendix A. It is possible to show that the updating mechanism for the estimated radius can be derived as an online subgradient descent scheme, using the subgradient of the pinball loss function. In simple terms, if the log-return y_t falls outside the prediction interval at time t ($err_t = 1$), the next interval widens ($\theta_{t+1} = \theta_t + \gamma\alpha$). Conversely, if y_t falls within the interval ($err_t = 0$), the next interval narrows ($\theta_{t+1} = \theta_t - \gamma(1-\alpha)$). The learning rate γ governs the speed at which the interval width adapts to the data and is the primary tuning parameter. Theoretical considerations on coverage error bounds suggest a larger γ to expedite coverage error decay over time. However, in practice, overly large γ values lead to intervals exhibiting significant oscillations. Conversely, overly small γ values result in intervals that adapt too slowly to distribution shifts. Hence, selecting an appropriate γ value is crucial. This issue has spurred the development of ACI algorithms that are robust to the choice of this parameter. The theoretical guarantees concerning the performance of the ACI algorithm remain unaffected by the selection of the initial value θ_1. Therefore, in practical applications any value can be chosen. Over time, the influence of the initial choice of θ_1 diminishes proportionally to the chosen learning rate. Following Susmann et al. (2023), we set $\theta_1 = \alpha$ when employing the quantile interval predictor, and $\theta_1 = 0$ otherwise.

Finally, we remark that in the evaluation of adaptive conformal inference (ACI) algorithms, traditional metrics such as the empirical coverage and the regret provide valuable insights into the overall performance of prediction intervals[2]. However, in the context of financial risk management, particularly concerning the estimation of risk measures in the tails of log-returns distributions, a more nuanced approach is required. Specifically, the focus is often directed towards assessing the quality of the estimated (tail) risk measures, such as quantiles (e.g., value at risk) or more comprehensive measures like the expected shortfall. Given the critical importance of accurately estimating tail risk, it is important to employ specialized evaluation techniques tailored to market risk measures. Consequently, backtesting procedures designed specifically for assessing the adequacy of these risk measures offer a more appropriate and rigorous means of evaluation in our case than the empirical coverage and the regret. An overview of the backtesting procedures employed in our empirical analysis is provided in Section 3.4.

3.2. ACI Algorithms: AgACI, FACI, SF-OGD, SAOCP

Aggregated ACI (AgACI) by Zaffran et al. (2022) resolves the challenge of selecting a suitable learning rate for ACI by executing multiple instances of the algorithm with varying learning rates. Subsequently, it combines the lower and upper interval bounds separately using an online aggregation-of-experts algorithm. Specifically, one aggregation algorithm aims to estimate the lower $(1-\alpha)/2$ quantile, while the other targets the upper $1-(1-\alpha)/2$ quantile. Zaffran et al. (2022) explored several online aggregation algorithms and observed similar outcomes. Therefore, we adopt their recommendation and utilize the Bernstein Online Aggregation (BOA) algorithm, implemented in the `opera` R package (Gaillard et al. 2023; Wintenberger 2017). BOA operates as an online algorithm, deriving predictions for the lower (or upper) prediction interval bound through a weighted average of candidate ACI prediction interval bounds, with weights determined by each candidate's past performance concerning the quantile loss. Therefore, the prediction intervals produced by AgACI may not be symmetric around the point prediction, given the separate weights assigned to the lower and upper bounds. The primary parameter to tune in AgACI is the set of candidate learning rates γ. Susmann et al. (2023) suggest using the following learning rates: $\gamma \in \{0.001, 0.002, 0.004, 0.008, 0.016, 0.032, 0.064, 0.128\}$. Additionally, each candidate ACI algorithm requires a starting value for θ_1, which can be arbitrarily set to α, as previously discussed. The AgACI algorithm is outlined in pseudo-code format in Appendix B, and it is implemented in the `AdaptiveConformal` R package; see Susmann et al. (2023) for more details. Finite sample bounds on the coverage error and the regret do not exist for the AgACI algorithm. Zaffran et al. (2022) performed a wide range of experiments on synthetic time series with different time dependence structures, showcasing the robustness of the AgACI algorithm and its superior performance compared to baseline methods. However, they noted at the conclusion of their paper that future research would involve a theoretical analysis of the aggregation algorithm, particularly to determine if the experimentally observed asymptotic validity holds.

Fully Adaptive Conformal Inference (FACI) by Gibbs and Candès (2022) was developed by the creators of the original ACI algorithm, in part to address the challenge of selecting the learning rate parameter γ. In this regard, FACI shares a similar objective with the AgACI algorithm, although it employs a slightly different approach. FACI also aggregates predictions from multiple instances of ACI, each executed with different learning rates. However, it differs in that it directly combines the estimated radii produced by each algorithm based on their pinball loss, employing an exponential reweighting scheme (Gradu et al. 2023). Unlike AgACI, FACI does not separately aggregate the upper and lower bounds of the intervals, and this enables the development of theoretical guarantees regarding the algorithm's performance in a more straightforward manner. The FACI algorithm is outlined in pseudo-code format in Appendix C, and it is implemented in the `AdaptiveConformal` R package; see Susmann et al. (2023) for more details. The process of tuning hyperparameters involves selecting a time interval length $|I|$ to control the pinball loss, which can be arbitrarily chosen. For the hyperparameter σ, Gibbs and Candès (2022) advocate for the optimal choice $\sigma = 1/(2|I|)$. Determining the third hyperparameter η poses a greater challenge. In the absence of distribution shifts, the optimal choice for η is

$$\eta = \sqrt{\frac{3}{|I|}}\sqrt{\frac{\log(K\cdot|I|)+2}{\alpha^2(1-\alpha)^3+(1-\alpha)^2\alpha^3}}$$

where K is the number of multiple copies of the ACI algorithm with different learning rates. We remark that this solution is optimal only for the quantile interval constructor, where θ_t represents a quantile of previous nonconformity scores. Alternatively, Gibbs and Candès (2022) suggest learning η in an online manner using the following update rule:

$$\eta_t = \sqrt{\frac{\log(K\cdot|I|)+2}{\sum_{s=t-|I|}^{t-1} L^{\alpha}(\theta_s, r_s)}}$$

Both approaches for selecting η yielded similar results in the empirical studies reported by Gibbs and Candès (2022). Following Susmann et al. (2023), we employed the former approach when the quantile interval construction function was selected, while we employed the latter approach for the linear interval construction function. Similar to AgACI, the grid for the learning parameter γ consists of values from the set $\gamma \in \{0.001, 0.002, 0.004, 0.008, 0.016, 0.032, 0.064, 0.128\}$. To establish a bound on the coverage error, Gibbs and Candès (2022) examined a slightly modified version of FACI in which θ_t is chosen randomly from the candidate $\theta_{t,k}$ with weights given by $p_{t,k}$, instead of taking a weighted average. They ensure that this randomized version of FACI yields results very similar to the deterministic version. The coverage error result also assumes that hyperparameters can change over time, meaning η_t and σ_t are specific to each time t, rather than being fixed. The authors demonstrate that the coverage error has the following specific bound, where $\gamma_{\min}$ and $\gamma_{\max}$ represent the smallest and largest learning rates in the grid, respectively:

$$|CovErr(T)| \leq \frac{1+2\gamma_{\max}}{T\gamma_{\min}} + \frac{(1+2\gamma_{\max})^2}{\gamma_{\min}}\exp(\eta_t(1+2\gamma_{\max}))\frac{1}{T}\sum_{t=1}^{T}\eta_t + 2\frac{1+\gamma_{\max}}{\gamma_{\min}}\frac{1}{T}\sum_{t=1}^{T}\sigma_t$$

Therefore, if both η_t and σ_t converge to zero as $t \to \infty$, the coverage error will also converge to zero. Additionally, under mild distributional assumptions, they provide a type of short-term coverage error bound for arbitrary time spans, along with several regret bounds. For more details, we refer to Gibbs and Candès (2022).

Scale-Free Online Gradient Descent (SF-OGD) is a versatile algorithm for online learning, initially proposed by Orabona and Pál (2018). This algorithm involves updating θ_t through a gradient descent step, with the learning rate adapting to the scale of previously observed gradients. While SF-OGD was initially introduced within the context of adaptive conformal inference (ACI) as a sub-algorithm for SAOCP (outlined below), it has demonstrated strong performance on its own in real-world applications; see Bhatnagar et al. (2023). The SF-OGD algorithm is outlined in pseudo-code format in Appendix D, and it is implemented in the `AdaptiveConformal` R package; see Susmann et al. (2023) for more details. It is possible to show that the optimal selection for the learning rate is $\gamma = D/\sqrt{3}$, where D represents the maximum possible radius. In cases where D is unknown, it can be estimated by employing an initial subset of the time series as a calibration set. D can then be estimated as the maximum of the absolute residuals between the observed log-returns and the corresponding forecasts (Bhatnagar et al. 2023; Orabona and Pál 2018). Bhatnagar et al. (2023) found a bound for the coverage error of this algorithm by showing that for any learning rate $\gamma = \Theta(D)$ (where $\gamma = D/\sqrt{3}$ is optimal) and any starting value $\theta_1 \in [0, D]$, then it holds that for any $T > 1$,

$$|CovErr(T)| \leq \mathcal{O}\big((1-\alpha)^{-2} T^{-1/4} \log T\big)$$

We remark that the coverage bounds for SF-OGD and SAOCP below (which is a generalization of SF-OGD) are distribution-free; see Theorems 4.2 and 4.3 and their proofs in Bhatnagar et al. (2023) for the full details.

The **Strongly Adaptive Online Conformal Prediction (SAOCP)** algorithm by Bhatnagar et al. (2023) was introduced as an enhancement over existing ACI algorithms, offering more robust theoretical guarantees. SAOCP operates similarly to AgACI and FACI, using a set of candidate online learning algorithms to generate prediction intervals, which are subsequently aggregated using a meta-algorithm. While SF-OGD was chosen as the candidate algorithm, any algorithm with anytime regret guarantees can be employed. Unlike AgACI and FACI, where each candidate employs a distinct learning rate but contributes consistently to the final prediction intervals, SAOCP assigns identical learning rates to all candidates. However, each candidate is allocated positive weight over a specific time interval. To address rapid distribution shifts, new candidate algorithms are continuously introduced, ensuring swift adaptation and positive weighting for the most recent candidates. In essence, SAOCP functions as a meta-algorithm overseeing multiple experts, with each expert constituting an independent online learning algorithm responsible for its own active interval with a finite lifetime. At each time point t, a new expert is created, active over a finite "lifetime" that is defined as

$$L(t) = g \cdot \max_{n \in Z} \{2^n : t \equiv 0 \mod 2^n\},$$

where $g \in \mathbb{Z}_{\geq 1}$ is a multiplier for the lifetime of each expert. Experts are weighted based on their empirical performance relative to the pinball loss function, resulting in intervals with robust regret guarantees. The SAOCP algorithm is outlined in pseudo-code format in Appendix E, and it is implemented in the `AdaptiveConformal` R package; see Susmann et al. (2023) for more details. The primary tuning parameter for SAOCP is the learning rate γ of the SF-OGD sub-algorithms, with the optimal choice established as $\gamma = D/\sqrt{3}$, as discussed earlier. Bhatnagar et al. (2023) typically determine D by selecting the maximum residual from a calibration set. The second tuning parameter, which is the lifetime multiplier g, governs the duration of each expert's lifetime. Following Bhatnagar et al. (2023), we set $g = 8$. Bhatnagar et al. (2023)—theorem 4.3—showed that a bound on the coverage error of SAOCP is given by

$$|CovErr(T)| \leq \mathcal{O}\big(\inf_{\beta}(T^{1/2-\beta} + T^{\beta-1} S_\beta(T))\big)$$

for any $T \geq 1$, and where $S_\beta(T)$ is a technical measure of the smoothness of the cumulative gradients and expert weights for each of the candidate experts. For example, if there exists $\beta \in (1/2, 1)$, then $S_\beta(T) \leq \tilde{\mathcal{O}}(T^\gamma)$ for some $\gamma < 1 - \beta$, and the previous bound becomes $|CovErr(T)| \leq \tilde{\mathcal{O}}\big(T^{-\min\{1/2-\beta, \beta-1+\gamma\}}\big) = o_T(1)$. Finally, we remark that the previous bound is distribution-free, and mild regularity assumptions on the distributions of the data are only required if we need to achieve approximately valid coverage on *every* sub-interval of time. For more details, see theorem C.3 in Bhatnagar et al. (2023).

3.3. Benchmark Volatility Models for Daily Data

The GARCH(1,1) model remains a prominent benchmark model for computing market risk measures with daily data for several reasons. Firstly, it captures essential characteristics of financial time series, such as volatility clustering and time-varying volatility, which are commonly observed in real-world financial markets. Secondly, the GARCH(1,1) model is relatively parsimonious compared to other volatility models, requiring only a small number of parameters for estimation. Given its widespread use in academic research and industry practice, the GARCH(1,1) model serves as a natural reference competitor when evaluating the performance of alternative market risk models. Its inclusion as a benchmark ensures that the proposed models undergo rigorous comparison against a well-established and widely recognized standard, thus enhancing the robustness and credibility of the assessment process in risk management applications. Specifically, a simple **GARCH(1,1) with constant mean μ and standardized errors z_t following a symmetric Student's t-distribution with ν degrees of freedom** was used in this work to model the conditional variance σ_t^2 of the log-returns y_t:

$$\begin{aligned} y_t &= \mu + \varepsilon_t, \quad \varepsilon_t = z_t\sqrt{\sigma_t^2}, \quad z_t \sim t_\nu \\ \sigma_t^2 &= \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \end{aligned}$$

More complex model specifications and error distributions were discarded because they resulted in much higher rates of numerical convergence failures; see Fantazzini (2022) and Fantazzini (2023) for similar evidence with crypto-assets. The complexity of estimating GARCH models and the necessity for sizable samples have been extensively documented in the literature. The seminal work by Fiorentini et al. (1996) highlighted the issues involved in GARCH model estimation, emphasizing the demand for large datasets. Furthermore, comprehensive simulation studies conducted by Hwang and Valls Pereira (2006), Fantazzini (2009), and Bianchi et al. (2011) underscored the requirement of a sample size ranging from 250 to 500 observations for obtaining reliable model estimates of basic GARCH models. For scenarios involving more complex data generating processes, even larger sample sizes were necessary to ensure robust estimation. For GARCH models with Student's t errors, the calculation of the 1-day-ahead value at risk (VaR) at the probability level p using information up to time $t-1$ is as follows:

$$VaR_{t,p} = \hat{\mu}_t + t_{p,\hat{\nu}}^{-1} \cdot \sqrt{(\hat{\nu}-2)/\hat{\nu}} \cdot \sqrt{\hat{\sigma}_t^2}$$

Here, $\hat{\mu}_t$ represents the 1-day-ahead forecast of the conditional mean, $\hat{\sigma}_t^2$ denotes the 1-day-ahead forecast of the conditional variance, and $t_{p,\hat{\nu}}^{-1}$ denotes the inverse function of the Student's t-distribution with estimated $\hat{\nu}$ degrees of freedom at the probability level p. The term $\sqrt{(\hat{\nu}-2)/\hat{\nu}} \cdot \sqrt{\hat{\sigma}_t^2}$ represents the scale parameter of the Student's t-distribution.

The second benchmark volatility model that we consider in our analysis employs the daily range to estimate the daily conditional variance of the log-returns y_t. The idea of using the price range has a rich history in both the academic and professional literature, starting from the 19th century; see Nison (1994) and references therein. Notably, volatility measures derived from the daily range emerged as efficient alternatives to return-based volatility estimators, as demonstrated by several authors, beginning with Parkinson (1980). Recent research has reignited interest in range-based estimators employing the open, high, low, and close (OHLC) prices for estimating daily volatility; see Patton (2011), Molnár (2012), Chou et al. (2015), and Fiszeder et al. (2019). Intriguingly, high-frequency volatility models have shown superior performance over low-frequency models using range-based estimators for short-term forecasts, typically one day ahead (Lyócsa et al. 2021). However, for longer forecast horizons, such as up to one month, the difference in forecast accuracy diminishes, particularly for most market indices. Moreover, Fantazzini (2023) conducted a comprehensive analysis on a dataset of over 2000 crypto-assets, evaluating their credit risk by computing their probability of "death", and found that ZPP-based models using range-based volatility estimators were a better choice for long-term forecasts up to 1 year ahead (which is the standard horizon for credit risk management). Building on Molnár (2012) and Fantazzini (2023), we will adopt the **Garman–Klass volatility estimator** (Garman and Klass (1980)). This estimator has been shown to produce standardized returns that are normally distributed and yields estimates comparable to those obtained from high-frequency data. The Garman–Klass estimator assumes a Brownian motion with zero drift and no opening jumps. Nonetheless, for cases involving opening jumps, as seen with illiquid assets, the jump-adjusted Garman–Klass volatility estimator described in Molnár (2012) will be employed. The formula for the jump-adjusted Garman–Klass (GK) volatility estimator for the daily conditional variance σ_t^2 of the log-returns y_t is presented below:

$$\sigma^2_{GK,t} \quad = \quad \left[\log(O_t/C_{t-1})^2 + \frac{1}{2}\log(H_t/L_t)^2 - (2\times\log 2 - 1)\log(C_t/O_t)^2\right]$$

To forecast the dynamics of range-based daily volatilities σ_t^2, we employed the heterogeneous autoregressive (HAR) model proposed by Corsi (2009), which posits that the daily volatility is influenced by past volatility over different time periods:

$$\begin{aligned} \sigma_t^2 \quad &= \quad \beta_0 + \beta_D\sigma^2_{t-1,D} + \beta_W\sigma^2_{t-1,W} + \beta_M\sigma^2_{t-1,M} + \epsilon_t, \quad \text{where} \\ &\sigma^2_{t-1,W} = \frac{1}{7}\sum_{j=1}^{7}\sigma^2_{t-j,D}, \quad \sigma^2_{t-1,M} = \frac{1}{30}\sum_{j=1}^{30}\sigma^2_{t-j,D} \end{aligned}$$

where σ_D^2, σ_W^2, and σ_M^2 denote the daily, weekly, and monthly volatility components, respectively. We adjusted the time periods for weekly and monthly volatilities to 7 and 30 days, respectively, instead of the usual 5 and 22 days, to accommodate the continuous trading in cryptocurrency exchanges. We set the conditional mean of the log-returns y_t to zero when using the Garman–Klass volatility estimator. Therefore, in the case of the HAR model with daily range data, the 1-day-ahead VaR can be computed as follows:

$$VaR_{t,p} = \Phi_p^{-1}\cdot\sqrt{\hat{\sigma}_t^2}$$

where Φ_p^{-1} denotes the inverse function of the normal distribution at the probability level p.

3.4. Backtesting Methods for Market Risk Measures

The assessment of different value-at-risk (VaR) models' forecasting performance entails comparing the forecast VaR values against actual returns for each day. Initially, the process involves tallying the number of violations T_1 when the forecast VaR is lower than the actual losses, with $T = T_1 + T_0$, where T_0 denotes the absence of VaR violations. The **unconditional coverage test** developed by Kupiec (1995) verifies whether the fraction of actual violations, $\hat{\pi} = T_1/T$, is statistically significantly different from p%, so the null hypothesis is given by $H_0 : \hat{\pi} = p$. This test employs the following likelihood ratio test statistic for the null hypothesis (Kupiec 1995):

$$LR_{uc} = -2\ln\Big[(1-p)^{T_0}p^{T_1} \;/\; \{(1-T_1/T)^{T_0}(T_1/T)^{T_1}\}\Big] \overset{H_0}{\sim} \chi_1^2$$

The **conditional coverage test** by Christoffersen (1998) tests the joint null hypothesis concerning the accuracy of the average number of VaR violations and the independence of violations. This test can identify models forecasting an excessive or insufficient number of clustered violations, but it requires at least several hundred observations for accuracy. The test statistic is presented as follows:

$$LR_{cc} = -2\ln\Big[(1-p)^{T_0}p^{T_1}\Big] + 2\ln\Big[(1-\pi_{01})^{T00}\pi_{01}^{T01}(1-\pi_{11})^{T10}\pi_{11}^{T11}\Big] \overset{H_0}{\sim} \chi_2^2$$

where T_{ij} is the number of observations with value i followed by j for $i, j = 0, 1$ and $\pi_{ij} = \frac{T_{ij}}{\sum_j T_{ij}}$ denotes the corresponding probabilities.

In addition to the count of VaR violations, financial regulators are concerned with their magnitude. Thus, the **asymmetric quantile loss (QL) function** proposed by González-Rivera et al. (2004) was computed in our analysis:

$$l(y_t, VaR_{p,t}) = (p - d_t^p)(y_t - VaR_{p,t})$$

where $d_t^p = \mathbf{1}(y_t < VaR_{p,t})$ is the indicator function for the VaR exceedances. This function penalizes realized losses below the p-th quantile level more heavily, facilitating cost comparison among different choices.

The previous asymmetric quantile loss functions are then used by the **model confidence set** (MCS) by Hansen et al. (2011) to select the best VaR forecasting models at a specified confidence level. Given the differences between the QLs of models i and j at time t (expressed as $d_{ij,t} = QL_{i,t} - QL_{j,t}$), the MCS approach is employed to evaluate the hypothesis of equal predictive capability, denoted as $H_{0,M} : E(d_{ij,t}) = 0$, for all i, j in M, where M represents the set of forecasting models. The initial step involves the computation of the following t-statistics:

$$t_{i\cdot} = \frac{\bar{d}_{i\cdot}}{\widehat{var}(\bar{d}_{i\cdot})} \quad \text{for} \quad i \in M,$$

where $\bar{d}_{i\cdot} = m^{-1}\sum_{j\in M}\bar{d}_{ij}$ is the simple loss of the i-th model relative to the average losses across models in the set M, $\bar{d}_{ij} = T^{-1}\sum_{t=1}^{T} d_{ij,t}$ measures the sample loss differential between models i and j, while $\widehat{var}(\bar{d}_{i\cdot})$ is a bootstrapped estimate of $var(\bar{d}_{i\cdot})$. Subsequently, the T-max statistic is calculated as follows: $T_{max,M} = \max_{i\in M}(t_{i\cdot})$. This statistic has a non-standard distribution, hence its distribution under the null hypothesis is determined via bootstrap methods involving 1000 replications. If the null hypothesis is rejected, one model is eliminated from the analysis, restarting the testing procedure anew; see Hansen et al. (2011) for more details.

Building upon an idea introduced by Emmer et al. (2015), Kratz et al. (2018) introduced a **multinomial value-at-risk (VaR) test** that implicitly evaluates the expected shortfall (ES) by approximating it with various VaR levels. Their approximation is defined as

$$ES_p \approx \frac{1}{4}[q(p) + q(0.75p + 0.25) + q(0.5p + 0.5) + q(0.25p + 0.75)]$$

where $q(\gamma) = VaR_\gamma$. A similar but more convenient approximation for the ES at the 2.5% level, as adopted by Basel III, was proposed by Wimmerstedt (2015) and Fantazzini and Shangina (2019):

$$ES_{2.5\%} \approx \frac{1}{5}[VaR_{2.5\%} + VaR_{2.0\%} + VaR_{1.5\%} + VaR_{1.0\%} + VaR_{0.5\%}]$$

Kratz et al. (2018) suggested using several VaR probability levels $p_1, \ldots, p_N$, where $p_j = p + [(j-1)/N](1-p)$ for $j = 1, \ldots, N$, starting from a given level p. If $\mathbb{I}_{t,j} = \mathbf{1}_{(Y_t < VaR_{p_j,t})}$ represents the usual indicator function for a VaR violation at level p_j and $X_t = \sum_{j=1}^{N}\mathbb{I}_{t,j}$, then the sequence $(X_t)_{t=1,\ldots,T}$ counts the number of VaR violations at level p_j. Now, define $MN(T, (\pi_0, \ldots, \pi_N))$ as a multinomial distribution with T trials, each of which may result in one of $N+1$ outcomes $\{0, 1, \ldots, N\}$ with probabilities $\pi_0, \ldots, \pi_N$ that sum to one, while the observed cell counts are defined by $O_j = \sum_{t=1}^{T} I_{(X_t=j)}$, $j = 0, 1, \ldots, N$. Then, under the assumptions of unconditional coverage and independence, as in Christoffersen (1998), it can be shown that the random vector $(O_0, \ldots, O_N)$ follows the multinomial distribution $MN(T, (p_1 - p_0, \ldots, p_{N+1} - p_N))$. Supposing that the estimated multinomial distribution is $MN(T, (\theta_1 - \theta_0, \ldots, \theta_{N+1} - \theta_N))$, where θ_j $(j = 1, \ldots, N)$ are the estimated distribution parameters, Kratz et al. (2018) consider the following null and alternative hypotheses:

$$\begin{aligned} H_0: \quad & \theta_j = p_j, \quad \text{for} \quad j = 1, \ldots, N \\ H_1: \quad & \theta_j \neq p_j, \quad \text{for at least one } j \in \{1, \ldots, N\} \end{aligned}$$

The null hypothesis can be tested using various test statistics. We refer to Cai and Krishnamoorthy (2006) for a comprehensive simulation study on the exact size and power properties of five possible tests, three of which were later employed by Kratz et al. (2018). In our empirical analysis, we utilized the *exact method*, the fifth test statistic reviewed by Cai and Krishnamoorthy (2006), which computes the probability of a given outcome under the null hypothesis using the multinomial probability distribution itself:

$$P(O_0, O_1, \ldots, O_N) = \frac{T!}{O_0! O_1! \ldots O_N!} (p_1 - p_0)^{O_0} (p_2 - p_1)^{O_1} \ldots (p_{N+1} - p_N)^{O_N}$$

Cai and Krishnamoorthy (2006) concluded that while the exact method performs well, it can be time-consuming for large numbers of cells N and sample sizes T. In such cases, simulation methods are preferable. For a comprehensive discussion on these backtesting methods and others, we refer to Fantazzini (2019), chap. 11.

3.5. Structure of the Empirical Analysis

In this study, we conduct a comprehensive empirical analysis to evaluate the performance and robustness of various methods for estimating market risk measures across a diverse set of cryptocurrencies. Our analysis consists of a baseline case that considers all assets, as well as a series of robustness checks to verify that the results for the baseline case also hold in different settings. It is structured as follows:

- *Baseline case: All 4000 assets*. In the baseline analysis, we included all 4000 cryptocurrencies in our dataset to provide a broad assessment of the methods under study. This diverse dataset allows us to capture a wide range of market behaviors and characteristics.
- *Robustness check 1: Market capitalization of crypto-assets*. We conducted a robustness check based on the market capitalization of the assets. Our dataset included daily market capitalization data for 2310 out of the 4000 assets. The remaining assets lacked these data, which may indicate transparency issues regarding their circulating supply. For a comprehensive analysis, we divided these 2310 assets into four groups of approximately equal size based on their market capitalization. The first group consists of assets with the highest market capitalization, while the fourth group includes those with the lowest capitalization.
- *Robustness check 2: Time-series size*. To examine the impact of time-series length on our results, we divided the assets into four groups according to the number of daily data points available. Each group contains approximately the same number of assets. The first group includes assets with the longest time series (ranging from 1613 to 4939 daily data points), and the fourth group includes assets with the shortest time series (ranging from 731 to 836 daily data points).
- *Robustness check 3: Different forecasting methods*. In the baseline case, we used a simple AR(1) model due to its ease of estimation and the generally weak mean dependence in crypto-assets' log-returns. As a third robustness check, we evaluated the impact of using a more complex model specification with a robust estimation method. Specifi-

cally, we employed a single-hidden-layer neural network, utilizing seven lagged daily log-returns as inputs and three hidden units:

$$y_t = \beta_0 + \sum_{j=1}^{3} \beta_j g\Big(\gamma_{0j} + \sum_{i=1}^{7} \gamma_{ij} y_{t-i}\Big)$$

Feed-forward neural networks with a single hidden layer are implemented in the `nnet` R package, and we refer to Venables and Ripley (2002), chapter 8, for the full theoretical details and the software implementation.

- *Robustness check 4: Comparison with methods that predict quantiles directly*. Engle and Manganelli (2004) proposed an alternative approach to quantile estimation that focuses on modeling the quantile directly rather than the entire distribution. They introduced a class of semi-parametric conditional autoregressive quantile models, known as *CAViaR*, which utilize quantile regression and mild distributional assumptions. These models have a structure similar to GARCH models and are formally defined as follows:

$$\begin{aligned}
\text{Symmetric absolute value}: q_t(p) &= \beta_1 + \beta_2 q_{t-1}(p) + \beta_3 |y_{t-1}| \\
\text{Asymmetric slope}: q_t(p) &= \beta_1 + \beta_2 q_{t-1}(p) + \beta_3 (y_{t-1})^+ + \beta_4 (y_{t-1})^- \\
\text{Indirect GARCH(1,1)}: q_t(p) &= [\beta_1 + \beta_2 q_{t-1}^2(p) + \beta_3 y_{t-1}^2]^{1/2} \\
\text{Adaptive}: q_t(p) &= q_{t-1}(p) + \beta_1 \Big\{ [1 + \exp(\beta_2 \cdot [y_{t-1} - q_{t-1}(p)])]^{-1} - p \Big\}
\end{aligned}$$

where $q_t(p)$ represents the p-quantile function associated with the conditional distribution of returns y_t, $(x)^+ = \max(x, 0)$, and $(x)^- = -\min(x, 0)$ and β_i are the model parameters. The asymmetric slope model is specifically designed to capture the asymmetric leverage effect, which is the tendency for volatility to be higher following a negative return than a positive return of equal magnitude. The indirect GARCH(1,1) CAViaR model is correctly specified if the underlying data are generated by a GARCH(1,1) model with an independent and identically distributed innovation process. The adaptive specification adjusts to past errors to minimize the probability of consecutively underestimating the VaR. The CAViaR parameters are estimated using the quantile regression minimization technique introduced by Koenker and Bassett (1978):

$$\hat{\boldsymbol{\beta}} = \arg\min_{\boldsymbol{\beta}} \sum_t [p - I(y_t < q_t(\boldsymbol{\beta}, p))] \cdot [y_t - q_t(\boldsymbol{\beta}, p)]$$

where $\boldsymbol{\beta}$ is the vector of parameters to be estimated, while I is the indicator function. When the quantile model is linear, this minimization can be formulated as a linear programming problem, for which the dual problem is conveniently solved. For this reason, and due to past empirical evidence, such as that provided by Abad et al. (2014) and references therein, we will use only the symmetric absolute value (SAV) model[3]. Moreover, given the computational burden of estimating the model for each quantile, we will limit our analysis to a selected group of crypto-assets: the two most capitalized assets (Bitcoin and Ethereum) and the two least capitalized assets (Bubble and Litecoin-Token) for which all models achieved numerical convergence.

The aim of this structure is to ensure that our empirical analysis is thorough and considers various factors that may influence the performance of the risk estimation methods.

4. Results

4.1. Data

Our study analyzed a dataset comprising 4000 crypto-assets spanning from July 2010 to January 2024. We obtained all assets, freely available from https://coinmarketcap.com/, in January 2024, ensuring that each had a time series consisting of at least 730 daily data points. We made this selection to ensure that all models used in our analysis had a minimum of one year's worth of data for initial training and calibration. The dataset included daily open, high, low, and close prices, as well as traded volume and market capitalization. Initially, we downloaded a dataset comprising 4003 assets. However, three assets were excluded due to their close prices remaining at zero throughout the entire time span, rendering them unusable. Additionally, approximately a dozen assets exhibited unusual reported prices in the weeks preceding their delisting from coinmarketcap.com. These anomalous trading days were excluded from our analysis to maintain its integrity. The names of the 4000 crypto assets used in our analysis are listed in Tables A1–A8 in Appendix F.

The first 365 daily observations were used to initialize the estimation of the GARCH model, with log-returns computed using the closing prices. For the HAR model, the daily range was estimated using the open, high, low, and close prices. Similarly, for the training and calibration of ACI models, log-returns were computed using the closing prices. An expanding window approach was then employed for the GARCH and HAR models, where one day of data was added incrementally to the initial sample. The models were re-estimated with the expanded dataset, and the value at risk (VaR) for the next day was computed. The ACI models were trained incrementally, one data point at a time, as detailed in the algorithms provided in Appendices B–E.

In our study, we utilize a dataset comprising 4000 cryptocurrencies, covering a wide range of market conditions and asset characteristics. This extensive dataset includes not only the most capitalized cryptocurrencies, like Bitcoin and Ethereum, but also those with lower capitalization and liquidity. The rationale behind this comprehensive approach is twofold. First, it allows us to assess the performance of ACI methods across a diverse set of assets, which is essential for understanding the general applicability and robustness of these methods. Second, by including a wide variety of cryptocurrencies, we can identify specific challenges and opportunities associated with different types of assets. This approach enables us to draw more nuanced and actionable insights that are relevant to a broader audience, including investors, portfolio managers, and regulators. Our analysis thus provides a detailed examination of market risk measures across the full spectrum of the cryptocurrency market, ensuring that our conclusions are both robust and broadly applicable.

As outlined in the previous section, we calculated the value at risk (VaR) across five probability levels ($p_1 = 0.5\%$, $p_2 = 1\%$, $p_3 = 1.5\%$, $p_4 = 2\%$, $p_5 = 2.5\%$) for the log-returns of each asset. This enabled us to conduct an approximate backtesting of the expected shortfall (ES) at the 2.5% level, a metric included in the Basel III agreement. While our primary focus was on the left tail of the distribution, given its significance in financial risk management, we also computed five quantiles for the right tail ($p_6 = 97.5\%$, $p_7 = 98\%$, $p_8 = 98.5\%$, $p_9 = 99\%$, $p_{10} = 99.5\%$) to ensure comprehensiveness and generality.

For the ACI models, we opted to employ a simple AR(1) model to capture the dynamics of the crypto-assets' log-returns. Although we initially attempted to utilize the Hyndman and Khandakar Hyndman and Khandakar (2008) algorithm for automatic selection of the optimal ARIMA model[4], this approach encountered challenges, particularly with extremely volatile crypto-assets possessing relatively short time series (fewer than 1000 observations). Consequently, we reverted to employing a straightforward AR(1) model. In this regard, it is worth noting that the mean dependence of crypto-assets' log-returns is generally weak. Nevertheless, as part of our robustness checks, we will examine the impact on our results when employing a more complex model specification with a robust estimation method.

4.2. Baseline Case: All 4000 Assets

In this section, we present the results of our comprehensive evaluation of value-at-risk (VaR) forecasting models applied to a dataset comprising 4000 crypto assets. Our analysis includes four adaptive conformal inference (ACI) models, one generalized autoregressive conditional heteroskedasticity (GARCH) model, and one heterogeneous autoregressive (HAR) model using daily range volatilities.

Our evaluation begins with an examination of the performance of each model using the Kupiec (1995) test, the Christoffersen (1998) test, and the multinomial VaR test by Kratz et al. (2018); see Table 1. Across all quantiles, we observed that the ACI models generally performed well, with FACI and SF-OGD emerging as the most effective models. However, AgACI and SAOCP, while providing accurate estimates for extreme quantiles ($p_1 = 0.5\%$ and $p_2 = 1\%$), were too conservative when estimating quantiles between 1% and 2.5%, with less violations than expected. In the right tail of the distribution, AgACI demonstrated better results, in line with the FACI and SF-OGD algorithms. According to the multinomial VaR test, FACI and SF-OGD were able to properly model the left and right tails of the distribution for the vast majority of crypto-assets (approximately 90% of assets), followed by AgACI (approximately 80%), while SAOCP had the worst performance among ACI algorithms, with only approximately 50% of assets where the multinomial VaR test was not rejected at the 5% probability level.

Differently from the ACI algorithms, the GARCH and HAR models faced challenges in achieving numerical convergence for approximately 2.5% of assets (96 and 104 assets, respectively), particularly those with extreme variability and/or relatively small datasets ($T < 1000$). Despite this, GARCH served as a reliable benchmark model, slightly underestimating VaR for the most extreme quantiles ($p_i \leq 1.0\%$) while maintaining accuracy for the other quantiles. Instead, the HAR model with daily range volatilities proved to be the least effective, underestimating lower quantiles up to $p_i = 1\%$, and severely overestimating higher quantiles. Similar problems emerged also for the right tail of the distribution. According to the multinomial VaR test, the GARCH model was able to model the left and right tails of the distribution for approximately 70% of assets, whereas for the HAR model this was approximately 20% of assets, thus confirming the previous problems with the tests for the single quantiles.

To identify the best VaR forecasting models, we utilized the asymmetric quantile loss (QL) function proposed by González-Rivera et al. (2004) and employed the model confidence set (MCS) method by Hansen et al. (2011); see Tables 2 and 3. Notably, we considered only assets for which all six models reached numerical convergence. Such a choice clearly penalized ACI models, which were able to estimate quantiles for all assets, whereas this was not the case for GARCH and HAR models. Nevertheless, given that financial regulators are concerned not only with the number of VaR violations but also with their magnitude, we also compared the models using the asymmetric quantile loss and the MCS.

Our analysis reveals that the GARCH model consistently emerged as the top-ranked model for the majority of assets and was almost always included in the MCS. This underscores the enduring relevance of the GARCH(1,1) model with a Student's t-distribution in finance when using daily data, even nearly four decades after it was originally proposed.

While ACI models demonstrated proficiency in estimating quantiles for most assets, they exhibited challenges in estimating the most extreme quantiles ($p_i \leq 1\%$ and $p_i \geq 99\%$), particularly the AgACI and FACI models that showed rather large asymmetric losses and lower ranking. However, the SF-OGD and SAOCP models displayed greater precision with smaller losses. These findings have significant implications for financial risk management: while a traditional benchmark like the GARCH model remains relevant, newer approaches such as ACI models offer promising alternatives, particularly for assets with complex dynamics such as crypto-assets, albeit with some caveats in extreme quantile estimation. Given that ACI models are more precise in terms of VaR violations, while GARCH models are better in terms of asymmetric quantile losses, forecasting combinations are a possibility. We leave this interesting issue as an avenue for further research.

Table 1. Average number of violations in % across all assets for each quantile; % of times the Christoffersen conditional coverage (CC) test was not rejected at the 5% probability level across all assets for each quantile; % of times the Kupiec unconditional coverage (UC) test was not rejected at the 5% probability level across all assets for each quantile. The last column shows the % of times the multinomial VaR test by Kratz et al. (2018) was not rejected at the 5% probability level across all assets, for the five quantiles in the left tail (ES_2.5_test) and in the right tail (ES_97.5_test), respectively. The results for the GARCH and HAR models only include assets for which numerical convergence was achieved.

Model	**VaR_0.5**	**CC_0.5**	**UC_0.5**	**VaR_1.0**	**CC_1.0**	**UC_1.0**	**VaR_1.5**	**CC_1.5**	**UC_1.5**	**VaR_2.0**	**CC_2.0**	**UC_2.0**	**VaR_2.5**	**CC_2.5**	**UC_2.5**	**ES_2.5_Test**
AgACI	0.63	74.95	87.80	0.96	78.50	88.38	1.30	72.35	84.45	1.64	69.28	80.18	2.00	66.05	76.10	77.70
FACI	0.58	78.10	91.53	0.92	85.43	94.38	1.34	81.85	93.18	1.78	80.95	92.78	2.23	81.08	91.73	88.10
SF-OGD	0.51	96.03	95.18	0.94	96.35	96.25	1.37	95.88	95.10	1.81	94.50	93.53	2.24	94.00	92.55	86.73
SAOCP	0.64	94.03	90.00	0.96	93.83	89.08	1.31	89.58	83.73	1.56	83.03	75.25	1.86	75.18	66.80	55.15
GARCH	0.76	76.56	68.60	1.27	73.05	67.83	1.76	69.75	64.98	2.24	67.78	63.19	2.70	66.11	62.30	68.01 (*)
HAR_DR	1.08	66.50	58.24	1.33	60.24	56.03	1.53	51.18	46.05	1.71	42.51	38.73	1.88	36.40	33.21	21.36 (**)
Model	**VaR_97.5**	**CC_97.5**	**UC_97.5**	**VaR_98.0**	**CC_98.0**	**UC_98.0**	**VaR_98.5**	**CC_98.5**	**UC_98.5**	**VaR_99.0**	**CC_99.0**	**UC_99.0**	**VaR_99.5**	**CC_99.5**	**UC_99.5**	**ES_97.5_Test**
AgACI	97.51	70.30	88.00	97.94	71.68	88.35	98.35	71.58	87.68	98.75	75.23	86.75	99.17	68.50	80.58	79.95
FACI	97.17	76.08	92.55	97.70	77.73	92.55	98.24	78.15	92.40	98.78	82.63	93.03	99.25	74.38	87.25	88.80
SF-OGD	97.07	92.18	92.48	97.63	92.98	93.00	98.18	92.98	93.55	98.74	94.55	94.68	99.29	92.98	94.85	88.55
SAOCP	97.58	82.20	77.08	97.96	86.88	81.80	98.27	88.15	82.33	98.72	91.03	85.70	99.13	84.95	78.25	49.08
GARCH	96.82	68.55	66.83	97.35	69.57	66.68	97.89	70.41	66.68	98.45	72.52	68.31	99.05	73.31	67.88	69.62 (*)
HAR_DR	97.94	42.92	42.43	98.11	49.87	49.05	98.29	57.16	55.11	98.50	61.88	59.03	98.76	58.21	52.28	19.33 (**)

(*) The GARCH(1,1) model with standardized errors following a symmetric Student's t-distribution did not reach numerical convergence for 96 assets (out of 4000). (**) The HAR model used for the dynamics of range-based daily volatilities did not reach numerical convergence for 104 assets (out of 4000).

Table 2. Average rank of the models across all assets for each quantile based on the asymmetric quantile loss (QL) function proposed by González-Rivera et al. (2004).

Quantile	AgACI	FACI	SF-OGD	SAOCP	GARCH	HAR_DR
VaR_0.5	4.22	4.95	3.36	3.05	2.33	3.09
VaR_1.0	4.13	4.33	3.72	3.37	2.17	3.29
VaR_1.5	3.99	3.75	3.95	3.67	2.06	3.58
VaR_2.0	3.82	3.41	4.04	3.95	1.96	3.82
VaR_2.5	3.64	3.19	4.12	4.13	1.88	4.04
VaR_97.5	3.73	3.33	4.06	3.84	1.91	4.14
VaR_98.0	3.89	3.52	3.96	3.70	1.99	3.94
VaR_98.5	4.11	3.79	3.83	3.46	2.09	3.72
VaR_99.0	4.22	4.23	3.58	3.21	2.21	3.55
VaR_99.5	4.21	4.67	3.21	3.00	2.39	3.51

Table 3. Number of times (in %) when the model was included into the model confidence set (MCS) at the 10% confidence level across all assets.

Quantile	AgACI	FACI	SF-OGD	SAOCP	GARCH	HAR_DR
VaR_0.5	57.23	43.52	68.56	76.71	89.56	81.70
VaR_1.0	68.85	61.57	69.01	75.17	93.32	78.20
VaR_1.5	75.22	75.93	69.82	74.73	94.83	73.71
VaR_2.0	78.38	83.08	69.16	70.99	95.80	68.80
VaR_2.5	82.19	86.55	67.21	68.22	95.98	64.02
VaR_97.5	89.45	93.26	76.29	79.16	97.44	69.32
VaR_98.0	87.00	90.10	79.19	81.78	97.08	73.97
VaR_98.5	83.32	85.51	80.68	85.69	96.87	79.45
VaR_99.0	79.40	75.40	82.72	87.55	96.06	82.79
VaR_99.5	73.26	61.36	85.17	90.23	94.99	85.72

4.3. Robustness Check 1: Market Capitalization of Crypto-Assets

In this section, we examined the 2310 assets with daily market capitalization data and categorized them into four groups, each containing approximately the same number of assets. The first group comprises assets with the highest market capitalization in dollars, while the fourth group consists of assets with the lowest capitalization.

We computed the Kupiec (1995) test, the Christoffersen (1998) test, and the multinomial VaR test by Kratz et al. (2018) for each group, with the results presented in Tables 4 and 5.

The empirical analysis broadly confirms the findings of the baseline case. However, it reveals that the performance of the GARCH model and, to a lesser extent, the SAOCP algorithm deteriorated significantly when focusing on assets with the lowest market capitalization. It appears that the extreme volatility of this asset class strongly impacted the numerical stability of these models. As a result, the GARCH model exhibited too many VaR violations, while the SAOCP model demonstrated too few.

It is well known that crypto-assets with lower market capitalization tend to experience higher levels of volatility. This heightened volatility can pose challenges for several modeling approaches, which may struggle to adequately capture and predict extreme movements in these assets' prices. As such, future research could explore alternative modeling techniques specifically tailored to address the unique characteristics and dynamics of lower-capitalization crypto-assets, potentially enhancing the accuracy and robustness of risk management strategies in this segment of the market.

Table 4. Backtesting results based on **market capitalization** (first 2 groups): Average number of violations in % across all assets for each quantile; % of times the Christoffersen conditional coverage (CC) test was not rejected at the 5% probability level across all assets for each quantile; % of times the Kupiec unconditional coverage (UC) test was not rejected at the 5% probability level across all assets for each quantile. The last column shows the % of times the multinomial VaR test by Kratz et al. (2018) was not rejected at the 5% probability level across all assets, for the five quantiles in the left tail (ES_2.5_test) and in the right tail (ES_97.5_test), respectively.

Highest Market Capitalization: $259, 874,508–$1,274,831,490,851																
Model	VaR_0.5	CC_0.5	UC_0.5	VaR_1.0	CC_1.0	UC_1.0	VaR_1.5	CC_1.5	UC_1.5	VaR_2.0	CC_2.0	UC_2.0	VaR_2.5	CC_2.5	UC_2.5	ES_2.5_test
AgACI	0.50	73.31	89.95	0.81	68.11	82.84	1.12	60.83	74.00	1.48	52.34	68.28	1.86	49.74	62.91	71.75
FACI	0.50	74.87	93.41	0.90	78.86	93.07	1.34	74.87	91.85	1.80	74.18	92.03	2.28	75.56	92.03	90.12
SF-OGD	0.49	93.41	96.88	0.95	94.11	97.92	1.42	94.63	95.84	1.90	94.45	95.15	2.37	94.63	95.15	86.83
SAOCP	0.59	92.20	90.29	0.92	92.20	87.69	1.32	88.21	81.98	1.62	82.32	77.47	2.01	77.99	70.71	51.65
GARCH	0.47	83.10	76.83	0.88	76.66	70.91	1.30	70.38	68.29	1.71	69.51	67.25	2.12	69.51	65.85	72.65
HAR_DR	0.65	73.34	70.56	0.87	65.51	62.54	1.07	51.57	49.30	1.24	37.63	36.24	1.41	29.62	28.75	18.82
Model	VaR_97.5	CC_97.5	UC_97.5	VaR_98.0	CC_98.0	UC_98.0	VaR_98.5	CC_98.5	UC_98.5	VaR_99.0	CC_99.0	UC_99.0	VaR_99.5	CC_99.5	UC_99.5	ES_97.5_test
AgACI	97.76	59.79	84.92	98.16	61.18	88.04	98.57	67.07	90.12	98.95	71.58	92.20	99.36	75.39	91.16	79.38
FACI	97.34	71.40	93.59	97.82	71.75	93.24	98.34	72.27	93.24	98.87	76.60	94.28	99.40	80.59	94.45	92.20
SF-OGD	97.28	88.39	94.97	97.79	89.95	94.63	98.31	90.12	94.45	98.84	91.16	97.05	99.36	93.93	96.01	88.21
SAOCP	97.72	80.59	76.78	98.08	86.31	81.63	98.42	89.60	84.92	98.84	92.03	87.00	99.27	89.25	84.40	50.95
GARCH	97.37	75.44	74.39	97.85	76.66	74.39	98.33	78.05	75.96	98.82	81.88	79.09	99.33	84.67	79.62	78.57
HAR_DR	98.25	43.73	47.39	98.43	54.18	56.62	98.63	63.59	66.03	98.84	69.16	68.12	99.10	59.06	57.14	17.42
Second-Highest Market Capitalization: $56,658,794–$258,810,481																
Model	VaR_0.5	CC_0.5	UC_0.5	VaR_1.0	CC_1.0	UC_1.0	VaR_1.5	CC_1.5	UC_1.5	VaR_2.0	CC_2.0	UC_2.0	VaR_2.5	CC_2.5	UC_2.5	ES_2.5_test
AgACI	0.55	72.62	88.56	0.87	72.10	85.27	1.22	63.78	79.90	1.56	60.49	73.48	1.94	56.67	69.32	75.56
FACI	0.51	76.78	92.55	0.89	80.94	93.24	1.34	76.26	92.37	1.80	76.60	92.20	2.28	77.12	91.85	88.21
SF-OGD	0.49	95.84	96.53	0.94	95.84	95.84	1.40	95.49	95.67	1.86	92.72	93.93	2.32	95.32	94.63	88.04
SAOCP	0.59	95.49	93.59	0.93	93.76	87.69	1.28	87.52	80.24	1.55	79.38	71.75	1.86	71.58	63.43	48.18
GARCH	0.54	80.04	74.61	0.96	76.18	72.33	1.38	70.23	67.08	1.80	67.25	63.57	2.23	64.62	63.05	69.53
HAR_DR	0.72	69.79	65.72	0.93	58.66	56.01	1.11	44.52	41.52	1.28	32.51	31.10	1.44	26.68	25.97	16.96
Model	VaR_97.5	CC_97.5	UC_97.5	VaR_98.0	CC_98.0	UC_98.0	VaR_98.5	CC_98.5	UC_98.5	VaR_99.0	CC_99.0	UC_99.0	VaR_99.5	CC_99.5	UC_99.5	ES_97.5_test
AgACI	97.63	68.28	90.64	98.05	69.84	92.20	98.44	71.92	91.51	98.84	75.56	92.37	99.28	75.74	89.77	83.36
FACI	97.24	72.27	93.07	97.75	75.04	94.11	98.28	75.04	93.41	98.82	80.94	93.24	99.34	80.94	92.89	92.03
SF-OGD	97.21	93.07	94.45	97.73	92.55	93.93	98.26	91.33	94.97	98.79	93.93	93.93	99.33	94.11	96.53	87.35
SAOCP	97.69	80.07	74.52	98.06	86.48	81.98	98.39	88.56	84.40	98.82	91.16	87.69	99.22	86.14	81.28	47.83
GARCH	97.16	73.03	71.10	97.66	75.83	74.78	98.16	77.06	73.73	98.66	78.63	75.13	99.22	78.98	75.66	74.61
HAR_DR	98.21	41.17	40.99	98.38	49.65	50.00	98.55	58.13	57.77	98.76	61.31	61.48	99.01	58.13	52.47	16.08

Table 5. Backtesting results based on **market capitalization** (last 2 groups): Average number of violations in % across all assets for each quantile; % of times the Christoffersen conditional coverage (CC) test was not rejected at the 5% probability level across all assets for each quantile; % of times the Kupiec unconditional coverage (UC) test was not rejected at the 5% probability level across all assets for each quantile. The last column shows the % of times the multinomial VaR test by Kratz et al. (2018) was not rejected at the 5% probability level across all assets, for the five quantiles in the left tail (ES_2.5_test) and in the right tail (ES_97.5_test), respectively.

Third-Highest Market capitalization: $12,235,621–$56,579,279																
Model	VaR_0.5	CC_0.5	UC_0.5	VaR_1.0	CC_1.0	UC_1.0	VaR_1.5	CC_1.5	UC_1.5	VaR_2.0	CC_2.0	UC_2.0	VaR_2.5	CC_2.5	UC_2.5	ES_2.5_test
AgACI	0.57	74.52	90.99	0.90	77.12	88.56	1.25	70.71	85.44	1.59	67.42	77.30	1.94	62.05	71.75	74.70
FACI	0.52	78.68	93.24	0.89	84.40	96.01	1.32	80.94	93.59	1.77	79.90	93.41	2.23	81.28	92.03	90.12
SF-OGD	0.48	97.23	95.32	0.93	96.71	96.01	1.36	96.01	95.67	1.83	96.71	95.84	2.28	95.32	95.49	84.23
SAOCP	0.59	94.63	91.51	0.89	93.41	88.04	1.26	86.83	83.88	1.52	81.11	72.96	1.84	71.58	64.99	51.99
GARCH	0.61	78.57	69.82	1.09	75.89	68.21	1.55	71.61	65.54	1.99	70.00	64.46	2.44	66.43	63.04	70.01
HAR_DR	1.02	64.59	61.74	1.28	61.74	56.76	1.48	50.71	46.09	1.67	41.46	39.15	1.84	35.41	31.49	20.46
Model	VaR_97.5	CC_97.5	UC_97.5	VaR_98.0	CC_98.0	UC_98.0	VaR_98.5	CC_98.5	UC_98.5	VaR_99.0	CC_99.0	UC_99.0	VaR_99.5	CC_99.5	UC_99.5	ES_97.5_test
AgACI	97.54	70.36	89.95	97.98	73.66	90.81	98.39	72.44	89.95	98.81	74.35	89.60	99.24	71.75	85.10	82.67
FACI	97.15	73.31	93.59	97.70	75.91	92.72	98.23	78.34	93.07	98.80	81.98	93.93	99.32	77.64	90.64	92.37
SF-OGD	97.14	94.11	94.28	97.67	93.93	94.28	98.19	93.24	93.93	98.75	94.11	94.11	99.29	94.45	94.45	88.39
SAOCP	97.63	80.76	74.52	97.97	86.48	81.46	98.30	89.25	83.54	98.74	91.33	85.62	99.17	84.92	79.90	45.75
GARCH	96.87	68.75	67.86	97.40	70.36	68.04	97.95	69.46	66.61	98.51	71.25	67.50	99.12	74.64	69.82	72.14
HAR_DR	97.89	43.06	44.48	98.07	50.71	50.89	98.26	58.19	57.12	98.49	60.32	60.32	98.77	51.60	49.82	18.51
Lowest Market Capitalization: $2589–$12,233,558																
Model	VaR_0.5	CC_0.5	UC_0.5	VaR_1.0	CC_1.0	UC_1.0	VaR_1.5	CC_1.5	UC_1.5	VaR_2.0	CC_2.0	UC_2.0	VaR_2.5	CC_2.5	UC_2.5	ES_2.5_test
AgACI	0.57	78.76	87.56	0.91	79.10	86.36	1.24	68.22	80.14	1.59	63.90	74.78	1.94	59.41	69.95	73.92
FACI	0.54	82.38	92.75	0.91	87.05	94.30	1.35	82.90	94.30	1.78	81.35	92.23	2.23	77.89	92.06	86.87
SF-OGD	0.49	96.37	93.96	0.92	95.68	95.51	1.36	96.03	94.82	1.83	94.65	93.26	2.27	93.78	93.96	86.01
SAOCP	0.61	93.26	89.98	0.93	89.98	83.42	1.27	83.07	76.34	1.53	73.92	66.67	1.80	63.56	56.13	45.08
GARCH	1.00	65.89	58.93	1.59	64.11	58.39	2.15	60.71	56.25	2.66	58.57	53.93	3.18	58.75	54.46	58.75
HAR_DR	1.26	54.51	44.96	1.54	54.34	49.38	1.75	50.62	43.72	1.94	44.42	39.29	2.11	37.70	35.93	15.22
Model	VaR_97.5	CC_97.5	UC_97.5	VaR_98.0	CC_98.0	UC_98.0	VaR_98.5	CC_98.5	UC_98.5	VaR_99.0	CC_99.0	UC_99.0	VaR_99.5	CC_99.5	UC_99.5	ES_97.5_test
AgACI	97.62	66.15	80.83	98.05	69.26	82.38	98.47	70.98	84.63	98.86	75.82	85.49	99.26	72.54	83.77	77.37
FACI	97.22	73.40	93.78	97.75	78.93	93.96	98.30	82.73	93.09	98.84	86.01	93.44	99.32	78.76	91.02	90.33
SF-OGD	97.15	94.13	93.96	97.71	95.34	93.96	98.23	94.30	94.47	98.78	95.85	95.34	99.33	94.82	94.82	86.87
SAOCP	97.76	70.98	66.67	98.11	79.62	73.23	98.43	84.80	77.89	98.84	90.50	82.56	99.22	86.70	80.48	39.55
GARCH	96.38	57.86	56.43	96.93	58.57	54.46	97.51	58.21	53.57	98.12	60.71	55.00	98.80	58.21	52.14	56.96
HAR_DR	97.70	42.30	41.42	97.87	46.19	43.54	98.07	52.57	47.08	98.29	55.22	50.62	98.57	49.20	44.78	15.04

4.4. Robustness Check 2: Time-Series Size

As a second robustness check, we divided our assets into four groups based on the size of their time series, with each group containing approximately the same number of assets. The first group encompasses assets with the longest time series, ranging from 1613 daily data points to 4939 daily data points, while the fourth group comprises assets with the shortest time series, ranging from 731 daily data points to 836 daily data points.

We computed the Kupiec (1995) test, the Christoffersen (1998) test, and the multinomial VaR test by Kratz et al. (2018) for each group, with the results presented in Tables 6 and 7.

The empirical analysis broadly confirms the findings of the baseline case. However, it unveils some intriguing trends: AgACI, FACI, and SF-OGD exhibit consistent performances across time series of varying lengths. Instead, GARCH models seem to perform best with time series close to 1000 observations. Assets with longer time series exhibit a higher number of VaR exceedances than expected, particularly in the extreme left tail, likely attributed to significant structural breaks. Conversely, shorter time series exhibit slightly inferior performance, likely due to relatively small datasets that are insufficient for accurate parameter estimation.

SAOCP and the HAR model with daily range data perform notably better with time series containing fewer than 1000 observations compared to longer time series. It appears that these methods are more sensitive to structural breaks, which occur more frequently in assets with longer time series. This evidence indirectly corroborates the simulation studies conducted by Susmann et al. (2023), which demonstrated that SAOCP (and to some extent, SF-OGD) tend to underestimate the quantiles when faced with a distributional shift. A notable departure from the findings of Susmann et al. (2023) is that the simple SF-OGD model turned out to be pretty robust across all time samples: despite showing slightly inferior performances compared to the FACI algorithm for very long time series, these differences were mostly statistically insignificant in terms of quantile losses (not reported). Moreover, SF-OGD emerged as the top-performing model for the shortest time series.

This evidence underscores the importance of considering both the length of the time series and the model's sensitivity to structural breaks when selecting appropriate risk forecasting methods. Future research could delve deeper into understanding the mechanisms underlying these performance disparities and explore potential refinements to enhance the accuracy and robustness of risk predictions across diverse time-series lengths.

Table 6. Backtesting results based on **time-series size** (first 2 groups): Average number of violations in % across all assets for each quantile; % of times the Christoffersen conditional coverage (CC) test was not rejected at the 5% probability level across all assets for each quantile; % of times the Kupiec unconditional coverage (UC) test was not rejected at the 5% probability level across all assets for each quantile. The last column shows the % of times the multinomial VaR test by Kratz et al. (2018) was not rejected at the 5% probability level across all assets, for the five quantiles in the left tail (ES_2.5_test) and in the right tail (ES_97.5_test), respectively.

Longest Time Series: 4939–1613 (Daily Data)																
Model	VaR_0.5	CC_0.5	UC_0.5	VaR_1.0	CC_1.0	UC_1.0	VaR_1.5	CC_1.5	UC_1.5	VaR_2.0	CC_2.0	UC_2.0	VaR_2.5	CC_2.5	UC_2.5	ES_2.5_test
AgACI	0.43	81.10	89.50	0.77	67.10	78.10	1.11	57.20	67.50	1.46	48.40	56.60	1.84	43.00	49.30	62.60
FACI	0.44	84.80	93.50	0.90	82.00	93.10	1.36	77.80	91.70	1.81	76.90	91.00	2.29	75.30	91.10	90.10
SF-OGD	0.47	97.50	95.90	0.93	93.80	94.90	1.40	94.50	94.70	1.89	92.90	93.90	2.37	93.80	95.40	83.30
SAOCP	0.50	96.00	91.40	0.80	86.80	77.90	1.16	76.40	67.70	1.43	62.40	53.50	1.73	49.30	41.30	31.00
GARCH	0.83	68.70	61.98	1.37	66.01	58.99	1.90	63.43	57.23	2.39	62.50	57.02	2.88	59.40	55.68	59.19
HAR_DR	1.01	56.72	50.92	1.25	51.83	47.15	1.44	43.08	38.59	1.61	34.22	32.69	1.78	29.84	27.90	3.05
Model	VaR_97.5	CC_97.5	UC_97.5	VaR_98.0	CC_98.0	UC_98.0	VaR_98.5	CC_98.5	UC_98.5	VaR_99.0	CC_99.0	UC_99.0	VaR_99.5	CC_99.5	UC_99.5	ES_97.5_test
AgACI	97.86	52.90	80.50	98.27	57.40	83.80	98.67	62.30	86.50	99.05	68.10	92.80	99.44	80.40	93.90	76.50
FACI	97.35	62.90	94.90	97.87	68.10	94.60	98.38	72.10	94.50	98.92	76.90	94.90	99.46	85.30	96.70	93.90
SF-OGD	97.34	91.40	96.40	97.86	91.70	94.90	98.36	90.60	95.40	98.89	91.90	96.20	99.42	95.80	97.10	85.90
SAOCP	98.06	63.50	57.40	98.36	77.30	69.70	98.67	85.30	79.20	99.04	92.80	87.90	99.40	92.40	89.00	35.30
GARCH	96.70	57.95	57.02	97.24	59.61	56.30	97.80	58.26	56.40	98.38	61.67	57.23	99.00	62.60	56.71	58.26
HAR_DR	97.99	36.97	38.09	98.17	42.87	44.09	98.36	50.61	50.41	98.57	52.55	51.73	98.84	42.16	40.02	3.87
Second-Longest Time Series: 1612–1039 (Daily Data)																
Model	VaR_0.5	CC_0.5	UC_0.5	VaR_1.0	CC_1.0	UC_1.0	VaR_1.5	CC_1.5	UC_1.5	VaR_2.0	CC_2.0	UC_2.0	VaR_2.5	CC_2.5	UC_2.5	ES_2.5_test
AgACI	0.59	74.90	88.90	0.94	78.00	90.40	1.28	69.40	87.10	1.64	65.90	82.50	2.01	62.30	79.60	80.30
FACI	0.54	78.50	93.90	0.94	85.20	94.90	1.42	79.80	95.00	1.91	78.30	95.40	2.40	78.20	94.80	91.10
SF-OGD	0.53	95.50	97.60	1.00	97.70	98.00	1.48	96.00	96.30	1.96	95.40	95.80	2.44	94.80	95.10	86.60
SAOCP	0.65	92.70	89.90	1.00	95.70	91.30	1.38	92.10	86.60	1.65	86.40	77.90	1.98	80.70	72.20	50.20
GARCH	0.73	72.91	71.30	1.22	69.69	65.56	1.69	66.06	61.63	2.15	62.84	59.52	2.61	62.64	60.62	66.06
HAR_DR	1.04	63.97	63.36	1.29	60.29	55.78	1.48	48.11	42.89	1.66	36.23	33.37	1.81	28.15	26.41	17.60
Model	VaR_97.5	CC_97.5	UC_97.5	VaR_98.0	CC_98.0	UC_98.0	VaR_98.5	CC_98.5	UC_98.5	VaR_99.0	CC_99.0	UC_99.0	VaR_99.5	CC_99.5	UC_99.5	ES_97.5_test
AgACI	97.81	72.60	88.90	98.20	75.30	91.20	98.58	76.80	92.40	98.95	81.60	92.90	99.34	77.70	90.70	82.70
FACI	97.42	79.60	95.40	97.89	82.60	95.60	98.40	83.00	95.50	98.91	86.50	95.40	99.40	83.10	95.70	92.90
SF-OGD	97.33	94.60	96.20	97.84	94.90	96.10	98.35	94.90	96.40	98.86	96.50	96.90	99.37	95.60	97.60	86.80
SAOCP	97.89	84.80	78.90	98.21	87.70	84.00	98.50	92.00	87.20	98.89	94.10	89.40	99.26	91.40	86.70	49.20
GARCH	97.16	70.80	68.48	97.63	71.70	69.08	98.12	74.92	69.69	98.63	76.74	72.61	99.18	77.95	73.11	70.09
HAR_DR	98.11	37.15	36.13	98.27	47.08	44.42	98.43	57.83	55.78	98.62	64.48	62.54	98.87	62.13	58.96	15.35

Table 7. Backtesting results based on **time-series size** (last 2 groups): Average number of violations in % across all assets for each quantile; % of times the Christoffersen conditional coverage (CC) test was not rejected at the 5% probability level across all assets for each quantile; % of times the Kupiec unconditional coverage (UC) test was not rejected at the 5% probability level across all assets for each quantile. The last column shows the % of times the multinomial VaR test by Kratz et al. (2018) was not rejected at the 5% probability level across all assets, for the five quantiles in the left tail (ES_2.5_test) and in the right tail (ES_97.5_test), respectively.

Third-Longest Time Series: 1038–837 (Daily Data)																
Model	VaR_0.5	CC_0.5	UC_0.5	VaR_1.0	CC_1.0	UC_1.0	VaR_1.5	CC_1.5	UC_1.5	VaR_2.0	CC_2.0	UC_2.0	VaR_2.5	CC_2.5	UC_2.5	ES_2.5_test
AgACI	0.72	69.20	87.70	1.04	83.60	92.20	1.37	78.80	92.10	1.71	79.60	90.90	2.05	76.80	87.50	82.20
FACI	0.65	72.90	90.80	0.94	86.90	95.20	1.34	84.40	94.20	1.77	83.10	94.30	2.20	84.20	93.50	88.00
SF-OGD	0.51	93.90	95.40	0.92	97.30	96.30	1.32	96.80	95.80	1.74	95.40	93.90	2.16	94.90	92.90	88.90
SAOCP	0.68	92.40	92.40	1.00	96.70	93.80	1.35	95.60	91.10	1.59	91.80	84.60	1.88	86.20	78.20	65.70
GARCH	0.70	80.57	74.79	1.19	79.31	73.11	1.64	73.63	71.43	2.11	72.16	68.70	2.55	69.43	66.07	73.74
HAR_DR	1.17	69.23	61.12	1.43	62.80	58.48	1.64	52.37	48.58	1.83	43.94	41.41	2.00	38.67	34.88	27.82
Model	VaR_97.5	CC_97.5	UC_97.5	VaR_98.0	CC_98.0	UC_98.0	VaR_98.5	CC_98.5	UC_98.5	VaR_99.0	CC_99.0	UC_99.0	VaR_99.5	CC_99.5	UC_99.5	ES_97.5_test
AgACI	97.41	79.10	93.60	97.85	82.40	92.40	98.28	78.90	91.60	98.69	80.60	86.30	99.12	64.90	78.70	84.20
FACI	97.11	82.80	92.70	97.66	85.10	93.80	98.23	82.00	93.20	98.77	86.70	93.90	99.24	71.00	87.60	90.10
SF-OGD	96.95	93.00	91.80	97.52	94.30	92.50	98.08	93.80	92.80	98.67	95.10	94.50	99.24	91.30	94.30	90.80
SAOCP	97.37	91.60	86.70	97.77	92.10	87.90	98.10	90.90	85.80	98.59	90.90	85.40	99.05	81.00	74.90	56.30
GARCH	96.88	75.00	74.89	97.42	77.21	74.68	97.97	77.73	73.74	98.52	77.52	72.90	99.11	78.68	75.32	77.84
HAR_DR	97.83	42.99	43.52	98.00	51.32	50.16	98.18	57.01	55.32	98.39	63.96	58.38	98.66	61.85	55.22	25.40
Shortest Time Series: 836–731 (Daily Data)																
Model	VaR_0.5	CC_0.5	UC_0.5	VaR_1.0	CC_1.0	UC_1.0	VaR_1.5	CC_1.5	UC_1.5	VaR_2.0	CC_2.0	UC_2.0	VaR_2.5	CC_2.5	UC_2.5	ES_2.5_test
AgACI	0.77	74.60	85.10	1.10	85.30	92.80	1.44	84.00	91.10	1.76	83.20	90.70	2.10	82.10	88.00	86.30
FACI	0.69	76.20	87.90	0.89	87.60	94.30	1.25	85.40	91.80	1.64	85.50	90.40	2.05	86.60	87.50	83.30
SF-OGD	0.53	97.20	91.80	0.91	96.60	95.80	1.28	96.20	93.60	1.64	94.30	90.50	1.99	92.50	86.80	88.40
SAOCP	0.73	95.00	86.30	1.01	96.10	93.30	1.36	94.20	89.50	1.59	91.50	85.00	1.83	84.50	75.50	74.20
GARCH	0.78	84.06	66.40	1.31	77.30	73.66	1.82	75.88	69.73	2.30	73.66	67.61	2.77	72.96	66.80	73.56
HAR_DR	1.09	76.11	57.69	1.35	66.09	62.75	1.56	61.13	54.15	1.74	55.57	47.47	1.92	48.89	43.62	37.25
Model	VaR_97.5	CC_97.5	UC_97.5	VaR_98.0	CC_98.0	UC_98.0	VaR_98.5	CC_98.5	UC_98.5	VaR_99.0	CC_99.0	UC_99.0	VaR_99.5	CC_99.5	UC_99.5	ES_97.5_test
AgACI	96.97	76.60	89.00	97.43	71.60	86.00	97.86	68.30	80.20	98.30	70.60	75.00	98.78	51.00	59.00	76.40
FACI	96.80	79.00	87.20	97.36	75.10	86.20	97.95	75.50	86.40	98.52	80.40	87.90	98.90	58.10	69.00	78.50
SF-OGD	96.68	89.70	85.50	97.30	91.00	88.50	97.93	92.60	89.60	98.54	94.70	91.10	99.13	89.20	90.40	90.70
SAOCP	97.03	88.90	85.30	97.49	90.40	85.60	97.81	84.40	77.10	98.36	86.30	80.10	98.83	75.00	62.40	56.10
GARCH	96.53	70.43	67.00	97.10	69.83	66.70	97.66	70.74	66.90	98.26	74.07	70.43	98.92	73.97	66.40	72.45
HAR_DR	97.84	54.45	51.92	98.00	58.20	57.49	98.19	63.16	58.91	98.42	66.60	63.46	98.69	66.80	55.06	33.00

4.5. Robustness Check 3: Different Forecasting Methods

As a third robustness check, we wanted to assess the impact on our results by employing a more complex model specification than an AR(1) model, namely, a single-hidden-layer neural network using seven lagged daily log-returns as inputs and three hidden units.

We computed the Kupiec (1995) test, the Christoffersen (1998) test, and the multinomial VaR test by Kratz et al. (2018) for the four ACI algorithms using the neural network as the forecasting model, and the results are presented in Table 8. We also computed the asymmetric QL function proposed by González-Rivera et al. (2004) and employed the MCS method by Hansen et al. (2011); see Tables 9 and 10. Similarly to the baseline case, we considered only assets for which all six models reached numerical convergence.

In terms of VaR violations, there are no notable differences among the models, except for SAOCP, where the number of instances where the Christoffersen test, the Kupiec test, and the multinomial VaR test did not reject the null hypothesis was 5–12% lower than the baseline case. This evidence suggests that the more volatile mean forecasts computed using a neural network penalized this algorithm. A similar phenomenon, albeit on a smaller scale (3–5% lower), was also observed for the AgACI algorithm.

Regarding quantile loss functions, all four ACI algorithms were strongly penalized in terms of average ranking, with SAOCP exhibiting the largest decline in ranking across all competing models. Likewise, all four ACI algorithms demonstrated a decrease in the percentage of times the models were included in the model confidence set (20–30% lower), particularly affecting the left tail of the distribution.

In general, employing a more complex forecasting model for the mean of the assets' log-returns with ACI algorithms did not result in more precise risk estimates. This outcome can probably be attributed to the lower model bias being outweighed by the higher variance in the model estimates. These findings underscore the intricate trade-offs involved in selecting forecasting models for risk management purposes, highlighting the importance of considering both model complexity and estimation accuracy in decision-making processes.

Table 8. Average number of violations in % across all assets for each quantile **using a neural network**; % of times the Christoffersen conditional coverage (CC) test was not rejected at the 5% probability level across all assets for each quantile; % of times the Kupiec unconditional coverage (UC) test was not rejected at the 5% probability level across all assets for each quantile. The last column shows the % of times the multinomial VaR test by Kratz et al. (2018) was not rejected at the 5% probability level across all assets, for the five quantiles in the left tail (ES_2.5_test) and in the right tail (ES_97.5_test), respectively.

Model	VaR_0.5	CC_0.5	UC_0.5	VaR_1.0	CC_1.0	UC_1.0	VaR_1.5	CC_1.5	UC_1.5	VaR_2.0	CC_2.0	UC_2.0	VaR_2.5	CC_2.5	UC_2.5	ES_2.5_Test
AgACI	0.65	70.00	87.80	0.97	73.48	87.43	1.29	66.58	82.58	1.63	63.60	77.70	1.98	61.98	73.88	74.20
FACI	0.61	75.18	92.18	0.94	83.20	95.43	1.37	80.63	94.33	1.81	78.90	93.18	2.27	78.20	93.08	87.90
SF-OGD	0.52	95.38	95.98	0.96	96.58	97.35	1.40	96.30	96.23	1.86	95.60	95.15	2.31	95.18	94.28	83.03
SAOCP	0.60	93.25	89.65	0.88	88.55	83.10	1.16	78.55	72.43	1.40	71.85	63.38	1.64	62.58	55.25	46.23
Model	**VaR_97.5**	**CC_97.5**	**UC_97.5**	**VaR_98.0**	**CC_98.0**	**UC_98.0**	**VaR_98.5**	**CC_98.5**	**UC_98.5**	**VaR_99.0**	**CC_99.0**	**UC_99.0**	**VaR_99.5**	**CC_99.5**	**UC_99.5**	**ES_97.5_Test**
AgACI	97.62	63.20	83.55	98.03	64.70	84.90	98.41	64.48	85.75	98.79	69.13	86.40	99.19	63.05	79.95	76.60
FACI	97.22	73.63	93.43	97.75	75.30	93.58	98.29	75.95	94.25	98.81	80.40	94.38	99.25	70.60	87.53	88.00
SF-OGD	97.18	93.70	93.90	97.72	94.85	95.15	98.24	95.25	95.95	98.79	95.85	95.93	99.33	92.93	95.20	84.48
SAOCP	97.97	67.70	61.80	98.27	74.35	68.58	98.55	77.85	73.30	98.90	87.90	82.60	99.24	86.95	83.15	42.40

Table 9. Average rank of the models across all assets for each quantile based on the asymmetric quantile loss (QL) function proposed by González-Rivera et al. (2004). ACI algorithms use a neural network.

Quantile	AgACI	FACI	SF-OGD	SAOCP	GARCH	HAR_DR
VaR_0.5	4.45	5.26	3.68	3.39	1.84	2.37
VaR_1.0	4.25	4.67	4.03	3.84	1.71	2.51
VaR_1.5	4.12	4.16	4.24	4.17	1.62	2.69
VaR_2.0	3.97	3.83	4.35	4.47	1.53	2.85
VaR_2.5	3.84	3.62	4.43	4.64	1.48	2.98
VaR_97.5	3.89	3.75	4.39	4.49	1.44	3.05
VaR_98.0	4.06	3.91	4.31	4.30	1.51	2.91
VaR_98.5	4.26	4.22	4.14	4.04	1.57	2.76
VaR_99.0	4.34	4.65	3.93	3.75	1.68	2.66
VaR_99.5	4.46	5.12	3.62	3.38	1.80	2.62

Table 10. Number of times (in %) when the model was included into the model confidence set (MCS) at the 10% confidence level across all assets. ACI algorithms use a neural network.

Quantile	AgACI	FACI	SF-OGD	SAOCP	GARCH	HAR_DR
VaR_0.5	0.39	0.27	0.44	0.51	0.90	0.81
VaR_1.0	0.46	0.37	0.43	0.48	0.94	0.76
VaR_1.5	0.51	0.48	0.43	0.46	0.95	0.72
VaR_2.0	0.56	0.56	0.42	0.44	0.96	0.68
VaR_2.5	0.59	0.62	0.40	0.41	0.97	0.67
VaR_99.5	0.67	0.70	0.48	0.50	0.99	0.74
VaR_99.0	0.64	0.65	0.51	0.53	0.98	0.76
VaR_98.5	0.59	0.58	0.52	0.55	0.97	0.78
VaR_98.0	0.55	0.48	0.53	0.58	0.96	0.82
VaR_97.5	0.50	0.37	0.57	0.62	0.95	0.84

4.6. A Comparison with Methods that Predict Quantiles Directly

As a fourth robustness check, we employed the symmetric absolute value (SAV)-CAViaR model with a selected group of crypto-assets: the two most capitalized assets (Bitcoin and Ethereum) and the two least capitalized assets (Bubble and Litecoin-Token) for which all models achieved numerical convergence. The plots of the prices of these four crypto-assets are reported in Figure 1, while the main descriptive statistics of their log-returns are shown in Table 11.

We computed the Kupiec (1995) test, the Christoffersen (1998) test, and the multinomial VaR test by Kratz et al. (2018) for the four ACI algorithms using the AR(1) as the forecasting model, for the GARCH model with Student's t errors, for the HAR model with the daily range, and for the CAViaR-SAV model. We also computed the asymmetric QL function proposed by González-Rivera et al. (2004) and employed the MCS method by Hansen et al. (2011). The results for Bitcoin and Ethereum are presented in Table 12, while for Bubble and Litecoin-Token they are presented in Table 13.

In terms of VaR violations, all four ACI algorithms were able to properly model both the left and right tails of the return distributions, with the exception of SAOCP, which continued to show issues when modeling the right tail of the distribution. The GARCH model worked well with Ethereum but was unable to correctly estimate the quantiles for Bitcoin and the assets with the lowest capitalization. The HAR model performed the worst across all assets, while the CAViaR model passed all coverage tests for the left tail of the assets with the highest market capitalization but failed the tests for the right tail and for the assets with the lowest capitalization.

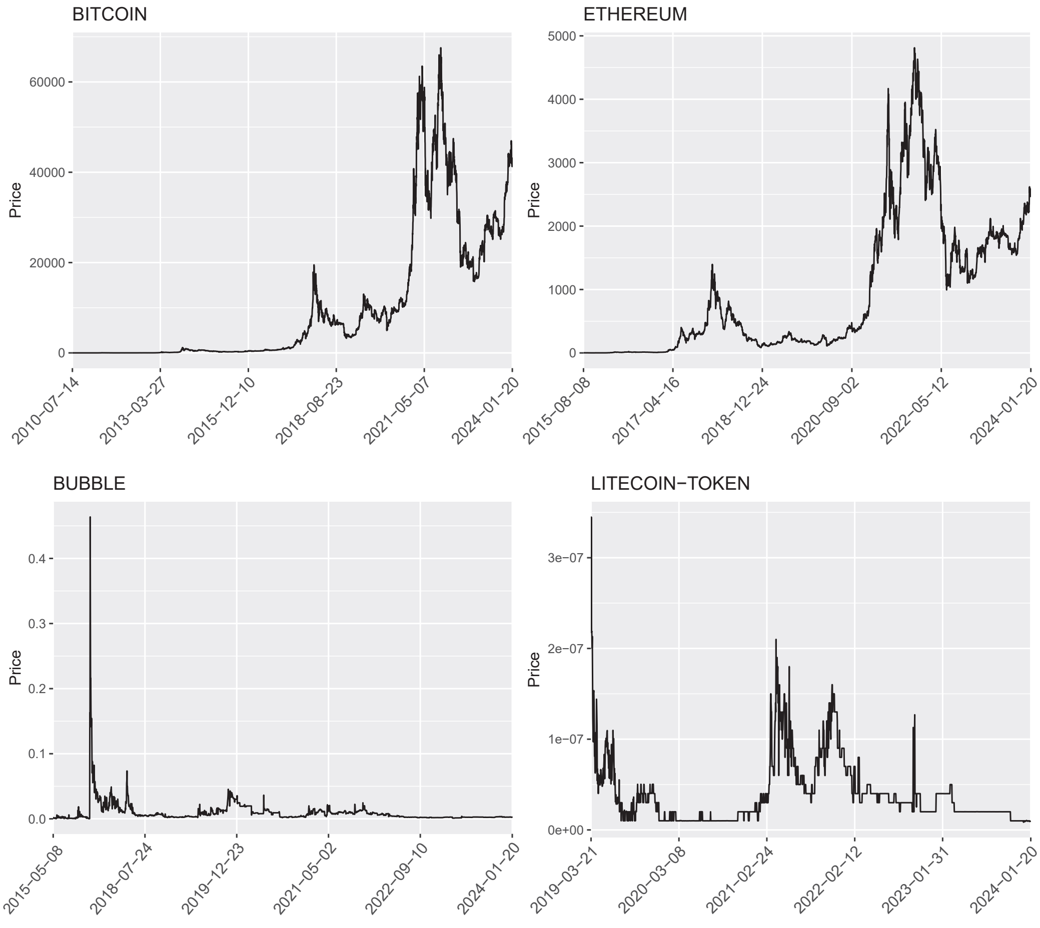

Figure 1. Plots of the prices of four crypto-assets: Bitcoin, Ethereum, Bubble, Litecoin-Token.

Table 11. Log-returns' main descriptive statistics: Bitcoin, Ethereum, Bubble, Litecoin-Token.

Asset	Mean	SD	Min	Max	Median	Skewness	Kurtosis
Bitcoin	0.27%	0.05	−0.68	0.40	0.00	−1.02	24.03
Ethereum	0.26%	0.06	−0.55	0.41	0.00	0.01	11.75
Bubble	0.05%	0.26	−2.45	6.67	0.00	6.93	192.23
Litecoin-Token	−0.18%	0.19	−1.15	1.73	0.00	0.08	16.32

Regarding quantile loss functions, the GARCH model generally exhibited the lowest asymmetric loss functions for Bitcoin and Ethereum, followed by the CAViaR model and the ACI models. However, the GARCH model showed the worst losses (along with the HAR model) for the assets with the lowest market capitalization, whereas the ACI methods performed the best. This confirms that the extreme volatility of these types of assets strongly impacts their numerical stability. Interestingly, the CAViaR model demonstrated remarkably low losses across all assets, indicating its greater computational robustness compared to the GARCH and HAR models. It is important to note that in most instances, the differences between the models' losses were not statistically significant, resulting in the vast majority of the considered models being included in the model confidence set.

In summary, while traditional models like GARCH and HAR exhibit strengths and weaknesses across different assets, the adaptive nature of ACI methods, particularly their robustness in highly volatile markets, highlights their potential as valuable tools in financial risk management. The CAViaR model's consistent performance across various assets further underscores its reliability, making it an interesting alternative to more conventional approaches.

Table 12. Number of VaR violations in % across **Bitcoin** and **Ethereum** for each quantile and model; *p*-values in % for the Christoffersen conditional coverage (CC) test; *p*-values in % for the Kupiec unconditional coverage (UC) test; asymmetric quantile loss (QL) function by González-Rivera et al. (2004); the model was included in the model confidence set (MCS): yes or no; *p*-values in % for the multinomial VaR test by Kratz et al. (2018), for the five quantiles in the left tail (ES_2.5_test) and in the right tail (ES_97.5_test), respectively.

Bitcoin (ID = 1)																									
Model	VaR_0.5	CC_0.5	UC_0.5	Asymmetric QL	MCS	VaR_1.0	CC_1.0	UC_1.0	Asymmetric QL	MCS	VaR_1.5	CC_1.5	UC_1.5	Asymmetric QL	MCS	VaR_2.0	CC_2.0	UC_2.0	Asymmetric QL	MCS	VaR_2.5	CC_2.5	UC_2.5	Asymmetric QL	MCS	ES_2.5_test
AgACI	0.46	0.00	69.10	5.76	YES	0.96	0.00	79.47	8.99	YES	1.49	0.00	94.08	11.74	YES	1.95	0.02	79.25	14.00	NO	2.32	0.00	42.34	15.73	YES	84.26
FACI	0.83	0.00	0.38	5.67	YES	1.27	0.00	8.03	8.86	YES	1.75	0.00	17.70	11.18	YES	2.27	0.00	19.56	13.24	YES	2.84	0.00	14.68	15.09	YES	10.04
SF-OGD	0.66	15.12	15.39	5.18	YES	1.22	3.54	14.08	8.76	YES	1.84	0.01	7.05	11.27	YES	2.34	1.47	11.03	13.60	YES	3.06	0.73	1.89	15.70	YES	18.25
SAOCP	0.68	22.07	10.60	5.22	YES	1.20	37.81	18.23	8.27	YES	1.57	91.36	68.25	10.93	YES	2.14	37.98	49.60	13.28	YES	2.60	28.32	66.17	15.60	YES	43.33
GARCH	0.83	1.10	0.38	4.69	YES	1.64	0.04	0.01	7.91	YES	2.36	0.01	0.00	10.57	YES	3.08	0.00	0.00	12.88	YES	3.72	0.00	0.00	14.96	YES	0.01
HAR_DR	1.29	0.00	0.00	5.80	YES	1.64	0.00	0.01	9.13	YES	2.14	0.17	0.08	12.12	YES	2.43	10.21	4.60	14.88	NO	2.60	29.07	66.17	17.42	NO	0.00
CAViaR	0.33	20.20	7.83	5.13	YES	0.72	10.81	4.63	8.33	YES	1.03	1.26	0.53	10.89	YES	1.60	12.78	4.31	13.20	YES	2.10	16.28	7.40	15.15	YES	12.59
Model	VaR_97.5	CC_97.5	UC_97.5	Asymmetric QL	MCS	VaR_98.0	CC_98.0	UC_98.0	Asymmetric QL	MCS	VaR_98.5	CC_98.5	UC_98.5	Asymmetric QL	MCS	VaR_99.0	CC_99.0	UC_99.0	Asymmetric QL	MCS	VaR_99.5	CC_99.5	UC_99.5	Asymmetric QL	MCS	ES_97.5_test
AgACI	98.56	0.00	0.00	14.38	NO	98.91	0.00	0.00	12.59	NO	99.23	0.00	0.00	10.58	NO	99.54	0.00	0.00	7.99	NO	99.80	0.40	0.09	4.90	NO	0.01
FACI	97.86	2.19	11.26	13.92	NO	98.25	22.60	21.55	12.05	NO	98.73	19.34	18.49	10.01	NO	99.34	1.91	1.26	7.68	NO	99.72	0.71	2.43	4.78	NO	10.97
SF-OGD	98.05	1.42	1.25	13.59	NO	98.34	20.05	9.23	11.91	NO	98.84	5.14	4.80	9.64	NO	99.23	2.32	9.59	7.55	NO	99.67	20.20	7.83	4.29	YES	8.26
SAOCP	98.51	0.00	0.00	13.55	NO	98.62	0.26	0.14	11.82	NO	98.91	3.40	1.74	9.69	NO	99.39	1.49	0.45	7.20	NO	99.74	4.18	1.22	4.29	YES	0.00
GARCH	96.87	0.48	0.90	12.18	YES	97.46	1.23	1.29	10.40	YES	98.19	22.03	9.01	8.46	YES	98.97	60.32	85.21	6.34	YES	99.43	70.13	52.08	3.87	YES	3.73
HAR_DR	97.44	0.10	80.26	15.83	NO	97.79	0.12	32.26	13.46	NO	98.05	0.01	1.77	10.91	NO	98.36	0.00	0.01	8.11	NO	98.84	0.00	0.00	4.98	NO	0.00
CAViaR	98.25	0.26	0.06	12.59	NO	98.67	0.28	0.06	10.83	NO	98.84	5.14	4.80	8.92	NO	99.21	18.47	13.27	6.93	NO	99.58	13.36	40.33	4.22	YES	0.29
Ethereum (ID = 1027)																									
Model	VaR_0.5	CC_0.5	UC_0.5	Asymmetric QL	MCS	VaR_1.0	CC_1.0	UC_1.0	Asymmetric QL	MCS	VaR_1.5	CC_1.5	UC_1.5	Asymmetric QL	MCS	VaR_2.0	CC_2.0	UC_2.0	Asymmetric QL	MCS	VaR_2.5	CC_2.5	UC_2.5	Asymmetric QL	MCS	ES_2.5_test
AgACI	0.46	0.00	69.10	3.29	YES	0.96	0.00	79.47	5.35	YES	1.49	0.00	94.08	7.31	YES	1.95	0.02	79.25	8.87	YES	2.32	0.00	42.34	10.20	YES	84.26
FACI	0.83	0.00	0.38	3.49	YES	1.27	0.00	8.03	5.45	YES	1.75	0.00	17.70	7.25	YES	2.27	0.00	19.56	8.77	YES	2.84	0.00	14.68	10.11	YES	10.04
SF-OGD	0.66	15.12	15.39	3.53	YES	1.22	3.54	14.08	5.65	YES	1.84	0.01	7.05	7.36	YES	2.34	1.47	11.03	9.08	NO	3.06	0.73	1.89	10.56	NO	18.25
SAOCP	0.68	22.07	10.60	3.44	YES	1.20	37.81	18.23	5.68	YES	1.57	91.36	68.25	7.45	YES	2.14	37.98	49.60	9.16	NO	2.60	28.32	66.17	10.74	NO	43.33
GARCH	0.55	85.93	71.12	3.22	YES	0.95	75.64	81.13	5.36	YES	1.29	40.58	34.49	7.10	YES	1.69	24.45	23.42	8.63	YES	2.09	29.67	16.21	9.98	YES	61.43
HAR_DR	1.21	0.00	0.00	3.44	YES	1.58	0.99	0.51	5.26	YES	1.95	12.83	6.68	6.84	YES	2.39	35.24	16.14	8.29	YES	2.75	57.88	40.29	9.64	YES	0.04
CAViaR	0.37	56.64	30.25	3.19	YES	0.88	66.03	52.55	5.39	YES	1.32	58.87	43.57	7.18	YES	1.91	94.41	73.44	8.64	YES	2.57	12.37	81.40	10.06	YES	71.25
Model	VaR_97.5	CC_97.5	UC_97.5	Asymmetric QL	MCS	VaR_98.0	CC_98.0	UC_98.0	Asymmetric QL	MCS	VaR_98.5	CC_98.5	UC_98.5	Asymmetric QL	MCS	VaR_99.0	CC_99.0	UC_99.0	Asymmetric QL	MCS	VaR_99.5	CC_99.5	UC_99.5	Asymmetric QL	MCS	ES_97.5_test
AgACI	98.56	0.00	0.00	9.34	YES	98.91	0.00	0.00	8.07	YES	99.23	0.00	0.00	6.57	YES	99.54	0.00	0.00	4.95	YES	99.80	0.40	0.09	3.05	YES	0.01
FACI	97.86	2.19	11.26	9.31	YES	98.25	22.60	21.55	7.90	YES	98.73	19.34	18.49	6.46	YES	99.34	1.91	1.26	4.81	YES	99.72	0.71	2.43	3.02	YES	10.97
SF-OGD	98.05	1.42	1.25	9.71	NO	98.34	20.05	9.23	8.23	NO	98.84	5.14	4.80	6.48	YES	99.23	2.32	9.59	4.80	YES	99.67	20.20	7.83	2.84	YES	8.26
SAOCP	98.51	0.00	0.00	9.83	NO	98.62	0.26	0.14	8.18	NO	98.91	3.40	1.74	6.68	NO	99.39	1.49	0.45	4.81	YES	99.74	4.18	1.22	2.81	YES	0.00
GARCH	97.91	29.67	16.21	8.87	YES	98.38	14.74	13.87	7.57	YES	98.90	14.32	7.28	6.14	YES	99.38	9.56	3.43	4.59	YES	99.63	56.64	30.25	2.81	YES	41.02
HAR_DR	96.73	2.52	1.41	9.20	YES	97.25	2.38	0.78	7.84	YES	97.80	1.58	0.47	6.40	YES	98.13	0.02	0.00	4.82	YES	98.68	0.00	0.00	2.99	YES	0.01
CAViaR	98.46	0.25	0.06	8.98	YES	98.79	0.44	0.15	7.64	YES	99.27	0.11	0.03	6.13	YES	99.52	0.89	0.23	4.51	YES	99.67	39.72	18.13	2.80	YES	0.48

Table 13. Number of VaR violations in % across **Bubble** and **Litecoin-Token** for each quantile and model; p-values in % for the Christoffersen conditional coverage (CC) test; p-values in % for the Kupiec unconditional coverage (UC) test; asymmetric quantile loss (QL) function by González-Rivera et al. (2004); the model was included in the model confidence set (MCS): yes or no; p-values in % for the multinomial VaR test by Kratz et al. (2018), for the five quantiles in the left tail (ES_2.5_test) and in the right tail (ES_97.5_test), respectively.

Bubble (ID = 918)																										
Model	VaR_0.5	CC_0.5	UC_0.5	Asymmetric QL	MCS	VaR_1.0	CC_1.0	UC_1.0	Asymmetric QL	MCS	VaR_1.5	CC_1.5	UC_1.5	Asymmetric QL	MCS	VaR_2.0	CC_2.0	UC_2.0	Asymmetric QL	MCS	VaR_2.5	CC_2.5	UC_2.5	Asymmetric QL	MCS	ES_2.5_test
AgACI	0.28	30.18	12.39	9.11	YES	0.76	44.77	23.79	13.42	YES	1.18	4.17	20.98	17.09	YES	1.65	2.93	24.03	20.41	YES	2.08	8.19	20.09	23.22	YES	70.88
FACI	0.43	85.55	61.61	9.54	YES	0.99	82.57	97.03	13.25	YES	1.65	25.43	56.81	16.99	YES	1.94	2.42	83.44	20.46	YES	2.36	8.75	68.11	22.92	YES	55.15
SF-OGD	0.38	69.08	40.51	8.56	YES	0.99	82.57	97.03	13.14	YES	1.46	74.03	89.22	17.20	YES	2.17	19.42	57.52	20.40	YES	2.69	45.03	57.52	22.80	YES	72.42
SAOCP	0.43	85.55	61.61	8.97	YES	0.80	56.74	34.56	14.00	YES	1.13	27.19	14.74	17.40	YES	1.42	9.31	4.34	20.98	YES	1.94	21.67	8.41	23.91	YES	45.28
GARCH	2.69	0.00	0.00	13.74	NO	3.73	0.00	0.00	17.64	NO	4.68	0.00	0.00	20.45	NO	5.05	0.00	0.00	22.73	YES	5.90	0.00	0.00	24.66	YES	0.00
HAR_DR	0.19	7.06	2.15	9.09	YES	0.29	0.05	0.01	15.98	NO	0.33	0.00	0.00	22.13	NO	0.43	0.00	0.00	27.73	NO	0.48	0.00	0.00	32.96	NO	0.00
CAViaR	1.81	0.00	0.00	10.82	YES	2.10	0.00	0.00	14.54	YES	2.14	1.63	2.24	17.79	YES	2.76	0.47	1.80	21.17	YES	2.86	17.09	30.18	23.64	YES	0.00
Model	VaR_97.5	CC_97.5	UC_97.5	Asymmetric QL	MCS	VaR_98.0	CC_98.0	UC_98.0	Asymmetric QL	MCS	VaR_98.5	CC_98.5	UC_98.5	Asymmetric QL	MCS	VaR_99.0	CC_99.0	UC_99.0	Asymmetric QL	MCS	VaR_99.5	CC_99.5	UC_99.5	Asymmetric QL	MCS	ES_97.5_test
AgACI	98.16	0.26	4.21	27.13	YES	98.39	2.38	18.02	24.26	YES	98.72	9.55	38.29	20.53	YES	99.06	4.45	79.64	16.77	YES	99.43	85.25	66.95	11.26	YES	19.94
FACI	97.64	9.91	68.11	26.77	YES	98.16	38.78	59.93	22.99	YES	98.35	5.77	56.81	20.49	YES	98.91	7.24	69.34	16.14	YES	99.48	93.65	89.89	10.86	YES	33.70
SF-OGD	97.73	23.42	48.62	26.37	YES	98.21	8.14	49.30	23.79	YES	98.49	4.22	96.51	19.60	YES	99.01	5.55	97.03	15.58	YES	99.39	14.48	47.25	10.57	YES	60.98
SAOCP	98.16	5.65	4.21	26.29	YES	98.35	16.40	24.03	23.61	YES	98.68	12.54	49.33	19.70	YES	98.91	7.24	69.34	15.31	YES	99.39	71.29	47.25	9.99	YES	5.37
GARCH	93.72	0.00	0.00	27.10	YES	94.47	0.00	0.00	24.68	YES	95.23	0.00	0.00	21.88	YES	96.08	0.00	0.00	18.52	YES	97.50	0.00	0.00	13.96	NO	0.00
HAR_DR	99.24	0.00	0.00	34.99	NO	99.29	0.00	0.00	29.54	NO	99.48	0.01	0.00	23.71	NO	99.52	2.61	0.73	17.35	YES	99.62	70.17	42.11	10.13	YES	0.00
CAViaR	98.24	2.90	2.27	25.24	YES	98.57	2.95	4.95	22.48	YES	99.05	0.41	2.73	19.26	YES	99.29	0.57	16.68	15.05	YES	99.14	3.74	3.50	10.68	YES	0.00
Litecoin-Token (ID = 3807)																										
Model	VaR_0.5	CC_0.5	UC_0.5	Asymmetric QL	MCS	VaR_1.0	CC_1.0	UC_1.0	Asymmetric QL	MCS	VaR_1.5	CC_1.5	UC_1.5	Asymmetric QL	MCS	VaR_2.0	CC_2.0	UC_2.0	Asymmetric QL	MCS	VaR_2.5	CC_2.5	UC_2.5	Asymmetric QL	MCS	ES_2.5_test
AgACI	0.21	22.85	8.65	5.56	YES	0.50	10.96	3.70	9.41	YES	1.14	2.12	24.87	12.51	YES	1.43	2.63	10.61	15.12	YES	1.78	4.13	7.02	17.67	YES	21.56
FACI	0.29	45.82	21.49	5.78	YES	0.64	33.36	14.93	8.62	YES	1.14	20.37	24.87	11.35	YES	1.43	15.40	10.61	14.42	YES	2.00	14.02	21.16	16.67	YES	57.56
SF-OGD	0.29	45.82	21.49	5.80	YES	0.71	48.74	25.54	9.21	YES	1.14	42.73	24.87	12.82	YES	1.71	53.42	42.95	15.36	YES	1.93	29.80	15.15	17.67	YES	43.39
SAOCP	0.43	90.24	69.49	5.64	YES	0.64	33.36	14.93	8.94	YES	1.07	32.08	16.27	12.49	YES	1.21	6.17	2.32	15.08	YES	1.57	4.01	1.67	17.47	YES	11.95
GARCH	4.35	0.00	0.00	16.43	NO	5.35	0.00	0.00	18.53	NO	5.92	0.00	0.00	20.03	NO	6.70	0.00	0.00	21.08	NO	6.85	0.00	0.00	21.91	YES	0.00
HAR_DR	4.49	0.00	0.00	14.24	NO	4.85	0.00	0.00	17.06	NO	4.85	0.00	0.00	19.19	NO	4.92	0.00	0.00	20.98	NO	5.06	0.00	0.00	22.57	YES	0.00
CAViaR	0.36	71.19	42.23	5.74	YES	0.50	10.96	3.70	9.49	YES	0.86	8.80	3.10	12.51	YES	1.43	20.29	10.61	15.20	YES	1.85	16.43	10.50	17.38	YES	26.40
Model	VaR_97.5	CC_97.5	UC_97.5	Asymmetric QL	MCS	VaR_98.0	CC_98.0	UC_98.0	Asymmetric QL	MCS	VaR_98.5	CC_98.5	UC_98.5	Asymmetric QL	MCS	VaR_99.0	CC_99.0	UC_99.0	Asymmetric QL	MCS	VaR_99.5	CC_99.5	UC_99.5	Asymmetric QL	MCS	ES_97.5_test
AgACI	98.00	2.47	21.16	17.82	YES	98.22	16.68	55.47	15.96	YES	98.50	1.01	99.47	13.61	YES	99.00	2.08	99.57	10.61	YES	99.22	0.01	16.33	7.10	YES	10.63
FACI	97.15	6.10	40.74	17.33	YES	97.57	1.55	27.10	15.60	YES	98.15	13.03	29.22	12.69	YES	98.93	2.69	79.48	9.97	YES	99.43	0.15	71.39	6.45	YES	80.43
SF-OGD	97.00	50.19	24.87	18.12	YES	97.79	43.48	57.87	16.02	YES	98.22	45.17	39.69	13.04	YES	98.79	60.89	43.89	9.76	YES	99.36	73.19	47.05	6.86	YES	72.73
SAOCP	98.72	0.46	0.13	17.87	YES	99.00	1.09	0.31	15.79	YES	99.00	22.71	10.02	13.53	YES	99.07	86.00	78.16	10.02	YES	99.57	90.63	69.49	6.55	YES	0.03
GARCH	92.72	0.00	0.00	21.00	YES	93.30	0.00	0.00	20.16	NO	93.72	0.00	0.00	19.18	NO	94.72	0.00	0.00	17.89	NO	95.93	0.00	0.00	15.95	NO	0.00
HAR_DR	95.08	0.00	0.00	22.68	NO	95.44	0.00	0.00	21.11	NO	95.44	0.00	0.00	19.36	NO	95.51	0.00	0.00	17.28	NO	95.86	0.00	0.00	14.57	NO	0.00
CAViaR	98.57	1.50	0.52	18.27	YES	98.86	3.69	1.25	16.66	YES	98.79	53.36	35.98	14.08	YES	99.22	64.28	39.96	10.78	YES	99.57	90.24	69.49	6.42	YES	0.75

5. Discussion and Conclusions

This paper compared the performance of four adaptive conformal inference (ACI) algorithms with traditional volatility models for daily data, such as GARCH models and daily range models, in computing the value at risk (VaR) at various probability levels for 4000 crypto-assets observed between 2010 and 2024. Additionally, this comparison indirectly assessed the quality of the models' expected shortfall (ES) by using a multinomial test of VaR violations across multiple levels as a means of backtesting the ES, as proposed by Kratz et al. (2018).

To achieve this objective, we employed four ACI algorithms, including Aggregated ACI by Zaffran et al. (2022), Fully Adaptive Conformal Inference by Gibbs and Candès (2022), Scale-Free Online Gradient Descent by Bhatnagar et al. (2023), and Strongly Adaptive Online Conformal Prediction by Bhatnagar et al. (2023). These algorithms, explicitly designed to address scenarios where data arrive sequentially, dynamically adjust the width of prediction intervals in response to observed data, thereby providing adaptive and accurate uncertainty quantification. As benchmark models for daily data, we used the GARCH(1,1) model with a symmetric Student's t-distribution for the standardized errors and the daily range volatilities computed using the Garman–Klass estimator together with an HAR model.

In terms of VaR violations across all quantiles, FACI and SF-OGD were able to properly model the left and right tails of the distribution for the vast majority of crypto-assets, followed by AgACI, while SAOCP exhibited the poorest performance among the ACI algorithms. Conversely, the GARCH and HAR models faced challenges in achieving numerical convergence for approximately 2.5% of assets, particularly those with extreme variability and/or relatively small datasets ($T < 1000$). Despite this, GARCH served as a reliable benchmark model, slightly underestimating the VaR for the most extreme quantiles ($p_i \leq 1.0\%$) while maintaining accuracy for the other quantiles. In contrast, the HAR model with daily range volatilities proved to be the least effective, underestimating lower quantiles by up to $p_i = 1\%$ and severely overestimating higher quantiles. Similar issues emerged for the right tail of the distribution.

Regarding asymmetric quantile loss functions, our analysis revealed that the GARCH model consistently emerged as the top-ranked model for the majority of assets and was almost always included in the model confidence set. While ACI models demonstrated proficiency in estimating quantiles for most assets, they exhibited challenges in estimating the most extreme quantiles ($p_i \leq 1\%$ and $p_i \geq 99\%$), particularly the AgACI and FACI models, which showed rather large asymmetric losses and lower rankings. However, the SF-OGD and SAOCP models displayed greater precision with smaller losses.

These findings have significant implications for financial risk management: while a traditional benchmark like the GARCH model remains relevant, newer approaches such as ACI models offer promising alternatives, particularly for assets with complex dynamics such as crypto-assets, albeit with some caveats in extreme quantile estimation. Given that ACI models are more precise in terms of VaR violations, while GARCH models are better in terms of asymmetric quantile losses, forecasting combinations are a possibility, and we leave this issue as an avenue for further research.

Finally, we performed a set of robustness checks to verify that our results also held with different settings. In terms of market capitalization of crypto-assets, the results were similar to the baseline case. However, we found that the performance of the GARCH model and, to a lesser extent, the SAOCP algorithm deteriorated significantly when focusing on assets with the lowest market capitalization. It is well known that crypto-assets with lower market capitalization tend to experience higher levels of volatility. This heightened volatility can pose challenges for several modeling approaches, which may struggle to adequately capture and predict extreme movements in these assets' prices. As such, future research could explore alternative modeling techniques specifically tailored to address the unique characteristics and dynamics of lower-capitalization crypto-assets, potentially enhancing the accuracy and robustness of risk management strategies in this segment of the market.

As a second robustness check, we divided our assets into four groups based on the size of their time series: AgACI, FACI, and SF-OGD exhibited consistent performances across time series of varying lengths. Instead, GARCH models seemed to perform best with time series close to 1000 observations. SAOCP and the HAR model with daily range data performed notably better with time series containing fewer than 1000 observations compared to longer time series. It appears that these methods are more sensitive to structural breaks, which occur more frequently in assets with longer time series. This evidence indirectly corroborates the simulation studies conducted by Susmann et al. (2023), which demonstrated that SAOCP tends to underestimate the quantiles when faced with a distributional shift. This evidence underscores the importance of considering both the length of the time series and the model's sensitivity to structural breaks when selecting appropriate risk forecasting methods. Future research could delve deeper into understanding the mechanisms underlying these performance disparities and explore potential refinements to enhance the accuracy and robustness of risk predictions across diverse time-series lengths.

As a third robustness check, we assessed the impact on our results of employing a single-hidden-layer neural network instead of a simple AR(1) like in the baseline case. In terms of VaR violations, there are no notable differences among the models (except for SAOCP), while regarding quantile loss functions all four ACI algorithms were strongly penalized in terms of average ranking, with SAOCP exhibiting the largest decline in ranking across all competing models. In general, employing a more complex forecasting model for the mean of the assets' log-returns with ACI algorithms did not result in more precise risk estimates. This outcome can probably be attributed to the lower model bias being outweighed by the higher variance in the model estimates. These findings underscore the intricate trade-offs involved in selecting forecasting models for risk management purposes, highlighting the importance of considering both model complexity and estimation accuracy in decision-making processes.

As a fourth robustness check, we tested the symmetric absolute value (SAV)-CAViaR model with four crypto-assets, including the most and least capitalized. The ACI algorithms effectively modeled both tails of the return distributions, except for SAOCP on the right tail. The GARCH model performed well for Ethereum but struggled with Bitcoin and low-capitalization assets. The HAR model performed the worst, while the CAViaR model passed coverage tests for the left tail of high-capitalization assets but failed for the right tail and low-capitalization assets. The GARCH model had the lowest asymmetric losses for Bitcoin and Ethereum but performed poorly for low-capitalization assets, where the ACI methods excelled. Overall, the ACI methods demonstrated robustness in highly volatile markets, and the CAViaR model showed consistent performance, making it a reliable alternative to traditional approaches.

The general recommendation for investors that emerges from our analysis is to utilize the Fully Adaptive Conformal Inference (FACI) and the Scale-Free Online Gradient Descent (SF-OGD) algorithms. These algorithms exhibit remarkable precision in providing VaR estimates across all examined quantiles, applicable to various types of crypto-assets and different market conditions. The risk estimates offered by these ACI algorithms can then be compared or even combined with those from traditional GARCH models, especially considering the latter's proficiency in offering small asymmetric quantile losses, provided a large dataset is available. We leave this issue as an avenue for future research. We note that while GARCH(1,1) is a parsimonious and analytically appealing model, its performance is highly dependent on the size and characteristics of the data sample. Our study found that GARCH(1,1) faces computational difficulties and often fails to achieve numerical convergence for smaller datasets (fewer than 1000 observations). Furthermore, for longer datasets, the model struggles with structural breaks, leading to suboptimal performance, particularly in the extreme parts of the left tail of the distribution, as observed with Bitcoin. In contrast, the ACI algorithms offer several advantages. They are computationally more efficient and robust across a wider range of dataset sizes, from small to medium. This makes them particularly suitable for crypto-assets, which often have limited historical data or exhibit high volatility. The ACI models dynamically adjust to new data, providing more accurate and adaptive risk estimates without the computational burdens associated with GARCH models. Additionally, the simplicity and speed of ACI models enhance their tractability, making them more practical for real-time risk management and forecasting in the fast-evolving cryptocurrency market. While GARCH(1,1) remains valuable for its analytical properties and its capacity to support further financial modeling, such as deriving explicit asset valuation formulas, the ACI models fill an important gap by offering robust performance and computational efficiency across various market conditions and data constraints. Therefore, incorporating ACI models into risk management frameworks provides a complementary approach, leveraging their strengths in scenarios where traditional models like GARCH may falter.

An important limitation of this paper is the reliance on time series consisting of at least 730 daily data points, ensuring each model had a minimum of one year's worth of data for initial training and calibration. This condition inevitably excluded a significant number of young crypto-assets, thereby restricting the depth of our analysis. One potential solution could involve utilizing high-frequency data if available, although alternative approaches should also be explored. Further research endeavors could address these limitations by incorporating additional data sources, exploring alternative model specifications, and examining the performance of forecasting models across varying time horizons and market conditions. This would enhance the robustness and applicability of risk management strategies in the dynamic landscape of crypto-assets.

As a final note, we wish to underscore that our findings align with the existing literature, highlighting the necessity of robust risk management frameworks for crypto-assets. For instance, Liu et al. (2020) emphasize the challenges and rewards of investing in cryptocurrencies, suggesting that value-at-risk (VaR) forecasting can benefit from parsimonious models. Although they discuss models under the generalized autoregressive score (GAS) framework, our study similarly finds that simpler models, such as GARCH, remain highly relevant and effective for VaR forecasting in specific scenarios. This resonates with Liu et al. (2020)'s assertion that more elaborate models do not always outperform simpler alternatives, particularly when considering the varying dynamics of crypto-assets. Trucíos and Taylor (2023) further contribute to the discourse by comparing various advanced risk forecasting methods, including long-memory processes and quantile regression-based models, and highlighting the efficacy of certain models for specific cryptocurrencies. Their exploration of the robustness of these models during turbulent periods, such as the COVID-19 pandemic, parallels our findings that no single model universally outperforms others. Additionally, their investigation into forecast combination strategies aligns with our suggestion that combining traditional models like GARCH with ACI approaches could enhance predictive performance. Müller et al. (2022) introduce the concept of range value at risk (RVaR) and demonstrate that GARCH models with various error distributions can effectively forecast RVaR for major cryptocurrencies. Our study corroborates their observation that non-normal distributions are often more suitable for VaR and expected shortfall (ES) predictions, reinforcing the notion that the choice of model and distribution significantly impacts the accuracy of risk measures and that simple volatility models, such as GARCH with a Student's t-distribution, can produce accurate risk forecasts. Alexander and Dakos (2023) provide one of the most comprehensive reviews of the cryptocurrency risk forecasting literature, advocating for the practical application of relatively simple models over more complex alternatives. Their extensive backtesting with hourly and daily data reveals that models capturing asymmetric volatility and heavy-tailed distributions are just as effective as more sophisticated models. Our results echo this sentiment, demonstrating that models like FACI and SF-OGD can achieve reliable forecasts for crypto-assets without the need for overly computationally complex specifications, thus addressing the practical constraints faced by investors.

In conclusion, our study situates itself within the broader context of the cryptocurrency risk forecasting literature, aligning with key findings from Liu et al. (2020), Müller et al.

(2022), Trucíos and Taylor (2023), and Alexander and Dakos (2023). By validating the efficacy of newer ACI models and recognizing the conditions under which they excel, our research contributes to a nuanced understanding of risk management in the cryptocurrency market. Future research should continue to explore the interplay between model complexity, data availability, and forecasting accuracy to develop robust risk management strategies that can withstand the unique challenges posed by crypto-assets.

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Data Availability Statement: The original data presented in the study were downloaded from the website https://coinmarketcap.com. However, the free web API used for this task is not longer available since early 2024, and a registration is required.

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

Appendix A. The Original Adaptive Conformal Inference (ACI) Algorithm

Input: starting value θ_1, user-specified learning rate $\gamma > 0$.
for $t = 1, 2, \ldots, T$ do
  Output: prediction interval $\hat{C}_t(\theta_t)$.
  Observe y_t.
  Evaluate $err_t = \mathbb{I}[y_t \notin \hat{C}_t(\theta_t)]$.
  Update $\theta_{t+1} = \theta_t + \gamma(err_t - (1 - \alpha))$.
end for

Appendix B. The Aggregated Adaptive Conformal Inference (AgACI) Algorithm

Input: candidate learning rates $(\gamma_k)_{1 \le k \le K}$, starting value θ_1.
Initialize lower and upper BOA algorithms:
  $\mathcal{B}^l = BOA(\alpha \leftarrow (1-\alpha)/2)$
  $\mathcal{B}^u = BOA(\alpha \leftarrow (1-(1-\alpha)/2))$.
for $k = 1, \ldots, K$ do
  Initialize ACI $\mathcal{A}_k = \mathrm{ACI}(\alpha \leftarrow \alpha, \gamma \leftarrow \gamma_k, \theta_1 \leftarrow \theta_1)$.
end for
for $t = 1, 2, \ldots, T$ do
  for $k = 1, \ldots, K$ do
    Retrieve candidate prediction interval $[l_t^k, u_t^k]$ from $\mathcal{A}_k$.
  end for
  Compute aggregated lower bound $\tilde{l}_t = \mathcal{B}^l((l_t^k : k \in \{1, \ldots, K\}))$.
  Compute aggregated upper bound $\tilde{u}_t = \mathcal{B}^u((u_t^k : k \in \{1, \ldots, K\}))$.
  Output: prediction interval $[\tilde{l}_t, \tilde{u}_t]$.
  Observe y_t.
  for $k = 1, \ldots, K$ do
    Update $\mathcal{A}_k$ with log-return y_t.
  end for
  Update $\mathcal{B}^l$ with observed log-return y_t.
  Update $\mathcal{B}^u$ with observed log-return y_t.
end for

Appendix C. The Fully Adaptive Conformal Inference (FACI) Algorithm

Input: starting value θ_1, candidate learning rates $(\gamma_k)_{1 \le k \le K}$,
  parameters σ, η.

for $k = 1, \ldots, K$ do
  Initialize expert $\mathcal{A}_k = \mathtt{ACI}(\alpha \leftarrow \alpha, \gamma_{\leftarrow}\gamma_k, \theta_1 \leftarrow \theta_1)$.
end for
for $t = 1, 2, \ldots, T$ do
  Define the probabilities $p_t^k = w_t^k / \sum_{i=1}^K w_t^i$, for all $1 \le k \le K$.
  Set $\theta_t = \sum_{k=1}^K \theta_t^k p_t^k$.
  Output: prediction interval $\hat{C}_t(\theta_t)$.
  Observe the log-return y_t and compute r_t.
  $\bar{w}_t^k \leftarrow w_t^k \exp(-\eta L^\alpha(\theta_t^k, r_t))$, for all $1 \le k \le K$.
  $\overline{W}_t \leftarrow \sum_{i=1}^K \bar{w}_t^i$
  $w_{t+1}^k \leftarrow (1-\sigma)\bar{w}_t^k + \overline{W}_t \sigma / K$
  Set $err_t = \mathbb{I}[y_t \notin \hat{C}_t(\theta_t)]$
  for $k = 1, \ldots, K$ do
    Update ACI $\mathcal{A}_k$ with y_t and obtain θ_{t+1}^k
  end for
end for

Appendix D. The Scale-Free Online Gradient Descent (SF-OGD) Algorithm

Input: starting value θ_1, learning rate $\gamma > 0$.
for $t = 1, 2, \ldots, T$ do
  Output: prediction interval $\hat{C}_t(\theta_t)$
  Observe the log-return y_t and compute r_t
  Update $\theta_{t+1} = \theta_t - \gamma \frac{\nabla L^\alpha(\theta_t, r_t)}{\sqrt{\sum_{i=1}^t \|\nabla L^\alpha(\theta_i, r_i)\|_2^2}}$
end for

Appendix E. The Strongly Adaptive Online Conformal Prediction (SAOCP) Algorithm

Input: initial value θ_0, learning rate $\gamma > 0$.
for $t = 1, 2, \ldots, T$ do
  Initialize expert $\mathcal{A}_t = \mathtt{SF\text{-}OGD}(\alpha \leftarrow \alpha, \gamma \leftarrow \gamma, \theta_1 \leftarrow \theta_{t-1})$,
    set weight $w_t^t = 0$
  Compute active set $\mathtt{Active}(t) = \{i \in \{1, \ldots, T\} : t - L(i) < i \le t\}$ (see
    below for definition of $L(t)$),
  Compute prior probability $\pi_i \propto i^{-2}(1 + \lfloor \log_2 i \rfloor)^{-1} \mathbb{I}[i \in \mathtt{Active}(t)]$.
  Compute un-normalized probability $\hat{p}_i = \pi_i [w_{t,i}]_+$ for all $i \in \{1, \ldots, t\}$
  Normalize $p = \hat{p} / \|\hat{p}\|_1 \in \Delta^t$ if $\|\hat{p}\|_1 > 0$, else $p = \pi$.
  Set $\theta_t = \sum_{i \in Active(t)} p_i \theta_t^i$ (for $t \ge 2$), and $\theta_t = 0$ for $t = 1$
  Output: prediction set $\hat{C}_t(\theta_t)$.
  Observe log-return y_t and compute r_t.
  for $i \in \mathtt{Active}(t)$ do
    Update expert $\mathcal{A}_t$ with y_t and obtain θ_{t+1}^i
    Compute $g_t^i = \begin{cases} \frac{1}{D}\left(L^\alpha(\theta_t, r_t) - L^\alpha(\theta_t^i, r_t)\right) & w_t^i > 0 \\ \frac{1}{D}\left[L^\alpha(\theta_t, r_t) - L^\alpha(\theta_t^i, r_t)\right]_+ & w_t^i \le 0 \end{cases}$
    Update expert weight $w_{t+1}^i = \frac{1}{t-i+1}\left(\sum_{j=i}^t g_j^i\right)\left(1 + \sum_{j=i}^t w_j^i g_j^i\right)$
  end for
end for

Appendix F. List of Crypto-Assets' IDs and Names

Table A1. Names and crypto-assets' coinmarketcap.com IDs: 1–500.

ID	Name	ID	Name	ID	Name	ID	Name	ID	Name
1	Bitcoin	760	Okcash	1353	TajCoin	1817	Voyager Token	2178	Upfiring
2	Litecoin	764	PayCoin	1368	Veltor	1826	Particl	2184	Privatix
3	Namecoin	788	Circuits of Value	1376	Neo	1828	SmartCash	2191	Paypex
4	Terracoin	799	SmileyCoin	1382	NoLimitCoin	1830	SkinCoin	2205	Phantomx
5	Peercoin	815	Kobocoin	1389	Zayedcoin	1831	Bitcoin Cash	2208	EncrypGen
6	Novacoin	819	Bean Cash	1392	Pluton	1834	Pillar	2209	Ink
8	Feathercoin	825	Tether USDt	1395	Dollarcoin	1838	OracleChain	2212	Quantstamp
10	Freicoin	831	Wild Beast Block	1396	MustangCoin	1839	BNB	2213	QASH
13	Ixcoin	833	Gridcoin	1414	Firo	1846	GeyserCoin	2215	Energo
16	WorldCoin WDC	837	X-Coin	1437	Zcash	1850	Cream	2222	Bitcoin Diamond
18	Digitalcoin	853	LiteDoge	1439	AllSafe	1853	OAX	2223	BLOCKv
25	Goldcoin	857	SongCoin	1447	ZClassic	1856	district0x	2230	MONK
35	Phoenixcoin	859	Woodcoin	1455	Golem	1861	Stox	2231	Flixxo
42	Primecoin	873	NEM	1466	Hush	1866	Bytom	2237	EventChain
43	Anoncoin	894	Neutron	1468	Kurrent	1876	Dentacoin	2241	Ccore
45	CasinoCoin	895	Xaurum	1473	Pascal	1878	Shadow Token	2242	Qbao
52	XRP	898	Californium	1474	Eternity	1881	DeepOnion	2243	Dragonchain
53	Quark	916	MedicCoin	1492	Obyte	1883	Adshares	2245	Presearch
56	Zetacoin	918	Bubble	1495	PoSW Coin	1886	Dent	2247	BlockCDN
61	TagCoin	921	Universal Currency	1500	Wings	1888	InvestFeed	2248	Cappasity
66	Nxt	934	ParkByte	1503	Jupiter	1896	0x Protocol	2249	Eroscoin
67	Unobtanium	938	ARbit	1505	Alias	1902	MyBit	2255	Social Send
69	Datacoin	945	Bata	1511	PureVidz	1903	HyperCash	2256	Bonpay
72	Deutsche eMark	948	AudioCoin	1514	ICOBID	1908	Nebulas	2273	Uquid Coin
74	Dogecoin	951	Synergy	1515	iBank	1916	BiblePay	2274	MediShares
77	Diamond	978	Ratecoin	1518	Maker	1918	Achain	2276	Ignis
78	HoboNickels	986	CrevaCoin	1521	Komodo	1925	Waltonchain	2277	SmartMesh
83	Omni	993	BowsCoin	1522	FirstCoin	1930	Primas	2279	Playkey
87	FedoraCoin	1004	HNC COIN	1528	Iconic	1934	Loopring	2280	Filecoin
90	Dimecoin	1019	Manna	1546	Centurion	1935	Bitcoin Dominica	2281	BitcoinX
93	42-coin	1020	Axiom	1552	Enzyme	1937	Po.et	2282	Super Bitcoin
99	Vertcoin	1027	Ethereum	1556	Chrono.tech	1947	Monetha	2286	MicroMoney
109	DigiByte	1032	TransferCoin	1558	Argus	1948	Aventus	2287	LockTrip
118	ReddCoin	1033	GuccioneCoin	1562	Swarm City	1949	Agrello	2288	Worldcore
122	PotCoin	1035	AmsterdamCoin	1567	Nano	1950	Hiveterminal Token	2289	Gifto
128	Maxcoin	1037	Agoras: Currency of Tau	1578	Zero	1954	Moeda Loyalty Points	2290	YENTEN
131	Dash	1038	Eurocoin	1582	Netko	1955	Neblio	2291	Genaro Network
132	Counterparty	1042	Siacoin	1586	Ark	1958	TRON	2293	United Bitcoin
141	MintCoin	1044	KWD	1596	Edgeless	1962	BUZZCoin	2295	Starbase
145	DopeCoin	1052	VectorAI	1609	Asch	1966	Decentraland	2296	OST
148	Auroracoin	1053	Bolivarcoin	1619	Skycoin	1967	Indorse Token	2297	StormX
154	Marscoin	1066	Pakcoin	1623	BlazerCoin	1968	XPA	2299	aelf
162	Magic Internet Money	1070	Expanse	1624	Atmos	1970	ATBCoin	2300	WAX
168	Uniform Fiscal Object	1082	SIBCoin	1629	Zennies	1974	Propy	2303	MediBloc
170	BlackCoin	1085	Swing	1630	Coinonat	1975	Chainlink	2305	NAGA
184	DNotes	1090	Save and Gain	1632	Concoin	1982	Kyber Network Crystal Legacy	2306	Bread
213	MonaCoin	1104	Augur	1636	XTRABYTES	1983	VIBE	2307	Bibox Token
215	Rubycoin	1106	StrongHands	1637	iExec RLC	1984	Substratum	2310	Bounty0x
217	Bela	1107	PAC Protocol	1638	WeTrust	1991	Rivetz	2313	SIRIN LABS Token
234	e-Gulden	1120	DraftCoin	1651	SpeedCash	1993	Kin	2315	HTMLCOIN
258	Groestlcoin	1135	ClubCoin	1654	BitCore	1996	SALT	2316	DeepBrain Chain
260	PetroDollar	1136	Adzcoin	1657	Bitvolt	1998	Ormeus Coin	2318	Neumark
263	PLNcoin	1146	AvatarCoin	1658	Lunyr	2001	ColossusXT	2320	xMoney
268	WhiteCoin	1154	Validity	1659	Gnosis	2002	TrezarCoin	2323	HEROcoin
276	Bitstar	1155	Litecred	1660	Monolith	2006	Cobinhood	2324	BigONE Token
278	Quebecoin	1156	Yocoin	1669	Humaniq	2009	Bismuth	2329	Hyper Pay
290	BlueCoin	1159	SaluS	1674	Bitcoin Palladium	2010	Cardano	2332	STRAKS
291	MaidSafeCoin	1164	Francs	1678	InsaneCoin	2011	Tezos	2335	Lightning Bitcoin
293	Bitcoin Plus	1165	Evil Coin	1680	Aragon	2019	Viberate	2336	Game.com
298	NewYorkCoin	1168	Decred	1681	PRIZM	2022	Internxt	2337	Lamden
313	Pinkcoin	1169	PIVX	1684	Qtum	2034	Everex	2341	SwftCoin
316	Dreamcoin	1175	Rubies	1693	Theresa May Coin	2041	BitcoinZ	2344	AppCoins
328	Monero	1185	FreedomCoin	1694	Sumokoin	2043	Cindicator	2345	High Performance Blockchain
333	Curecoin	1191	Memetic/PepeCoin	1697	Basic Attention Token	2044	Enigma	2346	WaykiChain
360	Motocoin	1194	Independent Money System	1698	Horizen	2047	Zeusshield	2348	Measurable Data Token
362	CloakCoin	1200	NevaCoin	1700	<U+00C6>ternity	2058	AirSwap	2349	Mixin
366	BitSend	1209	PosEx	1703	Metaverse ETP	2062	Aion	2354	GET Protocol
367	Coin2.1	1210	Cabbage	1706	Aidos Kuneen	2070	DomRaider	2359	Polis
372	Bytecoin	1212	MojoCoin	1710	Veritaseum	2071	Request	2363	Zap
377	Navcoin	1214	Lisk	1712	Quantum Resistant Ledger	2076	Blue Protocol	2364	TokenClub
389	Startcoin	1216	EDRCoin	1720	IOTA	2081	AirDAO	2367	Aigang
405	DigitalNote	1218	PostCoin	1721	Mysterium	2083	Bitcoin Gold	2370	Bitcoin God
416	HempCoin	1223	BERNcash	1727	Bancor	2087	KuCoin Token	2371	United Traders Token
460	Clams	1229	DigixDAO	1731	GlobalToken	2088	EXRNchain	2379	Kcash
463	BitShares	1230	Steem	1732	Numeraire	2090	LATOKEN	2386	KZ Cash
470	Viacoin	1241	FuzzBalls	1736	Unify	2092	NULS	2387	Bitcoin Atom
501	Cryptonite	1244	HiCoin	1745	Dinastycoin	2096	Ripio Credit Network	2391	EchoLink
502	Carboncoin	1247	AquariusCoin	1747	Onix	2099	ICON	2392	Bottos
506	CannabisCoin	1248	Bitcoin 21	1750	GXChain	2100	JavaScript Token	2394	Telcoin
512	Stellar	1250	Zurcoin	1757	FUNToken	2104	iEthereum	2395	Ignition
541	Syscoin	1252	2GIVE	1758	TenX	2110	OLD DOVU	2396	WETH
551	Donu	1254	PlatinumBAR	1759	Status	2112	Phoenix Global [old]	2398	SelfKey
558	Emercoin	1257	LanaCoin	1762	Ergo	2120	Etherparty	2399	INT
572	RabbitCoin	1259	PonziCoin	1765	EOS	2126	FlypMe	2405	IOST
576	GameCredits	1273	Citadel	1768	AdEx	2130	Enjin Coin	2407	AICHAIN
584	NativeCoin	1274	Waves	1769	Denarius	2131	iBTC	2410	SpaceChain
597	Opal	1279	PWR Coin	1772	Storj	2132	Powerledger	2415	ArbitrageCT
601	Acoin	1281	ION	1774	SocialCoin	2135	Revain	2416	Theta Network
624	bitCNY	1282	High Voltage	1779	Wagerr	2136	ATLANT	2424	SingularityNET
638	Trollcoin	1285	GoldBlocks	1784	Polybius	2137	Electroneum	2427	ChatCoin
644	GlobalBoost	1291	Comet	1785	Gas	2143	Streamr	2428	Scry.info
656	Prime-XI	1297	ChessCoin	1786	SunContract	2147	ELTCOIN	2429	Mobius
659	Bitswift	1298	LBRY Credits	1787	Jetcoin	2148	Desire	2430	Hydro Protocol
693	Verge	1299	PUTinCoin	1788	Metal DAO	2151	Autonio	2438	Double-A Chain
702	SpreadCoin	1306	Cryptojacks	1789	Populous	2153	Aeron	2443	Trinity Network Credit
703	Rimbit	1312	Steem Dollars	1799	Rupee	2158	Phore	2444	CRYPTO20
707	Blocknet	1320	Ardor	1807	Santiment Network Token	2160	Innova	2447	Crypterium
720	Crown	1321	Ethereum Classic	1808	OMG Network	2161	Raiden Network Token	2448	SparksPay
730	GCN Coin	1343	Stratis	1814	Metrix Coin	2162	Delphy	2452	Tokenbox
733	Quotient	1351	Aces	1816	Civic	2165	ERC20	2454	Bitcoin Unlimited

Table A2. Names and crypto-assets' coinmarketcap.com IDs: 501–1000.

ID	Name	ID	Name	ID	Name	ID	Name	ID	Name
2457	TrueChain	2725	Skrumble Network	3132	EtherGem	3519	Breezecoin	3843	BOLT
2458	Odyssey	2726	DAOstack	3133	Arepacoin	3580	Crystal Token	3849	WHEN Token
2459	indaHash	2737	Global Social Chain	3138	Noku	3581	Kleros	3850	OTOCASH
2462	AidCoin	2739	Digix Gold Token	3139	DxChain Token	3589	Ethereum Meta	3853	MultiVAC
2465	BUX Token	2742	Sakura Bloom	3140	Ubex	3600	Hippocrat	3854	Unification
2466	Moola	2745	Joint Ventures	3141	Blockpass	3602	Bitcoin SV	3855	Locus Chain
2467	OriginTrail	2748	Oxen	3142	BaaSid	3607	VestChain	3856	SF Capital
2468	LinkEye	2752	Datarius Credit	3149	Netkoin	3610	Micromines	3863	UGAS
2469	Zilliqa	2757	Callisto Network	3152	Obitan Chain	3611	Noir	3866	CONUN
2474	Matrix AI Network	2758	Unibright	3155	Quant	3613	Dash Green	3869	Alpha Token
2475	Garlicoin	2760	Cred	3156	Airbloc	3617	ILCOIN	3870	Lition
2476	Ruff	2762	Open Platform	3158	ZCore (old)	3620	Atlas Protocol	3871	Newton
2478	CoinFi	2763	Morpheus.Network	3159	Apollon	3621	BitNautic Token	3873	botXcoin
2481	Zeepin	2764	Silent Notary	3162	YoloCash	3625	QuadrantProtocol	3874	IRISnet
2482	CPChain	2765	XYO	3164	PumaPay	3626	Rootstock Smart Bitcoin	3875	Valor Token
2489	BitWhite	2771	RED	3166	Bitcoin Incognito	3627	Block-Logic	3877	WebDollar
2490	CargoX	2772	Digitex	3171	HeartBout	3628	MXC	3878	Swap
2492	Elastos	2776	AVA	3175	Maro	3632	Opacity	3880	OceanEx Token
2496	Polymath	2777	IoTeX	3179	Arbidex	3633	BitGuild PLAT	3884	Function X
2497	Medicalchain	2780	NKN	3181	ShowHand	3634	Kambria	3890	Polygon
2499	SwissBorg	2827	Phantasma	3182	HitChain	3635	Cronos	3893	ChangeNOW Token
2502	Huobi Token	2828	SPINDLE	3189	Mainstream For The Underground	3637	Aergo	3894	Crypto Sports Network
2503	DMarket	2830	Seele-N	3194	DPRating	3639	PlayGame	3897	OKB
2505	Bluzelle	2837	0xBitcoin	3198	KingXChain	3640	Livepeer	3898	Axe
2511	WePower	2838	Plian	3200	Nasdacoin	3644	TravelNote	3902	MoneroV
2513	GoldMint	2840	QuarkChain	3205	VeriDocGlobal	3645	Shivers	3908	Decimated
2529	Cashaa	2846	FuturoCoin	3208	YUKI	3646	Herbalist Token	3911	Ocean Protocol
2530	Fusion	2847	Abyss	3210	MIB Coin	3652	ZumCoin	3913	Titan Coin
2535	Edge	2856	CEEK VR	3217	Ontology Gas	3656	Beacon	3914	GlitzKoin
2536	Neurotoken	2859	XMax	3218	Energi	3657	Lambda	3915	Merebel
2537	Gems	2861	GoChain	3219	FUTURAX	3659	QUINADS	3918	Safe
2539	Ren	2862	Smartshare	3220	DAV Coin	3661	Stronghold Token	3925	Tratok
2540	Litecoin Cash	2866	Sentinel Protocol	3238	ABCC Token	3662	HedgeTrade	3928	IDEX
2542	Tidex Token	2868	Constellation	3242	Beetlecoin	3663	Footballcoin (XFC)	3930	ThunderCore
2544	Nitro Network	2870	FantasyGold	3243	Moneytoken	3664	AgaveCoin	3931	Elementeum
2545	Arcblock	2873	Metronome	3247	Fire Lotto	3667	Atomic Wallet Coin	3934	CNNS
2546	Remme	2874	Aurora	3255	CyberMusic	3672	DogeCash	3935	SparkPoint
2548	POA Network	2878	DigiFinexToken	3256	Bitether	3673	ASD	3936	GNY
2552	IHT Real Estate Protocol	2882	Zus	3260	AMO Coin	3686	Conscious Value Network	3939	Tronipay
2553	Refereum	2883	ZINC	3261	EvenCoin	3687	BitBall	3945	Harmony
2554	Lympo	2889	Bob's Repair	3263	Dinero	3698	Observer	3946	Carry
2556	Credits	2890	KanadeCoin	3265	Havy	3701	Rootstock Infrastructure Framework	3948	TERA
2561	BitTube	2891	Cardstack	3266	Carebit	3702	Beam	3950	Neom
2562	Education Ecosystem	2894	OTCBTC Token	3273	IQ.cash	3703	ADAMANT Messenger	3951	Pirate Chain
2563	TrueUSD	2896	Mainframe	3279	Rotharium	3704	v.systems	3953	Evedo
2565	StarterCoin	2901	FansTime	3280	RealTract	3708	Exosis	3956	BOMB
2566	Ontology	2906	Essentia	3285	Birake	3709	Grin	3957	UNUS SED LEO
2569	CoinPoker	2907	Karatgold Coin	3287	Abulaba	3712	Cloudbric	3964	Reserve Rights
2570	Viction	2908	HashCoin	3294	Bitcoin Adult	3714	LTO Network	3968	Elitium
2572	BABB	2909	LikeCoin	3296	MINDOL	3715	Cajutel	3973	Aryacoin
2573	Electrify.Asia	2912	TENT	3304	MobilinkToken	3716	Amoveo	3974	Bitcoin 2
2576	Tokenomy	2913	Databroker	3306	Gemini Dollar	3717	Wrapped Bitcoin	3976	Bitcoin Confidential
2577	Ravencoin	2915	Moss Coin	3316	smARTOFGIVING	3718	BitTorrent	3978	Chromia
2578	TE-FOOD	2916	Nimiq	3317	Cryptrust	3721	Huobi Pool Token	3986	StakeCubeCoin
2585	CENNZnet	2921	OneLedger	3325	Robotina	3722	TEMCO	3987	Beldex
2586	Synthetix	2927	sUSD	3327	SIX	3724	SOLVE	3992	COTI
2588	Loom Network	2930	IQ	3328	CMITCOIN	3730	The Currency Analytics	4001	MenaPay
2595	NANJCOIN	2933	BitMart Token	3330	Pax Dollar	3731	PlayChip	4003	Zenon
2603	Pundi X (Old)	2934	BitKan	3332	Gossip Coin	3733	S4FE	4006	STP
2605	BnkToTheFuture	2937	VITE	3334	X-CASH	3737	BTU Protocol	4013	SpectreSecurityCoin
2606	Wanchain	2938	Hashgard	3335	Shard	3738	Decentralized Crypto Token	4014	Mobile Crypto Pay Coin
2607	AMLT	2941	CoinEx Token	3337	QChi	3741	EurocoinToken	4017	EOSDT
2608	Mithril	2943	Rocket Pool	3344	Ecoreal Estate	3742	Chimpion	4018	Klimatas
2614	BlitzPick	2945	ContentBox	3345	DAPS Coin	3748	HXRO	4023	Bitcoin BEP2
2616	Stipend	2947	SoPay	3354	TRONCLASSIC	3750	eXPerience Chain	4024	Raven Protocol
2620	Carbon Protocol	2949	Kryll	3361	MintMe.com Coin	3752	uPlexa	4026	LiquidApps
2624	Sentinel Chain	2950	LemoChain	3362	Auxilium	3754	EveryCoin	4027	DeVault
2626	Friendz	2958	TurtleCoin	3364	PLATINCOIN	3759	Jinbi Token	4028	MotaCoin
2628	Rentberry	2960	Tourist Token	3366	SafeInsure	3760	Scanetchain	4030	Algorand
2630	PolySwarm	2965	VikkyToken	3371	MIR COIN	3763	Oduwacoin	4033	Native Utility Token
2631	ODEM	2976	Ryo Currency	3383	Knekted	3764	Save Environment Token	4035	Honest
2634	XDC Network	2980	WABnetwork	3388	FREEdom Coin	3768	PIBBLE	4036	Contentos
2638	Cortex	2982	MVL	3395	SteepCoin	3769	HashBX	4038	MovieBloc
2642	CyberVein	2988	Pigeoncoin	3397	Neural Protocol	3770	CustomContractNetwork	4039	ARPA
2643	Sentinel	2989	STASIS EURO	3404	Wixlar	3773	Fetch.ai	4041	MX TOKEN
2644	eosDAC	2991	NIX	3408	USDC	3779	CoTrader	4043	PayRue (Propel)
2645	U Network	2992	Apollo Currency	3417	Future1coin	3783	Ankr	4047	Naka Bodhi Token
2653	Auctus	2994	Bitcoin File	3418	Metadium	3792	USDe	4051	Parachute
2655	Monero Classic	2998	Vexanium	3422	SHPING	3794	Cosmos	4054	IG Gold
2658	Smart MFG	3006	Niobio	3432	Rapids	3795	ZEON	4056	Ampleforth
2660	Aditus	3008	Vivid Coin	3435	Snetwork	3798	Xuez	4058	FIBOS
2662	Haven Protocol	3012	VeThor Token	3437	ABBC Coin	3799	SafeCoin	4060	TrustVerse
2665	Dero	3013	PRiVCY	3441	Divi	3800	FidexToken	4064	USDK
2666	Effect Network	3018	Kalkulus	3446	Zenswap Network Token	3801	BORA	4066	Chiliz
2667	FintruX Network	3024	Arionum	3449	MMOCoin	3805	BoatPilot Token	4069	Blockburn
2674	Masari	3029	Flux	3452	Etho Protocol	3806	TigerCash	4074	ScPrime
2675	Dock	3052	GoCrypto Token	3454	Decentralized Asset Trading Platform	3807	LitecoinToken	4075	CryptoFranc
2677	Linker Coin	3056	Thore Cash	3456	PlusOneCoin	3809	DOS Network	4076	ETHplode
2682	Holo	3071	EUNO	3459	GoHelpFund	3810	Ethereum Gold Project	4077	Maya Preferred
2685	Zebi Token	3077	VeChain	3464	Cheesecoin	3814	Celer Network	4078	Super Zero Protocol
2689	Rublix	3079	X8X Token	3468	Fivebalance	3816	Verasity	4090	Wirex Token
2694	Nexo	3089	AVINOC	3469	TrueDeck	3820	BuckHathCoin	4092	Dusk
2696	DAEX	3097	XOVBank	3479	MODEL-X-coin	3822	Theta Fuel	4096	Switch
2700	Celsius	3106	PKG Token	3481	Peony	3826	TOP	4097	x42 Protocol
2704	Transcodium	3118	Graviocoin	3482	Teloscoin	3829	Nash	4102	TranslateMe Network Token
2705	Amon	3121	IGToken	3484	Waletoken	3830	Veil	4104	FUZE Token
2709	Morpheus Labs	3123	GSENetwork	3489	Escroco Emerald	3831	Safe Haven	4105	Coinmetro Token
2712	MyToken	3125	XDNA	3501	CryptoSoul	3835	Orbs	4114	Golden Token
2717	BoutsPro	3126	ProximaX	3512	Alpha Coin	3839	xRhodium	4116	TOKPIE
2724	Zippie	3128	SiaCashCoin	3513	Fantom	3840	1irstcoin	4118	ForTube

Table A3. Names and crypto-assets' coinmarketcap.com IDs: 1001–1500.

ID	Name	ID	Name	ID	Name	ID	Name	ID	Name
4119	VinDax Coin	4705	PAX Gold	5175	Bitcoin Vault	5552	Hathor	5925	Pkoin
4120	Prom	4709	XcelToken Plus	5176	Tether Gold	5560	Idea Chain Coin	5926	CoinZoom
4121	Sapphire	4710	Cere Network	5179	Celeum	5563	CryptoBharatCoin	5931	Darwinia Commitment Token
4122	CCA	4712	AmonD	5181	BiLira	5566	Keep Network	5939	Wrapped NXM
4124	EOS TRUST	4715	Tokenize Xchange	5185	KOK	5567	Celo	5945	Temtum
4134	Akropolis	4746	Quiztok	5187	Jarvis Network	5577	Litecoin SV	5947	TokenPocket
4139	Brazilian Digital Token	4747	Velas	5189	AK12	5578	LEVELG	5956	MUX Protocol
4144	TrueFeedBack	4757	Robonomics.network	5190	FLEX	5583	Hacken Token	5957	DFI.Money
4150	GLOBEX	4758	dForce	5198	Creditcoin	5589	DXdao	5963	Centric Swap
4157	THORChain	4761	NuCypher	5200	Gleec Coin	5590	GeoDB	5964	Trust Wallet Token
4160	Ycash	4769	EOS Force	5204	CitiOs	5595	MultiCoinCasino	5966	Student Coin
4162	Storeum	4777	Azbit	5219	USD Bancor	5599	XTRM COIN	5985	Limestone Network
4165	CREDIT	4779	HUSD	5220	QURAS	5600	Attila	5989	BNS Token
4166	Realio Network	4787	BitcoinV	5221	Handshake	5601	STAKE	5994	Shiba Inu
4167	Bitrue Coin	4793	D Community	5224	Juventus Fan Token	5604	Secret	5999	XT.com Token
4172	Terra Classic	4794	FinexboxToken	5225	FC Barcelona Fan Token	5608	BTCUP	6025	DigiMax DGMT
4173	Levolution	4797	SMILE	5226	Paris Saint-Germain Fan Token	5609	BTCDOWN	6039	Connectome
4174	BitcoinRegular	4801	Codex	5227	Atletico De Madrid Fan Token	5612	SOMESING	6051	888tron
4180	DDKoin	4804	ROOBEE	5228	Galatasaray Fan Token	5614	Zelwin	6053	Mineral
4182	GoWithMi	4805	VNDC	5229	AS Roma Fan Token	5616	MATH	6062	Shuffle
4183	Safex Cash	4807	Shentu	5236	Kemacoin	5617	UMA	6069	Assemble Protocol
4189	Ultra	4808	Bincentive	5246	ViteX Coin	5618	Dawn Protocol	6111	Ecoin official
4191	Syntropy	4809	Project WITH	5253	The Hustle App	5623	Skillchain	6113	BlackPearl Token
4193	Dynamite	4824	SymVerse	5263	Compound Dai	5625	LUKSO (Old)	6118	BitoPro Exchange Token
4195	FTX Token	4826	ZUM TOKEN	5266	MiL.k	5626	King DAG	6138	DIA
4197	ShareToken	4834	Golos Blockchain	5268	Energy Web Token	5630	WaykiChain Governance Coin	6156	Donut
4200	ChainX	4841	suterusu	5274	Edgeware	5631	Orion	6176	Mobility Coin
4206	WINkLink	4846	Kava	5275	Paycoin	5632	Arweave	6179	SeChain
4213	Uptrennd	4847	Stacks	5277	SynchroBitcoin	5633	UCROWDME	6180	Suku
4215	Eminer	4850	LINKA	5279	Sologenic	5634	Fuse	6187	Serum
4217	BOSagora	4860	Era Swap	5300	Inex Project	5640	PointPay	6193	Cream Finance
4224	Mcashchain	4862	DAD	5305	BTSE Token	5644	Blue Baikal	6194	Geeq
4228	Ferrum Network	4865	Nahmii	5309	OG Fan Token	5647	Kadena	6209	Spheroid Universe
4229	Yobit Token	4866	Grimm	5313	CONTRACOIN	5648	BlockNoteX	6210	The Sandbox
4245	Enecuum	4867	BeatzCoin	5320	Bonorum	5651	CryptoBet	6216	AXEL
4249	Findora	4881	Guider	5326	Orbit Chain	5659	Xank	6218	Arcona
4253	CryptoBonusMiles	4885	Diligence	5328	WOM Protocol	5662	Sylo	6236	Offshift (old)
4256	Klaytn	4887	Receive Access Ecosystem	5330	Shardus	5665	Helium	6237	MDsquare
4257	Bitball Treasure	4890	Newscrypto	5332	Cofinex	5667	Bitgesell	6243	DeFiPie
4261	Sucrecoin	4909	Merge	5336	Homeros	5673	EYES Protocol	6245	SocialGood
4264	Ritocoin	4915	UCX	5338	Somnium Space Cubes	5674	PhoenixDAO	6248	Coalculus
4268	NewYork Exchange	4916	Modex	5343	Five Star Coin	5686	Vectorium	6249	Ziktalk
4269	GateToken	4917	DEXA COIN	5350	XPR Network	5690	Render	6257	Berry
4275	COMBO	4920	Aerotoken	5354	PEAKDEFI	5691	SKALE	6262	Jubi Token
4279	Solar	4927	RigoBlock	5355	Chainpay	5692	Compound	6264	Dark Energy Crystals
4280	12Ships	4929	JD Coin	5358	IBStoken	5698	GM Holding	6283	Blocery
4283	BitForex Token	4940	Kuverit	5365	Historia	5702	MONNOS	6323	LinkCoin Token
4286	ZENZO	4943	Dai	5366	GoalTime N	5705	tGOLD	6375	ASTA
4287	Jobchain	4944	Tellor	5370	Hive	5713	Ravencoin Classic	6405	MiniSwap
4289	IOEX	4948	Nervos Network	5375	Hive Dollar	5721	SorachanCoin	6410	Feellike
4291	Krypton Galaxy Coin	4950	LCX	5380	Hunt Town	5728	Balancer	6430	Electric Vehicle Zone
4292	Nibble	4951	Zynecoin	5382	ELYSIA	5741	DMM: Governance	6447	Fisco Coin
4293	PERL.eco	4953	FirmaChain	5383	B ONE PAYMENT	5748	mStable Governance Token	6457	Globaltrustfund Token
4298	Rapidz	4956	MAP Protocol	5392	Scopuly	5765	sETH	6470	Hiblocks
4299	Tokoin	4957	Minter Network	5397	Castweet	5776	tBTC	6482	Jur
4306	BSOV Token	4974	EXMO Coin	5399	TILWIKI	5777	renBTC	6490	ITAM Games
4307	UNICORN Token	4983	Demeter Chain	5400	Charg Coin	5781	CashBackPro	6493	KStarCoin
4361	Bitpanda Ecosystem Token	4985	ArdCoin	5401	CoinLoan	5782	Bestay	6498	Metacoin
4365	Streamit Coin	4997	Blockzero Labs	5407	KingdomStarter	5785	STPAY	6500	ThreeFold
4366	MixMarvel	5002	SafeCapital	5409	4P FOUR	5792	Bananatok	6507	Kulupu
4381	MYCE	5005	ARCS	5410	PARSIQ	5794	pNetwork	6511	Strong
4388	ExchangeCoin	5007	TROY	5420	SonoCoin	5798	Darwinia Network	6520	HOPR
4411	TenUp	5011	ALLY	5423	DSLA Protocol	5800	Treecle	6535	NEAR Protocol
4424	XDAG	5015	HEX	5425	Mesefa	5802	SORA	6536	MANTRA
4427	BITICA COIN	5016	Innovative Bioresearch Coin	5426	Solana	5804	DeFiChain	6537	RioDeFi
4430	VNX	5024	ALL BEST ICO	5429	DEAPcoin	5805	Avalanche	6538	Curve DAO Token
4431	VIDY	5025	Jade Currency	5434	pTokens BTC	5809	Cap	6539	YAM V1
4441	Vectorspace AI	5026	Orchid	5435	Epic Cash	5815	BitcoinPoS	6542	Happy Birthday Coin
4452	BidiPass	5031	MimbleWimbleCoin	5437	BIZZCOIN	5816	Rewardiqa	6543	Barter
4460	PirateCash	5034	Kusama	5444	Cartesi	5818	Ormeus Cash	6554	GamerCoin
4466	Ormeus Ecosystem	5038	Litecash	5445	LBK	5821	Aleph.im	6564	ZenSports
4467	Nestree	5046	Streamity	5446	USDJ	5824	Smooth Love Potion	6565	TideBit Token
4487	Secure Cash	5049	VerusCoin	5449	Beer Money	5828	VN Token	6588	Etherisc DIP Token
4490	Emirex Token	5052	Apple Network	5450	WiBX	5829	TrustSwap	6598	Aureus Nummus Gold
4491	Flits	5060	XeniosCoin	5453	KardiaChain	5833	ASKO	6602	XFUEL
4502	Altbet	5062	Bepro	5455	Bitcoin XT	5835	Decentr	6607	MixTrust
4512	FINSCHIA	5067	MAX Exchange Token	5468	Isiklar Coin	5836	Idena	6609	Decentrahub Coin
4520	Decentralized Vulnerability Platform	5068	Neutrino Index	5473	CRDT	5837	CEREAL	6611	DuckDaoDime
4525	Lightyears	5070	Tap	5474	Ixinium	5841	NEST Protocol	6622	Hakka.Finance
4542	Scrypta	5072	Rakon	5478	ECOSC	5847	Defis	6626	SPACE-iZ
4546	01coin	5079	apM Coin	5479	UCA Coin	5857	FLAMA	6627	Meter Stable
4552	Aircoins	5084	PlayFuel	5480	Bali Coin	5858	QANplatform	6636	Polkadot
4558	Flow	5086	Pawtocol	5482	CCX	5864	yearn.finance	6638	UniLayer
4566	XDB CHAIN	5088	Guapcoin	5486	Jack Token	5865	FIO Protocol	6641	AhaToken
4568	JFIN Coin	5103	Tachyon Protocol	5488	JUST	5866	DEXTools	6649	Cat Token
4571	HEdpAY	5109	FRED Energy	5508	Algory Project	5873	NextDAO	6651	USDX [Kava]
4586	ProBit Token	5113	inSure DeFi	5513	Crypto Holding Frank Token	5877	Rarible	6653	FolgoryUSD
4630	Sierracoin	5114	Coinsbit Token	5518	Torex	5880	Props Token	6655	Krosscoin
4642	Hedera	5117	Origin Protocol	5520	Martkist	5882	StaFi	6665	LGCY Network
4647	PUBLISH	5130	K-Tune	5521	EzyStayz	5886	Rowan Token	6668	PROXI
4660	Telos	5135	AfroDex	5522	SENSO	5892	Anyswap	6669	PowerPool
4677	Tepleton	5143	Documentchain	5524	TNC Coin	5893	Frontier	6670	Axis DeFi
4678	Global Digital Content	5155	Nyzo	5529	ASYAGRO	5899	Casper	6679	WHALE
4679	Band Protocol	5159	Waves Enterprise	5530	REBIT	5900	DigiDinar	6680	Digex
4680	FYDcoin	5160	Dune Network	5536	AtromG8	5906	NerveNetwork	6682	Pollux Coin
4687	BUSD	5161	WazirX	5538	Buzzshow	5908	dKargo	6684	Dextoken
4691	Zano	5165	Freight Trust & Clearing Network	5539	VeraOne	5914	Intexcoin	6693	OC Protocol
4702	Rupiah Token	5168	Bitcoin Classic	5541	Xaya	5918	ModiHost	6697	TriipMiles
4703	BonusCloud	5169	PYRO Network	5544	Aluna.Social	5919	Meter Governance	6701	Burency
4704	Banano	5174	Buxcoin	5548	Massnet	5922	Swingby	6704	JBOX

Table A4. Names and crypto-assets' coinmarketcap.com IDs: 1501–2000.

ID	Name	ID	Name	ID	Name	ID	Name	ID	Name
6705	Lien	7096	Bridge Oracle	7486	Rari Governance Token	7878	MobileCoin	8258	CUDOS
6709	Vidya	7102	Linear Finance	7497	Marlin	7881	sKLAY	8259	Furucombo
6714	Libfx	7105	Permission Coin	7498	Yield Protocol	7882	Efforce	8260	Indexed Finance
6715	Sperax	7110	New BitShares	7501	WOO	7908	Guarded Ether	8264	Basis Gold Share
6719	The Graph	7116	Crypto Accept	7505	Everscale	7931	Forj (Bondly)	8265	Helmet.insure
6724	Klever	7126	Giftedhands	7512	Unistake	7933	Alpha5	8267	OKT Chain
6726	YUSRA	7127	Velo	7513	BitOnyx	7942	Curate	8270	Gera Coin
6727	Reserve	7129	TerraClassicUSD	7533	Oraichain	7952	Venus SXP	8271	Poolz Finance
6731	Tokamak Network	7131	YAM V3	7535	Keep3rV1	7957	Venus USDT	8276	Arianee
6735	Nexalt	7133	Ducato Finance Token	7539	Colibri Protocol	7958	Venus USDC	8278	VEROX
6739	ONBUFF	7150	Flamingo	7548	WEMIX	7959	Venus BUSD	8279	e-Money
6742	DxSale.Network	7158	BurgerCities	7552	Hyve	7960	Venus XVS	8282	Koinos
6744	Chain Games	7169	Chicken	7553	unFederalReserve	7964	Venus LTC	8284	TokenAsset
6747	Crust Network	7182	Billion Happiness	7570	Blurt	7965	Venus XRP	8290	SuperVerse
6748	Centrifuge	7186	PancakeSwap	7576	Kava Lend	7972	Honey	8292	Router Protocol
6754	Polkaswap	7187	S.Finance	7579	Mars Network	7974	Venus BCH	8294	Cometh
6758	SushiSwap	7189	Origin Dollar	7583	Auric Network	7975	Venus LINK	8295	CPUcoin
6765	ESR Coin	7190	PowerTrade Fuel	7585	Freeway Token	7976	Venus DOT	8296	KLAYswap Protocol
6766	Satopay Network	7192	Wrapped BNB	7586	Yearn Classic Finance	7977	Unit Protocol Duck	8298	Paralink Network
6771	DataHighway	7199	Ultra Clear	7588	Gameswap	7978	Bonfida	8299	Stake DAO
6773	FUTUREXCRYPTO	7200	Bidao	7590	Dvision Network	7980	MinePlex	8307	DIGG
6783	Axie Infinity	7202	OctoFi	7591	Misbloc	7986	Hub - Human Trust Protocol	8309	ARMOR
6789	Blockchain Cuties Universe Governance	7206	TitanSwap	7593	DefiDollar DAO	7988	Zugacoin	8310	TosDis
6801	TriumphX	7208	Polkastarter	7594	Smoothy	8000	Lido DAO	8320	PolkaBridge
6804	MiraQle	7216	LuaSwap	7596	SmartCredit Token	8002	SpiderDAO	8329	PAID Network
6810	Cyclub	7217	Morpher	7616	Lattice Token	8020	DeFiato	8335	Mdex
6824	Epanus	7219	Rubic	7617	saffron.finance	8029	Oxygen	8339	xFund
6829	Pearl	7222	yAxis	7618	Alpaca City	8031	governance ZIL	8340	Natus Vincere Fan Token
6830	KILT Protocol	7224	DODO	7619	Bitcoiva	8034	BioPassport Token	8341	Young Boys Fan Token
6833	Litentry	7225	DeFiner	7622	UBIX.Network	8035	Grom	8349	Onooks
6836	Moonbeam	7226	Injective	7623	Libartysharetoken	8036	YVS.Finance	8351	OptionRoom
6841	Phala Network	7227	APY.Finance	7628	Coral Swap	8037	Vanar Chain	8353	Beacon ETH
6843	Radworks	7228	DerivaDAO	7632	Rake Finance	8043	MahaDAO	8357	Bitcicoin
6852	Akropolis Delphi	7229	Gelato	7635	UniWorld	8044	Adappter Token	8358	Potentiam
6855	BIDR	7230	Opium	7636	Team Heretics Fan Token	8045	APY Vision	8364	Bridge Mutual
6859	Harvest Finance	7231	Nsure.Network	7637	Trabzonspor Fan Token	8049	Tornado Cash	8365	Seascape Crowns
6865	Crypton	7232	Stella	7638	Apollon Limassol	8056	UNION Protocol Governance Token	8368	Xeno Token
6866	TAI	7236	Celo Dollar	7639	Club Atletico Independiente	8057	AnRKey X	8372	XNODE
6867	STABLE ASSET	7242	cVault.finance	7641	Medicalveda	8063	Duck DAO (DLP Duck Token)	8376	MASQ
6868	Seigniorage Shares	7244	SaTT	7645	WadzPay Token	8066	Yield App	8377	SX Network
6870	OIN Finance	7245	Stobox Token	7647	Azuki	8068	Coinbase tokenized stock FTX	8378	Akita Inu
6872	Carrot	7255	Aitra	7653	Oasis Network	8071	OnX Finance	8384	CLV
6874	SalmonSwap	7256	Mettalex	7654	RFOX	8075	Rally	8385	Umbrella Network
6881	DefiDollar	7257	APEcoin.dev	7661	GYSR	8080	Dypius [Old]	8386	Gourmet Galaxy
6882	EXNT	7262	extraDNA	7664	UNCX Network	8083	Tokenlon Network Token	8387	Auto
6883	KittenFinance	7263	HLP Token	7665	NestEGG Coin	8085	Lido Staked ETH	8389	BambooDeFi
6887	Archethic	7270	SAFE DEAL	7669	UNCL	8100	Ankr Staked ETH	8394	Anime Token
6889	TRONbetLive	7276	Kirobo	7672	Unifi Protocol DAO	8104	1inch Network	8398	YFIONE
6890	TON Token	7278	Aave	7676	Axion	8105	ROCKI	8405	Butterfly Protocol
6891	Niftyx Protocol	7281	Persistence	7677	ReapChain	8107	Cobak Token	8406	Apron Network
6892	MultiversX	7288	Venus	7678	Rook	8117	Dymmax	8408	Govi
6896	CORN	7296	Truebit	7681	Ideaology	8119	SafePal	8409	Razor Network
6898	JackPool.finance	7301	AurusX	7684	ORO	8120	Whiteheart	8411	Marginswap
6901	Swerve	7305	Jackpot	7687	Folder Protocol	8123	Australian Dollar Token	8416	Finxflo
6905	Upper Euro	7310	Gem Exchange and Trading	7691	Farmland Protocol	8124	DRC Mobility	8419	APYSwap
6906	Upper Pound	7311	Beefy	7692	e-Radix	8125	Unique One	8420	DAO Maker
6907	Upper Dollar	7320	Neutrino Token	7694	Governor DAO	8129	Fire Protocol	8421	Argon
6911	BNSD Finance	7321	yOUcash	7697	Experty Wisdom Token	8130	Supreme Finance	8422	Pangolin
6928	Bella Protocol	7326	DeXe	7698	CorionX	8131	Curio Governance	8423	Public Mint
6929	Hegic	7332	EasyFi	7699	CyberFi Token	8132	BiFi	8424	Deri Protocol
6930	KIRA	7334	Conflux	7703	MileVerse	8133	Skey Network	8425	JasmyCoin
6933	Nuco.cloud	7336	Index Cooperative	7705	ANIVERSE	8136	WAXE	8426	Filda
6938	YFDAI.FINANCE	7349	Centaur	7725	TrueFi	8141	Mithril Share	8427	Lendhub
6940	Lead Wallet	7355	Reflex	7726	ICHI	8143	Nord Finance	8431	G999
6941	Huobi BTC	7363	POP Network Token	7732	Brother Music Platform	8144	OVR	8438	Hoge Finance
6942	Juggernaut	7367	SnowSwap	7737	API3	8145	SparkPoint Fuel	8442	EthicHub
6945	Amp	7375	SUP	7739	DexKit	8146	Zipmex	8443	LUXO
6949	Hedget	7377	Dogeswap	7740	Polaris Share	8156	GGDApp	8444	Gains Farm
6950	Perpetual Protocol	7380	Dracula Token	7742	88mph	8159	One Cash	8445	SharedStake
6951	Reef	7381	CoFiX	7749	Paypolitan Token	8160	One Share	8448	MCOBIT
6952	Frax	7382	ACoconut	7750	Eden	8162	AME Chain	8449	Goose Finance
6953	Frax Share	7386	Spaceswap MILK2	7755	Handy	8163	Exeedme	8452	Shield Protocol
6958	Alchemy Pay	7390	Spaceswap SHAKE	7761	BuildUp	8164	JulSwap	8458	Peanut
6960	DefiBox	7392	Talent Token	7762	Lyra	8166	MAPS	8463	Tapx
6975	YFFII Finance	7396	r/CryptoCurrency Moons	7772	Leverj Gluon	8167	Wise Token	8469	LavaSwap
6989	Zeedex	7398	Coreto	7784	BLink	8168	Bao Finance (old)	8476	Premia
6991	Sashimi	7399	Global Gaming	7789	OASISBloc	8173	Loon Network	8479	VAIOT
6992	Spartan Protocol	7404	Value Liquidity	7791	Pancake Bunny	8174	CircleSwap	8483	Berry Data
6993	REVV	7411	Covalent	7795	Bird.Money	8177	KnoxFS	8484	Olyverse
6997	SakeToken	7412	UniLend	7805	Muse	8182	VidyX	8487	TBCC
7009	BNBUP	7414	Behodler	7809	Carbon	8185	Trism	8489	XSGD
7010	BNBDOWN	7420	Digital Reserve Currency	7813	Basis Cash	8188	MoneySwap	8492	Vesper
7016	ETHUP	7422	PlotX	7814	Alaya	8191	NFTX	8494	Modefi
7022	Pickle Finance	7424	Hermez Network	7816	Basis Share	8196	Mantis	8495	Everest
7024	Autobahn Network	7425	PayAccept	7817	Bifrost	8200	Shapeshift FOX Token	8497	ApeSwap
7030	Betherchip	7429	Liquity	7819	Unicap.finance	8202	ZKBase	8499	300FIT NETWORK
7033	Empty Set Dollar	7430	Zenfuse	7821	Royale Finance	8206	QuickSwap [Old]	8500	NitroEX
7034	Golff	7431	Akash Network	7824	Vai	8212	Earn Defi Coin	8501	Luxurious Pro Network Token
7041	Gather	7436	BonFi	7826	Zoracles	8213	Venus Filecoin	8508	PoolTogether
7046	Aavegotchi	7438	ZeroSwap	7838	Base Protocol	8214	Venus DAI	8509	XMON
7048	Wing Finance	7440	BarnBridge	7841	Idle	8216	Electra Protocol	8510	QiSwap
7055	DeFi Pulse Index	7445	cCOMP	7844	ACryptoS	8224	Dequant	8519	Xend Finance
7064	BakeryToken	7455	Audius	7846	Unbound	8230	AI Network	8522	TOZEX
7074	Oracolxor	7460	Alpha Quark Token	7857	Mirror Protocol	8232	UniDex	8524	Wrapped Huobi Token
7077	UniFi Protocol	7461	PlayDapp	7859	Badger DAO	8236	Glitch	8525	Rai Reflex Index
7080	Gala	7462	United	7860	ClinTex CTi	8245	Hydra	8526	Raydium
7083	Uniswap	7463	RAMP	7864	DGPayment	8249	LP 3pool Curve	8528	HashBridge Oracle
7087	Dego Finance	7467	Swirge	7866	Monavale	8252	pBTC35A	8530	StarLink
7094	dHedge DAO	7474	Axia Protocol	7870	Plasma Finance	8255	Prosper	8531	Quantfury Token
7095	Unisocks	7475	Camp	7876	SORA Validator Token	8256	HollyGold	8534	Chintai

Table A5. Names and crypto-assets' coinmarketcap.com IDs: 2001–2500.

ID	Name	ID	Name	ID	Name	ID	Name	ID	Name
8536	Mask Network	8801	Light	9104	AIOZ Network	9466	Edgecoin	9783	Roseon
8537	Channels	8813	LABS Group	9107	ZilSwap	9467	Celo Euro	9789	ETH2x Flexible Leverage
8538	AC Milan Fan Token	8823	Poodl Token	9110	Kattana	9468	Spore	9792	ACENT
8540	HecoFi	8826	Moss Carbon Credit	9111	Push Protocol	9473	Unicly CryptoPunks Collection	9797	Avalaunch
8541	SifChain	8827	Boson Protocol	9115	WorkQuest Token	9479	KSwap	9798	VELOREX
8543	Kangal	8829	Pig Finance	9119	Alien Worlds	9481	Pendle	9805	EVAI
8544	Fractal ID	8831	Aurix	9120	Franklin	9487	Sheesha Finance [ERC20]	9816	APENFT
8545	Launchpool	8833	DeGate	9125	Gains	9488	ZooKeeper	9819	PalGold
8547	RamenSwap	8837	Scholarship Coin	9131	Alchemist	9492	Etherland	9825	NiiFi
8548	Aloha	8840	DailySwap Token	9132	MobiFi	9493	Reflexer Ungovernance Token	9827	Sportcash One
8549	Polkacity	8841	Arro Social	9134	NBX	9498	EnreachDAO	9828	Nafter
8554	PRivaCY Coin	8844	SPRINK	9148	Drep [new]	9502	Pippi Finance	9837	Flux Protocol
8558	BT.Finance	8849	AXIS Token	9155	DEFIT	9503	CryptoTycoon	9839	blockbank
8560	WhaleRoom	8850	Viper Protocol	9158	moonwolf.io	9504	NAOS Finance	9840	Pleasure Coin
8561	KeyFi	8857	Anchor Protocol	9169	MMAON	9505	Lever Token	9844	Atlantic Finance Token
8565	Exen Coin	8858	Cub Finance	9172	Professional Fighters League Fan	9507	Goztepe S.K. Fan Token	9848	Moonlight Token
8566	Ballswap	8862	Rage Fan	9173	Raze Network	9508	Universidad de Chile Fan	9854	Tiger King Coin
8567	HAPI Protocol	8863	SHOPX	9175	MOBOX	9509	Legia Warsaw Fan Token	9855	EthereumMax
8579	Polkamarkets	8865	vBSWAP	9176	RocketX exchange	9510	Fortuna Sittard Fan Token	9856	Knit Finance
8590	Cyclone Protocol	8866	BSC TOOLS	9177	Pitbull	9511	Dfyn Network	9859	YUMMY
8593	FileStar	8867	DeHive	9179	Defi For You	9512	Cubiex Power	9862	Sishi Finance
8602	Bounce Token	8868	50x.com	9180	myDID	9518	MemePad	9863	TrustBase
8605	WOWswap	8874	DAFI Protocol	9188	Globe Derivative Exchange	9522	Bonfire	9865	Ispolink
8607	Xion Finance	8875	Uno Re	9191	Occam.Fi	9524	Media Network	9866	FEAR
8610	DMEX(Decentralized Mining E.)	8877	KIWIGO	9193	Prostarter	9526	LOCGame	9867	Hot Cross
8611	VKENAF	8879	Pika	9194	Saito	9530	FaraLand	9868	XCAD Network
8612	Float Protocol (Bank)	8880	MacaronSwap	9196	Genesis Shards	9533	GreenTrust	9869	Spherium
8613	Alchemix	8882	Alliance Fan Token	9198	Hord	9537	EpiK Protocol	9870	xWIN Finance
8615	Ethernity	8883	Sint-Truidense Voetbalvereniging Fan	9200	Revomon	9543	Biconomy	9872	TheFutbolCoin
8616	Aurox	8884	Istanbul Basaksehir Fan Token	9205	K21	9544	POLKARARE	9879	Exohood
8617	Red Kite	8885	Novara Calcio Fan Token	9207	Metaverse Index	9545	NFTb	9889	Bistroo
8620	TOWER	8886	USDP Stablecoin	9212	CumRocket	9547	tSILVER	9891	BinaryX (old)
8621	yieldwatch	8891	Bitcoin Standard Hashrate Token	9214	MoonStar	9549	Mercurial Finance	9892	YooShi
8622	Bancor Governance Token	8894	Deeper Network	9217	XFai	9550	PERI Finance	9900	HODL
8625	SaltSwap Finance	8895	ORAO Network	9218	Mist	9553	B-cube.ai	9903	Convex Finance
8633	Nodestats	8897	KickPad	9220	StrikeX	9562	Coldstack	9904	GeroWallet
8635	xDAI	8899	xSUSHI	9225	Rigel Protocol	9566	Liquity USD	9905	Rune
8637	Tranche Finance	8904	renZEC	9237	Horizon Protocol	9576	Vulkania	9906	Bunicorn
8642	Fei USD	8905	BitSong	9241	Satozhi	9578	Dungeonswap	9908	Ki
8643	Shadows	8908	ImpulseVen	9245	Signata	9583	MELX	9920	RUSH COIN
8644	Kylin	8909	Stater	9247	Whole Earth Coin	9586	PRIVATEUM GLOBAL	9928	Space Token
8646	Mina	8910	Daily	9251	Standard	9588	O3 Swap	9931	SONM (BEP-20)
8647	MurAll	8911	Strike	9253	Twinci	9590	Obortech	9932	ElonDoge
8648	ChainGuardians	8912	Tidal Finance	9258	Chia	9592	Fortress Lending	9936	Elephant Money
8649	Oxbull.tech	8915	Hello Pets	9259	TheForce Trade	9595	CaliCoin	9938	OpenOcean
8657	wanUSDT	8916	Internet Computer	9260	Zignaly	9597	dFund	9941	Chihuahua
8658	Wrapped WAN	8917	Shyft Network	9262	UniFarm	9598	Lion Token	9943	American Shiba
8659	Jetfuel Finance	8925	Wrapped Matic	9263	Unizen	9604	Privapp Network	9946	Your Future Exchange
8660	BSCPAD	8926	A2DAO	9265	Porta	9605	TruePNL	9951	WaultSwap
8662	Starter	8936	Trias Token (New)	9269	Refinable	9607	Bankless DAO	9954	Netvrk
8665	Parallel	8937	Woonkly Power	9270	Bitcoin Bam	9608	SpookySwap	9958	SafeMoon Inu
8666	DFX Finance	8938	Ellipsis	9279	SuperLauncher	9613	Trustpad (Old)	9962	STARSHIP
8669	Sovryn	8942	Paybswap	9284	Secured MoonRat Token	9615	Polylastic	9967	SafeBlast
8670	Vow	8943	WHITEX	9285	Moonriver	9620	Wrapped Statera	9968	Corgidoge
8673	TotemFi	8961	Futureswap	9286	Doge Killer	9628	Raptor Finance	9976	Freela
8675	Minds	8962	ETNA Network	9288	BENQI	9632	UMI	9982	DINGO TOKEN (old)
8677	Symbol	8963	UnMarshal	9291	Ternoa	9635	SaveYourAssets	9984	CluCoin
8678	EHash	8964	Blizzard.money	9295	CLIMB TOKEN FINANCE	9637	Altura	9989	Solrise Finance
8679	Unido EP	8966	Safemars	9299	NFT Art Finance	9638	SingularityDAO	9991	Charli3
8681	Funder One Capital	8968	Polychain Monsters	9300	Zeppelin DAO	9639	Pussy Financial	9996	Bezoge Earth
8683	Asva	8970	Lokr	9302	MoMo KEY	9640	MetisDAO	9997	METANOA
8690	CAD Coin	8971	MerchDAO	9308	Vulcan Forged (PYR)	9643	Don-key	9998	Unicly
8691	Domani Protocol	8972	Seedify.fund	9316	Shipit pro	9651	Ethermon	10005	Zoo Token
8695	BlockWallet	8978	PooCoin	9318	BeforeCoinMarketCap	9653	Nabox	10011	CoinWind
8697	Konomi Network	8981	WardenSwap	9326	ROPE Token	9654	CryptoBlades	10023	Planet
8702	Ares Protocol	8985	Efinity Token	9342	Community Business Token	9656	CateCoin	10029	USD mars
8704	Playcent	8992	Cellframe	9344	1MillionNFTs	9663	ArGo	10030	Mars Ecosystem Token
8705	Bifrost	8994	Delta	9345	BSCS	9665	My DeFi Pet	10031	TEN
8707	Alpaca Finance	8996	Mogul Productions	9348	Crowny	9666	Terran Coin	10033	NFTMart Token
8708	Big Data Protocol	8997	Cook Finance	9353	Kalata	9670	GogolCoin	10036	BSClaunch
8709	ETHA Lend	9002	Busy DAO	9364	Unlock Protocol	9673	Loser Coin	10040	Wall Street Games
8710	bAlpha	9007	ZooCoin	9368	Euler Tools	9674	Wilder World	10042	Karura
8711	Pando	9008	AMMYI Coin	9377	TreeDefi	9675	Drops Ownership Power	10046	Dotmoovs
8715	Taraxa	9016	DAOhaus	9386	Kishu Inu	9679	MoonStarter	10047	EPIK Prime
8716	Convergence	9017	Polkadex	9395	Strite	9686	My Crypto Heroes	10049	Manchester City Fan Token
8717	Oddz	9020	Toko Token	9413	Vira-lata Finance	9691	Venus Reward Token	10052	Gitcoin
8719	Illuvium	9021	Wrapped XDAI	9416	The Crypto Prophecies	9693	DOGGY	10055	Crust Shadow
8720	Inverse Finance	9024	disBalancer	9417	Maple	9694	Upfire	10059	Pandora Finance
8723	Bogged	9025	Tribe	9421	Ampleforth Governance Token	9698	Tycoon	10061	CumInu
8726	Idavoll DAO	9026	Blind Boxes	9423	Phuture	9700	Microtuber	10079	Quidax Token
8730	Belt Finance	9027	Uhive	9428	Venus Cardano	9710	Kabosu	10081	SafeMoonCash
8732	Swop	9029	Graphlinq Chain	9430	Alphr finance	9711	Sanshu Inu	10083	ClassZZ
8733	BasketCoin	9035	Vidiachange	9436	Dogelon Mars	9712	Shih Tzu	10088	PolyDoge
8738	Pastel	9040	Pundi X (New)	9437	CherrySwap	9720	PlatON	10090	Friends With Benefits Pro
8741	Sovi Finance	9043	Stone DeFi	9438	Nominex	9721	Samoyedcoin	10093	Gold Secured Currency
8745	A2A	9045	JPY Coin v1	9440	Mochi Market	9737	Hummingbird Finance (Old)	10095	Elk Finance
8752	Landbox	9046	8PAY	9441	Jigstack	9740	Dot Finance	10098	Greenheart CBD
8755	Nerve Finance	9047	CARD.STARTER	9443	Step Finance	9741	Solanium	10099	KALM
8757	SafeMoon	9055	BerrySwap	9444	Kyber Network Crystal v2	9742	ElonTech	10101	Kwikswap Protocol
8759	ZCore Finance	9061	Rainicorn	9447	Synthetify	9747	Cryption Network	10102	BankSocial
8766	MyNeighborAlice	9062	LinkPool	9449	Sienna (ERC20)	9749	WallStreetBets DApp	10103	Lossless
8769	MeetPle	9065	Realfinance Network	9450	BLACKHOLE PROTOCOL	9752	AFEN Blockchain Network	10109	Feeder.finance
8771	GYEN	9067	Olympus v2	9451	Verso	9756	Virtue Poker	10117	Moonarch.app
8772	ZUSD	9070	CFX Quantum	9452	Bandot Protocol	9757	WeStarter	10121	ByteNext
8789	EDDASwap	9071	Chainge	9453	Agave	9760	Stratos	10127	JINDO INU
8790	KINE	9073	Popsicle Finance	9455	Lemond	9763	Copiosa Coin	10128	TeraBlock
8795	Mute	9083	Equalizer	9456	Australian Safe Shepherd	9764	MILC Platform	10134	Polycat Finance
8797	Chronicle	9089	Tenset	9458	HOKK Finance	9766	Rentible	10145	DeFinity
8798	Ramifi Protocol	9091	CPCoin	9461	X World Games	9767	Frenchie Network	10155	Vanity
8799	InsurAce	9103	GAMEE	9462	Wrapped AVAX	9780	Snowball	10158	SpaceGrime

Table A6. Names and crypto-assets' coinmarketcap.com IDs: 2501–3000.

ID	Name	ID	Name	ID	Name	ID	Name	ID	Name
10160	Swaperry	10502	SafeMars	10888	NewB.Farm	11223	MetaMUI	11530	Roush Fenway Racing Fan
10161	OptionPanda	10506	HitBTC Token	10889	DRIFE	11230	Sakura	11531	Portugal National Team Fan
10165	PornRocket	10508	Instadapp	10891	Only1	11232	Highstreet	11532	Arsenal Fan Token
10166	AstroElon	10514	HUNNY FINANCE	10893	Brokoli Network	11233	Monsoon Finance	11533	UFC Fan Token
10167	SpaceY	10519	Curio Stable Coin	10894	StorX Network	11234	Position Exchange	11534	Levante U.D. Fan Token
10172	DekBox	10522	Pacoca	10897	Alitas	11240	HI	11539	Vendit
10174	CreamPYE	10524	reBaked	10898	Wrapped Centrifuge	11242	Moonpot	11541	Ariva
10178	Rabbit Finance	10526	TribeOne	10899	Daddy Doge	11245	Landshare	11552	Talken
10180	Gomining	10527	Lithium	10900	Hachiko Inu	11247	Kephi Gallery	11556	CryptoZoo (new)
10182	Manifold Finance	10529	Sun (New)	10901	Shiba Floki Inu	11251	Dexlab	11557	The Doge NFT
10183	DeSpace Protocol	10530	CrossWallet	10903	Coin98	11254	Minifootball	11560	DeHub
10185	Moonlana	10532	Divergence	10904	BunnyPark	11258	Creaticles	11562	Kava Swap
10188	Automata Network	10554	Sekuritance	10905	AirNFTs	11271	Colana	11563	aiRight
10201	BitBook	10555	Canary	10908	KuSwap	11275	BinStarter	11566	ASH
10202	Starcoin	10556	B.Protocol	10914	BABY DOGE INU	11278	Project TXA	11568	Adventure Gold
10217	Cykura	10557	Swapz	10918	Crypto Village Accelerator	11279	Block Ape Scissors	11570	The Recharge
10221	Fanadise	10563	Decubate	10919	CoinsPaid	11283	Ryoshis Vision	11578	Cirus Foundation
10222	Vodra	10566	BlackHat	10928	DOJO	11289	Spell Token	11579	Cryptomeda
10223	Vega Protocol	10570	Binance Smart Chain Girl	10929	ZoidPay	11291	Kryptomon	11582	Lumi Credits
10225	Pera Finance	10576	MoonLift Capital	10932	Impossible Finance	11292	Unreal Finance	11584	Braintrust
10228	Omchain	10585	TrustFi Network	10933	Impossible Finance Launchpad	11293	Avaware	11586	Story
10232	MakiSwap	10586	TABOO TOKEN	10935	Aldrin	11294	SuperRare	11591	Raid Token
10234	Draken	10593	Flurry Finance	10949	Baanx	11299	POTENT	11596	SingularFarm
10237	QiDao	10603	Immutable	10953	Kaby Arena	11301	YEL.Finance	11599	Alita Finance
10238	MAI	10613	Empire Token	10954	MContent	11307	Beta Finance	11603	MarketMove
10239	SpiritSwap	10622	XCarnival	10967	YIN Finance	11308	Fenerbahce Token	11612	Sunny Aggregator
10240	Wrapped Fantom	10630	Guild of Guardians	10970	BabyDoge ETH	11309	OneRare	11614	Theos
10251	The Corgi of PolkaBridge	10631	Gods Unchained	10973	PureFi Protocol	11314	CWallet	11616	Score Token
10257	Shibaken Finance	10640	Kawakami	10974	Tranchess	11317	Relay Token	11620	IX Swap
10260	Thorstarter	10641	RichQUACK.com	10977	Mint Club	11318	Goldex Token	11621	Punk Vault (NFTX)
10262	KleeKai	10644	SafeBull	10984	Witch Token	11322	Mobius Finance	11646	Regen Network
10264	Charged Particles	10648	Eifi FInance	10987	AVME	11323	Crypto Carbon Energy	11649	Wicrypt
10265	Gold Fever	10657	YetiSwap	11013	LIQ Protocol	11324	Forest Knight	11654	VelasPad
10269	Cheems	10665	KogeCoin.io	11015	Team Vitality Fan Token	11329	KamPay	11660	MCFinance
10272	AladdinDAO	10666	Lanceria	11017	PolygonFarm Finance	11330	VIMworld	11663	Elemon
10275	Catgirl	10669	Pallapay	11018	CryptoArt.Ai	11336	Nobility	11664	YAY Games
10277	TRONPAD	10674	Synapse Network	11020	ZOO Crypto World	11338	Block Commerce Protocol	11670	DeFi Warrior (FIWA)
10278	Genshiro	10675	Hare Token	11023	Wrapped KuCoin Token	11340	Immutable	11672	Pocoland
10285	Bitspawn	10677	Pollen	11024	KingDeFi	11344	Mate	11678	Lumenswap
10289	Daisy Launch Pad	10685	Olive Cash	11033	RedFEG	11345	Civilization	11682	DeathRoad
10290	RFOX Finance	10686	Evanesco Network	11035	Splintershards	11346	RACA	11685	BetU
10291	Convex CRV	10688	Yield Guild Games	11036	Alkimi	11348	Identity	11690	Magic Beasties
10293	Swarm	10695	MoonEdge	11038	BFG Token	11349	ADAPad	11695	ChronoBase
10294	DeFi Land	10700	KickToken	11042	NFTBooks	11350	NFTLaunch	11696	Wrapped Harmony
10295	IOI Token	10704	Binamon	11053	Cogecoin	11352	Moonie NFT	11697	Phantom Protocol
10303	AutoShark	10705	CoinSwap Space	11056	Golden Doge	11354	WagyuSwap	11700	Life Crypto
10307	Project Quantum	10712	Flourishing AI	11060	Baby Shiba Inu	11366	Paribus	11701	Copycat Finance
10311	NFT STARS	10713	Burp	11061	Multiverse	11367	Aurory	11706	Acet
10312	EscoinToken	10714	Babylons	11066	DinoX	11368	Feisty Doge NFT	11707	Sona Network
10324	Gravity Finance	10715	AirCoin	11067	Step Hero	11371	RoboFi	11713	Shambala
10325	Safe Energy	10720	Black Phoenix	11076	JOJO	11373	Metaverse Miner	11714	Brazil National Football Team Fan
10326	BullPerks	10722	SolanaSail	11078	IAGON	11374	Mines of Dalarnia	11715	Snook
10334	BabySwap	10723	Waves Ducks	11079	Bitgert	11380	Dogecoin 2.0	11726	SideShift Token
10336	Hamster	10725	WaultSwap Polygon	11082	Arena Token	11387	CropperFinance	11727	Phoenix Token
10337	Sheesha Finance [BEP20]	10729	UFO Gaming	11083	TripCandy	11390	Hibiki Finance	11736	CryptoMines
10347	Human	10740	Liti Capital	11086	Gamerse	11392	Moon Rabbit	11739	Blox Token
10348	Sarcophagus	10742	NEXTYPE	11088	Enjinstarter	11394	Green Climate World	11740	DeFIL
10350	Black Eye Galaxy	10744	DeRace	11090	Invitoken	11395	BOHR	11746	Megatech
10351	HTMOON	10746	Biswap	11092	Bitget Token	11396	JOE	11750	Buying.com
10364	APWine Finance	10747	ETHPad	11093	Drip Network	11397	Kaiken Shiba	11752	XP NETWORK
10366	Cake Monster	10748	PolkaWar	11104	Artery Network	11409	Tarot	11753	Cycle Finance
10367	April	10750	Qredo	11105	PearZap	11412	Binemon	11765	BigShortBets
10368	Cryptex Finance	10753	Evodefi	11107	Birb	11413	Ceres	11770	EverETH Reflect
10372	Dacxi	10756	Omni Real Estate Token	11109	Electric Cash	11414	Qubit	11772	DeMon Token
10373	Tulip Protocol	10759	rhino.fi	11110	Spores Network	11415	Yield Yak	11779	Dreams Quest
10376	dAppstore	10763	Aston Martin Cognizant Fan	11112	MyBricks	11417	Gaj Finance	11783	GameFi.org
10386	Bitcoin Latinum	10768	KAKA NFT World	11114	xNFT Protocol	11419	Toncoin	11794	handleFOREX
10388	SupremeX	10774	Sonar	11126	Hypersign Identity	11420	Tune.FM	11796	Inter Milan Fan Token
10391	Creator Platform	10776	Signum	11129	CryptoZoon	11421	Marnotaur	11797	Cricket Foundation
10392	The Everlasting Parachain	10777	DinoSwap	11130	Plant Vs Undead	11422	Wanaka Farm	11801	Daily COP
10393	LEOPARD	10778	Metahero	11132	Wrapped OKT	11423	VEMP	11802	Project X
10394	Kuma Inu	10784	KCCPAD	11134	OEC BTC	11427	Coinary Token	11805	Structure finance
10403	Kommunitas	10789	Tether EURt	11146	Jswap.Finance	11431	Minimals	11809	Ref Finance
10404	Integral	10791	eCash	11148	Proxy	11437	DEEPSPACE	11810	Pirate Coin Games
10407	Baby Doge Coin	10793	Alfa Romeo Racing ORLEN Fan	11150	DeFine	11446	S.C. Corinthians Fan Token	11813	Afreum
10408	Formation Fi	10798	MiniDOGE	11153	EmiSwap	11448	The HUSL	11814	Potato
10409	Opulous	10800	Hungarian Vizsla Inu	11156	dYdX (ethDYDX)	11450	Skyrim Finance	11818	Waggle Network
10411	Moonfarm Finance	10803	RealFevr	11160	BOY X HIGHSPEED	11451	Shiden Network	11820	TORG
10412	HoDooi.com	10804	FLOKI	11164	Vabble	11455	Polinate	11821	Swarm Markets
10421	Torum	10805	Throne	11165	Orca	11456	SnowCrash Token	11823	Pocket Network
10427	POLKER	10807	CoinW Token	11168	Vent Finance	11458	EVRYNET	11835	Monsters Clan
10428	Alium Finance	10808	Ubeswap	11171	Mango	11461	Marinade Staked SOL	11836	Citadel.one
10429	HaloDAO	10810	Jetswap.finance	11178	Wrapped LUNA Classic	11463	Husky Avax	11838	MilkshakeSwap
10430	Argentine Football Association Fan	10814	One Basis	11181	Saber	11464	ApeXit Finance	11842	PolkaFantasy
10434	SafeLaunch	10818	Penguin Finance	11185	TABANK	11465	CATO	11848	Strips Finance
10436	Xiglute Coin	10820	Yieldly	11186	Vention	11469	Solpad Finance	11851	Crosschain IOTX
10439	StakeWise	10821	Starlink	11188	Dopex	11470	Boring Protocol	11854	ArbiNYAN
10442	Decentralized Social	10824	Hertz Network	11190	KittyCake	11486	WifeDoge	11857	GMX
10452	SolAPE Token	10831	Mimo Governance Token	11191	Lydia Finance	11492	TCGCoin 2.0	11861	PlanetWatch
10455	EQIFI	10832	Etherlite	11197	Sukhavati Network	11495	Tomb	11862	Arix
10461	Memecoin	10833	ADAX	11202	Tokemak	11497	Scream	11864	Meme Lordz
10462	SHILL Token	10839	Yield Parrot	11206	Bloktopia	11498	Chainbing	11865	Bone ShibaSwap
10463	Anypad	10841	Wolf Safe Poor People	11209	TRAVA.FINANCE	11499	AMATERAS	11869	Realm
10465	Polytrade	10853	ETHDOWN	11211	DNAxCAT Token	11500	Biconomy Exchange Token	11871	GameZone
10467	IRON Titanium Token	10854	Railgun	11212	Star Atlas	11503	Manga Token	11878	Arbidoge
10469	iMe Lab	10861	Gamestarter	11213	Star Atlas DAO	11512	Kalao	11880	EpicHero 3D NFT
10482	BULL FINANCE	10866	Million	11218	BoringDAO	11516	Ekta	11882	Bitcashpay (new)
10484	Iron	10868	Super Floki	11220	Port Finance	11522	Jenny Metaverse DAO	11885	HurricaneSwap Token
10494	Octopus Protocol	10875	ChainCade	11221	BitDAO	11528	Valencia CF Fan	11887	Mission Helios
10501	BaconDAO	10877	Ainu Token	11222	Nine Chronicles	11529	Clube Atletico Mineiro Fan	11888	Matrix Labs

Table A7. Names and crypto-assets' coinmarketcap.com IDs: 3001–3500.

ID	Name	ID	Name	ID	Name	ID	Name	ID	Name
11893	Teddy Cash	12253	WOOF	12590	AutoShark DEX	12971	Lunr Token	13592	Silva Token
11896	Morpheus Token	12254	Gro DAO Token	12591	LunaChow	12972	DEUS Finance	13606	Great Bounty Dealer
11907	Fantom Oasis	12255	BitOrbit	12595	Filecoin Standard Hashrate Token	12979	Sentre Protocol	13618	Shiba Girlfriend
11910	SokuSwap	12256	cheqd	12599	ASPO World	12981	BHAX Token	13626	ACA Token
11911	Larix	12257	XTRA Token	12604	FRAKT Token	12987	SatoshiStreetBets Token	13630	OOGI
11913	AcknoLedger	12258	StrongNode Edge	12607	Solberg	12988	LABEL Foundation	13632	Genopets
11916	Minerva Wallet	12265	Investin	12609	Sway Protocol	12991	MagnetGold	13636	GMCoin
11921	Nether NFT	12269	WELD	12613	Solareum Wallet	12996	FastSwap (BSC)	13637	XRdoge
11923	Elpis Battle	12271	CryptoBlades Kingdoms	12614	Dragon Kart	12999	ssv.network	13649	Energy8
11925	Monsta Infinite	12272	Boo Finance	12641	OBRok Token	13009	ITSMYNE	13655	Crabada
11926	Thetan Arena	12275	Dynamix	12644	The Three Kingdoms	13011	UNKJD	13656	Jacy
11930	HALO network	12278	Playermon	12648	Wrapped Curio Ferrari F12tdf	13012	Synchrony	13659	Crypto Global United
11931	Traders coin	12279	PixelVerse	12649	Alanyaspor Fan Token	13018	Paras	13663	Gains Network
11933	HalfPizza	12280	BHO Network	12650	GAIA Everworld	13020	Flare Token	13675	Kintsugi
11935	Parrot Protocol	12284	Bantu	12652	Hanu Yokia	13021	Moola Market	13676	BLOCKS
11939	Heroes & Empires	12293	Beyond Protocol	12653	ROCO FINANCE	13026	FOHO Coin	13698	Real Realm
11941	Xfinite Entertainment Token	12294	Ertha	12661	HashBit BlockChain	13030	Pegaxy	13702	STEMX
11945	My Master War	12295	Dinamo Zagreb Fan Token	12664	Scallop	13038	StarLaunch	13708	BFK Warzone
11948	Radix	12297	Lido Staked SOL	12671	FANG Token	13041	Solarbeam	13715	Fancy Games
11952	Wrapped Moonriver	12301	Retreeb	12675	Dark Matter DeFi	13047	Piccolo Inu	13718	GAMINGDOGE
11958	Knight War - The Holy Trio	12306	Raptoreum	12678	FireStarter	13051	ARC	13721	NovaXSolar
11961	Vee Finance	12307	Warena	12682	DecentraWeb	13068	COGI	13726	ENNO Cash
11962	Bright Token	12312	NASDEX	12687	S.S. Lazio Fan Token	13071	SquidGameToken	13727	Shiryo
11967	Hero Arena	12313	Kawaii Islands	12690	Wrapped PKT	13074	Baby Moon Floki	13731	Leeds United Fan Token
11973	Thales	12315	DOSE	12691	Safle	13080	dForce USD	13735	SolDoge
11977	Infinity PAD	12319	DeFi Kingdoms	12692	Poken	13103	Vigorus	13746	FLOOF
11978	Revolve Games	12325	MarsRise	12695	PolyPup Finance	13105	MetaWars	13748	Spartacus
11983	Hudi	12329	DBX	12703	Gyro	13118	Yoshi.exchange	13749	BabyXape
11993	HappyFans	12333	DAO Invest	12705	Pollchain	13119	Wolf Safe Poor People	13751	Liquid Collectibles
12040	Buff Doge Coin	12338	ShibaCorgi	12709	HZM Coin	13121	Atlantis Loans	13760	Shib Army
12041	Dimitra	12344	Affinity	12710	Shakita Inu	13133	Decentral Games ICE	13768	ZeLoop Eco Reward
12042	Sypool	12345	Steam Exchange	12722	Cryowar	13136	Kitty Inu	13769	World Mobile Token
12043	Octopus Network	12350	Triall	12731	Ideanet Token	13138	SugarBounce	13783	Afrostar
12044	Vera	12351	GreenZoneX	12735	Piggy Finance	13142	BTRIPS	13813	ENTERBUTTON
12046	Idexo Token	12355	Baby Floki Billionaire	12737	Umi Digital	13157	PolkaPets	13827	SavePlanetEarth
12049	Green Beli	12359	Wojak Finance	12739	Revolotto	13167	Mimir Token	13831	Crypto Classic
12050	Symmetric	12364	Youclout	12743	Open Rights Exchange	13197	KnoxDAO	13842	Bunscake
12051	Cryptopolis	12365	Lovely Inu Finance	12749	Nakamoto Games	13198	NuNet	13850	Santa Coin
12054	MatrixETF	12366	Demeter	12751	Blockchain Monster Hunt	13211	Algebra	13855	Ethereum Name Service
12057	Dopex Rebate Token	12373	ArchAngel Token	12752	ORE Token	13212	Ethera	13864	Shiba Lite
12058	Light DeFi	12380	PolyDragon	12754	Revault Network	13216	Ninneko	13868	Baby Squid Game
12060	XTblock	12381	Smile Coin	12760	Socean Staked Sol	13229	PaintSwap	13871	TaleCraft
12064	Cratos	12382	Zamio	12761	Angle	13236	Galaxy War	13874	GAMI World
12066	Shirtum	12387	Ribbon Finance	12767	FODL Finance	13237	FantomStarter	13877	e-Money EUR
12070	Quidd	12393	Lightcoin	12769	Ardana	13243	FoxGirl	13881	Hector Network
12071	XcelPay	12395	Merchant Token	12773	DfiStarter	13244	Beethoven X	13887	P2P Solutions foundation
12074	Gem Guardian	12397	Moonbeans	12775	Waste Digital Coin	13246	LiquidDriver	13889	ZUNA
12077	Zenith Coin	12398	Spain National Fan Token	12778	Ojamu	13250	ScarQuest	13901	Bit2Me
12078	DogeSwap	12400	Decimal	12780	French Connection Finance	13251	CryptoXpress	13913	Blockster
12082	CyberDragon Gold	12409	Lido wstETH	12781	xHashtag	13256	Flokimooni	13914	Oobit
12089	Coinweb	12411	Balkari	12784	Red Floki	13265	Fidira	13916	Omax Coin
12090	YoCoin	12414	MRHB DeFi Network	12785	Colony	13271	QUARTZ	13920	Popcorn
12100	Crystl Finance	12416	PulsePad	12797	ShoeFy	13272	Credefi	13932	Genesis Worlds
12109	Poof.cash	12417	Lovelace World	12799	Internet of Energy Network	13276	Squid Game	13933	ArcadeNetwork
12115	Orion Money	12418	Jax.Network	12807	DAOSquare	13277	UNIFEES	13936	Ari10
12118	Celestial	12431	StarSharks (SSS)	12813	Sinverse	13286	CorgiCoin	13937	Catena X
12119	Planet Sandbox	12432	StarSharks SEA	12814	Dexsport	13319	Flamengo Fan Token	13938	Game Coin
12120	AstroSwap	12435	Battle Hero	12815	CryptoPlanes	13323	Integritee Network	13943	GINZA NETWORK
12125	RazrFi	12436	Timeleap Finance	12818	gotEM	13326	RBX	13953	Scotty Beam
12131	Fruits	12439	BRCP TOKEN	12820	Treat DAO [new]	13336	Newsolution2.0	13967	Goldfinch
12133	X Protocol	12440	Buffer Finance	12833	Mech Master	13337	MMScash	13969	Phoenix
12136	IjasCoin	12448	EverGrow	12834	Envoy	13342	SoulSwap Finance	13973	nSights DeFi Trader
12137	NFTrade	12451	Mondo Community Coin	12835	FalconsInu	13351	ADACash	13977	DoragonLand
12140	RMRK	12452	TETU	12836	AutoCrypto	13352	Dinger Token	13978	MetaVPad
12147	Synapse	12457	ZEDXION	12843	Graphene	13383	CropBytes	13987	DYOR Token
12148	Swash	12458	Karus Starter	12844	The Flash Currency	13400	MojitoSwap	13989	BabyFlokiZilla
12150	Little Angry Bunny v2	12459	Holdex Finance	12851	BODA Token	13403	Howl City	13994	MetaDoge V2
12153	Kurobi	12460	United Emirate Decentralized Coi	12854	PAPPAY	13411	Titan Hunters	13996	AVNRich Token
12154	Everest Token	12463	Timechain Swap Token	12859	DogeBonk	13420	PlaceWar	14020	Samsunspor Fan Token
12156	Asia Coin	12464	Lox Network	12870	The CocktailBar	13425	NFT Champions	14027	Snowbank
12166	Starpad	12465	Ridotto	12873	KlimaDAO	13429	Doge Floki Coin	14052	FC Porto Fan Token
12172	Moniwar	12468	Equilibrium Games	12878	BEMIL Coin	13431	Agricoin	14053	GovWorld
12173	Revuto	12472	Elysian	12885	Astar	13436	ftm.guru	14063	FantOHM
12176	Hummingbird Egg	12480	Starchi	12886	bloXmove Token	13437	Kiba Inu	14069	FIA Protocol
12179	PolyAlpha Finance	12485	Arowana Token	12889	Hundred Finance	13439	CashCow	14073	Vagabond
12180	Rainbow Token	12487	Dark Frontiers	12890	Uplift	13449	GameStation	14075	POOMOON
12182	Blocto Token	12488	Dogira	12892	Linked Finance World	13453	Waifer	14079	Shibalana
12186	Songbird	12489	Guardian	12895	Lil Floki	13465	Altbase	14089	Tempus
12192	RugZombie	12494	Melo Token	12898	GooseFX	13471	Omni Consumer Protocols	14094	AlgoGems
12193	AquaGoat.Finance	12495	XGOLD COIN	12901	King Shiba	13472	XDEFI Wallet	14099	Mobius Money
12194	Baby Floki (BSC)	12500	Orca AVAI	12907	Vires Finance	13473	Apricot Finance	14114	Superalgos
12196	Kollect	12501	Qrkita Token	12912	Digital Bank of Africa	13479	WePiggy Coin	14119	Upper Swiss Franc
12198	Boss Token	12506	NFTY Token	12919	Universal Basic Income	13485	Smarty Pay	14133	WAM
12199	FUFU	12511	Wrapped NewYorkCoin	12924	XDoge Network	13493	Wanaka Farm Wairere	14161	1NFT
12200	Digital Swiss Franc	12516	Dog Collar	12929	OneArt	13509	Mytheria	14172	ADToken
12203	Defina Finance	12517	DEI	12930	Cpos Cloud Payment	13518	Ethereans	14179	Pintu Token
12208	Taxa Token	12524	Farmers Only	12932	Little Bunny Rocket	13521	Numbers Protocol	14188	Plugin
12212	Allbridge	12526	USD Open Dollar	12938	Catena	13523	Merit Circle	14195	Solar
12214	Shibaverse	12532	TTcoin	12942	THORSwap	13524	Solend	14205	Wakanda Inu
12215	Falcon 9	12536	Decentralized Community Investment P.	12949	Toucan Protocol: Base Carbon Tonne	13531	Keeps Coin	14210	Construct
12218	Continuum World	12537	PolyBeta Finance	12951	Riot Racers	13532	xDollar	14222	StrongHands Finance
12220	Osmosis	12546	Liquidus (old)	12952	MetaverseX	13534	xDollar Stablecoin	14235	Shiba Interstellar
12221	Rangers Protocol	12549	Dinosaureggs	12954	Vetter Token	13542	Stabledoc	14251	Freedom. Jobs. Business.
12225	TryHards	12562	Mononoke Inu	12956	Wanda Exchange	13543	Bamboo Coin	14253	Baby Samo Coin
12229	DogeGF	12566	PinkSale	12957	Galactic Arena: The NFTverse	13546	BabyDogeZilla	14256	QuizDrop
12230	Revest Finance	12573	Clearpool	12959	Pontoon	13548	BecoSwap Token	14261	Strip Finance
12236	Jet Protocol	12576	Geist Finance	12961	BullionFx	13560	ShibaZilla2.0 (old)	14265	MetaDoge
12238	OwlDAO	12577	PLĜnet	12965	Good Games Guild	13567	SmarterCoin (SMRTr)	14271	GM Wagmi
12240	MARS4	12581	CZodiac Farming Token	12967	GoldMiner	13571	All.Art Protocol	14285	OnGO
12252	Bombcrypto	12585	Demole	12969	Gari Network	13574	Neos Credits	14292	Coin Of Champions

Table A8. Names and crypto-assets' coinmarketcap.com IDs: 3501–4000.

ID	Name	ID	Name	ID	Name	ID	Name	ID	Name
14299	JUNO	14921	Microverse	15516	Pi INU	16080	Power Cash	16671	Multiverse
14319	dHealth	14925	Witnet	15517	WoopMoney	16086	BitTorrent (New)	16675	Ctomorrow Platform
14322	UPFI Network	14926	JPool Staked SOL (JSOL)	15528	Zodium	16091	MetaGods	16678	NFT Worlds
14324	Shiba Inu Empire	14928	Crypto Royale	15532	Moomonster	16093	Bitkub Coin	16679	AgeOfGods
14325	SmartNFT	14938	Jade Protocol	15535	Flux	16100	Crafting Finance	16686	AvaOne Finance
14327	SmartLOX	14943	Unique Venture Clubs	15539	NOSHIT	16103	SOLCash	16687	Galaxy Coin
14336	TRVL	14950	Operon Origins	15557	Mother of Memes	16105	Chumbi Valley	16706	Meta MVRS
14338	PlayPad	14968	Viral Inu	15563	Cornucopias	16116	Wrapped Solana	16727	X
14339	Cypherium	14969	Dragon Mainland Shards	15564	DEXGame	16128	Predictcoin	16742	Monster Galaxy
14340	MELI	14978	Let's Go Brandon Token	15565	CheeseSwap	16130	Wrapped Staked HEC	16749	FOX TOKEN
14341	BitShiba	14990	MetaSoccer	15572	Charm	16133	Frontrow	16751	Infinity Skies
14342	DKEY BANK	14996	MEDIA EYE NFT Portal	15574	KaraStar UMY	16135	Shib Generating	16753	Wild Island Game
14345	Botto	14997	Outrace	15575	Plastiks	16137	BTC 2x Flexible Leverage Index	16757	GroupDao
14349	Tutellus	15002	Kryxivia	15584	Humans.ai	16148	FreeRossDAO	16768	Dibs Share
14362	SportsIcon	15006	MetalSwap	15585	GuildFi	16160	Multi-Chain Capital (new)	16769	Sunflower Farm
14363	Pancake Games	15013	ReSource Protocol	15589	The Crypto You	16162	SafeMoon V2	16781	ZURRENCY
14371	Inflation Hedging Coin	15024	Angle Protocol	15592	MetaBrands	16168	Nitro League	16817	Wrapped EGLD
14374	Green Ben	15028	UXD Protocol	15608	TabTrader Token	16178	Imperium Empires	16819	Recovery Right Token
14382	Kitty Solana	15035	KEYS	15610	Terra Classic USD (Wormhole)	16181	Solice	16820	Blin Metaverse
14389	Sator	15039	MADworld	15617	Kyrrex	16182	ManuFactory	16821	Mean DAO
14391	Dali	15041	youves uUSD	15638	Ltradex	16185	Dingocoin	16831	Fantom USD
14392	Golden Ball	15050	Milk	15641	Kounotori	16191	TravGoPV	16832	Web3 Inu
14397	Dragon Crypto Aurum	15056	Wolf Game Wool	15652	GOGOcoin	16197	Luna Rush	16837	Covenant
14399	Cross-Chain Bridge Token	15060	Rocket Pool ETH	15659	Decentralized Eternal Virtual T.	16201	Day By Day	16842	Stargaze
14404	Etherconnect	15069	CRODEX	15664	BlockchainSpace	16209	Olympus v1	16849	OUSE Token
14421	SpritzMoon Crypto Token	15080	Suteku	15669	The Parallel	16218	Marvelous NFTs (Bad Days)	16863	Crypto Raiders
14422	HeroesTD	15084	Symbiosis	15678	Voxies	16219	FireBotToken	16868	Shadow Token
14446	Laqira Protocol	15085	The Killbox	15683	Musk Metaverse	16230	ETH Fan Token Ecosystem	16900	Optimus
14447	Swole Doge	15090	Cirrus	15687	Grim Finance	16231	Platypus Finance	16913	Millonarios FC Fan Token
14449	Jaiho Crypto	15097	Boryoku Dragonz	15688	Domi Online	16251	BitcoinBR	16923	Gamma
14452	Transhuman Coin	15098	Robo Inu Finance	15691	WX Token	16253	Tr3zor	16928	Elon GOAT
14458	Kaby Gaming Token	15100	RaceFi	15698	GFORCE	16254	OMarket Global LLC	16929	Experimental Finance
14461	Sphynx Labs	15110	MEGAWEAPON	15700	Cryptotem	16256	REDMARS	16936	2omb Finance
14463	Realy	15128	Niftify	15720	MetaFabric	16258	World of Defish	16937	2SHARE
14488	JK Coin	15131	Everton Fan Token	15721	MagicCraft	16260	impactMarket	16943	Tomb Shares
14489	CheckDot	15132	Davis Cup Fan Token	15723	HorizonDollar	16271	Jolofcoin	16946	Metacraft
14490	Bit Hotel	15134	Aston Villa Fan Token	15731	SORA Synthetic USD	16272	PLT	16962	XELS
14492	Nemesis PRO	15135	TFS Token	15734	bePAY Finance	16277	Ari Swap	16963	POW
14495	HappyLand	15138	Koda Cryptocurrency	15736	LUCA	16279	Changer	16979	Hillstone Finance
14515	MMPRO Token	15140	EVERY GAME	15737	Soldex	16283	ARTi Project	16981	Moola Celo
14516	DAOLaunch	15142	Katana Inu	15744	Prism	16290	GreenTek	16982	Moola Celo EUR
14519	VVS Finance	15175	DAWG	15747	MODA DAO	16296	Battle Saga	17002	BAHA
14522	Moonscape	15178	Gunstar Metaverse	15752	Blockasset	16300	Adana Demirspor Token	17010	Step
14523	SolChicks Token	15180	GamesPad	15758	LimoCoin Swap	16304	Astroport Classic	17017	VCGamers
14532	Wrapped CRO	15181	MonoX Protocol	15759	AAG	16305	Izumi Finance	17025	MarsColony
14534	ParaSwap	15182	Chives Coin	15762	Bitlocus	16326	Kitsumon	17027	CUBE
14535	NFTBomb	15185	Kujira	15764	Hololoot	16330	Chikn Egg	17047	WeWay
14538	Pundi X PURSE	15187	H3RO3S	15779	basis.markets	16334	APX	17049	Black Whale
14540	VLaunch	15188	DappRadar	15782	Geopoly	16350	Phaeton	17050	Multichain
14543	Treasure Under Sea	15193	Pexcoin	15784	LIT	16352	Green Satoshi Token (SOL)	17054	Comb Finance
14553	Panda Coin	15194	Sportium	15788	Royal Gold	16355	Tranquil Staked ONE	17057	Diyarbekirspor Token
14556	Boba Network	15211	Atlantis	15789	ThorFi	16357	TRYC	17059	Erzurumspor Token
14557	Cindrum	15212	RPS LEAGUE	15790	Propel	16359	Calo	17061	ClearDAO
14562	VIP Token	15231	Baby Bali	15799	LIFEBIRD	16363	Minto	17076	Wonderful Memories
14567	MetaCash	15235	GoldenWspp	15806	Attack Wagon	16386	Meblox Protocol	17081	LooksRare
14580	Greyhound	15236	CheersLand	15830	GAMER	16387	Poopsicle	17084	Quantum
14582	Embr	15240	SENATE	15840	Stamen Tellus Token	16388	Governance OHM	17088	chikn feed
14586	ShibElon	15241	Candylad	15841	KnightSwap	16394	SUPE	17097	SHIBIC
14587	Crypto Cavemen Club	15245	WingSwap	15842	Bedrock	16395	Kayserispor Token	17111	TheSolanDAO
14594	Maximus	15246	Surviving Soldiers	15853	Axl Inu	16397	Woozoo Music	17118	DarkCrypto
14599	PANDAINU	15248	Santos FC Fan Token	15857	QUASA	16402	Smart Marketing Token	17131	Planet IX
14613	XSwap Protocol	15250	Thetan Coin	15858	Galaxy Fight Club	16405	Brewlabs	17133	TopManager
14625	CronaSwap	15253	Infinite Launch	15862	Dash Diamond	16406	CakeSwap	17140	ArbiSmart
14627	SonarWatch	15257	EverRise	15866	PayNet Coin	16411	iPulse	17142	Shiba Inu Pay
14631	Notional Finance	15266	Metagalaxy Land	15870	League of Ancients	16412	Conjee	17157	Dream
14650	Andus Chain	15268	GalaxyGoggle DAO	15876	Bomb Money	16421	TinyBits	17169	Betswap.gg
14653	Tranquil Finance	15270	Vita Inu	15881	Voxel X Network	16430	Tectonic	17172	Revolution
14660	Reflecto	15284	SwinCoin	15882	Monetas	16434	Ooki Protocol	17183	Lum Network
14661	Sao Paulo FC Fan Token	15286	Degree Crypto Token	15889	Metaverse Face	16447	CryptoTanks	17186	Mindfolk Wood
14665	Centaurify	15288	TemplarDAO	15891	CryptoCart V2	16463	OpenDAO	17203	Deesse
14681	Fabwelt	15305	Calamari Network	15893	Ruby Currency	16466	BALI TOKEN	17207	Giveth
14682	EarthFund	15312	Hashtagger.com	15898	Metakings	16481	Kasta	17208	Chihuahua
14711	1Sol	15313	BunnyPark Game	15899	Last Survivor	16488	Artem Coin	17212	EVE Token
14713	Comdex	15326	XIDR	15906	Snap Token	16500	ShibaDoge	17213	Square Token
14721	RealLink	15338	CoreStarter	15907	HarryPotterObamaSonic10Inu	16503	A4 Finance	17215	Flag Network
14723	GenshinFlokiInu	15355	Baby Lovely Inu	15918	Artube	16509	Dreamverse	17228	Shitcoin
14728	Interstellar Domain Order	15366	XIDO FINANCE	15921	Poollotto.finance	16516	Ancient Kingdom	17242	UBXS Token
14734	Arker	15368	Egoras Credit	15922	New Order	16517	VaporNodes	17284	Dogelana
14745	Kromatika	15388	RIZON	15924	NvirWorld	16525	Scarab Finance	17285	Sperax USD
14767	The Coop Network	15395	Monster	15926	Rainmaker Games	16526	NanoMeter Bitcoin	17290	Solvent
14783	Treasure	15397	Firulais	15929	Metagame Arena	16528	Sivasspor Token	17299	Kingdom Karnage
14795	SappChat	15398	Rome	15931	FrogSwap	16529	Sakaryaspor Token	17302	ChinaZilla
14798	Pacific	15419	Zenlink	15933	Bomb Money	16531	Antalyaspor Token	17306	LaserEyes
14803	Aurora	15428	Euro Shiba Inu	15936	99Starz	16534	iDypius	17318	CATCOIN
14806	ConstitutionDAO	15438	ForthBox	15946	Polygen	16537	Marvin Inu	17334	JumpToken
14820	Infinity Rocket Token	15439	Age of Tanks	15951	Ftribe Fighters (F2 NFT)	16543	Avocado DAO Token	17336	Apollo Crypto DAO
14822	Victoria VR	15440	Txbit Token	15959	Vader Protocol	16552	RAI Finance	17354	Puli
14825	Viblos	15447	Lyra	15970	Agro Global	16555	ULAND	17364	linSpirit
14836	Day Of Defeat 2.0	15456	Juicebox	15973	ZERO	16559	Cherry Network	17374	Zamzam Token
14838	Artificial Intelligence	15463	SIDUS	15985	Mongoose	16575	Walter Inu	17399	Moebius
14840	ClassicDoge	15469	Sipher	16001	DarkShield Games Studio	16580	Traverse	17410	Thoreum V3
14843	Spintop	15471	4JNET	16003	TATA Coin	16582	SouloCoin	17420	Grape Finance
14849	Centcex	15476	LUXY	16007	Revenue Coin	16589	Dogewhale	17429	Puff
14871	Windfall Token	15478	Decentral Games	16010	Silo Finance	16600	NftEyez	17433	Topshelf Finance
14872	HUGHUG Coin	15480	Umami Finance	16013	XY Finance	16606	Gas DAO	17444	Froyo Games
14878	Alephium	15486	PumpETH	16016	Portuma	16607	Islander	17445	LORDS
14885	Coinscope	15489	Wizarre Scroll	16019	NKCL Classic	16612	Nosana	17447	Nova finance
14896	Tag Protocol	15493	Multiverse Capital	16032	HUH Token	16630	Evulus Token	17459	veDAO
14899	xExchange	15502	Peoplez	16035	Crypto Fight Club	16638	Metoshi	17468	Dhabi Coin
14915	Unix Gaming	15510	Decentral Games Governance	16049	THORWallet	16652	The Winkyverse	17483	ELIS

Notes

1. The ES is the average of the worst p losses, where p is the percentile of the returns distribution.
2. The empirical coverage is the proportion of log-returns y_t that fell within the corresponding prediction intervals, while the regret is the difference between the cumulative pinball loss given by a sequence θ_t versus the cumulative loss of the best possible fixed choice. Gibbs and Candès (2021) demonstrated that for all $\gamma > 0$, the ACI algorithm has the following finite sample bound on the coverage error (i.e., the difference between the empirical coverage and the nominal coverage): $|CovErr(T)| \leq (D+\gamma)/(\gamma T)$. This indicates that the coverage error is guaranteed to converge to zero for any choice of γ as T increases. Additionally, a similar bound exists for the regret, providing further insights into the algorithm's performance. For more comprehensive details, we refer to Gibbs and Candès (2021).
3. The R code using optimized C++ routines to estimate the CAViaR model can be found at https://github.com/Buczman/CaviaR (accessed on 15 April 2024).
4. The algorithm is implemented in the R (version 4.3.1) package `forecast` (version 8.22.0).

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DAO Dynamics: Treasury and Market Cap Interaction

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Abstract: This study examines the dynamics between treasury and market capitalization in two Decentralized Autonomous Organization (DAO) projects: OlympusDAO and KlimaDAO. This research examines the relationship between market capitalization and treasuries in these projects using vector autoregression (VAR), Granger causality, and Vector Error Correction models (VECM), incorporating an exogenous variable to account for the comovement of decentralized finance assets. Additionally, a Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model is employed to assess the impact of carbon offset tokens on KlimaDAO's market capitalization returns' conditional variance. The findings suggest a connection between market capitalization and treasuries in the analyzed projects, underscoring the importance of the treasury and carbon offset tokens in impacting a DAO's market capitalization and variance. Additionally, the results suggest significant implications for predictive modeling, highlighting the distinct behaviors observed in OlympusDAO and KlimaDAO. Investors and policymakers can leverage these results to refine investment strategies and adjust treasury allocation strategies to align with market trends. Furthermore, this study addresses the importance of responsible investing, advocating for including sustainable investment assets alongside a foundational framework for informed investment decisions and future studies in the field, offering novel insights into decentralized finance dynamics and tokenized assets' role within the crypto-asset ecosystem.

Keywords: carbon offset tokens; DeFi; GARCH; VAR; VECM; Granger causality; cointegration; treasury; DAO

1. Introduction

Effectively managing a community's assets on the blockchain can be transparent, mainly when the community oversees its assets and introduces its token. This study provides evidence of the relationship between the community's assets and the overall value of its issued tokens. The findings of this research hold the potential to significantly augment decision-making processes and strategic planning within the blockchain and cryptocurrency domain by underscoring the pivotal role played by a DAO's treasury. As such, comprehensively evaluating the composition, management, and growth trajectory of a DAO's treasury is essential in accurately assessing the viability and potential success of a DAO project. Moreover, identifying the correlation between a DAO's treasury and its market capitalization provides valuable insights for investors, stakeholders, and project evaluators, enabling them to proceed with informed decisions and effectively allocate resources in the ever-evolving decentralized finance landscape.

Decentralization, transparency, and security are foundational principles in the blockchain domain. The evolution of blockchain technology has led to the creation of DAOs, empowering communities to decide on their operations collaboratively. The concept of a DAO is incorporated in the Ethereum whitepaper (Buterin 2014), where it is mentioned to be a smart contract that contains the funds and the rules of an organization whose members have the right to allocate these assets and modify the rules that govern it, allowing for the automation of certain processes that are defined in the smart contract. A DAO can issue its token and form an ecosystem where each token provides voting rights to its holder, excluding its marketplace value. Consequently, every holder impacts the DAO's decision making through transparent voting processes, aligning with the fundamental tenets of decentralization in the blockchain.

Decentralized finance (DeFi) is rooted in traditional financial activities on the blockchain, like lending and trading without intermediaries. With the advent of DeFi 2.0, the field incorporated the idea of a DAO making decisions regarding a project's liquidity within the protocol. An advancement was implemented by OlympusDAO in 2021, and their paradigm led to the creation of numerous similar projects, where the community of the protocol owned and decided its treasury and its diversification (Spinoglio 2022). Additionally, token holders from the DAO possess voting privileges, which play a pivotal role in shaping the community's future choices, as observed in the KlimaDAO project (Freni et al. 2022). Finally, in DeFi projects, the tokenized assets owned by the protocol are held in the "treasury," which is in the form of smart contracts, and the use of a treasury's funds is decided through a voting process (Bhambhwani 2023). The purpose of the treasury in OlympusDAO is to support the DAO's issued token liquidity (Olympus Docs n.d.).

The KlimaDAO project, while related to OlympusDAO as a DeFi 2.0 project, is a pioneer in the Regenerative Finance (ReFi) sector (Baim 2023) and is referenced as such by other authors as well (Bordeleau and Casemajor 2023). ReFi is a term connected to DeFi, as they both use the same tools, but ReFi is focused on services linked to regenerative economics (Schletz et al. 2023). KlimaDAO, a project with the goal of combatting climate change (Oguntegbe et al. 2023), aims to establish a carbon-based cryptocurrency, participating in the voluntary carbon market using Web3 technology, where Web3 is a broader concept of the evolution of the internet, where the data is stored and distributed through a decentralized network, utilizing the transparency, inclusivity, and immutability that blockchain technology allows, and the processes can be automated using smart contracts (Murray et al. 2023). Each KlimaDAO token's (KLIMA) value is alleged to be backed by one carbon ton from tokens issued by Moss Earth, Toucan protocol, and C3 protocols, whose tokens are backed by carbon offset credits from carbon registries like Verra and Gold Standard (KlimaDAO 2022). The treasury of KlimaDAO consists of tokens that include carbon offset, such as Base Carbon Ton (BCT), and non-carbon offset tokens, such as stablecoins. However, KlimaDAO token holders benefit from the increase in the KlimaDAO token price, considering that token ownership is linked to financial rewards derived from the reserves of the KlimaDAO treasury (Dobrajska 2023), rendering the treasury a vital aspect of the project.

However, tokenizing carbon credits is a controversial subject that led to the subsequent announcements by Verra (Verra 2021, 2022, 2023), where it declared no responsibility and involvement for such activities. Therefore, Verra conducted a multi-week public consultation regarding the approach towards the activities associating tokens with instruments issued by Verra along with regulatory-associated concerns. Additionally, Babel et al. (2022) cite KlimaDAO when focusing on the transparency issues of voluntary carbon offsets by highlighting KlimaDAO as a market facilitating investment in projects targeting carbon dioxide consumption while integrating blockchain technology aids in tracking these offsets, thereby mitigating the risk of duplicate spending.

KlimaDAO and OlympusDAO represent significant advancements in decentralized finance, particularly integrating decentralized autonomous organizations into their operational frameworks. One fundamental similarity between the two projects is their reliance on DAO governance models, where community members hold voting privileges to influence protocol decisions and manage the project's treasury. Both projects prioritize liquidity management within their respective ecosystems, leveraging their treasuries to support token liquidity and ensure ecosystem stability.

However, there are notable differences between KlimaDAO and OlympusDAO regarding their primary objectives and focus areas. As a pioneer in the DeFi 2.0 space, OlympusDAO emphasizes the stability of its native token "OHM", backed by assets such as "DAI", which is a stablecoin issued by MakerDAO and is backed by collateral (Maker Team 2017), and wrapped Ether (wETH) (Rossello 2024), and the creation of a robust reserve currency. In contrast, KlimaDAO distinguishes itself as a pioneer in the emerging Regenerative Finance field, specifically focusing on leveraging blockchain technology to address environmental concerns. KlimaDAO aims to establish a carbon-based cryptocurrency backed by carbon offset credits, contributing to the voluntary carbon market and promoting sustainability initiatives. This divergence in objectives reflects the diverse applications and use cases within the broader DeFi ecosystem, showcasing the versatility and innovation inherent in decentralized finance projects.

Hence, our study exclusively centers on OlympusDAO and KlimaDAO for several reasons. Firstly, we aim to compare two projects with similar smart contract characteristics, given that KlimaDAO is a fork of OlympusDAO. Secondly, we emphasize the significance of these projects: OlympusDAO as a pioneer in the DeFi 2.0 sector and KlimaDAO as a pioneer in the ReFi sector, encompassing both DeFi 2.0 and ReFi. Lastly, the growing number of scholarly articles on OlympusDAO and KlimaDAO indicates ongoing interest in these projects.

While the significance of the examined projects has been acknowledged in the existing literature, there remains a gap in understanding the importance of their treasury management from an econometric perspective. Specifically, there is a lack of studies that econometrically analyze the relationship between these projects and their treasuries while considering external factors such as the comovement of similar assets. Furthermore, no previous research has explored how specific tokens might impact the market capitalization of a DAO, initiating an inquiry into the potential influence of carbon offsets within a diversified portfolio, potentially represented by tokenized carbon credits. This research aims to bridge these gaps by providing empirical evidence on the interplay between project significance, treasury management, and token dynamics within DAOs.

The current study examines whether a two-way relationship between the treasuries of OlympusDAO and KlimaDAO and their market capitalization exists by employing a Vector Autoregression model with exogenous variables, further cointegration tests, and two Vector Error Correction models regarding the returns of the market caps of the examined DAOs, and Granger causality tests. Moreover, it is within the scope of our analysis to ascertain whether carbon offset tokens can validate the concept of DAO-issued tokens possessing intrinsic value via tokenized carbon credits, potentially raising regulatory considerations. Therefore, we aim to evaluate the impact of carbon offset tokens on the conditional variance within a GARCH model to tackle issues of conditional heteroskedasticity in the time series, focusing specifically on the case study of KlimaDAO.

The structure of this study is as follows: Section 2 details the literature review, Section 3 explains the methodology, Section 4 presents the results, Section 5 details the discussion, and Section 6 encapsulates this study's conclusions.

2. Literature Review

Song et al. (2023), while documenting the mechanism behind OlympusDAO, highlighted the importance of the OlympusDAO token, as well as the treasury mechanism of the project. They explained in detail the staking and bonding mechanisms of the project, which are the main elements of increasing the treasury that supports the DAO's token. The bonding mechanism allows potential investors to buy the OlympusDAO token at a discount, resulting in the subsequent cash flows being directed to the DAO's treasury, and the staking mechanism gives an incentive to the DAO token holders to deposit their tokens in the treasury and obtain interest, in DAO tokens, for their deposit. Subsequently, the treasury assets are used to back the DAO's token, whose price should not fall under one dollar. When using the treasury funds, the DAO makes such decisions through a voting mechanism with transparent and secure procedures. Chitra et al. (2022) find the role of the treasury to be that of an indirect "insurance fund". The concept of a protocol owning its liquidity was coined initially by OlympusDAO (Pupyshev et al. 2022). The OlympusDAO token is alleged to represent its underlying collateral (Ante et al. 2023); however, Guo et al. (2024) state that the staking system employed by OlympusDAO encouraged users to stake their tokens by offering high rewards, but this system led to high inflation that resulted in the token's decreasing value. Mislavsky (2024) also refers to the high yields of OlympusDAO tokens that helped the project initially gain public exposure and market capitalization, but inevitably, these yields decreased along with its market capitalization.

Jirásek (2023) studied the organizational model of KlimaDAO, inspired by OlympusDAO, and characterized KlimaDAO as a notable example among other DAOs. Jirásek acknowledged KlimaDAO's commitment to its mission, which led to the acquisition of around 4% of all voluntary carbon market credits by October 2022. However, Foss and Xu (2023), while recognizing Jirásek's contributions, diverge from the author's conclusions regarding KlimaDAO's business model, citing the volatility of KlimaDAO tokens but refraining from analyzing this volatility. He and Puranam (2023) also note that KlimaDAO presents a unique organizational structure compared to similar entities; however, they notice weaknesses in KlimaDAO's organizational structure, including founder anonymity and legal ambiguity, alongside the broader challenges DAOs face. Hence, founder anonymity does not deter an individual from taking legal action against the alleged founders of a DAO project, as in the case of OlympusDAO (Ghodoosi 2022).

Sicilia et al. (2022) highlighted the similarities between KlimaDAO and the OlympusDAO protocol, underscoring the depth of inspiration, where both platforms center around establishing a treasury via bonding and staking mechanisms within a game theoretic framework aimed at price stabilization. In particular, staking in KlimaDAO mirrors OlympusDAO's strategy, incentivizing long-term token holding to garner compounded rewards and exposure to carbon price fluctuations. Similarly, bonding in KlimaDAO echoes OlympusDAO's approach, enabling discounted token acquisition over a vesting period, with pricing dynamics responding sensitively to demand fluctuations. Sicilia et al. also denoted the significance of the KlimaDAO project, exploring the mechanism behind the carbon offset tokens. Finally, the authors acknowledged the complexity of this mechanism and suggested that future works could be focused on assessing the impact of the tokenized carbon offsets in DeFi. Sorensen (2023) added that KlimaDAO aims to stimulate demand for carbon credits, establishing a "carbon economy", wherein the currency is backed by carbon, and the total cost of carbon is integrated into each transaction.

In their endeavor to develop a scale for assessing the readiness of blockchain applications for carbon markets, Sipthorpe et al. (2022) categorize KlimaDAO as a "fully competitive" project, the sole DAO project at the highest tier of their scale. Nonetheless, Sipthorpe et al. recognize the market's immaturity and the challenges associated with these endeavors, mainly due to the lack of pertinent regulations that might deter potential investors from participating in this domain.

Ziegler and Welpe (2022) highlighted the treasury as a crucial attribute of DAOs, while Metelski and Sobieraj (2022) suggested the potential for further investigation into the connection between a DeFi project's treasury and its valuation, leading to a more precise assessment of a DeFi's value, taking its treasury assets into account.

Nowak (2022) addressed the issue of carbon credit tokenization and noted its innovative significance for the carbon offset markets; Nowak also cites KlimaDAO and the tokens it creates in this context. Moreover, Armisen et al. (2024) analyze the disparity in user behavior between expert and regular users in utilizing carbon offsets within KlimaDAO based on blockchain data, and they observe differing choices made by these user categories in selecting carbon offsets.

In brief, our examination of the literature did not uncover any relevant studies concerning the econometric evaluation of either the treasury or the market capitalization of a DAO and their reciprocal influence on each other, while analyzing the market capitalization of the projects could be a better approach instead of analyzing the prices of the tokens, because of the inflation mechanism. Additionally, while several articles discuss the importance of KlimaDAO's organizational structure and economic model, there has been little research on how the tokenized carbon credits in its treasury influence the project's market capitalization or analyze the volatility of the project's tokens. Hence, this study adds to the body of literature by elucidating the interconnections between two significant DAOs, their respective treasuries, and the potential financial impact of carbon tokens.

3. Methodology

3.1. Data Collection and Filtering

The analyzed period in the daily data is between 27 October 2021 and 16 September 2023. The period analyzed was selected to encompass all variables under examination, guided by the data available during the study. Given that KlimaDAO was launched later than OlympusDAO, we aimed for uniformity in the examined variables, necessitating a period inclusive of all relevant data. The OlympusDAO and KlimaDAO treasury data were acquired from DefiLlama (n.d.) (accessed on 8 November 2023), and market capitalization data were sourced from CoinGecko (n.d.). The data regarding the treasuries of the DAOs are denominated in US dollars (USD). Moreover, we obtained the time series for the "Top 100 DeFi Coins by Market Capitalization" from Coingecko to account for the comovement of asset prices, representing the aggregate market capitalization of the top 100 DeFi coins, as determined by Coingecko. The variables that are examined in this analysis are presented in Table 1.

Table 1. Examined variables.

Variable	Meaning
Olympus_MC	Natural logarithm of the Market Cap of OlympusDAO
Klima_MC	Natural logarithm of the Market Cap of KlimaDAO
Olympus_Tr	Natural logarithm of the Treasury of OlympusDAO
Klima_Tr	Natural logarithm of the Treasury of KlimaDAO
Defi_MC	Natural logarithm of the Market Cap of the Top 100 DeFi Coins by Market Capitalization by Coingecko
KCT	Natural logarithm of the KlimaDAO Carbon Tokens total value
r_Olympus_MC	Returns of the Market Cap of OlympusDAO
r_Klima_MC	Returns of the Market Cap of KlimaDAO
r_Olympus_Tr	Returns of the Treasury of OlympusDAO
r_Klima_Tr	Returns of the Treasury of KlimaDAO
r_Defi_MC	Returns of the Market Cap of the Top 100 DeFi Coins by Market Capitalization by Coingecko
r_KCT	Returns of the KlimaDAO Carbon Tokens' total value

The variables chosen for analysis comprise the natural logarithm of the market capitalizations and treasuries of the projects under examination, along with the market capitalization of the leading DeFi coins, serving as a proxy for the comovement of similar assets and the total value of the KlimaDAO carbon tokens alongside their respective returns. This transformation was implemented to assess stationarity, present pertinent findings, and calculate returns where stationarity was not observed, as demonstrated in the subsequent results. We utilized market capitalization (MC) variables because the token price alone may not accurately reflect the total project value, as in crypto assets token supply is often subject to dynamic changes, a characteristic observed in the specific projects under scrutiny. The OlympusDAO market capitalization variable was selected for its status as a pioneer in DeFi 2.0, while the KlimaDAO market capitalization was chosen for its prominence in the ReFi sector. The KlimaDAO carbon tokens (KCT) variable is essential because it represents the total value of the carbon offset tokens in KlimaDAO.

In the context of our study, the variables are denoted with the suffix "_d" to represent daily measurements, and the monthly averages from the daily values are denoted with the suffix "_m" to indicate their monthly aggregation.

The OlympusDAO treasury data encompassed tokens in the DAO's treasury across Ethereum, Polygon, Arbitrum, and Fantom blockchains, along with their corresponding

USD values. Similarly, the KlimaDAO treasury comprised all the tokens under the DAO's management. The formula for the treasury is presented in Equation (1).

$$Treasury_{DAO,\, t} = \sum_{i=1}^{p} CA_{i,t} \tag{1}$$

In Equation (1), the treasury of a DAO consists of the total sum of the crypto assets (CAs) that are included in the respective treasury smart contracts managed by the DAO at time *t*.

Next, to analyze further the effects of the carbon offset treasury in KlimaDAO, we identify *KCT*, which consists of the tokens that KlimaDAO explicitly characterizes as "carbon tokens" (CTs) (KlimaDAO 2022), which are *BCT*, *NCT*, *MCO2*, *UBO*, *NBO*, and in the KCT, we include any liquidity pool token containing these assets, all of which are held in the KlimaDAO treasury, resulting in Equation (2).

$$KCT_t = \sum_{i=1}^{p} CT_{i,t} \tag{2}$$

In Equation (2), at the time *t*, the *KCT* is the sum of every *CT*.

3.2. VAR Model

A Vector Autoregressive (VAR) model is used to analyze the interdependence of system variables. This model assumes that every variable in the system is expressed as a function of its lags and the lags of all the other variables in the system. By estimating the parameters of the VAR model, we can gain insights into the dynamic relationships among the different variables and make predictions about their future values.

Our model incorporates $r\_Klima\_MC\_m_t$, $r\_Olympus\_MC\_m_t$, $r\_Klima\_Tr\_m_t$, and $r\_Olympus\_Tr\_m_t$ as endogenous variables, and $r\_Defi\_MC\_m_t$ as an exogenous variable. The optimal lag length for our model was determined to be one after analyzing the information criteria. Based on our best estimation, the VAR(1) model is presented in Equation (3).

$$Y_t = A_1 Y_{t-1} + BX_t + \varepsilon_t \tag{3}$$

Let Y_t be the vector of endogenous variables at time t, A_1 as the matrix containing the lag coefficients, Y_{t-1} as the lagged vector of endogenous variables, B as the matrix of coefficients for the exogenous variables, X_t as the vector of exogenous variables at time t, and ε_t as the vector of error terms. According to the above, the model may be written as Equation (4):

$$\begin{aligned} Y_t = \begin{bmatrix} r\_Klima\_MC\_m_t \\ r\_Olympus\_MC\_m_t \\ r\_Klima\_Tr\_m_t \\ r\_Olympus\_Tr\_m_t \end{bmatrix} \\ = \begin{bmatrix} a_1 \\ a_2 \\ a_3 \\ a_4 \end{bmatrix} + \begin{bmatrix} \beta_{1,1} & \beta_{1,2} & \beta_{1,3} & \beta_{1,4} \\ \beta_{2,1} & \beta_{2,2} & \beta_{2,3} & \beta_{2,4} \\ \beta_{3,1} & \beta_{3,2} & \beta_{3,3} & \beta_{3,4} \\ \beta_{4,1} & \beta_{4,2} & \beta_{4,3} & \beta_{4,4} \end{bmatrix} + \begin{bmatrix} r\_Klima\_MC\_m_{t-1} \\ r\_Olympus\_MC\_m_{t-1} \\ r\_Klima\_Tr\_m_{t-1} \\ r\_Olympus\_Tr\_m_{t-1} \end{bmatrix} \\ + \begin{bmatrix} \gamma_1 \\ \gamma_2 \\ \gamma_3 \\ \gamma_4 \end{bmatrix} r\_DeFi\_MC\_m\ _t + \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \\ \varepsilon_{3,t} \\ \varepsilon_{4,t} \end{bmatrix} \end{aligned} \tag{4}$$

3.3. Cointegration Tests and VECM

The Johansen cointegration test (Johansen 1991) has been utilized to investigate a long-term relationship among the variables in our model. This test aims to determine whether cointegrating vectors exist in the spectrum of a Vector Autoregression (VAR) model. Through this examination, we have determined if a cointegration equation exists, indicating a long-term relationship between the variables under consideration. The null hypothesis in this test assumes the absence of a cointegration equation. Therefore, the Johansen cointegration test results clearly understand the presence or absence of any underlying relationships between the variables in our model.

Finally, we incorporated a Vector Error Correction model (Engle and Granger 1987) for r_Olympus_MC and r_Klima_MC to examine the short-run deviations from the long-run equilibrium. This dynamic adjustment captures the short-term dynamics and helps understand how the system responds to shocks.

3.4. Granger Causality Test

In order to make accurate predictions using time series data, it is crucial to determine whether any variables can be used as predictors for one another. Causality plays a critical role in time series analysis, as it measures the extent to which one variable's values can be used to forecast another variable's values. By understanding causality, we can gain more insights into future outcomes of a time series based on the values of contiguous time series over time.

Granger causality, introduced by Granger in 1969, is a statistical technique that uses Vector Autoregressive Models to determine the direction and strength of causality between two time series. Although VAR modeling helps identify the relationships and dependencies among variables, it cannot establish causality. The Granger causality test can be used to determine whether past values of a variable can provide information about future values of another variable and, therefore, establish causality.

In order to apply this method, the variables must be stationary or cointegrated. A VAR model of order p can be defined as follows in Equation (5):

$$\begin{aligned} y_t &= \beta_{1,0} + \sum_{i=1}^{p} \beta_{1,i} y_{t-i} + \sum_{j=1}^{p} \beta_{1,p+j} x_{t-i} + e_{1t} \\ x_t &= \beta_{2,0} + \sum_{i=1}^{p} \beta_{2,i} y_{t-i} + \sum_{j=1}^{p} \beta_{2,p+j} x_{t-i} + e_{2t} \end{aligned} \tag{5}$$

For the sake of illustration, we use variables y_t and x_t. The order of the Vector Autoregression (VAR) model refers to the number of lags required to validate the hypothesis that each error term is white noise (Shojaie and Fox 2022). We can say that "y_t Granger causes x_t" if the past values of y_t are statistically significant. To examine if x_t Granger causes y_t, the testing process needs to be repeated in the opposite direction.

In our analysis, we will investigate whether the returns of OlympusDAO and KlimaDAO market capitalization and their treasuries Granger cause each other. In order to address the comovement of asset prices, we used the r_Defi_MC as a proxy.

3.5. GARCH Analysis

Based on our analysis, we have determined that a GARCH(1,1) model is the most appropriate. The conditional mean equation is a fundamental component in the statistical modeling of the expected or mean value of a financial time series. The conditional mean is presented in Equation (6).

$$r\_Klima\_MC\_d_t = \mu + \varphi_1 r\_Klima\_MC\_d_{t-1} + \xi_1 r\_Defi\_MC\_d_t + \xi_2 r\_Defi\_MC\_d_{t-1} + \varepsilon_t \tag{6}$$

where μ is the constant, and r_Klima_MC and r_Defi_MC are the logarithmic returns of KlimaDAO market cap and the "Top 100 DeFi Coins by Market Capitalization", respectively, to address the issues of stationarity, as the variables are I(1) series according to the augmented Dickey–Fuller (ADF) test and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests.

For this analysis, we shall employ the Generalized Autoregressive Conditional Heteroskedasticity model, an indispensable tool for comprehending the intricacies of volatility in financial markets (Bollerslev 1986). Our primary emphasis will be on the results of the GARCH analysis, which will furnish us with a granular comprehension of the dynamics of the conditional variance. The conditional variance equation is a pivotal facet of GARCH modeling, encapsulating insights into the volatility or dispersion evident in the financial series. The conditional variance equation of a GARCH(p, q) model, where *p* stands for the number of lagged conditional variances, and *q* denotes the number of lagged squared residuals, can be expressed as follows in Equation (7).

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} a_i \varepsilon^2{}_{t-i} + \sum_{j=1}^{q} \beta_j \sigma^2{}_{t-j} \tag{7}$$

We denote by ω the constant term representing the long-term average level of volatility, used as a baseline volatility measure in the absence of any shocks, α_i stands for the ARCH coefficients applied to capture the impact of past squared residuals on the current conditional variance. ε_{t-i}^2 are the squared residuals at time $t - i$, representing the unexpected shocks or errors in the model. By β_j, we define the GARCH coefficients to capture the impact of past conditional variances on the current conditional variance. As σ_{t-j}^2, we define the lagged conditional variances representing the past volatility of the model.

Greater values of α_i indicate a more persistent effect of past shocks on volatility. In comparison, greater values of β_j indicate a more persistent effect of past volatility on the current volatility.

Our findings suggest that we may model the conditional variance using a GARCH model of the first order for the ARCH effects, the first order for the GARCH, and the first order for leverage effects, plus the returns of the KlimaDAO Carbon Tokens as *r_KCT* as an exogenous variable in the conditional variance equation. The GARCH equation is now transformed as follows (8):

$$\sigma_t^2 = \omega + a_1 \varepsilon^2{}_{t-1} + \beta_1 \sigma^2{}_{t-1} + \psi_1 r\_KCT\_d_t \tag{8}$$

3.6. Utilized Software

"Grammarly 6.8.263" (Grammarly: Free AI Writing Assistance n.d.) was used for grammar and language correction, while "ChatGPT 3.5" (ChatGPT n.d.) helped in expressing the content and refined the English language where necessary. Additionally, "Zotero 6.0.36" (Zotero n.d.) was utilized to index pertinent references for the paper, noted in this manuscript's "Acknowledgments" section.

4. Results

4.1. Examined Variables

Table 2 presents the results regarding the stationarity tests and indicates the selection of the final variables to be examined in the subsequent analysis.

In Table 2, for our analysis, we selected the natural logarithmic values of the examined variables and their respective returns. We observe that in all cases where the variables are in their logarithmic form, the KPSS test for stationarity is rejected when testing for trend stationarity, even if the ADF test null hypothesis for the existence of a unit root is rejected in two cases. Therefore, to ensure that no unit root exists in our time series, we calculate the returns of the variables. In the returns of the variables, we observe that the null hypothesis of a unit root regarding the ADF test is rejected in all cases, and the null hypothesis of trend stationarity regarding the KPSS test is not rejected in all cases. Subsequently, in our analysis, we will use the logarithmic returns of the variables. The descriptive statistics of the examined variables are presented in Table 3.

Table 2. Stationarity tests.

Variable	ADF		KPSS	
	Statistic	*p*-Value	Statistic	*p*-Value
Olympus_MC	−3.73	0.00 ***	0.64	0.01 ***
Klima_MC	−2.94	0.04 **	0.69	0.01 ***
Olympus_Tr	−2.61	0.09 *	0.15	0.04 **
Klima_Tr	0.15	0.97	0.39	0.01 ***
Defi_MC	−1.72	0.42	2.00	0.01 ***
r_Olympus_MC	−22.43	0.00 ***	0.11	0.10
r_Klima_MC	−11.03	0.00 ***	0.12	0.10
r_Olympus_Tr	−12.28	0.00 ***	0.04	0.10
r_Klima_Tr	−11.55	0.00 ***	0.08	0.10
KCT_d	−2.69	0.08 *	0.68	0.01 ***
r_KCT_d	−15.56	0.00 ***	0.08	0.10
r_Defi_MC	−25.19	0.00 ***	0.18	0.10
Olympus_MC_m	1.33	0.00 ***	0.16	0.04 **
Klima_MC_m	−2.66	0.00 ***	0.17	0.03 **
Olympus_Tr_m	−0.79	0.80	0.41	0.05 **
Klima_Tr_m	0.23	0.96	1.87	0.01 ***
Defi_MC_m	−1.94	0.31	0.35	0.10
r_Olympus_MC_m	−3.64	0.01 ***	0.34	0.10
r_Olympus_Tr_m	−5.56	0.00 ***	0.05	0.10
r_Klima_MC_m	−3.28	0.03 **	0.37	0.10
r_Klima_Tr_m	1.13	0.00 ***	0.088	0.10
r_Defi_MC_m	−5.16	0.00 ***	0.12	0.10

Note: * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Table 3 shows that all variables' skewness and kurtosis values indicate asymmetry and peakedness in their distributions. Subsequently, the Jarque–Bera statistics, with *p*-values close to zero, reject the null hypothesis of a normal distribution for each variable. Figure 1 presents the box plots of the examined daily value variables.

Table 3. Descriptive statistics of the examined variables.

Variable	Statistic									
	Mean	Standard Deviation	Range	Max	Min	Median	Skewness	Kurtosis	Jarque–Bera (JB)	Jarque–Bera *p*-Value
r_Klima_MC_d	−0.007	0.061	0.713	0.267	−0.447	−0.004	−0.945	11.079	1978.948	0.000
r_KCT_d	−0.003	0.054	0.680	0.327	−0.354	−0.233	−0.021	13.338	3072.755	0.000
r_Defi_MC_d	−0.002	0.036	0.501	0.121	−0.380	0.001	−2.347	23.369	12,561.000	0.000
r_Olympus_MC_m	−0.004	0.010	0.049	0.006	−0.043	0.000	−2.664	10.697	87.623	0.000
r_Olympus_Tr_m	−0.001	0.009	0.051	0.018	−0.033	0.000	−1.571	9.524	52.435	0.000
r_Klima_MC_m	−0.009	0.017	0.078	0.017	−0.061	−0.006	−1.328	5.247	12.104	0.002
r_Klima_Tr_m	−0.003	0.010	0.056	0.031	−0.025	−0.005	1.333	6.696	20.775	0.000
r_Defi_MC_m	−0.002	0.007	0.035	0.010	−0.025	−0.001	−1.115	5.454	10.997	0.004

Note: all daily ("_d") variables have 690 observations, and all monthly ("_m") variables have 24 observations each.

As depicted in Figure 1, the daily box plot values indicate that the medians are approximately zero, with consistent interquartile ranges and whisker sizes across all instances. However, a notable difference emerges: for r_Klima_MC_d and r_KCT_d, the number of outlier values is relatively similar and more abundant compared to r_Defi_MC_d, where fewer outliers are observed. Figure 2 presents the box plots of the examined monthly value variables.

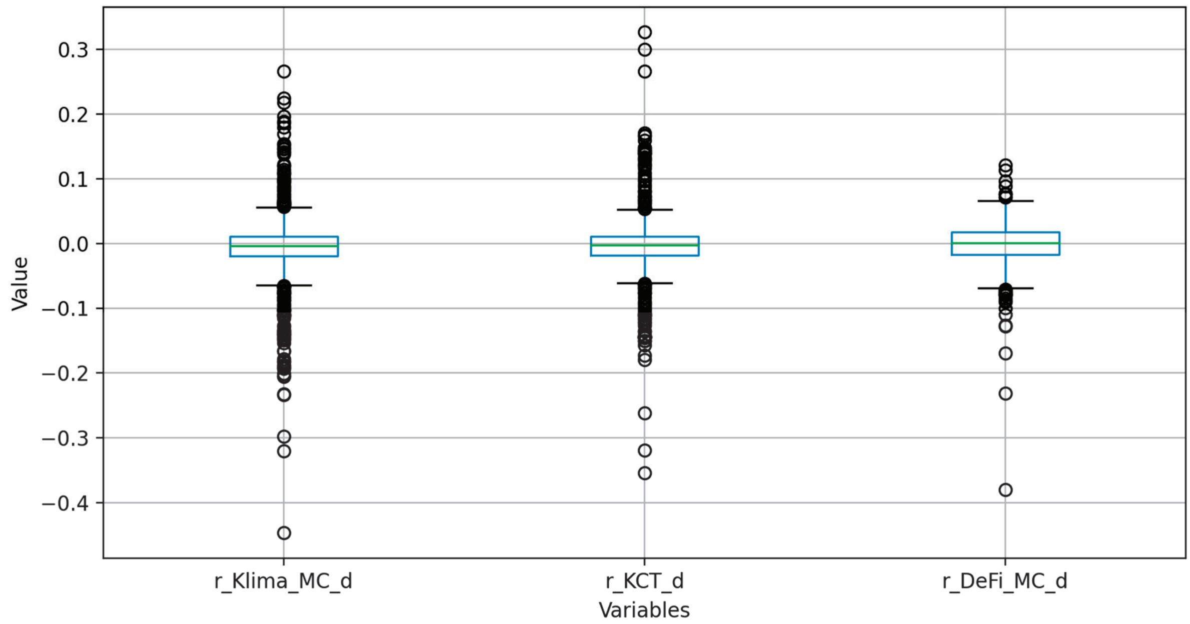

Figure 1. Box plots of the examined daily value variables.

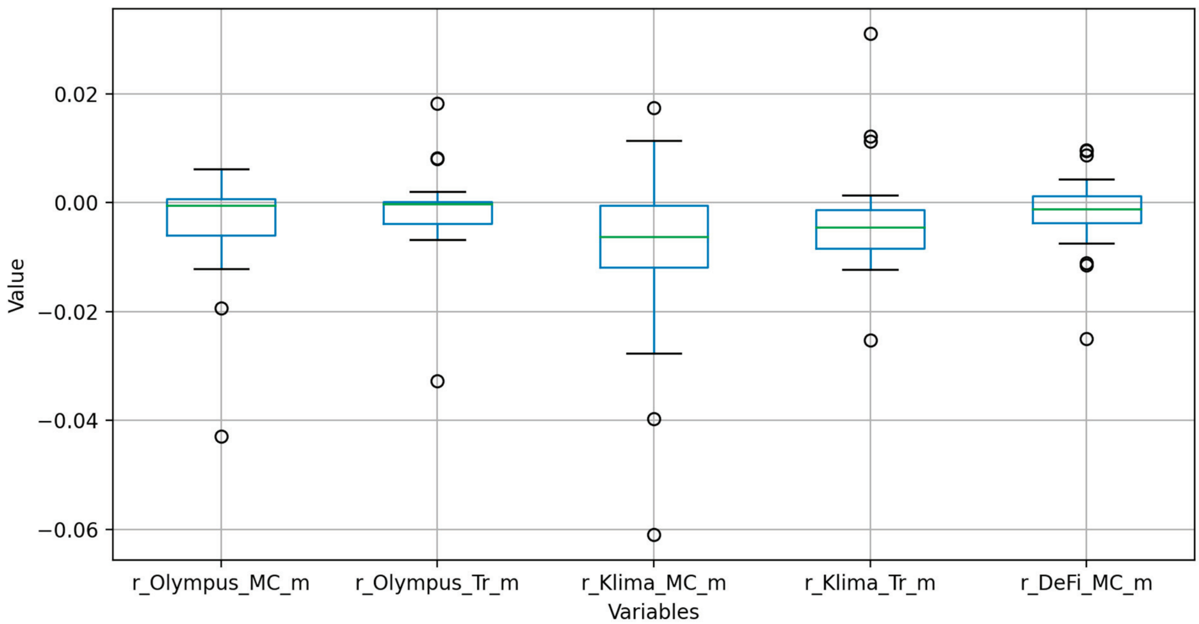

Figure 2. Box plots of the examined monthly value variables.

As depicted in Figure 2, the median values of the variables under examination hover around zero or slightly negative values close to zero. A comparative analysis of the variables reveals that r_Klima_MC_m exhibits somewhat longer whiskers than the others, which maintain similar whisker ranges. The interquartile ranges vary among the variables, with the upper quartiles of r_Olympus_Tr_m and r_Olympus_MC_m being relatively small. Regarding outliers, r_Defi_MC_m displays a higher count than the other variables, while r_Olympus_MC_m exhibits no positive value outliers. The remaining variables show outlier variation ranging from three to four outliers per analyzed variable, with values ranging from 0.02 to −0.06.

4.2. VAR Results

Table 4 presents the results of the VAR estimations and the diagnostics in Appendix A in Table A1.

Table 4. VAR estimation results.

Variable	Dependent Variable			
	r_Klima_MC_m	**r_Olympus_MC_m**	**r_Klima_Tr_m**	**r_Olympus_Tr_m**
r_Klima_MC_m(−1)	0.143 (0.140) [1.023]	0.318 (0.094) [3.382]	−0.339 (0.169) −[2.004]	0.170 (0.114) [1.489]
r_Olympus_MC_m(−1)	0.358 (0.213) [1.681]	−0.137 (0.143) −[0.955]	0.264 (0.258) [1.024]	0.041 (0.174) [0.234]
r_Klima_Tr_m(−1)	−0.543 (0.222) −[2.449]	−0.605 (0.149) −[4.055]	0.196 (0.269) [0.731]	−0.814 (0.181) −[4.499]
r_Olympus_Tr_m(−1)	0.383 (0.209) [1.837]	0.857 (0.140) [6.114]	0.135 (0.253) [0.534]	−0.057 (0.170) −[0.335]
C	−0.003 (0.002) −[1.353]	−0.001 (0.001) −[0.977]	−0.003 (0.002) −[1.270]	−0.002 (0.002) −[1.392]
r_Defi_MC_m	1.148 (0.223) [5.138]	0.569 (0.150) [3.789]	0.562 (0.271) [2.077]	−0.112 (0.182) −[0.613]
R^2	0.716	0.792	0.363	0.566

Note: standard errors are indicated within parentheses (), while t-statistics are denoted within square brackets [].

According to our findings, the lagged variable $r\_Klima\_MC\_m_{t-1}$ significantly impacts $r\_Olympus\_MC\_m_t$ and $r\_Klima\_Tr\_m_t$. The lagged variable $r\_Olympus\_MC\_m_{t-1}$ does not seem statistically significant at the 5% level. Next, the lagged variable $r\_Klima\_Tr\_m_{t-1}$ has a significant relationship with $r\_Klima\_MC\_m_t$ and $r\_Olympus\_MC\_m_t$, just as with $r\_Olympus\_Tr\_m_t$. Furthermore, the lagged variable $r\_Olympus\_Tr\_m_{t-1}$ has a significant impact on $r\_Olympus\_MC\_m_t$. Finally, the exogenous variable $r\_Defi\_MC\_m_t$ is statistically related to $r\_Klima\_MC\_m_t$, $r\_Olympus\_MC\_m_t$, and $r\_Klima\_Tr\_m_t$.

4.3. Granger Causality Results

In Table 5, we present the Granger causality test results.

As shown in Table 5, there is evidence of Granger causality from r_Klima_Tr_m to r_Klima_MC_m. Next, there is strong evidence of Granger causality from r_Klima_MC_m, r_Klima_Tr_m, and r_Olympus_Tr_m to r_Olympus_MC_m, with the null hypothesis rejected at the 1% level for all cases. Furthermore, the null hypothesis of no Granger causality from r_Klima_MC_m to r_Klima_Tr_m is rejected at the 5% level. Finally, there is strong evidence of Granger causality from r_Klima_Tr_m to r_Olympus_Tr_m.

Table 5. Granger causality results.

Excluded Variable	Chi-square Statistic	Degrees of Freedom	Prob.
Dependent Variable: r_Klima_MC_m			
Excluded Variable	**Chi-square Statistic**	**Degrees of Freedom**	**Prob.**
r_Olympus_MC_m	2.825	1	0.093 *
r_Klima_Tr_m	5.996	1	0.014 **
r_Olympus_Tr_m	3.374	1	0.066 *
All	14.983	3	0.002 ***
Dependent Variable: r_Olympus_MC_m			
Excluded Variable	**Chi-square Statistic**	**Degrees of Freedom**	**Prob.**
r_Klima_MC_m	11.440	1	0.001 ***
r_Klima_Tr_m	16.440	1	0.000 ***
r_Olympus_Tr_m	37.386	1	0.000 ***
All	49.610	3	0.000 ***
Dependent Variable: r_Klima_Tr_m			
Excluded Variable	**Chi-square Statistic**	**Degrees of Freedom**	**Prob.**
r_Klima_MC_m	4.016	1	0.045 **
r_Olympus_MC_m	1.049	1	0.306
r_Olympus_Tr_m	0.286	1	0.593
All	5.211	3	0.157
Dependent Variable: r_Olympus_Tr_m			
Excluded Variable	**Chi-square Statistic**	**Degrees of Freedom**	**Prob.**
r_Klima_MC_m	2.218	1	0.136
r_Olympus_MC_m	0.055	1	0.815
r_Klima_Tr_m	20.239	1	0.000 ***
All	21.535	3	0.000 ***

Note: asterisks ***, **, and * represent significance at the 1%, 5%, and 10% levels, respectively.

4.4. VECM and Cointegration Results

After applying the Trace and Maximum Likelihood criteria, as shown in Table 6, we have rejected the null hypothesis, indicating that long-term relationships exist among the variables in question. These findings mean that any external shocks will not affect the long-run stability of the model, as the returns will eventually converge over time.

Table 6. Unrestricted Cointegration Rank Test (Trace).

Hypothesized Number of Cointegrating Equations	Eigenvalue	Trace Statistic	0.05 Critical Value	Probability
None	0.951	129.577	47.856	0.000 ***
At most 1	0.756	63.120	29.797	0.000 ***
At most 2	0.661	32.084	15.495	0.000 ***
At most 3	0.315	8.311	3.841	0.004 ***

Note: asterisks "***" denote rejection of the null hypothesis at the 1% level.

Initially, our attention is directed towards establishing the equilibrium state in the long run, which involves deriving the cointegration equation concerning r_Klima_MC_m, as shown in Table 7, and the diagnostics of the VECM estimations are in Appendix A in Table A2.

Table 7. VECM KlimaDAO MC results.

Cointegrating Equation	Cointegrating Equation (1)			
r_Klima_MC_m(−1)	1.000			
r_Olympus_MC_m(−1)	−0.066 (0.187) −[0.354]			
r_Klima_Tr_m(−1)	−2.819 (0.208) −[13.569]			
r_Olympus_Tr_m(−1)	−3.459 (0.312) −[11.098]			
C	−0.005			
Error Correction	**d(r_Klima_MC_m)**	**d(r_Olympus_MC_m)**	**d(r_Klima_Tr_m)**	**d(r_Olympus_Tr_m)**
Cointegrating Equation (1)	0.036 (0.169) [0.215]	0.174 (0.091) [1.920]	0.157 (0.131) [1.196]	0.525 (0.038) [14.002]
d(r_Klima_MC_m(−1))	−0.247 (0.364) −[0.678]	−0.014 (0.196) −[0.069]	−0.003 (0.283) −[0.011]	−0.029 (0.081) −[0.356]
d(r_Olympus_MC_m(−1))	0.206 (0.246) [0.837]	−0.336 (0.132) −[2.540]	−0.007 (0.192) −[0.038]	0.012 (0.055) [0.222]
d(r_Klima_Tr_m(−1))	−0.155 (0.671) −[0.230]	0.102 (0.361) [0.282]	−0.141 (0.522) −[0.271]	0.484 (0.149) [3.241]
d(r_Olympus_Tr_m(−1))	0.253 (0.288) [0.877]	0.906 (0.155) [5.845]	0.286 (0.224) [1.273]	0.248 (0.064) [3.862]
C	0.002 (0.003) [0.640]	0.001 (0.002) [0.709]	−0.002 (0.002) −[0.672]	−0.001 (0.001) −[1.776]
r_Defi_MC_m	1.155 (0.444) [2.599]	0.385 (0.239) [1.611]	0.440 (0.346) [1.273]	−0.420 (0.099) −[4.247]
R^2	0.503	0.800	0.459	0.967

Note: standard errors are indicated within parentheses (), while t-statistics are denoted within square brackets [].

According to the KlimaDAO MC results, the ECT of r_Klima_Tr_m(−1) and r_Olympus _Tr_m(−1) are statistically significant and have a negative impact on the ECT. This finding suggests deviations from long-term equilibrium in the Treasury bond returns for both KlimaDAO and OlympusDAO are corrected in the current period, indicating a tendency for the returns to converge towards equilibrium.

For KlimaDAO, the significant impact of the error correction term (ECT) on changes in the Treasury returns suggests a robust mechanism for correcting any short-term deviations from the long-term equilibrium relationship. This finding implies a stable equilibrium between MC and Treasury returns, indicating a well-established and potentially predictable relationship for KlimaDAO. Conversely, the insignificance of the ECT for r_Klima_MC_m implies a less systematic correction mechanism and potentially a less stable equilibrium.

Next, we examine the cointegration equation concerning r_Olympus_MC_m, as shown in Table 8.

Table 8. VECM OlympusDAO MC results.

Cointegrating Equation	Cointegrating Equation (1)			
r_Olympus_MC_m(−1)	1.000			
r_Klima_MC_m(−1)	−15.159 (1.526) −[9.932]			
r_Klima_Tr_m(−1)	42.730 (3.171) [13.477]			
r_Olympus_Tr_m(−1)	52.431 (3.720) [14.094]			
C	0.078			
Error Correction	**d(r_Olympus_MC_m)**	**d(r_Klima_MC_m)**	**d(r_Klima_Tr_m)**	**d(r_Olympus_Tr_m)**
Cointegrating Equation (1)	−0.011 (0.006) −[1.920]	−0.002 (0.011) −[0.215]	−0.010 (0.009) −[1.196]	−0.035 (0.002) −[14.002]
d(r_Olympus_MC_m(−1))	−0.336 (0.132) −[2.540]	0.206 (0.246) [0.837]	−0.007 (0.192) −[0.038]	0.012 (0.055) [0.222]
d(r_Klima_MC_m(−1))	−0.014 (0.196) −[0.069]	−0.247 (0.364) −[0.678]	−0.003 (0.283) −[0.011]	−0.029 (0.081) −[0.356]
d(r_Klima_Tr_m(−1))	0.102 (0.361) [0.282]	−0.155 (0.671) −[0.230]	−0.141 (0.522) −[0.271]	0.484 (0.149) [3.241]
d(r_Olympus_Tr_m(−1))	0.906 (0.155) [5.845]	0.253 (0.288) [0.877]	0.286 (0.224) [1.273]	0.248 (0.064) [3.862]
C	0.001 (0.002) [0.709]	0.002 (0.003) [0.640]	−0.002 (0.002) −[0.672]	−0.001 (0.001) −[1.776]
r_Defi_MC_m	0.385 (0.239) [1.611]	1.155 (0.444) [2.599]	0.440 (0.346) [1.273]	−0.420 (0.099) −[4.247]
R^2	0.800	0.503	0.459	0.967

Note: standard errors are indicated within parentheses (), while t-statistics are denoted within square brackets [].

The cointegrating equation derived for OlympusDAO market cap reveals insightful relationships between the lagged variables, shedding light on long-term dynamics within decentralized autonomous organizations. However, intriguing patterns emerge concerning the lagged returns on market capitalization and treasuries for OlympusDAO and KlimaDAO. Specifically, while a negative relationship is observed in KlimaDAO's market capitalization returns, positive associations are evident between OlympusDAO's returns and both KlimaDAO and its treasuries. These findings underscore the interconnectedness of DAOs' financial dynamics and hint at potential arbitrage opportunities and risk management strategies within the decentralized finance landscape.

The short-run equation for the change in the return on the treasury for OlympusDAO includes the ECT, represented by −0.035. This coefficient indicates the speed at which deviations from the long-term equilibrium in the return on treasury for OlympusDAO are corrected. The negative sign suggests that when the return on treasury deviates from its equilibrium level, there is a tendency for it to decrease in subsequent periods, thereby moving closer to the equilibrium. The t-statistic of −14.002 indicates that the coefficient is highly statistically significant, reinforcing the reliability of this relationship. Overall, this result highlights the importance of the error correction mechanism in adjusting the return on the treasury for OlympusDAO toward its long-term equilibrium level.

Examining the VECM results in Tables 7 and 8 uncovers intricate dynamics among the variables studied. Some coefficients in the cointegrating equation elucidate long-term relationships, whereas negative coefficients imply inverse connections. These negative coefficients could mean that we have an inverse long-term relationship between the variables, where there could be divergent effects or adjustment mechanisms toward equilibrium. Moreover, the error correction terms illuminate the pace at which adjustments occur toward equilibrium, with notable values indicating swift corrections of deviations. Additionally, the significance of the coefficients reinforced by the t-statistics bolstered the reliability of the findings. In sum, these outcomes thoroughly comprehend the interactions among the examined variables, aiding informed decision making in economic analysis and forecasting endeavors. For instance, DAOs may reassess their asset allocation within their treasuries and adapt their strategies accordingly, given that their treasury plays a crucial role in supporting the price of their DAO-issued token. Likewise, investors could leverage this insight to enhance their forecasting accuracy and adjust portfolio allocations, leading to more effective risk management. This understanding of the interaction among the variables enables stakeholders to make informed decisions that align with their objectives and market dynamics.

4.5. GARCH Results

The results of the GARCH estimation parameters are presented in Table 9, and the diagnostics are presented in Appendix A in Table A3.

Table 9. GARCH results.

Variable	Coefficient	Std. Error	z-Statistic	Probability
Conditional Mean Equation				
μ	−0.003	0.002	−2.021	0.043 **
r_Klima_MC _d(−1)	0.157	0.042	3.740	0.000 ***
r_Defi_MC_d	0.260	0.043	6.080	0.000 ***
r_Defi_MC_d(−1)	0.095	0.036	2.647	0.008 ***
Conditional Variance Equation				
ω	<0.001	<0.001	10.361	0.000 ***
α_1	0.117	0.013	8.680	0.000 ***
β_1	0.849	0.010	81.707	0.000 ***
r_KCT_d	−0.001	<0.001	−6.275	0.000 ***

Note: ** $p < 0.05$. *** $p < 0.01$.

The negative coefficient associated with the intercept mu is of particular interest as it implies an inherent downward bias that influences the mean return, indicating a significant systemic negative effect on the variable's mean.

On the other hand, the positive coefficients associated with the lagged values of r_Klima_MC, r_Defi_MC, and r_Defi_MC at time t − 1 indicate a positive relationship with the r_t. The coefficient of r_Defi_MC deserves special attention, as it significantly impacts the average value of the financial series. As a result, it is essential to identify the underlying trends present in the market (Glosten et al. 1993). Additionally, the observed significance of variable r_KCT in the conditional variance equation underscores its influential role in shaping asset return volatility, underscoring its importance in risk management and asset pricing analyses.

Bollerslev's 1986 study noted that the GARCH model is crucial for analyzing financial data as it captures the time-varying nature of volatility. The baseline volatility is represented by the constant term in the variance equation, with a low value of omega indicating a relatively stable market environment. Engle's (1982) research also supports this finding, as it shows that a low value of omega indicates a period of low volatility. The ARCH coefficient indicates that past unexpected shocks contribute to the current volatility, with periods of higher volatility tending to occur together. Glosten et al.'s (1993) study also supports this finding, showing that volatility clusters together.

The GARCH model highlights the persistence of past volatility, implying the presence of long-term volatility patterns. Nelson (1991)'s study suggests that the GARCH model provides a more accurate representation of the volatility process than traditional models. The negative coefficient for alpha in the variance equation indicates the dampening effect on volatility, which could be interpreted as a stabilizing factor in the market. Poon and Granger's (2003) study supports this finding, showing that the GARCH model can capture the effects of news announcements on volatility. The coefficients' relevance, highlighted by their significantly low *p*-values, emphasizes the GARCH model's effectiveness in capturing the complex dynamics inherent in the cryptocurrency market.

In Figure 3, we notice significant volatility fluctuations depicted by the conditional variance, particularly during the initial months of the time series. These early months exhibit exceptionally high values compared to the subsequent periods, indicating heightened volatility during this initial phase. However, there is a discernible pattern wherein the conditional variance experiences a sudden and significant drop following this initial period. Subsequently, the conditional variance stabilizes, remaining nearly constant with some sudden fluctuations for the remainder of the observed period. This pattern suggests a period of heightened uncertainty or volatility during the initial phase, possibly driven by specific market events or external factors, such as the sudden crash in December 2021, where approximately USD 300 billion reduced the crypto asset market in two days following an announcement by the United States Federal Reserve Bank (Azimli 2024). The subsequent decrease in conditional variance could indicate a period of relative stability or adjustment within the system, leading to reduced volatility levels. The sustained stability of conditional variance in the subsequent months implies a consistent level of volatility, highlighting the importance of understanding and monitoring the underlying factors driving these fluctuations over time. This uncertainty is evident for this period, where the total crypto asset market from a total market capitalization of approximately USD 3 trillion in early November 2021 fell to approximately USD 1.8 billion at the end of January 2022 and subsequently to about USD 900 billion by the end of June 2022 and remained at approximately these levels up to the late September 2023, according to data from Coingecko. A similar pattern is evident in the variable regarding the "Top 100 DeFi Coins" by Coingecko, which we used as a proxy for the comovement of similar assets, where in early November 2021, the variable had a value of approximately USD 160 billion, and at the end of January 2022, a value of approximately USD 105 billion and from the end of June 2022 up to the end of September 2023, the values range from USD 36 to 45 billion.

Possible explanations for the significant volatility fluctuations in the initial months could be spillover from the general crypto market, as in the fourth quarter of 2021 because of the effect of COVID-19 and the first and second quarter of 2022 because of the Russo-Ukrainian war, as documented by Poddar et al. (2023) in their research, which finds connectedness in the cryptocurrency returns for these periods.

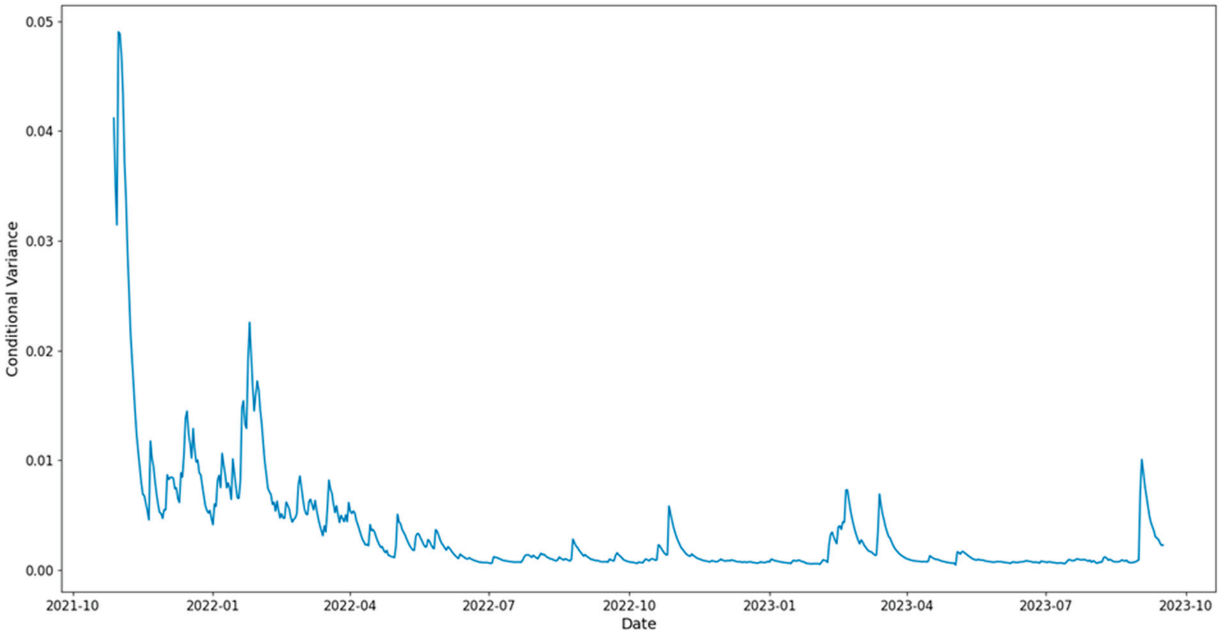

Figure 3. GARCH results: conditional variance.

5. Discussion

The results of the VAR model, Granger causality, and VECM analyses provide the policymakers, who in this context are the community that governs the protocols of the examined DAOs, with valuable insights into the dynamic interplay between OlympusDAO and KlimaDAO, facilitating informed decision making. The decision-making process might involve presenting a new proposal in the governance forums of the DAOs, which could entail altering the allocation of their treasury or adjusting parameters such as the rebasing frequency or token staking yield rates. The VAR model reveals the short-term dependencies and interactions between the variables of interest, such as the treasury balances and the token prices, and other relevant factors, such as the "Top 100 DeFi Coins by Market Capitalization" index.

Granger causality analysis identifies the direction and significance of causal relationships between the variables, aiding policymakers in understanding which DAO may influence the other and to what extent. The outcomes of the Granger causality tests, as depicted in the results section, elucidate compelling relationships within our study. The significant causal connection between the returns of OlympusDAO MC, the returns of KlimaDAO MC, and the returns of their treasuries suggests that these factors may hold predictive value for their future returns.

Additionally, the VECM model captures the long-term equilibrium relationships between OlympusDAO and KlimaDAO, helping policymakers anticipate how changes in one DAO's treasury or token values may affect the other over time. By considering these results collectively, policymakers can devise strategies to better manage funds related to OlympusDAO and KlimaDAO and optimize their resource allocation.

Furthermore, after examining the KlimaDAO treasury, we observe that the returns of KCT may also affect the KlimaDAO conditional variance. For policymakers, identifying KCT as statistically significant in the conditional variance equation offers valuable insights into the determinants of volatility within the system under consideration. Understanding the factors driving volatility is crucial for designing effective policy interventions to promote stability and mitigate risks regarding managing a portfolio containing KlimaDAO tokens.

While this study provides valuable insights into the interaction between market capitalization and treasuries within specific DAO projects, namely OlympusDAO and KlimaDAO, several limitations warrant consideration. Firstly, the scope of the research is confined to these particular projects, potentially limiting the generalizability of findings to other DeFi contexts or similar DAO projects because of differences in their economic model, the underlying assets in their treasury, and the utility of the DAO-issued tokens. Secondly, while Granger causality tests offer insights into potential causal relationships, they do not establish causality definitively, making alternative interpretations possible. Moreover, the sample size of both the daily and monthly data may not fully represent the overall behavior of the treasury and the interaction between the two projects under examination, given that it spans approximately two years. Furthermore, the econometric models could also be extended to include more complexities inherent in market dynamics by including additional essential factors influencing the relationships studied, such as events regarding regulatory concerns or market conditions, trading volume from both decentralized and centralized exchanges, user interaction and sentiment analysis, staking rewards, and token supply dynamics. Finally, this study's acknowledgment of regulatory uncertainties underscores the need for further investigation into the evolving regulatory landscape and its implications for tokenized assets within DAO treasuries. Addressing these limitations in future research endeavors will be crucial to advancing our understanding of decentralized finance dynamics and enhancing the applicability of findings to real-world contexts.

6. Conclusions

This study explored the interaction between market capitalization and treasuries in two popular DAO projects, OlympusDAO and KlimaDAO. Furthermore, we explored the effect of the returns of KlimaDAO treasury carbon tokens on KlimaDAO market capitalization returns' conditional volatility.

The results could contribute to the predictive modeling toolkit, emphasizing the utility of the returns of OlympusDAO MC and shedding light on the distinct behaviors of OlympusDAO and KlimaDAO. The discoveries could offer investors valuable insights, aiding them in identifying additional variables like the DAO treasury and carbon token offsets to better understand the dynamics of the two DAOs and make more informed investment decisions. Policymakers, potentially the governing bodies of the DAOs, could adjust their treasury allocation strategies and the parameters of the DAO smart contracts to align with current market trends. Additionally, policymakers, which could be market regulators, may recognize the influence of carbon tokens on DAO market capitalization, providing further support for the efficacy of this new technology in tokenizing carbon offsets, which could lead to the expansion and organization of carbon offset markets on the blockchain. Researchers can now emphasize the significance of DAO treasuries and the impact of carbon offset tokens, thereby extending research into the importance of other DAO treasuries and potentially tokenized assets.

This study could be a headstart to support whether questionable tokenized assets could be considered to have value or some other form of financial impact. It also provides more evidence that if a token is backed by assets in a DAO treasury, these assets could influence the token's value dynamics, enabling the potential managers of such assets to make better investment decisions. This study's contribution lies in examining the intricate interplay between market capitalization and treasuries within prominent DAO projects, such as OlympusDAO and KlimaDAO, along with the potential influence of treasury-held carbon tokens on market capitalization returns. By elucidating these dynamics, the research augments the existing literature by providing insight into the behavioral patterns between DAOs and sheds light on tokenized asset valuation mechanisms.

One significant innovation of this research lies in its investigation of the influence of environmental factors and the necessity to comprehend the functioning of market dynamics that incorporate these variables. Furthermore, our study delves into sustainability concerns within the crypto asset ecosystem and explores the convergence of environmental preservation and blockchain technology, offering potential avenues for advancing eco-friendly advancements within the digital asset realm.

These findings enrich our understanding of decentralized finance dynamics, offering practical implications for investors, policymakers, and researchers. An implication is that the DAOs are related to the DeFi market cap index examined in this study. Another implication is that this study could be used as a benchmark to create an investment strategy in the future when including the examined variables of this study. Finally, this study underscores the significance of responsible investing, demonstrating its efficacy not only in advancing environmental and social welfare goals but also as a robust investment strategy, suggesting the potential for expanding the scope of sustainable investment assets or indices, which not only prioritize social welfare but also offer profitable returns for investors.

Furthermore, this research explored the importance of a DAO's treasury and identified a potential link between the returns from the carbon offset tokens stored in the treasury, which may contribute to the market capitalization returns volatility of the DAO when employed as collateral for its token, even in the presence of regulatory uncertainties, providing a foundational framework for informed investment decisions and future research endeavors within the field. While prior studies have illuminated these projects' organizational and innovative frameworks, this is the first study to undertake an econometric evaluation as a pioneering effort to offer such invaluable insight.

Future studies could focus on further evaluating the significance of the treasury in DeFi projects, emphasizing its role in assessing the overall value of a DeFi project. Finally, there is an opportunity for scholarly inquiry to extend into appraising the relevance of alternative tokenized assets within this framework.

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Appendix A. Diagnostic Tests

Table A1 displays the diagnostic findings concerning the estimated VAR model. No instances of autocorrelation, heteroskedasticity, or normality issues are detected in the estimated model. The lag length selection criteria display the Likelihood Ratio (LR) test, the Akaike Information Criterion, and the Schwarz Criterion. The test shows that the optimal lag length is equal to one.

In Table A2, a joint test is employed to evaluate the presence of residual heteroskedasticity in the model. The statistical analysis revealed a high p-value of 0.646, indicating a lack of significant evidence to reject the null hypothesis of no residual heteroskedasticity in the model. Thus, the model does not exhibit noticeable heteroskedasticity at the joint level, implying that the model's assumptions are met.

We performed a normality test on the VEC model and observed that the p-values for skewness, kurtosis, and Jarque–Bera tests were mostly elevated across most components. This finding implies that the residuals in each component are more likely to conform to a multivariate normal distribution. The joint tests also lacked substantial evidence against the null hypothesis of normality for the combined residuals. These outcomes suggest that the residuals of the VEC model do not significantly veer from multivariate normality.

Table A1. VAR diagnostics.

Residual Serial Correlation LM TEST			
Lag	**LRE Stat**	**d.o.f.**	**Prob.**
1	21.982	16	0.144
2	13.678	16	0.623
VAR Residual Heteroskedasticity			
Joint test			
Chi-square	**d.o.f.**	**Prob.**	
107.069	100	0.296	
VAR Residual Normality Tests			
Component	**Jarque–Bera**	**d.o.f.**	**Prob.**
1	0.025	2	0.988
2	0.666	2	0.717
3	1.325	2	0.516
4	3.090	2	0.213
Joint	5.106	8	0.746
Lag Length Selection Criteria			
Lag	**LR**	**AIC**	**SC**
0	NA	−28.49	−28.09
1	50.37 *	−30.32	−29.13 *
2	23.63	−30.94	−28.95
3	12.58	−31.22 *	−28.43

Note: The asterisk (*) indicates the optimal model length based on lag selection criteria.

Table A2. VEC diagnostics.

Residual Serial Correlation LM TEST			
Lag	**LRE Stat**	**d.o.f.**	**Prob.**
1	19.132	16	0.262
2	14.149	16	0.588
VAR Residual Heteroskedasticity			
Joint test			
Chi-square	**d.o.f.**	**Prob.**	
113.647	120	0.646	
VAR Residual Normality Tests—KlimaDAO			
Component	**Jarque–Bera**	**d.o.f.**	**Prob.**
1	1.059	2	0.589
2	6.888	2	0.032
3	1.424	2	0.491
4	1.055	2	0.590
Joint	10.425	8	0.236
VAR Residual Normality Tests—OlympusDAO			
Component	**Jarque–Bera**	**d.o.f.**	**Prob.**
1	0.107	2	0.948
2	1.266	2	0.531
3	1.424	2	0.491
4	1.055	2	0.590
Joint	3.851	8	0.870

We also conducted LM tests to check for any serial correlations in the residuals of the VEC model. The results of the tests indicate that there is no substantial evidence to reject the null hypothesis of no residual autocorrelations or serial correlation within the specified lags. The *p*-values obtained from the tests are relatively high, which suggests that any autocorrelations or serial correlations that may exist are not statistically significant.

Table A3 illustrates the diagnostic test outcomes for the estimated GARCH model. The results indicate the absence of autocorrelation and heteroskedasticity issues in the residuals. Moreover, no ARCH effects were identified. The Sign-bias test revealed no statistically significant values, and the Nyblom parameter test detected no coefficient instability problems.

Table A3. GARCH diagnostics.

Correlogram of Standardized Residuals					**Engle-Ng Sign-Bias Test**		
Number of Lag	**AC**	**PAC**	**Q-Stat**	**Prob.**		**t-Statistic**	**Prob.**
1	0.024	0.024	0.406	0.524	Sign Bias	0.047	0.963
2	−0.019	−0.020	0.665	0.717	Negative Bias	−1.488	0.137
3	0.037	0.038	1.619	0.655	Positive Bias	0.185	0.853
4	0.025	0.023	2.045	0.728	Joint Bias	2.754	0.432
5	0.031	0.031	2.699	0.746	**Heteroskedasticity Test: ARCH**		
Correlogram of Standardized Residuals Squared					Obs*R-squared	3.136	
Number of lag	AC	PAC	Q-stat	Prob.	Prob. Chi-Square(1)	0.077	
1	0.068	0.068	3.154	0.076	**Heteroskedasticity Test: White**		
2	−0.029	−0.034	3.745	0.154	Obs*R-squared	8.172	
3	−0.026	−0.021	4.204	0.240	Prob. Chi-Square(9)	0.517	
4	−0.022	−0.020	4.553	0.336			
5	0.005	0.006	4.568	0.471			
Nyblom Parameter Stability Test							
Variable	**Statistic**	**1% Crit.**	**5% Crit.**	**10% Crit.**			
Joint	1.325	2.590	2.110	1.890			

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