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Artificial Intelligence, Digital Finance, and the Green Bond Market Nexus: Volatility Spillover Effects*

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ABSTRACT

The study examines the volatility dynamics and spillover effects among artificial intelligence, FinTech, and green bond indices during the period from June 15, 2018, to April 17, 2025, using ARCH/GARCH-type conditional heteroskedasticity models, as well as the CCC-GARCH, QDCC-GARCH, and QFCON approaches. The findings indicate that the most appropriate model for the FinTech index is EGARCH(1,1), while TGARCH(1,1) is the most suitable for the artificial intelligence and green bond indices. Significant volatility clustering was observed in all indices during the pandemic period. FinTech shocks are more persistent and asymmetric. The artificial intelligence market, however, exhibits the highest shock persistence. CCC-TGARCH results reveal a bidirectional volatility spillover between FinTech and artificial intelligence, while green bonds exhibit weaker spillover behavior. QDCC-GARCH findings show that conditional correlations vary by time and quantiles, with the strongest link observed between artificial intelligence and FinTech. QFCON results confirm that FinTech acts as a net shock transmitter, while green bonds are predominantly shock absorbers.

***Keywords**: Fintech, Artificial Intelligence, Green Bond, Volatility Spillover*

***Jel Classification**: C58, G10*

Yapay Zekâ, Dijital Finans ve Yeşil Tahvil Piyasası İlişkisi: Volatilite Yayılım Etkileri

ÖZET

Çalışma, 15 Haziran 2018–17 Nisan 2025 döneminde yapay zeka, FinTech ve yeşil tahvil endeksleri arasındaki volatilite dinamiklerini ve yayılma etkilerini ARCH/GARCH tipi koşullu heteroskedastisite modelleri, CCC-GARCH, QDCC-GARCH ve QFCON yaklaşımlarıyla incelemektedir. Bulgular, FinTech endeksi için en uygun modelin EGARCH(1,1), yapay zeka ve yeşil tahvil endeksleri için ise TGARCH(1,1) olduğunu göstermektedir. Pandemi döneminde tüm endekslerde belirgin volatilite kümelenmesi gözlemlenmiştir. FinTech şokları daha kalıcı ve asimetriktir. Yapay zeka piyasası ise en yüksek şok kalıcılığına sahiptir. CCC-TGARCH sonuçları, FinTech ile yapay zeka arasında çift yönlü volatilite yayılımı olduğunu, yeşil tahvillerin ise daha zayıf yayılım davranışı sergilediğini ortaya koymaktadır. QDCC-GARCH bulguları, koşullu korelasyonların zaman ve kantillere göre değiştiğini ve en güçlü bağlantının yapay zeka ile FinTech arasında olduğunu göstermektedir. QFCON sonuçları ise FinTech'in net şok yayıcı, yeşil tahvillerin ise çoğunlukla şok alıcı olduğunu doğrulamaktadır.

***Anahtar Kelimeler:** Fintek, Yapay Zekâ, Yeşil Tahvil, Volatilite Yayılımı*

***Jel Sınıflandırması**: C58, G10*

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1. INTRODUCTION

Increasing global uncertainty has encouraged investors to diversify their portfolios and turn to safe-haven assets more than ever. Demand for safe-haven assets rises significantly during times of crisis, and this trend is further reinforced by rising correlations between financial assets, contagion effects, and herd behavior among investors. The COVID-19 pandemic that followed the 2008 global financial crisis and, most recently, the Russia-Ukraine war have brought risk mitigation and diversification to the forefront of investment strategies. In this regard, gold and crude oil have historically been preferred as hedging instruments during stability and as safe-haven assets during times of uncertainty. However, the investment world has been transforming in recent years with different investment alternatives and new-generation risk management methods. Green bonds, renewable energy investments, and cryptocurrencies stand out among these new financial instruments and are preferred by investors and portfolio managers to reduce risks due to their haven characteristics. However, the digitalization process of Industry 4.0 has increased investors' interest in alternative investment opportunities, particularly in digital asset classes (Yadav et al., 2023: 929; Ha, 2023: 83530). On the other hand, among the fundamental elements of the Fourth Industrial Revolution, artificial intelligence (AI) and robotic technologies are reshaping business practices and production processes. Businesses widely use them to reduce costs, improve quality, and manage supply chains more efficiently (Huynh et al., 2020: 1).

AI-related assets are financial instruments that are an integral part of this technology and the associated industrial ecosystem. These assets are divided into three main groups: AI-themed exchange-traded funds (AI ETFs), publicly traded company shares based on AI technology that derive a significant portion of their revenue, and AI-integrated cryptocurrencies. AI-related stocks include companies that place AI at the center of their business model. These groundbreaking investment vehicles have led the way in tech innovation, becoming appealing financial tools for institutional and individual investors. By heavily investing in AI, they have built a strong IT infrastructure that's driving major tech and productivity advancements (Shao et al., 2025: 1-2).

Financial services are at the heart of this technological shift. Due to the financial technology (FinTech) revolution, innovative solutions are transforming financial services by lowering transaction costs, boosting accessibility, and streamlining capital flows. Merging FinTech and sustainable finance is currently key to revolutionizing financial markets. The combination of these two major trends makes financial services more resource efficient. It allows for a better assessment of environmental risks and more strategic management of investment opportunities through digital transformation. A key aspect of FinTech is its ability to process large amounts of data quickly and cost-effectively. This significantly impacts investment decisions and portfolio management, particularly in sustainable finance. Consequently, financial resources can be more effectively and efficiently allocated to projects that support environmental sustainability goals (El Khoury et al., 2023: 281). This trend signifies a substantial shift toward ensuring portfolio diversification and developing more robust strategies in the face of financial volatility.

Notably, the linkage between clean energy and digital finance is a strategic partnership with the potential to create solutions to pressing global issues like sustainable development and climate change. In this regard, green bonds designed to fund projects with environmental benefits are gaining growing interest from traditional investors and the digital finance sector (Chen, 2023: 82286; Dai, 2023: 100188-100189). Green bonds are a reliable, eco-friendly way to fund long-term social and environmental initiatives. For example, wind and solar energy infrastructure projects often require significant upfront investment and take years to pay off. As a result, large-scale bond markets are becoming a viable option for long-term financing. Green bonds (GB) offer investors stable returns, regular income, and long-term growth potential. Additionally, issuing these bonds for social benefit increases political and social interest, and allows investors to fulfill their environmental responsibilities without disrupting their portfolio balances (Park et al., 2020: 1-2).

When considered together, FinTech, AI, and green bond markets represent the dimensions of modern finance, digital finance, technology-driven innovation, and sustainable investment. As investors increasingly allocate capital to these asset classes amid global uncertainty, shocks originating in one market can spill over into others. This transmission can occur through common channels such as movements in technology stocks, risk appetite, investor sentiment, interest rate expectations, and shifts in sustainable investment preferences. Therefore, analyzing these markets together will enable an assessment of whether technology-driven shocks are spreading to sustainable finance markets and whether green bonds can mitigate risks stemming from the FinTech and AI markets.

Based on the above discussions, this study spans from June 15, 2018, to April 17, 2025. The study uses daily data to reveal the volatility spillover between these dates. Within this scope, the study aims to address the following research questions: (1) Do FinTech, AI, and GB indices exhibit volatility clustering, asymmetric responses, and shock persistence? (2) Is there a bidirectional volatility spillover relationship among FinTech, AI, and GB markets? (3) Do the conditional correlations among these markets vary over time and across quantile levels? (4) How do volatility connectedness and net shock transmission differ across market conditions and short- and long-term investment horizons? (5) Which market acts as the dominant shock transmitter or shock receiver under different market conditions? To answer these questions, the study analyzes volatility dynamics, bidirectional spillover relationships, time-varying conditional correlations, and quantile- and frequency-based connectedness among the three indices. In this way, the study provides evidence on systemic risk transmission, shock transmitter and receiver roles, and portfolio diversification opportunities under different market conditions and investment horizons.

The study adds several new contributions to existing literature in this context. First, it presents empirical findings on the volatility spillover between FinTech and GB. However, studies examining the relationship between AI, FinTech, and GB indices are limited. This study is one of the limited number of studies examining the volatility spillover between FinTech, AI, and GB markets using the S&P Kensho Future Payments Index, S&P Kensho AI Index, and S&P Green Bond Index. Furthermore, findings in the existing literature are uncertain depending on the period, sample, and method. Therefore, this study fills this gap by presenting a volatility spillover analysis that evaluates FinTech, AI, and GB. Second, the study guides investors in integrating digital and sustainable asset classes into their portfolio diversification strategies. Determining the direction and intensity of volatility spillover allows for the development of more effective hedging strategies. Third, the relationship between GB, digital assets, and AI sectors provides important insights for making investment decisions consistent with environmental sustainability goals.

2. LITERATURE REVIEW

2.1. An Overview of Green Bond Markets

GB is a relatively new financial instrument. Unlike traditional bonds, all their proceeds are allocated to environmentally friendly projects. GB are defined by the GB Principles, voluntary standards based on four core principles: allocating proceeds to environmental projects, establishing clear criteria for eligible projects, documenting transparent use of proceeds processes, and providing annual reports to investors (Pham, 2016). Since its first issuance in 2007, the GB market has grown rapidly, with an average annual growth rate of 95%. By the end of 2020, the total issuance volume reached $1 trillion (Liu, 2022: 289).

Thanks to their many advantages, green bonds are actively traded on the market and are the subject of increasing academic studies. Since bonds are more stable than stocks, they are a portfolio risk-balancing tool. Understanding how volatility flows between the bond and stock markets is crucial for managing portfolios and developing risk strategies (Park et al., 2020: 2). GBs are also considered a potential diversifier that can mitigate risks related to carbon markets, energy assets, and financial portfolios. The characteristics of haven and hedge have become more pronounced, particularly during the COVID-19 pandemic. Due to the volatility of GB and the necessity of calculating optimal hedge ratios with other assets, it is essential for investment strategies to predict the volatility of these bonds accurately (Xia et al., 2022: 1-2).

Previous research has offered empirical findings on the connection and volatility spillover effects between GB and various markets. Most studies have focused on the linkage between GB and equity (Reboredo, 2018; Mensi et al., 2022; Tiwari et al., 2023), energy (Liu et al., 2021; Tang et al., 2023; Zhang & Umair, 2023), carbon (Jin et al., 2020; Wang et al., 2023), crypto (Hassan et al., 2022; Khalfaoui et al., 2023; Zhao & Park, 2024), and traditional bond markets (Pang et al., 2023; Jovovic & Popovic, 2025). When examining some empirical results, Tang et al. (2023) investigated the connections between GB, clean energy, and fossil fuel markets using Bayesian DCC-MGARCH and frequency-based cointegration analysis. The study found that GB exhibits a weak negative correlation with fossil fuels and clean energy and therefore could be an effective hedge against these assets. In addition, it has been determined that volatility caused by WTI oil and heating oil has been transferred to green bond and clean energy markets in the short run. It is also noteworthy that WTI has had a more substantial impact than Brent. Generally, it has been emphasized that GB play a crucial role in sustainable investment decisions in terms of both risk hedging and carbon reduction. Yadav et al. (2023) analyzed the volatility relationship between GB and renewable energy and cryptocurrency markets using daily data from 2015 to 2022. The study found that, in the long term, GB spread volatility to both the renewable energy and cryptocurrency markets. In addition, it was observed that volatility spillovers between the series were lower in the short term and became more pronounced in the medium and long term. This finding indicates that there are more opportunities for short-term portfolio diversification. The authors emphasize that these results provide important insights for investors, portfolio managers, and policymakers in the context of strategic planning for sustainable investments. However, Mensi et al. (2023) analyzed the hedging capacity of GB, silver, gold, oil, the USD index, and VIX against short- and long-term US stock market declines before and during COVID-19. The study found that short-term volatility spillovers were more dominant, with GB acting as net spread providers in the short term and buyers in the long term. It has been emphasized that gold and GB served as safe-haven assets during the COVID-19 period, while mixed portfolios provided greater diversification. In addition, it has been noted that hedge effectiveness varies depending on the crisis period and time horizon.

Conversely, Umar et al. (2024) examined the volatility spillovers between GB issued in twelve developed countries and oil price shocks, categorizing them as demand, supply, or risk shocks. Using daily data from 2008 to 2022, the study analyzed cross-market dynamics comprehensively, including during global crisis periods. The study revealed that the US and European GB markets dominate international returns and volatility spillovers. Furthermore, the weak link between oil shocks and GB markets indicates that these bonds could benefit portfolio diversification. This is particularly evident in markets such as the US, the Eurozone, Denmark, and Hong Kong. Wu and Qin (2024) examined the asymmetric dynamic volatility linkages between China's new energy, environmental, social, and governance (ESG), GB, and carbon markets. They uncovered important findings regarding the internal risk transmission mechanisms of the green finance system. Their study shows that new energy and ESG market volatility shocks are longer-lasting and more persistent. Negative volatility spillovers increased significantly, especially during the post-COVID-19 period. Furthermore, the study found that ESG and GB markets act as net volatility transmitters, while new energy and carbon markets act as net absorbers. Notably, positive volatility effects on GB and carbon markets were more prevalent than negative.

Yousaf et al. (2024) analyzed the volatility spillover and correlation between GB returns and the oil market at various frequencies. Using the BK-18 method, they observed a more substantial spillover among GB in the short term. BEKK-GJR-GARCH results, however, indicated a one-way negative volatility spillover from oil to global GB markets. These results suggest that green bonds may serve as a hedge against oil. Furthermore, industrial and asset-backed securities type GB were found to have weaker connections with oil and other bonds than other green bond types. Wavelet analyses emphasized oil's directional influence in the short term, indicating a low overall correlation level. The study concludes that oil- and GB-based portfolios offer portfolio managers and investors significant diversification benefits. Maneejuk et al. (2025) analyzed risk spillovers from energy, agriculture, GB, and uncertainty markets to European carbon markets and found that these spillovers are asymmetric. Downward risk spillovers are stronger than upward ones. The agriculture and energy sectors have emerged as the areas most affected by carbon markets during periods of uncertainty, such as Brexit, the global pandemic, and the Russia-Ukraine war. Research emphasizes these sectors' crucial role in stabilizing carbon markets during crises. Naifar (2025) analyzed the dynamic interactions between the Chinese market's fintech, robotics, renewable energy, and green bond sectors, evaluating the structures of their collective behavior, macroeconomic determinants, and the impacts on portfolio strategies. Using extended cointegration and quantile regression methods, we found that the fintech sector plays a key role in transferring returns and that the robotics sector is more sensitive to external shocks. Furthermore, minimum correlation-based portfolio strategies have been found to optimize investment performance when environmental policy changes reduce sectoral correlations. The study emphasizes the importance of cross-sectoral cooperation between investors and policymakers to achieve sustainable growth and technological transformation goals.

2.2. An Overview of Fintech and AI-Related Assets

FinTech's rapid growth has sparked discussions about its potential impacts on financial stability and market volatility. By increasing both the volume and speed of financial transactions, FinTech apps can have a significant effect. Simultaneously, this rapid development has led to closer interactions between FinTech companies and traditional financial institutions, as they integrate FinTech into the financial system. Conversely, FinTech firms are joining the sector as new competitors. At the same time, traditional financial institutions create their own FinTech solutions, form partnerships with these firms, or make direct investments. This tight network of linkages can lead to systemic risks by spreading extreme risks between FinTech and traditional financial institutions. Consequently, the effect of FinTech on the financial system should be viewed not only in terms of speed and efficiency, but also in terms of potential risk transfer mechanisms and threats to stability (Chen et al., 2022: 1; Wen et al., 2023: 190). Conversely, increased investment in the AI sector has accelerated the growth of computing infrastructure and technological developments. However, this development causes environmental issues due to high energy consumption. On the other hand, AI contributes significantly to the green economy in areas such as renewable energy integration, environmental monitoring, and energy efficiency. To transition to a global low-carbon economy, financial markets are considering environmental factors more carefully, and green finance is emerging. During this process, areas where AI intersects with green technologies have become attractive to investors (Shao et al., 2025: 2).

In this context, empirical studies focus on the spillover effects of fintech and AI-related stocks on various markets such as energy, green bonds, and equity. When examining some studies, Li et al. (2020) used a quantile-based Granger causality test to analyze risk propagation between FinTech firms and traditional financial institutions under different market conditions, creating pessimistic, optimistic, and neutral scenarios networks. The findings show that risk linkages are stronger in adverse market conditions and that risk spreading from FinTech firms to traditional institutions is positively related to the systemic risk levels of these institutions. The study highlights the potential impact of this interaction on the financial system and emphasizes the importance of strengthening the regulation and supervision of FinTech companies for financial stability. According to Adekoya et al. (2022), the dynamic relationships between investor interest and FinTech and Robotics & Artificial Intelligence stock returns are shaped by volatility spillover, market asymmetry, and market conditions. The study reveals that investor interest absorbs shocks from the returns of these assets, and this relationship holds up even when returns are negative.

However, a study by Ha (2023) examined the relationship between ARKF and FINX FinTech ETFs and energy volatility indicators from 2019 to 2022 using an extended co-integration and ETVP-VAR model. The results indicate that ARKF and FINX were net shock emitters during this time, whereas green bonds acted as net shock absorbers, particularly during the pandemic and war periods. Additionally, the research revealed that the wind energy indicator acted as an emitter until mid-2021 but then switched to an absorber. This study sheds light on the FinTech sector's impact on spreading shocks and highlights the fragility of green finance, offering valuable insights into how financial dependencies have evolved. Research by Gharbi et al. (2023) examined how investor biases, macroeconomic uncertainty, and Value at Risk (VaR) in the US FinTech market interacted before and during the COVID-19 pandemic. The study found a strong connection between VaR and other factors, especially in the medium to long term. It identified excess confidence and financial stress as key drivers, while VaR and herd behavior were shown to be significant contributors.

Abakah et al. (2023) studied the relationship between FinTech, Bitcoin, and AI stocks, looking at how they are distributed and how predictable their movements are. They found these assets have a complex predictability structure that changes depending on market conditions. The study showed a two-way causal relationship between volatility and market conditions, and how these assets relate to each other shift over time. Furthermore, the conclusion was that the correlation strengthens during extreme price movements, both positive and negative, suggesting that technology-based assets can serve as tools for portfolio diversification and as haven assets. Yousaf et al. (2024) also conducted a three-dimensional volatility correlation analysis based on time, frequency, and quantile among AI stocks, AI tokens, and fossil fuel markets. Research based on data from 2019 to 2023 found that connections between markets shifted over time. Specifically, AGIX, BRENT, FET, MSFT, and WTI were more likely to absorb shocks, while AMZN, natural gas, GOOG, and OCEAN were more likely to transmit them in the median quantile. The study also highlights that short-term fluctuations play a bigger role in how shocks spread within the system, and that long-term factors can alter the relationships between assets. Shao et al. (2025) examined the risk distribution and performance of portfolios that include AI ETFs, clean energy, GB, and AI tokens, shedding light on the systemic importance of these assets. The study found that AI ETFs and clean energy assets are risk-averse, while AI tokens and GB are more risk-seeking. It also revealed that AI tokens have low hedging capacity, making a minimum correlation portfolio strategy the most effective way to mitigate AI asset risks. This research offers valuable insights for policymakers and investors looking to understand better the role of AI and green assets in portfolio management.

2.3. Research Gap

Current studies focus on the connections between FinTech, AI, and GB and their connections to stocks, energy, traditional bonds, and carbon markets. However, there is limited empirical research on the mutual volatility spillovers between FinTech, AI, and GB. A literature review reveals that results vary depending on the methods, sample, and period. These results differ significantly considering recent developments, such as the war in Ukraine and the pandemic. The present study aims to address this gap within this framework by examining the volatility spillover between FinTech, AI, and GB markets through S&P indices for the first time. Thus, this study aims to contribute new, up-to-date empirical findings on the intersection of sustainable finance and digital transformation into literature.

3. METHODOLOGY

This study examines the volatility structures of FinTech, AI, and green finance indices and how volatility spills over between them. Data from June 15, 2018, to April 17, 2025 (1,720 days) were analyzed. The data was obtained from the S&P Global database. The indices were analyzed after undergoing logarithmic transformations. To observe changes within and between the series during the examined period, graphs were created within the scope of volatility modeling. Then, histograms were created for all indices, and descriptive statistics were calculated. Next, the Jarque-Bera test was applied to evaluate whether the series followed a normal distribution. Since stationarity is a requirement for volatility analysis, the series' stationarity was tested using the Dickey-Fuller (ADF) test (1981), the

Augmented Dickey-Fuller (ADF) test, and the Phillips-Perron (PP) test. Three models were created for the ADF test, and the corresponding regression equations are shown in Eq.

$$\Delta\gamma_t = \delta\gamma_{t-1} + \sum_{i=2}^{p} \beta_i \Delta\gamma_{t-i+1} + \varepsilon_t \tag{1}$$

$$\Delta\gamma_t = \mu + \delta\gamma_{t-1} + \sum_{i=2}^{p} \beta_i \Delta\gamma_{t-i+1} + \varepsilon_t \tag{2}$$

$$\Delta\gamma_t = \mu + \delta\gamma_{t-1} + \delta_2 \sum_{i=2}^{p} \beta_i \Delta\gamma_{t-i+1} + \varepsilon_t \tag{3}$$

Equation (1) represents a model with no trend and a constant. Equation (2) represents a model with a trend and a constant. Equation (3) represents a model with a trend and a constant. The basic assumptions and hypotheses of the PP test are the same as those of the ADF test. However, in the PP test, the series must follow a normal distribution, be heterogeneous, and have no autocorrelation among the error terms. Three different models have also been developed for the PP test. The regression equations of these models are shown in equations 4-6.

$$\gamma_t = \delta\gamma_{t-1} + \varepsilon_t \tag{4}$$

$$\gamma_t = \beta_1 + \delta\gamma_{t-1} + \varepsilon_t \tag{5}$$

$$\gamma_t = \beta_1 + \delta\gamma_{t-1} + \beta_2 \left(\mathrm{t} - \frac{\mathrm{T}}{2}\right) + \varepsilon_t \tag{6}$$

Like the ADF test, equation (4) of the PP test represents a model with a constant and trend-free term. Equation (5) represents a model with a constant and trend-containing term. Equation (6) represents a model with a constant and trend-containing term. In addition, stationarity was tested at different quantile levels with the Quantile ADF and Quantil PP tests developed by Adebayo and Ozkan (2024).

After the stationarity condition was met, the initial ARMA model was estimated to use Box-Jenkins methodology based on the Akaike information criterion with a maximum of five AR and MA terms. After determining the ARMA models for all indices, we applied the ARCH-LM test to determine if the error terms of these models had constant variance. We used the correlogram Q statistics to test for correlation between consecutive error term values. Finally, we applied the Broock et al. (1996) BDS linearity test to assess the presence of nonlinear elements in the series. Suppose the estimated models for the FinTech, AI, and GB indices exhibit diagnostic issues related to error terms. In that case, conditional heteroskedasticity techniques should be employed to examine the series' volatility. If these issues are absent, the ARMA model is sufficient. Since the series examined in the current study exhibited serial correlation, heteroskedasticity, and nonlinear components, using ARCH/GARCH-type conditional heteroskedasticity techniques is recommended for volatility modeling. In this context, we investigated volatility models using ARCH, GARCH, TGARCH, and EGARCH. The symmetric nature of the series was examined using linear ARCH and GARCH models, and the asymmetric nature was examined using EGARCH and TGARCH models.

Engle (1982) proposed the ARCH model, which describes conditional variance as a function of past error term values. He also defined the autoregressive conditional variance model, shown in Equation 7.

$$h_t = \alpha_0 + \sum_{t=1}^{q} \alpha_j u_{t-i}^2 \tag{7}$$

In the above equation, u_t is a stochastic process, α_0 and α_j are constant variables, and $\alpha_0 > 0$ ve $0 < \alpha_j < 1$ are constant. In the ARCH model proposed by Engle (1982), the statistical significance of the error term lags must be estimated. Bollerslev (1986) developed the generalized autoregressive conditional heteroskedasticity (GARCH) model to address this issue. In the GARCH model, conditional variance is expressed as an ARMA (p, q) process containing autoregressive and moving average terms, as shown in equation 8.

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i u_{t-i}^2 + \sum_{i=1}^{p} \beta_i h_{t-i} \tag{8}$$

In equation 8, u_t denotes a discrete-time, real-valued stochastic process, and α_j represents a vector of unknown parameters. The conditional variance also depends on the square of the error term and its past. Traditional ARCH/GARCH models only consider the magnitudes of shocks and assume that conditional variance responds symmetrically to negative and positive shocks. However, negative shocks impact volatility more than positive shocks in financial markets. Therefore, models that consider asymmetric effects have been developed for volatility modeling. In the present study, the EGARCH and TGARCH models were used, as they take asymmetric effects into account. The EGARCH model, proposed by Nelson (1991), defines conditional variance logarithmically and allows the coefficients to take on negative values. The EGARCH model is shown in Equation 9.

$$\log(\mathrm{h_t}) = \alpha_0 + \sum_{j=1}^{q} \beta_j \log(\mathrm{h}_{t-j}) + \sum_{i=1}^{p} \alpha_i \left|\frac{u_{t=i}}{\sqrt{h_{t=i}}}\right| + \sum_{k=1}^{r} \gamma_k \frac{u_{t-k}}{\sqrt{h_{t-k}}} \qquad (9)$$

In the above equation, γ_k represents the asymmetric coefficient, and when this coefficient is negative, it indicates the presence of asymmetric effects. When the $\frac{u_{t-k}}{\sqrt{h_{t-k}}}$ coefficient takes a positive value, the effect of the positive shock on the logarithm of the conditional variance is equal to $\alpha_i + \gamma_k$. On the other hand, when the $\frac{u_{t-k}}{\sqrt{h_{t-k}}}$ coefficient takes a negative value, the effect of the shock on the logarithm of the conditional variance is equal to $-\alpha_i + \gamma_k$ (Enders, 2008). Another model that researches the impact of asymmetry on volatility is the TGARCH model developed by Glosten, Jagannathan, and Runkle (1993). The TGARCH model specification is shown in Equation 10.

$$\mathrm{h_t} = \alpha_0 + \sum_{i=1}^{q} \alpha_i u_{t-i}^2 + \gamma_i u_{t-i}^2 d_{t-1} \sum_{i=1}^{p} \beta_j h_{t-j} \qquad (10)$$

The TGARCH model differs from the GARCH model in terms of the $\gamma_i u_{t-i}^2 d_{t-1}$ term. In Equation 10, the function *d*(.) indicates the function used to model asymmetry. The parameter γ represents the asymmetric effect, and a positive value of this coefficient indicates the presence of asymmetry. In the current study, volatility estimation was performed using traditional ARCH and GARCH models for symmetric effects and EGARCH and TGARCH models for asymmetric effects. To determine the most successful model among the alternative models that meet the parameter significance and conditions, the Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Theil Inequality Coefficient (TIC) criteria were used.

Following the volatility model estimation for FinTech, AI, and GB indices, the MultiGARCH (MGARCH) model developed by Bollerslev, Engle, and Wooldridge (1988) was utilized to determine whether volatility spillover among these indices. This model demonstrates volatility spillover in a multivariate system. In the current study, the Constant Conditional Correlations (CCC) GARCH technique, which estimates volatility based on the assumption that conditional covariances are variable and conditional correlations are constant, as developed by Bollerslev (1990), was applied to estimate volatility spillover. The CCC GARCH model allows for applying a single-variable GARCH (p, q) model-like estimation process under the assumption that the conditional variance for each series is $h_{it,} i=1,\ldots n$. In the present study, since the existence of the financial leverage effect in volatility estimation for

FINTECH, AI, and GB indices was confirmed, the TARCH effect was also included in the CCC GARCH model. The CCC TGARCH model is shown in Equation 11. The methodological process followed for volatility modeling and dispersion is shown in Figure 1.

$$h_{it} = \omega_i + \sum_{j=1}^{q} \alpha_{ij}\varepsilon_{i,-j}^2 + \sum_{j=1}^{p} \beta_{ij}h_{i,t-j} + \gamma_i \Delta CVI_t \quad (11)$$

In addition to the CCC TGARCH model, the study examined the propagation relationship between the Quantile Dynamic Conditional Correlation Generalized Autoregressive Conditional Heteroskedasticity (QDCC-GARCH) model and the series. The DCC-GARCH method developed by Gabauer (2020) calculates the volatility spillover using Volatility Action-Reaction Functions (VIRF) and Generalized Estimation Error Variance Decomposition (GFEVD). In this context, the total connectedness index is expressed as in Eq. 12.

$$C_t^g(J) = \frac{\sum_{i,j=1,i\neq j}^{N} \phi_{ij,t}^g(J)}{N} \quad (12)$$

Here, $\phi_{ij,t}^g(J)$ shows the generalized estimation error variance decomposition calculated based on the VIRF. This expression measures the total volatility correlation in the system. The QDCC-GARCH method allows us to examine the changes of the two series at different quantile levels over time. The study also applied the Quantile Frequency Connectedness (QFCON) approach developed by Chatziantoniou et al. (2022) for the reliability of the findings. The QVAR model is expressed as in Eq. 13.

$$x_t = \mu(\tau) + \sum_{j=1}^{p} B_j(\tau)x_{t-j} + u_t(\tau) \quad (13)$$

Here, x_t represents the vector of variables in the model; τ represents the quantile level; μ(τ) is the constant term dependent on the quantile level; p represents the delay length; $B_j(\tau)$, represents the coefficient matrix depending on the quantile level; $u_t(\tau)$ indicates the error term vector. The QVAR model is then converted to the Quantile Vector Moving Average form:

$$x_t = \mu(\tau) + \sum_{i=0}^{\infty} A_i(\tau)u_{t-i}(\tau) \quad (14)$$

Here, $A_i(\tau)$, refers to the dynamic effect coefficients depending on the quantile level. Generalized estimation error variance decomposition is expressed as in Eq. 15.

$$\phi^{g}_{i\leftarrow j,\tau}(F) = \frac{\sum_{f=0}^{F-1}\left(e_i' A_f(\tau) H(\tau) e_j\right)^2}{H_{jj}(\tau)\sum_{f=0}^{F-1}\left(e_i' A_f(\tau) H(\tau) A_f'(\tau) e_i\right)} \qquad (15)$$

Here, $\phi^{g}_{i\leftarrow j,\tau}(F)$ represents the generalized shock contribution from variable j to variable i; F represents the forecast horizon; $A_f(\tau)$ represents the action-reaction coefficients depending on the quantile level; H(τ) represents the covariance matrix of the error terms; e_i and $e_j$shows the selection vectors. Generalized variance decomposition is normalized on a row-by-line basis to make it comparable:

$$\tilde{\phi}^{g}_{i\leftarrow j,\tau}(F) = \frac{\phi^{g}_{i\leftarrow j,\tau}(F)}{\sum_{j=1}^{K}\phi^{g}_{i\leftarrow j,\tau}(F)} \qquad (16)$$

Thanks to this normalization process, it is possible to compare the extent to which each variable receives shocks from other variables in the system. The total directional relatedness that a variable transfer to other variables in the system is as in Eq. 17.

$$S^{gen}_{i\rightarrow\cdot,\tau}(F) = \sum_{j=1,i\neq j}^{K}\tilde{\phi}^{g}_{j\leftarrow i,\tau}(F) \qquad (17)$$

The total directional relatedness of a variable from other variables in the system is as in Equation 18.

$$S^{gen}_{i\leftarrow\cdot,\tau}(F) = \sum_{j=1,i\neq j}^{K}\tilde{\phi}^{g}_{i\leftarrow j,\tau}(F) \qquad (18)$$

The measure of net connectedness is expressed in Eq. 19.

$$S^{gen,net}_{i,\tau}(F) = S^{gen}_{i\rightarrow\cdot,\tau}(F) - S^{gen}_{i\leftarrow\cdot,\tau}(F) \qquad (19)$$

A positive net connectedness value indicates that the relevant variable is a net shock emitter in the system, while a negative value indicates that it is a net shock receiver. The total level of connectedness across the system is calculated through the Total Connectedness Index and is as in Equation 20.

$$TCI_\tau(F) = \frac{K}{K-1}\sum_{i=1}^{K} S_{i\leftarrow\cdot,\tau}^{gen}(F) \quad (20)$$

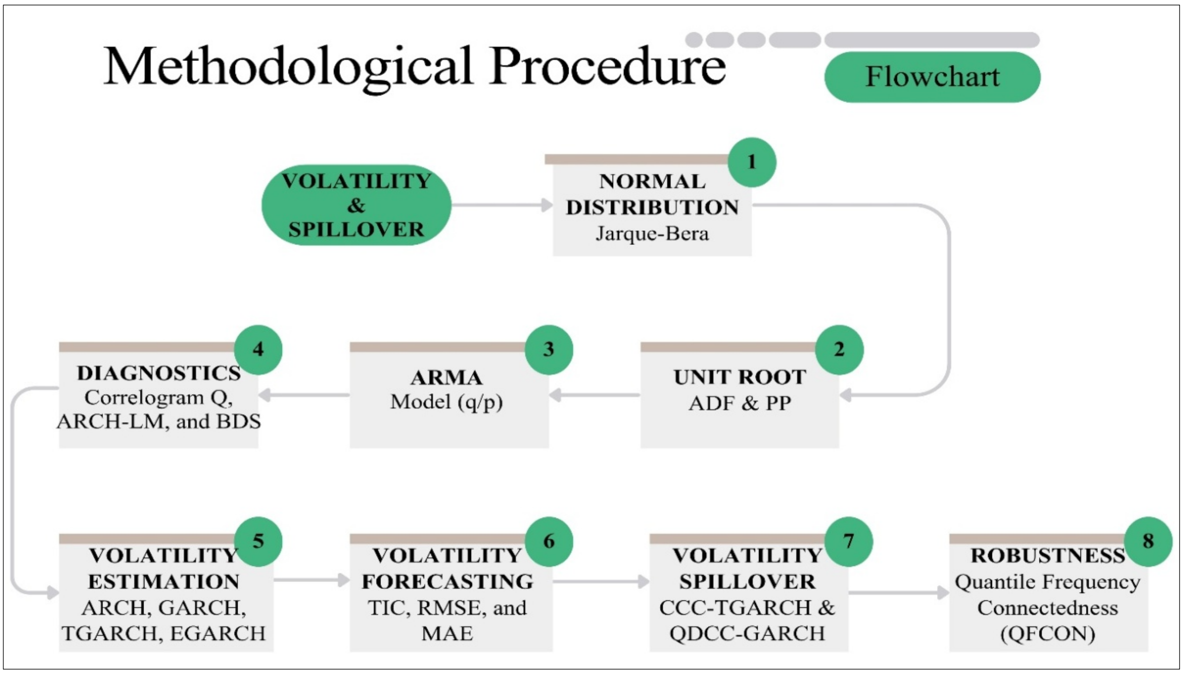


Figure 1. Research method flow chart

4. RESULTS

4.1. Preliminary Test Results

Table 1 and Figure 2 present the preliminary statistical information for the FinTech, AI, and GB series. The average values are 5.88 for FinTech, 5.06 for AI, and 4.91 for GB. All index series were found to have left-skewed and sharp tails, and according to J-B test results, none of the series follow a normal distribution.

Table 1. Descriptive and distributional statistics

	Obs.	Mean	SD	Med.	SE	Trim.	Mad.	Min.	Max.	Range	Skew.	Kurt.	J-B
AI	1720	5.06	0.37	5.07	0.01	5.05	0.37	4.34	5.79	1.46	0.09	-0.95	67.69***
FINTECH	1720	5.88	0.23	5.84	0.01	5.87	0.25	5.36	6.34	0.99	0.17	-1.01	81.35***
GB	1720	4.91	0.09	4.90	0.00	4.91	0.09	4.70	5.07	0.37	0.02	-0.86	53.38***

*** $p < 0.01$

According to the time series charts (Figure 2), the AI, FinTech and GB indices follow a fluctuating course throughout the period, with significant volatility increases, especially in some periods. According to the QQ plot and density plots, it is understood that the series deviates from the normal distribution. For this reason, it can be said that quantile-based approaches would be appropriate instead of classical average-based models. Correlation heatmaps show a strong and positive relationship between AI and FinTech. GB's relationship with AI and FinTech is weaker.

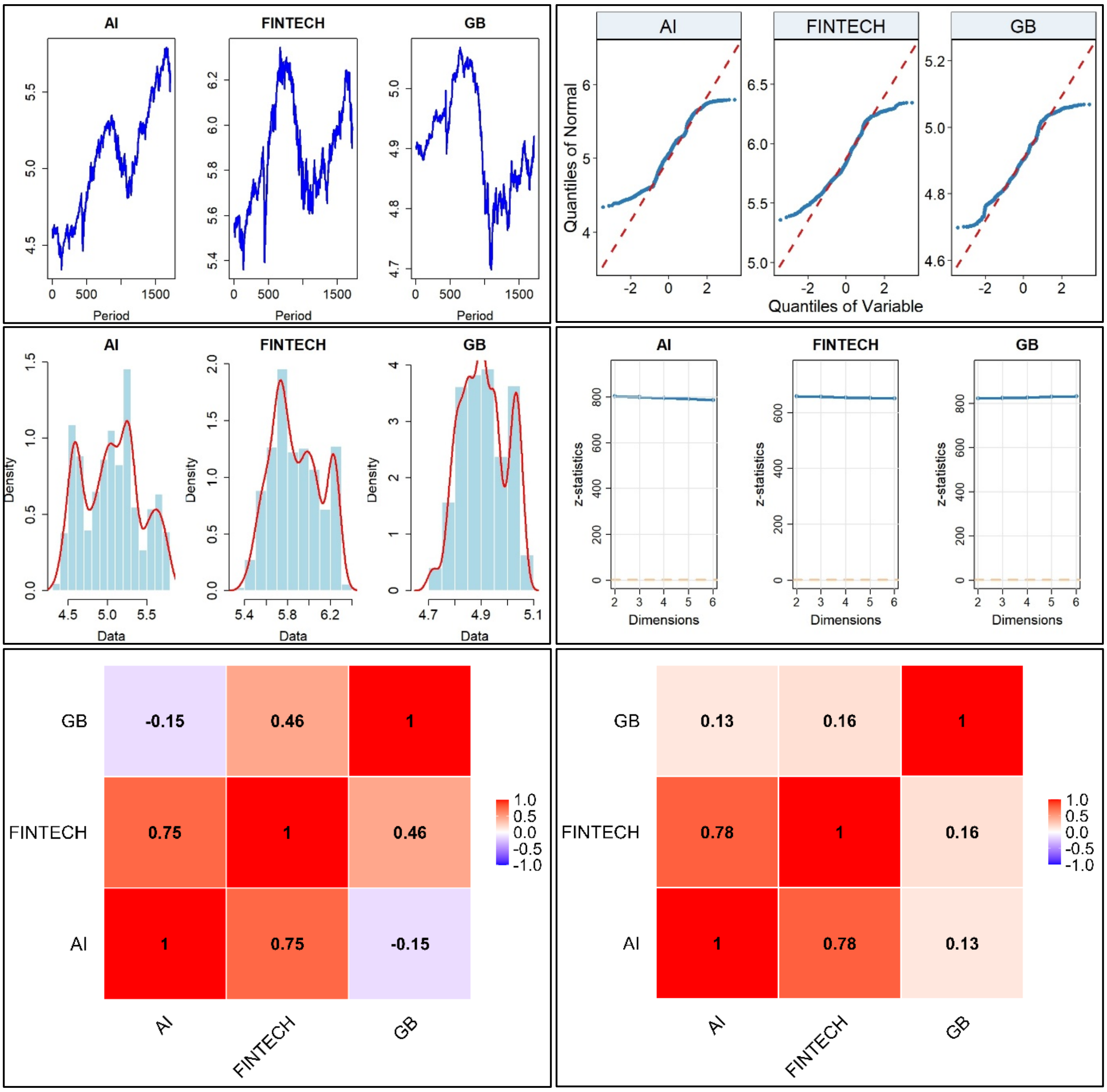


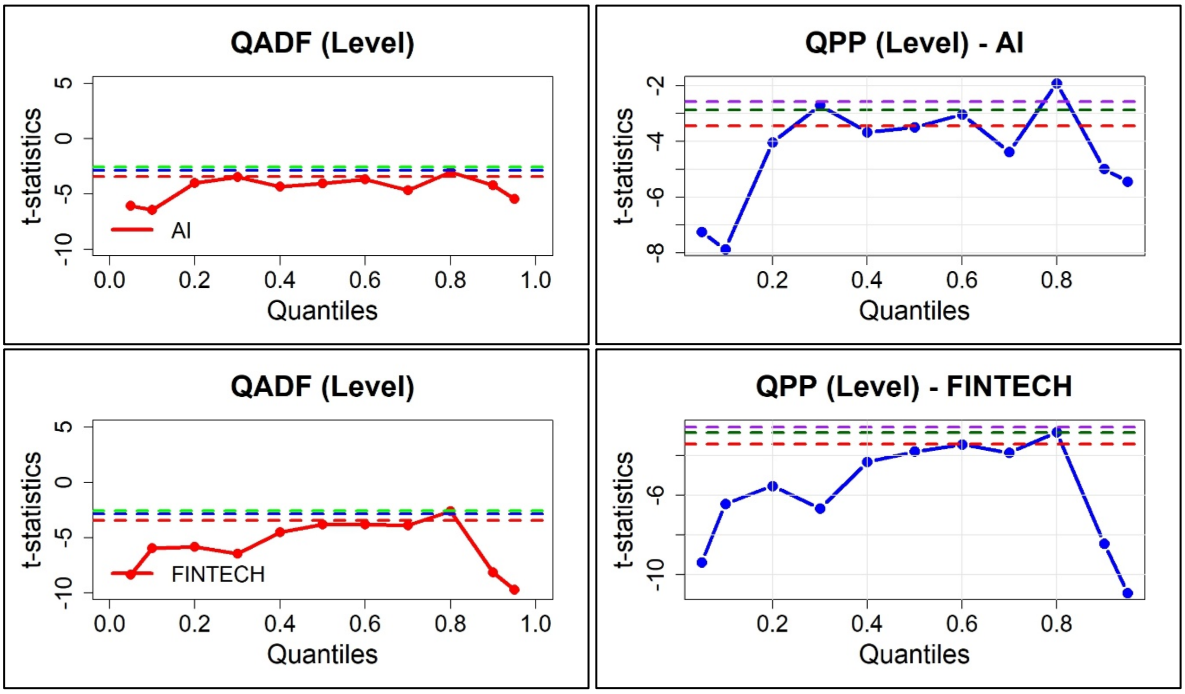
Figure 2. Preliminary Data Diagnostics

Stationarity of a series is a prerequisite for volatility modeling. The current study used the ADF, PP, QADF and QPP unit root tests to determine stationarity. The results of the ADF and PP unit root tests applied to the constant and constant-trend models in Table 2 indicate that the FinTech, AI, and GB series are statistically stationary at the 1% significance level. The ADF and PP findings support each other and reinforce the stationarity results.

Table 2. Stationarity Results

	Intercept				Intercept and trend			
	ADF		PP		ADF		PP	
Series	t-stat.	Prob.	t-stat.	Prob.	t-stat.	Prob.	t-stat.	Prob.
FINTECH	-27.939	0.000	-43.901	0.000	-27.938	0.000	-43.896	0.000
AI	-47.496	0.000	-47.505	0.000	-47.482	0.000	-47.492	0.000
GB	-35.049	0.000	-35.177	0.000	-35.038	0.000	-35.167	0.000
Critical Value	1% (-3.433) 5% (-2.863) 10% (-2.567)				1% (-3.963) 5% (-3.412) 10% (-3.128)			

QADF and QPP unit root test results are shown in Figure 3. According to the QADF results, the test statistics in the AI, FINTECH, and GB series are below critical values at most quantile levels. This shows that the unit root hypothesis can be rejected, especially in low and high quantiles, and the series are stationary at the quantile levels. QPP results also generally support QADF findings. In the AI, FinTech, and GB series, test statistics remain below critical limits in many quantiles, but evidence of stationarity appears weaker in some medium quantiles. This shows that the stationarity structure of the series can vary according to the quantiles.



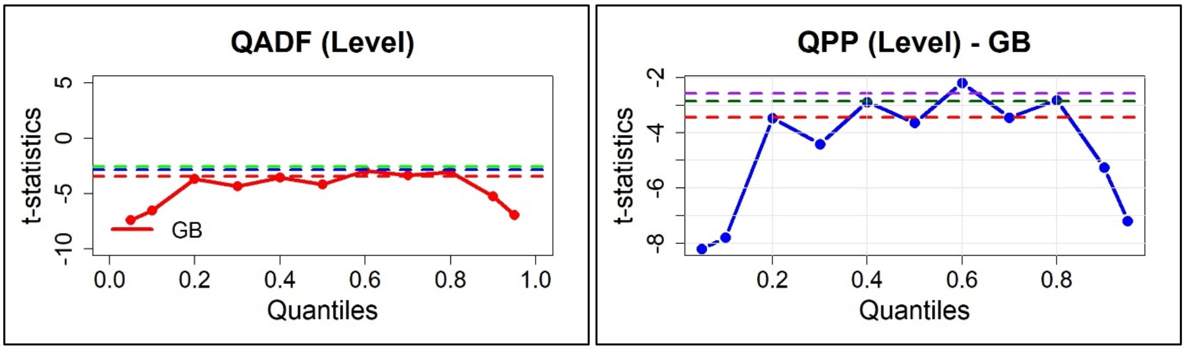


Figure 3. QADF and QPP results.

Note: The green, blue, and red dashed lines represent the 10%, 5%, and 1% critical values, respectively.

Once the stationarity condition was met, the average equations for the FinTech, AI, and GB series were estimated using the Akaike information criterion with a maximum of five AR and MA terms (see Table 3). The resulting average equations were ARMA (4, 4) for FinTech, ARMA (2, 2) for AI, and ARMA (5, 4) for GB.

Table 3. ARMA (p/q) Selection

			FINTECH			
p/q	0	1	2	3	4	5
0	-5.133895	-5.134643	-5.139473	-5.139427	-5.138734	-5.137611
1	-5.135103	-5.136908	-5.138934	-5.139329	-5.145606	-5.145029
2	-5.139492	-5.138497	-5.15833	-5.15853	-5.157564	-5.143456
3	-5.138717	-5.144682	-5.158575	-5.157463	-5.156567	-5.156261
4	-5.13959	-5.149084	-5.157524	-5.156656	**-5.166751**	-5.165624
5	-5.138533	-5.148591	-5.146954	-5.156507	-5.165623	-5.164466
			AI			
p/q	0	1	2	3	4	5
0	-5.321783	-5.336445	-5.338875	-5.340393	-5.339841	-5.338871
1	-5.338316	-5.339581	-5.338875	-5.342555	-5.348803	-5.348124
2	-5.339727	-5.338743	**-5.362852**	-5.361858	-5.361061	-5.359903
3	-5.339147	-5.347061	-5.361850	-5.361259	-5.360240	-5.359102
4	-5.340629	-5.353055	-5.361011	-5.360245	-5.361372	-5.361306
5	-5.340091	-5.352543	-5.359853	-5.359128	-5.361262	-5.362461
			GB			
p/q	0	1	2	3	4	5
0	-8.131164	-8.155298	-8.155110	-8.153945	-8.154656	-8.154378
1	-8.156320	-8.155209	-8.153999	-8.152838	-8.153762	-8.154938
2	-8.155200	-8.154043	-8.154026	-8.152654	-8.154553	-8.155757
3	-8.154152	-8.154027	-8.152963	-8.156866	-8.155722	-8.154709
4	-8.154968	-8.153802	-8.156391	-8.155720	-8.155021	-8.153601
5	-8.153802	-8.153968	-8.155841	-8.154681	**-8.159790**	-8.153350

After determining the ARMA models for the FinTech, AI, and GB series, we investigated the presence of varying variance, autocorrelation, and nonlinear elements using the ARCH-LM, Correlogram Q, and BDS tests. As shown in Table 4, the variance of the error terms in the estimated ARMA models for FinTech, AI, and GB is not constant at lags of 10, 20, and 30. Additionally, there is a correlation between consecutive error terms. Additionally, non-linear components were identified in the error terms of the FinTech, AI, and GB models. Therefore, ARMA models are inadequate for forecasting the volatility of the FinTech, AI, and GB series; symmetric and asymmetric conditional heteroskedasticity models are necessary.

Table 4. Diagnostic Test Results

Index	Model	Heteroscedasticity				Autocorrelation			
	ARMA (4,4)	**F-stat**	**F-prob**	**Obs*R^2**	**Prob.$\chi2$**	**AC**	**PAC**	**Q-stat**	**Prob.**
FINTECH	Lag 10	55.756	0.000	422.217	0.000	0.092	-0.027	944.520	0.000
	Lag 20	29.508	0.000	441.814	0.000	0.053	0.008	1056.100	0.000
	Lag 30	19.812	0.000	445449	0.000	0.052	0.006	1100.400	0.000
	ARMA (2,2)	**F-stat**	**F-prob**	**Obs*R^2**	**Prob.$\chi2$**	**AC**	**PAC**	**Q-stat**	**Prob.**
AI	Lag 10	29.550	0.000	253.248	0.000	0.108	0.043	562.760	0.000
	Lag 20	15.285	0.000	261.740	0.000	0.045	0.015	636.400	0.000
	Lag 30	10.362	0.000	266.602	0.000	0.037	-0.001	661.610	0.000
	ARMA (5,4)	**F-stat**	**F-prob**	**Obs*R^2**	**Prob.$\chi2$**	**AC**	**PAC**	**Q-stat**	**Prob.**
GB	Lag 10	17.990	0.000	163.687	0.000	0.170	0.109	342.300	0.000
	Lag 20	10.886	0.000	195.079	0.000	0.094	0.015	506.450	0.000
	Lag 30	7.949	0.000	212.326	0.000	0.074	-0.010	673.470	0.000

BDS					
Index	Dim.	BDS-stat	Std. Er.	z-stat	Prob.
	2	0.014	0.002	7.092	0.000
	3	0.034	0.003	10.577	0.000
FINTECH	4	0.049	0.004	12.838	0.000
	5	0.059	0.004	14.792	0.000
	6	0.064	0.004	16.752	0.000
	2	0.012	0.002	5.728	0.000
	3	0.027	0.003	8.413	0.000
AI	4	0.041	0.004	10.608	0.000
	5	0.051	0.004	12.786	0.000
	6	0.058	0.004	15.043	0.000
	2	0.023	0.002	10.066	0.000
	3	0.044	0.004	12.146	0.000
GB	4	0.060	0.004	13.918	0.000
	5	0.069	0.005	15.280	0.000
	6	0.073	0.004	16.733	0.000

4.2. Volatility Estimation Results

Table 5 shows the estimated volatility for FinTech, AI, and GB. Symmetric ARCH and GARCH models and asymmetric EGARCH and TGARCH models were used to estimate all series. Different ARCH, GARCH, and asymmetric effects were tested for each series, and the valid models that satisfy the parameter and significance constraints are reported. Since the volatility model estimation error terms are not normally distributed, they were tested using a student’s t-test. The following models are valid:

- For FinTech: ARCH (1-2-3-4), GARCH (1,1), TGARCH (1,1), and EGARCH (1,1)

- For AI: ARCH (1-2-3), GARCH (1,1), TGARCH (1,1), and EGARCH (1,1)

- For GB: ARCH (1), GARCH (1,1), TGARCH (1,1), and EGARCH (1,1)

Table 5. Volatility Estimation Results

Index	Model	Coefficients								
		α_0	α_1	α_2	α_3	α_4	β_1	β_2	β_3	γ_1
FINTECH	ARCH (1)	0.0002	0.1713	-	-	-	-	-	-	-
	ARCH (2)	0.0003	0.1500	0.0500	-	-	-	-	-	-
	ARCH (3)	0.0001	0.1331	0.0442	0.0442	-	-	-	-	-
	ARCH (4)	0.0002	0.1198	0.0398	0.0398	0.0398	-	-	-	-
AI	ARCH (1)	0.0002	0.1714	-	-	-	-	-	-	-
	ARCH (2)	0.0002	0.1499	0.0499	-	-	-	-	-	-
	ARCH (3)	0.0002	0.1332	0.0444	0.0444	-	-	-	-	-
GB	ARCH (1)	0.0001	0.1714	-	-	-	-	-	-	-
$h_t = \alpha_0 + \sum_{t=1}^{q} \alpha_j u_{t-i}^2$										
FINTECH	GARCH (1,1)	0.0001	0.1498	-	-	-	0.5998	-	-	-
AI	GARCH (1,1)	0.0001	0.1497	-	-	-	0.5997	-	-	-
GB	GARCH (1,1)	0.0001	0.1499	-	-	-	0.5999	-	-	-
$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i u_{t-i}^2 + \sum_{i=1}^{p} \beta_i h_{t-i}$										
FINTECH	TGARCH (1,1)	0.0001	0.0381	-	-	-	0.8779	-	-	0.1218
AI	TGARCH (1,1)	0.0001	0.0333	-	-	-	0.8676	-	-	0.1479
GB	TGARCH (1,1)	0.0001	0.0329	-	-	-	0.9555	-	-	0.0189
$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i u_{t-i}^2 + \gamma_i u_{t-i}^2 d_{t-1} \sum_{i=1}^{p} \beta_j h_{t-j}$										
FINTECH	EGARCH (1,1)	-0.3755	0.1791	-	-	-	0.9717	-	-	-0.0990
AI	EGARCH (1,1)	-0.4314	0.1862	-	-	-	0.9661	-	-	-0.1190
GB	EGARCH (1,1)	-0.1212	0.1015	-	-	-	0.9959	-	-	-0.0128
$\log(h_t) = \alpha_0 + \sum_{j=1}^{q} \beta_j \log(h_{t-j}) + \sum_{i=1}^{p} \alpha_i \left\| \frac{u_{t=i}}{\sqrt{h_{t=i}}} \right\| + \sum_{k=1}^{r} \gamma_k \frac{u_{t-k}}{\sqrt{h_{t-k}}}$										

To determine the most successful volatility model among those that provide significant constraints on parameters for the FinTech, AI, and GB series, valid models are expected to address the issues of autocorrelation and heteroskedasticity identified in preliminary tests. The diagnostic test results in Table 5 show that the TGARCH (1,1) and EGARCH (1,1) models with asymmetric conditional heteroskedasticity resolve the issues of autocorrelation and heteroskedasticity for the FinTech, AI, and GB series at lag values of 10, 20, and 30, respectively. However, no applicable symmetric ARCH or GARCH models resolve these issues (Table 6).

Table 6. Diagnostic Test Results

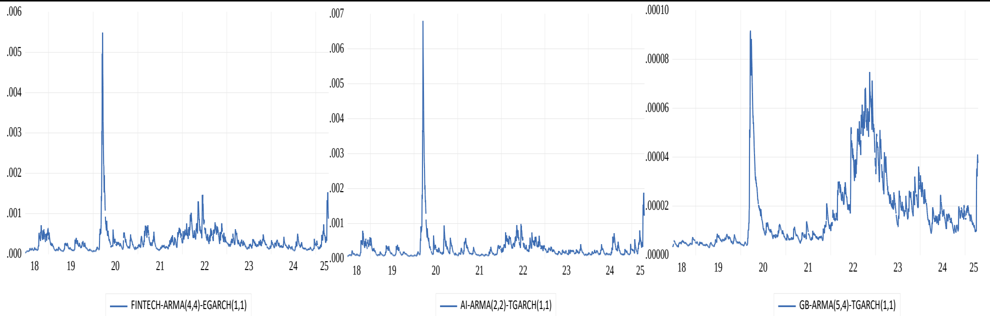
		Heteroscedasticity					
		FINTECH		**AI**		**GB**	
Model	**Lag**	**F Stat.**	**F Prob.**	**F Stat.**	**F Prob.**	**F Stat.**	**F Prob.**
ARCH(1)	10	29.410	0.000	17.825	0.000	10.353	0.000
	20	15.838	0.000	9.848	0.000	6.897	0.000
	30	10.942	0.000	7.174	0.000	4.885	0.000
ARCH(2)	10	19.908	0.000	12.881	0.000	-	-
	20	11.464	0.000	7.449	0.000	-	-
	30	7.923	0.000	5.599	0.000	-	-
ARCH(3)	10	13.812	0.000	14.223	0.000	-	-
	20	8.285	0.000	8.294	0.000	-	-
	30	5.768	0.000	6.057	0.000	-	-
ARCH(4)	10	13.148	0.000	-	-	-	-
	20	7.880	0.000	-	-	-	-
	30	5.515	0.000	-	-	-	-
GARCH(1,1)	10	13.859	0.000	4.959	0.000	4.177	0.000
	20	8.093	0.000	3.655	0.000	3.776	0.000
	30	5.658	0.000	3.210	0.000	3.420	0.000
EGARCH(1,1)	10	1.140	0.327	1.081	0.372	1.679	0.080
	20	0.825	0.684	0.724	0.804	1.355	0.134
	30	0.952	0.540	0.851	0.697	1.138	0.277
TGARCH(1,1)	10	1.027	0.417	1.137	0.329	1.637	0.090
	20	0.953	0.517	0.814	0.698	1.368	0.127
	30	0.948	0.546	0.971	0.510	1.157	0.255
		Autocorrelation					
		FINTECH		**AI**		**GB**	
Model	**Lag**	**Q Stat.**	**Prob.**	**Q Stat.**	**Prob.**	**Q Stat.**	**Prob.**
ARCH(1)	10	425.35	0.000	276.15	0.000	134.78	0.000
	20	579.95	0.000	392.51	0.000	229.48	0.000
	30	641.2	0.000	448.61	0.000	306.32	0.000
ARCH(2)	10	316.68	0.000	171.07	0.000	-	-
	20	473.86	0.000	249.85	0.000	-	-
	30	540.6	0.000	304.37	0.000	-	-
ARCH(3)	10	190.18	0.000	219.42	0.000	-	-
	20	310.39	0.000	330.28	0.000	-	-
	30	373.16	0.000	394.77	0.000	-	-
ARCH(4)	10	210.01	0.000	-	-	-	-
	20	345.49	0.000	-	-	-	-
	30	426.23	0.000	-	-	-	-
GARCH(1,1)	10	234.84	0.000	52.274	0.000	44.36	0.000
	20	359.59	0.000	87.442	0.000	92.695	0.000
	30	438.23	0.000	127.79	0.000	151.18	0.000
EGARCH(1,1)	10	11.352	0.331	10.913	0.364	16.591	0.084
	20	16.077	0.712	14.036	0.829	26.672	0.145
	30	27.778	0.582	24.789	0.735	33.743	0.291
TGARCH(1,1)	10	10.703	0.381	11.437	0.325	16.44	0.088
	20	18.758	0.538	15.627	0.739	26.167	0.160
	30	28.279	0.556	28.908	0.522	33.678	0.294

To compare the forecasting performance of volatility models expected to resolve issues of autocorrelation and heteroskedasticity in model error terms and identify the most successful model, the RMSE, MAE, and TIC forecasting coefficients were estimated. The volatility model with the smallest coefficient is considered the most successful. Table 7 shows that the EGARCH (1,1) model is the most successful for FinTech, and the TGARCH (1,1) model is the most successful for AI and GB. The EGARCH and TGARCH models, which take asymmetry into account, appear to capture volatility dynamics more accurately for FinTech, AI, and GB. Table 6 presents conditional variance plots created using conditional variance series from the most successful volatility prediction models for FinTech, AI, and GB. The plots reveal that the pandemic impacted all indices and caused volatility clustering.

According to the EGARCH (1,1) estimation results for FinTech, it was found that 0.179 of the current period volatility in the FinTech index was caused by past shocks, while current period shocks caused 0.971. The estimated α and β coefficients indicate that these shocks exhibit a long memory effect and have a lasting impact on volatility in the index. Additionally, negative shocks have a 0.099-unit effect on index volatility and are more effective than positive shocks. Half-life (HL) is frequently used to show differences in the persistence of shocks and to measure the time (number of days) it takes for a shock to reduce to half of its original magnitude on volatility (Malik et al., 2005; Zivot, 2009). It is computed as $HL=\ln(0.5) / \ln(\alpha_1+\beta_1)$. According to HL, the shock effect on the FinTech index volatility is effective for approximately 4.93 days, meaning it persists for that duration.

TGARCH (1,1) estimation results for AI and GB indicate that the current period volatility in these indices is 0.033 (AI) and 0.032 (GB) due to past shocks, while 0.8676 (AI) and 0.9555 (GB) are due to current period shocks. It can be stated that GB is more affected by current-period shocks. According to the α and β coefficients, shocks affect AI and GB indices similarly. $\gamma > 0$ was calculated for both indices. Therefore, it has been found that the leverage effect is valid in index volatilities and exhibits asymmetric characteristics. Additionally, positive shocks have a unit effect of 0.147 (AI) and 0.018 (GB) on index volatility, and they are more effective than negative shocks. The index where the leverage effect is most effective on volatility is AI. According to the HL coefficient, the effect of shocks on AI index volatility persists for approximately 6.64 days, while the shock effect on GB index volatility is practical for 6.61 days. These findings indicate that shocks have the most persistent effect on AI index volatility, while the index with the least persistent effect on volatility is FinTech.

Table 7. Forecasting Performance of Volatility Models

Index	Valid Model	TIC	RMSE	MAE
FINTECH	TGARCH (1,1)	0.948663	0.018541	0.013269
	EGARCH (1,1)	0.944107	0.018535	0.013269
AI	TGARCH (1,1)	0.947907	0.016889	0.011837
	EGARCH (1,1)	0.969077	0.016899	0.011863
GB	TGARCH (1,1)	0.958857	0.004146	0.002908
	EGARCH (1,1)	0.962280	0.004146	0.002909
Index	**Best Model**	α_1	β_1	γ_1
FINTECH	EGARCH (1,1)	0.1791	0.9717	-0.0990
AI	TGARCH (1,1)	0.0333	0.8676	0.1479
GB	TGARCH (1,1)	0.0329	0.9555	0.0189
Conditional Variance Graphs				

4.3. Volatility Spillover Results (CCC-TGARCH and QDCC-GARCH)

Volatility spillovers between volatility series were examined using MGARCH models. Table 8 reports the estimation results of the CCC TGARCH model. When the Rho coefficient, which is accepted as an indicator of volatility spillover, is positive and significant, volatility spillovers between series are confirmed. Accordingly, an increase in FinTech volatility increases AI and GB volatility. Here, it was calculated that FinTech volatility has a spillover effect on AI and GB volatility, with this effect being 0.794 on AI and 0.092 on GB. Therefore, the findings suggest that the FinTech index may act as a shock transmitter, while the AI and GB indices are shock receivers. Volatility spillover from AI volatility to FinTech and GB volatility is confirmed, with this spillover effect found to be significant for FinTech (0.794) and GB (0.092). These results indicate the existence of a bidirectional causal spillover between FinTech volatility and AI volatility. Volatility spillover from GB volatility to FinTech and AI volatility is confirmed, with the effect of this spillover calculated as 0.157 for FinTech and 0.109 for AI. The volatility spillover results reveal mutual spillover effects between FinTech, AI, and GB index volatilities, while also showing that the indices act as both shock transmitters and receivers. The findings support the studies by Ha (2023), Abakah et al. (2023), Shao et al. (2025), and Naifar (2025), which identified a spillover effect between

FinTech, AI, and green finance. Findings related to volatility modeling and spillover are presented in Figure 4.

Table 8. CCC TGARCH Spillover Results

Transformed Variance Coefficients					
Indices	**Model**	**Coef.**	**Std. Er.**	**z-Stat.**	**Prob.**
	ARCH(AI)	0.045	0.014	3.223	0.001
FINTECH	TARCH(AI)	0.049	0.014	3.603	0.000
	GARCH(AI)	0.870	0.018	47.321	0.000
↓	ARCH(FINTECH)	0.033	0.013	2.547	0.011
	TARCH(FINTECH)	0.054	0.016	3.464	0.001
	GARCH(FINTECH)	0.887	0.017	53.064	0.000
AI	Rho (AI, FINTECH)	0.794	0.008	104.947	0.000
	Df	7.028	0.745	9.429	0.000
	ARCH(GB)	0.050	0.007	7.401	0.000
FINTECH	TARCH(GB)	0.006	0.008	0.702	0.483
	GARCH(GB)	0.944	0.005	195.969	0.000
↓	ARCH(FINTECH)	0.038	0.016	2.371	0.018
	TARCH(FINTECH)	0.123	0.019	6.402	0.000
	GARCH(FINTECH)	0.869	0.018	48.960	0.000
GB	Rho (GB, FINTECH)	0.138	0.020	6.861	0.000
	Df	8.092	0.890	9.087	0.000
	ARCH(FINTECH)	0.033	0.013	2.547	0.011
AI	TARCH(FINTECH)	0.054	0.016	3.464	0.001
	GARCH(FINTECH)	0.887	0.017	53.064	0.000
↓	ARCH(AI)	0.045	0.014	3.223	0.001
	TARCH(AI)	0.049	0.014	3.603	0.000
	GARCH(AI)	0.870	0.018	47.321	0.000
FINTECH	Rho (FINTECH, AI)	0.794	0.008	104.947	0.000
	Df	7.028	0.745	9.429	0.000
	ARCH(GB)	0.051	0.007	7.559	0.000
AI	TARCH(GB)	0.007	0.009	0.810	0.418
	GARCH(GB)	0.944	0.005	201.436	0.000
↓	ARCH(AI)	0.045	0.013	3.492	0.001
	TARCH(AI)	0.127	0.017	7.358	0.000
	GARCH(AI)	0.863	0.015	58.764	0.000
GB	Rho (GB, AI)	0.092	0.022	4.281	0.000
	Df	7.261	0.789	9.207	0.000
	ARCH(FINTECH)	0.028	0.020	1.379	0.168
GB	TARCH(FINTECH)	0.116	0.026	4.548	0.000
	GARCH(FINTECH)	0.890	0.018	49.853	0.000
↓	ARCH(GB)	0.036	0.010	3.628	0.000
	TARCH(GB)	0.019	0.012	1.598	0.110
	GARCH(GB)	0.949	0.008	113.126	0.000
FINTECH	Rho (FINTECH, GB)	0.157	0.026	5.997	0.000
	Df	7.000	0.782	8.948	0.000
	ARCH(AI)	0.027	0.017	1.565	0.118
GB	TARCH(AI)	0.141	0.027	5.274	0.000
	GARCH(AI)	0.875	0.018	48.698	0.000
↓	ARCH(GB)	0.035	0.010	3.562	0.000
	TARCH(GB)	0.020	0.012	1.668	0.095
	GARCH(GB)	0.951	0.008	118.153	0.000
AI	Rho (AI, GB)	0.109	0.027	3.989	0.000
	Df	7.261	0.789	9.207	0.000

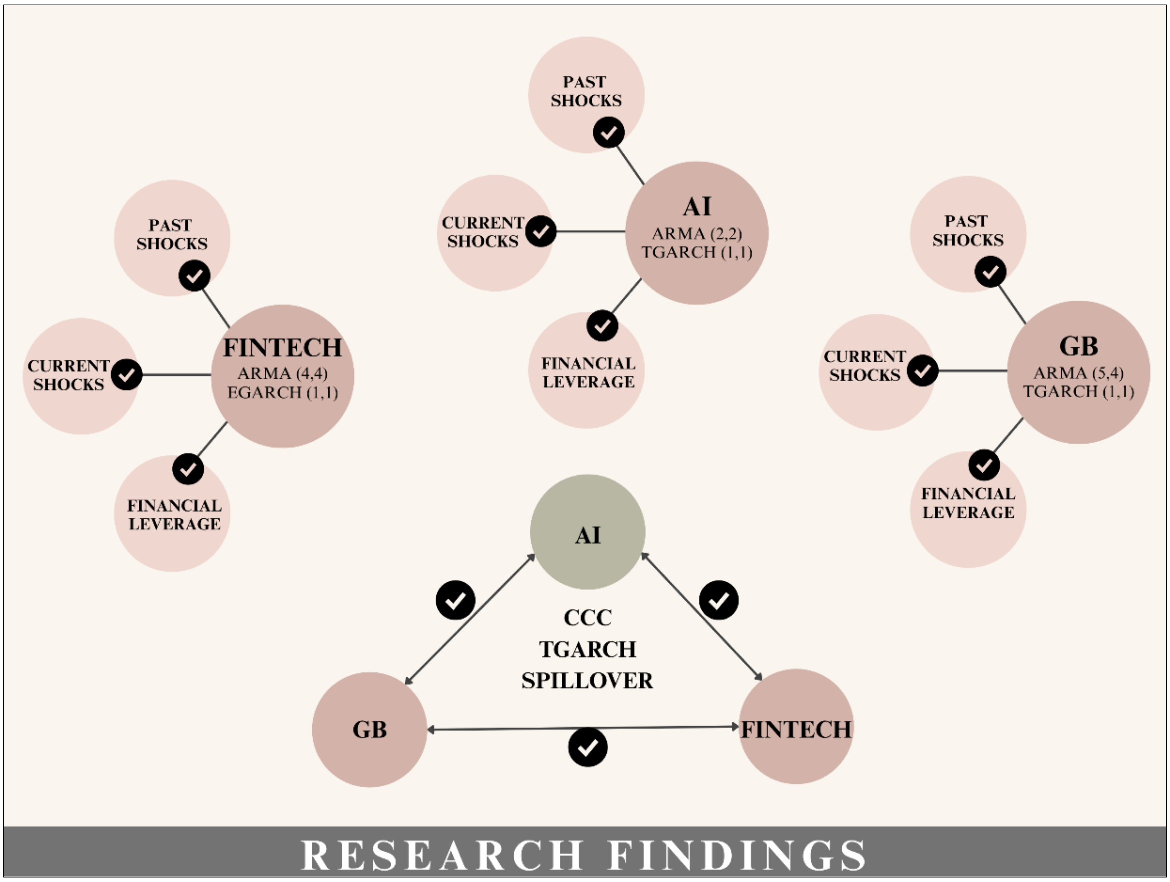


Figure 4. Graphical summary of CCC-TGARCH results

The study also examines the spread of volatility between the series with the QDCC GARCH method. The QDCC-GARCH results are shown in Figure 5. The QDCC-GARCH findings show that the conditional correlations between the AI, FinTech, and GB indices vary over time and at different quantile levels. The concentration of red areas in the graphs indicates that the positive conditional correlation has strengthened, while the blue areas indicate periods when the relationship has weakened or become negative. According to the findings, the strongest and most stable positive connection is seen between the AI-FinTech pair. This suggests that AI and FinTech indices are sensitive to similar market conditions, with a growing tendency to move together, particularly in mid and high quantiles. There is a more heterogeneous structure in FinTech-GB and AI-GB relations. While the positive correlation strengthens in these couples in some periods, it is seen that the relationship weakens in some quantiles and time intervals. The increase in red areas, especially in the 2021-2023 period, indicates that the interconnectedness between indices strengthens during periods of high market stress. On the other hand, a more fragmented and fluctuating outlook emerged after 2024. Overall, the results show that the relationship between AI, FinTech, and GB is not constant; It reveals that it varies according to market conditions, time size and quantile levels. Therefore, the QDCC-GARCH findings show that the volatility spillover relationships determined in the CCC-TGARCH model are valid under different market conditions.

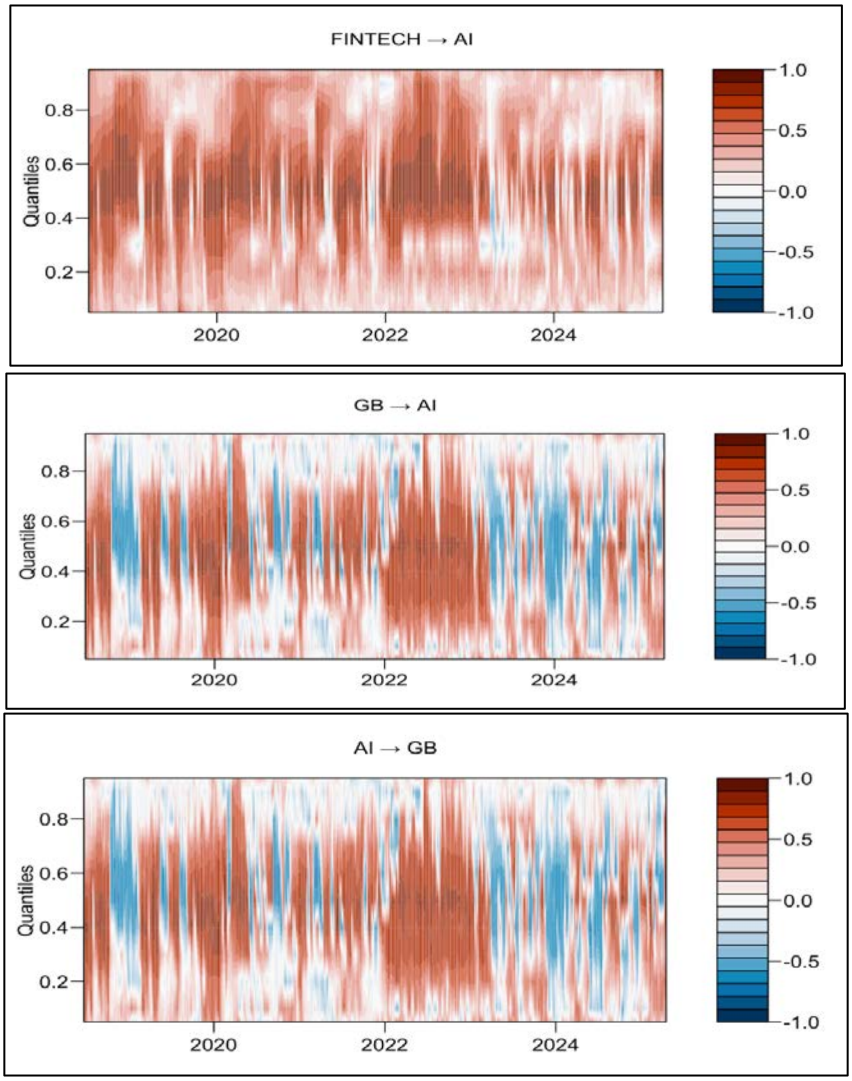


Figure 5. QDCC-GARCH results

4.4. Robustness Check: Quantile Frequency Connectedness Analysis

To test the robustness of the volatility spillover findings obtained from the CCC-TGARCH model, the QFCON approach was additionally applied in the study. The QFCON method examines the shock transmission mechanism in terms of different quantile levels and different frequency domains, showing whether volatility correlation persists in low, medium, and high market conditions and short- and long-term investment horizons. Net connectedness and TCI graphs are shown in Figure 6. When the network graph is examined, it is observed that the risk spread between FinTech-GB and FinTech-AI has strengthened in the short term at the 0.10 quantile level, which represents excessive declines and adverse market conditions. While GB is a total and long-term net risk taker, it becomes a net risk spreader in the short term. At the 0.50 quantile level, which represents normal market conditions, risk spread in total connectedness appears to be predominantly from AI and FinTech to GB. In the short-term frequency area, it shows that FinTech has become a risk-taker and GB has become a more active risk spreader. It is observed that GB is more of a net risk-taker in the long run. At the 0.90 quantile level, i.e. in optimistic/high market conditions, the Network Graph results show a similar structure in all three frequency domains. GB is more of a net risk-taker, while FinTech and AI are risk-spreaders, especially against GB. When the Net Connectedness results are examined, FinTech is clearly a net shock emitter in poor market conditions, while GB is mostly a net shock receiver; AI, on the other hand, exhibits a more limited and near-zero role. Under normal market conditions, FinTech's role as a net shock spreader continues, especially in the post-2022 period, while GB maintains its position as a net shock receiver by being in the negative zone. AI, on the other hand, was a net shock emitter in the 2020-2021 period and showed a more volatile structure in the following periods. In optimistic market conditions, connectedness becomes more volatile, with FinTech being a net shock emitter in general and GB being a strong net shock receiver. The role of AI varies over time, acting as a shock emitter in some periods and a shock receiver in others. Overall, the findings suggest that FinTech is the most prominent risk emitter in the system, while GB is more risk-taking, especially in medium and high quantiles. According to TCI plots, it is observed that the strongest total correlation occurs at the level of 0.90 quantiles in the long run.

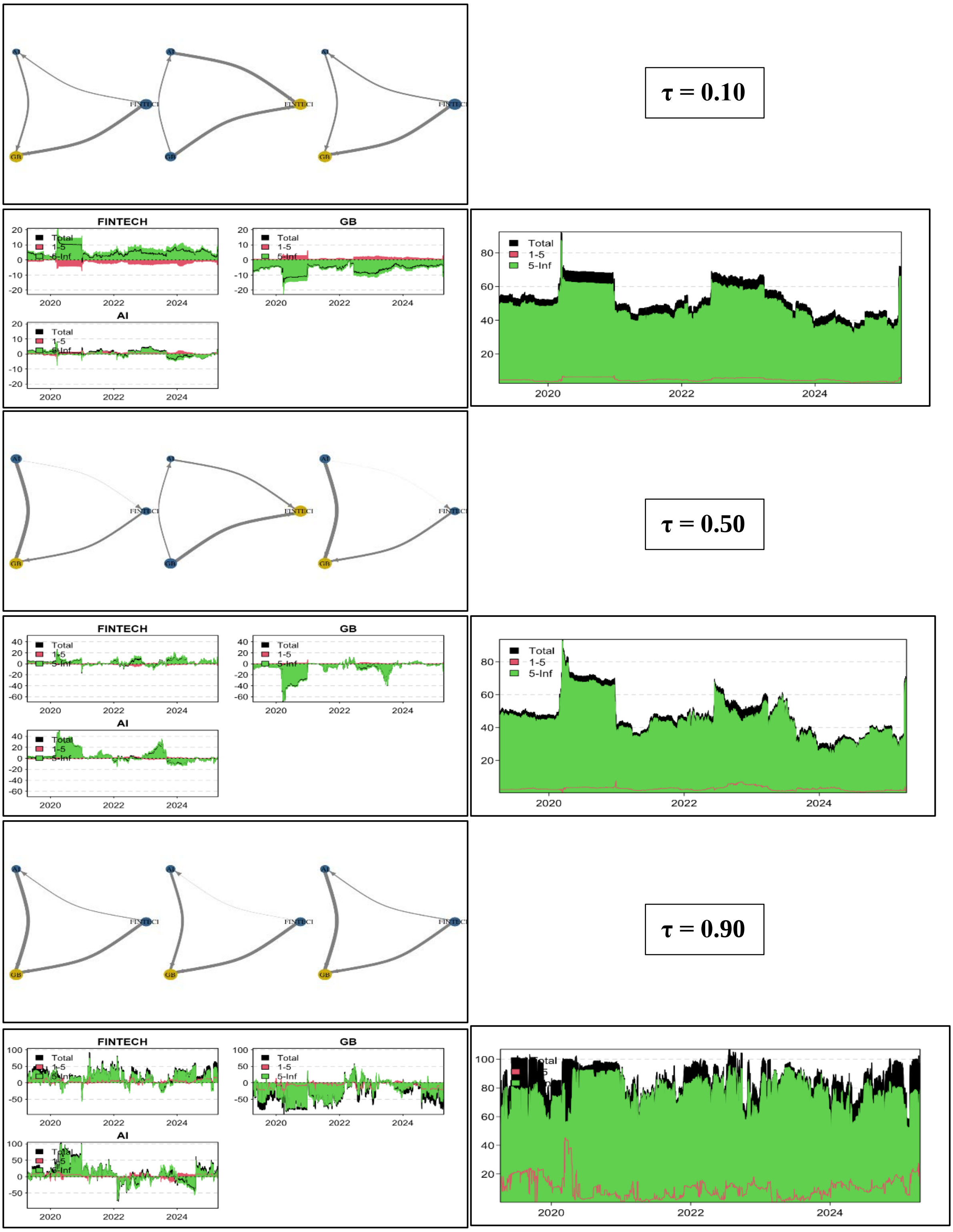
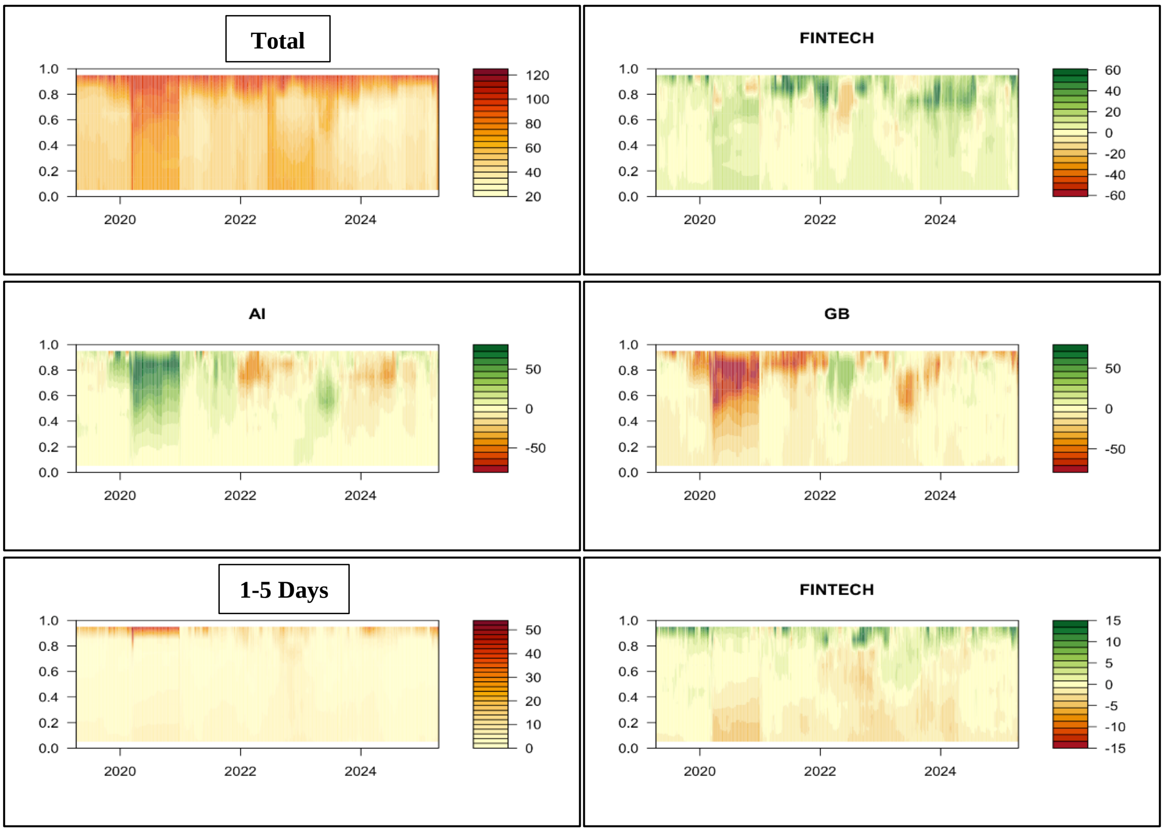


Figure 6. Net connectedness and TCI graphs

Note: Network graphs represent the results of total, 1-5 days and 5lnf from left to right.

Figure 7 presents the net connectedness dynamics of FinTech, AI, and GB across total, short-term (1–5 days), and long-term (5–Inf) horizons. In both the total and long-term periods, the shock-transmitting and shock-absorbing roles of the variables vary considerably across quantiles and over time, indicating substantial heterogeneity in the connectedness structure. FinTech predominantly acts as a net shock transmitter, particularly at upper quantiles and during the post-2022 period, while GB frequently switches between transmitting and absorbing shocks depending on market conditions. AI exhibits a mixed pattern, serving as a net shock transmitter during some periods, especially around 2020–2021, but becoming a net shock absorber at higher quantiles in subsequent years. In the short-term horizon, connectedness levels are generally weaker, and most net spillovers fluctuate around zero, suggesting that short-lived shocks have a limited impact on the system. Furthermore, the strongest net connectedness is concentrated at the extreme quantiles, especially in the total and long-term horizons, implying that tail market conditions intensify the transmission of shocks among FinTech, AI, and green bond markets. The pronounced spillovers observed during 2020–2021 also indicate that periods of heightened uncertainty strengthen interconnectedness across the system.



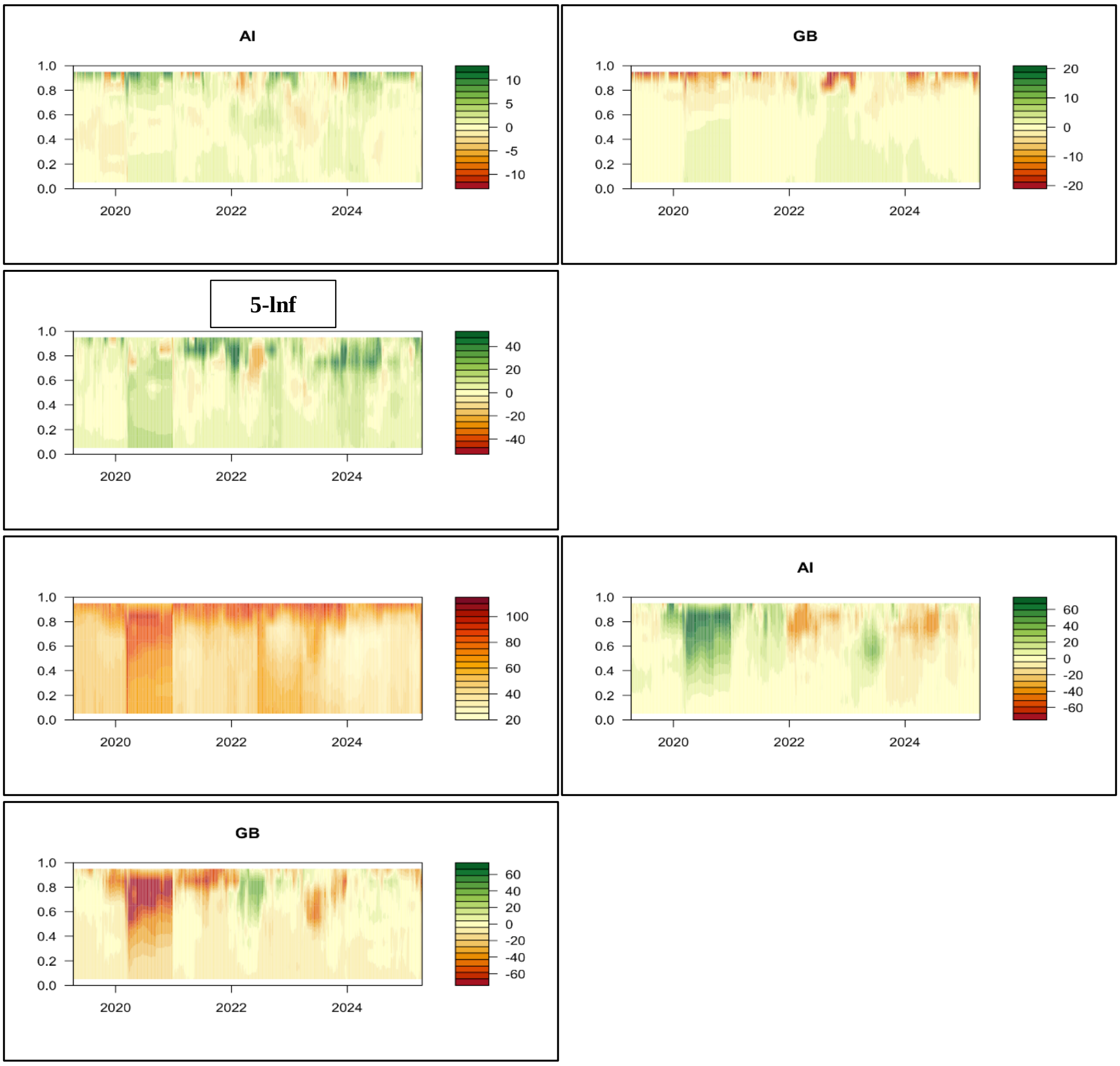


Figure 7. All Quantiles TCI and Net Connectedness Graph
Authors' own work

When the findings are evaluated as a whole, the strong conditional correlation and cross-volatility between FinTech and AI indices can be explained by the fact that these two markets are economically sensitive to common technology-driven factors. Both markets are influenced by common macro-financial channels such as growth expectations, pricing of technology stocks, Nasdaq movements, interest rates, risk appetite, and investor sentiment. In particular, rising expectations regarding AI and increased investment interest in digital finance applications may lead these two indices to react similarly to the same market news. This situation strengthens FinTech's role as a shock transmitter due to its more direct connection to the financial system. The literature emphasizes that the increasing integration of

FinTech firms with the financial system, while enhancing transaction speed and market connectivity, may also amplify systemic risk transmission channels. Similarly, while Li et al. (2020) note that risk transmission from FinTech firms intensifies particularly under adverse market conditions, Abakah et al. (2023) demonstrate that the relationship between FinTech, Bitcoin, and AI stocks varies depending on market conditions and that correlations strengthen during extreme price movements. From this perspective, the study's QDCC-GARCH and QFCON findings support the strengthening of the AI-FinTech link, particularly in the middle and upper quantiles. Additionally, Ha (2023)'s findings, which reveal that FinTech ETFs act as net shock transmitters while green bonds act as net shock absorbers, particularly during pandemic and war periods, align with this study's conclusion that FinTech is the primary net shock transmitter and green bonds are more of a shock absorber., a Furthermore, the fact that green bonds exhibit weaker transmission behavior is consistent with the results of previous studies that evaluate green bonds as portfolio diversification and risk-hedging instruments.

5. CONCLUSION AND POLICY IMPLICATIONS

This study investigates the volatility structures of FinTech, AI, and GB indices and the volatility spillover between these indices. This scope has determined that EGARCH (1,1) models are valid for FinTech and TGARCH(1,1) models for AI and GB indices regarding volatility prediction performance. According to the findings, the COVID-19 pandemic caused volatility clustering in the indices. According to EGARCH (1,1) estimates, FinTech volatility is affected by past shocks at a rate of 17.9% and by current shocks at 97.1%. Additionally, it was found that negative shocks are stronger than positive shocks and that shocks have lasting effects on volatility. According to the half-life (HL) calculation, the effect of a shock on the FinTech index lasts approximately 4.93 days. According to TGARCH (1,1) results for AI and GB indices, current volatility is primarily driven by current period shocks (86.8% for AI, 95.5% for GB). The green bond index was found to be more sensitive to current shocks. A leverage effect was observed in both indices, with positive shocks significantly impacting volatility. The leverage effect was most potent in the AI index. Half-life values were calculated as 6.64 days for AI and 6.61 days for green bonds, indicating that the most persistent effects of shocks are observed in the AI index. In conclusion, shocks lead to shorter-term effects in the FinTech index and longer-term effects in the AI and GB indices.

According to the CCC-TGARCH model, an increase in FinTech volatility increases AI and GB volatility; this indicates that the FinTech index is a shock transmitter, while the AI and GB indices are shock receivers. Additionally, volatility transmission from AI to FinTech and GB, and from GB to FinTech and AI, has been identified. In conclusion, it has been demonstrated that there is mutual volatility spillover between FinTech, AI, and GB indices, and that all three indices act as both shock propagators and shock absorbers. Furthermore, according to the findings, the impact of volatility spillover from the green bond index to FinTech and AI markets is limited. This suggests that the green bond market primarily acts as a shock absorber rather than a shock transmitter.

The QDCC-GARCH results indicate that the conditional correlations among the FinTech, AI, and green bond indices are not constant; rather, they vary depending on the time period and quantile level. The strongest and most stable dynamic correlation was observed between the AI and FinTech indices. This finding suggests that these two technology-driven markets are exposed to similar market conditions and shared risk factors. In contrast, the relationships between FinTech and green bonds, as well as between AI and green bonds, exhibit a more heterogeneous structure. QFCON findings also support these results by showing that shock transmission varies across quantiles and frequency bands. FinTech emerges as the most prominent net shock transmitter, particularly under adverse and high-volatility market conditions, while green bonds are mostly in a net shock-absorbing position. AI, however, plays a role that varies over time, acting as a shock transmitter in some periods and a shock absorber in others. The results also indicate that connectedness is stronger over the long term and at the extreme tails. This suggests that tail market conditions intensify volatility spillovers between technology-based and sustainable finance assets. These findings suggest that FinTech assets may play a significant role in risk transmission, while green bonds may offer diversification and risk-hedging benefits, though their safe-haven role may weaken during periods of systemic stress.

Based on the findings, specific policy implications can be drawn. First, the persistence and asymmetric structure of volatility shocks in the FinTech, AI, and green bond markets indicate a need for sector-specific monitoring mechanisms and preventive regulations to support financial stability. Since FinTech and AI markets are technology-driven and may be sensitive to macro-financial factors, regulatory authorities should closely monitor transmission channels arising from technology stock valuations, investor sentiment, interest rate changes, and speculative market behavior. Second, the strong volatility spillover between FinTech and AI indicates that investments in these sectors must be managed with a high degree of risk awareness, particularly during periods of market stress and negative news. Third, while the green bond market exhibits a relatively more shock-absorbing structure and offers diversification potential against FinTech and AI risks, it should not be regarded as a completely risk-free haven. The role of green bonds may change as intermarket connectivity increases during global crises. Therefore, investors should develop dynamic portfolio strategies that account for evolving correlations, quantile-specific risks, and short- and long-term spread patterns. Finally, policy frameworks supporting sustainable finance and technology-driven growth should be backed by risk-mitigating tools, transparency mechanisms, and confidence-building regulations aimed at reducing systemic fragility.

Future studies could expand on the current analysis by incorporating structural break tests into the model to determine the effects of major disruptive events, such as the COVID-19 pandemic, the Russia-Ukraine war, and the AI boom on volatility dynamics. Additionally, by comparing different regional or sectoral green bond indices, alternative AI-based assets, and various FinTech subsectors, it is possible to examine whether volatility diffusion patterns vary across markets. Furthermore, by expanding the scope to include green and technology-based asset groups, the effectiveness of hedging, optimal portfolio weights, and risk management strategies can be analyzed in greater detail using a dynamic portfolio approach.

REFERENCES

Abakah, Emmanuel J. A.-Tiwari, Aviral K.- Lee, Chi-Chuan- Ntow Gyamfi, Matthew (2023). “Quantile price convergence and spillover effects among Bitcoin, Fintech, and artificial intelligence stocks”. International Review of Finance, 23(1), 187-205. https://doi.org/10.1111/irfi.12393

Adebayo, T. S.- Özkan, O. (2024). “Evaluating the Role of Financial Globalization and Oil Consumption on Ecological Quality: A New Perspective from Quantile-on-Quantile Granger Causality”. Heliyon, 10(2), e24636. https://doi.org/10.1016/j.heliyon.2024.e24636

Adekoya, O. B.- Oliyide, Johnson A.- Saleem, O.- Adeoye, Habeeb A. (2022). “Asymmetric connectedness between Google-based investor attention and the fourth industrial revolution assets: The case of FinTech and Robotics & Artificial intelligence stocks". Technology in Society, 68, 101925. https://doi.org/10.1016/j.techsoc.2022.101925

Bollerslev, T. (1990). "Modelling the coherence in short-run nominal exchange rates: A multivariate generalized ARCH model". The Review of Economics and Statistics, 498-505. https://doi.org/10.2307/2109358

Bollerslev, T.- Engle, Robert F.- Wooldridge, Jeffrey M. (1988). "A capital asset pricing model with time-varying covariances". Journal of Political Economy, 96(1), 116-131. https://doi.org/10.1086/261527

Bollerslev, T. (1986). "Generalized autoregressive conditional heteroskedasticity". Journal of Econometrics, 31(3), 307-327. https://doi.org/10.1016/0304-4076(86)90063-1

Broock, William. A.- Scheinkman, Jose. A.- Dechert, W. D.- LeBaron, Blake. (1996). "A test for independence based on the correlation dimension". Econometric Reviews, *15*(3), 197-235. https://doi.org/10.1080/07474939608800353

Chatziantoniou, I., A.- Emmanuel J. A.- Gabauer, D. - Tiwari, Aviral K. (2022). "Quantile Time–Frequency Price Connectedness Between Green Bond, Green Equity, Sustainable Investments and Clean Energy Markets". Journal of Cleaner Production, 361, 132088. https://doi.org/10.1016/j.jclepro.2022.132088

Chen, H. (2023). "Fintech and investment risk of digital finance: mediating role of clean energy and green bonds through the dynamics of spill over". Environmental Science and Pollution Research, 30(34), 82286-82296. https://doi.org/10.1007/s11356-023-28181-w

Chen, Y.- Chiu, J.- Chung, H. (2022). "Givers or Receivers? Return and volatility spillovers between Fintech and the Traditional Financial Industry". Finance Research Letters, 46, 102458. https://doi.org/10.1016/j.frl.2021.102458

Dai, Z. (2023). "Exploring the synergies between digital finance and clean energy: a case study of green bond spillover effects". Environmental Science and Pollution Research, 30(44), 100188-100202. https://doi.org/10.1007/s11356-023-29205-1

Dickey, D. A.- Fuller, Wayne A. (1979). "Distribution of estimators for autoregressive time series with a unit root". Journal of the American Statistical Association 74:427–431. https://doi.org/10.1080/01621459.1979.10482531

El Khoury, R.- Nasrallah, N.- Hussainey, K.- Assaf, R. (2023). "Spillover analysis across FinTech, ESG, and renewable energy indices before and during the Russia–Ukraine war: International evidence". Journal of International Financial Management & Accounting, 34(2), 279-317. https://doi.org/10.1111/jifm.12179

Enders, Walter (2008). "Applied econometric time series". John Wiley & Sons.

Engle, R. F. (1982). “Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation”. Econometrica: Journal of the econometric society, 987-1007. https://doi.org/10.2307/1912773

Gabauer, D. (2020). “Volatility Impulse Response Analysis for DCC-GARCH Models: The Role of Volatility Transmission Mechanisms”. Journal of Forecasting, 39(5), 788–796. https://doi.org/10.1002/for.2658

Gharbi, O.- Trichilli, Y.- Boujelbéne, M.(2023). “Risk spillovers connectedness between the US Fintech industry VaR, behavioral biases and macroeconomic instability factors: COVID-19 implications”. China Finance Review International, 13(3), 410-443. https://doi.org/10.1108/CFRI-12-2022-0277

Glosten, L. R.- Jagannathan, R.- Runkle, D. E. (1993). “On the relation between the expected value and the volatility of the nominal excess return on stocks”. The Journal of Finance, 48(5), 1779-1801. https://doi.org/10.1111/j.1540-6261.1993.tb05128.x

Ha, Le T. (2023). “Dynamic connectedness between FinTech innovation and energy volatility during the war in time of pandemic”. Environmental Science and Pollution Research, 30(35), 83530-83544. https://doi.org/10.1007/s11356-023-28089-5

Hassan, M. Kabir- Hasan, M. Bokhtiar- Halim, Zairihan Abdul- Maroney, Neal- Rashid, M. Mamunur (2022). “Exploring the dynamic spillover of cryptocurrency environmental attention across the commodities, green bonds, and environment-related stocks”. The North American Journal of Economics and Finance, 61, 101700. https://doi.org/10.1016/j.najef.2022.101700

Huynh, Toan L. D.- Hille, E.- Nasir, M. A. (2020). “Diversification in the age of the 4th industrial revolution: The role of artificial intelligence, green bonds and cryptocurrencies”. Technological Forecasting and Social Change, 159, 120188. https://doi.org/10.1016/j.techfore.2020.120188

Jin, J.- Han, L.- Wu, L.- Zeng, H. (2020). “The hedging effect of green bonds on carbon market risk”. International Review of Financial Analysis, 71, 101509. https://doi.org/10.1016/j.irfa.2020.101509

Jovović, J.- Popović, S. (2025). “Investigating volatility spillovers: Connectedness between green bonds, conventional bonds, and energy markets”. Research in International Business and Finance, 76, 102850. https://doi.org/10.1016/j.ribaf.2025.102850

Khalfaoui, R.- Mefteh-W., Salma- D., Buhari- Ghosh, S. (2023). Extreme spillover effect of COVID-19 pandemic-related news and cryptocurrencies on green bond markets: A quantile connectedness analysis. International Review of Financial Analysis, 86, 102496. https://doi.org/10.1016/j.irfa.2023.102496

Li, J.- Li, J.- Zhu, X.- Yao, Y.- Casu, B. (2020). “Risk spillovers between FinTech and traditional financial institutions: Evidence from the US”. International Review of Financial Analysis, 71, 101544. https://doi.org/10.1016/j.irfa.2020.101544

Liu, M. (2022). “The driving forces of green bond market volatility and the response of the market to the COVID-19 pandemic”. Economic Analysis and Policy, 75, 288-309. https://doi.org/10.1016/j.eap.2022.05.012

Liu, N.- Liu, C.- Da, B.- Zhang, T.- Guan, F. (2021). “Dependence and risk spillovers between green bonds and clean energy markets”. Journal of Cleaner Production, 279, 123595. https://doi.org/10.1016/j.jclepro.2020.123595

Malik, F.- Ewing, B. T.- Payne, James E. (2005). “Measuring volatility persistence in the presence of sudden changes in the variance of Canadian stock returns”. Canadian Journal of Economics/Revue canadienne d'économique, 38, 1037-1056. https://doi.org/10.1111/j.0008-4085.2005.00315.x

Maneejuk, P.- Huang, W.- Yamaka, W. (2025). “Asymmetric volatility spillover effects from energy, agriculture, green bond, and financial market uncertainty on carbon market during major market crisis”. Energy Economics, 108430. https://doi.org/10.1016/j.eneco.2025.108430

Mensi, W.- Shafiullah, M.- Vo, Xuan V.- Kang, Sang H. (2022). “Spillovers and connectedness between green bond and stock markets in bearish and bullish market scenarios”. Finance Research Letters, 49, 103120. https://doi.org/10.1016/j.frl.2022.103120

Mensi, W.- Vo, Xuan V.- Ko, H. U.- Kang, S. H. (2023). “Frequency spillovers between green bonds, global factors and stock market before and during COVID-19 crisis”. Economic Analysis and Policy, 77, 558-580. https://doi.org/10.1016/j.eap.2022.12.010

Naifar, N. (2025). “Dynamic connectedness and portfolio strategies: Insights from fintech, robotics, renewable energy, and green bonds in China”. Journal of Climate Finance, 10, 100060. https://doi.org/10.1016/j.jclimf.2025.100060

Nelson, D. B. (1991). “Conditional heteroskedasticity in asset returns: A new approach”. Econometrica: Journal of the econometric society, 347-370. https://doi.org/10.2307/2938260

Park, D.- Park, J.- Ryu, D. (2020). “Volatility spillovers between equity and green bond markets”. Sustainability, 12(9), 3722. https://doi.org/10.3390/su12093722

Peng, G.- Ding, J.- Zhou, Z.- Zhu, L. (2023). “Measurement of spillover effect between green bond market and traditional bond market in China”. Green Finance, 5(4), 538. https://doi.org/10.3934/GF.2023021

Pham, L. (2016). “Is it risky to go green? A volatility analysis of the green bond market”. Journal of Sustainable Finance & Investment, 6(4), 263-291. https://doi.org/10.1080/20430795.2016.1237244

Phillips, P. C.- Perron, P. (1988). “Testing for a unit root in time series regression”. Biometrika, 75(2), 335-346. https://doi.org/10.1093/biomet/75.2.335

Reboredo, J. C. (2018). "Green bond and financial markets: Co-movement, diversification and price spillover effects". Energy Economics, 74, 38-50. https://doi.org/10.1016/j.eneco.2018.05.030

Shao, Y. H.- Yang, Y. H.- Zhou, W. X. (2025). "Dynamic spillovers and investment strategies across artificial intelligence ETFs, artificial intelligence tokens, and green markets". arXiv preprint arXiv:2503.01148. https://doi.org/10.48550/arXiv.2503.01148

Standard & Poor's (2025). Data & Analytics. https://www.spglobal.com

Tang, C.- Aruga, K.- Hu, Y. (2023). "The dynamic correlation and volatility spillover among green bonds, clean energy stock, and fossil fuel market". Sustainability, 15(8), 6586. https://doi.org/10.3390/su15086586

Tiwari, A. K.- Abakah, E. J. A.- Adekoya, O. B.- Hammoudeh, S. (2023). "What do we know about the price spillover between green bonds and Islamic stocks and stock market indices?". Global Finance Journal, 55, 100794. https://doi.org/10.1016/j.gfj.2022.100794

Umar, Z.- Hadhri, S.- Abakah, E. J. A.- Usman, M. – Umar, M. (2024). "Return and volatility spillovers among oil price shocks and international green bond markets". Research in International Business and Finance, 69, 102254. https://doi.org/10.1016/j.ribaf.2024.102254

Wang, K. H.- Wang, Z. S.- Yunis, M.- Kchouri, B. (2023). "Spillovers and connectedness among climate policy uncertainty, energy, green bond and carbon markets: A global perspective". Energy Economics, 128, 107170. https://doi.org/10.1016/j.eneco.2023.107170

Wen, S.- Li, J.- Huang, C.- Zhu, X. (2023). "Extreme risk spillovers among traditional financial and FinTech institutions: A complex network perspective". The Quarterly Review of Economics and Finance, 88, 190-202. https://doi.org/10.1016/j.qref.2023.01.005

Wu, R.- Qin, Z. (2024). "Asymmetric volatility spillovers among new energy, ESG, green bond and carbon markets". Energy, 292, 130504. https://doi.org/10.1016/j.energy.2024.130504

Xia, Y.- Ren, H.- L., Y.- Xia, J.- He, L.- Liu, N. (2022). "Forecasting green bond volatility via novel heterogeneous ensemble approaches". Expert Systems with Applications, 204, 117580. https://doi.org/10.1016/j.eswa.2022.117580

Yadav, M. P.- Pandey, A.- Taghizadeh-H., Farhad- Arya, V.- Mishra, N. (2023). "Volatility spillover of green bond with renewable energy and crypto market". Renewable Energy, 212, 928-939. https://doi.org/10.1016/j.renene.2023.05.056

Yousaf, I.- Ijaz, M. S.- Umar, M.- Li, Y. (2024). "Exploring volatility interconnections between AI tokens, AI stocks, and fossil fuel markets: evidence from time and frequency-based connectedness analysis". Energy Economics, 133, 107490. https://doi.org/10.1016/j.eneco.2024.107490

Yousaf, I.- Mensi, W.- Vo, X. Vinh- K., Sang H.(2024). "Dynamic spillovers and connectedness between crude oil and green bond markets". Resources Policy, 89, 104594. https://doi.org/10.1016/j.resourpol.2023.104594

Zhang, Y.- Umair, M. (2023). "Examining the interconnectedness of green finance: an analysis of dynamic spillover effects among green bonds, renewable energy, and carbon markets". Environmental Science and Pollution Research, 30(31), 77605-77621. https://doi.org/10.1007/s11356-023-27870-w

Zhao, M.- Park, H. (2024). "Quantile time-frequency spillovers among green bonds, cryptocurrencies, and conventional financial markets". International Review of Financial Analysis, 93, 103198. https://doi.org/10.1016/j.irfa.2024.103198

Zivot, E. (2009). "Practical Issues in the Analysis of Univariate GARCH Models". Springer Science and Business Media, Germany, 113–15. https://doi.org/10.1007/978-3-540-71297-8_5