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ORIGINAL RESEARCH

The Feature Importance of Quantile Connectedness among Islamic Sectoral Indices and Meme Assets

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Abstract

This study investigates the feature importance of return and volatility connectedness between Islamic sectoral indices and meme assets across quantiles. Using daily data from August 2020 to March 2024, we adopt a multistage approach combining the quantile extended joint connectedness framework, robust OLS regression, and tree-based machine learning of feature importance. The findings reveal that Islamic indices act as net return transmitters in bearish and bullish markets, while meme assets are net receivers; both are disconnected in normal conditions. In volatility spillovers, Islamic indices lead during bearish and normal markets, whereas meme assets dominate during bullish periods. Feature importance analysis shows that the global financial stress index is the most influential driver of return spillovers, while cyber-attacks emerge as the primary determinant of volatility spillovers. These findings highlight that spillover dynamics, and thus portfolio diversification benefits, vary significantly across market states and should be incorporated into risk-sensitive asset allocation strategies.

Keywords Islamic sectoral indices · Meme assets · Spillovers · Quantile connectedness · Feature analysis · Machine learning

JEL Classification G12 · G11 · G15 · G17 · C32

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1 Introduction

In the context of investment, digital assets such as meme assets[1] present a distinctive risk–return profile that appeals to investors seeking high-risk, high-reward opportunities (Elsayed et al., 2024). Empirical studies suggest that these assets can enhance portfolio optimization, particularly under turbulent market conditions (Aloosh et al., 2023). Anecdotally, during the COVID-19 market downturn, meme assets like Dogecoin and GameStop (GME) experienced outsized returns at times when traditional equities suffered severe losses. For instance, in early 2021, amid pandemic-induced volatility, GME surged over 1,700% within weeks, offering significant hedging potential for investors willing to tolerate elevated risk. Such episodes illustrate the unconventional diversification benefits meme assets may provide during systemic stress periods.

In contrast to meme assets, Islamic indices represent a stable and principled asset class in the digital era, guided by Sharia-compliant investment principles that prioritize ethics, financial stability, and long-term sustainability. Empirical evidence suggests that Islamic equity markets exhibit strong resilience during periods of market stress (Akhtar & Jahromi, 2017; Hasan et al., 2022; Mirza et al., 2022), providing a robust foundation for diversified portfolio construction (Braiek et al., 2022). Their crisis-resistant characteristics contribute to improved risk-adjusted returns and enhanced portfolio optimization, especially in turbulent market conditions (Abu-Alkheil et al., 2017; Braiek et al., 2022), making them a valuable tool for reducing overall portfolio risk.

The contrasting characteristics of meme assets and Islamic indices present a unique portfolio opportunity: pairing speculative, high-volatility assets with stable, Sharia-compliant equities may enhance diversification (Akhtar et al., 2023). Their divergent risk-return profiles and asymmetric spillovers, especially across market regimes (Iqbal et al., 2022), suggest that investors could balance short-term upside with long-term resilience. However, this potential hinges on whether a dynamic financial linkage exists. If connectedness is present, shocks in meme assets may transmit risk to Islamic markets, undermining their perceived stability. Changes in connectedness during volatile periods also inform whether Islamic assets maintain their safe-haven role and support adaptive allocation strategies.

More importantly it is crucial to identify the key factors (hereafter the features) that influence the spillover between meme assets and Islamic indices. The current body of knowledge (see Appendix 2) focus on revealing the dynamic connectedness of meme assets and Islamic index. However, this literature rarely investigates

[1] Meme assets include meme stocks and meme coins that got special attention in early 2021 due to social media hype on platforms such as Reddit, Twitter, and TikTok. For instance, GameStop (GME) was a struggling video game retailer, but in January 2021, its share price hit a record high of $347.51, with gains up to 1700% since December 2020. This is because retail investors joined their horses and executed strategies such as short squeezes and gamma squeezes based on information from social media pages "WallStreetBets." Afterwards, this triggered a wider interest of retail investors in other tumbling companies' stocks like AMC Entertainment (AMC), BlackBerry (BB), and Nokia (NOK), among others. A similar picture was evident for the meme coins market, such as Dogecoin (DOGE) and Shiba Inu (SHIB), with massive gains of around 12,000% and 5,130,000%, respectively. For full GameStop story see: https://www.nytimes.com/2021/01/27/business/gamestop-wall-street-bets.html.

what enhances the intensity of these spillovers, and even less, *which* factor is most influential. Nonetheless, addressing this gap is essential for both academic inquiry and practical application. Knowing the most important features of spillover dynamics offers three core benefits. First, it allows investors and policymakers to anticipate and mitigate systemic risk by focusing on the dominant contagion channels. Second, it informs the development of adaptive asset allocation and risk management strategies that respond to evolving market conditions. Third, it advances the methodological frontier by introducing feature-based analysis into the study of financial interconnectedness.

To that end, we implement a tree-based machine learning framework to predict dynamic connectedness and identify the most influential predictors. Following the literature (e.g., Baur & Lucey, 2010; Apostolakis & Papadopoulos, 2015; Prasad et al., 2018; Corbet et al., 2019; Boateng et al., 2021; Khalfaoui et al., 2023; Mensi et al., 2024; Elsayed et al., 2024), we include financial stress, oil price volatility, cyberattacks, bitcoin sentiment, economic policy uncertainty, volatility index, and stock market fluctuations as the important features for the function of dynamic connectedness. The role of the tree-based machine learning model here is to predict dynamic connectedness and then exploring the most influential features on that prediction. Therefore, this study addresses these gaps by posing several key questions: Does the connectedness between meme assets and Islamic indices persist under extreme market conditions? Are spillover effects symmetric across bearish and bullish states? Which asset class acts as the dominant transmitter or receiver? Which features contribute to strengthening or weakening this dynamic connection? Lastly, which factor is most crucial for understanding these connections and spillover effects?

We answer those research questions by using multistage approach. First, we investigate the dynamic return and volatility spillovers between Islamic sectoral indices and meme assets using the quantile extended joint connectedness framework proposed by Cunado et al. (2023). This method, applied to a daily dataset spanning August 1, 2020, to March 21, 2024, enables us to capture quantile-dependent propagation patterns across market conditions. To visualize direct interlinkages, we also present a network connectedness plot.

Having established the existence and structure of dynamic connectedness, we then identify the key features influencing the total spillover index. To this end, we employ tree-based machine learning techniques, Feature Importance and Permutation Importance, to determine which factors most significantly drive the spillovers. This final stage allows us to uncover the most influential determinants of connectedness across different market regimes.

Our key findings are as follows. First, we find stronger return spillover contributions among meme stocks, meme coins and Islamic sectors in upper and lower quantiles. Most Islamic sectors are net transmitters in those quantiles, whereas the meme assets are net recipients. This suggests that Islamic sector indices are not decoupled from meme assets during stress periods and highlights the need for stricter Sharia screening criteria. However, meme assets and Islamic sectors (i.e., oil and gas, utilities, and telecom) have relatively lower return contributions in the middle quantile, which suggests the value of adding meme assets to Islamic sector portfolios. We also find lesser total volatility spillovers in lower and median quantiles but significantly

higher in the upper quantile. Interestingly, SHIB and AMC are major net volatility spillovers above the 60th quantile toward other markets in extreme market conditions. In addition, the time-varying return and volatility spillover rose significantly at specific intervals during February 2022 towards the end of our sample period. Moreover, we noticed stronger spillovers among Islamic indices that question the portfolio hedging opportunities, mainly for faith-based investors. For instance, the Islamic oil and gas sector is a net returns transmitter towards financials and consumer services sectors in bullish market conditions. Similarly, Islamic consumer services and utilities sectors are net volatility receivers, while other sectors are net transmitters during bearing market conditions.

Another innovation of this study is the machine learning feature analysis, which is to assess the most important factor in determining connectedness. Using four different machine learning-based predictive models (decision tree, random forest, light gradient boosting, and XGBoost), our findings highlight global financial stress as the primary determinant of return spillovers across bearish, normal, and bullish markets. In contrast, volatility spillovers are primarily shaped by cyber-attacks. These consistent conclusions emphasize the impactful nature of global financial stress on investor sentiment and market behavior, driving interconnected price movements. Equally, volatility spillovers, reflecting price fluctuation magnitude, are less vulnerable to such influences. Cyber-attacks, disrupting market stability and heightening uncertainty, manifest in irregular price fluctuations, thereby influencing volatility spillovers among Islamic index and meme assets.

This study's contributions are at least threefold. First, we empirically investigate the return and volatility spillovers between meme stock, meme coins, and Islamic sectoral indices. The current literature on Islamic stock markets focuses on exploiting remarkable resilience during crises (Akhtar & Jahromi, 2017; Hasan et al., 2022; Mirza et al., 2022; Arfaoui & Raggad, 2023). Other studies (For instance, Al-Khazali et al., 2014, Ali et al., 2018; Foglie & Panetta, 2020) extensively surmise that Islamic indexes outperform conventional peers during crisis regimes, with a recent focus on connectedness between Islamic indices and other highly-volatile asset classes (e.g., Mensi et al., 2020; Ahmed, 2021; Chkili et al., 2021; Ali et al., 2022; Yousaf & Yarovaya, 2022; Ali et al., 2024; Ashraf et al., 2023). They provided inconclusive evidence of return (volatility) spillover connectedness between them which has implications for portfolio diversification. Therefore, this study enriches the literature by exploring the spillover among steadily stable markets like Islamic indices and highly volatile assets like meme assets. To the best of our knowledge, this is the first attempt in the literature to exploit the dynamic connectedness between Islamic indices and meme assets.

Secondly, we explore the return and volatility spillovers in the Islamic sector levels because existing literature (mentioned above or referred to in Appendix 2) focused on market levels. On the other hand, amid attempts (i.e., Yousaf & Yarovaya, 2022; Elsayed et al., 2024) studied the connectedness between meme assets (crypto assets) and conventional sectors but overlooked Islamic sectors. The sectoral level analysis is because investors have differing performance expectations for various sectors, which can lead to varying levels of sectoral return and volatility transmissions (Prasad et al., 2018). By analyzing different sectors, investors can bet-

ter understand the impact of these transmissions on their portfolio, and adjust their sectoral exposure based on their risk preferences (Khoury et al., 2025). Moreover, the sectoral-level analysis provides comprehensive insights into specific sectors and their connectedness with meme assets. These insights are crucial in making informed decisions regarding portfolio allocation, risk management, and investment strategy development, and can greatly enhance the effectiveness of your investment approach.

Lastly, this study takes a step further by identifying the most crucial spillover determinants through machine learning feature analysis. The current literature on spillover emphasizes dynamic connectedness, and little is known about the determinant (see Appendix 2). We extend the study by using feature analysis, not only examining the determinants but also selecting the relative importance features. It is done by using a machine learning predictive model under the feature importance and permutation importance approaches. The aim is to assess the most important factor for the returns and volatility spillover prediction. This insight can be invaluable for portfolio managers and investors, facilitating a deeper comprehension of interconnected asset classes, refining risk management strategies, enhancing market efficiency, and guiding regulatory decisions.

The remainder of this paper is organized as follows: Section 2 presents the literature review, followed by methods and data in Section 3. The empirical findings and their discussion are in Section 4. Lastly, Section 5 concludes this research and provides valuable implications.

2 Literature Review

The study of spillover effects between Islamic and conventional financial markets has grown significantly in recent years, shedding light on market interdependence and the diversification potential offered by Islamic finance. For instance, Ajmi et al. (2014) challenged the notion of market decoupling by demonstrating significant linear and nonlinear causal links between Islamic and conventional stock markets. Their findings indicated that Islamic markets are not as isolated as previously believed and that their sensitivity to interest rate changes limits their potential for diversification. In a similar vein, Majdoub et al. (2016) identified long-run linkages between Islamic and conventional stock indices except the UK, highlighting the significant correlation between Islamic and conventional equity markets, which weakens the diversification benefits of Islamic indices. Likewise, Shahzad et al. (2017) revealed strong return and volatility spillovers between Islamic and conventional markets, suggesting that Islamic equities are susceptible to the same global shocks, thus limiting their role in risk diversification and hedging. This finding was supported by Ben Rejeb and Arfaoui (2019), who found that while Islamic stock indices were more informationally efficient, they exhibited higher volatility than conventional markets and were not immune to the global financial crisis, thus challenging the notion of superior stability in Islamic finance during financial turmoil.

The impact of the crisis periods on Islamic and conventional markets was another focal point for recent studies. For example, Hasan et al. (2021) explored how both markets reacted during the pandemic, finding identical volatility patterns and strong

co-movement, thus refuting the decoupling hypothesis once again. Their results suggested that the Shariah screening process did not protect Islamic markets from the financial crisis, further questioning the idea of Islamic stocks as safe havens during economic turmoil. Bahloul and Khemakhem (2021) expanded the analysis of Islamic markets' connectedness by investigating their relationship with commodity markets, specifically oil. Their study revealed that commodities acted as significant sources of shocks to Islamic stock markets, especially during the COVID-19 crisis, with oil prices showing strong spillover effects. This finding highlighted the fact that the Islamic stock market is more of a net recipient of spillovers than a transmitter, a conclusion that challenges traditional assumptions about the diversification benefits of Islamic financial markets. Moreover, Yarovaya et al. (2021) assessed the spillover effects between Islamic and conventional stock markets during the COVID-19 pandemic. They found that Islamic bonds (Sukuk) exhibited safe-haven properties during the crisis, while conventional stock markets became more strongly interconnected with Islamic markets. Their work also identified oil and gold as key drivers of these spillovers, highlighting their importance in the Islamic finance landscape during periods of global financial instability.

In a more recent study, Mezghani and Abbes (2023) found that financial market connectedness in GCC countries rose during major crises, with oil acting as a net shock receiver in 2014 and during COVID-19. Islamic and conventional stock markets emerged as key shock transmitters, while oil's weak linkage with stocks during COVID-19 provided diversification benefits. Similarly, Husain et al. (2024) examined the interconnectedness of European financial markets with green and Islamic instruments from 2015 to 2023 and challenged the decoupling hypothesis, showing that both sukuk and green bonds exhibited resilience during crises. Complementing this, with a little focus on sector level, Mensi et al. (2017) assessed the efficiency of Islamic stock markets using sectoral indices and found greater inefficiencies in the short term, especially post-crisis, underscoring the need for dynamic asset allocation. Similarly, Al-Yahyaee et al. (2020) revealed that sectoral co-movements between Islamic and conventional indices varied across crises, with industrials and utilities offering stronger diversification benefits, while sectors like consumer goods and energy showed limited hedging potential.

While research on Islamic financial markets has matured, there is a growing interest in exploring the interconnectedness between Islamic indices and more speculative assets, such as meme stocks and cryptocurrencies. The increasing popularity of meme assets has prompted several studies to assess their role in financial market dynamics, particularly their spillover effects on conventional and Islamic financial markets. Yousaf and Yarovaya (2022) examined the spillovers between Islamic gold-backed cryptocurrencies (e.g., Onegram and X8X) and global Islamic equity sectors during the pre-COVID and COVID-19 periods. Their findings showed that the pandemic intensified the spillover effects between cryptocurrencies and Islamic stock markets. Notably, they discovered that investors could reduce risk by increasing their allocation to Onegram, a gold-backed cryptocurrency, although hedging costs increased during the COVID-19 period, suggesting that meme assets may offer diversification benefits at a higher cost during times of crisis.

The interconnectedness of meme assets, such as meme stocks and meme coins, with broader financial markets has also been explored by Elsayed et al. (2024), who examined the spillover effects and network connectedness between meme coins, meme stocks, and sectoral markets across different investment horizons. They reported that meme assets were primarily net receivers of shocks, especially in the short-term, with meme stocks and meme coins showing limited correlation with sectoral markets. Global risk factors, such as financial crises and geopolitical tensions, were found to reduce the overall dynamic connectedness across time horizons, suggesting that the speculative nature of meme assets may decouple them from traditional market movements under certain conditions.

Additionally, Aharon et al. (2024) explored the interconnectedness between real estate cryptocurrencies and real estate stocks. They highlighted a strong dependence between the two at the extremes of the return distribution, while weaker correlation was observed in the median quantile. This study showed the limited diversification benefits of meme assets during extreme market conditions, calling for investors to employ careful risk management strategies when dealing with such speculative assets. In contrast to these findings, Ghaemi Asl et al. (2024) focused on the role of ESG factors in shaping the spillover dynamics between Islamic and conventional stock markets. Their study revealed that time-varying spillovers between ESG factors and sectoral indices were particularly pronounced during the COVID-19 crisis, with bidirectional and asymmetric effects. This highlighted the growing importance of ESG factors in the interconnectedness of Islamic and conventional markets, especially in the context of global economic shocks.

The existing literature provides valuable insights into the spillover dynamics between Islamic and conventional financial markets, commodities, and, more recently, cryptocurrencies. However, several critical gaps remain that limit our holistic understanding of interconnectedness in today's rapidly evolving financial landscape. First, while prior studies (e.g., Ajmi et al., 2014; Majdoub et al., 2016; Shahzad et al., 2017; Ben Rejeb & Arfaoui, 2019; Yarovaya et al., 2021; Mezghani & Abbes, 2023; Husain et al., 2024) have explored linkages between Islamic and conventional assets, none have examined the intersection between Islamic financial markets and speculative meme assets, an emergent and highly volatile asset class that has gained prominence in recent years. This omission is significant given the potential for such assets to disrupt conventional portfolio diversification logic, particularly in the context of faith-based or ethical investing.

Second, while the spillover literature increasingly recognizes the importance of sector-level analysis, Islamic financial markets remain largely understudied in this regard (Mensi et al., 2017; Al-Yahyaee et al., 2020). Most existing studies focus on aggregate indices, overlooking sector-specific dynamics that could provide more comprehensive insights into risk transmission and hedging potential. The recent work by Elsayed et al. (2024), for instance, analyzed spillovers between meme assets and conventional sectoral markets but entirely ignored Islamic sectoral indices. As such, the sectoral transmission mechanisms within Islamic markets, especially in the context of interactions with speculative assets, remain an open question.

Third, although studies (e.g., Yarovaya et al., 2021; Ghaemi Asl et al., 2024) have proposed theoretical determinants of spillovers (e.g., market volatility, macroeco-

nomic uncertainty, and geopolitical risk), there is a notable lack of empirical work that systematically quantifies the relative importance of these factors using advanced analytical tools. To date, machine learning models have been underutilized in the context of Islamic sectoral indices, despite their capacity to uncover complex, nonlinear relationships and to rank spillover determinants under different market conditions.

Therefore, this study addresses these research gaps by investigating, for the first time, the spillover dynamics between Islamic financial markets and meme assets and conducting a sector-level analysis of Islamic indices to identify heterogeneity in spillover patterns. Also, we employ machine learning algorithms (decision trees, random forest, lightGBM, and XGBoost) to assess the relative importance of various spillover determinants. By doing so, this study contributes novel empirical evidence that enhances our understanding of how Islamic and speculative markets interact, offering actionable insights for portfolio diversification, ethical investing, and systemic risk management in the post-pandemic era.

3 Methodology & Data

3.1 Quantile Extended Joint Connectedness Approach

We employ the quantile extended joint connectedness approach (QEJC) proposed by Cunado et al. (2023) to examine the return and volatility transmission mechanisms between meme assets and Islamic sectoral indices across various market conditions. This approach extends the quantile vector autoregression (QVAR) connectedness framework of Ando et al. (2022) and Chatziantoniou et al. (2021), while also incorporating the joint connectedness normalization enhancements introduced by Balcilar et al. (2021).

Our choice of QEJC over conventional models such as BEKK-GARCH, DCC-GARCH, and TVP-VAR is motivated by several methodological advantages. First, QVAR models are inherently more robust to outliers and non-normality than standard VAR or GARCH-type models (Kyriazis & Corbet, 2024), properties that are particularly relevant when analyzing speculative assets like meme coins and stocks, which often exhibit extreme volatility and heavy tails. Second, the quantile-based structure allows us to capture asymmetric dynamics and tail-specific spillover effects (e.g., during bearish or bullish market extremes), which traditional mean-based models may overlook (Ando et al., 2022). This provides a more comprehensive understanding of systemic risk, especially under stress scenarios. Moreover, the extended joint connectedness component of this method improves the standard GFEVD by ensuring a consistent and scale-independent normalization of spillover measures, which enhances comparability across quantiles and between return and volatility connectedness structures (Balcilar et al., 2021). This is particularly valuable for practitioners seeking accurate systemic risk assessments and for policymakers aiming to design targeted interventions.

The quantile and extended joint connectedness approaches have gained considerable traction in recent empirical literature, highlighting their methodological robustness and relevance for analyzing financial market interdependencies. For instance,

Bouri et al. (2021) employed this framework to examine connectedness among major cryptocurrencies, while Xia et al. (2022) applied it to investigate return and volatility spillovers between non-fungible tokens (NFTs) and traditional asset classes. Cunado et al. (2023) used it to assess dynamic spillovers across realized volatilities of precious metals and oil. Similarly, Yousaf et al. (2023) explored interconnectedness among meme tokens, meme stocks, and broader financial assets. Kyriazis and Corbet (2024) utilized the approach to study linkages between financial and banking assets during black swan events, and Cao and Xie (2024) applied it to capture extreme risk spillovers between energy and carbon markets. These diverse applications highlight the model's capacity to capture heterogeneous transmission mechanisms across assets, especially under varying market regimes and tail-risk scenarios.

We will begin by estimating quantile vector autoregression, QVAR (p) that can be represented as follows:

$$y_t = \mu\ (\tau\ ) + \sum\nolimits_{j=1}^{p} \Phi_{\ j}\ (\tau\ )\, y_{t-j} + \mu_{\ t}\ (\tau\ ) \tag{1}$$

where is τ quantile level, y_t and y_{t-j} are $K \times 1$ dimensional exogenous variable vector, p is the lag order of the QVAR model, $\Phi_{\ j}$ is the $K \times K$ dimensional QVAR coefficient matrix, $\mu_{\ t}\ (\tau\ )$ shows the $K \times 1$ dimensional error vector. To convert QVAR(p) to its QVMA (∞) form, we can apply World's theorem.

$$y_t = \mu\ (\tau\ ) + \sum\nolimits_{j=1}^{p} \Phi_{\ j}\ (\tau\ )\, y_{t-j} + \mu_{\ t}\ (\tau\ ) = \mu\ (\tau\ ) + \sum\nolimits_{j=1}^{\infty} \mathrm{A}_i\ (\tau\ )\, \mu_{\ t-i}\ (\tau\ ) \tag{2}$$

In the next stage, we compute the H-step ahead Generalized Forecast Error Variance Decomposition (GFEVD) as described by Pesaran and Shin (1998). This analytical process clearly showcases the subsequent impact of a shock in series j on series c, given below:

$$\psi_{\ ij}^{\ gen} = \frac{\sum\ (\tau\ )_{ij}^{-1} \sum_{h=0}^{H-1} \left(e_i' A_h\ (\tau\ ) \sum\ \tau\ e_j \right)^2}{\sum_{h=0}^{H-1} \left(e_i' A_h\ (\tau\ ) \sum\ (\tau\ )'\, e_i \right)^2} \tag{3}$$

$$gSOT_{ij}\ (H) = \frac{\psi_{\ ij}^{\ gen}\ (H)}{\sum_{j=1}^{K} \varphi_{\ ij}^{\ gen}\ (H)} \tag{4}$$

Moreover, we can calculate the total directional connectedness from all other variables to series i and the total directional connectedness from series i to all other variables. This calculation helps us understand how much the network influences series i and how much series i influences the rest of the variables in the network, presented as follows:

$$S_{i \leftarrow \bullet}^{gen,from}\ (H) = \sum\nolimits_{j=1, i \neq j}^{K} gSOT_{ij}\ (H) \tag{5}$$

$$S_{i\rightarrow\bullet}^{gen,to}(H)=\sum_{j=1,i\neq j}^{K}gSOT_{ji}(H) \tag{6}$$

The net directional connectedness of series i can be determined by finding the difference between the TO and FROM connectedness measures of the series. This value represents the net influence that series i has on the network. This value can be calculated as follows:

$$S_{i}^{gen,net}(H)=S_{i\rightarrow\bullet}^{gen,to}(H)-S_{i\leftarrow\bullet}^{gen,from}(H) \tag{7}$$

If $S_{i}^{gen,net}(H)>0\,(S_{i}^{gen,net}(H)<0)$, the series i is more driven by others than influencing them which makes it a net transmitter or receiver of shocks. The Total Connectedness Index (TCI) is the core of the connectedness framework that shows the level of network interconnectedness and market risk. The TCI is calculated by averaging the total directional connectedness from (to) others, given as follows:

$$gSOI(H)=\frac{1}{K}\sum_{i=1}^{K}S_{i\leftarrow\bullet}^{gen,from}(H)=\frac{1}{K}\sum_{i=1}^{K}S_{i\rightarrow\bullet}^{gen,to}(H) \tag{8}$$

When the TCI value is high, the market risk is also high, and vice versa. Furthermore, the QVAR connectedness combined with the extended joint connectedness technique. This process can be summed up as follows:

$$\xi_{t}(H)=y_{t+H}-E(y_{t+H}|y_{t},y_{t-1},\dots)=\sum_{h=0}^{H-1}A_{h}\varepsilon_{t}+H-h \tag{9}$$

$$E\left(\xi_{t}(H)\,\xi_{t}^{'}(H)\right)=A_{h}\Sigma\,A_{h}^{'} \tag{10}$$

$$\begin{aligned}&S_{i\leftarrow\bullet}^{gen,from}(H)\\&=\frac{E\left(\xi_{i,t}^{2}(H)\right)-E\left[\xi_{i,t}(H)-E\left(\xi_{i,t}(H)\right)|\varepsilon_{\forall\neq i,t+1},\dots,\varepsilon_{\forall\neq i,t+1+H}\right]^{2}}{E\left(\xi_{i,t}^{2}(H)\right)}\\&=\frac{E\sum_{h=0}^{H-1}e_{i}A_{h}\sum M_{i}\left(M_{i}\sum M_{i}^{'}\right)^{-1}M_{i}\sum A_{h}^{'}e_{j}}{\sum_{h=0}^{H-1}e_{i}A_{h}(\tau)\sum A_{h}^{'}e_{i}}\end{aligned} \tag{11}$$

where M_i is $K\times K-1$ rectangular matrix and $\varepsilon_{\forall\neq i,t+1}$ denotes the $K-1$ dimensional vector of shocks at time $t+1$ for all series except series i. In addition, to compute the joint total connectedness index, we follow the steps below:

$$jSOI(H)=\frac{1}{K}\sum_{i=1}^{K}S_{i\leftarrow\bullet}^{jnt,from}(H) \tag{12}$$

To link $gSOT$ and $jSOT$, we use multiple factors that are important extensions of Balcilar et al. (2021) and utilized by Cunado et al. (2023) as follows:

$$\lambda_{t}(H) = \frac{S_{i\leftarrow\bullet}^{jnt,from}(H)}{S_{i\leftarrow\bullet}^{gen,from}(H)} \tag{13}$$

$$jSOT_{ij}(H) = \lambda_{i} gSOT_{ij}(H) \tag{14}$$

This equality can calculate directional connectedness from variable i a to all others, as well as net total and pairwise directional connectedness:

$$S_{i\rightarrow\bullet}^{jnt,to}(H) = \sum\nolimits_{j=1,i\neq j}^{K} jSOT_{ji}(H) \tag{15}$$

$$S_{i}^{jnt,net}(H) = S_{i\rightarrow\bullet}^{jnt,to}(H) - S_{i\leftarrow\bullet}^{jnt,from}(H) \tag{16}$$

$$S_{ij}^{jnt,net}(H) = jSOT_{ji}^{jnt,to}(H) - jSOT_{ij}^{jnt,from}(H) \tag{17}$$

3.2 Machine Learning Regression Model and Feature Analysis

This study aims to identify the most important drivers of dynamic connectedness between Islamic sectoral indices and meme assets, a gap largely overlooked in the literature. While prior research documents the presence of spillover effects (e.g., Shahzad et al., 2017; Ben Rejeb & Arfaoui, 2019; Yarovaya et al., 2021; Mezghani & Abbes, 2023; Husain et al., 2024), few studies explore their determinants (Boateng et al., 2021; Mensi et al., 2024; Elsayed et al., 2024; Assaf et al., 2025), and virtually none evaluate the relative importance of these drivers. We address this gap by applying a tree-based machine learning model to assess feature importance. This approach offers several advantages: it captures nonlinear and interactive effects common in financial networks, handles multicollinearity without imposing parametric constraints, and produces interpretable rankings of predictor relevance. This allows us to systematically quantify which factors most strongly influence spillover intensity across varying market regimes.

The literature on tree-based machine learning highlights several key models for feature importance analysis, including Decision Trees, Random Forests, Gradient Boosting, and XGBoost. In this section, we outline each model and its corresponding evaluation metrics. Furthermore, we conduct two complementary feature importance analyses to identify the most influential factors across models, ensuring robustness in the selection of key spillover determinants.

3.2.1 Decision Tree

Decision Trees (DT) are foundational in machine learning for their simplicity and interpretability. Introduced by Quinlan (1986), DTs represent decision-making through a tree-like structure. Despite their interpretability, DTs may overfit noisy data. However, they serve as benchmarks for more complex models. DTs remain valuable for understanding baseline performance in predictive tasks. However, they may struggle with complex relationships and require optimization techniques to con-

trol model complexity. Despite limitations, DTs provide a straightforward approach to decision-making and serve as an essential steppingstone in machine learning. The DT function is as follows.

$$Y_t = f_x \tag{18}$$

Note that Y_t is the predicted value for a given input vector x. f_x represents the function that determines the predicted value by traversing the decision tree based on the features in x.

3.2.2 Random Forest

Recent finance literature highlights the effectiveness of random forest regression (RF) in various economic and financial contexts (Krauss et al., 2017; Loureiro et al., 2018; Mercadier & Lardy, 2019). RF, a tree-based regression method, has attracted attention due to its robust performance compared to traditional models, as emphasized by Babar et al. (2020). Proposed by Breiman (2001), RF operates as an ensemble learning framework that leverages a multitude of regression trees. It can be seen as an extended version of the decision tree algorithm, offering improved predictive power and generalization capabilities. RF generates diverse models by randomly sampling feature subgroups for each decision tree. This process, facilitated by bootstrap sampling, involves creating a random subset of each base tree model and trimming linear nodes from the same sample. After the training process, the predicted values of total spillover are expressed as follows:

$$Y_t = \frac{1}{T} \sum {}^{T}_{h=1} l_k\,(x) \tag{19}$$

Note that each tree in the random forest ensemble is denoted as $l_k\,(x)$, represents a separate learner, with (x) being the vector containing the input values for T variables. These trees are constructed using binary recursive partitioning, where at each node, the dataset is divided into two subsets based on a chosen feature and threshold value. This recursive splitting process continues until a stopping criterion is reached, forming a hierarchical structure of binary decisions within each tree.

3.2.3 Light Gradient Boost Model (GBM)

Light gradient boosting machine (GBM) is an innovative framework in gradient boosting introduced by Ke et al. (2017), utilizing gradient-based one-side sampling to determine split points by evaluating variance gain. Within the GBM algorithm, two distinctive methods are incorporated: gradient-based one-side sampling and exclusive feature bundling, as outlined by Sun et al. (2021). In contrast to traditional random forest (RF) algorithms, GBM employs a different approach to decision-making, focusing on gradient-based optimization rather than random sampling. This results in a more efficient and precise splitting process, which is particularly advantageous for large-scale datasets with numerous features. Additionally, in predictive regres-

sion modelling, GBM often outperforms RF due to its ability to handle complex relationships and interactions within the data more effectively. Its gradient-based approach tends to produce more accurate predictions, especially in scenarios with high-dimensional feature spaces or nonlinear relationships. The estimated function of GBM integrates some T regression trees and is defined as follows:

$$Y_t = \sum {}^{T}_{h=1} f_t\left(x\right) \tag{20}$$

Note that $f_t\left(x\right)$ is the regression tree.

3.2.4 eXtreme Gradient Boosting Model (XGBoost)

XGBoost has attracted attention in finance literature as a cutting-edge predictive model, finding applications in various domains such as credit scoring (Jiang et al., 2019), forecasting financial distress (Rahman & Zhu, 2024), predicting stock prices (Wang & Zhu, 2023), and estimating housing prices (Zaki et al., 2022). Developed by Chen and Guestrin (2016), the XGBoost algorithm builds upon the boosting model proposed by Friedman (2001). XGBoost employs normalization in its objective function to optimize the learning process, mitigate overfitting, and reduce model complexity. This ensemble model efficiently combines decision trees to enhance predictive performance beyond what individual techniques can achieve alone. However, to optimize model performance and address overfitting concerns, careful adjustment of several parameters in XGBoost is necessary. Cross-validation techniques are commonly employed to identify the optimal parameter combination, with our study utilizing tenfold cross-validation for parameter tuning. We also utilize hyperparameters. Following Mo et al. (2019), the output function is calculated as follows.

$$\widehat{Y}_i^T = \sum {}^{T}_{k=1} f_k\left(x_i\right) = \widehat{Y}_i^{T-1} + f_T\left(x_i\right) \tag{21}$$

Note that $\widehat{Y}_i^{T-1}$ is the generated tree, $f_T\left(x_i\right)$ is the newly created tree model. T is the total number of tree models.

3.2.5 Evaluation Metrics

This research evaluates the forecast performance of four machine learning models using four common evaluation metrics. These metrics include the root mean square error (RMSE), mean square error (MSE), mean absolute error (MAE), and coefficient of determination (R2). RMSE measures the average deviation between predicted and actual values, while MSE calculates the average squared differences. MAE provides the average magnitude of errors, and R2 indicates the proportion of variance in the target variable explained by the model. By analyzing these metrics, this study aims to assess the accuracy and reliability of the machine learning models in forecasting tasks.

3.2.6 Feature Analysis: Feature Importance

Feature Importance (FI) is a method used in machine learning to quantify the significance of each feature in predicting the target variable. It provides insights into which features contribute the most to the model's predictive performance and helps prioritize the most relevant variables for further analysis and decision-making (Meyer et al., 2014; Ding et al., 2023). The popular scikit-learn library of Python provides functionality for calculating feature importance in machine learning models. Specifically, Scikit-learn offers various algorithms and methods for assessing feature importance, depending on the type of model being used. For example, the feature importance attribute is available in decision tree-based models such as decision trees, random forest, gradient boosting machine (GBM), and XGBoost to access feature importance scores.

FI is typically calculated based on the contribution of each feature to the model's performance metrics (Meyer et al., 2014; Ding et al., 2023). Features that result in the largest decrease in performance when removed are considered more important. Interpreting the results of feature importance involves assessing the relative importance scores assigned to each feature. Higher importance scores strongly influence the model's predictions, suggesting that these features are more critical for understanding the target variable or, in our study, the spillover.

3.2.7 Feature Analysis: Permutation Importance

Permutation Importance (PI) assesses the Importance of each feature by measuring the impact of randomly shuffling its values while keeping other features unchanged (Altmann et al., 2010; Musolf et al., 2022). Unlike FI, which directly measures feature contribution, PI evaluates how changes in feature values affect model predictions (Altmann et al., 2010; Musolf et al., 2022), providing a more comprehensive understanding of feature importance.

By considering feature perturbation, PI captures nonlinear and complex relationships between features and the target variable, enhancing the understanding of feature importance compared to FI alone. In Python, the Scikit-learn library provides functionality for calculating Permutation Importance using the permutation importance function. Interpreting PI results involves assessing the relative importance scores assigned to each feature, like FI. Higher scores indicate stronger feature influence.

3.3 Data Description

As we focus on examining spillover effects within Islamic sectoral indices and meme assets, we gather data from various sources. First, the daily Islamic sectoral index prices, consisting of 10 sectors, namely, Basic Materials, Information Technology, Consumer Services, Consumer Goods, Financials, Healthcare, Industrials, Oil & Gas, Utilities, and Telecommunications, are collected from DataStream. We consider Dow Jones a proxy for our Islamic indices (Yilmaz et al., 2015), as they employ Sha-

riah Supervisory Board-established screenings, i.e., sector-based, and accounting-based leverage compliance screens, to construct Islamic indices[2].

Second, Following the approach of Elsayed et al. (2024), we select two meme coins (DOGE and SHIB) and two meme stocks (AMC and GME). These assets are selected due to their prominence, sustained retail investor attention, and the significant role they have played in the meme asset phenomenon. For instance, DOGE and SHIB are among the most widely traded and socially discussed meme cryptocurrencies, frequently cited as symbols of speculative retail behavior and social media-driven trading (Li & Yang, 2022; Yousaf et al., 2023). Similarly, AMC and GME were central to the 2021 retail trading surge driven by platforms such as Reddit and Twitter, making them ideal proxies for meme stock behavior (Aloosh et al., 2023; Nobanee & Ellili, 2023). Their inclusion allows us to capture the behavioral dynamics, sentiment-driven volatility, and potential contagion effects associated with meme assets. The meme coins are sourced from Coin Metrics (https://coinmetrics.io/), while the meme stocks are obtained from Bloomberg.

Furthermore, our regression analysis includes nine independent variables: Gold Market Volatility (GVZ), S&P500 returns (SP500), Volatility Market Index (VIX), Economic Policy Uncertainty (GEPU), Equity Market Volatility (EMV), Global Bitcoin Sentiments (BTC sentiments), Global Cyber Attacks (Cyber-attacks), Crude Oil Volatility (OVX), and Global Financial Stress Index (GFS). Each of these factors has been widely employed in connectedness and spillover literature to capture risks originating from traditional financial markets, global uncertainty, digital threats, and investor sentiment. Specifically, GVZ and OVX are included to reflect uncertainty in global commodity markets, particularly precious metals and energy, which are known to influence investor behavior and asset co-movements (e.g., Baur & Lucey, 2010; Boateng et al., 2021; Mensi et al., 2024; Elsayed et al., 2024). The S&P 500 and VIX are widely used benchmarks to capture US market performance and investor fear, respectively, both of which are strong influencers of global asset markets (Ozcelebi & Kang, 2024; Assaf et al., 2025).

The GEPU index is used to proxy for global macroeconomic policy-related uncertainty (Baker et al., 2016; Karanasos et al., 2022). EMV and GFS provide additional insights into market-level volatility and systemic stress, complementing our focus on cross-asset spillovers (Apostolakis & Papadopoulos, 2015; Prasad et al., 2018). To incorporate behavioral aspects, we include Bitcoin sentiment, derived from Google Trends data, which captures public interest and attention in the crypto space, an important factor in the pricing of digital assets (Corbet et al., 2019; Khalfaoui et al., 2023). Cybersecurity threats, represented through the number of global cyberattack incidents are included to account for risks related to the digital economy and financial infrastructure, as suggested by Eckert et al. (2023).

Data for GVZ, SP500, VIX, EMV, OVX, and GFS are sourced from Bloomberg, while GEPU data is retrieved from policy uncertainty website (https://www.policyuncertainty.com/). BTC sentiments are obtained from Google Trends, and cyber-attacks data is sourced from Hackmageddon website (https://www.hackmageddon.com/).

[2] See for more detail on Islamic index methodology: https://www.spglobal.com/spdji/en/documents/methodologies/methodology-dj-islamic-market-indices.pdf.

The research period extends from August 1, 2020, to March 21, 2024. The research period extends from August 1, 2020, to March 21, 2024. This timeframe was selected primarily due to data availability, as SHIB, the most recent among the selected meme assets, was launched on August 1, 2020. Additionally, this period captures several critical global events that significantly influenced financial markets, including the COVID-19 recovery phase, the 2021 meme assets trading frenzy, the onset of the Russia–Ukraine war in early 2022, and periods of elevated economic and geopolitical uncertainty. These events provide an ideal setting for analyzing dynamic spillover behavior and connectedness between Islamic sectoral indices and meme assets under diverse market regimes. Definitions for the variables used in the study are provided in Appendix 1.

Table 1 provides summary statistics for daily returns, standard deviations, normality, and unit root measures. Except for AMC, all mean returns are positive. Notably, SHIB has the highest daily return at 1.15%. The Islamic oil & gas index shows the highest daily return at 0.07% among Islamic sectoral indices. Regarding risk, SHIB is the most volatile asset with a standard deviation of 24.59%, while the Islamic telecom index is the least risky at 0.57%. It is worth mentioning that all Islamic sectoral indices have standard deviations close to 0%, supporting the notion of stability within this asset class. Excessive kurtosis is widespread, particularly among meme assets. This aligns with their market behavior, characterized by speculation (Premaratne & Bera, 2000), thin trading (Pece & Petria, 2015), and a lack of fundamental value (Zhong et al., 2003). Furthermore, skewness tends to be negative for most Islamic indices, except for Islamic financial and telecom indices. However, even in these cases, skewness values remain close to zero. On the other hand, meme assets typically exhibit positive skewness values exceeding 5, except for GME. The Jarque-Bera (JB) test results reveal that none of the returns follow a normal distribution. Additionally, findings from the augmented Dickey-Fuller (ADF) test suggest that all return series maintain stationarity. These characteristics suggest the presence of asymmetries and justify the use of quantile-based connectedness approach that allows us to examine spillovers under low, medium, and high volatility conditions.

4 Results and Discussion

4.1 Quantile Return Connectedness

We begin our analysis by estimating the quantile extended joint connectedness approach between meme stock, meme coins, and Islamic sectoral indices. Tables 2, 3 and 4 present the return spillovers between meme assets and Islamic sectoral indices at lower extreme (0.05th), median (0.5th), and upper extreme (0.95th) quantiles, respectively. The results show the total connectedness index (TCI) is 88.06% at the lower extreme and 89.15% at the upper extreme, which is high compared to the median of 55.87%. These findings suggest that TCI increased during extreme events, reflecting extreme shocks' impact on the connectedness system. These results are consistent with Mensi et al. (2017), which showed evidence of higher spillover contribution among Islamic sector indices with other markets during extreme periods.

Table 1 Descriptive statistics

	Material	Technology	Service	Consumer	Financials	Health	Industrial
Mean	0.01%	0.06%	0.02%	0.01%	0.03%	0.01%	0.04%
SD	0.0103	0.0144	0.0124	0.0094	0.0109	0.0081	0.0094
Skewness	−0.164	−0.1094	−0.315	−0.1094	0.0067	−0.1422	−0.033
Kurtosis	4.1346	4.3113	5.6619	4.3137	5.5783	4.3498	4.3125
Jarque-Bera	55.10***	69.81***	295.56***	70.06***	262.59***	75.17***	68.21***
Ljung-Box	79.13***	11.78***	10.61**	28.50***	17.72***	42.71***	59.25***
ARCH	32.92***	45.97***	53.45***	39.74***	23.51***	31.91***	32.02***
ADF	−9.85***	−9.84***	−10.29***	−9.16***	−10.25***	−9.99***	−9.29***
	Oil	Utilities	Teleco	AMC	DOGE	GME	SHIB
Mean	0.07%	0.00%	0.01%	−0.24%	0.40%	0.27%	1.15%
SD	0.0153	0.0086	0.0057	0.0974	0.0933	0.09	0.2459
Skewness	−0.075	−0.0309	0.3926	2.5413	5.2832	0.7839	12.2787
Kurtosis	5.3721	4.7139	7.9138	57.2382	82.5785	35.5887	252.251
Jarque-Bera	223.16***	116.18***	978.09***	117220.80***	254553.20***	42047.04***	2477791.00***
Ljung-Box	13.10***	21.96***	46.81***	79.31***	10.02**	66.55***	4.24
ARCH	35.40***	20.13***	50.15***	108.46***	9.51**	259.13***	1.23
ADF	−10.08***	−8.75***	−9.01***	−9.52***	−9.28***	−9.75***	−10.57***

Note: This table displays the descriptive statistics for the Islamic sectors, meme stock and meme coins. SD represents standard deviation. Jarque-Bera (JB) test (Jarque & Bera, 1987) assesses normality. The Ljung-Box Q-statistic tests for serial correlation in returns (Ljung & Box, 1978), and the ARCH test evaluates heteroskedasticity (Engle, 1982). The Augmented Dickey-Fuller (ADF) test (Dickey & Fuller, 1979) is applied to check unit roots using an intercept and Schwarz Information Criterion for lag selection. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively

Table 2 Return connectedness at extremely lower quantile

	Material	Technology	Service	Consumer	Financials	Health	Industrial	Oil	Utilities	Teleco	AMC	DOGE	GME	SHIB	FROM
Material	8.60	7.72	8.35	7.69	7.94	7.49	8.26	7.72	7.36	7.21	5.79	5.52	5.96	4.38	91.40
Technology	7.88	8.28	8.62	8.18	8.23	7.69	8.13	6.91	7.14	6.53	5.80	5.79	6.32	4.50	91.72
Service	8.05	8.50	8.17	8.09	8.18	7.66	8.32	7.23	7.11	6.57	5.73	5.71	6.23	4.45	91.83
Consumer	8.08	8.37	8.43	8.22	8.06	7.83	8.22	6.90	7.20	6.74	5.79	5.60	6.21	4.34	91.78
Financials	8.07	8.19	8.43	7.81	8.80	8.04	8.15	7.12	6.94	6.55	5.60	5.88	6.04	4.37	91.20
Health	7.97	7.94	8.18	7.77	8.13	9.77	7.86	6.96	7.15	6.74	5.59	5.54	5.97	4.42	90.23
Industrial	8.68	8.34	8.87	8.21	8.47	7.85	6.35	7.44	7.21	6.73	5.87	5.51	6.18	4.28	93.65
Oil	8.19	6.92	7.61	6.94	7.37	6.87	7.45	12.78	7.18	6.77	5.81	5.72	5.99	4.40	87.22
Utilities	7.94	7.21	7.37	6.87	7.05	6.80	7.02	7.06	14.11	7.09	5.56	5.43	5.97	4.51	85.89
Teleco	8.48	7.17	7.67	7.32	7.36	7.10	7.40	7.09	7.36	11.24	5.73	5.54	6.04	4.50	88.76
AMC	7.18	7.04	7.10	6.82	6.74	6.29	6.72	6.78	6.72	6.41	14.40	5.43	7.57	4.80	85.60
DOGE	6.95	6.69	6.79	6.38	6.75	6.27	6.16	6.42	6.67	6.06	5.45	18.74	6.00	4.65	81.26
GME	6.82	7.13	7.15	6.77	6.97	6.37	6.56	6.56	6.40	6.05	7.21	5.70	15.90	4.44	84.10
SHIB	6.46	6.30	6.43	5.87	6.29	5.88	6.04	5.97	6.42	5.69	5.18	6.07	5.62	21.77	78.23
TO	100.76	97.53	100.99	94.72	97.54	92.15	96.30	90.15	90.85	85.15	75.11	73.45	80.10	58.04	**TCI**
Own	109.37	105.81	109.16	102.94	106.34	101.93	102.66	102.94	104.96	96.40	89.52	92.19	96.00	79.81	
NET	9.37	5.81	9.16	2.94	6.34	1.93	2.66	2.94	4.96	−3.60	−10.48	−7.81	−4.00	−20.19	88.06

Note: This table shows the total, net and pairwise return spillovers between Islamic sectors, meme stock and meme coins at the extremely lower quantile (0.05th). TCI stands for the total connectedness index. Diagonal elements represent own-market shocks, while off-diagonal elements show pairwise spillovers. “FROM” indicates how much a market receives from others, and “TO” reflects how much a market transmits to others. “NET” is the difference between TO and FROM, showing net directional influence

Table 3 Return connectedness at median quantile

	Material	Technology	Service	Consumer	Financials	Health	Industrial	Oil	Utilities	Teleco	AMC	DOGE	GME	SHIB	FROM
Material	27.15	6.55	7.92	8.66	7.76	6.69	13.52	6.25	4.98	5.37	1.37	1.73	1.68	0.36	72.85
Technology	5.55	24.40	14.41	11.89	11.15	8.70	11.74	1.46	2.51	1.45	2.00	1.73	2.65	0.36	75.60
Service	6.66	13.81	23.60	11.43	10.25	7.52	13.25	2.23	2.38	1.89	2.20	1.69	2.67	0.41	76.40
Consumer	7.29	10.87	11.03	28.31	8.95	8.38	11.55	1.43	2.97	2.57	1.91	1.64	2.82	0.28	71.69
Financials	6.65	10.70	10.23	9.15	29.60	9.59	12.56	2.47	2.18	1.84	1.61	1.64	1.63	0.16	70.40
Health	6.00	8.91	7.77	8.74	10.05	37.24	10.23	1.63	2.79	2.11	1.42	1.49	1.34	0.29	62.76
Industrial	11.33	11.09	12.79	11.41	12.11	9.48	15.53	3.78	3.61	3.06	1.74	1.45	2.21	0.42	84.47
Oil	10.03	2.52	3.67	2.46	4.41	2.60	7.00	59.19	2.52	1.93	0.56	1.68	1.08	0.35	40.81
Utilities	6.94	3.67	3.98	4.59	3.96	4.38	5.67	1.73	57.95	3.74	0.98	1.36	0.74	0.31	42.05
Teleco	8.29	2.92	3.80	4.62	4.04	3.93	5.72	1.97	4.08	56.69	1.06	1.39	1.29	0.19	43.31
AMC	1.78	3.41	3.71	3.44	2.55	2.21	2.94	0.68	0.89	0.84	58.82	1.72	16.63	0.39	41.18
DOGE	1.87	2.04	2.23	2.16	2.05	1.72	1.86	1.30	0.81	0.82	1.29	79.38	1.21	1.28	20.62
GME	1.84	4.02	4.49	4.77	2.57	1.82	3.73	1.02	0.64	0.87	16.82	1.80	54.99	0.62	45.01
SHIB	1.88	2.62	2.35	2.63	1.97	1.95	2.21	1.13	0.59	0.66	0.84	14.80	1.37	65.00	35.00
TO	76.12	83.14	88.39	85.95	81.81	68.98	101.97	27.07	30.96	27.13	33.79	34.11	7.32	5.42	**TCI**
Own	103.27	107.53	111.99	114.26	111.42	106.22	117.50	86.26	88.91	83.82	92.61	113.49	2.31	70.42	
NET	3.27	7.53	11.99	14.26	11.42	6.22	17.50	−13.74	−11.09	−16.18	−7.39	13.49	−7.69	−29.58	55.87

Note: This table shows the total, net and pairwise return spillovers between Islamic sectors, meme stock and meme coins at the median quantile (0.50th). TCI stands for the total connectedness index. Diagonal elements represent own-market shocks, while off-diagonal elements show pairwise spillovers. "FROM" indicates how much a market receives from others, and "TO" reflects how much a market transmits to others. "NET" is the difference between TO and FROM, showing net directional influence

Table 4 Return connectedness at extremely upper quantile

	Material	Technology	Service	Consumer	Financials	Health	Industrial	Oil	Utilities	Teleco	AMC	DOGE	GME	SHIB	FROM
Material	8.91	7.29	6.96	7.82	7.36	7.40	7.68	8.05	7.53	7.29	5.88	6.36	5.95	5.51	91.09
Technology	7.43	7.38	7.99	8.40	7.80	7.45	7.52	7.17	7.15	6.76	6.25	6.56	6.47	5.66	92.62
Service	7.57	8.47	7.04	8.31	7.71	7.44	7.67	7.28	7.13	6.82	6.14	6.50	6.32	5.61	92.96
Consumer	7.49	7.82	7.30	10.29	7.20	7.25	7.21	7.25	7.04	6.66	6.08	6.35	6.36	5.70	89.71
Financials	7.52	7.90	7.26	7.95	8.00	7.55	7.39	7.46	7.02	6.85	6.28	6.70	6.43	5.71	92.00
Health	7.52	7.59	7.05	7.84	7.67	10.31	7.24	7.10	7.10	6.70	5.91	6.44	5.99	5.53	89.69
Industrial	8.37	8.15	7.74	8.28	8.06	7.83	5.59	7.68	7.44	6.98	5.88	6.31	6.03	5.66	94.41
Oil	7.73	6.66	6.27	6.83	6.57	6.43	6.48	15.01	7.13	6.74	5.86	6.58	6.16	5.55	84.99
Utilities	7.70	6.80	6.37	7.15	6.52	6.88	6.53	7.33	14.38	7.26	5.66	6.20	5.71	5.53	85.62
Teleco	7.81	6.75	6.30	7.36	6.79	6.72	6.55	7.41	7.53	12.23	6.07	6.55	6.12	5.79	87.77
AMC	6.81	6.75	6.26	6.89	6.46	6.33	5.88	7.20	6.72	6.98	13.36	6.54	7.99	5.82	86.64
DOGE	6.78	6.52	6.01	6.96	6.53	6.39	5.85	7.27	6.76	6.98	6.45	14.82	6.57	6.12	85.18
GME	6.87	7.03	6.47	7.32	6.50	6.32	6.10	7.44	6.78	6.90	7.87	6.72	12.03	5.66	87.97
SHIB	6.78	6.50	6.18	7.23	6.30	6.28	5.80	7.44	6.84	6.95	6.46	8.31	6.47	12.47	87.53
TO	96.36	94.23	88.15	98.34	91.47	90.25	87.90	96.08	92.17	89.88	80.77	86.13	82.58	73.86	**TCI**
Own	105.27	101.61	95.20	108.63	99.47	100.57	93.49	111.09	106.54	102.12	94.14	100.95	94.61	86.32	
NET	5.27	1.61	−4.80	8.63	−0.53	0.57	−6.51	11.09	6.54	2.12	−5.86	0.95	−5.39	−13.68	89.15

Note: This table shows the total, net and pairwise return spillovers between Islamic sectors, meme stock and meme coins at the extremely upper quantile (0.95th). TCI stands for the total connectedness index. Diagonal elements represent own-market shocks, while off-diagonal elements show pairwise spillovers. “FROM” indicates how much a market receives from others, and “TO” reflects how much a market transmits to others. “NET” is the difference between TO and FROM, showing net directional influence

Moreover, we calculate "TO and FROM" connectedness to assess the impact of each variable on the system in our sample period. Our results reveal intensified spillover activity between Islamic sectors and meme assets, particularly in the lower (bearish) and upper (bullish) quantiles. For example, Islamic sectors such as Service (100.99), Materials (100.76), and Technology (97.53) exhibit the highest outward spillovers under extreme bearish conditions in Table 2. This elevated TO connectedness implies that these sectors, though governed by ethical and Sharia-compliant investment principles, are actively transmitting return shocks to the wider market, including speculative meme assets, rather than remaining insulated from volatility (Shahzad et al., 2017). Likewise, meme assets such as SHIB, DOGE, GME, and AMC, while traditionally considered reactive, also display notable TO values in both tails of the distribution. This suggests that, under certain market conditions, these speculative assets may play a non-trivial role in influencing return dynamics within Islamic sectors, indicating a potential shift in their systemic relevance (Jones & Hietanen, 2023).

Similarly, the FROM values reinforce this interconnectedness, with Islamic sectors and meme assets both receiving significant return shocks across quantiles. The presence of high FROM values for Islamic sectors during stress periods implies that they are not immune to speculative influences and may be increasingly exposed to sentiment-driven market behavior (Aloui et al., 2021). This undermines the assumption that Sharia-compliant sectors operate in isolation from speculative bubbles (Majdoub et al., 2016) and highlights the need to revisit screening mechanisms to ensure these sectors maintain their ethical investment mandate. In particular, the observed bidirectional spillovers call into question the robustness of existing Sharia filters in shielding Islamic markets from high-volatility, non-fundamental assets, especially during turbulent market phases.

However, meme assets and Islamic sectors (i.e., oil and gas, utilities, and telecom) have relatively lower return contributions in the middle quantile. Our results align with prior literature such as Elsayed et al. (2024), which reported greater dynamic connectedness between meme coins, stocks, and conventional sectoral markets. Also, they observed short-term spillovers leading the long- and medium-term spillovers in conventional sectoral indices. However, we find return spillovers are denominating in lower and upper quantiles in Islamic sectoral indices with the exception of medium connectedness, in particular, oil&gas, utilities, and telecom sectors. These findings are in line with Cao and Xie (2024) showed that energy sectors are major contributors to risk transmissions. Regarding "NET" transmissions, the meme assets have negative values but vary across Islamic sectors. Therefore, the Islamic sectoral indices are the main contributor of return transmissions towards meme assets in the system, which can result in challenges for diversification strategies.

4.2 Quantile Volatility Connectedness

Further, we examine volatility spillovers to offer deeper insights into systemic risk transmission and inform robust risk management within the Islamic financial system. Volatility is modeled using the GARCH(1,1) framework of Bollerslev (1986), which effectively captures time-varying volatility and accounts for the persistence

and clustering often observed in financial returns. The resulting conditional variances are employed in a quantile connectedness framework, as financial markets typically exhibit asymmetric behaviors, particularly during extreme market conditions. Traditional mean-based connectedness measures may fail to detect such nonlinear dependencies, whereas quantile-based analysis, following Cunado et al. (2023), allows for the assessment of spillovers across the distribution, capturing dynamics in the lower tail (bearish markets), median (normal conditions), and upper tail (bullish markets). This approach enhances the understanding of heterogeneous shock transmissions. Importantly, integrating volatility connectedness alongside return connectedness yields a more comprehensive depiction of market interlinkages. While return connectedness captures price co-movements, volatility connectedness reflects the diffusion of uncertainty and financial stress across assets (Bahloul & Khemakhem, 2021). These dimensions may diverge, as heightened volatility does not necessarily align with stronger return spillovers. Therefore, examining both return and volatility connectedness is essential for identifying spillovers channels, understanding market interdependencies, and optimizing risk-adjusted portfolio strategies across different market regimes.

Tables 5, 6, and 7 display the volatility connectedness among meme assets and Islamic sectoral indices in the lower, middle, and upper quantiles. Lower and median quantiles have lower total volatility spillovers, with 39.47% and 43.84%, respectively. However, our result shows significantly higher total volatility spillovers in the upper quantile, with 84.68% in Table 7. From the "direction to others" row, we can see that meme assets like AMC (130.19%) and DOGE (166.38%), followed by SIHB (86.56%), present higher gross volatility spillovers to Islamic sectoral indices. This indicates short or gamma squeeze events in meme asset markets can affect Islamic sector indices[3]. These results are consistent with Assaf et al. (2025) reported that cryptocurrencies transmit significantly larger shocks. Particularly, Sharia-based investors who hold Islamic asset portfolios may incur significant losses. Noteworthy, AMC (52.21) and DOGE (89.64) have higher positive "NET" volatility spillovers in the upper quantile (Table 6). This suggests that meme assets are a major contributor to Islamic indices rather than what they receive from other variables in the system. Our findings are consistent with those of Yousaf et al. (2023), who state that meme stocks are major shock contributors to other asset classes.

4.3 Dynamic Connectedness

Now, we proceed with our spillover findings into the total dynamic connectedness and directional connectedness. It consists of three important findings: (i) Total dynamic returns and volatility connectedness (ii) The returns connectedness of each asset (iii) The volatility connectedness of each asset, and (iv) Dynamic network plot.

The total dynamic returns and volatility connectedness is to portray how the overall level of spillovers changes over time and across different market conditions (quantiles). Panel A of Fig. 1 shows that the return spillover is high, below 40% quantile and above 60%. It also reveals a significant return spillover at specific intervals during

[3] For details: https://www.ft.com/content/47e3eaad-e087-4250-97fd-e428bac4b5e9.

Table 5 Volatility connectedness at extremely lower quantile

	Material	Technology	Service	Consumer	Financials	Health	Industrial	Oil	Utilities	Teleco	AMC	DOGE	GME	SHIB	FROM
Material	53.42	3.89	4.03	5.02	4.48	6.06	7.98	3.97	3.54	4.82	0.42	1.04	0.62	0.72	46.58
Technology	4.01	42.79	10.13	8.22	7.89	7.51	9.19	2.26	2.24	2.20	0.68	1.24	0.85	0.80	57.21
Service	4.46	10.79	41.82	8.68	8.30	7.34	9.72	1.99	1.92	1.78	0.87	0.79	1.02	0.53	58.18
Consumer	4.67	7.91	7.91	46.80	6.63	7.51	8.63	2.36	2.21	2.14	0.62	0.92	1.10	0.58	53.20
Financials	4.91	7.95	7.96	6.95	46.05	7.90	9.01	2.67	2.05	1.43	0.79	0.95	0.96	0.42	53.95
Health	6.07	7.07	6.54	7.37	7.44	47.06	8.56	2.66	2.28	2.08	0.55	0.94	0.82	0.57	52.94
Industrial	7.78	8.82	8.71	8.61	8.83	8.75	38.59	2.77	2.47	2.12	0.57	0.85	0.61	0.51	61.41
Oil	4.60	2.25	2.02	2.79	2.83	2.93	3.28	69.97	2.95	2.38	0.37	1.97	0.86	0.81	30.03
Utilities	4.24	2.75	2.25	3.01	2.71	3.12	3.13	3.31	68.83	3.23	0.69	0.88	1.01	0.83	31.17
Teleco	5.30	2.26	1.75	2.67	1.48	2.40	2.25	2.65	3.67	72.51	0.36	0.66	0.52	1.51	27.49
AMC	1.10	1.14	2.04	1.31	1.36	1.48	0.99	0.70	0.99	0.56	80.18	0.97	6.87	0.31	19.82
DOGE	1.39	1.65	1.01	1.36	1.30	1.37	1.25	2.91	1.08	1.02	1.00	80.50	0.99	3.16	19.50
GME	1.19	1.53	2.33	2.22	1.86	1.68	1.17	1.40	1.45	0.77	6.37	1.06	76.12	0.85	23.88
SHIB	1.11	1.66	0.91	1.19	0.83	0.93	0.98	1.15	1.34	1.81	0.39	4.11	0.81	82.79	17.21
TO	50.84	59.66	57.59	59.41	55.93	59.01	66.13	30.79	28.19	26.32	13.69	16.37	17.03	11.60	**TCI**
Own	104.26	102.45	99.41	106.21	101.99	106.07	104.72	100.76	97.02	98.83	93.87	96.87	93.16	94.40	
NET	4.26	2.45	−0.59	6.21	1.99	6.07	4.72	0.76	−2.98	−1.17	−6.13	−3.13	−6.84	−5.60	39.47

Note: This table shows the total, net and pairwise volatility spillovers between Islamic sectors, meme stock and meme coins at the extremely lower quantile (0.05th). TCI stands for the total connectedness index. Diagonal elements represent own-market shocks, while off-diagonal elements show pairwise spillovers. "FROM" indicates how much a market receives from others, and "TO" reflects how much a market transmits to others. "NET" is the difference between TO and FROM, showing net directional influence

Table 6 Volatility connectedness at median quantile

	Material	Technology	Service	Consumer	Financials	Health	Industrial	Oil	Utilities	Teleco	AMC	DOGE	GME	SHIB	FROM
Material	48.80	3.71	4.36	4.67	6.20	7.37	7.97	5.42	3.64	4.77	0.64	1.18	0.74	0.52	51.20
Technology	5.39	35.86	9.61	7.13	10.15	8.22	9.04	2.41	4.74	3.03	0.88	1.08	1.71	0.74	64.14
Service	5.28	9.37	40.73	7.23	9.11	7.54	9.07	1.75	3.35	3.24	0.97	0.67	1.17	0.52	59.27
Consumer	7.94	6.37	8.29	39.02	7.97	7.78	8.75	2.51	3.44	3.11	1.32	0.85	1.98	0.67	60.98
Financials	5.34	7.71	9.42	6.57	42.86	8.81	9.22	2.39	2.52	1.95	0.94	0.80	1.08	0.39	57.14
Health	6.68	6.02	6.14	5.98	8.40	47.04	7.85	3.56	3.00	2.23	0.72	1.01	0.83	0.54	52.96
Industrial	9.32	6.91	7.98	6.61	9.69	8.06	39.30	3.11	3.55	2.66	0.64	0.95	0.66	0.55	60.70
Oil	7.13	2.67	2.89	3.51	4.87	4.79	5.42	57.12	4.63	2.34	0.51	2.36	1.02	0.73	42.88
Utilities	6.03	3.67	3.10	4.42	4.06	4.67	4.52	4.09	57.78	3.67	0.69	1.16	1.30	0.84	42.22
Teleco	5.86	2.12	3.19	3.12	2.79	3.50	4.28	3.14	5.12	63.44	0.40	0.78	1.09	1.15	36.56
AMC	0.97	0.80	1.97	0.78	1.41	1.38	0.59	0.53	0.89	0.37	81.63	0.67	7.79	0.22	18.37
DOGE	1.06	1.34	0.55	1.05	1.03	0.92	0.88	3.21	0.66	0.53	0.65	83.98	0.43	3.71	16.02
GME	2.33	1.29	3.11	1.97	2.70	2.35	1.33	1.75	2.44	0.90	9.39	1.32	68.22	0.90	31.78
SHIB	1.05	1.59	1.16	0.82	1.20	0.85	1.22	1.27	1.23	1.30	0.23	6.98	0.67	80.43	19.57
TO	64.39	53.58	61.79	53.85	69.58	66.24	70.13	35.15	39.20	30.10	17.98	19.82	20.47	11.48	**TCI**
Own	113.19	89.43	102.52	92.88	112.44	113.28	109.43	92.27	96.98	93.54	99.61	103.81	88.69	91.91	
NET	13.19	−10.57	2.52	−7.12	12.44	13.28	9.43	−7.73	−3.02	−6.46	−0.39	3.81	−11.31	−8.09	43.84

Note: This table shows the total, net and pairwise volatility spillovers between Islamic sectors, meme stock and meme coins at the median quantile (0.50th). TCI stands for the total connectedness index. Diagonal elements represent own-market shocks, while off-diagonal elements show pairwise spillovers. "FROM" indicates how much a market receives from others, and "TO" reflects how much a market transmits to others. "NET" is the difference between TO and FROM, showing net directional influence

Table 7 Volatility connectedness at extremely upper quantile

	Material	Technology	Service	Consumer	Financials	Health	Industrial	Oil	Utilities	Teleco	AMC	DOGE	GME	SHIB	FROM
Material	13.09	5.76	5.73	6.11	6.52	6.02	6.01	5.71	4.69	5.40	9.99	12.82	5.39	6.75	86.91
Technology	5.26	14.24	5.69	6.04	6.51	6.01	6.01	5.73	4.65	5.38	10.11	12.72	5.15	6.48	85.76
Service	5.13	5.67	14.83	6.00	6.44	5.99	5.99	5.63	4.62	5.30	9.88	12.79	5.16	6.55	85.17
Consumer	5.26	5.74	5.71	13.68	6.56	6.10	6.01	5.68	4.69	5.45	10.12	12.77	5.38	6.84	86.32
Financials	5.14	5.60	5.57	5.91	15.86	5.90	5.89	5.65	4.60	5.23	9.93	12.72	5.33	6.65	84.14
Health	5.19	5.74	5.71	6.11	6.60	13.98	6.00	5.61	4.71	5.40	9.99	12.99	5.32	6.64	86.02
Industrial	5.33	5.79	5.80	6.17	6.70	6.17	13.27	5.76	4.83	5.51	9.66	12.84	5.36	6.82	86.73
Oil	5.20	5.74	5.73	6.10	6.54	6.02	5.98	13.77	4.64	5.33	10.01	12.84	5.34	6.75	86.23
Utilities	5.17	5.70	5.69	6.14	6.55	6.10	6.03	5.65	12.90	5.40	9.96	12.81	5.24	6.66	87.10
Teleco	5.30	5.77	5.75	6.14	6.56	6.14	6.07	5.79	4.75	12.75	9.94	12.80	5.52	6.71	87.25
AMC	4.91	5.38	5.33	5.75	6.21	5.67	5.73	5.34	4.31	5.08	22.02	12.68	5.07	6.54	77.98
DOGE	4.99	5.43	5.39	5.88	6.18	5.64	5.69	5.50	4.39	5.12	10.44	23.27	5.33	6.76	76.73
GME	4.80	5.22	5.21	5.62	6.01	5.58	5.48	5.35	4.31	4.90	9.51	12.11	19.50	6.39	80.50
SHIB	5.39	5.89	5.89	6.30	6.75	6.23	6.20	5.96	4.86	5.52	10.65	13.50	5.49	11.38	88.62
TO	67.07	73.43	73.22	78.27	84.13	77.59	77.09	73.36	60.07	69.03	130.19	166.38	69.07	86.56	**TCI**
Own	80.15	87.68	88.06	91.95	99.99	91.56	90.36	87.14	72.97	81.78	152.21	189.64	88.57	97.93	
NET	−19.85	−12.32	−11.94	−8.05	−0.01	−8.44	−9.64	−12.86	−27.03	−18.22	52.21	89.64	−11.43	−2.07	84.68

Note: This table shows the total, net and pairwise volatility spillovers between Islamic sectors, meme stock and meme coins at the extremely upper quantile (0.95th). TCI stands for the total connectedness index. Diagonal elements represent own-market shocks, while off-diagonal elements show pairwise spillovers. "FROM" indicates how much a market receives from others, and "TO" reflects how much a market transmits to others. "NET" is the difference between TO and FROM, showing net directional influence

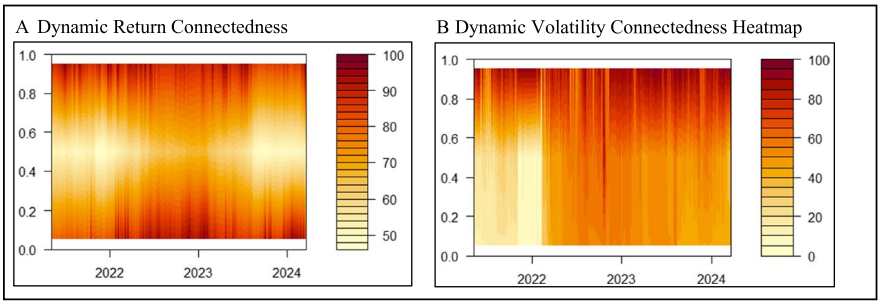


Fig. 1 Dynamic connectedness. Note: These figures show the heat map for total dynamic return and volatility connectedness among Islamic sectors and meme assets. The hot-colored shade indicates a high level of connectedness, whereas cold colored shade denotes weak connectedness. The x-axis represents the timeline, and the y-axis reports the quantiles

February 2022 towards the end of our sample period, as shown by darker red bands. A similar picture is evident in Panel B for intense volatility spillover connectedness among meme stock and Islamic sectoral indices. This is because retail investors are selling mainstream cryptocurrencies and choosing to invest in meme coins due to the crypto exchange Coinbase, which was ranked in the top 100 again in the U.S. Apple App Store in February 2022[4]. This phenomenon might trigger investor behavior towards meme assets from other asset classes, including Islamic stock markets, to maximize their gains and cause unrest in other markets. Such findings are supported byJawadi et al. (2020), which showed investor attention significantly impacts Islamic returns and investor attention helps to drive Islamic stock returns higher.

Figure 2 illustrates the directional return spillovers between meme assets and Islamic sectoral indices. The purpose is to examine how return spillovers are transmitted and absorbed across assets over time and market conditions to identify potential safe haven properties during stress periods. The figure depicts that the DOGE, technology, consumer services, consumer goods, financials, healthcare, and industrial sectors transmit to all other markets. However, GME, AMC, SHIB, oil and gas, utilities, and telecommunication are net recipients of return shocks throughout the sample period. Our results contradict Umar et al. (2021), which found that crypto markets are less integrated with technological systems and structurally less exposed to systemic risk.

Our analysis also examines the directional volatility connectedness of each asset. We aim to explore how volatility spillovers are transmitted and absorbed across assets over time and market conditions to assess their risk contagion and safe haven potential during stress periods. Figure 3 presents the results where all Islamic sectoral indices and a few meme assets (i.e., GME and SHIB) are moving across time among net transmitting and receiving roles. Notably, the AMC and DOGE are net transmitters to all other markets above the 60th quantile during the start of our sample period, but AMC is transmitting spillovers until the end as well. This is consistent with Khalfaoui et al. (2023), who demonstrated that the cryptocurrencies and BRICS

[4] For more details: https://www.morningstar.com/news/marketwatch/20240306456/meme-coins-like-dogecoin-and-pepe-are-rallying-again-heres-what-it-means-for-crypto.

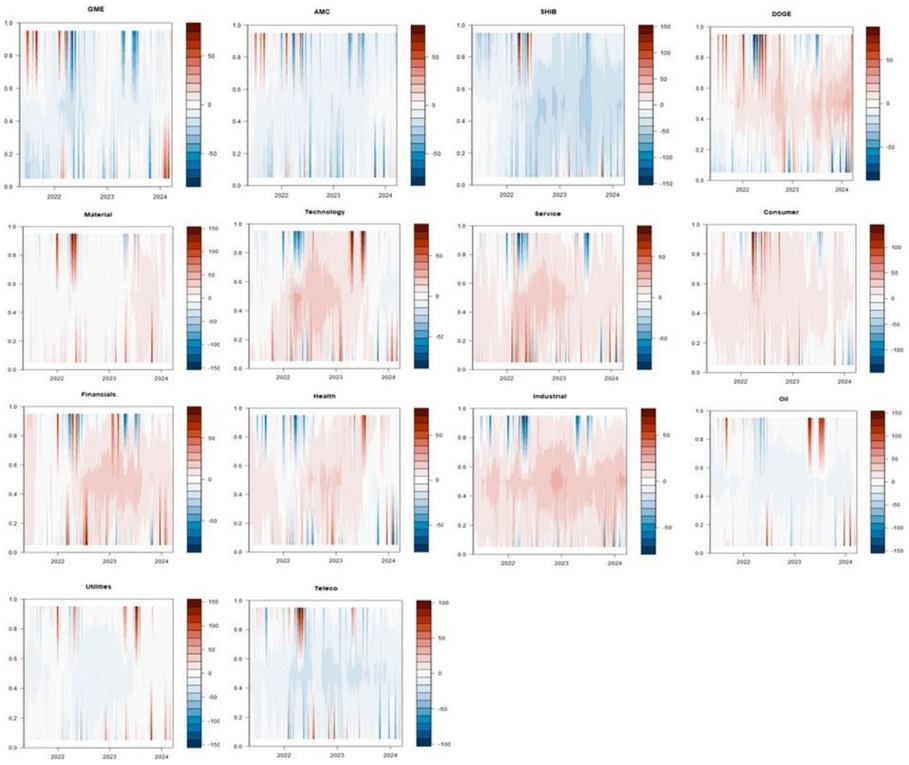


Fig. 2 Total directional returns connectedness. Note: These figures show the heat map for total directional dynamic return connectedness among Islamic sectors and meme assets. Warmer colored zone indicates a net contributor index, while colder colored area demonstrates a net receipt index

stock markets have played both roles: net transmitters and receivers of shocks under several market states.

In order to gain a more comprehensive understanding of connectedness between meme assets and Islamic sectoral indices, we document the directional connectedness network under various market circumstances, such as bearish, normal, and bullish states. Figure 4 shows the return network connectedness between meme assets and ten Islamic sectoral indices at three quantile levels. Our findings highlight that most of the Islamic sector is net transmitters in lower and upper quantiles, whereas the meme assets are net recipients. This suggests that Islamic stock strongly influences the behavior of other stocks or meme assets in the system and that investors need to be careful in portfolio construction and risk management. These findings oppose Bossman et al. (2024) which Islamic stocks from various sectors are responsive to shocks in cryptocurrencies and Islamic sectors Basic materials, consumer goods, industrial, oil, and gas offer better diversification.

However, our results confirm that the Islamic sectors are decoupled from meme assets during normal market conditions. This recommends that Islamic sectoral indices and meme stocks move together in extremely high/low periods but remain stable during crisis periods, suggesting a lack of portfolio diversification opportunities. A

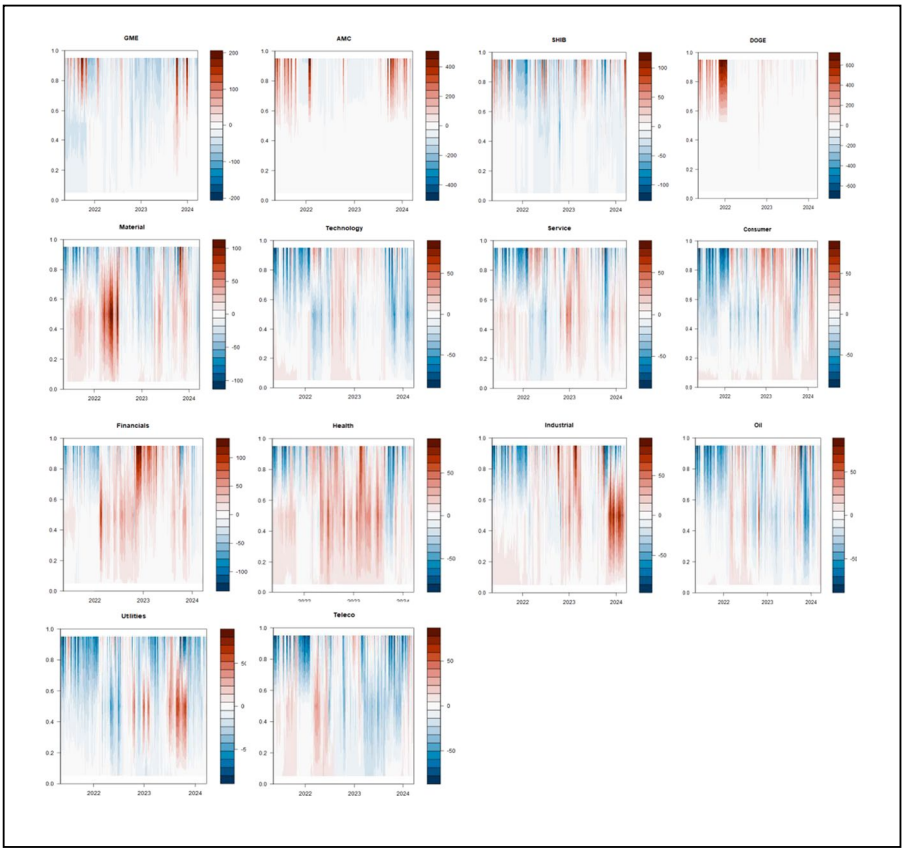


Fig. 3 Total directional volatility connectedness. Note: These figures show the heat map for total directional dynamic volatility connectedness among Islamic sectors and meme assets. Warmer colored zone indicates a net contributor index, while colder colored area demonstrates a net receipt index

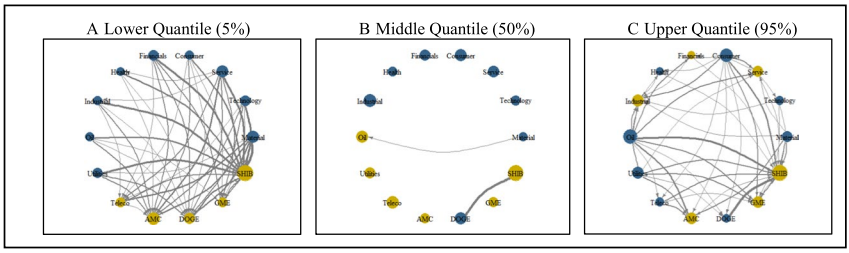


Fig. 4 Network returns connectedness. Note: These figures display the net-pairwise directional network return connectedness within Islamic sectors and meme assets. Blue nodes represent strong net transmitters of shocks, while yellow nodes indicate net receivers. Arrow direction illustrates the flow of return spillovers, and the thickness of each line corresponds to the magnitude of the connectedness

similar conclusion was drawn by literature (e.g., Al-Khazali et al., 2016; Hoque et al., 2016) that Islamic indices remained stable during after-crisis periods compared to their conventional counterparts. Likewise, in Fig. 5, SHIB and AMC are major net volatility spillovers toward other markets in extreme market conditions. Various research (For example, Bouri et al., 2021; Nyakurukwa & Seetharam, 2023; Qiao et al., 2023; Dang et al., 2024) on connectedness on cryptocurrencies, meme assets, and stock market indices supported our findings (Aslam & Brahmana, 2025). In addition, we found strong evidence or return and volatility spillovers among Islamic sectoral indices during bullish and bearish market conditions. For instance, the Islamic oil and gas sector net returns transmitter towards financials and consumer services sectors in bullish market conditions. Similarly, Islamic consumer services and utilities sectors are net volatility receivers, while other sectors are net transmitters during bearing market conditions. A similar finding by Yilmaz et al. (2015) reported significant evidence of cross-sectoral correlations among Islamic sectoral indices.

4.4 Features for Dynamic Connectedness

To identify the underlying drivers of the spillover effect, we estimate a regression model using several theoretically motivated explanatory variables (The Features). Our identification strategy draws on prior literature in the spillover domain. Specifically, we include the following features: Gold Market Volatility (GVZ) (Mensi et al., 2024), S&P 500 returns (SP500) (Ozcelebi & Kang, 2024), Volatility Index (VIX) (Assaf et al., 2025), Global Economic Policy Uncertainty (GEPU) (Karanasos et al., 2022), Equity Market Volatility (EMV) (Prasad et al., 2018), Global Bitcoin Sentiment (Khalfaoui et al., 2023), Global Cyber Attacks (Eckert et al., 2023), Crude Oil Volatility (OVX) (Boateng et al., 2021), and Global Financial Stress Index (GFSI) (Apostolakis & Papadopoulos, 2015). The dependent variable is the Total Connectedness Index (TCI), evaluated at different quantiles (lower, median, and upper). We regress the TCI on these features to assess spillover dynamics across Islamic sectoral indices and meme assets.

Theoretically, these factors could impact the dynamic spillover across Islamic indices and meme assets for three reasons. First, VIX, EMV, OVX, and BTC sentiments

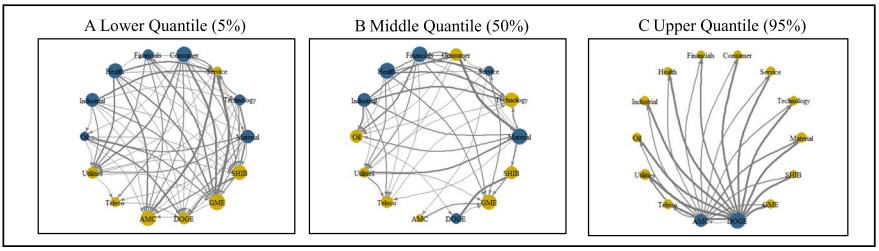


Fig. 5 Network volatility connectedness. Note: These figures display the net-pairwise directional network volatility connectedness within Islamic sectors and meme assets. Blue nodes represent strong net transmitters of shocks, while yellow nodes indicate net receivers. Arrow direction illustrates the flow of volatility spillovers, and the thickness of each line corresponds to the magnitude of the connectedness

provide insights into market expectations related to risk and sentiment indicators (Elsayed et al., 2024). High volatility levels may signal uncertainty and nervousness among investors, affecting their willingness to take on risk or invest in speculative assets like meme assets. Therefore, changes in those four variables might lead investors to reassess risk and adjust their investment strategies accordingly.

Second, GVZ and SP500 portray shifts in investor sentiment and risk appetite (Golitsis et al., 2022; Elsayed et al., 2024). Investors may flock to safe-haven assets like gold and SP500 during heightened uncertainty or economic instability. The changes in GVX and SP500 could influence the behavior of investors in both Islamic sectoral indices and meme assets, potentially leading to spillover effects as investors adjust their portfolios in response to changing market conditions.

Third, GEPU, cyber-attacks, and GFS are indicators of broader macroeconomic and geopolitical conditions, which are important factors for market connectedness (Caporale et al., 2021; Elsayed et al., 2024). Heightened uncertainty surrounding economic policies or geopolitical events may lead investors to seek safe-haven assets or reduce exposure to riskier assets, potentially impacting Islamic sectoral indices and meme assets. Similarly, global cyber-attacks and financial stress can disrupt markets and undermine investor trust, influencing investment decisions and market dynamics, thus affecting spillovers across different asset classes.

The regression employed an OLS time-series model with robust standard error, utilizing GVZ, SP500, VIX, GEPU, EMV, BTC sentiments, cyber-attacks, OVX, and GFS as independent variables. The model was run for returns and volatility spillovers, resulting in six distinct findings (each spillover type having three different TCI quantiles). The estimated results are presented in Tables 8 and 9.

For returns spillover in Table 8, SP500 is the only variable with a trivial effect across the quantiles. Meanwhile, GVZ is statistically significant only for the upper quantile, and EPU is only for the middle quantile. VIX and BTC sentiments statistically affect dynamic connectedness for the lower and middle quantiles but not the upper quantiles. EMV positively affects the middle and upper quantile connectedness but not the lower quantile. Only Cyber Attacks, OVX, and GFS consistently affect connectedness across the quantiles. Cyber-attacks and OVX negatively affect connectedness, implying increased cyber-attacks or uncertainty in oil prices. This decreases total connectedness and spillover among Islamic indices and meme assets. A similar conclusion could be found for GFS, where it has positive effects on lower and middle quantiles but negatively on upper quantiles. This indicates that increasing global financial stress would increase connectedness and spillover during extreme negative shocks and normal conditions. However, the effect of financial stress would decrease connectedness and spillover during extreme positive shocks.

The findings regarding the determinants of return spillovers align with previous studies (e.g., Fasanya et al., 2021; Nakagawa & Sakemoto, 2022; Tabash et al., 2022; Umar et al., 2022; Ding et al., 2023). The variation in the effects of each factor across quantiles suggests that differing frequencies have implications for the dynamic connectedness of Islamic indices and meme assets. Existing literature, including studies by Karim and Naeem (2022); Billah et al. (2023), confirmed the asymmetric impact of global risks on the dynamic spillovers of financial markets.

Table 8 Determinants of returns connectedness

	Lower	Middle	Upper
Gold Volatility	−0.1743	0.0424	0.3793***
	(0.1110)	(0.0936)	(0.0961)
SP500 Returns	−0.0717	−0.0084	0.1371
	(0.1420)	(0.1384)	(0.1120)
VIX	−0.2263***	−0.3504***	−0.0598
	(0.0675)	(0.0707)	(0.0558)
GEPU	−0.0043	−0.0194***	−0.0008
	(0.0067)	(0.0059)	(0.0056)
EMV	0.0294	0.2408***	0.1609***
	(0.0395)	(0.0433)	(0.0364)
BTC Sentiments	0.0315**	−0.0324**	0.0054
	(0.0140)	(0.0137)	(0.0155)
Cyber Attacks	−0.0371***	−0.0409***	−0.0253***
	(0.0048)	(0.0044)	(0.0045)
Oil Volatility	−0.0192	−0.7245***	−0.5039***
	(0.1846)	(0.1605)	(0.1330)
Financial Stress Index	2.5087***	4.0010***	−0.1378
	(0.2305)	(0.2146)	(0.2126)
Constant	98.6450***	78.6917***	83.4816***
	(3.7365)	(3.0192)	(3.0464)
N	750	750	750
F-Value	141.42	243.33	11.62
Adj. R2	0.4241	0.6161	0.0967

Note: Figures of each variable are beta coefficients, except those inside parentheses, which are robust standard errors. *, **, and *** denote significant level at 10%, 5%, and 1%, respectively

Turning to the volatility spillover, Table 9 reveals different significant factors. For instance, only OVX has no effect across quantiles. Meanwhile, BTC Sentiments only negatively affect connectedness and spillover during normal conditions but not extreme shocks (lower and upper quantiles). GVZ, SP500, VIX, and GEPU statistically influence the connectedness across Islamic sectoral indices and meme assets during extreme negative and normal conditions, but no effect during extreme positive shocks. It implies higher gold volatility, S&P 500 returns, market volatility, or economic policy uncertainty would decrease the volatility spillover among Islamic sectoral indices and meme assets during extreme negative shocks and normal conditions. Further, EMV, cyber-attacks, and GFS significantly affect all quantiles, signifying the changes in those three variables would affect the volatility spillover during extreme and normal market conditions. EMV and GFS positively affect the volatility spillover, and cyber-attacks have negative impacts.

Our findings affirm the literature by revealing that Oil volatility and BTC sentiments may work for the returns, but its effects on volatility are marginal. This is consistent with the findings from Zhang et al. (2022), who address the distinct investment objectives as the cause of the minimal impacts. Meanwhile, Cyber-attacks and GFS once again come as significant factors for the spillover of Islamic sectoral indices and meme assets. Consistent with the findings from Caporale et al. (2021), one reason is their potential to disrupt market stability and investor confidence. Cyber Attacks

Table 9 Determinants of volatility connectedness

	Lower	Middle	Upper
Gold Volatility	−0.5086***	−0.3197*	−0.234
	(0.1467)	(0.1864)	(0.2277)
SP500 Returns	−0.7781***	−0.5883**	−0.0917
	(0.2409)	(0.2837)	(0.4105)
VIX	−1.5399***	−1.5955***	−0.0747
	(0.1018)	(0.1364)	(0.1472)
GEPU	−0.0334***	−0.0526***	0.0074
	(0.0121)	(0.0145)	(0.0181)
EMV	0.5341***	0.3527***	0.2133*
	(0.0861)	(0.1062)	(0.1184)
BTC Sentiments	−0.0016	−0.0688***	−0.0216
	(0.0206)	(0.0263)	(0.0405)
Cyber Attacks	−0.0173***	−0.0146**	−0.0492***
	(0.0061)	(0.0074)	(0.0101)
Oil Volatility	0.2238	0.1555	0.2167
	(0.3191)	(0.3827)	(0.4487)
Financial Stress Index	10.5143***	10.7898***	−1.5644**
	(0.3563)	(0.4532)	(0.6061)
Constant	80.6147***	99.8247***	69.3400***
	(4.4847)	(5.6360)	(7.1416)
N	750	750	750
F-Value	595.17	284.48	12.44
Adj. R2	0.8483	0.7761	0.1179

Note: Figures of each variable are beta coefficients, except those inside parentheses, which are robust standard errors. *, **, and *** denote significant level at 10%, 5%, and 1%, respectively

targeting financial systems can lead to increased market volatility as investors react to data security uncertainties and operational disruptions. These disruptions can trigger panic selling or heightened risk aversion, amplifying volatility spillovers across asset classes, specifically the meme cryptocurrencies. Similarly, financial stress indicators reflect broader systemic risks and vulnerabilities (Elsayed et al., 2024), leading to increased market turbulence and volatility spillovers.

4.5 Most Important Feature of Dynamic Connectedness: Tree-Based Machine Learning Approach

The primary objective of this section is to identify the key variables driving spillover dynamics between Islamic sectoral indices and meme assets. To this end, we employ two complementary feature analysis techniques: (i) Feature Importance (FI) and (ii) Permutation Importance (PI), both derived from our earlier machine learning-based regression models. FI quantifies the relative contribution of each variable to the model's predictive performance, while PI assesses how random permutations of individual features affect prediction accuracy. Together, these methods offer a robust understanding of the underlying spillover drivers.

To run the feature analysis (Both FI and PI) we use the estimation results from the regression as the baseline of the predictive model. We apply both FI and PI across four

tree-based machine learning models, decision tree (DT), random forest (RF), gradient boosting machine (GBM), and XGBoost. Model performance is evaluated using standard metrics: root mean square error (RMSE), mean square error (MSE), mean absolute error (MAE), and the coefficient of determination (R^2). Following Jabeur et al. (2024), we use a 20% hold-out test sample to mitigate overfitting. Table 10 reports strong predictive performance across models, particularly in return spillover across quantiles.

For volatility spillover, Table 11 presents the model diagnostics. Notably, the R^2 scores for volatility models are consistently higher than those for return spillover models (Table 9), suggesting better explanatory power in capturing volatility dynamics. The RMSE, MSE, and MAE values further confirm the robustness of the models.

We next investigate the most influential drivers of dynamic return connectedness. As shown in Fig. 6, the FI results consistently identify the GFS as the dominant predictor of spillovers across different market regimes. This highlights the central role of global financial stress in shaping return spillovers between Islamic indices and meme assets, aligning with findings by Elsayed et al. (2024), who report a similar influence of GFS on spillovers across financial markets. While variables such as OVX, bitcoin sentiment, VIX, S&P500, and GVZ exhibit modest relevance, primarily under normal conditions, cyber-attacks emerge as the second most impactful factor, indicating their growing importance in return interdependence.

Figure 7 presents intriguing findings regarding volatility spillover. For instance, Cyber-attacks emerge as the most critical feature for predicting volatility spillover, but only during bearish and normal market conditions. The influence of GFS (financial stress) diminishes when predicting volatility spillover under these market con-

Table 10 Performance metrics for machine learning regression model of each quantile return connectedness

	Lower Quantile			
	MAE	MSE	RMSE	R2
Decision Tree	0.0497	0.0067	0.082	0.792
Random Forest	0.0315	0.0051	0.072	0.863
Gradient Boost	0.0192	0.0042	0.064	0.848
XGBoost	0.0239	0.0025	0.05	0.895
	Middle Quantile			
	MAE	MSE	RMSE	R2
Decision Tree	0.0428	0.0048	0.069	0.988
Random Forest	0.0517	0.0076	0.087	0.989
Gradient Boost	0.0457	0.0113	0.107	0.972
XGBoost	0.0339	0.0031	0.0560	0.99
	Upper Quantile			
	MAE	MSE	RMSE	R2
Decision Tree	0.1735	0.0779	0.2791	0.6373
Random Forest	0.1142	0.0621	0.2492	0.7236
Gradient Boost	0.1046	0.0701	0.2647	0.7177
XGBoost	0.0573	0.0045	0.0671	0.7074

Note: This table shows performance metrics for machine learning regression models of upper, middle, and lower quantiles return connectedness

Table 11 Performance metrics for machine learning regression model of each quantile volatility connectedness

	Lower Quantile			
	MAE	MSE	RMSE	R2
Decision Tree	0.3266	0.044	0.2098	0.983
Random Forest	0.2145	0.0304	0.1745	0.9883
Gradient Boost	0.1463	0.0406	0.2016	0.9844
XGBoost	0.0817	0.0031	0.056	0.9836
	Middle Quantile			
	MAE	MSE	RMSE	R2
Decision Tree	0.1956	0.1239	0.3521	0.9492
Random Forest	0.1146	0.0722	0.2688	0.9704
Gradient Boost	0.0960	0.0898	0.2996	0.9632
XGBoost	0.2451	0.1045	0.3232	0.9572
	Upper Quantile			
	MAE	MSE	RMSE	R2
Decision Tree	0.1841	0.1529	0.3910	0.8602
Random Forest	0.1517	0.0769	0.2772	0.8232
Gradient Boost	0.1463	0.0839	0.2896	0.7802
XGBoost	0.1565	0.0873	0.2954	0.8076

Note: This table shows performance metrics for machine learning regression models of upper, middle, and lower quantiles volatility connectedness

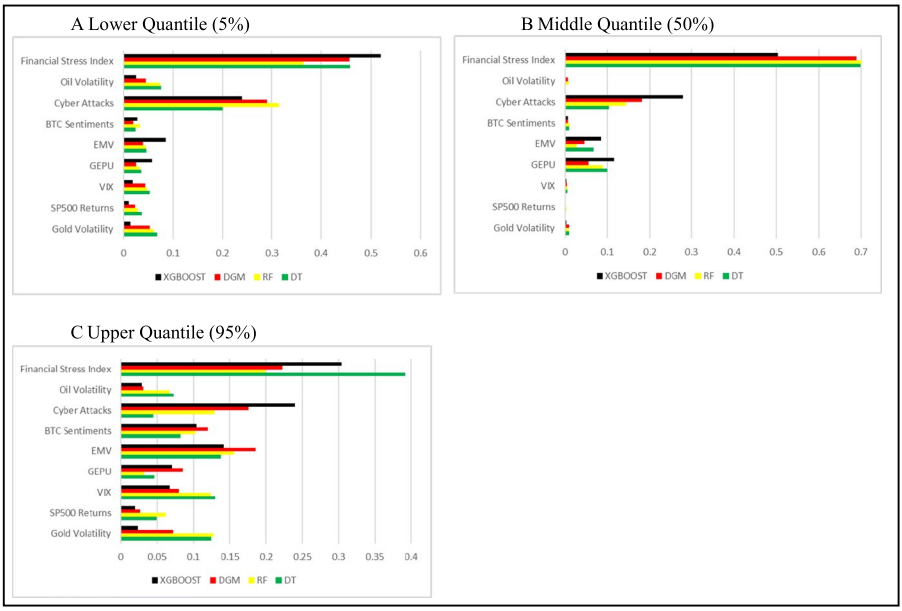


Fig. 6 Feature importance of returns connectedness from machine learning-based regression. Note: These figures show feature importance of returns connectedness from machine learning-based regression upper, middle, and lower quantiles

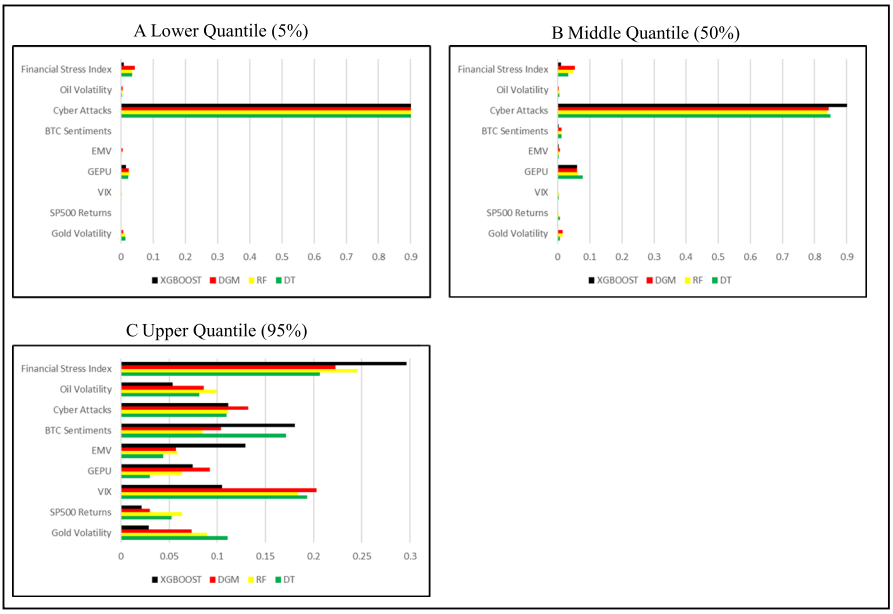


Fig. 7 Feature importance of volatility connectedness from machine learning-based regression. Note: These figures show feature importance of volatility connectedness from machine learning-based regression upper, middle, and lower quantiles

ditions. However, during bullish markets, all variables contribute significantly as the features in predicting volatility spillover. Specifically, the financial stress index emerges as the most crucial feature for volatility spillover at the upper quantile (bullish market), followed by VIX. These findings align with research by Elsayed et al. (2024), highlighting the significant impact of cyber-attacks and GFS on volatility spillover among financial assets.

Continuing our feature analysis, we turn to PI. Figure 8 illustrates the feature analysis of the primary factor influencing return spillover. Consistent with FI findings, GFS emerges as the key predictor of returns spillover between Islamic Indices and meme assets, a trend observed across all quantiles. Similarly, Cyber-attacks maintain their significance as the second most influential factor, reflecting broader financial stability and security dynamics impacting interconnectedness and volatility within these asset classes.

In the analysis of volatility spillover, the PI results depicted in Fig. 9 highlight cyber-attacks and GFS as central factors. Specifically, Cyber-attacks emerge as the primary feature influencing volatility spillover at lower and middle quantiles, emphasizing their significant impact during periods of bearish and normal conditions. Conversely, GFS assumes prominence as the leading predictor of volatility spillover at the upper quantile, indicating its heightened relevance during bullish markets. These findings validate our earlier observations regarding the crucial role of these variables in understanding and forecasting volatility spillover among Islamic indices and meme assets.

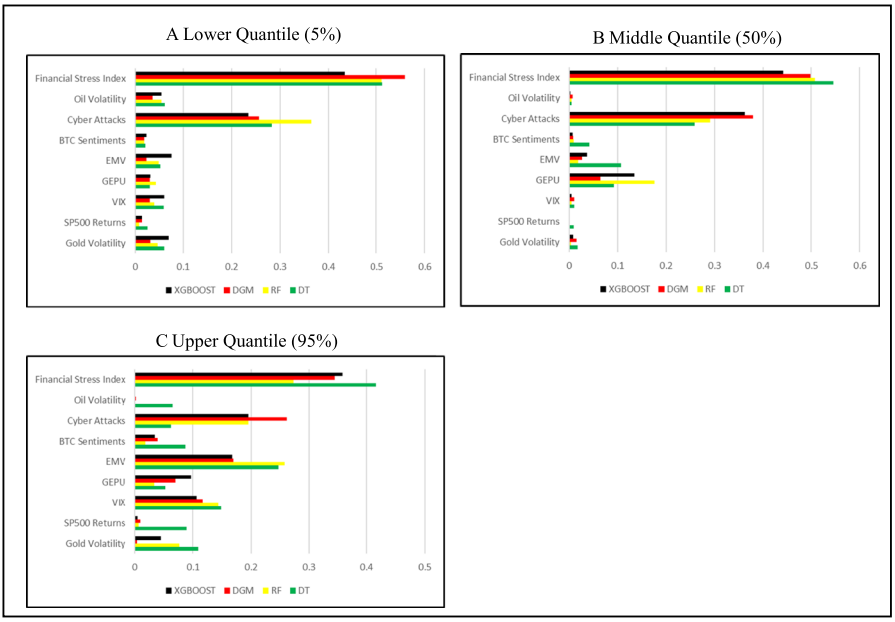


Fig. 8 Permutation importance of returns connectedness from machine learning-based regression. Note: These figures show permutation importance of returns connectedness from machine learning-based regression upper, middle, and lower quantiles

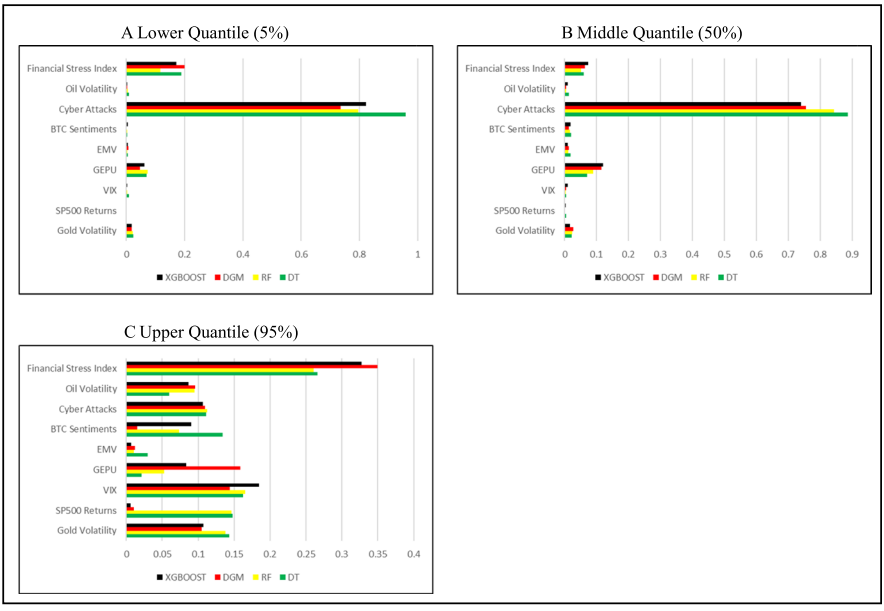


Fig. 9 Permutzation importance of volatility connectedness from machine learning-based regression. Note: These figures show permutation importance of volatility connectedness from machine learning-based regression upper, middle, and lower quantiles

5 Conclusion and Implication

Predicting the most significant feature in spillovers between Islamic sectoral indices and meme assets holds great importance for academic literature and the portfolio industry. This paper introduces a multistage approach to uncovering it. Initially, we explore quantile connectedness among Islamic sectoral indices and meme assets, highlighting their networked relationships across various market conditions. Subsequently, employing machine learning regressors, we forecast determinants and employ feature analysis to identify the pivotal factor driving the spillover.

The findings share several interesting conclusions. Firstly, there is a distinction in the connectedness behavior between return spillover and volatility spillover. The market appears more integrated for volatility spillover in comparison to return spillover. Yet, Islamic sectoral indices exhibit disconnection from meme assets during normal market conditions. Secondly, all Islamic sectoral indices tend to transmit returns, particularly during bearish and normal market conditions. However, their behavior differs during bullish markets, with three Islamic sectoral indices becoming recipients of returns. Most meme assets act as return recipients, except for the DOGE in bullish market conditions.

In terms of volatility spillover, most Islamic sectoral indices serve as transmitters during bearish and normal market conditions. Conversely, during bullish markets, all Islamic sectoral indices shift to being receivers of volatility, with AMC and DOGE playing significant roles as risk transmitters. Notably, the volatility of each Islamic sectoral index remains unconnected during bullish markets. We further address the Global financial stress index and Cyber-attack as the most important determining factors for the connectedness and spillover among Islamic sectoral indices and meme assets. Our findings suggest that the Global financial stress index emerges as the most influential factor for return spillover across various market conditions, while Cyber-attack is identified as the key determinant for volatility spillover. Although regression results also highlight the significance of GVX, SP500, VIX, GEPU, and EMV as contributing factors to the spillover, GFS and Cyber-attack remain the foremost predictors of spillover.

Our findings carry several practical implications. Firstly, the results from our dynamic connectedness highlight a compelling case for dynamic asset allocation in portfolios combining Islamic sectoral indices and meme assets. Islamic indices act as net return transmitters and lead volatility during bearish and normal markets, suggesting that increasing exposure to these indices in downturns can enhance portfolio stability and risk management. Conversely, meme assets dominate volatility in bullish periods, presenting tactical opportunities to increase their allocation to capture outsized gains during market upswings. This approach—commonly known as tactical asset allocation—involves actively adjusting portfolio weights based on evolving market conditions and asset connectedness. Asset managers, hedge funds, and family offices, particularly those involved in alternative investments and digital asset markets, increasingly adopt such strategies to optimize returns while managing risks. For meme assets, which often exhibit high volatility and speculative behavior, tactical allocation allows investors to capitalize on momentum during bullish phases while limiting exposure during down-

turns, making the portfolio more resilient and adaptive. Note that the findings also imply the benefits of a suboptimal portfolio may vary across different market conditions.

Moreover, unlike prior studies, we advance literature by identifying the most influential features driving dynamic connectedness. Our tree-based machine learning feature analysis highlights key indicators with direct industry relevance. Notably, the global financial stress index emerges as the primary driver of return spillovers, while cyber-attacks stand out as the main determinant of volatility spillovers. These findings carry significant practical implications. Portfolio managers should monitor global financial stress closely to anticipate shifts in return linkages between meme assets and Islamic indices, enabling timely portfolio adjustments. Similarly, vigilance around cybersecurity risks is critical, as such events can provoke abrupt volatility spikes. Integrating these macro-financial and security factors into risk models and early-warning systems enhances portfolio robustness and supports proactive risk management. Furthermore, it also sends signals to industry that the use of feature analysis might be fruitful for portfolio management, especially to assess the most important features among all available risk factors.

However, it is important to note that our findings require validation through additional research to achieve broader generalization, given the limitations of our study. For instance, while this study offers a novel approach to identifying the key drivers of dynamic connectedness between high-risk assets (meme assets) and crisis-resilient assets (Islamic sectoral indices), its scope remains limited to these two asset classes. Future research could extend this framework to a wider array of asset classes, including conventional equities, private markets, commodities, cryptocurrencies, fixed-income securities and other types of meme assets. Such extensions would enhance our understanding of the most influential features shaping connectedness patterns across diverse market environments and asset types.

Second, while there is no consensus on the optimal data frequency for analyzing spillover dynamics, this study is based on daily data due to its balance between noise reduction, data completeness and availability, and market responsiveness. However, extending the analysis to intraday or high-frequency data could enrich the literature by capturing more granular transmission mechanisms and real-time contagion effects, particularly during periods of heightened volatility. High-frequency data may uncover transient but critical episodes of connectedness that daily data might overlook, especially in different asset classes setting. Therefore, future research could explore the robustness and temporal sensitivity of spillover dynamics using intraday datasets to provide deeper insights into the immediacy and persistence of shocks between Islamic indices and meme assets. Additionally, there is potential for extending our analysis beyond Islamic sectoral indices to cover Islamic equity markets or Islamic bonds globally. Another limitation worth noting is the potential omission of high-order spillover effects, which could provide further insights into the dynamics of interconnected financial markets.

Appendix 1

Table 12 Variable definition

Variable	Ticker	Symbol	Source
Islamic Sectoral Indices			DataStream (London Stock Exchange Group)
Basic Materials	DJIMBML	Material	
Information Technology	DJITHY$	Technology	
Consumer Services	DJIMCSL	Service	
Consumer Goods	DJIMCGL	Consumer	
Financials	DJIMFNL	Financial	
Healthcare	DJIMH1L	Health	
Industrials	DJIMIDL	Industrial	
Oil&Gas	DJIMO1L	Oil	
Utilities	DJIMU1L	Utilities	
Telecommunications	DJIMT1L	Teleco	
Meme Assets			
Doge Coin		DOGE	Coin Metrics
Shiba Inu		SHIB	Coin Metrics
AMC Entertainment Holdings		AMC	Bloomberg
GameStop-GME		GME	Bloomberg
Determinants			
Gold Market Volatility		GVZ	Bloomberg
S&P500 returns		SP500	Bloomberg
Volatility Market Index		VIX	Bloomberg
Economic Policy Uncertainty		GEPU	https://www.policyuncertainty.com/
Equity Market Volatility		EMV	Bloomberg
Global Bitcoin Sentiments		BTC Sentiments	Google Trends
Global Cyber Attacks		Cyber Attacks	https://www.hackmageddon.com/category/security/cyber-attacks-statistics/
Crude Oil Volatility		Crude Oil Volatility	Bloomberg
Global Financial Stress Index		GFS	Bloomberg

Appendix 2

Table 13 Body of knowledge of islamic indices and meme assets spillover

Panel A. Literature summary for Islamic indices spillover	
Methods:	Modified GARCH and QVAR
Spillover with:	References
Conventional Equity Markets	Elsayed et al. (2024), Sheikh et al. (2024), Ghaemi et al. (2024), Yarovaya et al. (2021), Rejeb (2017), Majdoub & Sassi (2017), Mensi et al. (2017)
Commodities	Ghaemi et al. (2024), Ghallabi et al. (2024), Mensi et al. (2017)
Cryptocurrencies	Ali et al. (2024), Yousaf & Yarovaya (2022), Ali et al. (2022)
Proposing Determinants	Elsayed et al. (2024)
Methods:	Classic DY or TVP-VAR
Spillover with:	
Conventional Equity Markets	Mezghani & Abbes (2023), Tabash et al. (2022), Trabelsi (2019)
Commodities	Billah et al. (2024), Mezghani & Abbes (2023), Bahloul & Khemakhem (2021), Trabelsi (2019)
Cryptocurrencies	-
Proposing Determinants	Tabash et al. (2022)
Panel B. *Literature summary for Meme Assets spillover*	
Methods:	Modified GARCH and QVAR
Spillover with:	
Conventional Equity Markets	Aharon et al. (2024)
Commodities	-
Cryptocurrencies	Li (2022)
Proposing Determinants	-
Methods:	Classic DY, TVP-VAR, or quantile connectedness
Spillover with:	
Conventional Equity Markets	Elsayed et al. (2024)
Commodities	Yousaf et al. (2023)
Cryptocurrencies	Mensi et al. (2024), Yousaf et al. (2023)
Proposing Determinants	Elsayed et al. (2024)

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Declarations

Conflict of Interest None.

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