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# Multiscale Transmission of Volatility Between Short and Long-Term Investment Preferences: Evidence from Malaysia's KLCI

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**Abstract:** This study examines how short-term and long-term investments in Malaysia's stock market influence each other through volatility spillovers. Using daily data from the KLCI index from 2014 to 2024, the research applies a combination of wavelet analysis and the Dynamic Granger Causality Multivariate Stochastic Volatility (DGC-t-MSV) model. This method allows us to study market behavior across different time periods and frequencies. The results show that there are significant volatility spillovers between short-term and long-term investments, with stronger effects coming from long-term (institutional) investments to short-term (retail) investments. Both types of investments also show strong persistence in volatility, meaning that once volatility appears, it tends to last. These findings are important for investors who need to manage risks and returns more effectively. They also provide useful insights for policymakers who aim to improve the stability of financial markets. By introducing a new approach to analyzing volatility spillovers, this research contributes to a better understanding of risk management in emerging markets like Malaysia.

**Keywords**: *Volatility Spillovers, Wavelet Decomposition, Multivariate Stochastic Volatility (MSV), Malaysian Stock Market*

## 1. Introduction and Background

In the rapidly evolving financial landscape of Malaysia, market volatility presents a constant challenge for investors. Market volatility, defined as the conditional standard deviation of asset returns, reflects the degree of risk and unpredictability associated with financial instruments (Tsay, 2010; Brooks, 2008). The phenomenon of volatility spillovers, where fluctuations in one market impact another, plays a pivotal role in shaping investment decisions. This interconnectedness underscores the importance of understanding and managing these spillovers to optimize investment outcomes and mitigate risks. In recent years, this concern has intensified globally, driven by macroeconomic uncertainties, geopolitical tensions such as the Ukraine–Russia conflict, and inflation shocks following the COVID-19 pandemic.

An important turning point in the development of regional financial integration was the Asian Financial Crisis of 1998, which demonstrated the degree to which return and volatility spillovers might spread shocks throughout markets (Yilmaz, 2010). Key factors affecting volatility spillovers include market integration, interest rate fluctuations, exchange rate movements, and broader global economic conditions. As such, investors must comprehend the potential impact of these spillovers on their portfolio returns and manage associated risks accordingly.

Financial market volatility, particularly stock market volatility, can undermine the efficient functioning of economic systems (Merton & Bodie, 1995; Mala & Reddy, 2007). Malaysia's capital market is recognized for its relatively high volatility and its strong interconnectedness with global financial systems. This makes it particularly vulnerable to external shocks and foreign capital movement. Events such as the sharp rise and fall in glove-related stocks during the COVID-19 pandemic, and capital flight driven by domestic political instability, exemplify how both international developments and internal factors can amplify local market volatility. In the context of investor behavior and preferences in Malaysia, understanding the nature and extent of volatility spillover transmission is essential for achieving risk-adjusted portfolio performance and policy stability.

Factors such as global interest rate hikes, fiscal policy shifts, and geopolitical uncertainties can trigger significant volatility episodes in Malaysia. Between 2015 and 2022, the KLCI index demonstrated recurring patterns of volatility clustering, particularly during periods of US Federal Reserve policy normalization and foreign capital outflows. These dynamics affected investor confidence and altered portfolio allocation strategies for both institutional and retail investors. Identifying how these volatility episodes emerge and

persist can help market participants design more effective hedging strategies and risk mitigation frameworks. Numerous studies have explored volatility spillovers and risk behavior in global and emerging markets. Dutt and Humphery-Jenner (2013) highlighted the link between price volatility, firm operating performance, and stock returns, finding that low-volatility stocks with strong operational fundamentals tend to outperform. Weng et al. (2018) examined how trader attention and online financial information platforms influence investment behavior, leading to the development of predictive models for short-term stock price forecasting. Abdullah et al. (2022) and Alfreedi (2019) used a multivariate volatility framework to study the effect of return shocks on volatility in developed markets, revealing how return shocks propagate through conditional variance-covariance structures. Gee and Karim (2010) emphasized that international portfolio managers increasingly focus on stock volatility in emerging markets for diversification and return enhancement opportunities. Beirne et al. (2013) reinforced the relevance of the Malaysian stock market to global investors due to its reform-driven structure and openness to cross-border capital flows.

Furthermore, investors increasingly recognize the sensitivity of financial markets to extreme events such as natural disasters, systemic financial crises, war, and global pandemics. The Global Financial Crisis and the COVID-19 pandemic have demonstrated the disruptive impact of such systemic events on traditional equity indices (Sahoo & Kumar, 2023). Despite these insights, few studies have rigorously explored the dynamics of volatility spillovers between different investor classes, particularly within the same national market. For instance, Li Yu et al. (2023) noted the lack of quantitative investigations into volatility behavior across investment preferences. More recently, a 2025 study published in Qual Quant employed wavelet coherence and the Diebold–Yilmaz spillover index to examine volatility dynamics across financial, cryptocurrency, and commodity markets from 2017 to 2023. This work reaffirms the importance of multiscale methods in capturing spillovers across diverse asset classes and offers methodological support for the current paper's multiscale volatility approach.

The Asian Financial Crisis of 1998 marked a critical juncture in the evolution of regional financial integration. Building upon this historical context, the present study examines multiscale volatility spillovers between short-term and long-term investment preferences in Malaysia's stock market. Utilizing a wavelet-based Dynamic Granger Causality Multivariate Stochastic Volatility (DGC-t-MSV) model and drawing on daily KLCI index data from 2014 to 2024, the analysis captures both the directional influence and persistence of volatility across different time–frequency domains.

This investigation is theoretically grounded in the Intertemporal Capital Asset Pricing Model (ICAPM), the Fractal Market Hypothesis (FMH), and the Heterogeneous Market Hypothesis (HMH). Together, these frameworks offer a robust lens for understanding how diverse investor types (with varying risk tolerances, information processing behaviors, and investment horizons) contribute to the transmission and amplification of volatility across time scales. By integrating these theoretical perspectives with a multiscale modeling approach, the study aims to generate meaningful implications for portfolio risk management, enhance the behavioral segmentation of financial market participants, and support more informed decision-making by policymakers and institutional stakeholders navigating Malaysia's increasingly complex and globally exposed investment environment.

This research contributes to the literature in three significant ways. First, it offers empirical insights into volatility clustering and persistence at different investment scales, which have direct implications for asset allocation, hedging strategies, and regulatory oversight. Second, the methodological adoption of the DGC-t-MSV model enables the integration of nonlinear structures, regime shifts, and multiscale behavior, the features commonly overlooked by traditional GARCH-type models. Third, the study bridges an important gap by examining intra-market volatility spillovers between investor classes rather than across countries or sectors. While previous studies (Dutt and Humphery-Jenner, 2013; Weng et al., 2018; Alfreedi, 2019; Abdullah et al., 2022) have investigated spillovers using multivariate models, few have contextualized these dynamics within a single national market differentiated by investment horizon. As such, this research provides both theoretical and practical advancements in understanding market behavior and managing financial risk.

The article is organized as follows: The "Literature Review" section reviews preceding literature; the "Research Methodology" section describes the data and methodology used in this study; the "Empirical Analysis" section

presents preliminary analysis and empirical results; and the "Discussion and Conclusion" section concludes the article.

## 2. Literature Review

Volatility spillovers are a major topic in the field of financial economics since they involve the exchange of information between various financial markets (Long et al., 2021). It relates risks transferred from different markets to spillovers, which have important ramifications for risk management, asset allocation, and option pricing (Khalfaoui et al., 2015; Naeem et al., 2023; Wang & Wu, 2012). Some researchers have previously examined various facets of this market interaction. Because of the steadily rising financial integration over the past fifteen years, which may have contributed to the greater risks brought on by the financial crisis, Diebold & Yilmas (2009) find that volatility spillovers exhibit clear bursts associated with financial crises. According to Nishimura et al. (2018), there is a greater degree of spillover effect in accessible markets compared to inaccessible markets, as stock investors' transactions across international markets primarily cause volatility spillovers to intensify with increased openness.

According to Liu et al. (2020), the majority of volatility spillovers are produced during long-term trade and are susceptible to significant financial events, helping explain how financial crises continue to propagate through directional volatility channels. Given that health and geopolitical risks significantly impact the return-volatility system, studies suggest that spillovers intensified during the COVID-19 pandemic and the Russia–Ukraine war (Naeem et al., 2023; Chen et al., 2023; Hanif et al., 2023). Extending this theme, Chen et al. (2025) employed wavelet coherence and time-varying causality analysis to assess volatility spillovers between climate risk and stock markets, reinforcing the value of multiscale decomposition in understanding transmission effects under systemic shocks. While much of the existing literature focuses on cross-market contagion, this study narrows in on volatility spillovers within the stock market, specifically between different investor segments operating at divergent time scales.

To conceptualize these interactions, this study draws on three interrelated theories: the Intertemporal Capital Asset Pricing Model (ICAPM), the Fractal Market Hypothesis (FMH), and the Heterogeneous Market Hypothesis (HMH). The ICAPM (Merton, 1973) posits that investors allocate wealth not only for immediate gains but also to hedge against future uncertainties, particularly volatility shifts, highlighting the temporal dimension of risk in investment behavior. This aligns with the view that institutional investors, with longer horizons, may be more sensitive to intertemporal volatility changes. Meanwhile, the FMH (Peters, 1994) emphasizes that financial markets are made up of heterogeneous participants with differing time horizons whose coexistence contributes to market stability, but whose imbalance can induce volatility. This is especially relevant when analyzing multiscale volatility through wavelet decomposition. Similarly, the HMH (Müller et al., 1997) suggests that market dynamics emerge from the asynchronous reactions of investors to information and shocks, reinforcing the importance of modeling volatility transmission between retail and institutional segments. These theories collectively form the backbone of this study's empirical strategy.

From a methodological perspective, early studies often adopted observation-driven approaches such as univariate GARCH-type models (Gao et al., 2021; Zhang et al., 2022). Liu et al. (2017), for example, used a BEKK-GARCH model to analyze the evolution of volatility spillovers during financial crises. The intensification of volatility spillovers across sectors revealed contagion patterns during the Global Financial Crisis. However, limitations persist within these models, notably the rigid assumptions on error structures and the inability to fully capture regime shifts and multiscale behavior (Chen et al., 2023; Belhassine, 2020).

To overcome these constraints, multivariate stochastic volatility (MSV) models have gained prominence. These models treat error variance as a stochastic process, offering a more flexible and accurate representation of financial time series dynamics (Tsionas et al., 2022; Zhang & He, 2021). Asai et al. (2006) highlight the diagnostic strength of MSV models using Markov Chain Monte Carlo (MCMC) estimation, which is now standard in this literature. Tian and Hamori (2016), using the SVAR-MSV framework, demonstrate temporal lags in spillover effects across U.S. markets. Wu et al. (2020) applied the DGC-MSV model to show persistent volatility links between stock and exchange rate markets, features not adequately captured by GARCH models.

This research extends the MSV framework through the integration of wavelet analysis, allowing for simultaneous decomposition of financial data in the time and frequency domains. Rua and Nunes (2012) first demonstrated how wavelet methods can isolate spillovers across sectors at different time scales. Volatility patterns often differ substantially across wavelet scales, suggesting that spillovers operate asynchronously across investment horizons (Liu et al., 2017). To capture these dynamics, this study introduces the wavelet-based DGC-t-MSV model, which integrates maximum overlapping discrete wavelets with MSV estimation to analyze volatility transmission between short-term (retail) and long-term (institutional) investors in the same market. This model is supported by recent evidence from Wang (2024), where DGC-t-MSV was successfully applied to capture structural transformation effects in carbon and energy markets.

Over the last decade, multiscale volatility in Malaysia's KLCI index has become increasingly evident, reflecting economic shocks, political instability, and sector-specific disturbances, such as the glove industry's rapid boom and bust. Understanding volatility spillovers across investor types is therefore critical for market resilience. For instance, Younis et al. (2023) documented bi-directional causality between Malaysian and Chinese equity markets across time scales during crises, while Lestari et al. (2023) found a negative correlation between KLCI movements and China's Economic Policy Uncertainty index. Building on the foundation laid by Yu et al. (2023), who used the DGC-t-MSV model to assess institutional–retail volatility spillovers in China, this study offers a novel contribution by applying the same framework to Malaysia's capital market, where such intra-market volatility segmentation remains underexplored.

## 3. Research Methodology

**Wavelet Decomposition of the Original Series:** The study utilizes the Maximum Overlap Discrete Wavelet Transform (MODWT) for wavelet decomposition, following the methodology proposed by Percival and Walden (2000). MODWT was chosen for its advantages over traditional Discrete Wavelet Transform (DWT), including the ability to analyze any number of samples without special provisions for data selection starting points, constant data amounts in each scale post-decomposition, translation invariance, and time-varying wavelet coefficients. These features enable a more refined capture of low-frequency information and improved resolution.

In this study, the MODWT is applied to the daily returns of the KLCI Index from March 13, 2014, to March 13, 2024, encompassing decomposing the original time series into multiple scales. The Symlet wavelet with a width of eight, an improvement over the Daubechies wavelet, is selected for its nearly symmetric, tightly supported, regular, and smooth characteristics, making it ideal for noise reduction and orthogonal wavelet decomposition of financial time series.

**Multivariate Model of Volatility: DGC-t-MSV:** To investigate the volatility spillovers between different investment preferences, the study employs the Dynamic Granger Causality Multivariate Stochastic Volatility (DGC-t-MSV) model, based on the Student's t-distribution. This model allows for the characterization of both mean and volatility spillovers as well as dynamic correlations between short-term and long-term investment returns. The DGC-t-MSV model is defined as follows:

$$y_t = \text{diag}\,(\exp(h_t / 2)) * \varepsilon_t$$

$$h_t = \mu + \Phi(h_{t-1} - \mu) + \eta_t,\ \eta_t \sim N(0, \text{diag}(\sigma^2{}_{\eta 1}, \sigma^2{}_{\eta 2}))$$

$$q_t = \psi_1 + \psi(q_{t-1} - \psi_0) + \tau z_t,\ z_t \sim N(0, 1)$$

Where $y_t$ represents the vector of returns for short-term and long-term investments, $\varepsilon_t$ is the random error term following a Student's t-distribution with a time-varying correlation matrix $\Sigma_t$. The parameters of volatility persistence and spillovers are captured in the matrix $\Phi$, and the dynamic correlation persistence is represented by $\psi$. The Markov Chain Monte Carlo (MCMC) method with Gibbs sampling is employed to estimate all model parameters, ensuring the robustness and accuracy of the results.

**Convergence Check and Granger Causality:** The convergence of the MSV model is assessed using the Gelman-Rubin statistic, which approaches 1 when the sample iterations are sufficient, indicating model stability. Granger causality is tested to determine the presence of volatility spillovers between the different wavelet

scales. The significance of the spillover coefficients is evaluated using a t-statistic:

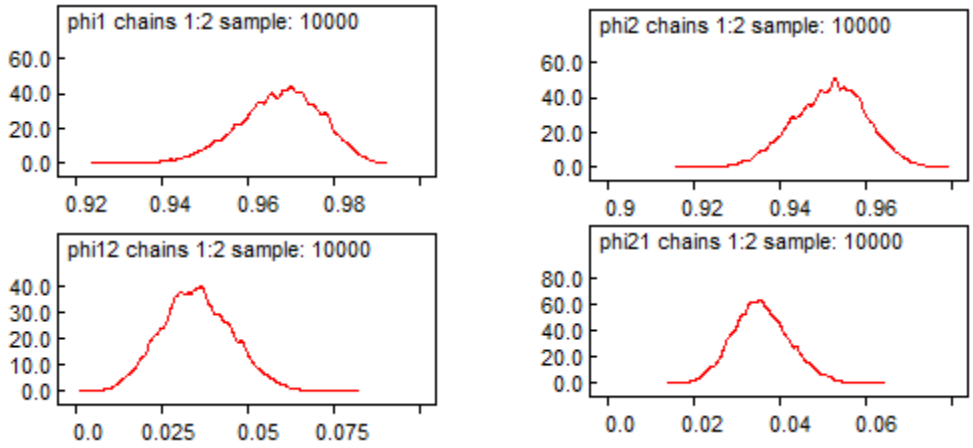
$$t = \varphi_{ij} / SE(\varphi_{ij}),\ SE(\varphi_{ij}) = \sqrt{(Var(\sum \varphi_{ij}))}\ (i \neq j)$$

Where $\varphi_{ij}$ represents the estimated parameter of volatility spillovers, and its significance is determined by comparing the t-statistic with critical values.

## 4. Results

To ensure the accuracy of the results, the DGC-t-MSV model estimations are performed using the MCMC method and a Gibbs sampler. For posterior computing in the multivariate stochastic volatility model, we use the WinBUGS software, which offers a specialized implementation of the MCMC technique as well as an effective Gibbs sampler. When it comes to the volatility spillovers between short-term and long-term investments of the D1 and D3 scales, the parameters $\phi_1$, $\phi_2$, $\phi_{12}$, and $\phi_{21}$ are involved. The iteration and convergence are as follows:

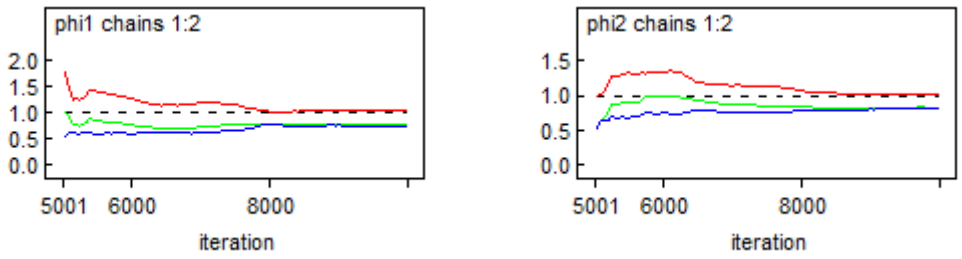
**Figure 1: The density curves for the short-term and long-term investments' volatility spillovers**

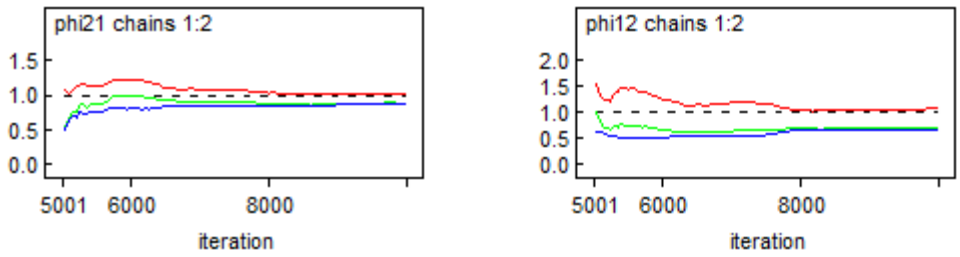



Source: Author's calculations from WinBUGS.

The parameters' posterior density curves for the volatility spillovers between KLCI's short-term and long-term investments are shown in Figure 1. Given that the sample data iterations increase and the curves are generally smooth, the approach's efficacy and good convergence are confirmed. It tends toward asymptotic normality.

**Figure 2: The Markov Chain of DGC-t-MSV Model**






As illustrated in Figure 2, every Markov chain of parameters quickly approaches 1, indicating that the Gibbs sampler-based MCMC methodology fits the marginal posterior distribution. As a result, it demonstrates that the DGC-t-MSV model is suitable for characterizing the KLCI's short- and long-term volatility spillovers in the Malaysian stock market.

**Estimation results:** The DGC t MSV model estimation results for the whole 2014–2024 period of KLCI original data are shown in Table 1. It presents the pairwise combined MODWT decompositions. In the daily return of KLCI, wavelet decompositions D1 and D3, which represent short-term retail investor investment and long-term institutional investment, respectively, are studied for their mean and volatility spillover dynamics. Additional estimations at the remaining decomposition scales are included only as a point of reference.

**Table 1: The Pairwise Combined MODWT Decompositions**

| Coefficient | Prior distribution | Scale | Mean | Standard Deviation | MC error | Distribution interval |
|---|---|---|---|---|---|---|
| $\psi$ | Beta (20, 1.5) | D1-D2 | 0.1359 | 0.0685 | 0.005754 | (0.03742, 0.3022) |
| | | D1-D3 | 0.8171 | 0.1553 | 0.01298 | (0.5273, 0.9830) |
| | | D2-D3 | 0.7347 | 0.1052 | 0.008616 | (0.5009, 0.8866) |
| $\mu_1$ | N (0, 25) | D1-D2 | 0.5043 | 0.1746 | 0.007444 | (0.1547, 0.8489) |
| | | D1-D3 | 0.5025 | 0.1968 | 0.005331 | (0.1127, 0.8830) |
| | | D2-D3 | 0.3953 | 0.1925 | 0.007249 | (0.00741, (0.7678) |
| $\mu_2$ | N (0, 25) | D1-D2 | -0.02914 | 0.1713 | 0.00762 | (-0.3768, 0.3030) |
| | | D1-D3 | -0.1148 | 0.1850 | 0.005995 | (-0.4810, 0.2440) |
| | | D2-D3 | -0.05753 | 0.1796 | 0.0058883 | (-0.4142, 0.2949) |
| $\sigma_{n^1}^1$ | Inverse-Gamma (2.5, 0.025) | D1-D2 | 0.4197 | 0.03850 | 0.003049 | (0.3349, 0.4907) |
| | | D1-D3 | 0.3855 | 0.03038 | 0.002372 | (0.3350, 0.4459) |
| | | D2-D3 | 0.3061 | 0.02735 | 0.002169 | (0.2633, 0.3678) |
| $\sigma_{n^2}^2$ | Inverse-Gamma (2.5, 0.025) | D1-D2 | 0.2745 | 0.02168 | 0.001682 | (0.2379, 0.3200) |
| | | D1-D3 | 0.3423 | 0.02703 | 0.002094 | (0.2966, 0.3951) |
| | | D2-D3 | 0.3404 | 0.02584 | 0.001991 | (0.2903, 0.3927) |

Note: There are partial estimations of the parameters in the DGC-t-MSV model run by the MCMC method with Gibbs sampler. Each parameter between different wavelet scales consists of a total of 2464 observations, respectively.

The Monte Carlo (MC) errors of all the parameters are less than their standard deviations. It is therefore possible to conclude the DGC t MSV model's applicability and validity for the MODWT decompositions of different investment preferences, specifically between short-term (D1) and long-term (D3) investment horizons. This approach is grounded in the Intertemporal Capital Asset Pricing Model (ICAPM), which emphasizes how investors allocate assets over multiple periods under uncertainty (Merton, 1973). Moreover, the Fractal Market Hypothesis (FMH) and Heterogeneous Market Hypothesis (HMH) support this analysis by positing that financial markets consist of investors with differing investment horizons and reactions to volatility, causing fluctuations across various time scales (Peters, 1994; Müller et al., 1997).

To analyze investment dynamics over a range of time periods, financial modeling requires an understanding of time-varying coefficients. Five coefficients $\psi$, $\mu_1$, $\mu_2$, $\sigma_{n^1}^1$ and $\sigma_{n^2}^2$ are the subject of this research which analyzes their mean values in relation to institutional investors' long-term investments and individual investors' short-term investments. The persistence of correlation dynamics across investor groups is represented by the time-varying coefficients $\psi$. Table 1 presents the average values and standard deviations of $\psi$, which progressively decrease from the low decomposition scale of pairwise pairings to the high level. In terms of dynamic correlation, the correlation persistence on the D1–D3 scale ranges from 0.5273 to 0.9830, confirming a positive relationship between short-term and long-term returns. This persistence mirrors recent findings in the literature, such as Chen et al. (2025), who observed multiscale volatility transmissions under systemic risk using wavelet and causality approaches in the context of climate and financial market linkages. Similarly, a 2024 study by Wang et al. (2024) validated the DGC t MSV model's power to capture temporal volatility spillovers between carbon and energy markets, which reinforces the methodological robustness of the current approach.

The detail coefficients' mean μ1 and μ2 are shown in Table 1 together with their average values and standard deviations. It demonstrates that, on the same decomposition scale, μ1 is essentially greater than μ2. In particular, the D1–D3 scale estimation results show that the average return on short-term investments in Malaysia's stock market is larger than that of long-term investments. The findings in daily stock market return forecasts (Zhong and Engke, 2017) are partially in line with this observation. These results also correspond with HMH assumptions, suggesting that short-term investors react more aggressively to market signals, hence creating sharper return dynamics than long-term investors who tend to stabilize volatility.

Table 1 also reports the conditional variances $\sigma_{n^1}^1$ and $\sigma_{n^2}^2$ of the detail coefficients at various wavelet scales. The conditional variances exhibit high average values and standard deviations, particularly in the D1–D2 scale and progressively diminish with low wavelet decomposition. In fact, the short-term investment's departure from the standard value is greater than that of the long-term investments, as indicated by the higher value of $\sigma_{n^2}^2$. This is essentially consistent with observed behavior in the Chinese stock market, where high-yield, high-risk assets attract short-term trading due to volume volatility (Yu et al., 2023).

To sum up, the average values of the time-varying coefficients offer both institutional and individual investors insightful information. These coefficients can be used by institutional investors to improve long-term portfolio management, and by short-term investors to maximize their trading strategies. Comprehending these coefficients aids both types of investors in navigating the intricacies of market dynamics and aligning their strategies with their financial objectives. These insights reinforce the importance of multiscale modeling for dynamic portfolio management, especially in emerging markets like Malaysia, where investor heterogeneity significantly influences volatility behavior.

**Mean spillovers:** The mean spillovers are captured by the $\phi_1$ and $\phi_2$ coefficients in Table 2. Regarding short-term volatility persistence, the mean value of $\phi_1$ (= 0.9673) is significantly positive. Strong persistence in volatility is indicated by this high score, which is close to 1, meaning that once volatility arises, it usually lasts for a considerable amount of time. The persistence value indicates that variations in short-term returns do not soon abate, which is consistent with the result that short-term investments are more volatile. Comparably, the mean value for long-term volatility persistence, $\phi_2$ (= 0.9516), is likewise significantly positive and only slightly lower than that of $\phi_1$. This suggests that long-term volatility shows an even greater level of persistence. Long-term investors should anticipate volatility, which is more persistent than short-term investments. This variation in persistence highlights how volatility dynamics differ over various investment horizons.

**Table 2: The Mean Spillovers of $\Phi_1$ and $\Phi_2$**

| Coefficient | Prior distribution | Scale | Mean | Standard Deviation | MC error | Distribution interval |
|---|---|---|---|---|---|---|
| $\phi_1$ | Beta (20, 1.5) | D1-D2 | 0.9307 | 0.01963 | 0.0014490 | (0.8912, 0.9691) |
| | | D1-D3 | 0.9673 | 0.009523 | 0.0005983 | (0.9472, 0.9841) |
| | | D2-D3 | 0.9788 | 0.009826 | 0.0006589 | (0.9571, 0.9944) |

| | | | | | | |
|---|---|---|---|---|---|---|
| $\phi_2$ | Beta (20, 1.5) | D1-D2 | 0.9164 | 0.01112 | 0.0007513 | (0.8953, 0.9378) |
| | | D1-D3 | 0.9516 | 0.008470 | 0.0004767 | (0.9345, 0.9675) |
| | | D2-D3 | 0.9368 | 0.009385 | 0.0005671 | (0.9166, 0.9538) |

Note: Table 2 provides the estimations of the mean spillover parameters $\phi 1$ and $\phi 2$ in the DGC-t-MSV Model with the posterior distribution run on the whole periods of daily returns. Each parameter is estimated by the MCMC method with the Gibbs sampler and consists of a total of 2464 observations.

These observations are well aligned with the Fractal Market Hypothesis (FMH) and Heterogeneous Market Hypothesis (HMH), both of which suggest that financial markets are composed of agents operating at various temporal horizons with distinct risk perceptions and behavioral responses (Peters, 1994; Müller et al., 1997). The observed persistence in both short- and long-term volatilities further validates the assumption that investor reactions are not uniform across timeframes. This is echoed in recent findings by Chen et al. (2025), who employed wavelet and causality techniques to demonstrate the long-lasting impact of systemic risks on volatility patterns, reinforcing the argument for multiscale modeling in capturing persistent shocks. Similarly, the Wang et al (2024) study confirms that volatility dynamics across investment horizons, when modeled through DGC t MSV frameworks, exhibit unique, time-dependent persistence that conventional models often overlook.

The need for investors to understand the behavioral patterns of volatility across various investment horizons is highlighted by the high persistence values for both $\phi_1$ and $\phi_2$. Short-term investors must manage the risks associated with immediate returns by realizing that volatility can stay high for extended periods of time. The possibility that long-term volatility will continue to exist must also be taken into consideration by long-term investors, as this could have an impact on their long-term risk management and strategic planning strategies. These insights are consistent with the Intertemporal Capital Asset Pricing Model (ICAPM), which posits that forward-looking investors adjust their asset allocations over time in response to changing volatility expectations (Merton, 1973). Understanding the duration and consistency of volatility across time scales enhances decision-making under uncertainty, supporting more adaptive and time-sensitive risk management strategies.

The standard deviation values for coefficients $\phi_1$ (= 0.009523) and $\phi_2$ (= 0.008470) shed light on the variability of volatility spillovers. The higher standard deviation for $\phi_1$ suggests that the short-term spillover effects are more erratic and prone to more fluctuations. Accordingly, short-term investors can encounter more abrupt shifts in how market or asset volatility propagates, necessitating more responsive and tactical risk management. Long-term investors may find it easier to predict and control these impacts over time if the standard deviation of $\phi_2$ is lower, which suggests that long-term volatility spillovers are steadier and more reliable. Overall, more consistent and predictable risk exposure is made possible by the reduced variability in long-term spillovers, whereas short-term investors need to be ready for a more dynamic market environment with greater volatility uncertainty. This further reinforces the premise of market heterogeneity, as highlighted in the FMH and HMH, where differing investor behaviors across scales create divergent volatility responses, calling for customized investment strategies depending on horizon and risk appetite.

**Volatility spillovers:** Estimations in Table 3 reflect that the volatility spillover effects are captured by the $\phi_{12}$ and $\phi_{21}$ coefficients, and the means of which vary within a certain range in all the sectors. The positive mean values of $\phi_{12}$ (from short-term to long-term) and $\phi_{21}$ (from long-term to short-term) suggest that there are notable volatility spillovers between short-term and long-term investments, though the positive value is not so high. Compared to $\phi_{12}$ (= 0.03525), the mean value of $\phi_{21}$ (= 0.03560) is slightly higher, indicating stronger spillovers from long-term to short-term investments. This result is consistent with the original study's finding that there are important interactions between different kinds of investments. These spillovers are bidirectional, meaning that fluctuations in one investment horizon may have an impact on the other. For example, higher volatility in long-term investments may have an impact on the stability of short-term investments and vice versa. This interdependence emphasizes how crucial it is to take both investment horizons into account when assessing market circumstances and possible hazards.

**Table 3: The Volatility Spillover Parameters $\phi_{12}$ and $\phi_{21}$ in the DGC-T-MSV Model**

| Coefficient | Prior distribution | Scale | Mean | Standard Deviation | MC error | Distribution interval |
|---|---|---|---|---|---|---|
| $\phi_{12}$ | N (0, 25) | D1-D2 | 0.06729 | 0.01907 | 0.0013990 | (0.02839, 0.1048) |
| | | D1-D3 | 0.03525 | 0.01024 | 0.0006462 | (0.01619, 0.05622) |
| | | D2-D3 | 0.01604 | 0.00901 | 0.0005924 | (0.000494, 0.0154) |
| $\Phi_{21}$ | N (0, 25) | D1-D2 | 0.07792 | 0.01022 | 0.0007007 | (0.05902, 0.0986) |
| | | D1-D3 | 0.03560 | 0.006546 | 0.0003375 | (0.02345, 0.04922) |
| | | D2-D3 | 0.05815 | 0.009081 | 0.0005289 | (0.04066, 0.07692) |

Note: Table 3 provides the estimations of the volatility spillover parameters $\phi 12$ and $\phi 21$ in the DGC-t-MSV model with the posterior distribution run on the whole periods of daily returns, which are based on the prior distribution N (0, 10) according to previous literature. Each parameter is estimated by the MCMC method with the Gibbs sampler and consists of a total of 2464 observations.

The observed bidirectional spillover pattern is theoretically supported by the Heterogeneous Market Hypothesis (HMH), which posits that financial markets comprise investors with different time horizons and informational processing speeds, thereby contributing to cross-horizon volatility dynamics (Müller et al., 1997). The fact that $\phi_{21}$ slightly exceeds $\phi_{12}$ supports the idea that institutional investors (typically long-term) can exert structural influence over short-term investor sentiment, consistent with the Fractal Market Hypothesis (FMH). According to FMH, markets are stable only when investors with diverse time horizons coexist; any imbalance in this structure, such as increased institutional reallocation, may propagate through shorter time-scale behaviors. The asymmetry in volatility transmission also lends empirical support to the Intertemporal Capital Asset Pricing Model (ICAPM) framework, which emphasizes that rational investors adjust their portfolios in anticipation of future risk-return trade-offs, affecting current volatility levels across horizons (Merton, 1973).

Understanding the asymmetry in the spillover effects, where $\phi_{21}$ is greater than $\phi_{12}$, is crucial to comprehending the interactions between various assets or marketplaces. For investors with lengthy time horizons, the moderate value of $\phi_{21}$ indicates that volatility contagion is more possible over longer time horizons, particularly from particular assets or markets with wider implications. Nonetheless, the numbers are still low enough to imply that, even while spillovers occur, it does not control the dynamics of overall volatility. These findings are in line with Chen et al. (2025), who demonstrated that volatility spillovers stemming from climate risks affected both short- and long-term stock market behavior through multiscale feedback channels. Additionally, the Wang et al (2024) study using the DGC t MSV model emphasized how volatility initiated in structurally sensitive long-horizon markets could cascade into more reactive short-horizon instruments, mirroring the modest but persistent spillover seen here.

The comparatively low standard deviations for both coefficients suggest that these spillover effects are steady and reliable throughout time. Both short-term and long-term investors can accurately forecast the degree of volatility transmission between assets or markets due to this low variability. This stability, which implies that there are spillover effects but that they do not fluctuate greatly, is essential for short-term investors to manage immediate risks. Because they can predict how volatility in one area of the portfolio may affect other assets, long-term investors can improve risk management and portfolio adjustment over time thanks to the relative constancy of spillover patterns. The complex relationship between markets and assets is ultimately highlighted by these coefficients, where spillover effects are present but kept within an acceptable range for both short-term and long-term investors.

By integrating behavioral heterogeneity, forward-looking portfolio theory, and time-scale-specific market dynamics, the study's findings advance the conceptualization of volatility spillovers beyond simplistic contagion models. Together, these grounded theories offer a robust lens through which to interpret the observed multiscale interactions and enhance volatility forecasting and policy implications in Malaysia's stock market.

## 5. Conclusion

This study investigates the dynamic and multiscale nature of volatility spillovers between short-term and long-term investment preferences in the Malaysian stock market using a wavelet-based Dynamic Granger Causality Multivariate Stochastic Volatility (DGC t MSV) model. By decomposing daily KLCI index data (2014–2024) across multiple frequency bands, the study identifies persistent yet asymmetric volatility spillover effects, with long-term investment segments exerting marginally stronger transmission onto short-term behavior. The analysis reveals meaningful time–frequency interactions in volatility patterns, reaffirming that institutional and retail investor behaviors are interlinked and that market volatility is not uniform across horizons. These findings reinforce the applicability of multiscale approaches in financial modeling and align with grounded theories such as the Intertemporal CAPM, Fractal Market Hypothesis, and Heterogeneous Market Hypothesis, which explain investor segmentation and market persistence.

The implications of these findings are twofold. First, for institutional investors and portfolio managers, the results emphasize the importance of accounting for multiscale volatility structures when designing long-term investment strategies, particularly during periods of systemic shocks or political uncertainty. Second, for regulators and policymakers, the bidirectional spillover dynamics underscore the need for surveillance tools that capture temporal interdependencies and horizon-based vulnerabilities. This study contributes to the expanding body of literature on intra-market volatility transmission by offering a novel empirical framework that bridges theoretical insights and applied risk modeling in an emerging market context. Future research can extend this work by integrating cross-country spillover analysis, high-frequency trading signals, or behavioral factors to deepen our understanding of volatility co-movements in interconnected financial systems.

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