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Investigating Volatility Spillover between the Energy Market and the Sectoral Stock Markets in Malaysia: Evidence from VHAR-Type Models

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Abstract

This study examines the realised volatility spillover effects between Malaysia's energy market and other sectoral indices on the Kuala Lumpur Stock Exchange from September 2018 to December 2024. To address the limitations of current volatility modelling approaches, this study employs the Vector Heterogeneous Autoregressive (VHAR) model combined with the Realised Range-Based Volatility (RRV) measure to capture heterogeneous market behaviours at daily, weekly, and monthly time horizons. High-frequency data from September 2018 to December 2024 (earlier data are unavailable for some sectors) were collected from the financial data provider Bloomberg. The findings reveal that the energy sector exhibits strong volatility persistence, with past volatility having a significant influence on current volatility levels. More importantly, this study documents spillover effects. While the energy sector experiences limited volatility transmission from other sectors, it exerts substantial influence on the volatility of most other sectors, notably demonstrating adverse long-term effects but positive short- and medium-term impacts. The healthcare sector appears to be uniquely immune to the energy market volatility contagion. A comparative analysis confirms that the VHAR-RRV model substantially outperforms traditional Vector Autoregressive (VAR) models and modestly surpasses VHAR models using standard realised volatility measures. These results offer valuable insights into portfolio diversification strategies, risk management

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practices, and policy formulation in Malaysia and similar emerging markets, where energy sector dynamics have a significant impact on broader market stability.

Keywords: Vector Heterogeneous Autoregressive (VHAR), Realised-Range Volatility, Malaysia, Kuala Lumpur Stock Exchange (KLSE), Volatility Spillover, Energy Sector

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1.0 Introduction

Oil price volatility has become a critical concern for policymakers and businesses, contributing to inflationary pressures and influencing the costs of essential goods (Min, 2022). In oil-exporting economies such as Malaysia, this volatility disrupts fiscal planning and corporate performance through financial market interlinkages, thereby heightening uncertainty and undermining government revenue stability. The structure of Malaysia's stock market (KLSE), particularly its benchmark index (the FTSE Bursa Malaysia KLCI), contains a significant proportion of companies whose performance depends on the oil and gas sector (FTSE Russell, 2025). Owing to this composition, when global oil prices rise or fall sharply, the share prices of these energy-related firms move significantly, which, in turn, affects the overall market index and the broader economy. In other words, Malaysia's stock market is not neutral to oil shocks; it is structurally linked to them. Historical episodes such as the 1998 Asian financial crisis illustrate how abrupt price shocks can severely strain non-energy sectors and compel drastic macroeconomic adjustments (Mabro, 2001).

Despite the growing interest in volatility modelling, the existing literature faces three methodological and empirical limitations. First, heightened global financial integration has diminished traditional diversification benefits, making sector-specific volatility analysis increasingly crucial for risk-adjusted portfolio allocation (Ha, 2023; Kim & Baek, 2024; Nardo et al., 2022; Wang et al., 2023). Malaysia's capital market is dominated by institutional investors, including the Employees Provident Fund (EPF), Permodalan Nasional Berhad (PNB), and Khazanah Nasional Berhad. These institutions hold large cross-sector portfolios, meaning that losses or gains in one major sector (such as energy) ripple across multiple holdings. Second, low-frequency data tend to obscure volatility clustering, leading to biased forecasts, underestimation of market risk, and potentially delayed policy responses (Jahan-Parvar & Zikes, 2023; Nhlapho et al., 2025). Third, recent empirical evidence, including Liao and Anderson (2019) and Tang et al. (2020), who stated that it increasingly challenges assumptions of the efficient market hypothesis (EMH) by suggesting that financial markets operate under heterogeneous behavioural conditions better captured by the Heterogeneous Market Hypothesis, acknowledges that investors act on different time horizons and respond differently to shocks.

To address these gaps, this study employs high-frequency intraday data and applies realised range volatility (RRV) measures within a multivariate Heterogeneous Autoregressive (VHAR) framework. This approach allows for a detailed assessment of volatility transmission between Malaysia’s energy sector and other key market sectors, while capturing investor heterogeneity across daily, weekly, and monthly horizons. By integrating high-frequency realised-range volatility into a VHAR structure, this study is one of the first sector-specific analyses of volatility spillovers in Malaysia’s energy-linked capital markets. This approach enhances the accuracy of risk detection and captures the dynamic linkages that are overlooked by conventional models. Beyond reaffirming the influence of the energy sector, this study extends the global literature by examining volatility transmission within Malaysia’s market, which is recognised as an emerging energy-exporting economy with deep institutional participation and extensive Shariah-compliant equity integration into capital markets. The findings are expected to guide policymakers in designing targeted market stability tools, assist portfolio managers in refining hedging and diversification strategies, and inform regulatory frameworks that strengthen financial resilience in Malaysia and comparable emerging economies.

2.0 Literature Review

Malaysia presents a fascinating case study examining the volatility of energy markets. As a significant oil and gas producer in Southeast Asia with a rapidly developing economy, Malaysia's energy sector plays a crucial role in the country’s economic landscape (Ariyon et al., 2023). The interconnectedness between Malaysia's energy sector and other sectors within the Kuala Lumpur Stock Exchange (KLSE) provides an excellent opportunity to study volatility spillover effects in an emerging market context. In addition to its technical and methodological dimensions, Malaysia’s stock market is shaped by a unique policy and regional context that influences volatility behaviour and sectoral integration. Following several capital market reforms and liberalisation measures under the Capital Market Masterplan (Securities Commission Malaysia, 2021) and the Financial Sector Blueprint (Bank Negara Malaysia, 2016), the Kuala Lumpur Stock Exchange (KLSE) has become increasingly integrated into global and ASEAN financial markets (Robiyanto et al., 2021). Previous studies have shown that regional linkages with Singapore, Thailand, and Indonesia have intensified over time, contributing to faster volatility transmission during periods of market stress (Goswami et al., 2025; Kesumah & Azhar, 2025). This contextual understanding highlights why sectoral volatility analysis in Malaysia is relevant not only domestically but also regionally, as shocks in the energy and financial sectors often spill over to neighbouring ASEAN markets through both trade and capital flow channels.

2.1 Energy Market

According to the National Energy Policy 2022–2040 (2022), Malaysia contributed about 28% of the country's GDP and employed 25% of its workforce. The Malaysian government has implemented several reforms and initiatives aimed at enhancing Malaysia's competitive edge in the energy market, particularly in the global renewable energy sector. Thus, Malaysia was recognised by the World Economic Forum as the best country in Southeast Asia for the Energy Transition Index (Fostering Effective Energy Transition, 2023).

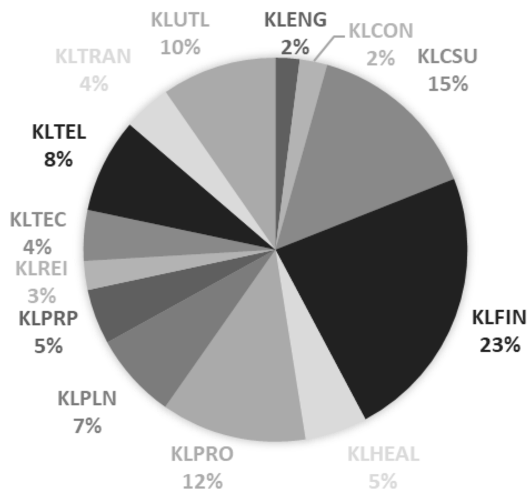

Figure 1: KLSE Sectors by Market Cap

Source: Bursa Malaysia Sectorial Index Series Factsheet (2024)

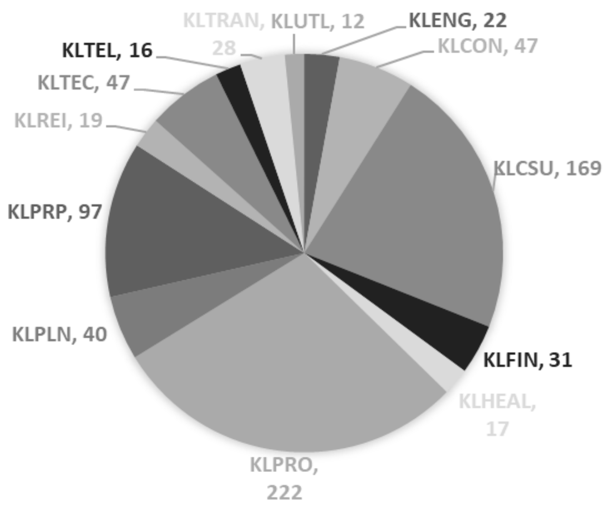

Figure 2: KLSE Sectors by Number of Market Constituents

Source: Bursa Malaysia Sectorial Index Series Factsheet (2024)

Figures 1 and 2 illustrate the KLSE sectors by market capitalisation percentage and the number of market constituents, respectively. Although the Malaysian energy sector is rather small compared to others, research has shown that the energy market is one of the most influential sectors in the rest of the economy. Oil prices influence inflation, transportation costs, industrial input costs, and government fiscal balances. Therefore, even small fluctuations in energy stocks signal broader economic shifts, prompting revaluations in other sectors. Numerous studies, including those by Bui et al. (2022); Lu et al. (2022) and Tang et al. (2022) have proven the significance of the energy market in the performance of other economic sectors.

Oil is the predominant force in the energy industry and plays a pivotal role in the national economic development. As the world's most traded commodity, it contributes significantly, accounting for 34% of global primary energy consumption (Energy Institute, 2024). However, recent times have witnessed pronounced volatility in crude oil prices, leading to substantial losses for investors and adverse impacts on the economy. The dynamics of oil prices, influenced by supply and demand, as well as a multitude of external factors, including geopolitical events, natural disasters, and trends in energy transition and renewable energy, have intensified this volatility (Wen et al., 2019).

This heightened volatility in oil prices introduces uncertainty, prompting consumers and firms to defer expenditures and investments. The resulting ambiguity may necessitate costly reallocation of resources, ultimately placing strain on the economy. Thus, the modelling and forecasting of volatility have emerged as focal points of interest for manufacturers, investors, consumers, and policymakers (Azad & Serletis, 2024; Blomkvist et al., 2023; Charles et al., 2021; Kocaarslan et al., 2020). This aspect has become paramount in the realms of risk management, derivative pricing, portfolio decisions, and determining optimal ratios for hedge pricing, as stakeholders seek to navigate and mitigate the far-reaching consequences of unpredictable oil price fluctuations.

2.2 Theoretical Background

Most studies conclude that major financial markets are not predictable based on the following two assumptions: First, market prices reflect all available information (the Efficient Market Hypothesis, or EMH) (Han, 2025). Second, the market consists of rational and homogeneous agents. The first assumption is that stock markets are efficient. However, the second assumption poses a challenge (Brianzoni et al., 2025; Müller, 1997). Shiller (2003) argues that most market participants are irrational. Most participants responded differently to information and displayed irrational behaviour as a common emotional reaction. Recent literature has reported that financial markets are recognised by the heterogeneous behaviour of market participants (Brianzoni et al., 2025). This heterogeneity is observable in the clustering of volatility and long-memory properties in financial time series. Because price movements and volatility persistence vary across trading horizons, market dynamics cannot be fully captured by single-scale models.

To model this complexity, the Heterogeneous Market Hypothesis (HMH) provides the theoretical foundation for multi-horizon volatility models, such as HAR-type models, which explicitly decompose volatility into daily, weekly, and monthly components to reflect differing investor horizons. The VHAR extension allows for cross-sectoral interactions, aligning with the notion that investors in different industries respond asymmetrically to market news. Coupled with realised-Range Volatility (RRV), which utilises high-frequency intraday data for more accurate volatility measurement, this approach captures both the persistence and transmission of shocks across Malaysia's energy and non-energy sectors. Thus, the VHAR–RRV framework operationalises the HMH by empirically representing how heterogeneous behaviours generate observed volatility clustering and intersectoral spillovers.

2.3 Volatility Proxies

A prevailing consensus in past scientific studies asserts that high-frequency volatility models generally demonstrate enhanced forecasting capabilities compared to those constructed exclusively from daily return data (Baek & Park, 2021; Lyócsa et al., 2021; Shin et al., 2022; Tang et al., 2022). Furthermore, studies such as Shin et al. (2022) and Tang et al. (2020) emphasise the advantages of using 5-minute interval data, as this sampling frequency effectively balances measurement precision with the mitigation of market microstructure noise. A growing body of literature exists on the multivariate analysis of the energy stock market; however, existing studies have a major drawback in that they rely on variance-covariance variations using daily or lower-frequency information. The squared daily return is a latent (unobservable) variable and a noisy estimate of volatility. According to Souropanis and Vivian (2023), the noisier a volatility proxy is, the less accurate the forecast evaluation. This is because low-frequency data fail to detect the effect of information that is incorporated very quickly and are unable to sufficiently report the stylised facts detected in financial time series. As a result, Andersen and Bollerslev (1998) proposed the RV using high-frequency information to curb this issue. RV is theoretically proven and empirically backed as an observable proxy, consistent, less noisy, and an unbiased estimator.

Past literature reveals that RV models have increased precision for forecasting volatility (Degiannakis et al., 2022; Wang & Liu, 2021; Wen et al., 2022) and accuracy of risk assessment (Chen et al., 2023) and normally outperform traditional Stochastic Volatility (SV) models as well as GARCH models that use squared daily returns (low-frequency data) (Bergsli et al., 2022). In addition, Merton (1980) first introduced the notion of utilising high-frequency price data to model daily volatility. The current measure at hand, the realised range, or RRV, is based on Parkinson's (1980) high-low measure. Martens and Van Dijk (2007) and Christensen and Podolskij (2007) simultaneously proposed the realised range-based volatility (RRV), utilising Parkinson's measure for intradaily intervals to estimate daily volatility.

Martens and Van Dijk (2007) conducted simulation studies and found that the range-based realised volatility (RRV) exhibited a lower mean squared error (MSE) compared to the traditional realised volatility (RV), which tends to be less consistent and more prone to distortion. In contrast, the RRV demonstrated superior stability and was up to five times more efficient than RV at both 5-minute and 30-minute sampling frequencies (Aït-Sahalia et al., 2005; Bandi & Russell, 2006). Furthermore, Degiannakis and Livada (2013) demonstrated that volatility measured using the range-based approach (high–low prices) outperforms traditional close-to-close return volatility (RV) when applied to lower-frequency data. Similarly, Gerlach and Wang (2016) employed range-based realised volatility (RRV) within the realised GARCH framework as an alternative to RV and found that it delivered significantly better performance than both RV and the intra-day range. They concluded by recommending the integration of RRV in volatility forecasting for financial applications. Building on this, Gerlach and Wang (2022) incorporated both RRV and RV into enhanced models, while Wang et al. (2023) applied this approach to forecast Value-at-Risk (VaR) and Expected Shortfall (ES), concluding that combining both measures is particularly effective for tail-risk forecasting. Consistent with these findings, Wu et al. (2023) utilised price range volatility within a conditional autoregressive model incorporating economic policy uncertainty to successfully predict crude oil futures volatility.

2.4 Volatility Models

HAR models (Heterogeneous Autoregressive models), proposed by Corsi et al. (2008) and Andersen et al. (2007), and later expanded on by Corsi (2009). Based on the HMH concept, Corsi (2009) proposed the HAR model, which can separate the spillover effects into monthly, weekly, and daily time frames, a feature that is unattainable with traditional

GARCH models. This is because GARCH fails to sufficiently describe whole-day volatility information. Thus, HAR models have become the more favoured specification to extend RV-based models because of their ability to facilitate greater flexibility with the parameters, achieve long memory in a parsimonious process, and guarantee positive definite estimates. It can also be easily altered by using external variables to improve the explanatory power of volatility (Alfeus et al., 2024)

In addition, Bubák et al. (2011) developed a multivariate version of Corsi's (2009) HAR and called it the VHAR. The idea behind the VHAR creates a vector (v_t) by stacking the logarithms of the RVs of a group of assets. They also incorporated a vector innovation term to generalise the multivariate model, which is guided by an MGARCH process (Tang et al., 2022). Logs are generally preferred in the field of statistical analysis because they make the data closer to normality, allowing us to avoid being restricted to non-negative variables. This reduces the number of restrictions that a statistician or analyst must adhere to, which makes VHAR more versatile and favourable than HAR. Similar to the HAR, the VHAR also has monthly, weekly, and daily RV components, which enable the model to represent the various reaction times of market participants to the news. This allows us to capture behaviours in the market over both the short and long terms, for example, for daily versus long-term stock traders (Lee & Baek, 2023; Tang et al., 2022)

In addition, Symitsi et al. (2018) compared multiple models of modelling and forecasting covariance. They found that high-frequency data models generally outperform multivariate GARCH-type models on both statistical and economic grounds. More specifically, they concluded that VHAR performs best among all the other models and that high-frequency data-based models result in lower portfolio risk compared to MGARCH models. They conduct their analysis using data from various European markets and test the robustness of their findings using an alternative sample of U.S.-based stocks. They also compared VHAR with another variation, GVHAR, and concluded that it offers an insignificant improvement over VHAR, causing a slightly higher loss in the out-of-sample performance. This suggests that it adds unnecessary complexity for little or no improvement.

Simultaneously, Baek and Park (2021) considered a sparse VHAR model. It is estimated using the adaptive lasso and is said to improve the performance of forecasts and show explicit connections between international stock markets. They improved Kim and Baek's (2020) factor-augmented HAR, which in turn improved the HAR by adding factors for foreign stocks. For their analysis, they compared the performance of univariate HAR, multivariate HAR (VHAR), and sparse VHAR. They conclude that sparse VHAR outperforms both and that VHAR can effectively quantify the effect of one market on the other markets considered. Sparse VHAR is best suited for observing worldwide volatility dynamics. In addition, Alves et al. (2023) used VHAR models to forecast the realised covariance (RCov) matrices of returns of S&P500 companies with various numbers of factors estimated with Lasso. They tested their models and compared them with those of other models. In most tests, their VHAR models outperformed the other models, produced lower standard deviations, improved forecasting precision, and provided better estimates for portfolios.

3.0 Methodology

3.1 Data

The data used for this analysis were historical data from the Kuala Lumpur Stock Exchange (KLSE) indices. Data were collected for the composite index (KLCI), as well as the 13 sectoral indices in the KLSE: construction (KLCON), finance (KLFIN), energy (KLENG), technology (KLTEC), property (KLPRP), plantation (KLPLN), healthcare (KLHEAL), consumer product (KLCSU), REIT (KLREI), industrial production (KLPRO), transportation and logistics (KLTRAN), telecommunication (KLTEL), and utilities (KLUTL). The intradaily data, collected at 5-minute intervals, were selected because they strike a perfect balance between minimising noise and achieving accuracy (Baek & Park, 2021; Clements & Preve, 2021).

This choice is particularly suitable for the KLSE, where trading volume and liquidity are moderate compared with major global exchanges. Using higher-frequency data (e.g. 1-minute) may amplify microstructure noise due to a relatively lower transaction intensity, leading to biased volatility estimates. Conversely, lower-frequency data (e.g., 15-minute) may smooth out essential intraday variations, reducing the model's sensitivity to short-term market dynamics. Therefore, the 5-minute interval represents an empirically validated compromise that minimises market microstructure effects while preserving the informational richness required for an accurate realised volatility estimation (Baek & Park, 2021). The data were collected from 24 September 2018 to 23 December 2024 from Bloomberg. Trading days on the Kuala Lumpur Stock Exchange include non-weekend and non-public holiday days of the year, and trading hours are from 9:00 am to 12:30 pm and again from 2:00 pm to 5:00 pm, as the 12:30 to 2:00 pm period is considered a lunch break. This results in a total number of observations of 72 per day.

3.2 Data Pre-processing

First, as there were a few missing data points (less than 1% of the data), data imputation was carried out in SPSS using the linear interpolation method. While linear interpolation is a standard and efficient approach for handling small amounts of missing high-frequency financial data, it may introduce a minor smoothing bias by slightly dampening the magnitude of extreme volatility changes. However, given that the proportion of missing observations in this dataset is less than 1%, the likelihood of bias affecting the results is minimal. To ensure robustness, diagnostic checks confirmed that the imputed series retained the statistical characteristics of the original data, suggesting that interpolation did not distort the volatility dynamics or spillover patterns. This approach aligns with previous studies that used high-frequency data in similar contexts (Niako et al., 2024; Liu & Yin, 2025). The data were then cleaned and arranged in MS Excel, and the volatility measures were also calculated. The volatility data are then imported to EViews for further analysis. First, graphical representations and descriptive statistics were obtained, followed by preliminary testing using Augmented Dickey-Fuller, Phillips-Perron, and Ljung-Box Q and Q^2 tests before proceeding with the estimation of the three volatility models detailed in this section.

3.3 Volatility Measures

This study compares the estimation accuracy of several combinations of volatility proxies and models. Most notably, the VHAR model has two volatility proxies, RV and RRV. The more traditional RV uses squared daily returns (shown in Equation 1), while RRV is calculated by subtracting the lowest from the highest price returns detected at a specific point in time (see Equation 2). For this study, 5-minute intervals were used throughout each trading day. The results of the estimation are compared for the two models (VHAR-RV and VHAR-RRV) and the more traditionally used VAR model to determine which model performs best. The realised variance or realised volatility estimator (RV) is also referred to as the squared returns, which are computed by summing the squared daily or intraday returns of a specific asset or index. It was first developed in 1998 by Andersen and Bollerslev. According to Corsi (2009), the formula for the daily realised volatility is as follows:

$$RV_t = \sqrt{\sum_{j=0}^{M-1} r^2_{t-j.\Delta'}} \tag{1}$$

Where:

- M is the sampling frequency,
- $r_{t,i}$ represents the returns (*r*) on day *t* and time interval *i*.

Realised range-based volatility (RRV) measures volatility by subtracting the lowest from the highest price returns detected in a specific timeframe. Kirby (2025) demonstrate that this measure is an unbiased estimate of daily volatility and is more efficient than the squared daily return by a factor of five. Furthermore, Martens and Van Dijk (2007) propose the scaled high-low range for intraday intervals to calculate RRV as such

$$RRV_t = \frac{1}{4\log 2}\sum\nolimits_{i=1}^{M}\left(\log H_{t,i} - \log L_{t,i}\right)^2 \tag{2}$$

where:

- $H_{t,i}$ and $L_{t,i}$ are the highest and lowest prices, respectively, at interval i of day t.

Building on Corsi’s 2009 model, Bubák et al. (2011) introduced the vector HAR model or VHAR to model the cumulative behaviours of RV and multivariate HAR. The model is formed by forming a vector of logarithms of the realised variances of a group of assets and is expressed as follows:

$$Y_t^{(d)} = \beta_0 + a^{(d)}Y_{t-1}^{(d)} + a^{(w)}Y_{t-1}^{(w)} + a^{(m)}Y_{t-1}^{(m)} + \varepsilon_t,$$

$$\varepsilon_t \sim WN(0,\Sigma), \quad t = 1,2,\ldots,T, \tag{3}$$

Where

- $\beta_0, a^{(m)}, a^{(w)}, a^{(d)}$ are square matrices of the constant and coefficients,
- $(m), (w), (d)$ denote the time horizons of a month, a week, and a day,
- Weekly and monthly partial estimators are computed as

$$Y_t^{(w)} = \frac{1}{5}\sum_{j=0}^{4} Y_{t-jd}^{(d)}, \qquad Y_t^{(m)} = \frac{1}{22}\sum_{j=0}^{21} Y_{t-jd}^{(d)}$$

Numerous studies have been motivated by Corsi’s (2009) model of modelling and forecasting RV using the HAR-RV model. For instance, Xie & Clements (2024), Wang and Liu (2021), and Kambouroudis et al., 2021), among many others, have been published. In this study, the HAR-RRV is formulated from the univariate to the multivariate HAR-RRV, also known as the Vector Heterogeneous Autoregressive model for realised range-based volatility (VHAR-RRV).

$$RRV_{k,t}^{(d)} = a_{k,0} + a_k^{(d)} RRV_{k,t-1}^{(d)} + a_k^{(w)} RRV_{k,t-1}^{(w)} + a_k^{(m)} RRV_{k,t-1}^{(m)} + \varepsilon_{k,t}$$

$$\varepsilon_t | \Omega_{t-1} \sim NIID(0,1) \quad (4)$$

Such that:

- Subscripts $k = 1, 2$ represent the market
- $RRV_{k,t-1}^{(d)}, RRV_{k,t-1}^{(w)}, RRV_{k,t-1}^{(m)}$ are lagged daily, weekly, and monthly RRV vectors, respectively
- ε_t is assumed to be Gaussian WN
- α_0 is an $n \times 1$ vector of constants
- $\alpha^{(m)}, \alpha^{(w)}, \alpha^{(d)}$ are $n \times 1$ vectors of parameters for the monthly, weekly, and daily measures, respectively

The monthly and weekly RRV estimators were calculated as follows:

$RRV_{k,t-1}^{(m)} = \frac{1}{22} \sum_{i=1}^{22} RRV_{k,t-i}^{(d)}$ and $RRV_{k,t-1}^{(w)} = 0.5 \sum_{i=1}^{5} RRV_{k,t-i}^{(d)}$, respectively.

4.0 Results and Discussion

The detailed results of the preliminary analysis, model estimation, and evaluation are presented in Appendices A and B, respectively. The graphical analysis in Figures 3 and 4 displays the daily returns and the density distribution histogram, respectively, for sectors of the Malaysian stock market, including the composite index (KLCI), construction (KLCON), finance (KLFIN), energy (KLENG), technology (KLTEC), property (KLPRP), plantation (KLPLN), healthcare (KLHEAL), consumer products (KLCSU), REIT (KLREI), industrial production (KLPRO), transportation and logistics (KLTRAN), telecommunication (KLTEL), and utilities (KLUTL) for the period from September 2018 to December 2024.

The analysis revealed that all sectors exhibited pronounced leptokurtic patterns, characterised by higher peaks and fatter tails than expected for a normal distribution.

Most sectors displayed negative skewness, which is particularly evident in the KLENG, KLREI, and KLPRO indices. These significant deviations from normality were confirmed by the highly significant Jarque-Bera test results across all sectors. Overall, these patterns are consistent with what one might expect in emerging or developing financial markets such as Malaysia. The sectors demonstrate varying degrees of volatility, as shown in Figure 3 and the standard deviation statistics in Appendix A. KLENG, KLCON, KLHEAL, and KLPLN exhibit greater fluctuations in daily returns. Simultaneously, KLREI, KLFIN, and KLPRP display relatively smooth return profiles. KLHEAL and KLUTL displayed more consistent upward trends, whereas KLENG and KLFIN showed mixed results with both positive and negative movements. Statistical testing confirmed that all series were stationary, as evidenced by the highly significant ADF and PP test results.

The presence of significant serial correlation across all sectors, indicated by the highly significant Ljung-Box Q statistics, challenges the Efficient Market Hypothesis by suggesting a degree of predictability in returns. Additionally, extremely high and significant Q^2 statistics confirm strong ARCH effects, demonstrating pronounced volatility clustering behaviour where periods of high volatility tend to be grouped. The combination of fat tails, skewed distributions, and volatility clustering renders traditional risk models, which are based on normal distribution assumptions, inadequate. VHAR models are particularly well-suited for this data for several critical reasons: the model explicitly accounts for heterogeneous market behaviour by incorporating volatility components at different time scales (daily, weekly, monthly), which aligns with the multimodal patterns and regime-like behaviour visible in the volatility histograms. The empirical data display significant deviations from normality with pronounced positive skewness and leptokurtosis in the realised range of volatility distributions. VHAR specifications can accommodate these non-Gaussian features (Hatem et al., 2022)

Notably, the healthcare (KLHEAL) and utilities (KLUTL) sectors exhibit comparatively lower volatility and more stable return distributions than the other sectors. This behaviour can be attributed to their defensive characteristics: both sectors provide essential goods and services that maintain relatively stable demand, regardless of macroeconomic fluctuations. Consequently, they are less reactive to energy price shocks or speculative movements that strongly influence sectors, such as energy, construction, and finance. This aligns with evidence from emerging markets, where defensive sectors tend to exhibit weaker contagion and greater persistence during periods of market turbulence (Bui et al., 2022; Hoque & Batabyal, 2022).

Moving on to the model estimation, the results of the in-sample bivariate volatility models estimation between KLENG and the other 13 indices individually, starting with the bivariate relationship between KLENG and the composite index, KLCI, are presented entirely in Panel I of Appendix B, all the way through to the bivariate relationship between KLENG and KLUTL. The VHAR-RV and VHAR-RRV models consider the bivariate daily, weekly, and monthly aspects of the volatility effect on both sectors. On the other hand, the VAR model only considers the bivariate effects of daily volatility on both sectors. For each bivariate relationship, two equations were estimated. Equation 1 estimates the effect of the lagged volatility estimates of KLENG and Sector 2 on KLENG. Equation 2 estimates the effect of the lagged volatility estimates of sector 2 and KLENG for sector 2. This is repeated 13 times to capture the bivariate relationship between KLENG and KLCI, as well as the other 12 sectoral indices, each arranged in a column in Appendix B. R^2 statistics are used to evaluate the goodness of fit of each model. Table 1 presents the means of all R^2 statistics of each volatility model. Overall, both VAR models significantly outperformed the VHAR model. VHAR-RV and VHAR-RRV both conclude that the predicted index is explained by lagged values by over 60% on average, with VHAR-RRV being 5% better than VHAR-RV.

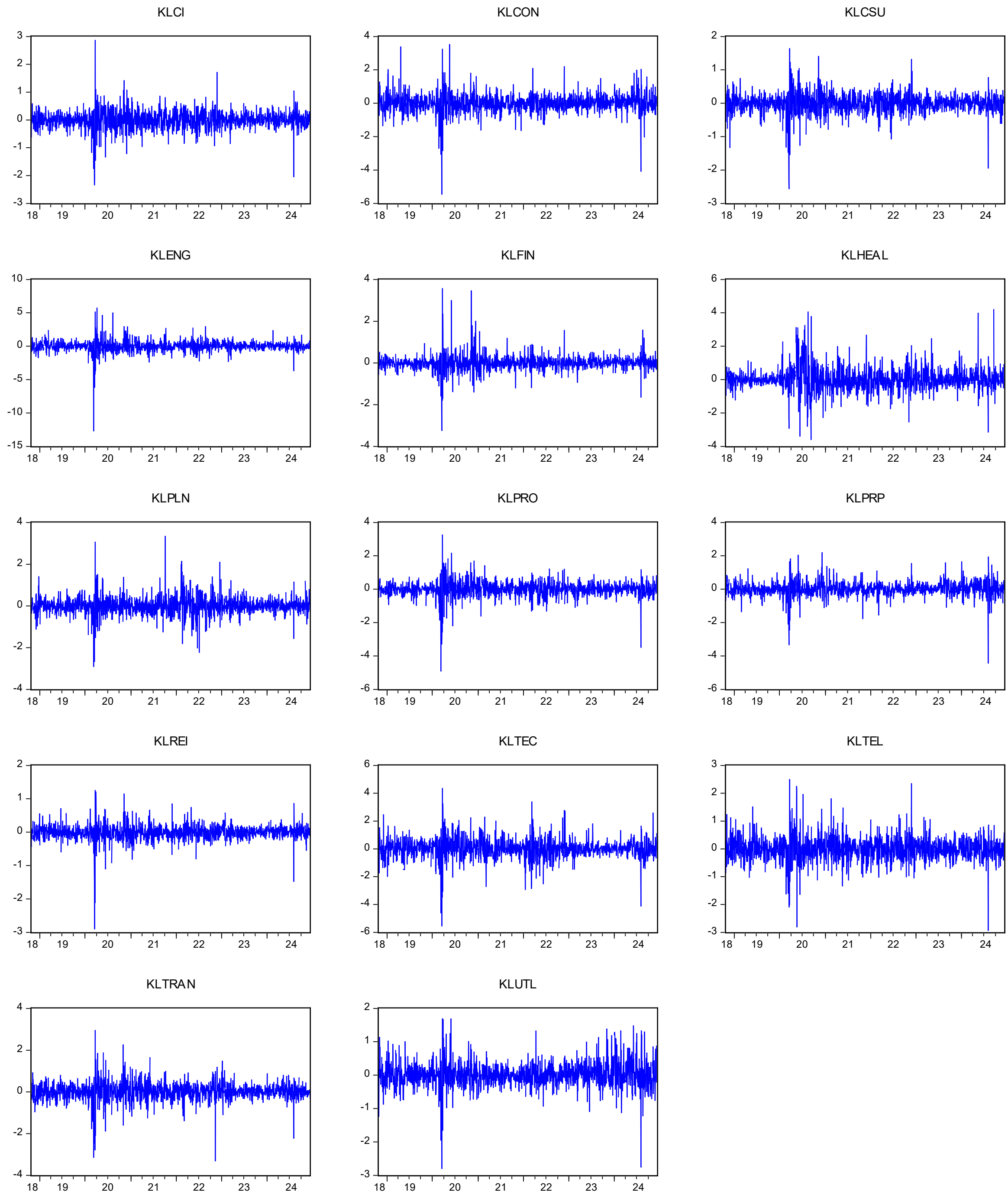

Figure 3: Daily Return Series

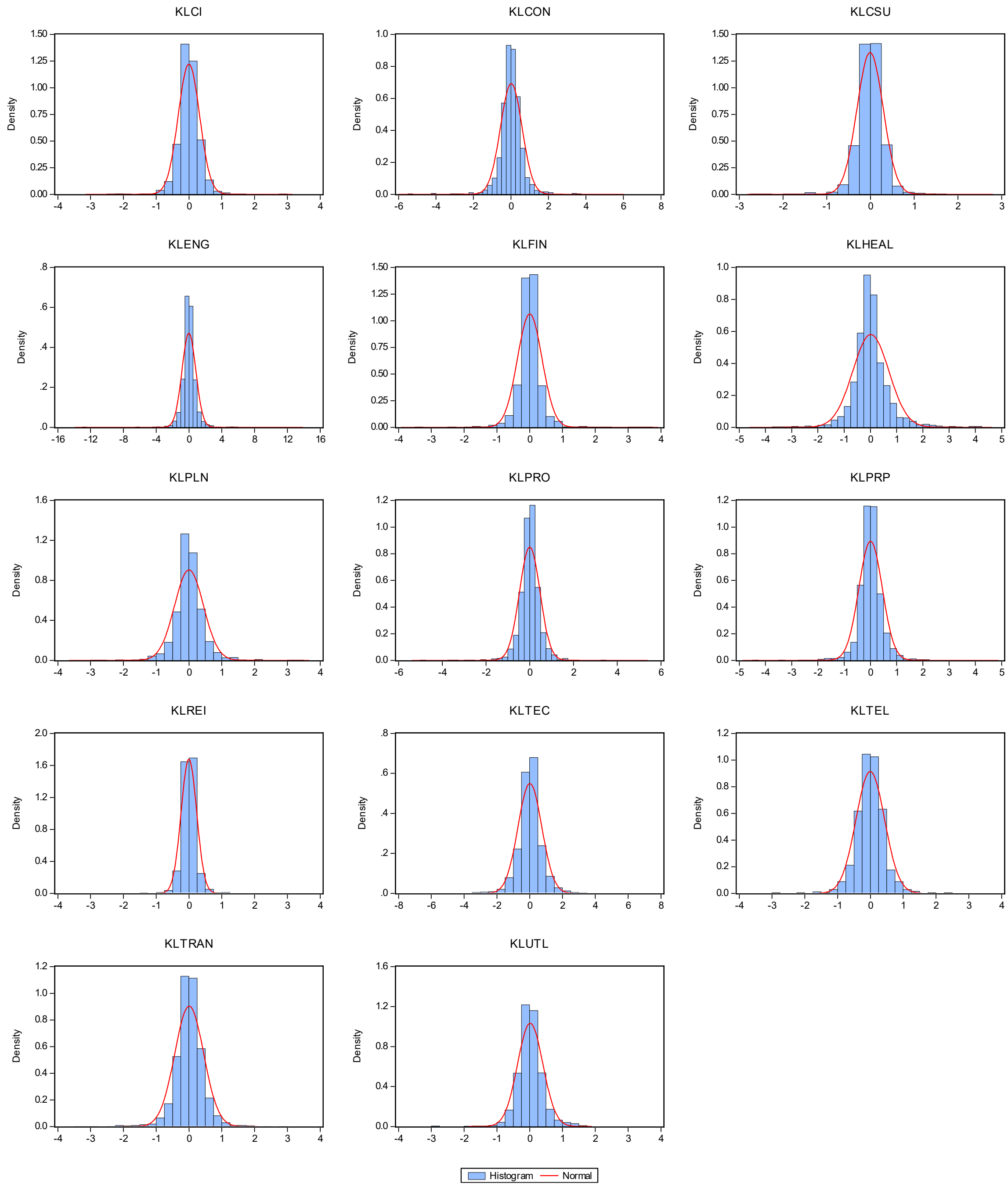

Figure 4: Density Distribution Histogram to a Normal Distribution

Table 1: Summary of Estimation Evaluation

Model	Average of R^2
VHAR-RRV	0.6566
VHAR-RV	0.6075
VAR	0.0056

Upon closer examination of the models' results in Appendix B, Panel I, several conclusions can be drawn. Due to the low R^2 statistics of the VAR model, the analysis going forward is based solely on the two VHAR models, which yield similar outcomes in model estimation with a few exceptions. Starting with the constants $\alpha_{1,0}$ and $\alpha_{2,0}$ represent the constants for KLENG and index 2, respectively. The null hypothesis was that the baseline value is not reliably different from zero. The constants of the KLENG equations are almost consistently insignificant; thus, they do not reject the null hypothesis, and there is no long-run average daily volatility present if all the lagged variables of both sectors are zero. In contrast, the constants of all second-order index equations are significant, mostly at the 1% significance level, indicating that all indices, except KLENG, have a baseline volatility level, even when not impacted by past volatilities.

Furthermore, the lagged volatility values of the KLENG index have a positive and highly significant impact on the current volatility of KLENG. Thus, the null hypothesis that the lagged volatility coefficients are equal to zero is rejected, concluding that past volatility in the energy market will contribute to more volatility in the future (periods of high volatility are followed by periods of high volatility). The effect of the volatilities of other indices on the volatility of the energy market is not as pronounced. One day lagged volatility of KLCSU, KLPRO, KLPRP, KLTEC, KLREI, KLTEL, and KLUTL has a low or moderate impact on the volatility of KLENG. Meaning that elevated volatility levels in these sectors have a low or moderate impact on increasing the volatility of energy market stocks the following day. The longer-term (weekly and monthly) spillover effect is much less prominent, with only KLPLN, KLTRAN, and KLCON having a moderate to low significance on the volatility of KLENG.

On the other hand, past volatility in the energy market appears to have a significantly more pronounced impact on the volatility of the other indices. The long-term volatility of KLENG has the most significant impact on all sectors, except for KLHEAL, which appears to be unaffected by KLENG volatility in the long-, medium, or short-term. Interestingly, the highly significant relationships between KLENG and the other sectors seem to be consistently negative. This means that heightened volatility in the energy market tends to dampen volatility in other markets in the long run. In the short and medium terms, the relationship was consistently positive; however, it was not always significant. This could mean that volatility in the stock market causes temporary panic in other sectors, eventually leading to a relatively stable period across all sectors. Moreover, for other indices, there is a consistently positive and highly significant risk spillover from the short- and medium-term past volatility to the present volatility of the same indices. The same cannot be said for the long-term risk spillover for KLCI, KLCSU, KLFIN, KLPLN, KLPRO, and KLREI, according to the VHAR-RRV model.

Interestingly, the equations of KLENG consistently have higher R^2 statistics than those of other indices. This is the case for both VHAR-RV and VHAR-RRV models. This, coupled with the conclusions drawn from the model estimates, suggests that past volatility in KLENG has a more significant impact on its present volatility than the past volatility of other indices. While other indices are indeed highly impacted by risk spillover from the KLENG and their past volatilities in the short and medium terms, their models could be expanded to include more components to better model and forecast their volatilities.

5.0 Conclusion and Future Research

This study investigates realised volatility spillover effects between Malaysia's energy sector and other sectoral indices, as well as the composite index, using high-frequency data and employing the VHAR model with realised range volatility (RRV). The performance of this model was compared with that of the traditional VHAR model, which utilises the realised volatility measure and the more commonly known VAR model.

The findings reveal important insights for market participants and policymakers. More specifically, the VHAR-RRV model consistently outperformed both the traditional VAR and VHAR-RV models, confirming the superiority of range-based volatility measures and heterogeneous autoregressive frameworks for capturing the complex dynamics of volatility transmission. The findings confirm the importance of accounting for market heterogeneity when modelling volatility in financial markets. The most notable takeaway from the findings is that other indices are more prone to risk contagion from KLENG than the other way around. Apart from the healthcare sector, which appears not to be impacted by the energy sector in terms of risk spillover at any level. The relationship between the two sectors appears to be relatively understudied by researchers. Conversely, all the other 12 indices are significantly affected by the energy market to varying degrees.

For policymakers, the results underscore the pivotal role of energy market stability in overall market stability and suggest that regulatory interventions aimed at mitigating energy market volatility may yield significant cross-sectoral benefits. Policymakers should prioritise the stability of the energy sector, as it plays a central role in influencing the volatility of other sectors. Regulatory efforts could focus on enhancing transparency in energy-pricing mechanisms, encouraging the use of renewable sources to reduce dependency risks, and implementing macroprudential tools to cushion the spillover of energy shocks to other industries. For investors and portfolio managers, the findings suggest that cross-sector diversification strategies can be optimised by combining defensive sectors (such as healthcare and utilities) with energy-related assets to mitigate short-term volatility exposure. The identified short- and medium-term positive spillovers suggest that sectoral hedging instruments, such as energy-linked ETFs or derivatives, can be utilised to manage portfolio risk during periods of heightened energy market uncertainty.

These practical implications demonstrate how the VHAR-RRV framework can support more informed investment and policy decisions, ensuring that market participants in Malaysia are better positioned to anticipate and respond to volatility transmissions across sectors. Future research could extend this analysis by incorporating additional exogenous and endogenous variables, such as accounting for different bivariate or multivariate relationships between the sectors. Exploring the impact of structural breaks, particularly those related to energy policy shifts or global market disruptions, could also yield valuable insights into the transmission of cross-sectoral volatility in Malaysia's financial markets.

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Appendix A: Descriptive Statistics and Preliminary Tests

Daily Returns									
	Mean	**St. Dev.**	**Skewness**	**Kurtosis**	**JB**	**ADF**	**PP**	**Q**	Q^2
KLCI	-0.0064	0.3379	-0.0282	11.7299	3979.003	-20.877***	-591.99***	24.088**	637.42***
KLCON	0.0026	0.5683	-0.6738	16.4285	9509.304	-19.526***	-634.42***	50.632***	561.53***
KLCSU	-0.0079	0.3113	-0.9005	12.4482	4829.895	-19.063***	-571.07***	58.311***	1010.3***
KLENG	-0.0101	0.8952	-1.9606	40.9468	75980.8	-20.283***	-737.81***	70.213***	164.20***
KLFIN	-0.0024	0.3913	1.0432	23.8927	23016.37	-18.434***	-371.55***	49.957***	458.25***
KLHEAL	0.0104	0.6971	0.6066	8.2350	1507.649	-19.078***	-388.02***	79.189***	657.45***
KLPLN	-0.0022	0.4637	0.2955	10.6828	3099.87	-19.774***	-702.95***	38.605***	242.83***
KLPRO	-0.0004	0.4835	-1.2070	17.6609	11526.06	-18.275***	-653.45***	46.357***	819.33***
KLPRP	-0.0019	0.4191	-0.6724	11.7345	4077.434	-16.397***	-414.63***	113.36***	1167.0***
KLREI	-0.0064	0.2471	-1.9039	27.4798	32043.29	-16.227***	-393.38***	72.808***	831.22***
KLTEC	0.0171	0.7501	-0.4434	9.4968	2244.716	-20.746***	-522.96***	41.765***	941.31***
KLTEL	-0.0041	0.4484	0.1994	7.8439	1233.292	-20.756***	-512.77***	25.101**	360.61***
KLTRAN	0.0044	0.4629	-0.6586	11.5077	3869.523	-18.800***	-565.91***	36.892***	696.98***
KLUTL	0.0090	0.3515	-0.2982	9.8868	2494.72	-15.141***	-322.79***	74.914***	893.61***

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Appendix B: In-sample Model Estimation

		KLENG-KLCI	KLENG-KLCSU	KLENG-KLHEAL	KLENG-KLFIN	KLENG-KLPLN	KLENG-KLPRO	KLENG-KLPRP	KLENG-KLTEC	KLENG-KLREI	KLENG-KLTEL	KLENG-KLTRAN	KLENG-KLCON	KLENG-KLUTL
Panel I: Conditional Mean Equation														
VHAR-RRV	$\alpha_{1,0}$	0.0067	0.0099	0.0422**	0.0258	0.0128	0.0007	0.0356	0.0196	0.0074	0.0289	0.0249	0.0189	0.0342
		(0.0233)	(0.0243)	(0.0173)	(0.0196)	(0.0212)	(0.0198)	(0.0291)	(0.0208)	(0.0282)	(0.0264)	(0.0183)	(0.0273)	(0.0310)
	$\alpha^{d}_{1,1}$	0.3239***	0.3108***	0.3245***	0.3306***	0.3267***	0.2978***	0.3076***	0.3121***	0.3104***	0.3033***	0.3256***	0.3294***	0.3134***
		(0.0345)	(0.0343)	(0.0343)	(0.0344)	(0.0342)	(0.0352)	(0.0346)	(0.0349)	(0.0344)	(0.0351)	(0.0342)	(0.0341)	(0.0342)
	$\alpha^{w}_{1,1}$	0.4340***	0.4246***	0.4874***	0.4692***	0.4189***	0.4320***	0.4896***	0.4710***	0.4464***	0.4813***	0.4622***	0.4500***	0.4621***
		(0.0587)	(0.0596)	(0.0547)	(0.0582)	(0.0582)	(0.0582)	(0.0573)	(0.0577)	(0.0573)	(0.0575)	(0.0553)	(0.0578)	(0.0562)
	$\alpha^{m}_{1,1}$	0.1637***	0.2054***	0.1490***	0.1371***	0.2008***	0.1684***	0.1608***	0.1685***	0.1893***	0.1666***	0.1514***	0.1741***	0.1870***
		(0.0492)	(0.0500)	(0.0442)	(0.0486)	(0.0473)	(0.0486)	(0.0464)	(0.0463)	(0.0470)	(0.0482)	(0.0452)	(0.0467)	(0.0456)
	$\alpha^{d}_{1,2}$	0.0400	0.2808**	0.0095	-0.0357	0.0060	0.1363*	0.2218**	0.1049*	0.1686*	0.1402**	-0.0088	-0.0245	0.1475*
		(0.0914)	(0.1228)	(0.0335)	(0.0899)	(0.0661)	(0.0712)	(0.0887)	(0.0635)	(0.0878)	(0.0614)	(0.0694)	(0.0614)	(0.0880)
	$\alpha^{w}_{1,2}$	0.2226	0.1540	0.0381	0.1440	0.2480**	0.1945	-0.0901	0.0078	0.1676	0.0072	0.1927*	0.1832*	0.1217
		(0.1430)	(0.1957)	(0.0558)	(0.1351)	(0.1071)	(0.1265)	(0.1411)	(0.0969)	(0.1438)	(0.1011)	(0.1136)	(0.1011)	(0.1405)
	$\alpha^{m}_{1,2}$	-0.0263	-0.2244	-0.0549	0.0213	-0.1464	-0.0321	-0.1163	-0.0523	-0.1750	-0.1067	-0.0983	-0.1037	-0.2627**
		(0.1600)	(0.1978)	(0.0538)	(0.1405)	(0.0977)	(0.1382)	(0.1367)	(0.0790)	(0.1627)	(0.1103)	(0.1018)	(0.0919)	(0.1223)
	$\alpha_{2,0}$	0.0494***	0.0430***	0.0303*	0.0327***	0.0612***	0.0420***	0.0535***	0.0446***	0.0663***	0.0773***	0.0240***	0.0906***	0.0633***
		(0.0086)	(0.0068)	(0.0168)	(0.0072)	(0.0112)	(0.0098)	(0.0111)	(0.0115)	(0.0108)	(0.0147)	(0.0091)	(0.0155)	(0.0122)
	$\alpha^{d}_{2,1}$	0.0217*	0.0169*	0.0424	0.0326***	0.0653***	0.0320*	0.0107	0.0498**	0.0132	0.0424	0.0147	0.0517***	0.0105
		(0.0127)	(0.0096)	(0.0333)	(0.0126)	(0.018)	(0.0174)	(0.0132)	(0.0193)	(0.0132)	(0.0195)	(0.0169)	(0.0193)	(0.0135)
	$\alpha^{w}_{2,1}$	0.0642***	0.0611***	0.0303	0.0591***	0.0313	0.0207	0.0493**	0.0263	0.0612***	0.0317***	0.0574**	0.0842**	0.0459**
		(0.0216)	(0.0168)	(0.0531)	(0.0213)	(0.0307)	(0.0288)	(0.0218)	(0.032)	(0.0221)	(0.032)	(0.0273)	(0.0327)	(0.0222)
	$\alpha^{m}_{2,1}$	-0.0455**	-0.0595***	-0.0395	-0.0611***	-0.0831***	-0.0199	-0.0500***	-0.0774***	-0.0559***	-0.0302***	-0.0593***	-0.1261***	-0.0641***
		(0.0181)	(0.0141)	(0.0429)	(0.0178)	(0.0249)	(0.0241)	(0.0177)	(0.0257)	(0.0181)	(0.0268)	(0.0223)	(0.0264)	(0.0180)

	$\alpha_{2,2}^{d}$	0.0336***	0.0345***	0.0325***	0.0329***	0.0348***	0.0353***	0.0337***	0.0352***	0.0338***	0.0341***	0.0343***	0.0348***	0.0347***
		(0.0336)	(0.0345)	(0.0325)	(0.0329)	(0.0348)	(0.0353)	(0.0337)	(0.0352)	(0.0338)	(0.0341)	(0.0343)	(0.0348)	(0.0347)
	$\alpha_{2,2}^{w}$	0.3046***	0.4034***	0.2930***	0.2847***	0.5462***	0.4427***	0.3144***	0.4859***	0.2919***	0.2936***	0.4316***	0.5072***	0.4412***
		(0.0526)	(0.055)	(0.0541)	(0.0495)	(0.0564)	(0.0626)	(0.0537)	(0.0537)	(0.0554)	(0.0562)	(0.0561)	(0.0572)	(0.0554)
	$\alpha_{2,2}^{m}$	0.0153	0.0409	0.1997***	0.0597	0.0398	0.0996	0.1255**	0.1223***	0.0770	0.0763**	0.1780***	0.1000*	0.1161**
		(0.0588)	(0.0556)	(0.0522)	(0.0515)	(0.0514)	(0.0684)	(0.0520)	(0.0438)	(0.0626)	(0.0614)	(0.0503)	(0.0520)	(0.0482)
VHAR-RV	$\alpha_{1,0}$	0.0218	0.0245	0.0324**	0.0301*	0.0104	0.0108	0.0386	0.0229	0.0341	0.0264	0.0224	0.0276	0.0335
		(0.0157)	(0.018)	(0.0149)	(0.0157)	(0.0182)	(0.0165)	(0.0266)	(0.0169)	(0.0311)	(0.0245)	(0.0186)	(0.0218)	(0.0299)
	$\alpha_{1,1}^{d}$	0.2941***	0.2984***	0.2957***	0.301***	0.2935***	0.2703***	0.2889***	0.2902***	0.2921***	0.2936***	0.3035***	0.3061***	0.2803***
		(0.0343)	(0.0344)	(0.0341)	(0.0344)	(0.0337)	(0.0341)	(0.0345)	(0.0346)	(0.0343)	(0.0347)	(0.0343)	(0.0340)	(0.0341)
	$\alpha_{1,1}^{w}$	0.4260***	0.3875***	0.4746***	0.4506***	0.3804***	0.4221***	0.4587***	0.4362***	0.4261***	0.4609***	0.4386***	0.4195***	0.4592***
		(0.0600)	(0.062)	(0.056)	(0.0609)	(0.0592)	(0.0593)	(0.0589)	(0.0598)	(0.0608)	(0.0596)	(0.0581)	(0.0616)	(0.0580)
	$\alpha_{1,1}^{m}$	0.1990***	0.2646***	0.1825***	0.1962***	0.2693***	0.2128***	0.2142***	0.2248***	0.2443***	0.1980***	0.2068***	0.2324***	0.2234***
		(0.052)	(0.0541)	(0.0464)	(0.0525)	(0.0501)	(0.0525)	(0.0492)	(0.0498)	(0.0519)	(0.0510)	(0.0488)	(0.0518)	(0.0486)
	$\alpha_{1,2}^{d}$	0.0806	0.0201	0.0203	0.0096	0.0546	0.2159***	0.1086	0.0575	0.1013	0.0426	-0.0375	-0.0397	0.1909***
		(0.0707)	(0.0928)	(0.0251)	(0.0645)	(0.0493)	(0.0563)	(0.0713)	(0.0476)	(0.0848)	(0.0511)	(0.0570)	(0.0526)	(0.068)
	$\alpha_{1,2}^{w}$	0.1423	0.3892**	0.0278	0.1004	0.2627***	0.0632	0.0668	0.0647	0.2227	0.0589	0.2136**	0.2065**	0.0424
		(0.1206)	(0.1526)	(0.0435)	(0.105)	(0.0892)	(0.1035)	(0.1217)	(0.0735)	(0.1504)	(0.0908)	(0.1000)	(0.0875)	(0.1228)
	$\alpha_{1,2}^{m}$	-0.0131	-0.3316**	-0.0339	-0.0547	-0.2148**	-0.0616	-0.1944	-0.0794	-0.3340*	-0.0719	-0.1255	-0.1495*	-0.2397**
		(0.1496)	(0.1614)	(0.0436)	(0.1168)	(0.0907)	(0.1218)	(0.1277)	(0.0627)	(0.1770)	(0.1022)	(0.0946)	(0.0810)	(0.1192)
	$\alpha_{2,0}$	0.0299***	0.0374***	0.0308	0.0320***	0.0630***	0.0403***	0.0649***	0.0510***	0.0817***	0.0830***	0.0380***	0.0854***	0.0822***
		(0.0074)	(0.0068)	(0.0195)	(0.0082)	(0.0125)	(0.0098)	(0.0127)	(0.0127)	(0.0124)	(0.0163)	(0.0113)	(0.0145)	(0.0150)
	$\alpha_{2,1}^{d}$	-0.0006	0.0053	0.0497	0.0127	0.0117	0.0036	0.0110	0.0550**	0.0242*	0.0196	0.0362*	0.0456**	0.0001
		(0.0163)	(0.0130)	(0.0447)	(0.0180)	(0.0230)	(0.0203)	(0.0165)	(0.0261)	(0.0136)	(0.0230)	(0.0208)	(0.0226)	(0.0171)
	$\alpha_{2,1}^{w}$	0.1352***	0.1151***	0.0461	0.1554***	0.1707***	0.1203***	0.0738***	0.0699	0.0863***	0.1128***	0.0750**	0.1843***	0.0964***
		(0.0285)	(0.0234)	(0.0734)	(0.0319)	(0.0405)	(0.0354)	(0.0282)	(0.0450)	(0.0242)	(0.0394)	(0.0353)	(0.0409)	(0.0291)
	$\alpha_{2,1}^{m}$	-0.0752***	-0.0909***	-0.0514	-0.1193***	-0.1554***	-0.0702**	-0.0688***	-0.1124***	-0.0861***	-0.0874***	-0.0984***	-0.2146***	-0.1064***

		(0.0247)	(0.0205)	(0.0608)	(0.0275)	(0.0343)	(0.0313)	(0.0235)	(0.0374)	(0.0206)	(0.0337)	(0.0296)	(0.0344)	(0.0244)
	$\alpha^{d}_{2,2}$	0.0336***	0.0351***	0.0328***	0.0338***	0.0338***	0.0336***	0.0341***	0.0358***	0.0337***	0.0338***	0.0346***	0.0349***	0.0342***
		(0.0336)	(0.0351)	(0.0328)	(0.0338)	(0.0338)	(0.0336)	(0.0341)	(0.0358)	(0.0337)	(0.0338)	(0.0346)	(0.0349)	(0.0342)
	$\alpha^{w}_{2,2}$	0.2446***	0.4325***	0.3166***	0.2847***	0.4283***	0.2589***	0.3311***	0.5700***	0.2609***	0.2618***	0.4316***	0.4861***	0.3846***
		(0.0572)	(0.0577)	(0.0569)	(0.055)	(0.0611)	(0.0617)	(0.0582)	(0.0553)	(0.0597)	(0.0601)	(0.0607)	(0.0582)	(0.0617)
	$\alpha^{m}_{2,2}$	0.0803	0.0721	0.2262***	0.0931	0.1458**	0.1631**	0.1530**	0.0660	0.1298*	0.1645**	0.2309***	0.1448***	0.2000***
		(0.0710)	(0.0610)	(0.0571)	(0.0612)	(0.0621)	(0.0727)	(0.0611)	(0.0472)	(0.0703)	(0.0677)	(0.0574)	(0.0538)	(0.0598)
VAR	θ_{01}	-0.0099	-0.0091	-0.0095	-0.0095	-0.0095	-0.0095	-0.0096	-0.0098	-0.0095	-0.0094	-0.0102	-0.0102	-0.0106
		(0.0253)	(0.0253)	(0.0253)	(0.0253)	(0.0253)	(0.0253)	(0.0253)	(0.0253)	(0.0253)	(0.0253)	(0.0253)	(0.0253)	(0.0253)
	θ_{11}	0.0196***	-0.0091	0.0036	0.0213	0.0079	0.0083	-0.0383	-0.0032	0.0036	-0.0127	-0.0215	-0.0381	-0.017
		(0.0330)	(0.0341)	(0.0289)	(0.0321)	(0.0309)	(0.0356)	(0.0337)	(0.0328)	(0.0307)	(0.0325)	(0.0328)	(0.0339)	(0.0321)
	θ_{12}	-0.0830***	0.0649	-0.0010	-0.0864	-0.0212	-0.0146	0.1634**	0.0157	-0.0014	0.0656	0.0949	0.1188**	0.1106
		(0.0874)	(0.0982)	(0.0371)	(0.0734)	(0.0597)	(0.0659)	(0.072)	(0.0391)	(0.1114)	(0.0649)	(0.0635)	(0.0534)	(0.0819)
	θ_{02}	-0.0061***	-0.0076	0.0087	-0.0017	-0.0020	0.0003	-0.0008	0.0154	-0.0056	-0.0035	0.0051	0.0032	0.0088
		(0.0095)	(0.0088)	(0.0195)	(0.011)	(0.0131)	(0.0137)	(0.0116)	(0.0211)	(0.0069)	(0.0127)	(0.0131)	(0.016)	(0.0099)
	θ_{22}	0.0087	0.0232*	-0.0306	0.0063	0.0168	0.0389**	0.0212	-0.0874***	0.0374***	0.0179	0.0375**	0.0313	0.006
		(0.0124)	(0.0119)	(0.0222)	(0.014)	(0.0160)	(0.0192)	(0.0155)	(0.0273)	(0.0084)	(0.0162)	(0.017)	(0.0214)	(0.0125)
	θ_{21}	-0.0398**	-0.0400	0.1556***	0.0546*	-0.0666**	-0.0301	0.1536***	0.0866***	0.0204	-0.0602*	-0.0171	0.0626*	0.099***
		(0.0330)	(0.0341)	(0.0285)	(0.032)	(0.0309)	(0.0355)	(0.0332)	(0.0326)	(0.0304)	(0.0324)	(0.0328)	(0.0338)	(0.032)

Panel II: Model Evaluation

V	R_1^2	0.7751	0.7762	0.7739	0.7742	0.7757	0.7774	0.7550	0.7749	0.7760	0.7752	0.7749	0.7745	0.7754
	R_2^2	0.5608	0.5341	0.5544	0.6113	0.5255	0.5002	0.5045	0.6517	0.4028	0.5016	0.6642	0.4823	0.5203
V	R_1^2	0.7535	0.7541	0.7523	0.7522	0.7559	0.7574	0.7529	0.7533	0.7534	0.7523	0.7530	0.7531	0.7545
	R_2^2	0.4640	0.4989	0.4930	0.5022	0.4395	0.4795	0.3926	0.5841	0.3385	0.4162	0.5425	0.4860	0.3592
V	R_1^2	0.0007	0.0004	0.0000	0.0011	0.0001	0.0000	0.0041	0.0001	0.0000	0.0008	0.0018	0.0040	0.0015
	R_2^2	0.0011	0.0030	0.0233	0.0039	0.0037	0.0035	0.0333	0.0093	0.0210	0.0028	0.0043	0.0097	0.0114

Panel III: Diagnostic Tests

VHAR-RRV	$Q_{LB}(12)$	12.951	14.378	14.080	13.538	12.818	14.425	13.832	14.569	14.367	14.792	13.581	12.816	13.427
	$Q^2_{LB}(12)$	12.276	9.9863	14.362	14.571	10.424	9.6927	10.611	13.071	9.0722	13.613	13.914	12.753	9.8618
	ADF	-35.829***	-35.842***	-35.849***	-35.831***	-35.791***	-35.768***	-35.866***	-35.876***	-35.766***	-35.813***	-35.879***	-35.800***	-35.835***
	PP	-35.826***	-35.839***	-35.848***	-35.829***	-35.788***	-35.771***	-35.867***	-35.874***	-35.764***	-35.815***	-35.878***	-35.797***	-35.834***
	$Q_{LB}(12)$	33.758***	73.269***	30.633***	23.546***	50.476***	20.680*	19.973*	32.767***	77.259***	37.932***	16.000	85.704***	15.543
	$Q^2_{LB}(12)$	241.17***	288.21***	67.601***	154.12***	531.95***	316.63***	59.592***	452.75***	59.685***	332.22***	173.22***	204.34***	170.66***
	ADF	-23.162***	-21.909***	-34.785***	-35.774***	-36.093***	-35.657***	-35.904***	-23.192***	-21.012***	-20.721***	-35.480***	-13.636***	-35.686***
	PP	-36.371***	-36.851***	-34.785***	-35.778***	-36.086***	-35.657***	-35.901***	-36.052***	-35.296***	-36.172***	-35.486***	-36.353***	-35.708***
VHAR-RV	$Q_{LB}(12)$	10.421	10.422	10.907	10.348	9.8636	12.146	11.108	10.869	10.952	10.695	10.449	10.213	10.048
	$Q^2_{LB}(12)$	195.31***	199.90***	201.53***	195.24***	173.73***	189.38***	190.35***	206.62***	189.31***	192.08***	191.81***	191.89***	175.94***
	ADF	-35.847***	-35.712***	-35.772***	-35.772***	-35.723***	-35.851***	-35.730***	-35.831***	-35.720***	-35.785***	-35.812***	-35.701***	-35.804***
	PP	-35.845***	-35.714***	-35.771***	-35.771***	-35.722***	-35.850***	-35.728***	-35.829***	-35.719***	-35.785***	-35.813***	-35.699***	-35.804***
	$Q_{LB}(12)$	43.453***	61.477***	15.547	13.513	31.751***	23.241***	9.7077	42.934***	41.071***	8.6985	20.857	37.021***	13.959
	$Q^2_{LB}(12)$	207.81***	291.76***	15.686	298.33***	538.63***	323.33***	10.116	663.40***	143.85***	274.18***	193.63***	540.11***	49.515***
	ADF	-22.776***	-13.451***	-35.013***	-35.682***	-35.811***	-35.660***	-35.512***	-22.810***	-22.267***	-35.568***	-35.185***	-16.215***	-35.511***
	PP	-36.476***	-36.266***	-35.015***	-35.704***	-35.810***	-35.659***	-35.515***	-35.962***	-36.627***	-35.569***	-35.185***	-35.965***	-35.512***

VAR	$Q_{LB}(12)$	69.816***	69.992***	70.159***	69.167***	70.380***	70.380***	69.357***	70.945***	70.168***	70.355***	68.688***	70.810***	70.481***
	$Q^2_{LB}(12)$	168.59***	162.97***	164.71***	166.85***	165.73***	165.27***	159.12***	164.46***	164.61***	165.68***	164.77***	160.22***	161.48***
	ADF	-12.818***	-12.909***	-12.845***	-12.804***	-12.829***	-12.827***	-12.828***	-12.847***	-12.845***	-12.896***	-13.026***	-12.991***	-12.937***
	PP	-35.981***	-36.095***	-36.059***	-36.004***	-36.055***	-36.053***	-36.029***	-36.085***	-36.060***	-36.120***	-36.065***	-36.108***	-36.176***
	$Q_{LB}(12)$	23.087**	55.777**	44.811**	41.934**	37.241***	45.003***	51.620***	39.285***	62.476**	20.737*	31.598***	41.992***	48.974**
	$Q^2_{LB}(12)$	638.74***	999.06***	496.81***	452.75***	238.14***	820.72***	1264.6***	893.49***	904.90***	377.26***	702.20***	655.67***	962.10***
	ADF	-22.851***	-12.456***	-17.883***	-22.169***	-22.509***	-17.623***	-22.618***	-22.876***	-22.056***	-35.354***	-23.088***	-35.609***	-22.141***
	PP	-35.313***	-36.123***	-36.095***	-35.670***	-35.781***	-36.054***	-34.616***	-35.748***	-35.770***	-35.615***	-36.094***	-35.726***	-36.218***

Note: ***, ** and * indicate the significance level at 1%, 5% and 10%. Values in parenthesis are standard errors. Ljung Box Serial Correlation Test (Q and Q^2-statistics) Null hypothesis – No serial correlation; Augmented Dickey-Fuller and Phillips-Perron – unit root present.