International Journal of Management, Finance and Accounting

Does Realised Range Volatility Improve Multivariate Volatility Forecasting? Evidence from Bursa Malaysia Sectors

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Abstract

This study examines whether realised range volatility improves multivariate volatility forecasting performance in an emerging equity market setting. A comparison between vector heterogeneous autoregressive models constructed with realised volatility, realised range volatility, and conventional return-based volatility measures is conducted using sectoral data from the Bursa Malaysia. High-frequency data from September 2018 to December 2024 were collected from the financial data provider Bloomberg. The analysis evaluates out-of-sample forecasting accuracy using a set of 5 loss functions, including symmetric (MSE and MAE) and asymmetric (QLIKE) criteria. The outcomes provide compelling and strong evidence that realised range volatility measures deliver superior forecasting performance across sectoral pairs. Realised range volatility models consistently dominate alternatives relying on realised volatility and daily returns, underscoring the significance of efficient and effective volatility measurement in multivariate frameworks. These findings have direct implications for portfolio risk management, regulatory capital assessment, and volatility modelling in emerging markets featured by microstructure frictions and sectoral interdependence.

Vol. 7, Issue 2 (2026) https://doi.org/10.33093/ijomfa.2026.7.2.12

Published by MMU PRESS. URL https://journals.mmupress.com/ijomfa

Keywords: VHAR, Realised-Range Volatility, Multivariate Volatility Forecasting, High Frequency Data, Sectoral Markets, Bursa Malaysia

Received on 23 February 2026; Accepted on 23 May 2026; Published on 30 August 2026

To cite this article: Badawi, M. M. A. M., Ng, S. L., Razak, R. A., & Rahman, S. F. (2026). Does realised range volatility improve multivariate volatility forecasting? Evidence from Bursa Malaysia sectors. *International Journal of Management, Finance and Accounting, 7*(2), 355–386. https://doi.org/10.33093/ijomfa.2026.7.2.12

1.0 Introduction

In recent decades, volatility forecasting has been widely recognised globally as a fundamental tool in the financial sector, with applications in asset pricing, risk minimisation, and portfolio management (Qiu et al., 2025). Measuring accurate volatility in emerging markets is very crucial, as it finds the profound depth of the market, using advanced technical tools, highlighting the external stocks which generate higher levels of price uncertainty compared to the stable market (Aggarwal et al., 1999; Ajiga et al., 2024; Bekaert & Harvey, 1997). Fund managers, regulatory commissioners, and corporate risk managers work in this area and ensure reliable forecasting, which is essential for value-at-risk calculations and capital adequacy determination (Christoffersen & Diebold, 2000; Jorion, 2007). A group of Malaysian market researchers conducted a salient case study on market volatility from an Asian perspective.

Bursa Malaysia, a prominent stock exchange in Malaysia, developed an inclusive feature in its market volatility models to capture emerging-market characteristics (Roy et al., 2019; Worthington & Higgs, 2004). The Malaysian stock market focuses on the energy, financial services, and plantation sectors, which are considered to have uneven market capitalisation (Badawi et al., 2026; Lean & Smyth, 2009). Moreover, Petroleum products, subject to dual exposure to global and regional capital flows, exhibit diversified volatility in market mechanisms (Arouri et al., 2011; Ewing & Malik, 2013). Energy sectors, such as net oil exporters, and the substantial contribution of hydrocarbons play a significant role in generating revenue for the government's monetary policy (Basher & Sadorsky, 2006; Kumar et al., 2012; Shaheen & Alamktoom, 2023).

However, cross-sectoral volatility spillovers in Malaysia have significant implications for portfolio management and strategic risk assessment. Existing univariate volatility models can provide independent assumptions, particularly for confidential data that prevents inter-market dependencies (Engle, 2002). Intermarket dependencies limit the analysis of sectoral indices, as financial linkages and other macroeconomic data influence market movements (Diebold & Yilmaz, 2012; Forbes & Rigobon, 2002; Vidal-Llana et al., 2022). As a result, multivariate models that explicitly model dynamic volatility linkages across sectors have emerged as a comprehensive approach to risk characterisation (Asai et al., 2006; Bauwens et al., 2006).

Furthermore, assessing the main volatility methodology is appropriate, as it provides a volatility proxy that captures latent data and represents the time-varying volatility process (Patton, 2006). For ages, empirical research has used squared daily returns, considered the standard volatility proxy, on which Engle (1982) formulated generalised autoregressive conditional heteroskedasticity (GARCH), later extended by Bollerslev (1986). However, squared returns yield daily volatility based on opening and closing prices, thereby ignoring full-day market volatility and providing an incomplete overview (Andersen & Bollerslev, 1998; Zhao et al., 2024). Insufficient information affects emerging markets, where prices frequently change direction; sometimes transactions are halted, causing volatility in intraday trading (Bekaert & Harvey, 2002; Castro et al., 2020).

The development of realised volatility (RV) for high-frequency financial data has brought about a revolution, defining volatility as the sum of squared high-frequency returns over a given day (Andersen et al., 2001; Barndorff-Nielsen & Shephard, 2002). RV accumulates inter-day observations and produces a clear estimate of daily integrated volatility relative to squared returns (Andersen et al., 2003; Caporin et al., 2020; Meddahi, 2002). Theoretical findings indicate that as the sampling frequency increases, RV yields more reliable estimates of integrated volatility under certain regularity conditions (Barndorff-Nielsen & Shephard, 2004). On the other hand, RV has limitations in practical applications. Microstructure noise, including the bid-ask price bounce effect, price discrepancy, and overtreading, affects high-frequency return calculations, thereby introducing bias and conflict in RV, which in turn manipulates the sampling frequency (Hansen & Lunde, 2006; Takahashi et al., 2016). These microstructures affect emerging markets, where money flows are lower; large differences in bid-ask spreads and fewer orders create measurement errors (Arnerić & Matković, 2019; Cajueiro & Tabak, 2004; Liu et al., 2012).

However, recent theoretical and empirical advances suggest that realised range volatility (RRV), constructed from intraday high and low prices over specified intervals, offers a superior alternative to return-based volatility measures (Shu & Luo, 2025). The theoretical foundations, established independently by Martens and Van Dijk (2007) and Christensen and Podolskij (2007), demonstrate that realised range volatility estimators are approximately four to five times more efficient than return-based measures for estimating integrated volatility at identical sampling frequencies. This efficiency gain derives from the range statistic's ability to capture the full extent of price variation within each interval, rather than merely endpoint values (Abruzzo & Park, 2014; Parkinson, 1980; Garman & Klass, 1980). Furthermore, Brandt and Jones (2006) establish that realised range estimators are more robust to microstructure noise than RV, as high-low ranges are less sensitive to temporary price deviations induced by bid-ask bounce and discreteness effects. Empirical applications confirm these theoretical predictions, with Christensen and Podolskij (2007) documenting that RRV achieves estimation precision comparable to RV while requiring substantially fewer intraday observations. Gerlach and Wang (2016) extend this evidence, demonstrating that RRV outperforms RV in volatility forecasting applications across multiple asset classes and market conditions.

Despite accumulating evidence of RRV's superior measurement properties, its application in multivariate volatility-forecasting frameworks remains relatively scarce, particularly in emerging Asian equity markets (Tseng et al., 2018). The heterogeneous autoregressive (HAR) model introduced by Corsi (2009) has emerged as the benchmark specification for forecasting realised volatility measures, capturing long-memory characteristics through a parsimonious cascade of volatility components at daily, weekly, and monthly frequencies (Corsi, 2008; Liu & Maheu, 2009). The HAR framework's empirical success stems from its ability to approximate fractionally integrated processes while maintaining computational simplicity and interpretability (Andersen et al., 2007; Corsi, 2009; Peiris et al., 2024). Multivariate extensions, particularly the Vector HAR (VHAR) model, enable explicit modelling of cross-market volatility spillovers and dynamic interdependencies (Bibinger et al., 2025; Bubák et al., 2011; Luo et al., 2019). However, existing VHAR applications predominantly employ RV as the volatility proxy, with limited investigation of whether RRV's superior measurement characteristics translate into enhanced multivariate forecasting performance across sectors (Sévi, 2014; Vortelinos & Gkillas, 2018).

Finally, this research addresses these research gaps and makes three major contributions to the existing literature. First, it offers new empirical evidence on cross-sectoral volatility forecasting in the Malaysian stock market based on multivariate heterogeneous autoregressive models, which is a major research void given the fact that there are only a handful of studies on this topic related to emerging markets in the Southeast Asian region (Badawi et al., 2026; China et al., 2007). Second, it systematically integrates realised range volatility measures into a vector HAR model and makes a comprehensive comparison of the forecasting performance of these measures relative to both RV and conventional return-based volatility proxies, which aims to empirically validate whether the theoretical efficiency benefits of RRV can be realised in a multivariate forecasting setting (Huang et al., 2018). Third, by using a comprehensive set of five different econometric loss functions: mean squared error (MSE), mean absolute error (MAE), mean absolute percentage error (MAPE), quasi-likelihood (QLIKE), and logarithmic error (LE), this research can rigorously show that realised range volatility measures have systematically superior out-of-sample forecasting performance for sectoral indices, especially in terms of extreme volatility episodes that are of prime importance for tail risk management and regulatory capital purposes.

2.0 Literature Review

2.1 Volatility Forecasting and HAR Models

Accurate prediction of the volatility in the financial markets has continued to remain a major issue for researchers in financial econometric analysis, motivated by the importance of the problem for the pricing of derivatives, the construction of the optimal portfolio, and risk analysis (Mansilla-Lopez et al., 2025; Wu & Karmakar, 2023). Traditional methods for the modelling and prediction of volatilities, including the family of the popular general auto-regressive conditional heteroskedasticity (GARCH) model, introduced by Engle (1982) and Bollerslev (1986), which specify the volatility condition depending on the lags for the squares of the returns and the lags for the conditional volatilities, have played a major role in the field for the past several decades (Sharma et al., 2022; Zhang et al., 2023). However, the methodology relies on low-frequency returns and accounts for the latent nature of volatility, which precludes deriving an accurate forecast.

Therefore, the development of RV measures by Andersen et al. (2001) and Barndorff-Nielsen and Shephard (2002) revolutionised volatility forecasting by treating volatility as an observed entity derived from high-frequency intraday return data. This approach facilitated the creation of more general time-series models that forecast RV measures while avoiding restrictive parametric assumptions regarding return densities (Chen et al., 2016; Chen & Jin, 2022; Clements et al., 2007; Moreno-Pino & Zohren, 2024). The most prominent model in this class, based on various studies, is the Heterogeneous Autoregressive model described by Zhang et al. (2023), which describes a standard base case for RV forecasts. The HAR model accommodates long-memory characteristics inherent in volatility through a simple cascade-based approach that includes daily, weekly, and monthly volatility measures, representing various trader horizons and approaches to information arrival processes (Corsi, 2009; Müller et al., 1997; Özbekler et al., 2021).

The empirical success of HAR can largely be attributed to these models' ability to capture fractionally integrated processes, their ease of understanding, and their simplicity (Huang et al., 2024). Simulated results have shown that HAR is, overall, much better at forecasting asset volatility than the standard GARCH model (Clements & Preve, 2023; Corsi et al., 2012; Zhuo & Morimoto, 2024). The Vector HAR, on the other hand, can forecast contagion, making it an essential component of risk management, especially at the portfolio level (Bubák et al., 2011; Kuang, 2024; Luo et al., 2019). Recent refinements incorporate realised semi-variances, jumps, and leverage effects to enhance forecasting performance, particularly during turbulent market conditions (Buncic & Gisler, 2017; Clément, 2024).

2.2 Realised Volatility versus Realised Range Volatility Measures

Realised volatility (RV) represents a significant improvement over squared returns as a volatility proxy; two fundamental limitations affect this approach. First, microstructure noise arising from bid-ask bounce, price discreteness, and non-synchronous trading contaminates high-frequency return calculations, introducing bias that worsens as sampling frequency increases (Christensen et al., 2024; Liu & Maheu, 2023; Takahashi et al., 2016). Second, RV requires relatively broad intraday data, which may be unavailable or unreliable in thin markets (Hautsch et al., 2022).

The promise of realised range volatility estimators, which use intraday high and low prices, comes with both theoretical and practical advantages. Parkinson first showed in 1980 that the range itself provides a better, more efficient volatility estimator than squared returns. This idea was further refined by Garman and Klass in 1980, and later by Rogers and Satchell in 1991, to include opening and closing prices to capture drift. Articles by Christensen and Podolskij in 2007 and Martens and Van Dijk in 2007 confirmed that using "realised range volatility" or "RRV," where we square each range and add across all intraday returns, offers an improvement of four to five times greater efficiency compared to RV at equal frequencies. Most importantly, Brandt and Jones (2006) demonstrated that range estimators are more "robust to noise corruption," as "high-low ranges are considerably less sensitive to short-term temporary price deviations due to bid-ask induced effects."

These theoretical results have been strongly supported empirically, as we can now show. For example, Christensen and Podolskij (2007) found that, on one hand, the precision of the realised range volatility can, for certain combinations of parameters, reach a level equivalent to that of the realised volatility, whilst on the other hand, the number of intra-daily data points underlying the calculation of the realised range volatility can be considerably smaller compared to the number of intra-daily data points underlying the calculation of realised volatility, especially when dealing with emerging markets where intra-daily data is scarce (Arnerić & Matković, 2019; Kuang, 2024). Gerlach and Wang (2016) extended this application to include realised range volatility in GARCH-type specifications, where volatility forecastability is much better than that of standard volatility forecasts based on realised volatility. Later on, we find an application of realised range volatility in the context of energy markets by Molnár (2016), which confirmed that one can achieve much better volatility forecastability, especially when volatility is large, compared to standard volatility forecasts based on realised volatility. Most recently, Caporale and Gil-Alana (2021) confirmed strong long-memory characteristics of realised range volatility. Although numerous studies have verified and presented its advantages, multivariate HAR estimations still rely more on RV, and few studies have utilised RRV (Zhuo & Morimoto, 2024).

2.3 Evidence from Emerging Markets

Volatility dynamics in emerging markets exhibit specific features that are difficult to forecast, such as an increased volatility threshold, stronger volatility clustering, enlarged volatility spillovers, and more frequent structural breaks (Aggarwal et al., 1999; Bekaert & Harvey, 1997). All this has created the need to develop models that can account for volatility persistence and spillovers between markets (Beirne et al., 2013). Research undertaken on Asian emerging markets volatility spillover effects in Asia's emerging markets, which transfer volatility from developed countries and commodity centres to these economies' stock sectors. In a study, Li and Giles (2015) identified high-volatility spillover effects between China's stock sectors and oil prices, revealing stronger spillovers in the energy and industrial sectors. Another study by Narayan and Sharma (2011) revealed Asymmetric volatility effects among Asian emerging economies, driven by oil price spillovers. The study further revealed higher spillover effects for oil-importing countries. Malik and Hammoudeh (2007), in a study of the Gulf Cooperation Council (GCC) national stock markets, found evidence of high volatility spillover effects.

While fewer in comparison, several investigations have already been conducted to evaluate financial market stability in Malaysia. Lean and Smyth (2009) analysed the stability of shocks affecting financial prices in Malaysia, concluding that volatility effects are transitory during crises. Another investigation, conducted by Ahmad and Ping (2014), employed multivariate GARCH models to identify volatility spillovers from commodity prices to sectoral financial indices in Malaysia. More recent scholarly work, proposed by Yousaf et al. (2022), analysed odd volatility spillovers amongst sectoral financial indexes in Malaysia resulting from COVID-19-triggered volatility. Although these investigations predominantly employed conventional GARCH models, the use of alternative data frequencies, such as intraday data, in conjunction with HAR-GARCH models to obtain potentially superior volatility forecasting performance in Malaysia was not analysed. Therefore, building on such discussions, it was proposed to evaluate whether volatility forecasting performance would be superior, as predicted by theory, when employing RRV.

3.0 Methodology

3.1 Data

The data used for this analysis is historical data from the Bursa Malaysia indices. Data were collected for the composite index (KLCI), as well as the 13 sectoral indices in Bursa Malaysia: 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). Missing data points were detected in the raw data, accounting for less than 1% of the dataset. To impute missing data points, the Linear Interpolation method was used in SPSS prior to data preprocessing.

3.2 Volatility Measures

The basic calculation of daily returns is given as

$$r_i = 100(\ln P_t - \ln P_{t-1}),\ t = 1, 2, \ldots, T \qquad (1)$$

Statistical measures are generally divided into parametric and non-parametric measures, and the same holds for volatility. Parametric volatility modelling methods are based on assumptions about the explicit functional form of instantaneous and/or expected volatility, such as ARCH models, Stochastic Volatility Models, and Continuous Sample Path Diffusions. Conversely, nonparametric methods of volatility modelling are generally unbound by those assumptions and can produce volatility estimates that are flexible and consistent at the same time, such as realised volatility measures. (Andersen et al., 2007)

The realised volatility estimator is computed by summing squared daily or intradaily returns of a specific asset or index. It was first created in 1998 by Andersen and Bollerslev. The formula for daily realised volatility according to Corsi (2009) is as follows:

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

where:

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

RV consistently estimates integrated volatility and is asymptotically unbiased as the sampling frequency tends to infinity. RV becomes less consistent as the price frequency is contaminated by microstructure noise. Thus, the asymptotic theory is invalidated. To mitigate this, lower-frequency data is used, but this poses another issue, which is the loss of information. Researchers like Bandi and Russell (2006) and Hansen and Lunde (2006) have found RV to be inconsistent and biased in the presence of noisy prices. Christensen and Podolskij (2007) introduced a new estimator called realised range variance, or RRV for short.

The precision of volatility estimates is dependent on the price process. The volatility level is also highly sensitive to estimator performance with respect to daily price ranges. Changes made in the Christensen and Podolskij (2007) and Martens and

Van Dijk (2007) model led to improvements on previous estimators, which provide decisive support for the realised range volatility (Todorova, 2012)

RRV measures volatility by subtracting the lowest price return from the highest price return over a specific timeframe. Degiannakis and Livada (2013) show that this measure is an unbiased estimate of daily volatility and is fivefold more efficient than the squared daily return. Furthermore, Martens and Van Dijk (2007) propose the scaled high-low range for intraday intervals to calculate RRV as such:

$$RRV_t = \sqrt{\frac{1}{4\log 2}\sum_{i=1}^{M}\left(\log H_{t,i} - \log L_{t,i}\right)^2} \quad (3)$$

where:

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

3.3 Intra-day Multivariate Models

The Heterogeneous Autoregressive (HAR) model, introduced by Corsi (2009), is a statistical model commonly used for analysing financial time series data. It was introduced to capture volatility's heterogeneous nature in financial markets, as in the HMH presented by Müller et al. (1997). The HAR model is the extension of the ARCH and GARCH models. These models are designed to model a time series' conditional variance, meaning the series' variance is allowed to change over time based on past observations. The key idea behind the HAR model is to incorporate multiple past measures of volatility with various sampling frequencies. It recognises that financial time series may exhibit both long and short-term memory effects in volatility. Building upon Corsi's 2009 model, the vector HAR model or VHAR was introduced by Bubák et al. (2011) to model the cumulative behaviours of RV and a multivariate HAR. The model is formed by forming a vector of the logarithms of realised variances of a group of assets and is expressed as follows:

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

$$\varepsilon_t \sim WN(0, \Sigma), \quad t = 1, 2, \ldots, T, \quad (4)$$

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, including the HAR-RV model; among these are Gong and Lin (2017), Liu et al. (2017), and Liu et al. (2022). In this study, we extend the univariate HAR-RRV to the multivariate HAR-RRV, or Vector Heterogeneous Autoregressive model for realised range volatility (VHAR-RRV).

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

$$\varepsilon_t | \Omega_{t-1} \sim NIID(0,1) \tag{5}$$

Such that:

- subscript k = 1, 2 represents 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 can be calculated as follows: $RRV_{k,t-1}^{(m)} = \frac{1}{22}\sum_{i=1}^{22} RRV_{k,t-i}^{(d)}$ and $RRV_{k,t-1}^{(w)} = \frac{1}{5}\sum_{i=1}^{5} RRV_{k,t-i}^{(d)}$, respectively.

In summary, three models are estimated to evaluate the forecasting performance of alternative volatility proxies. The first two variants employ the VHAR framework but change the volatility proxy, VHAR-RRV and VHAR-RV as the respective volatility proxies. The third variant uses a diagonal BEKK-GARCH(1,1) model estimated on daily returns, serving as the return-based benchmark. All three variants are estimated as bivariate systems, pairing the energy sector index (KLENG) with each of the 12 remaining sectoral indices and the composite index in Bursa Malaysia, yielding 13 sector pairs in total.

For the VHAR variants, each bivariate system consists of two equations estimated equation-by-equation, where each equation includes daily, weekly, and monthly components of both own- and cross-sector log-volatility, yielding 14 parameters across the system. For the BEKK-GARCH variant, the mean equation follows a bivariate VAR(1) structure with 6 mean parameters, while the variance equation is specified as a diagonal BEKK-GARCH(1,1) with a Student-t error distribution to account for the fat-tailed nature of return innovations, yielding 16 parameters in total, including the degrees of freedom parameter. All three models are estimated using a rolling window scheme with a fixed window of 1,028 observations, generating 245 one-step-ahead out-of-sample forecasts, with full model re-estimation at each step. For the VHAR variants, forecasts of log-volatility are generated by applying the estimated coefficients directly to current regressor values, with a log-normal bias correction applied when transforming forecasts back to levels. For the BEKK-GARCH variant, one-step-ahead conditional variance and covariance forecasts are generated analytically using the estimated ARCH, asymmetric TARCH, and GARCH parameters, together with the current-period residuals and conditional variances. Lastly, five loss functions are calculated for each pairwise out-of-sample forecast to evaluate which model performs best among the three.

3.4 Breakpoint Testing

The Bai-Perron multiple breakpoint tests of “L+1 vs L sequentially determined breaks” were performed in EViews for both volatility proxies, as well as the daily returns and closing price, for all 14 indices in order to identify any structural breaks in the data. Using Least Squares estimation, the trimming percentage was set to 15%. The maximum number of breaks is set to 5, and the significance level is set to 0.05. The test statistics employ HAC covariances (Bartlett kernel, Newey-West fixed bandwidth) assuming a common data distribution. The results of the Bai-Perron test show that the data have zero significant breakpoints.

4.0 Discussion

Preliminary analysis of all three volatility proxies across the 14 Bursa Malaysia indices confirms stationarity via ADF and PP unit root tests, non-normality via Jarque-Bera tests, and significant serial correlation and volatility clustering via Ljung-Box Q and Q^2 statistics. These properties collectively justify the use of the VHAR framework as the appropriate modelling approach. Table 1 presents the comprehensive results of the out-of-sample forecasting evaluation through five loss functions. It is divided into three vertical sections to present the three models this paper compares: VHAR-RV, VHAR-RRV, and the daily returns-based model, BEKK-GARCH. Each section consists of two columns: the first is the energy sector (KLENG), and the second is the second sector in the model. Furthermore, there are 13 horizontal sections, each presenting a bivariate sector relationship. In each horizontal section, five rows present the five loss functions employed to evaluate the out-of-sample forecasts: Mean Squared Error (MSE), Mean Absolute Error (MAE), Quasi-Likelihood (QLIKE), Logarithmic Error (LE), and Mean Absolute Percentage Error (MAPE). To summarise the results in Table 1, Table 2 presents the out-of-sample forecast evaluation for the three volatility proxies. The table structure displays model names in the first column and the frequency of superior performance relative to competing models, across all bivariate sector relationships and all five loss functions, in the second column.

The out-of-sample evaluation results demonstrate clear performance hierarchies among the three volatility models, VHAR-RV, VHAR-RRV, and BEKK-GARCH, across all bivariate models. The Realised Range Volatility (RRV) based model consistently outperforms both the standard Realised Volatility (RV) and simple daily return-based models. The daily returns-based model (BEKK-GARCH) consistently yields the highest error rates across all sectors and loss functions, particularly in the healthcare (KLHEAL), finance (KLFIN), and technology (KLTEC) sectors, confirming the inadequacy of using daily returns as volatility proxies. Across all loss function categories, including traditional measures (MSE, MAE), likelihood-based measures (QLIKE, LE) and percentage-based errors (MAPE), the VHAR-RRV model demonstrates superior forecasting accuracy.

These results have significant implications for risk management, as the RRV model's superior performance enables better portfolio diversification, more precise risk budgeting, and enhanced hedging effectiveness for energy-sector exposures. The comprehensive evaluation across multiple sectors and loss functions provides strong evidence for adopting the RRV model as the preferred choice for volatility modelling and forecasting in Malaysian stock market analysis, particularly for investigations into energy sector risk spillovers.

Table 1: Out-Of-Sample Forecast Evaluation

LF	VHAR-RV		VHAR-RRV		BEKK-GARCH	
	KLENG	KLCI	KLENG	KLCI	KLENG	KLCI
MSE	0.0166	0.0007	0.0198	0.0011	1.1034	0.0852
MAE	0.0782	0.0122	0.092	0.0159	0.2845	0.0685
QLIKE	0.0582	0.0806	0.0512	0.0344	5.878	5.2189
LE	0.1126	0.1737	0.0968	0.0767	49.0572	46.1126
MAPE	0.1340	0.1545	0.1241	0.0936	1.0616	1.0155
	KLENG	KLCSU	KLENG	KLCSU	KLENG	KLCSU
MSE	0.0168	0.0011	0.0194	0.0004	1.1032	0.0004
MAE	0.0790	0.0128	0.0906	0.0097	0.2844	0.0097
QLIKE	0.0578	0.0682	0.0501	0.0306	6.0956	0.0306
LE	0.1126	0.1497	0.0954	0.0677	49.8888	0.0677
MAPE	0.1346	0.1368	0.1226	0.0935	1.1137	0.0935
	KLENG	KLHEAL	KLENG	KLHEAL	KLENG	KLHEAL
MSE	0.0130	0.0356	0.0232	0.0065	1.1038	2.9769
MAE	0.0874	0.0973	0.1192	0.0489	0.2848	0.3991
QLIKE	0.0559	0.0854	0.0469	0.0139	7.1570	12.0819
LE	0.0961	0.1864	0.0836	0.0286	76.3318	26.4409
MAPE	0.1266	0.1548	0.1182	0.0642	1.0049	1.4246
	KLENG	KLFIN	KLENG	KLFIN	KLENG	KLFIN
MSE	0.0166	0.001	0.0197	0.0009	1.1038	0.0768
MAE	0.0779	0.016	0.0914	0.0156	0.2848	0.0786
QLIKE	0.0572	0.0796	0.0502	0.0388	7.1570	283.928
LE	0.1118	0.1667	0.0959	0.0848	76.3318	18.7523
MAPE	0.1331	0.1485	0.1229	0.1034	1.0049	2.6569
	KLENG	KLPLN	KLENG	KLPLN	KLENG	KLPLN
MSE	0.0166	0.0023	0.0196	0.0016	1.1037	0.0597
MAE	0.0770	0.0301	0.0894	0.0259	0.2847	0.0905
QLIKE	0.0556	0.1063	0.0482	0.0835	6.5285	5.3326

LE	0.1097	0.1979	0.0935	0.1542	65.1545	41.6974
MAPE	0.1305	0.1881	0.1193	0.1595	1.0030	1.0505
	KLENG	KLPRO	KLENG	KLPRO	KLENG	KLPRO
MSE	0.0163	0.0056	0.0199	0.0029	1.1038	0.6571
MAE	0.0771	0.0271	0.0924	0.0236	0.2848	0.1515
QLIKE	0.0571	0.0914	0.0513	0.0546	7.2303	58.5755
LE	0.1104	0.1880	0.0965	0.1147	76.9943	47.4141
MAPE	0.1325	0.1643	0.1246	0.1259	1.0066	1.4702
	KLENG	KLPRP	KLENG	KLPRP	KLENG	KLPRP
MSE	0.0165	0.0156	0.0195	0.0141	1.0832	1.8207
MAE	0.0783	0.0487	0.0898	0.0441	0.2775	0.3099
QLIKE	0.0566	0.0734	0.0486	0.0402	7.0404	6.3886
LE	0.1117	0.1596	0.0946	0.0922	23.5301	22.2849
MAPE	0.1333	0.1481	0.1203	0.1050	1.3238	1.3286
	KLENG	KLTEC	KLENG	KLTEC	KLENG	KLTEC
MSE	0.0165	0.0188	0.0194	0.0181	1.1037	1.6773
MAE	0.0778	0.0615	0.0906	0.0662	0.2848	0.3430
QLIKE	0.0571	0.1233	0.0492	0.0905	7.3158	1225.58
LE	0.1113	0.2744	0.0942	0.2213	79.6387	32.2564
MAPE	0.1331	0.1893	0.1218	0.1673	0.9985	4.6973
	KLENG	KLREI	KLENG	KLREI	KLENG	KLREI
MSE	0.0166	0.0030	0.0199	0.0011	1.1038	0.0236
MAE	0.0779	0.0456	0.0921	0.0243	0.2848	0.0323
QLIKE	0.0572	0.2419	0.0507	0.0479	7.4790	15.4348
LE	0.1118	0.6636	0.0973	0.0956	81.9989	24.3287
MAPE	0.1331	0.2858	0.1240	0.1227	1.0038	1.3114
	KLENG	KLTEL	KLENG	KLTEL	KLENG	KLTEL
MSE	0.0165	0.0057	0.0194	0.0056	1.1030	0.3381
MAE	0.0780	0.0545	0.0891	0.0550	0.2843	0.1364
QLIKE	0.0568	0.0539	0.0487	0.0444	5.8659	5.0897
LE	0.1115	0.1062	0.0945	0.0897	46.984	40.0559
MAPE	0.1331	0.1304	0.1196	0.1207	1.0973	1.0592
	KLENG	KLTRAN	KLENG	KLTRAN	KLENG	KLTRAN
MSE	0.0168	0.0074	0.0199	0.0057	1.1032	0.1239
MAE	0.0786	0.0508	0.0911	0.0428	0.2843	0.0965
QLIKE	0.0588	0.1152	0.0507	0.1045	4.9541	5.7509
LE	0.1146	0.2256	0.0971	0.2109	41.9145	38.6113
MAPE	0.1344	0.1877	0.1226	0.1775	1.0358	1.0771
	KLENG	KLCON	KLENG	KLCON	KLENG	KLCON
MSE	0.0171	0.0369	0.0205	0.0325	1.0962	1.6831
MAE	0.0786	0.0738	0.0916	0.0748	0.2823	0.3744
QLIKE	0.0577	0.0968	0.0506	0.0736	10.0779	4.7630
LE	0.1135	0.1975	0.0973	0.1497	27.5089	35.7695
MAPE	0.1334	0.1749	0.1223	0.1456	1.3338	1.0723
	KLENG	KLUTL	KLENG	KLUTL	KLENG	KLUTL
MSE	0.0154	0.0215	0.0177	0.0140	1.1000	0.4459

MAE	0.0770	0.0714	0.0866	0.0568	0.2819	0.2769
QLIKE	0.0546	0.0929	0.0461	0.0519	14.8787	3.9745
LE	0.1067	0.1908	0.0889	0.1166	26.2576	25.4447
MAPE	0.1313	0.1603	0.1166	0.1159	1.3592	1.0965

Table 2: Summary Of Out-Of-Sample Forecast Evaluation

Model	Count
VHAR-RRV	99
VHAR-RV	31
BEKK	0

5.0 Conclusion and Implications

This study investigates whether realised range volatility offers real benefits for multivariate volatility forecasting in an emerging equity market characterised by sectoral heterogeneity and significant spillover effects. Using sectoral indices from Bursa Malaysia, the analysis integrated alternative volatility proxies within a vector heterogeneous autoregressive (VHAR) framework and evaluated their out-of-sample performance across a broad set of loss functions. The empirical evidence consistently favours models built upon the realised range volatility measure.

Among all bivariate sectoral relationships and evaluation metrics, the VHAR-RRV specification outperforms both its realised volatility counterpart and returns-based benchmark. The dominance of the realised range specification is not confined to a single loss function or sector but appears systematically across symmetric and asymmetric criteria. This suggests that the superior efficiency of the realised range volatility, demonstrated in theoretical and univariate settings, are meaningfully applicable to multivariate volatility forecasting environments where cross-market dependence is central.

The results also emphasise the limitations of return-based volatility proxies in multivariate applications. Models relying on daily returns regularly generate larger forecast errors, particularly in sectors such as finance, healthcare, and technology, where volatility dynamics are more sensitive to information flows and intersectoral linkages.

This finding suggests that low-frequency volatility measures are limited and inefficient for risk assessment in emerging markets, where microstructure frictions and episodic shocks amplify short-horizon volatility dynamics.

From a practical perspective, the findings carry important implications for risk management and portfolio construction. For instance, more accurate multivariate volatility forecasts improve the precision of portfolio allocation and elevate hedging effectiveness. Additionally, they support more reliable estimation of tail-risk measures such as value-at-risk and expected shortfall. The superior performance of realised range measures during periods of heightened volatility is of particular importance for regulatory capital planning and stress testing, where underestimating risk can have material consequences.

From a methodological standpoint, this study contributes to the volatility forecasting literature by demonstrating that developing an improved framework for volatility measurement yields tangible gains in multivariate forecasting accuracy. While prior research has largely focused on realised volatility within HAR-type models, the present findings suggest that the choice of volatility proxy remains a first-order concern even within well-established forecasting frameworks. Incorporating realised range volatility enables researchers and practitioners to capitalise on intraday price information more efficiently, without incurring the full costs of ultra-high-frequency data.

Several limitations warrant acknowledgement. The analysis focuses on a single emerging market and a specific set of sectoral indices, which may limit the generalisability of the results to other market structures. In addition, the study abstracts from structural breaks and regime-switching dynamics that may further influence volatility transmission across sectors. Future research could extend the framework to higher-dimensional systems, alternative asset classes, or time-varying parameter specifications to explore whether the advantages of range volatility persist under more complex dependence structures and more robust statistical testing procedures. In general, the evidence strongly supports the adoption of realised range volatility measures in multivariate forecasting applications, particularly in emerging markets where data frictions and sectoral spillovers are pronounced. By demonstrating consistent forecasting gains across a comprehensive evaluation framework, this study provides a compelling case for re-examining standard volatility modelling practices in both academic research and applied risk management.

Author Contributions Statement: Formal analysis and investigation, Writing - original draft preparation, Writing - review and editing: M.M.A.M.B.; Writing: S.F.R.; Conceptualisation, Methodology, and Funding acquisition: S.L.N; Resources: Multimedia University; Supervision: N.S.L. and R.A.R. All authors have read and approved the final manuscript.

Funding Statement: This study was supported by the Ministry of Higher Education of Malaysia FRGS fund [grant number: MMUE/220030.02].

Informed Consent Statement: No consent was needed for the completion of this study.

Data Availability Statement: The data is available from the corresponding author upon request.

Acknowledgement: The authors are grateful for the help and support from family and friends, Multimedia University, the editors, and reviewers of the International Journal of Management, Finance and Accounting.

Conflict of Interest Statement: The authors have no competing interests to declare that are relevant to the content of this study.

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