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EXPLORING THE RELATION BETWEEN REALISED VOLATILITY AND TRADING VOLUME: EVIDENCE FROM INTERNATIONAL STOCK MARKET

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ABSTRACT

Objective: The sequential information theory and mixed distribution hypothesis contends that there exists a bi-directional relation between realised volatility and trading volume. This position has led to the proposition that new information spreads sequentially and reaches market participants at varying times. The purpose of this study was to re-examine these theories. **Research Design & Methods:** A Granger causality test, Mean Square Error and Mean Average error models were applied to investigate the relationship between realised volatility and trading volume for a sample of five international stock markets from March 5, 2018, to March 5, 2023. **Findings:** The findings of this study contradict the proposition put forth by the sequential information theory and mixed distribution hypothesis where no meaningful relationship was observed between realised volatility and trading volume except for the CAC 40. Hence, new information rather filters through financial markets at the same time. This finding maybe the explanation for the ever-increasing financial contagion between financial markets. **Contribution & Value Added:** Traders may need to rely on other indicators and adjust their strategies to incorporate different signals or factors that are more relevant for predicting or identifying market movements. It may become more challenging to gauge the liquidity conditions in the market based solely on volatility. Market participants may need to rely on other liquidity indicators, such as bid-ask spreads, order book depth, or trade size distribution, to assess market liquidity.

Keywords: Granger causality test; mixed distribution hypothesis; realised volatility; sequential information theory; trading volume.
JEL codes: G11, G15, G17
Article type: research paper

INTRODUCTION

Stock market microstructure involves understanding several complicated layers of traditional trading functions to provide a vivid understanding of the price formation system. Till date, market participants and investors are interested in the price discovery system for better capital allocation. Modelling the relationship between realised volatility (RV) and trading volume (VOL) encapsulates a major part of price formation due to the volume of information flow in financial markets (O'hara, 2015). This idea is postulated by the sequential information flow hypothesis which contends that new information is transmitted systematically to market participants (Gueyie et al., 2022). In essence, new information reaches security traders at varying times giving rise to information asymmetry (An et al., 2022). This leads to disequilibrium in security markets where market prices will enhance the direction of trade and trading volume. Information and parameters of previous trading volumes can be used to forecast and predict price volatility and vice versa. The sequential information flow hypothesis is supported by the

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mixed distribution theory which contends that stock price returns and trading volumes are related (He & Velu, 2014).

The main bone of contention from these theories is that trading in financial markets is based on new information which ultimately affects market prices and trading volumes (Preis et al., 2013). Considering the heterogeneity of market participants, new information can also be used for trading signals. The above theories however contradict the market efficiency hypothesis where stock prices tend to follow a stochastic process (Enow, 2022b). Till date, prior empirical literature on the relationship between RV and VOL focused mainly on time series models such as GARCH and causality effect where a significant relationship between the variables was observed (Adhikari, 2020; Choi et al., 2020; Ozdemir, 2020). Despite the perceived relevance, other forecasting models such as the Mean Square Error (MSE) and Mean Average error (MAE) are also required to assess the dynamic relationship between RV and VOL in order to access the consistency of other traditional models such as GARCH and TGRACH (Hodson, 2022). However, very little is known on assessing the relationship between RV and VOL using MAE and MSE models. Hence, due to the lack of research on the MAE and MSE models from earlier studies, this study aims to fill in the gap. Furthermore, the degree to which new information is integrated into security prices and the existence of any lag effects may be better understood by observing the extent to which RV can reliably predict VOL using MAE and MSE.

This study therefore investigates the following research question; using the most recent data, is there any contemporaneous relationship between RV and VOL? Is there any evidence of causality between RV and VOL in financial markets? Can RV and VOL be used as predictors of each other? In providing answers to the above questions, this study makes a significant contribution to the frontier of the dynamic relationship between RV and VOL as well as the literature of price formation and transmission mechanism in international financial markets. This study is structured as follows; section 2 outlines the literature review followed by the methodology in section 3. The results, and discussion in section 4 and 5 respectively. Section 6 which is the conclusion provides recommendations from the study.

LITERATURE REVIEW

The theoretical underpinning of this study is the market efficiency theory. The main idea of this concept is that security prices reflect all available information (Fama, 1965). Accordingly, investing based on public information cannot systematically outperform the market overtime (Enow, 2022a). Also, it is impossible to forecast stock price returns based on the arrival of new information as it will be quickly reflected in the stock price (Duarte et al., 2021). Hence price signals from volume trading will be unfruitful, at least in the long run. Future price movements are expected to continue in a stochastic manner as investors are unlikely to beat the market. The market efficiency principle also underpins the Arbitrage pricing theory (APT), Capital asset pricing model (CAPM) and concepts such as beta (Roll & Ross, 1980). However, the market efficiency hypothesis developed by Fama (1965) has received several criticisms among academics and industry experts especially with the emergence of behavioural finance in the early 90s. The fact that security prices are far more volatile appear to be justified by new information. The main assumption of market efficiency is also challenged on the premise that investors are not always rationale (Enow, 2022b). Also, new information is not always free, and it is at times costly to obtain, hence it is unlikely that all available information will be reflected in the security price. From the above proposition put forth by the market efficiency theory, it can be suggested that there may be no relationship or causation effect between RV and VOL considering the randomness in price patterns. However, more recent prior literature has suggested otherwise. There are several implications if there exists a relationship between RV and VOL, some of these are.

Liquidity and market depth. Higher RV often leads to increased trading volume as investors and traders adjust their positions in response to changing market conditions. This can improve liquidity and market depth, as there are more participants willing to buy and sell securities. Increased trading volume provides more opportunities for executing trades at desired prices and reduces the likelihood of experiencing significant price fluctuations due to large imbalances in supply and demand.

Trading costs. Higher VOL resulting from increased RV can impact trading costs. In general, higher trading volume tends to be associated with lower transaction costs, such as bid-ask spreads because of increased liquidity. However, during periods of extreme volatility, bid-ask spreads may widen as market makers and liquidity providers demand higher compensation for taking on the additional risk associated with volatile market conditions. This can increase the cost of executing trades, particularly for larger orders.

Price efficiency. RV can affect the speed and accuracy of price discovery in the market. Higher volatility can lead to faster incorporation of new information into asset prices as traders react to changing market conditions. This can improve price efficiency, as prices more quickly reflect relevant news and market developments. Increased trading volume during volatile periods facilitate the process of price discovery by incorporating a broader range of opinions and trading strategies.

Market dynamics. RV can influence market dynamics and the behaviour of market participants. Higher volatility often attracts more speculative traders who seek to profit from short-term price fluctuations. This can increase market activity and trading volume, but it may also introduce additional risks and contribute to increased price volatility. Moreover, periods of high volatility can lead to heightened investor anxiety and uncertainty, potentially impacting investor sentiment and decision-making.

Risk management. RV plays a crucial role in risk management for market participants. Traders and investors often adjust their risk exposure based on the level of volatility in the market. Higher volatility typically implies greater uncertainty and risk which may prompt market participants to adjust their trading strategies, portfolio allocations, and hedging activities. Increased trading volume during volatile periods provide opportunities for managing and mitigating risk through the execution of trades. Table 1 summarises the most recent studies on the relationship between RV and VOL.

Table 1. Summary of Prior Studies on the Relationship between RV and VOL

Study (Author & year of study)	Model	Period	Findings
Gupta et al. (2018)	MODWT-VAR approach	January 4, 2002 – September 18, 2017 and January 1, 2001- September 18, 2017	A significant bi- directional relationship between trading volume and price returns
Ligocká (2019)	Correlation analysis and Granger Causality test	January 1, 2008 – December 31, 2018	Significant positive relationship between volatility and trading volume.
Bajzik (2020)	Meta-Analysis	44 studies in the literature	An inverse relationship exists between trading volumes and price returns. Stock price returns decreases as trading volume increases.
Adhikari (2020)	Granger Causality and VAR	July 2011 - July 2018	An unidirectional relationship between VOL and security price return.
Ozdemir (2020)	Causality test	January 02, 1997– December 29, 2017	A significant bi-directional relationship between price volatility and trading volume
Choi et al. (2020)	GARCH	January 2, 2004 – September 28, 2012	Price volatility is partly explained by trading volume

Source: Computed by Author

Table 1 presents a review of the most recent studies on RV and VOL from 2018. The findings in Table 1 contends that there is a relationship between RV and VOL, hence inferring that, the concept of market efficiency is not relevant. However, none of the studies indicated the predictive proportion between stock price returns and trading volume. In other words, the forecasting proportion between the dependent and independent variables are still not evident. Hence, this study will attempt to extend the findings of prior literature.

METHODS

To achieve the objective of this study, two variables were used which were RV calculated as the natural log of today's closing price divided by yesterday's price and VOL which was the daily trading volumes for four financial markets namely, the JSE (Johannesburg Stock Exchange), the Borsa Istanbul 100 (BIST 100), CAC-40 (the French Stock Market Index), the DAX (the German blue chip companies) and the NASDAQ Index. Apart from Asia, the chosen financial markets were the most active indices from several continents. All the required data was retrieved from yahoo finance which provides credible and real time data sets. These data were mainly daily share prices which are secondary data. The sample period was the most recent 5 years (March 5, 2018, to March 5, 2023). The data analysis process was in four stages, firstly a descriptive statistic was first conducted to glean the stylist facts of RV and VOL followed by a unit root test. This unit root test was conducted to ensure that RV and VOL were stationary. RV and VOL are said to be stationary if their statistical properties such as the mean, variance and covariance are constant overtime, or no trends exist (Nkoro & Uko, 2016). As described in prior literature (Holder et al., 1990), a stationary test is important because non-stationary variables produce spurious results. Accordingly, an Augmented Dickey Fuller (ADF) test was applied to determine the stationarity status of the variables. Where the p-values were less than 5%, RV and VOL were confirmed to be stationary and vice versa. According to Tam (2013) an ADF test is given by Equation 1 and 2

$$\Delta y_t = \alpha + \delta y_{t-1} + \sum_{i=1}^{n} \beta_i \Delta y_{t-1} + \varepsilon_t \qquad \text{Equation 1}$$

$$y_t = \alpha + 6 y_{t-1} + \varepsilon_t \qquad \text{Equation 2}$$

H_0: Stationary variable if the P-value is less than 5%

H_1: Non- Stationary variables if the P-values is more than 5%.

A granger causality test was conducted to examine whether the information provided by the lag values of RV allows for a more accurate prediction of VOL and vice versa. In other words, a Granger causality test was used to provide evidence of correlation between RV and VOL. If RV Granger causes VOL, then RV can be used to predict future values of VOL and vice versa. Albeit inference must be done cautiously taking into consideration that Granger causality is used for short run relationships. Mathematically, a granger model is given by Equation 3.

$$RV_t = a_0 + a_1 RV_{t-1} + a_2 VOL_{t-1} + \epsilon \qquad \text{Equation 3}$$

Where a_0 is the coefficient of the intercept and ϵ is the error term (Song & Taamouti, 2019). In essence,

H_0: No Causality effect between RV and VOL because the p-value is more than 5%.

H_1: Granger Causality effect between RV and VOL because the p-value is less than 5%.

Finally, a MSE and MAE model was utilized to provide a forecasted proportion between RV and VOL. These models provide the absolute and average magnitude error generated by a regression model (Chiang et al., 2010). The MSE and MAE also highlights the square differences between the observed and predicted values of RV and VOL, hence a notable advancement from the studies cited in the prior literature (Chiang et al., 2010). Equation 4 and 5 represent the mathematical expression of MSE and MAE.

$$MSE = \frac{1}{N} \sum_{i=1}^{n} (RV - VOL)^2 \qquad \text{Equation 4}$$

$$MAE = \frac{1}{N} \sum_{i=1}^{n} |RV - VOL| \qquad \text{Equation 5}$$

Adapted from Chiang et al. (2010).

FINDINGS

As already alluded in section 1 and 3, the first part of the data analysis was to provide a basic description of RV and VOL. These stylised facts are presented in Table 2.

Table 2. Descriptive Statistics

		Mean	Median	Maximum	Minimum	Standard Deviation	Skewness	Kurtosis	Obs
JSE	RV	-0.04%	0	6%	-10%	1.60%	-31%	6.35	1250
	VOL	180696	131102	1701513	3895	165748.3	3.29	19.75	1250
BIST 100	RV	-0.20%	0.20%	9.40%	-4.6	13.10%	-34.37	1202.43	1245
	VOL	26800000	22600000	94600000	0	16200000	1.01	3.6	1245
CAC 40	RV	0.02%	0.09%	8.05%	-13%	1.29%	-1.01	16.63	1282
	VOL	81599969	78157950	37100000	0	38053315	1.77	12.56	1282
DAX	RV	0.02%	0.07%	10.40%	-13%	1.30%	-0.66	15.79	1268
	VOL	83630964	76933300	40000000	0	37236275	2.6	16.4	1268
NASDAQ	RV	0.03%	0.11%	8.90%	-13%	1.60%	-0.59	9.68	1258
	VOL	38000000	40000000	11600000	95900000	1.54	0.61	3.61	1258

Source: Author analysis

Table 2 presents the descriptive properties of the sampled financial markets. JSE and BIST 100 had the lowest mean price volatilities while the NASDAQ, the CAC 40 and DAX had positive RV. From Table 2, it can also be suggested that less developed stock markets have lower trading volumes compared to developed stock markets as evident in the JSE and BIST 100 which had the lowest trading volumes respectively. Also, all the price returns for the sampled financial markets were skewed to the left with the lowest variations seen in the CAC 40. Several extreme outliers can also be seen in the price returns of the BIST 100 with a very high kurtosis value of 1202.43 which concurs with the 13.1% standard deviation. Table 3 presents the findings on the extent to which the RV and VOL changes over time.

Table 3. Unit Root Test Results

		Augmented Dickey-Fuller test t-Statistic	1% level	5% level	10% level
JSE	RV	-39.54(0.000)*	-3.435373	-2.863646	-2.567941
	VOL	-13.05(0.000)*	-3.435385	-2.863651	-2.567944
BIST 100	RV	-34.97 (0.000)*	-3.435394	-2.863655	-2.567946
	VOL	-3.59(0.005)*	-3.435411	-2.863662	-2.56795
CAC 40	RV	-36.09 (0.000)*	-3.435243	-2.863588	-2.56791
	VOL	-6.92(0.000)*	-3.435259	-2.863595	-2.567914
DAX	RV	-36.54 (0.000)*	-3.435299	-2.863613	-2.567923
	VOL	-6.712(0.000)*	-3.435315	-2.86362	-2.567927
NASDAQ	RV	-11.14(0.000)*	-3.435373	-2.863646	-2.567941
	VOL	-20.68(0.000)*	-3.435369	-2.863644	-2.56794

MacKinnon (1996) one-sided p-values.
Lag Length: 3 (Automatic - based on SIC, maxlag=22)
significant at 5%
Source: Author analysis

From Table 3, the mean, variance and covariance of RV and VOL stay constant with time which is evident in the ADF values are less than 5%. Thus, the model used in this study purely captures the relationship between RV and VOL. Therefore, there were no seasonality, error mean or de-trending shortcomings in the variables. Furthermore, Table 4 presents the findings of the Granger causation effect between RV and VOL for the different financial markets under consideration.

From the results in Table 4, the lag values of RV and VOL do not provide any significant prediction of each other except for the CAC 40. In essence, apart from the CAC 40, the bi-directional relationship between RV and VOL are not significant at 5%. Hence RV and VOL cannot be used to predict each other. This finding contradicts the findings of Adhikari (2020); Ozdemir (2020); and Choi et al. (2020) who found a significant relationship between RV and VOL. More specifically, Gupta et al.

(2018); Ligocká (2019); Bajzik (2020); and Adhikari (2020) all found significant relationships between RV and VOL in which they concluded that when RV is high, larger price movements are expected which in turn affects VOL. The direct implication is that market news, earnings reports and even unexpected events can increase RV and VOL. Some of these authors also contend that bearish and bullish phases in financial markets, are as a result from panic selling and increased market uncertainty, leading to heightened VOL. This particularly position is not concurrent with the findings of this study. Contrary to the evidence presented in prior study, during bullish phases when prices and RV tends to be increase, VOL can still low. Price patterns in the CAC 40 relays a significant volume of information and vice versa. The bi-directional effect in the CAC 40 also conveys important information through RV and VOL. These findings extend the proposition put forth by Enow (2022b) who contends that the volatility between stock market prices for different periods are independent. Considering that some authors (Alhussayen, 2022; Chiang et al., 2010; Gueyie et al., 2022) also found an insignificant bi-directional relationship between RV and VOL, it can be suggested that the relationship between RV and VOL is not static but dynamic in nature. The Table 5 highlights the forecast proportions for each variable.

Table 4. Pairwise Granger Causality Tests

	Granger Causality Hypothesis	Observations	F-Statistic	P-value
JSE	VOL does not Granger Cause RV	1248	2.88453	0.0563
	RV does not Granger Cause VOL		1.674	0.1879
BIST 100	VOL does not Granger Cause RV	1243	0.26037	0.7708
	RV does not Granger Cause VOL		0.99501	0.37
CAC 40	VOL does not Granger Cause RV	1280	4.87223	0.0078*
	RV does not Granger Cause VOL		5.16445	0.0058*
DAX	VOL does not Granger Cause RV	1266	2.80658	0.0608
	RV does not Granger Cause VOL		2.41897	0.0894
NASDAQ	VOL does not Granger Cause RV	1256	1.44093	0.2371
	RV does not Granger Cause VOL		0.26643	0.7662
Sample: 1 1258 and 2 Lags				

Source: Author analysis

Table 5. MSE and MAE PARCH Model for RV and VOL

	Model	Forecast variable	MSE	MAE	Forecast proportion
JSE	PARCH	RV	0.016	0.012	0.0060%
		VOL	1.65	1.04	0.28%
BIST 100	PARCH	RV	0.313	0.016	0.0008%
		VOL	2.01	1.42	35.43%
CAC 40	PARCH	RV	0.012	0.008	0.007%
		VOL	3.75	2.28	0.49%
DAX	PARCH	RV	0.013	0.0089	0.010%
		VOL	3.79	2.37	5.32%
NASDAQ	PARCH	RV	0.016	0.011	0.0015%
		VOL	1.58	1.29	4.43%

Table 5 presents a predictive model for exploring the relationship between RV and VOL. The MSE values are well greater than the MAE values recorded as seen above. However, the forecasting proportions are very low with 35% being the highest value as seen in the BIST 100. In all the RV cases, the forecasting proportion is close to zero inferring that VOL cannot be used to predict RV. Also, the VOL forecasting proportions are very low with the highest number recorded in BIST 100. This may be due to the higher standard deviation value reported in Table 2. The results in Table 5 strengthens the findings in Table 4 where there are no meaningful relationship and causation between RV and VOL in all the sampled financial markets except for the CAC 40.

DISCUSSION

This result contradicts the argument against using VOL to forecast RV as proposed in the studies of Chiang et al. (2010) but is in line with the studies of Gueyie et al. (2022) and Alhussayen (2022). In essence, VOL can be significantly affected by various other factors beyond market sentiments, such as new events, market manipulation, or changes in market structure. Also, market participants have different trading strategies, and their activity may not always correlate with future volatility. High volume could be driven by speculative trading, hedging activities, or even algorithmic trading strategies that don't necessarily signal an impending increase in volatility. It is also important to note that RV is influenced by a wide range of factors including economic data, geopolitical events, and changes in investor sentiment. Relying solely on VOL may overlook crucial information that is not reflected in trading volumes. The historical relationship between VOL and RV does not necessarily mean it will persist in the future. Market conditions, regulations, and trading patterns can change over time, rendering historical patterns less reliable. Hence, depending solely on VOL to forecast RV might lead to overfitting, where a model performs well historically but fails to generalize to new, unseen data. While VOL can be a useful tool in understanding market dynamics, it should be used in conjunction with other indicators and analyses to make well-informed decisions about forecasting RV.

CONCLUSION

The aim of this study was to investigate the relationship between RV and VOL, to ascertain or rebuff the sequential information and the mixed distribution theories as well as the findings of prior literature using the most recent data. The results of this study reveals that there is no meaningful relationship between RV and VOL, hence they cannot be used as estimators to predict one another. Based on the findings of this study, sequential information and mixed distribution theories are irrelevant, at least in the current dispensation. The findings of this study also suggests that new information entering financial markets tend to be disseminated faster to active market participants probably due to regional and global integration. Also, financial market contagion which has increased recently may be a propelling factor for new information transmission. Since there is no relationship between RV and VOL, traders may need to rely on other indicators or factors to make trading decisions. They may need to adjust their strategies to incorporate different signals or factors that are more relevant for predicting market movements or identifying trading opportunities. It may become more challenging to gauge the liquidity conditions in the market based solely on volatility. Market participants may need to rely on other liquidity indicators, such as bid-ask spreads, order book depth, or trade size distributions, to assess market liquidity. Active market traders may need to reassess their risk management strategies and approaches, considering alternative risk indicators or measures that better capture the risk dynamics in the market.

Traders should be cautious about relying solely on VOL as a predictor of RV and vice versa. Also, financial markets are more efficient than previously thought. If VOL doesn't consistently signal impending RV, it may imply that information is quickly and efficiently incorporated into asset prices. Hence, researchers may need to reevaluate their models and methodologies when studying market dynamics which could lead to a shift in focus towards exploring other potential predictors of RV.

This study's key drawback is that it only employed equity securities to analyse the relationship between VOL and RV using the sequential information and mixed distribution theories. However, the connections between the two variables may vary for other asset types. As a result, it's crucial to consider the distinctive traits of the item under analysis. Further research should investigate the relationship between VOL and RV across various asset classes to determine whether recurrent patterns or notable deviations exist. Additionally, future research should consider cutting-edge machine learning techniques like deep learning or ensemble approaches to analyse the association between RV and VOL since they could produce results that are more precise and detailed.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

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