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Estimation of stock market index volatility using the GARCH model: Causality between stock indices

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ABSTRACT

This paper aims to model the volatility of returns for selected stock indices and examine the causal relationships between the markets using the historical daily prices of the Financial Times Stock Exchange (FTSE), Bursa Malaysia Kuala Lumpur Composite Index (KLCI), the Indonesia Stock Exchange Index (LQ45), and the Stock Exchange of Thailand (SET) from January 2008 to November 2019. The study employs univariate GARCH models that are prominent in capturing the volatility clustering of financial instruments in association with the Box–Jenkins methodology for better estimation. Generally, the ARMA-GARCH model is used to capture the volatility series, while the Granger causality test examines the causal directions between the markets. The findings revealed leverage effects on the markets, with the outperformance of the EGARCH in analyzing the empirical properties of stock returns. An initial test that yielded positive correlations suggests the existence of co-movement between the derived volatility series. The study concluded bidirectional causal relationships between the selected markets, and based on the resulting relationships, it is proposed that supervision of markets among the ASEAN members could be advantageous in predicting the corresponding market performance.

Contribution/Originality: This study contributes to the functioning of the global financial system by providing insight on future stock market developments among emerging countries, concurrently offering additional reference to investors in making financial decisions while enhancing risk management. The paper also provides added value in modelling market volatility using the ARMA-GARCH model.

1. INTRODUCTION

According to the International Monetary Fund's World Economic Outlook database, the gross world product growth is improving after a continual decline since 2010. With the increasing market potential, economies and consumption in developing countries are expected to continue growing. The increase in the growth rate in developing countries and the associated emerging markets have contributed to the increasing world product growth. On the other hand, developed countries mostly consist of replacement economies. Generally, investors invest in emerging markets to enhance their portfolio growth and reduce the associated risk via efficient international portfolio diversification. In the process of transforming into a developed country, a rapidly emerging market offers a great return for investors in exchange for a greater risk exposure due to its developing status. With the associated increased risk, an accurate forecast of market volatility is vital for risk management. Thus, this study estimates the volatility of stock indices for further action. Over a 21-year period, a positive relationship between stock market performance and economic growth was concluded among 21 emerging markets, both directly and indirectly (Mohtadi & Agarwal, 2001). Therefore, this study focuses on emerging markets by analyzing the stock indices of three developing countries, the FTSE Bursa Malaysia KLCI (Malaysia), the LQ45 (Indonesia), and the SET Index (Thailand).

A stock market index is a hypothetical portfolio of influencing stocks representing segments of the financial market. A portfolio that comprises the most significant stocks is a fair representation of the overall market, thus it is treated as a benchmark for comparison purposes as well as an indicator of stock market performance. The calculation of a stock index value is through weighting mathematics using the prices of the underlying stocks. Generally, index values are weighted by metrics such as stock price, market capitalization or shares outstanding. The value represents a change from a base value, which is the weighted average stock price of all the stocks included. In addition, stock indices show trends in investment patterns by providing useful information of the changes in investor behavior in a specific period, thereby giving an overall image of the market activity. However, index volatility provides more meaning for analysis as the changes in values over time offer a better idea of the index performance.

The volatility of the stock market index is a statistical measure of return dispersion for the given index. In other words, volatility is the range of value change experienced by the stock market index over time. It is often measured using the standard deviation or variance between returns from the same market index. Stock market index volatility is the 360-day standard deviation of the return on the national market index (World Bank, 2013). Overall, stock returns can be used as an indication of the general market level, whereas stock volatility can be treated as an estimation of market risk (Wang & Liu, 2016). In stock markets, volatility is shown by big swings in either direction. Higher volatility is associated with higher risk as it becomes less predictable. However, higher volatility also represents a wider potential range of future returns. Therefore, market returns are affected by the outcome of volatility due to the loss of investor confidence or the possibility of gaining high returns. Typically, high volatility reduces investor confidence since it indicates higher risk and more uncertainties; therefore, financial market uncertainty has an important link with public confidence (Poon & Granger, 2003). This link causes policy makers to often rely on market volatility estimates as the barometer for financial markets and economy vulnerability.

Investors and financial institutions typically forecast stock market index volatility to help them in risk management and portfolio optimization. The most well-known volatility forecasting models include the exponentially weighted moving average (EWMA), the autoregressive integrated moving average (ARIMA), and the generalized autoregressive conditional heteroskedasticity (GARCH) model. GARCH models are superior to EWMA models in volatility forecasting (Ayele, Gabreyohannes, & Tesfay, 2017; El Jebari & Hakmaoui, 2018; Guo, 2012). In addition, the volatility of stock market index returns varies depending on past variance. Thus, a homoskedastic model such as the ARIMA model that assumes constant variance is unsuitable in volatility forecasting. On the contrary, a number of studies support the use of the GARCH model in stock market index volatility forecasting (John, 2004; Minkah, 2007).

Co-movement has received a great deal of attention in finance, primarily due to its importance for asset allocation, risk management, portfolio diversification and the functioning of global financial systems in both developed countries and emerging market economies. Co-movement is referred to as a pattern of positive correlation (Barberis, Shleifer, & Wurgler, 2002). The precise meaning or measure of co-movement is not defined in economic literature; however, the general meaning of co-movement is publicly understood to be the tendency for two or more entities or time series to "move together" over time. Co-movement is often linked with contagion or spillover effects, which tend to have no distinct difference in economic literature (Andries & Galasan, 2020). Basically, contagion means the transmission of shocks between countries or regions and global correlation through direct or indirect contact (Khositkulporn, 2013). Contagion happens when a market's enthusiasm causes enthusiasm in other markets. Meanwhile, spillover is commonly known as the impact of an unrelated event in one nation on the economies of other nations. The distinction between contagion and spillover has not been defined, so contagion and spillover highly depend on the researcher's beliefs regarding the magnitude of co-movement. It can be construed as spillover if the co-movement strength reaches a magnitude that is in accordance with the researcher's beliefs. In contrast, if the co-movement is of a larger magnitude, it is interpreted as a contagion (Rigobon, 2019). Nevertheless, co-movement between volatilities could provide a forecast of the returns through offering an additional reference on the stock market performance, facilitating investors in identifying the market's general pattern. Another term that is similar to co-movement is causation. The objective of this study is to examine the causal relationship of stock market index volatility between Malaysia, Indonesia, and Thailand.

This study is useful in providing an estimation on the best period to invest, particularly by observing the trends of the neighboring markets, thus helping to increase the general confidence level and the rate of investment to boost the economy. The study enables and enhances risk management, portfolio diversification, and asset allocation, whereby the formation of a well-diversified portfolio can be achieved, which is dependent on the understanding of the degree of correlation between the respective stock markets. Observation of the changes in investing patterns enables investors to make prompt adjustment to their portfolios. In addition, close monitoring of the neighboring markets will alert policymakers to any economic instability, enabling them to minimize the forecasted contagion effect. Policymakers can make use of the correlations as a sign of the functional stability of the global financial system. This could help in the preparation of monetary policy that is affected by global stock market developments.

2. REVIEW OF LITERATURE

Previous research has established the use of GARCH model in estimating the conditional volatility of time series for forecasting purposes (Abdalla & Winker, 2012; Nikmanesh & Nor, 2016). A number of studies have proven a better performance from the exponential GARCH (EGARCH) and GARCH(1,1) models when compared with other univariate GARCH models. Chong, Ahmad, and Abdullah (1999) examined the forecasting performance of the GARCH, GARCH-M, EGARCH, and IGARCH with Malaysia's Composite Index, Tins Index, Finance Index, Properties Index, and Plantations Index from 1989 to 1990. It was concluded that the EGARCH was superior in out-of-sample forecasting and outperformed in describing index skewness. In contrast, the IGARCH was found to be the poorest model. Gabriel (2012) concluded that the threshold GARCH (TGARCH) was the best model in forecasting the Romanian stock index (BET Index). However, Lupu, Lupu, and Slavescu (2007) suggested that the EGARCH is better in forecasting the volatility of the Romanian Composite Index (BET-C). Their study was supported by Miron and Tudor (2010), who showed a higher accuracy level of the EGARCH in estimating Romania's daily returns compared to the TGARCH and the power GARCH (PGARCH).

On the other hand, the GARCH(1,1) was found to outperform the random walk, EGARCH, and TGARCH by assuming a normal distribution on the Databank Stock Index (Frimpong & Oteng-Abayie, 2006). The superior forecasting ability of the GARCH(1,1) model was supported by John (2004) in examining the volatility of India's stock market. Kalyanaraman (2014) validated the efficiency of the standard GARCH in estimating the volatility of the Saudi stock market. The superiority of the GARCH compared with the other forecasting models was mainly due to its ease in estimating and its high availability of diagnostic tests (Drakos, Kouretas, & Zarangas, 2010). The GARCH(1,1) was found to perform well in capturing stochastic dependencies, whereas the asymmetric GARCH models were concluded to be superior when a significant inverse relationship exists between volatility and shock. Furthermore, the standard GARCH was found to be more robust than the advanced GARCH in one-step-ahead forecasts (Sharma, 2015). A comparative study by Liu and Hung (2010) analyzed the performance of the GARCH-N, GARCH-t, GARCH-SGT, and GARCH-HT (i.e., GARCH with normal, Student's t, skewed generalized Student's t distribution, and heavy tailed distributions) the with EGARCH and GJR-GARCH (i.e., the threshold GARCH by Glosten, Jagannathan and Runkle) and concluded that the GJR-GARCH model produced a more accurate forecast, while the EGARCH was the second best model.

The ARCH and GARCH models are commonly used in combination with an ARMA model in empirical finance for its better performance than pure ARCH or GARCH models (Hossain & Nasser, 2011; Rachev, Stoyanov, Biglova, & Fabozzi, 2005). Ample studies exist to support the usage of the ARMA-GARCH in predicting stock prices. Tang, Chiu, and Xu (2003) concluded that the prediction of stock prices of Cheung Kong Holding and the Hong Kong and Shanghai Banking Corporation (HSBC) Holding using an ARMA-GARCH model yielded a better result than the AR and AR-GARCH models. The modelling of the mean and volatility of wind speed using ARMA-GARCH and ARMA-GARCH-M models showed high efficiency of ARMA-GARCH-M in capturing the movement of change in mean and volatility, where both models showed a relatively fair performance (Liu, Erdem, & Shi, 2011). A similar study was conducted in 2013 by examining the mean and volatility of electrical prices using ARMA-GARCH-M, ARMA-Symmetric GARCH-in-mean (ARMA-SGARCH-M), and ARMA-GJRGARCH-M models. It was concluded that an ARMA-GARCH-M model is generally effective, the ARMA-SGARCH-M is simple and robust, while the ARMA-GJRGARCH-M is relatively competitive (Liu & Shi, 2013).

Using the I-GARCH, Antoniou and Holmes (1995) investigated how trading FTSE-100 Stock Index Futures affected the volatility of the underlying spot market. The authors concluded that futures trading enhances the speed and quality of information flowing into the spot markets and that this increase in information leads to a rise in spot price volatility. Several studies have established the use of the multivariate GARCH in assessing the correlations of market returns. Berben and Jansen (2005) proposed a novel bivariate GARCH model when investigating co-movement in global equity markets from a sectorial perspective. The correlation between the German, UK, and US stock markets increased twofold between 1980 and 2000, whereas it remained constant for Japan's stock market. Lee (2006) used Engle's dynamic conditional correlation GARCH (DCC-GARCH) model to examine the co-movement between output and prices. The analysis found that the overall price level moved in the same direction as the output prior to World War II, in contrary to the opposite direction after the war. Syllignakis and Kouretas (2011) investigated the time-varying conditional correlations of stock market index returns among seven emerging stock markets of Central and Eastern Europe (CEE) using the multivariate DCC-GARCH model. The study noted a significant rise in conditional correlations between the CEE, US, and German stock returns, particularly from 2007 to 2009, when the financial crisis peaked. This suggests a significant regime shift in the conditional correlation and exposure to external shocks for emerging markets. In addition, Dajčman (2012) adopted the DCC-GARCH model and the Granger causality test to examine the co-movement and spillovers of market returns in the Czech Republic, Austria, France, Poland, Germany, Hungary, Slovenia, and the UK. On the other hand, Gjika and Horvath (2013) examined the co-movement among three major Central European markets and the aggregate euro area market using the DCC-GARCH model, the constant conditional correlation (CCC) model, and the ordinary least squares (OLS) regression. An increase in the correlations was observed, while the conditional correlations and variances were typically positively related. This implies a strong correlation during periods of high volatility where the benefits of diversification faced a disproportionate drop.

Various studies have assessed the efficacy of the GARCH and Granger causality tests in examining the relationships between stock market volatility. Jakpar, Vejayon, Johari, and Myint (2013) examined the co-movement of stock market volatility between China and the five Association of Southeast Asian Nations (ASEAN-5) countries using the standard linear GARCH (1,1) model and the Granger causality test. A fair relation was found between the countries, where bi-directional causality was observed between China and Indonesia, China and Thailand, and China and Singapore, and zero causality was found between China and Malaysia, and China and the Philippines. Nikmanesh, Nor, Sarmidi, and Janor (2014) examined the returns and volatility spillover effects between the Standard and Poor's

100 Index (S&P100), KLCI Composite Index, and the Nikkei Stock Average (NIKKEI 225) by employing a cross-correlation method. The study concluded a unidirectional causality-in-mean from S&P100 and NIKKEI 225 to KLCI, whereby an immediate 12-week reaction of KLCI occurred following a shock received from the S&P100 and the NIKKEI 225. Based on the variance causality test, the study showed that the S&P100 had a bigger influence on the KLCI than that of NIKKEI 225. Jiang, Yu, and Hashmi (2017) conducted a study using the Granger causality test to discover the degrees of interdependence, co-movement, dynamic responses of the US, UK, China, Japan, Hong Kong, and Germany stock markets. It was concluded that the financial crisis strengthened the interdependence relationship of the selected stock markets, although the overall co-movement persisted and even became stronger after the crisis. Jebran, Chen, and Tauni (2017) found strong co-movement and volatility spillovers between the Islamic and conventional stock market indexes in Pakistan by using the vector error correction model (VECM), GARCH, EGARCH, and Granger causality test. Thinagar, Khalid, and Karim (2019) examined the causal directions between stock markets pre-, during, and post-crisis by employing univariate GARCH models and the Granger causality test. The study found asymmetric effects in all selected markets and a mixed indication of unidirectional and bidirectional causality. The bidirectional causality is clearly observed during crisis, while unidirectional causality is clearly seen post-crisis. It was concluded that the developed countries held a leading position in all three periods, while the emerging countries performed as market followers.

3. MATERIALS AND METHODS

This study was conducted based on daily historical prices of the FTSE Bursa Malaysia KLCI (Malaysia), LQ45 (Indonesia), and SET Index (Thailand) from January 2, 2008, to November 29, 2019, retrieved from Investing.com. The prices were converted into return series using the following equation:

$$R_t = ln\frac{P_t}{P_{t-1}} \tag{1}$$

Equation 1 presents the logarithmic return of the price series to be used for data analysis; P_t refers to the stock price at time t, and P_{t-1} is the price at time t-1.

For simplicity, the return series for the FTSE Bursa Malaysia KLCI is denoted as RKLCI, RQ-45 as RLQ, and SET Index as RSET in the remainder of the paper.

This paper focuses on estimating the volatility series of stock returns and the examination of the relationships in between. The generalized autoregressive conditional heteroscedasticity (GARCH) model was employed in combination with Box–Jenkins methodology to yield an ARMA-GARCH model to complete the first objective. The Granger causality test was used to achieve the second objective. The study was conducted using EViews.

3.1. Box–Jenkins Methodology

Box–Jenkins methodology uses the autoregressive moving average (ARMA) or autoregressive integrated moving average (ARIMA) to forecast time series data. ARMA and ARIMA models are time series forecasting models that regress on their past values to predict future trends or movements. The ARMA model, often denoted as ARMA(*p*,*q*) consists of two components, namely the autoregressive AR(*p*) model and the moving average MA(*q*) model. A combination of the AR(*p*) and MA(*q*) models form an ARMA(*p*,*q*) model expressed as:

$$Y_t = c + \varepsilon_t + \sum_{i=1}^{p} \emptyset_i Y_{t-i} + \sum_{i=1}^{q} \theta_i \varepsilon_{t-i} \tag{2}$$

Equation 2 represents an ARMA(*p*,*q*) model with Y_t and Y_{t-i} equal to the actual value and past value of the time series, respectively; ε_t and ε_{t-i} are the error terms, also known as the random variable of white noise; and $\emptyset_i$ and θ_i are the parameters for the AR(*p*) and MA(*q*) model, respectively. In addition, *c* is a constant, while *p* and *q* are the number of lags of the dependent variable, such that *p* is the order of the AR(*p*) model determined using the partial autocorrelation function (PACF) and q is the order of the MA(q) model determined using the autocorrelation function (ACF). The same denotation applies for the equations in the remaining paper.

Often denoted as ARIMA(p,d,q), the ARIMA model consists of an additional component, integration, denoted by "I". Generally, p refers to the order of the autoregressive, d indicates the degree of differencing, while q is the order of the moving average. The additional component indicates that the time series has gone through differencing before becoming stationary. The ARIMA(p,d,q) can be expressed as:

$$Y_t = \emptyset_0 + \emptyset_1 Y_{t-1} + \emptyset_2 Y_{t-2} + \cdots + \emptyset_p Y_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_q \varepsilon_{t-q} \quad (3)$$

The Box–Jenkins methodology used in this study has a three-step modelling approach – model identification, model estimation, and diagnostic checking.

3.1.1. Model Identification

The first step helps to identify the degree of differencing and the number of lags required for the AR or MA models. Model identification begins with a stationarity test to ensure that the passage of time will not change the distributional shape for a good forecast. Two methods used to test for stationarity are time series plotting and unit root tests. A time series with a unit root indicates an unpredictable systematic pattern, which is one of the criteria of non-stationarity. The two unit root tests used in this study are the augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) tests; the asymptotic distribution of the PP test is identical to the ADF test statistic (Gujarati, 2003). In the event where the time series is found to be non-stationary, differencing is carried out to transform the series to stationary. A series is known to be integrated of order d after d times of differencing to become stationary. The first and second differencing can be expressed as:

$$R_t^{'} = R_t - R_{t-1}$$
$$R_t^{'''} = R_t^{'} - R_{t-1}^{'} \quad (4)$$

In Equation 4, differencing is done by subtracting the previous return, R_{t-1}, from the current return, R_t, whereby a higher order of integration is calculated using the returns of one integration level lower.

On the other hand, correlograms are observed to identify the possible models to be used, as indicated in Table 1. Correlograms are the plots of the autocorrelation function (ACF) and the partial autocorrelation function (PACF) to the lag length. The ACF is the correlation of two values in a series and can be expressed as $Corr(Y_t, Y_{t-k})$, where k refers to the considered time gap known as the "lag". The PACF is obtained by filtering out the correlations of random variables between Y_{t-1} and $Y_{t-(k-1)}$. The ACF measures the direct and indirect relationships between Y_t and Y_{t-k}, and the PACF measures the direct relationship between them. The ACF and PACF patterns help to identify which model is followed by the time series.

Table 1. Correlogram patterns.

Model	ACF pattern	PACF pattern
AR (p)	Exponential decay	Cuts off after lag q
MA (q)	Cuts off after lag q	Exponential decay
ARMA (1,1)	Exponential decay from the first lag	Exponential decay from the first lag
ARIMA (p,q)	Exponential decay	Exponential decay

3.1.2. Model Estimation

The second step involves estimating the parameters of the identified models. The most appropriate model is chosen according to the following criteria:

- Has the highest number of significant coefficients with a p-value less than 0.05.
- Has the lowest volatility indicated by σ^2.
- Has the highest adjusted R^2.
- Has the lowest Akaike Information Criterion (AIC).

- Has the lowest Schwarz Bayesian Information Criterion (SBIC).

3.1.3. Diagnostic Checking

This step aims to check the adequacy of the selected model. This can be done through examining the autocorrelation and heteroskedasticity in the model. Heteroskedasticity refers to unequal scatter, where a variable's standard errors or residuals are non-constant over different observation periods. However, heteroskedasticity is accepted in this phase since the GARCH model is used to solve the problem. The Ljung–Box test is used to detect autocorrelation in a time series and it is highly recommended for evaluating a GARCH model's accuracy.

3.2. ARCH-LM Test

To proceed with the GARCH modelling, the ARCH effect must exist in a time series. Autoregressive conditional heteroskedasticity (ARCH) is a time series statistical model that explains the variance of the current error term as a function of the previous time periods' error terms' actual sizes. The ARCH model is often used in modelling financial time series where time varying volatility is exhibited. The ARCH model offers a measure of volatility that can be used in making financial decisions. It is a popular method used to forecast volatility and capture serial correlation and heteroskedasticity of returns. Engle's ARCH test refers to a Lagrange Multiplier (LM) test that assesses the significance of ARCH effects. The squared residual is represented in Equation 5, where β_0 refers to a constant.

$$\varepsilon_t^2 = \beta_0 + \left(\sum_{i=1}^{q} \beta_i \varepsilon_{t-1}^2\right) + v_t \tag{5}$$

3.3. GARCH Estimation

The GARCH is the generalized ARCH model established by Bollerslev (1986). The ARCH and GARCH models are designed to deal with time series with volatility clustering and leptokurtic behavior, which are common characteristics of stock returns. The ARCH model is extended to include additional autoregressive terms to enable higher complication of the dynamics of volatility forecasting in the GARCH model. Also, the additional terms enable it to decay more slowly. In addition, GARCH model requires fewer parameters to yield better results than ARCH as it consumes less degree of freedom. Generally, GARCH model can yield better volatility prediction than the ARCH model (Orskaug, 2009).

The simplest GARCH used is known as GARCH(1,1), while higher order GARCH models are denoted as GARCH(*p*,*q*), where *p* indicates the order of the GARCH terms σ^2, and *q* refers to the order of the ARCH terms $\in^2$. The conditional variance of the GARCH(1,1) used in this study is given by:

$$\sigma_t^2 = \omega + \alpha_1 \epsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \tag{6}$$

In Equation 6, coefficients α_1 and β_1 represent the ARCH and GARCH models, respectively; ω represents the constant; ϵ_{t-1}^2 is the lag of the squared residual from the mean equation of the ARCH term; and σ_{t-1}^2 indicates the lag of the squared residual from the mean equation of the GARCH term.

Stationarity is shown by $\alpha_1 + \beta_1 < 1$. The ARCH and GARCH coefficients represent the persistency of volatility, for which a value of less than one is desirable. The volatility is persistent if there is a large impact of today's return on future volatility. For the EGARCH, the persistency is represented by the GARCH coefficient alone.

The second model used is the GARCH-in-mean (GARCH-M) model, which has an additional heteroskedasticity term in the mean equation to model the return's volatility. To compensate for the risk taken, investors may demand a risk premium. The GARCH-M model helps to model the time-varying risk premium so that the returns can be explained. The GARCH-M(1,1) model can be defined by the below, where γ indicates the coefficient of volatility for the mean (risk premium).

$$Y_t = \mu + \gamma \sigma_t + \varepsilon_t \tag{7}$$

$$\sigma_t^2 = \omega + \alpha_1 \epsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \tag{8}$$

In Equation 7, μ and γ refer to the mean and the coefficient of volatility for the risk premium, respectively.

Traditional GARCH models assume symmetrical effects on volatility following positive and negative shocks. However, a leverage effect often occurs in reality. To account for this issue, asymmetric GARCH models have the advantage of capturing leverage effects in stock market returns, unlike the traditional GARCH models. Therefore, asymmetric exponential GARCH (EGARCH) and threshold GARCH (TGARCH) models are used to account for the asymmetric response.

Nelson (1991) extended the standard GARCH framework by introducing the EGARCH, with the conditional variance of the EGARCH (1,1) expressed as:

$$ln\sigma_t^2 = \omega + \beta_1 ln\sigma_{t-1}^2 + \alpha_1 \left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \tag{9}$$

In Equation 9, γ is the asymmetric part, where an asymmetric response exists as long as $\gamma \neq 0$. In the event where $\gamma < 0$, volatility tends to increase more following a negative shock than a positive shock. A negative shock is indicated by $\varepsilon_{t-1} < 0$, while a positive shock is indicated by $\varepsilon_{t-1} > 0$.

The TGARCH(1,1), as proposed by Zakoian (1994), has the following conditional variance equation:

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \gamma d_{t-1} \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \tag{10}$$

Where negative ε_t is represented by a binary decision variable:

$$d_{t-1} = \begin{cases} 1 & if\ \varepsilon_{t-1} < 0\ (negative\ shocks) \\ 0 & if\ \varepsilon_{t-1} \geq 0\ (positive\ shocks) \end{cases}$$

In the case where $\gamma = 0$, the TGARCH(1,1) model is reduced to the GARCH(1,1) model.

3.3.1. GARCH Modelling and Diagnostic Checking

The best fitted GARCH model is selected based on the following criteria:

- Consists of significant ARCH and GARCH coefficients.
- Has the highest log-likelihood.
- Has the highest adjusted R^2.
- Has the lowest Akaike Information Criterion (AIC).
- Has the lowest Schwarz Bayesian Information Criterion (SBIC).
- No heteroskedasticity.
- No autocorrelation.

3.4. Granger Causality Test

The Granger causality test examines the causality between time series and identifies the correlation patterns. It measures the ability of one time series to predict the other time series. Generally, given time series X and Y, X is said to Granger-cause Y if Y can yield better predictions using the historical values of both X and Y than Y. The Granger causality test is often performed by fitting the time series with the vector autoregressive model (VAR) and identifying the optimal lag to be used. The Granger causality can be examined by:

$$y_t = \alpha_0 + \sum_{i=1}^{p} \alpha_{1i} y_{t-i} + \sum_{i=1}^{p} \alpha_{2i} x_{t-i} + \mu_{1t} \tag{11}$$

$$x_t = \beta_0 + \sum_{i=1}^{p} \beta_{1i} x_{t-i} + \sum_{i=1}^{p} \beta_{2i} y_{t-i} + \mu_{2t} \tag{12}$$

The constants in Equation 11 and Equation 12 are represented by α_0 and β_0, respectively. Additionally, p can be determined by using the AIC, SBIC, final prediction error (FPE), and Hannan–Quinn Criterion (HQ).

4. RESULTS

4.1. Summary of Statistics

This section discusses the descriptive statistics, histograms and time series plots for the respective stock returns from January 2, 2008, to November 29, 2019. The discussion starts with a summary of the descriptive statistics listed in Table 2.

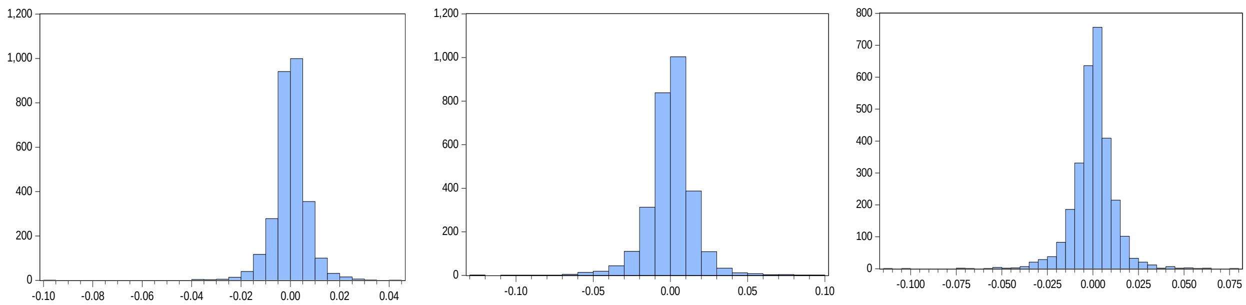
Table 2. Descriptive statistics for the RKLCI, RLQ and RSET.

Series	RKLCI	RLQ	RSET
Mean	0.0000	0.0002	0.0002
Median	0.0002	0.0007	0.0006
Maximum	0.041	0.098	0.075
Minimum	-0.010	-0.126	-0.111
Std. dev.	0.007	0.015	0.012
Skewness	-1.206	-0.500	-0.707
Kurtosis	20.335	11.078	12.283
Jarque–Bera	37167.760	8036.984	10696.960
Probability	0.000	0.000	0.000
Observations	2912	2912	2912

The mean returns vary from 0 to 0.0002, while the medians vary from 0.0002 to 0.0007. The highest daily return (0.098) and the lowest daily return (-0.126) come from the RLQ, which has the highest volatility indicated by the greatest standard deviation (0.015) among the three indices. This result is line with the risk-return trade-off theory.

In addition, all stock returns yield negative skewness, suggesting a longer left tail as the tail was pulled to the left as seen in Figure 1. According to the rule of thumb, the RKLCI is highly skewed, the RLQ is slightly skewed, and the RSET is moderately skewed. Next, all three returns were found to be leptokurtic as they have kurtosis values of more than three. Leptokurtic refers to fatter tails and sharper peaks than the normal distribution as illustrated in the respective histograms. There is sufficient evidence from the Jarque–Bera test to conclude that all returns are not normally distributed. Generally, the resulting descriptive statistics portray the common characteristics of financial data with high frequency. A similar pattern is observed from the respective histograms.

Based on the time series plots in Figure 2, the mean returns for the three indices are near to zero. The returns tend to revert to their mean, indicating stationarity of the series. The fluctuations over time indicate time-varying volatility in returns and show evidence of volatility clustering. Volatility clustering refers to the phenomenon where large movements tend to be followed by large movements, and small movements tend to be followed by small movements. The returns alternated between low and high volatility periods as volatility clustering fluctuates throughout the research time frame. It was also observed that the period between 2008 and 2009 had the highest returns fluctuations.



(a) (b) (c)

Figure 1. (a) RKLCI histogram; (b) RLQ histogram; (c) RSET histogram.

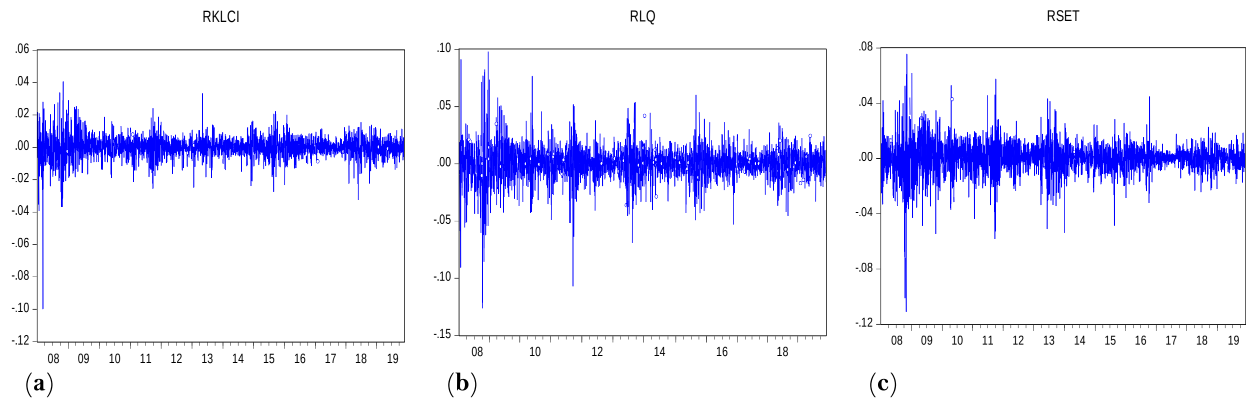


Figure 2. (a) RKLCI time series plot; (b) RLQ time series plot; (c) RSET time series plot.

4.2. Box–Jenkins Methodology

4.2.1. Stationarity Tests

The ADF and PP test statistics for the RKLCI, RLQ, and RSET presented in Table 3 show clear evidence of stationarity. Both unit root tests yield significant test statistics with probabilities less than 5%. Also, the test statistics are much lower than all critical values provided. Thus, the null hypothesis of a unit root is rejected, indicating that the series is stationary. Hence, no differencing is required.

Table 3. Stationarity test for return series.

Series	Augmented Dickey–Fuller test statistics		Phillips–Perron test statistics	
	t-stat./Adj. t-stat.	Prob.*	t-stat./Adj. t-stat.	Prob.*
RKLCI	-49.075	0.000	-49.075	0.000
RLQ	-32.968	0.000	-49.034	0.000
RSET	-51.181	0.000	-51.286	0.000

Note: t-stat. refers to the hypothesis test statistic; Adj. t-stat. indicates the adjusted test statistic; * refers to MacKinnon's approximate p-values.

4.2.2. Model Identification and Estimation

The correlograms, as seen in Table 4, show similar exponential decay patterns, where there is a high possibility of an ARMA model. In the selection of tentative models, this study considers lower lags to achieve parsimonious models that give better predictions. Among the tentative models, the AR(1), ARMA(1,3), and AR(2) AR(6) MA(1) models are the most desirable according to the selection criteria. The estimation output is shown in Table 5.

Table 4(a) RKLCI correlogram.

Date: 12/21/22 Time: 07:59
Sample: 1/02/2008–11/29/2019
Included observations: 2912

Autocorrelation	Partial correlation		AC	PAC	Q-stat	Prob.
|* |	|* |	1	0.093	0.093	25.469	0.000
| |	| |	2	0.011	0.002	25.829	0.000
| |	| |	3	0.023	0.022	27.341	0.000
| |	| |	4	0.026	0.022	29.294	0.000
| |	| |	5	-0.004	-0.009	29.350	0.000
| |	| |	6	-0.014	-0.014	29.947	0.000
| |	| |	7	-0.015	-0.013	30.576	0.000
| |	| |	8	0.002	0.004	30.586	0.000
| |	| |	9	-0.005	-0.005	30.665	0.000
| |	| |	10	0.009	0.011	30.908	0.001

Table 4(b). RLQ correlogram.

Date: 12/21/22 Time: 08:02
Sample: 1/02/2008–11/29/2019
Included observations: 2912

Autocorrelation	Partial correlation		AC	PAC	Q-stat	Prob.
*	*	1	0.091	0.091	24.072	0.000
		2	0.026	0.018	26.050	0.000
*	*	3	-0.097	-0.102	53.613	0.000
		4	-0.034	-0.017	57.058	0.000
		5	-0.027	-0.018	59.255	0.000
		6	-0.033	-0.038	62.416	0.000
		7	-0.000	0.002	62.416	0.000
		8	-0.010	-0.014	62.728	0.000
		9	-0.021	-0.027	63.971	0.000
		10	-0.027	-0.025	66.139	0.000

Table 4(c). RSET correlogram.

Date: 12/21/22 Time: 08:03
Sample: 1/02/2008–11/29/2019
Included observations: 2912

Autocorrelation	Partial correlation		AC	PAC	Q-stat	Prob.
		1	0.053	0.053	8.1134	0.004
		2	0.050	0.047	15.393	0.000
		3	-0.017	-0.022	16.189	0.001
		4	-0.008	-0.009	16.394	0.003
		5	0.000	0.003	16.394	0.006
		6	-0.064	-0.064	28.231	0.000
		7	0.014	0.020	28.768	0.000
		8	-0.026	-0.021	30.698	0.000
		9	0.026	0.024	32.617	0.000
		10	0.045	0.045	38.518	0.000

Table 5. Box–Jenkins estimation output.

Selected Box–Jenkins model	RKLCI	RLQ	RSET
	AR (1)	ARMA(1,3)	AR(2) AR(6) MA(1)
Significant coefficients	1	2	3
Sigma^2	0.0000	0.0002	0.0001
Adjusted R^2	0.008	0.018	0.008
AIC	-7.095	-5.533	-6.077
SBIC	-7.089	-5.525	-6.067

4.3. GARCH Estimation

The best-fitted GARCH models for the RKLCI, RLQ, and RSET are the AR(1)-EGARCH (1,1), ARMA(1,3)-EGARCH(1,1), and AR(2) AR(6) MA(1)-EGARCH(1,1), respectively. Based on the estimation output in Table 6, all terms are desirably significant at a 5% level for all series. The ARCH term shows the size of a shock, while the leverage effect term shows the sign of shock against volatility. The positive ARCH term shows a positive relationship between past volatility and current volatility. Also, a bigger shock causes higher volatility. The significant and negative sign of the leverage effect term shows clear evidence of asymmetry in the returns, where bad news causes higher volatility in the RKLCI than good news.

Table 6. GARCH estimation output.

Selected GARCH model	RKLCI AR(1)-EGARCH (1,1)	RLQ ARMA(1,3)-EGARCH(1,1)	RSET AR(2) AR(6) MA(1)-EGARCH(1,1)
Mean equation			
C	0.0000	0.0002	0.0003
AR	0.107	0.025 -0.069	0.031 -0.043 0.068
Variance equation			
Constant, ω	-0.332	-0.273	-0.333
ARCH term, α	0.165	0.149	0.203
Leverage effect term, γ	-0.080	-0.076	-0.072
GARCH term, β	0.980	0.982	0.981
Log-likelihood	10831.380	8585.716	9499.327
Heteroscedasticity	No	No	No
Autocorrelation	No	No	No

The exponential terms of the leverage effect prove the higher impact of negative shocks on the volatility series, as indicated in Table 7. Moreover, the GARCH terms with coefficients of less than one indicate that the volatility shock is considerably persistent, and hence desirable. A similar pattern is observed from the series movements, as shown in the time series plot of conditional variances in Figure 3. For the remainder of the paper, the conditional variances for the RKLCI, RLQ, and RSET are depicted as RKLCI_GARCH, RLQ_GARCH, and RSET_GARCH, respectively.

Table 7. Exponential terms of leverage effect and variance equations.

Series	e^{γ}	Variance equation
RKLCI	0.923	$ln\sigma_t^2 = -0.332 + 0.980 ln\sigma_{t-1}^2 + 0.165\left\lvert\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right\rvert - 0.080\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$
RLQ	0.927	$ln\sigma_t^2 = -0.273 + 0.982 ln\sigma_{t-1}^2 + 0.149\left\lvert\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right\rvert - 0.076\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$
RSET	0.930	$ln\sigma_t^2 = -0.333 + 0.981 ln\sigma_{t-1}^2 + 0.203\left\lvert\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right\rvert - 0.072\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$

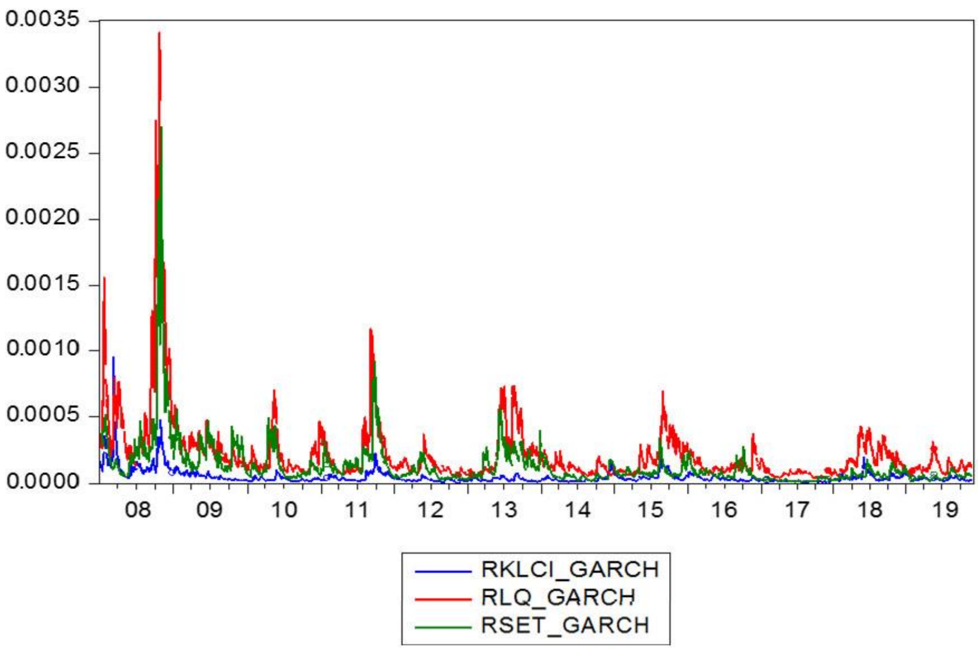


Figure 3. Time series plot of conditional variances.

4.4. Correlation Coefficient Test

Barberis et al. (2002) referred co-movement as a pattern of positive correlation. Based on the correlation coefficient test, the returns of the selected indices exhibit weak positive correlation, as indicated in Table 8. On the other hand, the volatility of the indices has a moderate to strong positive correlation, as presented in Table 9. However, the Granger causality test is necessary because the correlation measures do not present a full image of the relationship (Sanford, 2011). Correlation does not always indicate causation, so the correlation results may be meaningless. Thus, the Granger causality test is carried out to understand the causal direction between the volatility of the three indices.

Table 8. Correlation coefficients of returns.

Return series	RKLCI	RLQ	RSET
RKLCI	1	0.022	0.131
RLQ	0.022	1	0.003
RSET	0.131	0.003	1

Table 9. Correlation coefficients of the conditional variances.

Volatility series	RKLCI_GARCH	RLQ_GARCH	RSET_GARCH
RKLCI_GARCH	1	0.606	0.528
RLQ_GARCH	0.606	1	0.787
RSET_GARCH	0.528	0.787	1

4.5. Granger Causality Test

To proceed with the Granger causality test, the series are required to be stationary. The unit root test results in Table 10 show that all volatility series are stationary. Based on the VAR stability check, the VAR satisfies the stability condition. The series then proceeds to the optimal lag selection using VAR. According to the lag selection criteria, lag 8 is chosen as the optimal lag. The Granger/Wald test yields significant results, as shown in Table 11. Bidirectional causal relationships exist for all indices, such that the volatility of all selected markets have pairwise causality, which are also mutually causal-related. The result is further proven through the pairwise Granger causality test in Table 12 that yields significant results with probabilities of less than 0.05. Therefore, the null hypothesis of no Granger causality between the variables is rejected.

Table 10. Stationarity test for conditional variances.

Volatility series	RKLCI_GARCH		RLQ_GARCH		RSET_GARCH	
	t-statistic (ADF)/Adj. t-stat (PP)	Prob.*	t-statistic (ADF)/Adj. t-stat (PP)	Prob.*	t-statistic (ADF)/Adj. t-stat (PP)	Prob.*
ADF test statistic	-8.967	0.000	-5.302	0.000	-5.639	0.000
PP test statistic	-8.263	0.000	-5.805	0.000	-6.367	0.000

Note: t-stat. refers to the hypothesis test statistic; Adj. t-stat. indicates the adjusted test statistic; * refers to MacKinnon's approximate p-values.

Table 11. Granger causality/Wald test results.

Prob.	RKLCI_GARCH	RLQ_GARCH	RSET_GARCH
RKLCI_GARCH	-	0.002	0.000
RLQ_GARCH	0.000	-	0.000
RSET_GARCH	0.015	0.000	-
Overall	0.000	0.000	0.000

In this study, the Box–Jenkins and GARCH methods are used to capture the volatility of stock market returns, while the Granger causality test is used to examine the co-movement of the respective volatilities. According to the descriptive statistics, the Jakarta Stock Exchange represented by RLQ has the highest risk compared to the other two indices. The series are tested to meet the stationarity requirement to perform the Box–Jenkins methodology. The AR(1)-EGARCH(1,1); ARMA(1,3)-EGARCH(1,1); and AR(2) AR(6) MA(1)-EGARCH(1,1) are concluded as the ideal models for volatility estimation for the RKLCI, RLQ, and RSET, respectively.

Table 12. Pairwise Granger causality test results.

Null hypothesis	F-statistic	Prob.
RLQ_GARCH does not Granger cause RKLCI_GARCH	14.054	0.000
RKLCI_GARCH does not Granger cause RLQ_GARCH	3.814	0.000
RSET_GARCH does not Granger cause RKLCI_GARCH	4.573	0.000
RKLCI_GARCH does not Granger cause RSET_GARCH	15.967	0.000
RSET_GARCH does not Granger cause RLQ_GARCH	5.827	0.000
RLQ_GARCH does not Granger cause RSET_GARCH	99.737	0.000

The ideal models indicate leverage effects in the series. All models selected through the Box–Jenkins and GARCH methods have the best criteria among the selected tentative models. Also, the models have passed the residual tests, indicating the appropriateness of their usage. The volatility of the RKLCI, RLQ, and RSET is then identified and plotted in line graphs for better visualization. The conditional variances of the selected indices are derived from the estimated GARCH models, where conditional variance refers to volatility. The volatility series are used to examine the co-movement of volatility between stock market indices. The return series and conditional variance series both yield positive correlation coefficients. The Granger causality test indicates that bidirectional causality exists between the selected markets.

5. DISCUSSION

This study modelled the volatility of stock returns and examined the respective co-movement or causal relationship between returns volatility of the FTSE Bursa Malaysia KLCI, the Jakarta Stock Exchange (LQ45), and the Stock Exchange of Thailand (SET) Index from January 2, 2008, to November 29, 2019. Based on the time series plots, all three returns have the common property of volatility clustering. New information in the market is associated with stock market volatility, and a period with a high volume of new market-related information can be predicted to have high stock market volatility (Byström, 2016). The high volatility tends to persist for a longer period after the shocks, supporting the idea of volatility clustering. Byström (2016) concluded a unidirectional relationship from news to stock market volatility. This finding helps to explain the higher market volatility during the financial crisis period, as supported by the authors' analysis that observed the highest amount of news during the period of the Lehmann Brothers collapse. Also, the histograms and descriptive statistics show common properties of financial asset returns, whereby the series are leptokurtic and fat-tailed.

Next, the best-fitted GARCH models for all three returns are the EGARCH(1,1) model that is capable of capturing the asymmetric effects. The result matches previous studies that suggested the superiority of the EGARCH in estimating volatility. The fitted models for the RKLCI, RLQ, and RSET have concluded a leverage effect in the series. The existence of a leverage effect or asymmetric response is important for risk management that mainly concerns asymmetric returns. This is due to the fact that most investors are loss averse and have different responses to bad news and good news. In addition, unlike symmetrical returns that can be achieved through passive investments, asymmetric returns require active risk management along with the investment activities. In addition, the volatility shocks are concluded to be persistent based on the GARCH term coefficient that is less than one.

Through the derived conditional variance series, it is obvious that all three returns portrayed high volatility between 2008 and 2009, coinciding with the global financial crisis in 2007 and 2008. The highest volatility can be observed from the period of the Lehman Brothers bankruptcy on September 15, 2008, which led to the peak of the subprime mortgage crisis. The crisis caused a significant drop in stock markets worldwide. The gross domestic product (GDP) growth rates dropped from 6.299% to -1.514%, 6.345% to 4.629%, and 5.435% to –0.691% from 2007 to 2009 for Malaysia, Indonesia and Thailand, respectively (The World Bank, 2022). This provides a clear image of the significant impact of the financial crisis on the economy of the selected countries. Also, October 2008 was a period of maximum financial stress for emerging markets (Goldstein & Xie, 2009). The collapse of the financial environment hit emerging countries hard. Another similar volatility movement can be observed in 2011, coinciding with the European debt crisis.

The correlation coefficient test showed that the series are positively correlated. Moreover, the Granger causality test concluded a bidirectional relationship between the volatility of the three stock indices. This result can be proven by the relations between three countries. Firstly, Indonesia–Malaysia foreign bilateral relations is the most important relationship in Southeast Asia (Clark & Pietsch, 2014). In the effort to develop trans-border economic zones and a free-trade area, the two countries have a sub-regional economic cooperation. Malaysia and Indonesia also have many similarities in terms of culture, trades, religion, and language.

Secondly, there is a bilateral foreign relation between Malaysia and Thailand, often known as the Malaysia–Thailand relations. According to the Observatory of Economic Complexity (OEC) data platform retrieved on November 21, 2020, the bilateral trade by product between the two countries is in an upward trend, with a trade value of USD 25.7 billion recorded in 2018. With active cooperation for trade and investment, Thailand acts as the second largest trading partner for Malaysia among all ASEAN countries and is Malaysia's fifth largest trading partner worldwide (Rahim & Masih, 2016). Similarly, a bilateral relationship exists between Thailand and Indonesia, named as the Indonesia–Thailand relations. Indonesia was Thailand's fifth largest trading partner globally in 2018 and the second largest trading partner in the ASEAN region.

Malaysia, Indonesia, and Thailand founded ASEAN in 1967, along with Singapore and the Philippines, to ensure stability and peace. The formation of the multilateral alliance provides a reasonable anticipation of spillover effects between the nations. The bidirectional causal relationships found in this study can be justified by their official bilateral foreign relations.

6. CONCLUSIONS

In conclusion, all selected stock market indices are useful in giving a rough prediction of each other's volatility movement. The existence of co-movement and bidirectional causal relationships between the series enables investors and policymakers to make sound decisions. Moreover, the examination of co-movement or causality can be used as an implication of the system's stability. The co-movement between emerging stock markets is crucial to get an idea of the future performance of the respective markets. In addition, the causal relationship can identify the root causes of important events.

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