Available online at
https://journal.rescollacomm.com/index.php/ijqrm/index

e-ISSN 2721-477X
p-ISSN 2722-5046

International Journal of Quantitative Research and Modeling

Vol. 5, No. 1, pp. 20-25, 2024

Analysis Volatility Spillover of Stock Index in ASEAN (Case Study: Indonesia, Singapore, Malaysia)

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Abstract

Every country has its own income, including ASEAN countries such as Indonesia, Singapore, and Malaysia. One source of national income can come from stocks, which can be measured by the stock index. The income of each country depends on each other and can be influenced by a phenomenon, such as the Covid-19 pandemic. The Covid-19 pandemic can also cause volatility spillover. This research aims to analyze volatility spillover in ASEAN countries (Indonesia, Singapore, and Malaysia) before and during Covid-19 by looking at the effects of asymmetric volatility. Volatility spillover testing in this study uses the Exponential Generalized Autoregressive Conditional Heteroscedasticity (EGARCH) model, starting with creating a time series model and then modeling the residuals from that model, then finding the estimated parameter results of asymmetric volatility effects. The results of this study indicate that during the period before Covid-19, there is volatility spillover for Indonesia and Malaysia. Then, during the Covid-19 period, there is volatility spillover for Indonesia and Malaysia, for Indonesia and Singapore, and for Singapore and Malaysia.

Keywords: Stock Index, ASEAN, Volatility Spillover, EGARCH

1. Introduction

The Association of Southeast Asian Nations (ASEAN) is an organization consisting of countries in the Southeast Asian region. One of the goals of this organization is to enhance economic growth (Prajanto, 2022). Each ASEAN member has its own economic market and national income. In December 2019 in Wuhan, China, the Corona Virus Disease 2019 (Covid-19) emerged. The impact of Covid-19 affected the stock markets of ASEAN countries, including a significant decline in the Indonesian stock market in March 2020, when Covid-19 began spreading.

According to the Indonesia Stock Exchange (2022), a stock index is a statistical measure that represents the movement of prices for a group of stocks. Each country has its own stock index, including those in ASEAN, such as the Jakarta Stock Exchange Composite (JKSE) for Indonesia, Straits Times Singapore (STI) for Singapore, and Malaysia KLCI (KLSE) for Malaysia.

The emergence of the Covid-19 pandemic has a significant impact on the economic conditions of each country, especially on the stock markets, and can influence the volatility of each country's returns. Volatility is a measure that indicates how much prices fluctuate within a period (Mieg, 2022). Additionally, the Covid-19 pandemic can also lead to volatility spillover. Volatility Spillover is a condition where volatility in one market affects the volatility in another market. Another term for Volatility Spillover is also used to express a situation where there is instability that transmits from one market to another (Arini *et al.*, 2016).

Based on the above explanation, this research uses conventional stock index data in Indonesia, Singapore, and Malaysia with the aim of analyzing whether there is Volatility Spillover in the stock indices of ASEAN, especially in Indonesia, Singapore, and Malaysia. The results of this research can be utilized by investors to understand the stock market conditions before and during the Covid-19 pandemic.

2. Literature Review

2.1. Stock Return

Return is the income or yield obtained from financial assets. Stock return is the excess of the selling price of stocks over their purchase price. The higher the selling price of stocks over their purchase price, the higher the return obtained by the investor (Garcia-Vega, Zeng and Keane, 2020). The value of stock return can be calculated using equation (1).

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

R_t : Stock return at time t , $t = 1,2,...$
P_t : Closing stock price at time t
P_{t-1} : Closing stock price at time $t-1$

2.2. Volatility Spillover

Volatility is the change in the rate of return of securities or portfolios over time. Volatility can also be interpreted as the standard deviation of the existing rate of return against the continuously increasing rate of return per unit of time. One type of volatility is asymmetric volatility, which can be defined as the uneven or unbalanced changes in the rate of return of securities or portfolios. Volatility Spillover is a condition where volatility in one market affects the volatility in another market. Another term for Volatility Spillover is also used to express a situation where instability transmits from one market to another (Arini, *et al*, 2016).

2.3. Stationarity Test

In analyzing time series data, the data used must be stationary; hence, a stationarity test is conducted. Data is considered stationary if it has constant mean and variance (E.P.Box *et al.*, 2004).

For testing the stationarity of data regarding the mean, a Unit Root Test is performed using the Augmented Dickey-Fuller Test (ADF Test). The hypotheses of the ADF test are outlined as follows:
H_0 : $\delta = 0$, indicating the presence of a unit root, and the data is non-stationary.
H_1 : $\delta < 0$, indicating the absence of a unit root, and the data is stationary
Test statistic,

$$t = \frac{\hat{\delta}}{SE(\hat{\delta})} \tag{2}$$

t : The ratio value between the estimated parameter and standard error.
$\hat{\delta}$: The estimated value of δ
$SE(\hat{\delta})$: The standard error of $\hat{\delta}$

The test criteria used at a significance level of 5% are as follows:

1. If $|t| > |t_{critical}|$ or $p\text{-}value < \alpha = 0.05$, then H_0 is rejected.
2. If $|t| \leq |t_{critical}|$ or $p\text{-}value \geq \alpha = 0.05$, then H_0 is not rejected.

Subsequently, for testing the stationarity of data concerning variance, the Box-Cox transformation can be applied. The Box-Cox transformation is formulated as follows (Osborne, 2010) :

$$Z_t(\lambda) = \begin{cases} Z_t^{\lambda} - 1, \lambda \neq 0 \\ \ln Z_t , \lambda = 0 \end{cases} \tag{3}$$

λ: The transformation parameter

The estimation of the λ parameter can be obtained using the Maximum Likelihood method, where the value of λ is chosen based on the minimum residual sum of squares. The transformation is performed if the value of $\lambda = 1$ is not yet obtained, indicating stationarity in variance.

2.4. Autoregressive Moving Average (ARMA) Model

The autoregressive moving average model is a combined model consisting of the Autoregressive (AR) model and the Moving Average (MA) model. The Autoregressive (AR) model is a stationary model that utilizes time series data, where the observed value at time t is influenced by the observed value at the previous time. Meanwhile, the Moving Average (MA) model is a stationary model that utilizes time series data, depending on the previous residuals. The ARMA model of order p, q is symbolized as ARMA(p, q) and is represented by the following equation (4).

$$Z_t = c + \phi_1 Z_{t-1} + \cdots + \phi_p Z_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \cdots - \theta_q \varepsilon_{t-q} \tag{4}$$

Z_t : The value of the variable at time t
c : Intercept
ϕ_i : Autoregressive (AR) model parameter, $i = 1,2,\dots,p$
Z_{t-p} : The value of the variable at the previous time
ε_t : Residual at time t
θ_i : Moving Average (MA) model parameter, $i = 1,2,\dots,q$
ε_{t-q} : Residual at the previous time
p : Autoregressive order
q : Moving average order

2.5. Exponential Generalized Autoregressive Conditional Heteroscedasticity (EGARCH) Model

The Exponential Generalized Autoregressive Conditional Heteroscedasticity (EGARCH) model is a model that does not restrict the parameters used to ensure that the variance is always positive. This model frees the estimation of non-negative sizes to form a non-negative conditional variance, and the current residual variance is not only influenced by the residuals of the previous period but also influenced by the residual variances from the past. According to Tsay (2002), the EGARCH(p, q) model has the following equation.

$$\ln(\sigma_t^2) = \omega + \sum_{i=1}^{p} \alpha_i \left|\frac{\varepsilon_{t-i}^2}{\sigma_{t-i}}\right| + \sum_{j=1}^{q} \beta_j \ln(\sigma_{t-j}^2) + \sum_{i=1}^{p} \gamma_i \left|\frac{\varepsilon_{t-i}^2}{\sigma_{t-i}}\right| \tag{5}$$

$\ln(\sigma_t^2)$: EGARCH model
ω : Intercept
α_i : ARCH effect parameter, $i = 1,2,\dots,p$
β_i : GARCH effect parameter, $i = 1,2,\dots,q$
γ_i : Leverage effect/asymmetric effect parameter, $i = 1,2,\dots,p$

According to Brooks (2019), the gamma parameter represents asymmetric volatility as follows:

- If $\gamma_i = 0$ it implies the non-existence of asymmetric volatility.
- If $\gamma_i > 0$ it implies that positive shocks (good news) will amplify volatility more than negative shocks (bad news).
- If $\gamma_i < 0$ it implies that negative shocks (bad news) will amplify volatility more than positive shocks (good news).

3. Materials and Methods

3.1. Materials

The data used is secondary data, index stock closing data every day of Indonesia, Singapore, and Malaysia from www.investing.com. The period of data is during January 2018 – December 2021. The applications used are R Studio and Microsoft Excel.

3.2. Methods

a) Calculating stock returns using equation (1) and conducting stationarity tests.
b) Creating an ARMA(p, q) model based on equation (4).
c) Creating an EGARCH(p, q) model according to equation (5).
d) Analyzing the values of the gamma parameter.

4. Results and Discussion

a) Stationarity tests

The stock index return data is calculated using equation (1) and then this data is tested for stationarity against the mean and variance. Testing the stationarity of data against the mean is conducted using the ADF test, and the results can be seen in Table 1.

Table 1: ADF test results of the ASEAN stock index returns

ADF Test		
	Data	*p-value*
JKSE	Before Covid-19	0.01
	During Covid-19	0.01
STI	Before Covid-19	0.01
	During Covid-19	0.01
KLSE	Before Covid-19	0.01
	During Covid-19	0.01

Based on Table 1, a p-value of 0.01 is obtained, indicating the absence of a unit root, thus the data is stationary regarding the mean. Subsequently, the data is tested for stationarity against variance using the Box-Cox Transformation, and the results can be seen in Table 2.

Table 2: Box-Cox Transformation results of the ASEAN stock index returns

Box-Cox Transformation		
	Data	λ value
JKSE	Before Covid-19	1
	During Covid-19	1
STI	Before Covid-19	1
	During Covid-19	1
KLSE	Before Covid-19	1
	During Covid-19	1

Based on Table 2, the Box-Cox lambda value obtained is 1. Therefore, it can be concluded that the data is stationary concerning variance.

b) Creating ARMA(p, q) model

The next step is create ARMA models for each dataset and later the residual of the ARMA models will be used to build EGARCH models. The ARMA models for each dataset are obtained as shown in Table 3.

Table 3: ARMA model of the stock index ASEAN

Data	Model	Parameter	Estimation
JKSE before Covid-19	ARMA(0,2)	θ_2	-0.092803
JKSE during Covid-19	ARMA(3,3)	ϕ_1	-0.782887
		ϕ_3	0.440282
		θ_1	0.879021
		θ_3	-0.364401
STI during Covid-19	ARMA(2,3)	ϕ_1	-1.304542
		ϕ_2	-0.615293
		θ_1	1.263433
		θ_2	0.688198
		θ_3	0.169853
KLSE before Covid-19	ARMA(2,2)	ϕ_1	-0743765
		ϕ_2	-0928021
		θ_1	0771870
		θ_2	0889424
KLSE during Covid-19	ARMA(2,0)	ϕ_2	0116724

c) Creating EGARCH(p, q)

After obtaining the ARMA model, the residuals from that model are used to form the EGARCH model. The EGARCH models for each dataset are presented in Table 4.

Table 4: EGARCH model of the stock index ASEAN

Data	Model	Parameter	Estimation
JKSE and KLSE before Covid-19	EGARCH(2,4)	ω	-0.000379
		α_1	-0.248829
		α_2	0.243776
		β_1	0.962482
		β_2	0.166215
		β_3	0.435571
		β_4	-0.564245
		γ_1	0.110216
		γ_2	-0.114415
JKSE and KLSE during Covid-19	EGARCH(3,4)	ω	-0.90423
		α_1	-0.15091
		α_2	0.06006
		α_3	-0.14732
		β_1	0.40002
		β_2	-0.37292
		β_3	0.27717
		β_4	0.59614
		γ_1	0.21826
		γ_2	0.19901
		γ_3	0.20283
JKSE and STI during Covid-19	EGARCH(1,2)	ω	-0.54373
		α_1	-0.14340
		β_1	0.65643
		β_2	0.28189
		γ_1	0.38042
STI and KLSE during Covid-19	EGARCH(3,4)	ω	-0.030628
		α_1	-0.050838
		α_2	-0.112891
		α_3	0.112783
		β_1	0.854327
		β_2	0.356843
		β_3	0.194401
		β_4	-0.408769
		γ_1	0.325134
		γ_2	-0.109971
		γ_3	-0.191598

d) Analysis the values of the gamma parameter

To analyze the asymmetric volatility occurring in each stock of Indonesia, Singapore, and Malaysia, one can observe the gamma values in the EGARCH model. The gamma value for each pair of data shown in Table 5.

Based on Table 5, it can be concluded that for JKSE and KLSE before Covid-19, there is asymmetric volatility where bad news increases volatility more that good news. Then, for JKSE and KLSE during Covid-19, there is asymmetric volatility where good news increases volatility more that bad news. Furthermore, for JKSE and STI during Covid-19, there is asymmetric volatility where good news increases volatility more than bad news. Lastly, for STI and KLSE during Covid-19, there is asymmetric volatility where good news increases volatility more than bad news

Table 5: Gamma values of EGARCH model

Data	Parameter	Estimation
JKSE and KLSE before Covid-19	γ_1	0.110216
	γ_2	−0.114415
JKSE and KLSE during Covid-19	γ_1	0.21826
	γ_2	0.19901
	γ_3	0.20283
JKSE and STI during Covid-19	γ_1	0.38042
STI and KLSE during Covid-19	γ_1	0.325134
	γ_2	−0.109971

5. Conclussion

The results of this research indicate that in the period before Covid-19, there is volatility spillover between Indonesian and Malaysian stocks. Then during the Covid-19 period, there is volatility spillover between Indonesian dan Malaysian stocks, Indonesian and Singaporean stock, as well as between Singaporean and malaysian stocks, respectively.

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