Ekonomis: Journal of Economics and Business
Volume 7, No 2 (2023), September, 1102-1113
Online ISSN: 2597-8829, DOI: 10.33087/ekonomis.v7i2.1348

Volatility Composite Index and Exchange Rates in Indonesia: EGARCH/TARCH Model for VAR Estimation

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ABSTRACT
Composite index and exchange rate are important indicators that represent a country's economic performance, where there is a relationship between the two. In this study, the ideal model to capture the volatility of the composite index and exchange rate will be determined. to investigate the dynamic dependency relationship between the composite index and the exchange rate, first use a Vector Autoregressive (VAR) model. The best model in describing the volatility of the composite index is the EGARCH model while the exchange rate is using the TARCH model. According to research, there is an asymmetry relationship between the volatility of stock returns and the exchange rate, which means that the market will react to bad news more quickly than good news. According to the VAR model, the present volatility is influenced by the volatility of the prior period and there is a one-way causal relationship between the composite index and the exchange rate.

Keywords: *composite index, EGARCH, exchange rate, TARCH, VAR*

INTRODUCTION

The entrance and outflow of capital are significantly influenced by the domestic stock market. The stock market may be impacted by changes in the exchange rate, and vice versa: the exchange rate may be impacted by changes in the stock market. Due to a decline in the stock market index, investor wealth declines, which leads to reduced interest rates and a dip in demand for money, which inhibits capital inflows and finally results in currency depreciation (Liang Chun & Chia, 2015). Foreign exchange risk must be carefully assessed and cannot be disregarded because it has a substantial impact on investors' perceived investment value (Sikhosana, 2018). Currency fluctuations affect an investor's return in addition to the performance of the asset in question. According to Hung (2022) and Padhan & Prabheesh (2021), the stability of the currency rate is a key consideration when formulating policies for domestic trade, capital flows, and foreign debt. It is believed that the exchange rate serves as a crucial link between various economies. Exchange rates can also have an impact on stock prices when investors choose not to invest when the value of the currency declines, which can lower stock prices and lower stock returns (Riyadevi 2016). Stock returns can be expressed as risk or standard deviation. The higher the volatility the higher the level of uncertainty (Yu, 2020).

Short-term capital inflows are indicated by the link between stock market liquidity and rates of exchange. Greater foreign capital flows into the stock market boost the liquidity of the stock market when a country's local currency appreciates, allowing investors to profit from the appreciation. On the other side, a gain in market share prices might be supported by an increase in stock market liquidity. An increase in the value of the stock market draws international investment and motivates foreign investors to sell their foreign currencies and purchase local currencies (Hang 2022). Through their effects on global competition, actual output in the balance of payments, and stock market liquidity, exchange rate variations will eventually have an impact on a company's cash flows and share prices. A local currency devaluation will lower export costs, boost competition in global markets, and thereby improve a company's cash flow. Finally, it will improve the country's balance of payments and actual output, which will raise market liquidity (Qin dkk, 2015).

The connection between exchange rates and composit indexes has been extensively researched in the literature. However, on average, most research look at The connection between exchange rates and composit indexes has been extensively researched in the literature. However, in general, research that focus on causation get varying conclusions about the association between stock indices and exchange rates. Using a VECM model, Diamandis & Drakos (2011) conclude that there are positive correlations between stock indices and exchange rates in Mexico, Chile, Argentina, and Brazil for the monthly data from January 1980 to February 2009. However, it was shown that rate of exchange and composit indices had a negative association. Kubo (2012) found a causal relationship between the composit index and exchange rate in Thailand, South Korea, and Indonesia. Tsai (2012) found a causal relationship between composit index the exchange rate in Thailand, Taiwan, Philippines, South Korea, Singapore, and Malaysia. In China Tudor & Popescu-Dutaa (2012) found no relationship between the composit index and exchange rate. They used the VAR model to analyze monthly data from January 1997 to March 2012. Vo, (2018) uses vector autoregression (VAR), cointegration, and impulse response analysis to examine the relationship between stock indices and exchange rates, whereas Dahir et al. (2018) & Salisu (2018) use panel data analysis; and Bahmani-Oskooee & Saha (2015) used the lag autoregressive distribution (ARDL). Wong (2017) & Moore (2014) and use dynamic correlation conditions (CC); The GARCH or EGARCH models have also been used in a number of studies by Lim (2013) & Sikhosana (2018).

The discussion of the volatility transmission between rates of exchange and composite indices is the main goal of this study. There are four sections to the study. The relationship between the rate of exchange and the composite index is explained in the first section. The literature review on the connection between exchange rates and composite index returns is compiled in Section 2. The techniques for analyzing empirical data and econometric data are presented in the third section. The findings of the empirical research are discussed in Section IV. Recommendations are made in the final section.

Literature Review

According to the equilibrium model, there is a bad correlation between transaction and purchase price. Due to increased foreign capital inflows, rising domestic stock prices will result in a rise in the share of domestic trade. There are two theoretical views on the relationship between trade and price payment. The first opinion states that the relationship is positive and the second opinion concludes that it is negative (Lakshmanasamy 2021). Changes in exchange rates will affect a companys earnings and stock price. For exporting companies a depreciating exchange rate tends to boost revenue and profits leading to higher stock prices. On the other hand for importing firms currency depreciation will reduce profits due to higher import costs followed by lower stock prices (Hook 2022). Some exchanges discourage foreign investors from entering the country. The Companys business operations are greatly affected by exchange rate fluctuations especially in relation to its business activities dependent on Indonesian imports and exports. In addition the foreign operations of domestic companies directly affect exchange rate fluctuations. This means that changes in exchange rates can directly affect a companys profit through changes in costs and revenues. Finally it affects the companys share price (BIS 2013).

Tudor (2015) examined the comparative Granger causality of composit prices and rate of exchange movements in 13 advanced financial markets and found that exchange rate volatility has an effect on composit index returns one month in advance. Tudor has conducted a number of prior empirical studies on rates of exchange and stock prices. According to the findings of another study (Wu, Lu, and Perez, 2012), there is a correlation between the rate of exchange and composit index, which can serve as empirical support for the formulation of financial policy. According to Priyono & Bustaman's (2014) research, which used the GJR-GARCH approach to estimate the VAR model, the Jakarta Composite Index's (IHSG) previous month's volatility had a significant impact on the current exchange rate volatility (ER). However, other findings indicated that the current composite index was unaffected by previous exchange rate volatility changes. Wasiaturrahma (2020) used the EGARCH model to investigate the asymmetric behavior of stock return volatility and came to the conclusion that high volatility rather than low volatility is what generates instability. In addition to the fact that an unstable economy would react to changes in exchange rates more quickly than a stable economy, good and bad news have differing effects on the volatility of stock returns and changes in exchange rates.

According to Ho & Huang's (2015) research, while there was no causal relationship between the rate of exchange and stocks in the first lag but there was in the second lag for Brazil. For Russia, causation occurs in both the first and second lags, but only in the second lag for India. For China, there is no relationship between the first and second lags. The research results further support the notion that volatility can spread between stock indices and currency rates even in the absence of a statistically significant connection or causal relationship between the returns of the two variables. In contrast to the first lag, where there was no causal relationship between the rate of exchange and stocks, the second lag for Brazil did, according to Ho & Huang. For Russia, causation occurs in both the first and second lags, but only in the second lag for India. Ferreira, Menezes, & Mendes (2007) demonstrated using the TARCH and EGARCH models that negative shocks on composit prices will cause higher volatility than positive surprises when accounting for the effects of changes in macroeconomic variables. They also didn't discover any conclusive evidence of asymmetric market return share behavior in Portugal.proof of the asymmetric market return pattern in Portugal.

There is no connection between the first and second lags for China. The study's results further support the notion that volatility can spread between stock indices and currency rates even in the absence of a statistically significant connection or causal relationship between the returns of the two variables. Ferreira, Menezes, & Mendes (2007) demonstrated using the TARCH and EGARCH models that negative shocks on stock prices will cause higher volatility than positive surprises when accounting for the effects of changes in macroeconomic variables. They also didn't discover any conclusive evidence of asymmetric market return share behavior in Portugal. Malaysia's stock index and currency rate volatility had a significant impact in the years preceding up to and following the crisis, but not at that time, claims a study by Lim and Sek (2013) using GARCH asymmetry. The composite index utilized in China that uses EGARCH (1,1) has significant properties for time fluctuations and clustering, according to Lin's research from 2017.

From the standpoint of emerging markets, Perera (2013) conducted an empirical research of the effects of exchange rate volatility on stock market return volatility using the GARCH estimation model. The volatility of the Euro exchange rate, however, had a positive and statistically significant impact on the volatility of stock returns, while the volatility of the US dollar and the British pound was negative and not statistically significant. According to Lakshmanasamy's research (2021), the volatility of the Euro/rupee exchange rate is anticipated to have a significant positive influence on the volatility of the return composite index. The US dollar/rupee and the British pound/rupee exchange rates have a negative but minor effect on the ARCH/GARCH model. show that shocks have a very long-lasting effect on the return composite index and that volatility's impact is gradually lost as a result of stock returns' self-lag, which increases volatility. According to Haughton and Iglesias's (2017) analysis of the ARCH/GARCH model, stock prices in Jamaica, Trinidad, and Tobago had a sizable influence on the exchange rate during the lag 1 period.

According to research done in Turkey by Kilic, Kula, and Ozdemir in 2023, there is a two-way causal relationship between variables using the Granger causality test, the ARMA(2.2) model from the linear stationary stochastic model, and the EGARCH(2.2) model from the variance model. Given that the data period and the epidemic period are congruent, it is likely that the causal link found in this study is also seen in studies done prior to the pandemic. The relationship between the volatility of the US dollar/euro exchange rate and the volatility of the US stock market was empirically examined by Kennedy and Nourizad (2016) using the GARCH model (1,1). They found that the return volatility share had a positive and statistically significant influence as exchange rate volatility increased. Ramli (2019) examined exchange rate volatility in Brazil using the GARCH model (1.1), and the findings revealed that exchange rate volatility had a large impact on stock indices.

METHODS

Although some research have discovered a connection between stock indices and currency rates, other studies have not. In order to guide future study, this paper makes an effort to examine and explain the numerous empirical discoveries about the connection between stock indexes and exchange rates using weekly data. Daily or monthly data are used most often in the literature. Starting from 1 January 2019 to 31 March 2023 (the period was selected based on the consideration that this period was the period of Covid-19), the information was gleaned from the Indonesian Central Bank. for exchange rate data and the Indonesia Bond Pricing Agency for the composite index. The data were processed on a weekly basis. Testing will be done using each composite index's return parameters (RCI). the parameters are derived by using the formula: to the rupiah exchange rate (RER) against the US dollar.

$Rt = \log(Pt) - \log(Pt-1)$

The test of variance for causation can be used to identify broad trends in return volatility transmission that are not statistically connected or do not exhibit causality. Additionally, the transmission of volatility can make it easier to react to shocks from foreign information. In order to improve market volatility predictions, variation causality can also be used to analyze the conditional volatility dependence between two variables (Ho & Huang, 2015). The behavior pattern of exchange rate volatility and the composite index generally can be predicted using the ARCH/GARCH model, which stands for Auto Regressive Conditional Heteroskedasticity/General Auto Regressive Conditional Heteroskedasticity. The asymmetric fluctuations are accommodated by switching the model to the Threshold model if the volatility of the composite index and the exchange rate fluctuates asymmetrically, which means that a sharp decline (negative effect) in the market does not immediately follow by an increase in the market (positive effect) of the same size at a later time, or if the negative effect is greater than the positive effect. 2009 (Gujarati)

The relationship between the volatility of the composite index (RCI) and the return exchange rate (RER) will be assessed using the Vector Autoregressive (VAR) model. Additional analyses that can be produced using the VAR model include those involving the Granger Causality test, impulse response (IR), and variance decomposition (VD). First, check the data's stationarity using the Augmented Dickey Fuller (ADF) unit root test. The estimations from the ADF model are:

$\Delta Y_t = \alpha_+ \beta_t + \gamma Y_{t-1} + \beta_1 Y_{t-1} + \ldots.. + \beta_p \Delta Y_{t-p} + \varepsilon_t$

where p is the order (or lag) of the autoregressive process, is a constant, and stands for the temporal trend. The result will move on to the following stage if it remains static at this level. The difference is made if it is not stationary at the level (Tudor, 2012). Second, the Box-Jenkin model, sometimes referred to as the Autoregressive Integrated Moving Average (ARIMA) model, is a time series model forecasting method that is entirely reliant on the observed variable data behavior. Data creation techniques like the ARIMA model are used to identify the suitable pattern in the return or growth rate of financial or economic variables (Ekinci, 2021). The major justification for utilizing the Box-Jenkin model is that economic theory finds it challenging to explain the movements and variations of the variables under study, notably exchange rates and stock prices. The best model will be obtained if the residuals between the forecasting model and historical data are minimal, dispersed randomly, and independently, according to the iterative approach used by this model to get the best model. Widarjono (2016, pp. 267). The moving average component (MA(q)) and the autoregressive component (AR(p)) can be merged as an autoregressive moving average (ARMA(p,q)) model as follows:

$Yi_t = \mu + \varphi_1 Y_{i,t-1} + \varphi_2 Y_{i,t-2} + \ldots\ldots + \varphi_p Y_{i,t-p} + \varphi_1 \varepsilon_{i,t-1} + \varphi_1 \varepsilon_{i,t-2} + \ldots\ldots + \varphi_q \varepsilon_{i,t-q} + \varepsilon_t$

Third, an ARIMA model diagnostic test was performed, specifically by assessing the residuals that were very small or assumed to be random (white noise), to ascertain whether the selected model could sufficiently describe the data. He achieves this by analyzing the residuals of the correlogram using the Auto Correlation Function (ACF) and the Partial Auto Correlation Function (PACF). The residuals are random (white noise) if the ACF and PACF coefficients alone are not significant. The fourth stage, detection of ARCH (Autoregressive Conditional Heteroskedasticity) elements or heteroscedasticity test, determines whether there is volatility by examining the distribution of quadratic disturbance variables (Correlogram) or by using the ARCH-LM test to determine whether the variance of the residual data is not constant and changes over time.

The volatility model is decided at the fifth stage. The optimal ARIMA model order is included in the ARCH/GARCH model to give an estimate of the volatility (variance) of each variable suggesting a volatility grouping. Then, it contrasts the prognosticating capacities of the subsequent models, including GARCH, EGARCH, GJR-GARCH, TGARCH, IGARCH, APARCH, and CGARCH. The procedure for GARCH (l,k), which Bollerslev (1986) proposed, is as follows (Montgomery et al., 2007).

$$\sigma_t^2 = \beta_o + \sum_{i=1}^{k} \beta_1\ \sigma_{t-1}^2 + \sum_{j=1}^{l} \alpha_j\ \varepsilon_{t-j}^2$$

The analysis of the RCI and RER volatility of the chosen ARCH/GARCH model by examination of the distribution of the standard deviation criteria is the last step. It is also required to identify the variables in the VAR model system from the results of the best ARCH/GARCH model in order to compare all the criteria in the best lag selection process with various lags and guarantee that the VAR model system utilizes the same number of observations. Examining if the transmission structure changes during the chosen period (the COVID19 period) is the goal of the VAR system study. Additionally, the VAR model was used to gather data on impulse response and variance decomposition. The idea of impulse response (IR) is used to illustrate how any dynamic system will react to alterations in the surrounding environment. The Variance Decomposition (VD) method demonstrates the amount of information that each variable in the VAR system adds to the other variables. Lastly, In the VAR system, the Granger Causality Test is employed to search for causal relationships or causality tests between endogenous variable modifications during the selected period (covid19 period).

VAR model estimation: $Y_t = A_t\, Y_{t-1} + A_2Y_{t-2} + A_3Y_{t-3} + A_4Y_{t-4} + \beta + \mu_t$

Granger causality model estimation:

$Y_t = \alpha + \beta_t + \varphi Y_{t-1} + \ldots\ldots + \varphi Y_{t-p} + \beta_1 X_{t-1} + \ldots\ldots + \beta_q X_{t-q} + \varepsilon_t$

FINDING

Augmented Dickey Fuller Test

ADF Test for RCI

$\Delta(RCI)_t = 0.000292 - 0.949299RCI_{t-1}$

ADF Test for RER

$\Delta(RER)_t = 0.000263 - 0.877271RER_{t-1}$

Table 1
Augmented Dickey Fuller Test

Variable	t-statistic	Critical Value (1%)	Critical value (5%)	Critical Value (10%)	Prob.
RCI	-14.04212	-3.460035	-2.874495	-2.573751	0.0000
RER	-13.98639	-3.460035	-2.874495	-2.573751	0.0000

source: data processed

Because both the composite index and the exchange rate have t-statistic values that are below the McKinnon critical value and a probability value that is below 0.05%, it can be inferred from table 1 that the data do not have a unit root or that it has been stationary at the level.

Auto Regressive Integrated Moving Average (ARIMA) Modeling

The Box-Jenkins method determines which ARIMA model is most appropriate based on the values from the Akaike Info Criterion (AIC), Schwarzh Information Criterion (SIC), and Hannan-Quinn Criterion (HQC), as well as the ACF and PACF plots or the autocorrelation function (ACF) on the correlogram. Following an iterative process, the optimal forecasting model for the composite index and exchange rate is obtained, and it is as follows.

Table 2
ARIMA Modeling

Dependent Variable	Forecasti ng Model	Model	Coef	SE Coef	t-stat	Prob.
RCI	ARIMA(1,0,1)	AR(1)	-0.739355	0.127002	-5.821603	0.0000
		MA(1)	0.855734	0.114603	7.466922	0.0000
RER	ARIMA(1,0,3)	AR(1)	0.137846	0.049884	2.763305	0.0062
		MA(3)	0.186628	0.033407	5.586445	0.0000

source: data processed

ARIMA model diagnostic test

According to the results of the Ljung-Box statistical test, the statistical value for composite index data up to lag 36 is 25,230, with a probability value of 0.861 (86.1%), and the probability value for all lags starting at lag 3 shows more than = 0.05%. A probability value greater than the value = 0.05% is already seen in the Ljung Box statistical value for exchange rate 3 data. As a result, it can be stated that the residual ACF and PACF values from the ARIMA models (1,0,1) for composite index and (1,0,3) for exchange rate are white nouse residuals, indicating the model's suitability.

ARCH element detection

Both the results of the squared residual correlogram of the Q-Statistics are high enough to be statistically significant, as seen from the low ACF and PACF values and the Q-Stat probability values are all zero less than the value = 0.05%, indicating that the composite index and exchange rate data contain ARCH elements. These results are based on the results of the AR(1), MA(1) model for composite index data and the AR(1), MA(3) model for exchange rate data. The probability values of composite index and exchange rate are worth 0.0000 or < 0.05%, which indicates that the null hypothesis is rejected and that the residual variance is not constant, or, in other words, that the model used contains elements of ARCH. As a result, it is possible to continue determining the volatility model composite index and exchange rate with ARCH/GARCH models.

Table 3
Arc-LM test

Variable	Obs*R-squared	Prob. Chi-Square
RCI	39.67365	0.0000
RER	212.3671	0.0000

source: data processed

Volatility Models

The ARCH/GARCH model, which uses the order of the ARIMA model as input to the ARCH/GARCH estimation, is employed as the estimated volatility model. The biggest Log Likelihood value and the least Akaike Info Criterion (AIC) and Schwarz Info Criterion (SIC) values are used to determine which model is the best. The Exponential-GARCH/EGARCH(1,1) model was chosen as the best model for composite index volatility after iteration, and the best model estimate is shown below:
Composite Index Volatility, EGARCH(1,1)

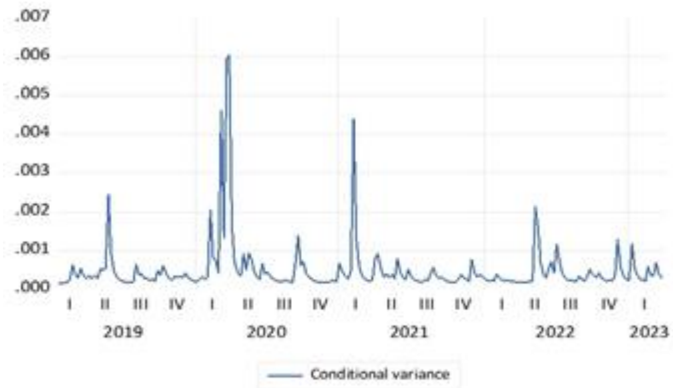
$$\log(\sigma_t^2) = -3.277444 + 0.393254 \frac{\varepsilon_{t-1}}{\sigma_{t-1}} - 0.374602 \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + 0.623079 log\sigma_{t-1}^2$$

The magnitude effect parameter, which is positive (0.393254) and statistically significant at = 1%, explains the existence of asymmetric volatility, leading to the conclusion that the volatility return composite index (RCI) model has an asymmetric effect. This implies that the current average volatility depends on the volatility of the prior period and will increase volatility by 0.393254. The current variance was affected differently by a negative shock in the t-1 period, as seen by the sign effect value of -0.374602, which reduced volatility by 0.374602. These results suggest that both shocks and volatility from the past and present have an impact on the return's volatility on the composite index. The study's findings are consistent with those of Haughton & Iglesias (2017), who used the EGARCH model to get to the conclusion that the composite index lags the exchange rate by a factor of 1. Therefore, in order to manage and lower market risk, investors should consider the volatility of the return on the composite index as well as the shocks that occurred in the previous period before deciding on an investment strategy. The likelihood of 0.8900, which is what the ARCH-LM test reveals, indicates that it is not statistically significant, hence the model no longer contains ARCH features.The TARCH(1) model is the best model for exchange rate (RER) volatility after iterating, and the best model estimate is given as follows: Volatility of RER, TARCH(1).

$$\sigma_t^2 = 0.00000590 + 0.191722\sigma_{t-1}^2 - 0.228027\varepsilon_{t-1}d_{t-1} + 0.854786\sigma_{t-1}^2$$

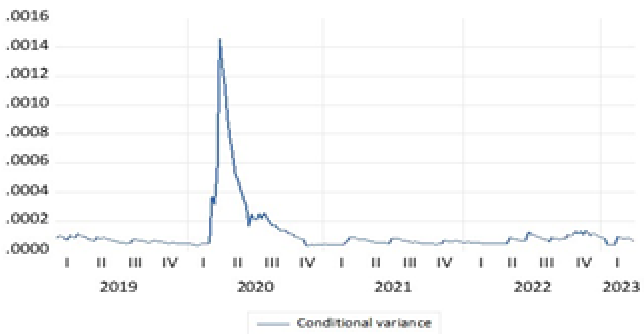
The variance equation of -0.228027, which explains the occurrence of asymmetric volatility in the TARCH model and is statistically significant at = 1%, leads to the conclusion that the return exchange rate behavior model exhibits an asymmetric effect. The constant value (α) will be impacted by the positive news in the t-1 period, as indicated by the value of -0.228027. Additionally, it shows that the good news from the preceding era (t-1) will make the exchange rate more volatile in the present period (t), advising investors to consider the exchange rate from the earlier time when formulating their investment strategy. The model no longer includes ARCH components since the probability of 0.9237 from the ARCH-LM test indicates that it is not statistically significant. The results of this study are in line with Wasiaturrahma's (2020) findings, which the conclusion that high volatility leads to instability and that both positive and negative news will affect the composite index and exchange rates. This is also consistent with research from Ferreira (2007), which found that using the TARCH model, negative surprises are higher than positive surprises.

As seen in the graph 1, the estimation of composite index volatility looked at the temporal distribution of price volatility of the clean price composite index while the exchange rate using the TARCH model looked at the distribution of exchange rate volatility. The examined RCI composite index and exchange rate's volatility behavior is identified using the conditional variance graph. Conditional variance that is significantly larger than others and occurs in 2020 at the end of the first quarter or the beginning of the second quarter indicates high volatility. This occurs as a result of the start of the COVID19 pandemic that occurred in Indonesia, which has an effect on the instability of economic conditions during that time. There is a substantial possibility for risk given the high values of the composite index and exchange rate volatility. Market participants panicked as the value of the rupiah fell against the US dollar, which weakened the movement of the composite index. The composite index has a significant risk potential as evidenced by the composite index's greater volatility when compared to the exchange rate.



Source: data processed

Graph 1
RCI volatility analysis model EGARCH (1,1)



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Graph 2
TARCH model RER volatility analysis

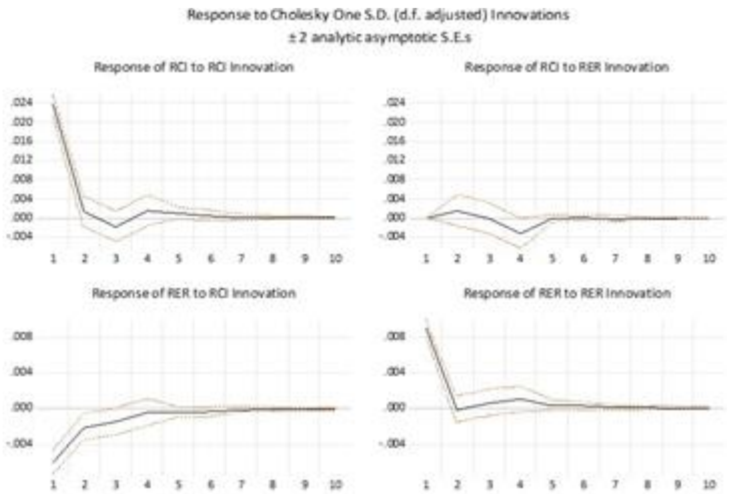
An estimation of the VAR(4) model is obtained or indicates that order p=4 is the best estimate of the VAR model with the following equation based on the comparison of the least AIC, SIC values and the biggest Likelihood, R^2 values:

$RCI = 0.10422RCI_{t-1} - 0.083521RCI_{t-2} - 0.006890RCI_{t-3} - 0.036581RCI_{t-4} + 0.169279RER_{t-1} - 0.044139RER_{-2} - 0.370358RER_{t-3}{*} + 0.026459RER_{t-4} + 0.000309$

$RER = -0.108860RCI_{t-1}{*} - 0.011834RCI_{t-2} + 0.029936RCI_{t-3} - 0.050051RCI_{t-4} - 0.010697RER_{t-1} + 0.156321RER_{-2} + 0.168367RER_{t-3}{*} - 0.176952RER_{t-4}{*} + 0.000263$

* indicates significant at α = 5%

The exchange rate during the preceding three periods is the sole component that significantly affects the volatility of the present composite index, according to the estimation results of the VAR model. The negative coefficient sign denotes that when the domestic exchange rate declines at this time, the value of shares in the following three periods will decrease, and vice versa, when the rupiah experiences appreciation in the previous three periods, the current stock price will decrease. The estimation of the current VAR exchange rate model is significantly harmed by the composite index from the previous period moving in the wrong direction, the exchange rates from the previous three periods, and the exchange rates from the four periods before that. These results concur with those of Priyono and Bustaman's (2014) study, which discovered that the volatility of the current exchange rate responds to the composite index of the previous period; Lin's (2007) study discovered a significant correlation between the composite index and exchange rate; Ramli (2019) discovered that the exchange rate determines the composite index; however, these results do not concur with those of Perera (2013), Lakshmanasamy (2021), Kenedy (20160), and Lia Wasiaturrahma (2020) also reached the same conclusion, supporting the conclusions of study by Lim & Sek (2013) that exchange rate volatility has little effect on the composite index during economic crises. Investors are very sensitive to economic risks and can easily enter and exit financial markets, which can contribute to exchange rate volatility. In addition, because Indonesian export companies primarily use imported materials, production costs rise and the domestic currency is subsequently under pressure. Increases in stock prices from the previous period will also have an impact.



Source: data processed

Graph 3
Impuls Response (IR)

According to the composite index reaction graph to exchange rate Innovation, the existence of the exchange rate shock leads the composite index to increase at the start of the period, decline to period 4 of the 10 periods, climb to period 5, and then level out or become stable in the next period. The stock prices recorded in Indonesia demonstrate that the Covid19 period to period 4 were the most affected by volatility shocks resulting from exchange rate volatility. The exchange rate response to composite index Innovation is illustrated by the response graph. The composite index shock caused the exchange rate to continue to climb until period 4 out of 10; the following period saw a modest increase until period 7; and finally, flat/stable conditions prevailed until period 10. The Indonesian exchange rate period reveals that the beginning of the COVID19 period to period 4 saw the biggest impact from volatility shocks resulting from stock price volatility. Additionally, it implies that the stock market and foreign exchange would fluctuate in response to alterations in the economy, raising the volatility transmission between the two. This increases the exchange rate's transmission volatility's impact on the Indonesian stock market and vice versa, making Indonesia's environment more conducive to an expansion in interdependent relations under the influence of covid19.

Table 4
Output Variance Decompotion

Variance Decomposition of RCI:

Period	S.E.	RCI	RER
1	0.023658	100.0000	0.000000
2	0.023744	99.58711	0.412892
3	0.023816	99.58956	0.410440
4	0.024083	97.83162	2.168377
5	0.024103	97.83322	2.166777
6	0.024107	97.83367	2.166335
7	0.024109	97.81762	2.182376
8	0.024110	97.81430	2.185701
9	0.024111	97.81327	2.186727
10	0.024111	97.81318	2.186824

Variance Decomposition of RER:

Period	S.E.	RCI	RER
1	0.010893	30.81414	69.18586
2	0.011096	33.30825	66.69175
3	0.011212	34.35778	65.64222
4	0.011269	34.15331	65.84669
5	0.011283	34.22196	65.77804
6	0.011293	34.27826	65.72174
7	0.011295	34.28497	65.71503
8	0.011295	34.28717	65.71283
9	0.011296	34.28806	65.71194
10	0.011296	34.28864	65.71136

Source: data processed

According Table 4., in period 1 the composite index variance is 100% described by the variable itself, in period 2 the composite index variance is 100% explained by the exchange rate variable variance, and the remaining portion is 99.587% explained by its own variance, while in period 10 the variance is 100% explained by the variable itself. The exchange rate variable variance accounts for just 2.186% of the composite index, with the remaining percentage being explained by the composite index variance. These findings suggest that the volatility of the return on the composite index itself, as well as the fact that there was a significant interaction with the stock market. In contrast, the exchange rate variant in period 1 was explained by the variable by 69.185% and the composite index variant by the remaining 30.814%. In period 2, the composite index variant accounted for 33.308% of the exchange rate variant's explanation, with the exchange rate variant alone accounting for the remainder. These circumstances show that beginning with the first period of the COVID19 period, the transmission of the return composite index had a significant impact on the exchange rate, and it will continue for the following period. For the 10th period, the exchange rate variant was explained by the composite index variant of 34,288%, and the remaining 65,711% was explained by the exchange rate variant itself.

Table 5
Granger Causality Test

Lags: 1

Null Hypothesis:	Obs	F-Statistic	Prob.
RER does not Granger Cause RCI	220	0.51713	0.4728
RCI does not Granger Cause RER		4.92242	0.0275

Lags: 2

Null Hypothesis:	Obs	F-Statistic	Prob.
RER does not Granger Cause RCI	219	0.24013	0.7867
RCI does not Granger Cause RER		3.19091	0.0431

Lags: 3

Null Hypothesis:	Obs	F-Statistic	Prob.
RER does not Granger Cause RCI	218	1.60299	0.1897
RCI does not Granger Cause RER		2.45599	0.0641

Lags: 4

Null Hypothesis:	Obs	F-Statistic	Prob.
RER does not Granger Cause RCI	217	1.25430	0.2892
RCI does not Granger Cause RER		2.95471	0.0210

Source: data processed

The findings of the Granger causation test indicate that there is one-way causation between the composite index and exchange rate in lags 1, 2, and 4. The Granger causality test results, however, show that there isn't a single lag from which it can be concluded that the exchange rate and composite index are causally related. This result is in line with Ho & Huang's (2015) research, which discovered that the exchange rate and composite index only had a causal relationship in latency 2, and that there was no causal association in lag 1. In contrast to Tudor's (2015) finding that exchange rate volatility has causation for the composite index one period into the future, Kilic's research from 2023 shows that there is a two-way causative relationship between the exchange rate and the composite index.

CONCLUSION

The model chosen to examine the volatility of the composite index is the AR(1) MA(1) EGARCH (1,1) model, in contrast to the exchange rate volatility model, which is AR(1) MA(3) TARCH. The direction of transmission and dependency of the two variables (composite index and exchange rate) are therefore examined using the VAR model. The results show that volatility is unevenly distributed in exchange rates and stock returns. This condition suggests that if a sharp decrease in the market (negative effect) is not immediately followed by an increase in the market (positive effect) of the same amount at a later period, the reaction (market upheaval) will be higher when the news that arrives is bad news rather than good news. The composite index's return volatility displays an exponential conditional, ensuring that the variance is always positive and that the volatility of the past period has a positive influence on the variance of the current period. The return exchange rate's (RER) volatility, meantime, indicates that good news in the t-1 period will have an impact on its constant value. According to the estimation of the VAR model, the return on the composite index is affected by the variable return on the exchange rate over the previous three periods, while the variable return on the exchange rate is affected by the return on the composite index over the prior period, the exchange rate over the prior three periods, and the exchange rate over the prior four periods. In response to changes in the economy, both the stock market and the currency market will move, ultimately increasing the volatility transmission of both markets. A substantial source of variance is the volatility of the return on the composite index itself, which also shows that there was significant stock market interaction during the COVI19 period. Since the first period of the COVID19 era, the transmission of the return composite index has had a substantial impact on the exchange rate and will do so going forward. Exchange rate and composite index are causally related in just one direction. There isn't a single lag that can be used to determine whether exchange rate influences composite index.

REFFERENCES

A. Sikhosana, G.C. Aye, 2018, Asymmetric Volatility Transmission between the Real Exchange Rate and Stock Returns in South Africa, *Econnomic Analysis Policy*, 60, 1-8

Ahmed S. Alimi a , Idris A. Adediran, 2023. A new look at stock price-exchange rate nexus: Analysis of COVID-19 pandemic waves in advanced and emerging economies. *Scientific African*

Andre Yone Haughton1 , Emma M. Iglesias, 2017. Exchange Rate Movements, Stock Prices and Volatility in the Caribbean and Latin America. *International Journal of Economics and Financial Issues*, 7(2), 437-447.

Anhar Fauzan Priyono & Arief Bustaman, 2014. Volatility Transmission between Exchange Rates and Stock Prices in Indonesia post 1997 Asia Crisis. *Working Paper in Economic and Development Studies* No. 201404. Department of Economics Padjadjaran University.

Aykut Ekinci, 2021. Modelling and forecasting of growth rate of new COVID-19 cases in top nine affected countries: Considering conditional variance and asymmetric effect. *Chaos, Solitons and Fractals*

Bank For International Settlement Paper, 2013. Market volatility and foreign exchange intervention in EMEs: what is changed. No.73

Bollerslev, T. 1986. Generalized Autoregressive Conditional Heteroskedasticity. *Journal of Econometrics*, 31(3), 307-327.

Ching Mun Lim, Siok Kun Sek, 2013. Comparing the performances of GARCH-type models in capturing the stock market volatility in Malaysia. *Procedia Economics and Finance*, 5. 478 – 487.

Dahir, A. M. et al. 2018. Revisiting the dynamic relationship between exchange rates and stock prices in BRICS countries: A wavelet analysis, *Borsa Istanbul Review*. Elsevier, 18(2), 101–113.

Diamandis, P. F., Drakos, A.A., 2011. Financial liberalization, exchange rates and stock prices: exogenous shocks in four Latin America countries. *J. Policy Model*. 33, 381–394.

Hock Tsen Wong, 2022. The impact of real exchange rates on real stock prices. *Jornal of Economics, Finance and Administration Science*, 27(54)

Hung, Nguyen, & Vo, 2022. Exchange rate volatility connectedness during Covid-19 outbreak: DECO-GARCH and Transfer Entropy Approach. *Journal International Financcial Market, Institutions & Money*. 81

Ishak Ramli, 2019. The Determinants of Exchange-Rate Volatility. *Advances in Economics, Business and Management Research*, 145.

K. Kennedy1 , F. Nourizad, 2016. Exchange rate volatility and its effect on stock market volatility. *Inrternatioanl Human Capital Urban Management*, 1(1), 37-46.

Kilic, Kula & Ozdemir, 2023. The Relationship between Exchange Rate Volatility and Stock Index Return : Evidence From Turkey. *Prizren Social Science Journal*. 7(1).

Kubo, A., 2012. The US tech pulse, stock prices, and exchange rate dynamics: evidence from Asian developing countries. *J. Asian Econ*. 23, 680–687.

Kuo-Jui Wua , Cheng-Cheng Lub, Haruhiro Jonoc and Irell Perez, 2012. Interrelationship between Philippine Stock Exchange Index and USD Exchange Rate. *Procedia - Social and Behavioral Sciences*, 40, 768-782.

Lakshmanasamy, 2021. The Relationship Between Exchange Rate and Stock Market Volatilities in India: ARCH-GARCH Estimation of the Causal Effects. *International Journal of Finance Research*. 2(4).

Liang-Chun Ho &Chia-Hsing Huang, 2015. The nonlinear relationships between stock indexes and exchange rates, *Japan and the World Economy*, 33, 20-27.

Lim, C. M. and Sek, S. K. 2013, Comparing the performances of GARCH-type models in capturing the stock market volatility in Malaysia, *Procedia Economics and Finance*. Elsevier, 5, 478-487

M. Bahmani-Oskooee, S. Saha, 2016, Do exchange rate changes have symmetric or asymmetric effects on stock prices?, *Global Financ. J*. 31, 57-72

Montgomery, D.C., C.L. Jennings, and M. Kulahci, 2007. *Introduction to Time Series Analysis and Forecasting.* Toronto: Wiley.

Moore, T. and Wang, P. 2014, Dynamic linkage between real exchange rates and stock prices: Evidence from developed and emerging Asian markets, *International Review of Economics & Finance*. Elsevier, 29, 1-11..

Nuno B. Ferreira, Rui Menezes, Diana A. Mendes, 2007. Asymmetric conditional volatility in international stock markets. *Physica A*, 382, 73-80.

Padhan Rakesh & K.P. Prabheesh, 2021, The Economics of Covid-19 pandemic: *A Survey. Economic Analysis and Policy*, 70, 220-237.

Perera H.A.P.K, 2014. Effect of Exchange Rate Volatility on Stock Market Return Volatility: Evidence from an Emerging Market. *International Journal of Science and Research* (IJSR). *Index Copernicus Value*, 6(14)

Qin, M., Liu, X., Zhou, X., 2020. COVID-19 shock and global value chains: is there a substitute for China? Emerging Markets Finance Trade 56, 3588–3598.

Riadevi, N. L. P. D. and Darma, G. S. 2016. Analisis Hubungan Indeks Harga Saham Gabungan dan Exchange Rate Terhadap Return Saham Dengan Profitabilitas Sebagai Variabel Intervening, *Jurnal Manajemen Bisnis*, 13(1), 123–133.

Salisu, A. A. and Ndako, U. B. 2018, Modelling stock price–exchange rate nexus in OECD countries: A new perspective, *Economic Modelling*. Elsevier, 74, 105-123.

Shu-hsien Liao, Pei-hui Chu, Ying-lu You, 2011. Mining the co-movement between foreign exchange rates and category stock indexes in the Taiwan financial capital market. *Expert Systems with Applications* 38, 4608-4617.

Sikhosana, A. and Aye, G. C. 2018, Asymmetric volatility transmission between the real exchange rate and stock returns in South Africa, *Economic Analysis and Policy*. Elsevier, 60, 1-8.

Tsai, I.C., 2012. The relationship between stock price index and exchange rate in Asianmarkets: a quantile regression approach.J.Int. *Financ.Markets Inst.Money* 22, 609–621.

Tudor, C., Popescu-Dutaa, C., 2012. On the causal relationship between stock returns and exchange rates changes for 13 developed and emerging markets. *Procedia: Soc. Behav. Sci*. 57, 275–282.

Vo, X. V. and Ellis, C. 2018, International financial integration: Stock return linkages and volatility transmission between Vietnam and advanced countries, *Emerging Markets Review*. Elsevier, 36, 19-27.

Wasiaturrahma, Dita Normalaksana Putri, Shochrul Rohmatul Ajija, 2020. Impact of Exchange Rate Volatility to Stocks' Return in Indonesia: The Augmented Markov-Switching Egarch Approach. *Jurnal Ekonomi Pembangunan: Kajian Masalah Ekonomi dan Pembangunan*, 21(2), 161-173

Wong, H. T. 2017, Real exchange rate returns and real stock price returns, *International Review of Economics & Finance*. Elsevier, 49, 340-352.

Yu, L., Zha, R., Stafylas, D., He, K., Liu, J., 2020. Dependences and volatility spillovers between the oil and stock markets: new evidence from the copula and VAR-BEKK-GARCH models. *International Review Finance Analysis*. 68

Zhe Lin, 2017. Modelling and Forecasting the Stock Market Volatility of SSE Composite Index Using GARCH Models.