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Exchange Rate Volatility and Cointegration of ASEAN Member Countries

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Abstract

This study investigates the volatility and cointegration of exchange rates in nine selected ASEAN member countries using five forms of the GARCH model. Daily data was sourced from the Bank of Thailand website, as Baht per foreign currency, over the period from October 2, 2018 to October 7, 2022. This data included Malaysia Ringgit, Singapore Dollar, Brunei Darussalam Dollar, Philippines Peso, Indonesia Rupiah, Myanmar Kyat, Cambodia Riel, Laos Kip, and Vietnam Dong. According to the findings of this study, only eight exchange rates were suitable for analysis. The GARCH (1,1), TGARCH (1,1), and PGARCH (1,1) models were determined to be the most applicable, with leverage effects observed in certain exchange rates. The analysis revealed a long-run and short-run relationship between these exchange rates. In order to mitigate the associated risk, investors and governments should carefully monitor news that may affect the value of exchange rates. It is thus essential to pay particular attention to the economic news and its potential impact on exchange rates.

Keywords: exchange rates volatility, cointegration, ARMA, ARCH-type model, ASEAN member countries

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1. Introduction

Since the end of the Bretton Woods system of fixed exchange rates, real and nominal exchange rates have been notoriously volatile due to market forces like supply and demand. This volatility of exchange rates poses a significant threat to the economy [1] and makes it difficult to predict prices, asset values, and currency values [2]. Such uncertainty can have far-reaching effects on businesses and the economy, including effects on stock prices [3], export performance [4], and foreign direct investment [5], all of which are indicators of economic stability and prosperity.

The 1997 Asian financial crisis raised significant concerns regarding the economic interdependence, investment flows, and exchange rate volatility of the Association of Southeast Asian Nations (ASEAN) member countries. In response to these concerns, some ASEAN member countries shifted from controlled floating regimes with no fixed path for currency rates to stable arrangements, while others moved to floating regimes. However, it was revealed that despite the different exchange rate management regimes in this region, the real exchange rates of the ASEAN currencies follow similar cycles and trends over the long term, indicating the interconnection between countries [6]. Also, it was recognized that the Thai baht served as the primary conduit through which regional currency fluctuations were transmitted [7].

Previous works have highlighted the potential risks associated with exchange rate volatility, which can have a negative impact on countries. For example, Ewubare and Merenini [8] found that countries with higher exchange rate volatility are more likely to experience a

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trade deficit, while Mosbei et al. [9] found that countries with higher exchange rate volatility were more likely to experience a decrease in exports. Similarly, Ekanayake and Dissanayake [10] established that countries with higher exchange rate volatility were more likely to experience a decrease in export performance. In contrast, Yussif et al. [11] could not confirm the impact of exchange rate volatility on import. For the investment, research conducted by Heroja [12] indicated that the effect of exchange rate volatility on foreign direct investment may differ depending on the context. In particular, ASEAN countries have experienced significant impacts of exchange rate volatility on their trade balances [13], foreign direct investment [14], and economic growth rate [15].

In response to the increasing efforts of governments and investors to mitigate exchange rate volatility, there is a growing need for effective measurement of this volatility. This is becoming increasingly pressing as it directly impacts policy and strategy design. By measuring exchange rate volatility and cointegration, policy and strategy designers can identify patterns and formulate more appropriate responses, benefiting both business opportunities and economic growth. This research aims to contribute to this area by extending the investigation of exchange rate volatilities in ASEAN member countries and their cointegration, which have received relatively limited attention in previous studies. The currencies of these countries are of interest mainly because they are recognized to have interconnections between them. To achieve these objectives, this work is organized as follows: Section 2 will present the academic works that support the research framework. Section 3 will outline the research methodology, and Section 4 will provide the results and discussion.

2. Literature Review

For decades, researchers have been fascinated by exchange rate volatility, but the precise cause of such extreme fluctuations remains elusive. Various explanations have been suggested to account for this phenomenon, with historical information and leverage effect emerging as two of the most prominent potential causes [16]. Regarding the leverage effect, defined as a negative correlation between return and volatility mediated by news and primarily observed in the stock market [17], it is anticipated that the leverage effect can persist in the foreign exchange market, as it has been established that news, particularly negative news, can have a significant impact on the conditional volatility of exchange rates when they are closely intertwined [18].

For the investigation of exchange rate volatility, models of the ARCH type have been widely employed. In order to gain a deeper understanding of the ARCH-type models used in current research, an overview of previous empirical studies employing these models is provided as follows.

Nguyen [19] conducted a research to investigate the nature of exchange rate volatility in the exchange rates of the Vietnamese dong (VND). Using ARMA-GARCH models to capture the mean and volatility process of USD-VND, GBP-VND, JPY-VND, and CAD-VND exchange rate returns, the author found that these models were well-adequate. Mahroowal and Salari [20] also investigated exchange rate volatility, finding that the GARCH model was the best model to explain the volatility of the return on the exchange of Afghanistan's foreign exchange rate with the US dollar. Ponziani [21] conducted a similar investigation into Southeast Asian countries, finding that the PARCH model was appropriate for Malaysian Ringgit (MYR), Vietnam Dong (VND), and Singapore Dollar (SGD), while the GARCH model was appropriate for THB and PHP, and the TARCH model was appropriate for Indonesia Rupiah (IDR). These findings indicate that different exchange rate volatility models may be better suited for different currencies.

The following academics' works contain evidence for the leverage effect in the exchange rate: Mohsin et al. [22] studied the Pakistan-US dollar exchange rate volatility and found a negative significance of the EGARCH's leverage value. Atabani [23] examined the volatility of the RMB exchange rate return for both onshore and offshore markets and revealed the presence of leverage effects in both. Abdulhakeem et al. [24] found that the best-fitting model for China, India, Spain, UK, and the USA is GJR-GARCH, followed by GARCH, TGARCH, and EGARCH. Also, Ali [25] modeled the volatility of Somali shilling against US dollar and found that the TCHARCH and EGARCH models were more suitable, with evidence of a leverage effect.

The previous mentioned studies were conducted to gain a better understanding of the effects of historical data and market news, implying a leverage effect, on the foreign exchange market. The most important takeaway from these previous studies is that different exchange rates are fitted with different models that reflect the diverse effects of historical data and market news on the foreign exchange market, which inspired the current investigation, which seeks to make a contribution to this field of research by implementing models utilized in previous work and extending their application to the currencies of ASEAN Member Countries.

3. Methodology

Volatility is the variation of the observed variable in time series data. This volatility is often forecast instead of the forecast of values conducted by conventional time series models, which are based on the assumption of homoscedasticity, as it allows for heteroscedasticity to exist in the data. This concept of volatility forecasting is reflected in the Autoregressive Conditional Heteroscedasticity (ARCH) model proposed by Engle in 1982 [26]. This model and its extensions, e.g. the GARCH model [27], the exponential GARCH (EGARCH) model [28], the Power GARCH (PGARCH) model [29], Threshold GARHC (TGARCH) model [30], become popular for analysts to forecast volatility.

In this research, various models within the ARCH family model, incorporated with the ARMA model, will be used to forecast the volatility of the selected exchange rates. Additionally, the Johansen Cointegration Test and Granger Causality Test will be employed to identify any long-term and short-term relationships between these exchange rates. Thus, in what follows, the details of the models, the related approaches, and the data used in this research will be presented.

3.1. AR Model

An autoregressive model is based on the idea that the current value of the dependent variable can be explained by its past values. This model can be presented by:

$$Y_t = \alpha + \sum_{i=1}^{p} \rho_i Y_{t-i} + \varepsilon_t \,, \tag{1}$$

where α is a constant. ρ_i , ρ_i , $i = 1, 2, ..., p$ is the parameter of the model AR, p is the order of the model, and ε_t represents the error that cannot be explained by the model.

3.2. MA Model

A moving model is based on the idea that the current value of the dependent variable can be explained by past errors. This model can be written by:

$$Y_t = \beta + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t \,, \tag{2}$$

where β is a constant. θ_j, $j = 1, 2, ..., q$ is the parameter of the model and q is the order of the model.

3.3. ARMA Model

The ARMA (p, q) model is the combination of the above two models. If Y_t is stationary, this model can be represented by:

$$Y_t = \delta + \sum_{i=1}^{p} \rho_i Y_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} + \varepsilon_t , \tag{3}$$

where δ is a constant.

3.4. ARCH-type Models

The autoregressive conditional heteroscedasticity (ARCH) family model can be used to justify the volatility of price and return in the financial market. This model enables the analysts to trace the patterns of market fluctuation. To understand how the model within the ARCH family was formed for this study, this section will provide a brief overview of five models used in this research. The details of each model are as follows.

3.4.1. ARCH model.

The Autoregressive Conditionally Heteroscedastic Model, ARCH (q), is used to describe the variance of the current error term. This model is commonly applied in modeling financial time series that exhibit time-varying volatility and volatility clustering, and it can be stated as follows:

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-2}^2 + ... + \alpha_q \varepsilon_{t-q}^2 , \tag{4}$$

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 , \tag{5}$$

where h_t is the conditional variances. ε_t denotes the error term. q is the number of lags. $\alpha_0 > 0$ and $\alpha_i \geq 0,\ i = 1, ..., q$. This implies that the conditional variance depends on previously squared residuals and needs to be non-negative. If $\alpha_i = 0$, h_t will equals to constant and thus conditional variance is homoscedastic.

3.4.2. GARCH Model

Generalized autoregressive conditional heteroscedastic models, GARCH (p, q), permit a longer memory and a more adaptable lag structure. GARCH (p, q) models incorporate the previous conditional variances, whereas ARCH models only consider that the conditional variance is linearly associated with the past variances. The p and q in the model denote the GARCH element and the ARCH element, respectively. The specification of the GARCH (p, q) process is as follows:

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_i h_{t-j} , \tag{6}$$

where p is the number of lags. $\beta_j \geq 0$. ε_{t-1} is an ARCH term that represents a previous shock. h_{t-1} is a GARCH term which represents the past forecasted conditional variance.

3.4.3. Threshold GARCH Model

The Threshold Autoregressive Conditionally Heteroscedastic Model (TARCH) employs a piecewise equation for the conditional standard deviation in order to accommodate asymmetry in the conditional variance. Mathematically, the TARCH model is defined as:

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{k=1}^{r} \gamma_k \varepsilon_{t-k}^2 I_{t-k} + \sum_{j=1}^{p} \beta_j h_{t-j} , \tag{7}$$

where $I_t = 1$ if $\varepsilon_t < 0$ and 0 otherwise. In this model, good news, $\varepsilon_{t-i} > 0$, and bad news. $\varepsilon_{t-i} < 0$, have differential effects on the conditional variance; good news has an impact of α_i, while bad news has an impact of $\alpha_i + \gamma_i$. If $\gamma_i > 0$, bad news increases volatility and there is a leverage effect for the i-th order. If $\gamma_i \neq 0$, the news impact is asymmetric.

3.4.4. Exponential GARCH Model

EGARCH, the Exponential Generalized Autoregressive Conditionally Heteroscedastic Model, regulates asymmetries in financial data. Even if the estimated coefficients are negative, the logarithmic features of the EGARCH model ensure that the conditional variance will be positive. The conditional variance of an EGARCH model can be expressed as follows:

$$\log h_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \left| \frac{\varepsilon_{t-i}}{h_{t-i}} \right| + \sum_{k=1}^{r} \gamma_k \frac{\varepsilon_{t-k}}{h_{t-k}} + \sum_{j=1}^{p} \beta_j \log h_{t-j}^2 ,$$

(8)

The left-hand side is the log of the conditional variance. This implies that the leverage effect is exponential, rather than quadratic, and that forecasts of the conditional variance are guaranteed to be nonnegative. The presence of leverage effects can be tested by the hypothesis that $\gamma_k < 0$. The impact is asymmetric if $\gamma_k \neq 0$.

3.4.5. Power GARCH model

PGARCH is modeled by standard deviation rather than variance. The PARCH model may be specified as follows:

$$h_t^{\delta} = \alpha_0 + \sum_{i=1}^{q} \alpha_i \left(|\varepsilon_{t-i}| + \gamma_i \varepsilon_{t-i} \right) + \sum_{j=1}^{p} \beta_j h_{t-j}^{\delta} , \tag{9}$$

where $\delta > 0$, $|\gamma_i| \leq 1$ for $i = 1, 2, ..., r$. $\gamma_i = 0$, for all $i > r$ and $r \leq p$. The optional γ_i parameters are added to capture asymmetry of up to order r. If $\delta = 2$ and $\gamma_i = 0$, the PARCH model is simply a GARCH model. The asymmetric effects are present if $\gamma_k \neq 0$.

3.4.6. Cointegration Test

To test the long run relationship, this work employs the Johansen Cointegration Test and Vector Error Correction Model (VECM) [31] [32]. The Johansen cointegration test can be expressed by:

$$\Delta y_t = \alpha_0 + \Pi y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + \varepsilon_t, \tag{10}$$

$$\Delta y_t = \alpha_0 + \beta_i y_{t-1} + \sum_{i=1}^{p-1} \delta_i \Delta y_{t-i} + \varepsilon_t , \tag{11}$$

where β_i and δ_i are the coefficient matrices, Δ is the symbol of difference operator and p is the lag order selected. This method employs two likelihood ratio test statistics, the Trace test and the Maximum Eigenvalue test, to determine the number of cointegrating vectors: the Trace test and the Maximum Eigenvalue test, which can be expressed as:

$$T(r) = -T\sum_{i=r+1}^{n} \ln\left(1-\hat{\theta}_i\right) , \tag{12}$$

$$\lambda_{max}\left(r, r+1\right) = -T\ln\left(1-\hat{\theta}_{r+1}\right), \tag{13}$$

where $\hat{\theta}_i$ is the expected eigenvalue of the characteristic roots ad T is the sample size. r and n are cointegrating vectors. For Vector Error Correction Model (VECM), it can be expressed by:

$$\Delta y_t = \alpha_1 + p_1 ecm1_{t-1} + \sum_{i=0}^{n}\omega_i \Delta y_{t-i} + \sum_{i=0}^{n}\gamma_i \Delta x_{t-i} + \varepsilon_{1t}, \tag{14}$$

$$\Delta x_t = \alpha_2 + p_2 ecm2_{t-1} + \sum_{i=0}^{n}\omega_i \Delta y_{t-i} + \sum_{i=0}^{n}\gamma_i \Delta x_{t-i} + \varepsilon_{2t}, \tag{15}$$

where ω_i and γ_i are the short-run coefficients. p is the lag order, $ecm1_{t-1}$ and $ecm2_{t-1}$are the Error Correction Term. ε_{1t} and ε_{2t} are the residuals.

To evaluate the error of the results from the model estimation, root-mean-square error (RMSE) and mean absolute error (MAE) will be used, and they can be written as follows:

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\hat{e}_i - e_i\right)^2} , \tag{16}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|\hat{e}_i - e_i\right|, \tag{17}$$

where N is the sample number, e is the actual exchange rate return, and $\hat{e}$ is the forecast exchange rate return.

The exchange rate data used for estimating the model was downloaded from the Bank of Thailand website as Baht/Foreign currency. These data are daily basic which include Baht/Malaysia Ringgit (MYR), Baht/Singapore Dollar (SGD), Baht/Brunei Darussalam Dollar (BND), Baht/Philippines Peso (PHP), Baht/Indonesia Rupiah (1000 Rupiah) (IDR), Baht/Myanmar Kyat (MMK), Baht/Cambodia Riel (100 Riel)(KHR), Baht/Laos Kip (100 Kip)(LAK), and Baht/Vietnam Dong (VND100)(VND). The data covers the time between October 2, 2018 and October 7, 2022, including 1,015 observations.

Table 1. Augmented Dickey-Fuller Unit Root Tests

Var.	t-Stat.	Prob.
LDBND	-27.246	0.000
LDIDR	-28.528	0.000
LDKHR	-31.712	0.000
LDLAK	-29.527	0.000
LDMMK	-30.879	0.000
LDMYR	-28.273	0.000
LDPHP	-26.145	0.000
LDSGD	-26.798	0.000
LDVND	-29.534	0.000

In order to examine the ARCH effect, the ARMA model for exchange rate returns was identified, and the result of analysis reveals that the ARCH effect does not persist in LDMMK, ARMA (2,2), ARCH(1) (F-stat.=0.34, P-value=0.56). Therefore only 8 exchange rates, i.e., LDBND, LDIDR, LDKHR, LDLAK, LDMYR, LDPHP, LDSGD, and LDVND, will be further investigated.

In this study the appropriate models will be selected based on AIC criteria such that the lowest value is the most appropriate one. From the analysis it show the appropriated models for each exchange rate as follows: LDBND ARMA (1,0) TGARCH (1,1) (AIC=-9.08); LDIDR ARMA (2,3) PGARCH (1,1) (AIC=-8.00); LDKHR ARMA (3,3) GARCH (1,1) (AIC=8.20); LDLAK ARMA (3,1) PGARCH (1,1) (AIC=-8.19); LDMYR ARMA (1,0) PGARCH (1,1) (AIC=-8.75); LDPHP ARMA (1,0) TGARCH (1,1) (AIC=-8.59); LDSGD ARMA (1,0) GARCH (1,1) (AIC=9.10); and LDVND ARMA(1,0) TGARCH (1,1) (AIC=-8.55). The results of model estimations are shown in Table 2.

In Table 2, it was found that the coefficients of the asymmetric parameter, γ, of LDBND, LDLAK, LDMYR, LDPHP, and LDVND were statistically significant, indicating that the leverage effect is present in these exchange rates. This suggests that these exchange rates are more sensitive to bad news than to good news in the specified period.

Table 2. Model estimations

	LDBND TGARCH (1,1)	LDIDR PGARCH (1,1)	LDKHR GARCH (1,1)	LDLAK PGARCH (1,1)
α_0	1.1E-07**	5.4E-06	2.6E-07	3.9E-10
α	0.050***	0.232***	0.038***	0.034***
γ_1	0.100**	0.062	-	-0.197***
γ_2	-0.129***	-	-	
δ	-	0.431***	-	0.953***
β	0.948***	2.046***	0.946***	2.760***

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Table 2. Model estimations (Cont.)

	LDMYR PGARCH (1,1)	LDPHP TGARCH (1,1)	LDSGD GARCH (1,1)	LDVND TGARCH (1,1)
α_0	0.000	1.5E-06**	1.0E-07**	6.5E-08**
α	0.043***	0.097***	0.037***	0.059***
γ_1	-0.583***	0.048		0.074
γ_2		-0.090**		-0.124**
δ	0.947***			
β	0.800**	0.784***	0.947***	0.962***

The properties of the models, i.e., serial correlation, ARCH effect, and normal distribution of residuals, are investigated based on the following hypotheses: H_0: there is no serial correlation in the residual; H_0: there is no ARCH; and H_0: residuals are normally distributed. The results from this investigation reveal that all models present no serial correlation and no ARCH effect. However, the residuals are not normally distributed, suggesting that these models may not be the most efficient choice.

The volatility estimation results depicted in Figure 1 reveal that among the 8 currencies analyzed, LDLAK, LDMYR, LDSGD, and LDVND not only have high volatility but also a rising trend. Table 3 displays the forecast error.

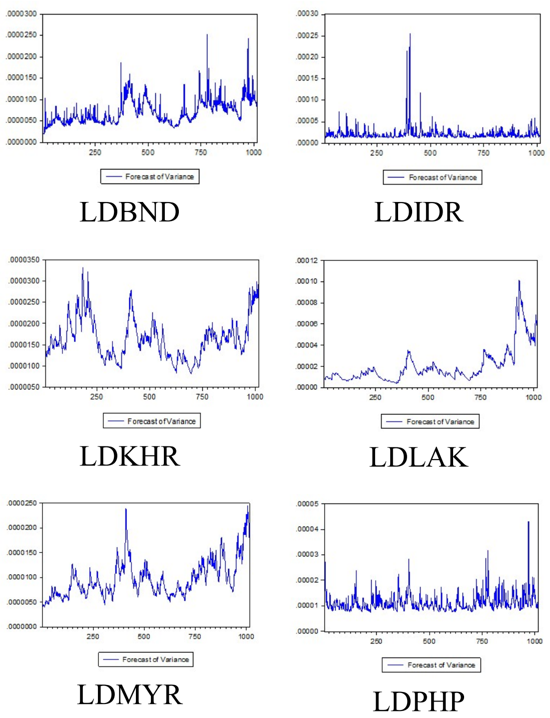

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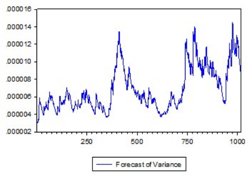
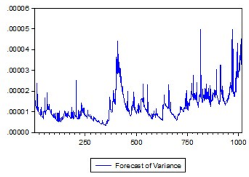
Figure 1. exchange rate volatility estimations



LDSGD



LDVND

Figure 2. exchange rate volatility estimations (Cont.)

Table 3. Errors of exchange rate estimation

Ex. rate	RMSE	MAE
LDBND	0.0026	0.0020
LDIDR	0.0046	0.0035
LDKHR	0.0040	0.0031
LDLAK	0.0045	0.0031
LDMYR	0.0031	0.0024
LDPHP	0.0033	0.0026
LDSGD	0.0026	0.0020
LDVND	0.0036	0.0026

The cointegration test will be described in the following sections. The outcome of the Johansen cointegration test is shown in Tables 4 and 5.

Table 4. Johansen Cointegration Test

Hypothesized		Trace	0.05	
No. of CE(s)	Eigenvalue	Statistic	Critical Value	Prob.**
None *	0.261361	1465.374	143.6691	0.0000
At most 1 *	0.234536	1161.822	111.7805	0.0000
At most 2 *	0.183213	894.0138	83.93712	0.0000
At most 3 *	0.161157	691.2321	60.06141	0.0000
At most 4 *	0.157562	515.1494	40.17493	0.0000
At most 5 *	0.125952	343.3516	24.27596	0.0000

At most 6 *	0.110635	208.4627	12.32090	0.0000
At most 7 *	0.086799	90.98063	4.129906	0.0000

Trace test indicates 7 cointegrating eqn(s) at the 0.05 level, * P-value < 0.05

Table 4 indicates that there are at most seven cointegrating equations at a 5 percent level of significance. The significant long-run relationships between normalized variables are shown in Table 5.

Table 5. Normalized Cointegrating coefficients

DGLDBND	DGLDIDR	DGLDKHR	DGLDLAK	DGLDMYR	DGLDPHP	DGLDSGD	DGLDVND
1.000	-0.664	0.027	0.007	0.907	0.542	-0.647	-0.291
	(0.039)	(0.141)	(0.116)	(0.340)	(0.160)	(0.726)	(0.218)

(.) is standard error

The results presented in Table 5 demonstrate the existence of a long-run relationship between DGLDBND, DGLDIDR, DGLDMYR, and DGLDPHP at the 5 percent level of significance.

Figure 2 is a network representation of the Granger causality test, indicating a short-run relationship between these exchange rates, either unidirectional or bidirectional.

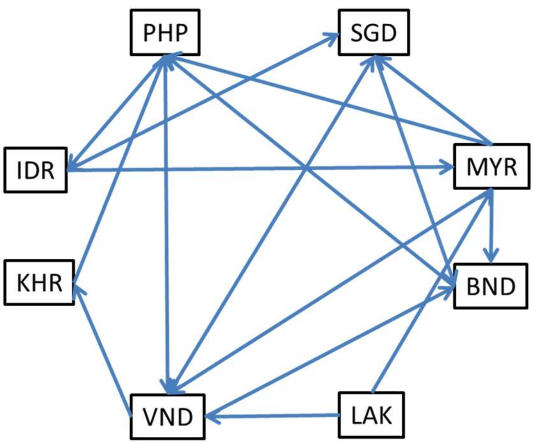


Figure 3. Granger causality network

From the results of the volatility analysis, it appears that market shocks and historical information influence exchange rate volatility. In addition, the significance of the asymmetric parameter can be utilized to divide the exchange rates into two groups: those that are consistent with a symmetric model and those that are consistent with an asymmetric model.

The exchange rates in the symmetric group include LDKHR, LDSGD, and LDIDR. These exchange rates fit with GARCH models, which have been used in a number of recent studies. For example, Mahroowal & Salari (2019), who used a GARCH model to explain the volatility of the return on the exchange of Afghanistan's foreign exchange rate; Nguyen (2018), who used a GARCH model to explain the volatility of USD-VND, GBP-VND, JPY-VND, and CAD-VND exchange rate returns; and SEKMEN & Ravanoğlu (2020), who used a

GARCH model to explain the volatility of some selected exchange rates.

In the case of the asymmetric group, it consists of LDBND, LDLAK, LDMYR, LDPHP and LDVND. These exchange rates contain the leverage effect expressed by the TGARCH and PGARCH models. Recent studies that used these models to estimate exchange rate volatility include, for instance, the work of Ponziani (2019) and Rehman & Salamat (2021), who indicated the existence of an asymmetric effect of good news and bad news on exchange rate volatility. For investors and governments that deal with exchange rates in this group, they should try to maintain current information and search for news that may affect the volatility of these exchange rates.

The discovery of long- and short-term relationships between exchange rates from cointegration and Granger causality test has important implications for investment and economic policy, as it suggests that shocks to one exchange rate can have an effect on its counterpart.

The above analysis of volatility patterns, cointegration, and leverage effects provides valuable insights into the factors influencing exchange rate volatility. This holistic view enhances the understanding of the underlying attributes that contribute to fluctuations in exchange rates.

5. Managerial Implication

On the basis of this study's findings, it is recommended that investors and government agents alike be prepared to respond to the potential risk posed by exchange rate volatility and co-integration when investing in the foreign currencies under investigation. For investors, they can consider using Hedging Techniques such as Forward Contracts and Options or diversifying their business operations across multiple currencies. Additionally, they may employ Forecasting Methods to obtain information and utilize it before making decisions. For governments, one fundamental approach to controlling exchange rate volatility is through the implementation of macroeconomic policies. These policies include fiscal and monetary measures aimed at stabilizing currency fluctuations. On the fiscal front, governments can employ strategies such as managing public debt, adopting flexible tax policies, and controlling government spending. By ensuring sound fiscal practices, governments can create an environment of certainty and strengthen investor confidence, thereby mitigating exchange rate volatility. Monetary policies, on the other hand, are orchestrated by central banks to manage exchange rate fluctuations. Actions such as adjusting interest rates, regulating money supply, and engaging in open market operations enable governments to influence the value of their currencies. Due to the results heightened news sensitivity and interdependence, special consideration should be given to LDBND, LDLAK, LDMYR, LDPHP, and LDVND. As a result, investors should use information regarding the expected value of the Baht relative to these currencies, financial market news, and the economic situation as a strategy to mitigate risk arising from trade and investment activities, whereas government agents should use this information to devise interventions to the exchange market to promote exchange rate stability.

6. Limitations and Future Research

This study has only demonstrated the impact of historical data and leverage on the volatility of ASEAN Member Countries' exchange rates. Additionally, only five ARCH-type models were utilized in this study. Consequently, future research may take into account additional alternative time series models to address volatility and utilize various forms of ARCH-type models. External factors such as inflation, interest rates, and international reserves may be considered variables.

7. Conclusion

This study examines the volatility and cointegration of the daily exchange rate for nine selected ASEAN member countries. The 8 forms of the GARCH models, i.e., ARCH (1), ARCH (2), GARCH (1,1), GARCH (1,2), TGARCH (1,1), EGARCH (1,1), and PGARCH (1,1) are used to address the volatility of these exchange rates. The exchange rate data used for estimating the model was downloaded from the Bank of Thailand website as Baht/Foreign currency. These data are daily basic and include Baht/Malaysia Ringgit (MYR), Baht/Singapore Dollar (SGD), Baht/Brunei Darussalam Dollar (BND), Baht/Philippines Peso (PHP), Baht/Indonesia Rupiah (IDR), Baht/Myanmar Kyat (MMK), Baht/Cambodia Riel (KHR), Baht/Laos Kip, and Baht/Vietnam Dong (VND). The data covers the time between October 2, 2018 and October 7, 2022. Before analyzing the volatility, these exchange rates are manipulated by the log of the first difference. The appropriate models are selected based on the AIC criteria. After consideration, it was discovered that BND matched TGARCH (1,1), IDR matched PGARCH (1,1), KHR matched GARCH (1,1), LAK matched PGARCH (1,1), MYR matched PGARCH (1,1), PHP matched TGARCH (1,1), SGD matched GARCH (1,1), and VND matched TGARCH (1,1). The model estimation shows that all models present no serial correlation and no ARCH effect. However, the residuals are not normally distributed. In addition, there are leverage effects in BND, LAK, MYR, PHP, and VND. The results of volatility estimation indicate that the exchange rates of LAK, MYR, SGD, and VND not only display a high degree of volatility but also an increasing trend. Furthermore, the analysis has revealed a long run and short run relationship between these exchange rates. Therefore, investors should search for news relating to these exchange rates to prevent risk from trade and investment activities. Also, government agents need to search for such news to design actions to intervene in the exchange market to foster exchange rate stability.

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