Modeling Exchange Rate Volatility of ASEAN Member Countries

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Abstract: - This study investigates the volatility 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 database, 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 of the exchange rates were suitable for analysis. In addition, the GARCH (1,1), TGARCH (1,1), and PGARCH (1,1) models were determined to be the most applicable, and leverage effects were observed in certain exchange rates. To mitigate the risk associated with trade and investment activities, investors should closely monitor news that is likely to affect the value of exchange rates. In order to design actions that promote exchange rate stability, government agents, on the other hand, must ensure they are current on such news.

Key-Words: - Exchange rates, Volatility modeling, ARMA, ARCH-type models, ASEAN member countries

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1. Introduction

Financial liberalization of the late 20th century caused dramatic fluctuations in international currencies and financial assets. This high degree of volatility has made it difficult to predict the future and has also raised the associated risks for investors. To reduce the risk of investing, it is necessary for investors to accurately evaluate the price of the assets and value of currencies [1].

Volatility in exchange rates is a factor that has far- reaching macroeconomic implications, including impacts on international trade, investment [2], inflation, and economic growth, which are all indicators of economic stability and prosperity. As a result, governments strive to implement policies to control this volatility in order to advance economic objectives.

The 1997 Asian financial crisis raised serious concerns about the economic interdependence, investment flows, and exchange rate instability of the Association of Southeast Asian Nations (ASEAN) member nations. To address these concerns, some ASEAN nations shifted from controlled floating regimes with no fixed path for currency rates to stable arrangements, while others moved to floating regimes. However, it was reveal 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 [3] and it was recognize that the Thai baht served as the primary conduit through which regional currency fluctuations were transmitted [4].

Previous works have highlighted the potential negative impacts of exchange rate volatility on countries. For example, [5] found that countries with higher exchange rate volatility are more likely to experience a trade deficit, while [6] found that countries with higher exchange rate volatility were more likely to experience a decrease in exports. Similarly, [7] found that countries with higher exchange rate volatility were more likely to experience a decrease in export performance. In contrast, [8] could not confirm the impact of exchange rate volatility on import. For the investment, research conducted by [9] indicates that the effect of exchange rate volatility on foreign direct investment (FDI) may differ depending on the context.

ASEAN countries, in particular, may experience substantial effects of exchange rate volatility on trade balances [10], foreign direct investment [11], economic growth rate [12], imports and exports [13], as well as domestic consumer and producer prices [14].

For the benefit of policy design, academics frequently employ ARCH-type models, such as ARCH, GARCH, TGARCH, EGARCH, PGARCH, SGARCH, and TCHARCH, to examine the volatility of the exchange rate. This research therefore aims to apply the ARCH family model to investigate the exchange rate volatility of ASEAN member countries. The results of this research are set to aid investors and governments in designing strategies and policies to prevent risk and foster economic and business growth and stability. The work is structured as follows: Section 2 presents the academic works that support the research framework. Section 3 then outlines the research methodology. Section 4 provides the results and discussion.

2. Literature Review

Exchange rate volatility is a phenomenon that has intrigued researchers for decades. While the exact cause of such extreme fluctuations has yet to be determined, multiple explanations have been suggested to explain this phenomenon, e.g., historical information and leverage effect [15].

In the case of the leverage effect, a negative correlation between return and volatility has been observed in the stock market [16]. This effect is expected to persist in the foreign exchange market as well, as it has been established that news, especially bad news, can have a substantial effect on the conditional volatility of exchange rates when they are closely intertwined [17]. This is because the volatility of one currency can spill over to other currencies, which can lead to significant losses for investors.

Utilizing ARCH-type models has been a prominent method for analyzing exchange rate volatility from various perspectives and identifying the model that best describes the characteristics of exchange rate volatility. In order to gain a deeper understanding of the ARCH-type models in current research, the following will present an overview of prior empirical studies employing these models.

In [18], the scholars investigated 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. In [19], they 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. In [20], the scholars 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 [21], they conducted a study on the Pakistan-US dollar exchange rate volatility and found a negative significance of the EGARCH's leverage value. In [22], the scholar examined the volatility of the RMB exchange rate return for both onshore and offshore markets and revealed the presence of leverage effects in both. In [23], they found that the best-fitting model for China, India, Spain, UK, and the USA is GJR-GARCH, followed by GARCH, TGARCH, and EGARCH. Also, in [24], the scholars 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 - positive news having a greater effect on volatility than bad news of the same magnitude.

Numerous studies have been conducted in an effort to better comprehend the effects of historical data and market news on the foreign exchange market. These studies demonstrate that various exchange rates are fitted with models that reflect the diverse effects of historical data and market news on the exchange rate. The most important takeaway from these previous studies is that different exchange rates are fitted with various models that reflect the diverse effects of historical data and market news on the foreign exchange market.

3. Methodology

The ARMA model, also known as the Box-Jenkins methodology, encompasses autoregressive and moving average methods. This model estimates the dependent variable by using its own lags and past errors. The proper number of lags and past errors, determined by ACF and PACF, that are included in the model is often evaluated by the AIC criteria, which indicates the proper model by the smallest AIC value. The details of this model are as follows.

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:

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

where α is a constant. 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.

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:

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

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.

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:

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

where δ is a constant.

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.

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:

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

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

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.

GARCH Model

Generalized autoregressive conditional heteroscedastic models, GARCH (p, q), allow for both a long memory and a more flexible lag structure. While ARCH models only concern that the conditional variance is linearly associated with the past variances, GARCH (p, q) models added the previous conditional variances into the model. 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:

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

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.

Threshold GARCH Model

The Threshold Autoregressive Conditionally Heteroscedastic Model, TARCH, uses a piecewise equation for the conditional standard deviation to permit asymmetry in the conditional variance. The TARCH model is mathematically defined as:

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

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 we say that there is a leverage effect for the i-th order. If $\gamma_i \neq 0$, the news impact is asymmetric.

Exponential GARCH Model

The Exponential Generalized Autoregressive Conditionally Heteroscedastic Model, EGARCH, controls asymmetry in financial data. Even if the estimated coefficients are negative, the logarithmic characteristics of the EGARCH model guarantee that the conditional variance is positive. The expression of the conditional variance for an EGARCH model is stated as follows:

$$\log h_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \left| \frac{\varepsilon_{t-i}}{h_{t-i}} \right| + \sum_{k=1}^{r} \gamma_k \frac{\varepsilon_{t-k}}{h_{t-k}} + \sum_{j=1}^{p} \beta_j \log h_{t-j}^2, \qquad (8)$$

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 $\gamma_k \neq 0$.

Power GARCH model

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

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

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 $\gamma_k \neq 0$.

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:

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (\hat{e}_i - e_i)^2}, \qquad (10)$$

$$MAE = \frac{1}{N} \sum_{i=1}^{N} |\hat{e}_i - e_i|, \qquad (11)$$

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 database 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.

4. Result and Discussion

The Unit Root Tests of the exchange rate are reported in Table 1 which indicates the stationary of the exchange rates.

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. = 0.342428, P-value=0.558). 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 best. From the analysis it show the appropriated models for each exchange rate as follows: LDBND ARMA (1,0) TGARCH (1,2) (AIC=-9.0760); LDIDR ARMA (2,3) PGARCH (1,1) (AIC=-8.0025); LDKHR ARMA (3,3) GARCH (1,1) (AIC=8.2041); LDLAK ARMA (3,1) PGARCH (1,1) (AIC=-8.1935); LDMYR ARMA (1,0) PGARCH (1,1) (AIC=-8.7470); LDPHP ARMA (1,0) TGARCH (1,2) (AIC=-8.5894); LDSGD ARMA (1,0) GARCH (1,1) (AIC= 9.0961); and LDVND ARMA(1,0) TGARCH (1,2) (AIC=-8.5482). The results of model estimations are shown in Table 2.

From LDBND TGARCH (1,2) in Table 2, it was found that the coefficients of the asymmetric parameter are significant. This shows that the leverage effect is present in this exchange rate and leads to the conclusion that LDBND reacts more to good news than to bad news.

Table 2: Model estimations

	LDBND TGARCH (1,2)	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***

	LDMYR PGARCH (1,1)	LDPHP TGARCH (1,2)	LDSGD GARCH (1,1)	LDVND TGARCH (1,2)
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***

For LDIDR PGARCH (1,1), it demonstrates that the asymmetric coefficient is not statistically significant, establishing the nonexistence of the leverage effect and implying that GARCH (1,1) is more suitable. According to LDKHR GARCH

(1,1), all coefficients are significant. Thus, both past conditional variances and errors influence the current conditional variance. LDLAK PGARCH (1,1) demonstrates that the asymmetric coefficient is statistically significant, proving the existence of the leverage effect and indicating that this exchange rate reacts more to positive than negative news.

The remaining model estimation results can be interpreted in a similar manner. The results led us to the conclusion that the leverage effect exists in LDBND, LDLAK, LDMYR, LDPHP, and LDVND, indicating that these exchange rates are responsive to news on the foreign exchange market.

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.

The results of the volatility estimation in Figure 1 indicate that DLLAK, DLMYR, DLSGD, and DLVND not only have high volatility but also a rising trend. Table 3 displays the forecast error.

The results of the analysis indicate that market shocks and historical information influence exchange rate volatility. In addition, the significance of coefficients and leverage effect parameters can be utilized to divide the exchange rate 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 the 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, e.g., 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.

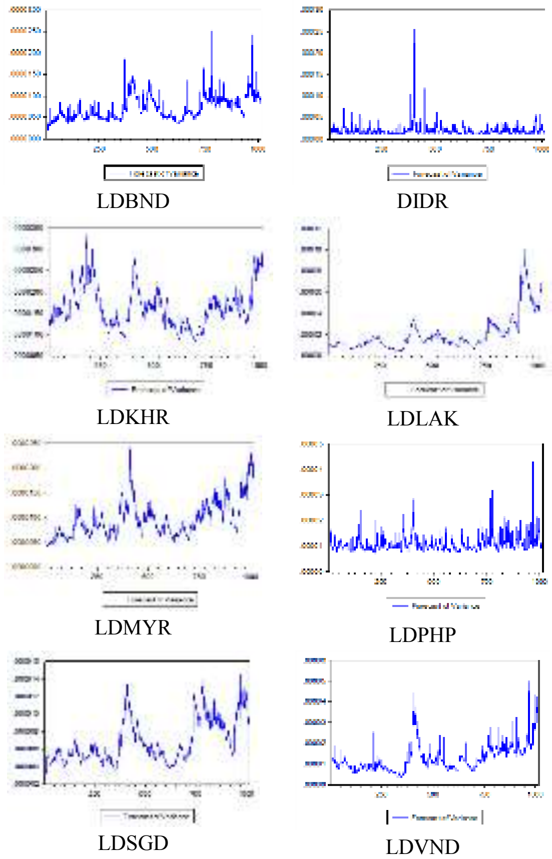

Figure 1: exchange rate volatility estimations

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

Given the preceding information, investors in LDBND, LDLAK, LDMYR, LDPHP, and LDVND should maintain current information, search for news that may affect the volatility of these exchange rates, and restructure their investments to avoid losing money due to the volatility risk associated with these rates. However, investors can reduce the risk of volatility through prudent investment planning. This can be accomplished by selecting appropriate investment currencies. In addition, investors can employ hedging strategies, such as the use of options, to reduce their risk of volatility-related losses (Bhunia & Ganguly, 2020).

This is also significant for central banks, as these exchange rates are integral to the businesses and economic activities that rely on them. A significant change in these exchange rates could have far-reaching effects on the economy. Therefore, central banks should have contingency plans for any potential shocks.

5. Managerial Implication

Based on the findings, this research suggests that investors who are interested in investing in foreign currencies investigated in this research and government agents who respond to the stability of macroeconomic indicators, e.g., aggregated price, trade balance, GDP growth rate, and value of Baht, be prepared to deal with the potential risk from exchange rate volatility. They should pay special attention to LDBND, LDLAK, LDMYR, LDPHP, and LDVND as their volatility is sensitive to the news. Therefore, searching for information about the expected value of the Baht should be a good strategy for investors to prevent risk from trade and investment activities and for government agents to design actions to intervene in the exchange market to foster 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. Inflation, interest rates, and international reserves may be considered variables.

7. Conclusion

In this study, the characteristics of the daily exchange rate returns of the 9 selected ASEAN member countries are examined. 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 database 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 (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 result of volatility estimation shows that LAK, MYR, SGD, and VND not only have high volatility but also an increasing trend. 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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