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Currency Market Waves in Asean Amid Red Sea War Event

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Abstract

This study examines how the Red Sea War (July 21, 2023–January 17, 2024) influenced the volatility and patterns of financial assets like ASEAN-6 exchange rates and crypto currencies such as Bitcoin, Ethereum, and Ripple. The aim is to understand the impact of geopolitical uncertainty on these assets and offer guidance for investors. Data was sourced from Yahoo Finance, and analysed using GARCH models (GARCH (1, 1), GJR-GARCH (1, 1), and E-GARCH (1, 1) to assess volatility and leverage effects. The findings show that GARCH (1, 1) best describes the behaviour of USD/PHP, USD/VND, Ethereum, and Ripple, while GJR-GARCH (1, 1) fits USD/MYR and USD/THB more accurately. E-GARCH (1, 1) proved ideal for USD/IDR, USD/SGD, and Bitcoin, capturing the asymmetric nature of volatility. Crypto currencies, particularly Bitcoin, experienced higher volatility and risk compared to exchange rates, with Bitcoin showing sharp price movements. On the other hand, assets like the Malaysian Ringgit (MYR) and Ripple were more stable, especially after the crisis, making them more appealing to risk-averse investors. In conclusion, the study highlights the value of advanced GARCH models in managing financial risks during geopolitical uncertainty. The results offer useful insights for investors looking to adjust their strategies and make better decisions in volatile market conditions.

Keywords: ASEAN, Crypto Currency, Exchange Rate, Red Sea War Event, Volatility.

Introduction

In recent years, the global economy has faced significant challenges, such as geopolitical tensions, trade uncertainties, and the impact of the COVID-19 pandemic, which have placed heavy pressure on financial markets, particularly in developing countries. One issue that has garnered special attention is the fluctuation of exchange rates and the volatility of digital assets, such as cryptocurrencies, which are increasingly becoming an integral part of global financial system. Amid this situation, Red Sea War event, triggered by political tensions and conflicts in the region, has added strain to stability of both regional and global economies. The impact of this crisis is not only felt in international trade but has also disrupted investment flows. Exchange rate fluctuations serve as a key indicator of economic impact, while cryptocurrencies, as alternative financial instruments, display intriguing volatility patterns during this crisis. Figure 1 illustrates the fluctuations in exchange rates during Red Sea War event period. Data obtained from Yahoo Finance shows that exchange rates for currencies such as IDR, MYR, SGD, THB, PHP, and VND against USD experienced high volatility. This reflects market uncertainty arising from the crisis, where these exchange rates showed sharp movements, both increases and decreases, in response to geopolitical tensions and global economic impacts. Meanwhile, Figure 2 depicts the fluctuations in crypto currency prices, such as Bitcoin, Ethereum, and Ripple, during same period. Crypto currencies, as alternative financial instruments, exhibit significant volatility, with sharp price spikes and declines. This reflects the market's response to global uncertainty, where investors shift towards or sell crypto currencies in reaction to events affecting economic stability. This study aims to analyze the relationship between the Red Sea War event and the volatility of exchange rates and crypto currencies in the ASEAN-6 region. ASEAN-6 was chosen because it consists of countries with significant economic dynamics and financial markets in Southeast Asia, characterized by high economic interdependence and a substantial impact on global economic stability. These nations—Indonesia, Malaysia, Singapore, Thailand, the Philippines, and Vietnam represent a

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diverse mix of emerging and developed markets, each with varying levels of financial market integration, trade exposure, and exchange rate policies. Additionally, their strategic role in global trade, particularly through the Strait of Malacca, makes them highly susceptible to geopolitical events such as the Red Sea crisis. Given that developing markets in ASEAN are often more vulnerable to external shocks and exhibit different market characteristics compared to developed economies, this study aims to provide a deeper understanding of financial market response patterns to global crises, specifically within this region. Several previous studies have explored the effects of geopolitical crises on financial markets, particularly focusing on exchange rates and crypto currencies, but findings remain mixed. For exchange rates, some studies have documented increased volatility in response to geopolitical tensions, reflecting heightened uncertainty and risk aversion among investors (2-4).

Figure 1: Exchange Rate Performance Before and After the Red Sea War Event (1)

Figure 2: Cryptocurrency Performance Before and After the Red Sea War Event (1)

In contrast, other research suggests that the extent of volatility depends on a country's economic fundamentals and market openness, leading to heterogeneous impacts across different currencies (5-8). These inconsistencies highlight the importance of contextual factors, such as the nature of the crisis and regional economic resilience, when assessing exchange rate behavior. In the case of cryptocurrencies, several studies emphasize their speculative nature and their heightened sensitivity to global shocks. For example, in the past researchers find that cryptocurrencies tend to exhibit significant price swings during crisis periods, often driven more by investor sentiment than by underlying fundamentals (9-14). However, other researchers argue that major cryptocurrencies like Bitcoin may function as alternative assets or even safe havens during extreme market turmoil, albeit inconsistently (15-18). This duality, being both highly volatile and occasionally serving as risk diversifiers, further complicates their role in times of geopolitical distress. Based on the above description, the Red Sea War event demonstrates how geopolitical tensions can affect global economic stability, including in ASEAN countries. Fluctuations in exchange rates and cryptocurrency volatility serve as key indicators in responding to the uncertainties arising from this global uncertainty. This study, which employs the GARCH model to analyze volatility, is expected to provide significant implications for understanding how financial markets, particularly in developing countries, respond to external events that may impact economic stability. The implications of this study will offer insights for policymakers, investors, and market participants in managing risks arising from global uncertainty, and can serve as a foundation for designing more effective mitigation strategies to address economic fluctuations in the future.

Methodology

This study is experimental research aimed at examining the impact of the Red Sea War event. The research model is utilized to predict the exchange rate volatility of ASEAN-6 countries, namely Indonesia (USD/IDR), Malaysia (USD/MYR), Singapore (USD/SGD), Thailand (USD/THB), Philippines (USD/PHP), and Vietnam (USD/VND), as well as crypto currencies including Bitcoin, Ethereum, and Ripple, in response to a global economic event—the Red Sea War event. The dataset used in this study consists of secondary data obtained from the reputable website Yahoo Finance; therefore, a formal data quality assessment was not deemed necessary. The data used in the research spans 90 days before and after Red Sea War event, specifically from July 21, 2023, to January 17, 2024. The selection of this window length is consistent with previous studies (7, 17). The selection of a 90-day period before and after the Red Sea War event was based on the need to capture both anticipatory and delayed responses in the financial markets. Such a window is commonly employed in event studies, especially when examining exchange rates and cryptocurrency markets, which often react to geopolitical events over extended periods due to investor sentiment shifts, gradual information dissemination, and ongoing market uncertainties. A shorter window might fail to reflect volatility clustering or delayed adjustments, whereas a significantly longer period could dilute the event-specific effects by incorporating unrelated macroeconomic developments. While some prior studies have employed shorter windows, typically ranging from 10 to 30 days - to capture immediate market reactions (11, 19), such narrow frames may overlook gradual or persistent volatility responses, especially in the context of sustained geopolitical tensions like the Red Sea conflict. Therefore, the 90 day window offers a balanced approach to capturing both immediate and evolving market dynamics. To manage instances of missing values within the observation period, a forward imputation technique was applied, whereby any missing value was replaced by the value of the following date. This method ensured data completeness throughout the entire event window, allowing for consistent analysis without compromising the sample size.

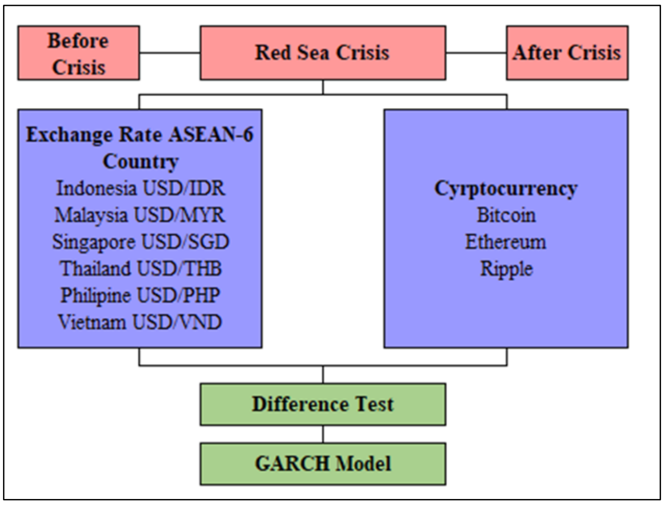

Figure 3: Theoretical Framework

Figure 3 presents the theoretical framework of this study, illustrating the relationships between key variables and the stages of analysis. The framework is structured around the Red Sea Crisis, distinguishing between the pre-crisis and post-crisis periods. The study examines the impact of this event on two financial markets, Exchange Rates and Cryptocurrencies. The analysis follows a two-step approach, Difference Test and GARCH Model. The data analysis methods used in this study involve the Statistical Product and Service Solutions (SPSS) version 25 and E-Views version 9 applications, with the following several testing stages. The first stage involves descriptive statistics,which aims to identify the characteristics of research data, including mean, median, maximum, and minimum values. Descriptive statistics are used to evaluate data distribution patterns and key characteristics of research dataset. The second stage is the difference test, conducted toconducted to identify whether there are significant differences between conditions before and after Red Sea War event. Prior to conducting the difference test, a normality test is performed to ensure that data follows a normal distribution. The normality test is conducted using Shapiro-Wilk method, with following criteria: if Shapiro-Wilk significance (sig) value is greater than 0.05, the data is considered normally distributed. Conversely, if sig value is less than 0.05, the data is considered not normally distributed. Based on the results of normality test, hypothesis testing method is selected: if data is normally distributed, the One-Sample T-Test is used. If data is not normally distributed, One-Sample Wilcoxon Signed Rank Test is applied (20). The third stage involves the GARCH model, which is commonly used to analyze financial time series data that often exhibits a volatility clustering pattern, where periods of high volatility are followed by periods of low volatility, or vice versa. To analyze this phenomenon in economic and financial time series data, ARCH and GARCH models are commonly used (21). This approach has been frequently utilized in prior studies to assess the impact of external shocks on the financial markets (12, 15, 16, 22). The GARCH model is widely recognized for its ability to capture dynamic changes in volatility, with GARCH (1,1) being one of the most commonly used models for depicting volatility clustering. Additionally, the GJR-GARCH model is designed to identify asymmetrical patterns in financial market returns, emphasizing the greater impact of negative shocks compared to positive ones, a phenomenon known as the leverage effect (23). Finally, the Exponential GARCH (E-GARCH) model is employed to capture asymmetrical patterns that are not evident in conventional GARCH models, allowing for projections of conditions with more complex lag variations (24). The use of these models aligns with previous empirical works that emphasize the importance of modeling asymmetry and non-linearities in financial markets (14, 25, 26), particularly during periods of heightened geopolitical uncertainty or crisis.

Results

Descriptive statistical analysis serves to provide a comprehensive overview and detailed characterization of the research data. This analysis facilitates the identification of patterns, distribution, and fluctuations within the observed dataset. In this study, the analysis is based on closing prices of variables under investigation during observation period, which encompasses 90 days prior to and 90 days during Red Sea War event observation. The analysis covers period from July 21, 2023, to January 17, 2024, and is presented as follows in Table 1.

Table 1: Descriptive Statistics

Variables/ Statistics	Exchange Rate						Cryptocurrency		
	USD_IDR	USD_ MYR	USD_ PHP	USD_ SGD	USD_ THB	USD_ VND	Bitcoin	Ethereum	Ripple
	Entire Period								
Mean	15.456,90	4,66	56,03	1,35	35,38	24.204,65	33.514,17	1.911,05	0,58
Median	15.457,00	4,67	56,09	1,35	35,24	24.270,00	29.908,74	1.849,94	0,60
Maximum	15.920,00	4,79	57,22	1,37	37,09	24.604,00	46.970,50	2.618,08	0,77
Minimum	15.007,00	4,52	54,47	1,32	34,19	23.647,00	25.162,65	1.539,70	0,47
Std. Dev.	214,20	0,06	0,70	0,02	0,73	266,63	6.821,97	285,86	0,07

Skewness	0,19	-0,34	-0,35	-0,17	0,37	-0,73	0,42	0,60	0,28
Kurtosis	2,66	0,34	1,87	1,64	2,31	2,53	1,64	2,22	2,19
Jarque-Bera	2,01	0,34	13,38	14,86	7,66	17,99	19,26	15,34	7,24
Probability	0,37	0,34	0,00	0,00	0,02	0,00	0,00	0,00	0,03
Before Period									
Mean	15.342,15	4,64	56,30	1,36	35,51	24.049,56	27.481,11	1695,22	0,56
Median	15.337,55	4,65	56,62	1,36	35,47	24.060,00	27.076,78	1650,49	0,52
Maximum	15.739,00	4,73	57,22	1,37	37,09	24.490,00	30.084,54	1891,75	0,77
Minimum	15.007,00	4,52	54,47	1,33	34,19	23.647,00	25.162,65	1539,70	0,47
Std. Dev.	191,76	0,06	0,74	0,01	0,83	281,25	1.397,81	110,18	0,08
Skewness	0,44	-0,51	-1,47	-0,85	0,20	-0,00	0,35	0,57	1,12
Kurtosis	2,56	2,01	3,67	2,58	2,01	1,52	1,63	1,79	2,79
Jarque-Bera	3,58	7,66	34,04	11,57	4,29	8,23	8,89	10,47	18,84
Probability	0,17	0,02	0.00	0,00	0,12	0,02	0,01	0,01	0,00
After Period									
Mean	15.567,75	4,68	55,75	1,34	35,24	24.355,84	39.600,51	2.130,72	0,61
Median	15.511,00	4,67	55,62	1,34	35,20	24.322,50	40.611,11	2.185,12	0,61
Maximum	15.920,00	4,79	56,88	1,37	36,53	24.604,00	46.970,50	2.618,08	0,71
Minimum	15.259,00	4,59	54,83	1,32	34,20	24.130,00	29.682,95	1.603,89	0,51
Std. Dev.	170,01	0,05	0,53	0,02	0,60	125,91	4.200,69	2.364,14	0,04
Skewness	0,71	0,69	0,94	0,53	0,28	0,69	-0,31	-0,12	-0,16
Kurtosis	2,61	2,76	2,75	2,03	2,20	2,18	2,09	2,40	3,24
Jarque-Bera	8,12	7,42	13,51	7,71	3,60	9,70	4,56	1,57	0,59
Probability	0,02	0,02	0,00	0,02	0,17	0,01	0,10	0,46	0,75

The results of descriptive statistical analysis for selected variables over entire period (from July 21, 2023, to January 17, 2024) are presented in Table 1. Based on standard deviation, Bitcoin was the most volatile variable, with a value of 6,821.974, while the exchange rate of SGD was the least volatile, with a value of 0.02. This indicates that Bitcoin was more prone to experiencing large price fluctuations compared to SGD exchange rate. The price distributions of all ASEAN-6 exchange rates were negatively skewed, except for IDR exchange rate, suggesting a higher probability of price decreases compared to price increases. Overall, SGD exchange rate exhibited minimal volatility during this period, indicating that investing in this currency posed moderate to low risk. However, during the period before Red Sea War event (from July 21, 2023, to October 18, 2023), exchange rate of MYR was one of the least volatile variables, but its price distribution exhibited negative skewness. This suggests that prior to Red Sea War event; probability of a price decrease for MYR was higher than that of a price increase. During this pre-crisis period, the exchange rates of PHP and Ripple demonstrated greater stability compared to other variables. In contrast, during the period after Red Sea War event (from October 20, 2023, to January 17, 2024), exchange rate of MYR emerged as second least volatile variable, following Ripple. The low volatility of MYR during this period was accompanied by positive skewness, indicating that probability of a price increase was higher than that of a price decrease. This shift suggests that, following the crisis, investing in MYR became a safer choice for investors seeking moderate to low-risk options.

Table 2: Normality Test

Variables	Before war	After war	Test
USD/IDR	0,003	0,000	*Wilcoxon signed rank test*
USD/MYR	0,000	0,000	*Wilcoxon signed rank test*
USD/SGD	0,000	0,000	*Wilcoxon signed rank test*

Variables	Before war	After war	Test
USD/THB	0,004	0,011	*Wilcoxon signed rank test*
USD/PHP	0,000	0,000	*Wilcoxon signed rank test*
USD/VND	0,000	0,000	*Wilcoxon signed rank test*
Bitcoin	0,000	0,000	*Wilcoxon signed rank test*
Ethereum	0,000	0,092	*Wilcoxon signed rank test*
Ripple	0,000	0,042	*Wilcoxon signed rank test*

Based on the results of the normality test in Table 2 for various variables before and after the Red Sea War event, most variables exhibit a non-normal distribution in both periods, with p-values below 0.05. Exchange rate variables, such as USD/IDR, USD/MYR, USD/SGD, USD/THB, USD/PHP, and USD/VND, consistently show significance values indicating a non-normal data distribution in both periods, with p-values of 0.000 for most variables. For digital asset variables, Bitcoin and Ripple demonstrate non-normal distributions in both periods, whereas Ethereum approaches a normal distribution after the Red Sea War event, with a p-value of 0.092. However, despite this post-event indication of normality, Ethereum's pre-event distribution did not satisfy the normality assumption (p-value = 0.000). Since paired statistical tests require normality in both pre- and post-event distributions for a parametric approach, a non-parametric test remains the most appropriate choice. To ensure methodological consistency and robustness against deviations from normality, the Wilcoxon Signed-Rank Test is applied for all variables in the subsequent analysis. This approach prevents inconsistencies that could arise from switching between parametric and non-parametric tests within the same dataset and ensures that the analysis remains statistically valid. Table 3 presents the results of Wilcoxon Signed Rank Test.

Table 3: Difference Test

Variables	Difference Testing	
	Sig	Result
USD/IDR	0,000	Significant
USD/MYR	0,036	Significant
USD/SGD	0,000	Significant
USD/THB	0,084	No Significant
USD/PHP	0,001	Significant
USD/VND	0,000	Significant
Bitcoin	0,000	Significant
Ethereum	0,000	Significant
Ripple	0,000	Significant

Based on the results of difference test in Table 3, conducted using event study method on Red Sea War event, most exchange rates and cryptocurrencies show significant differences during the crisis period, except for USD/THB variable. This can be seen from significance values (Sig.) being smaller than 0.05 for almost all variables. The exchange rates of USD/IDR, USD/MYR, USD/SGD, USD/PHP, and USD/VND experienced significant changes with significance values below 0.05, indicating that Red Sea War event had an impact on exchange rate fluctuations in these countries. These findings support previous research which states that USD/IDR, USD/MYR, USD/SGD, and USD/PHP experienced differences after occurrence of global economic events (2-5, 25, 27, 28). Similarly, this is supported by earlier studies that state USD/VND variable differed as a result of global economic events (5, 6). However, for USD/THB exchange rate (Sig. = 0.084), no significant difference was found, indicating that this exchange rate was not greatly affected by Red Sea War event. The same trend was observed in cryptocurrencies, namely Bitcoin, Ethereum, and Ripple, which showed significant differences during Red Sea War event period. This finding is supported by prior research stating that Bitcoin market was affected by global economic events (7, 9, 10, 12, 13, 17). Likewise, previous studies have shown that Ethereum experienced differences during global economic events (12-14, 19). The Ripple market, which also showed significant differences, is similarly supported by other previous studies (10, 12). These results reflect that Red Sea War event had a broad and significant impact, not only on stock markets and exchange rates but also on commodities and crypto currencies. Before proceeding to GARCH modelling stage for time series data analysis, the stationarity of research data must first be identified. This step is crucial because, in constructing a model, data under study must be stationary. Stationarity in time series data is essential for analysis, as only stationary data allow for accurate modelling and prediction of relationships between variables. Stationarity ensures that statistical properties, such as mean and variance, remain constant over time, which is a prerequisite for reliability of analytical results and predictions derived from the model. One method for testing data stationarity is Unit Root Test, performed using Augmented Dickey-Fuller (ADF) Test. Table 4 presents the results of the Augmented Dickey-Fuller (ADF) test, which examines the stationarity of exchange rate and cryptocurrency data before and after the Red Sea War event. The results of ADF test conducted using E-Views 9 are as follows. The consistently low ADF probability values (<0.01) indicate that all variables are stationary at the 1% significance level, allowing for further analysis without additional differencing.

Table 4: Augmented Dickey–Fuller Test

Variables	Before Red Sea War			After Red Sea War			Entire Period		
	ADF t	ADF Prob	Trend Prob	ADF t	ADF Prob	Trend Prob	ADF t	ADF Prob	Trend Prob
USD_IDR	-10,288	0,000*	0,651	-8,408	0,000*	0,173	-11,131	0,000*	0,297
USD_MYR	-9,965	0,000*	0,805	-8,302	0,000*	0,476	-11,226	0,000*	0,125
USD_SGD	-9,128	0,000*	0,246	-8,647	0,000*	0,096	-12,307	0,000*	0,238
USD_THB	-9,215	0,000*	0,209	-7,027	0,000*	0,591	-11,934	0,000*	0,393
USD_PHP	-8,744	0,000*	0,086	-10,051	0,000*	0,655	-11,666	0,000*	0,162
USD_VND	-9,799	0,000*	0,730	-8,251	0,000*	0,922	-11,644	0,000*	0,312
Bitcoin	-11,797	0,000*	0,921	-12,099	0,000*	0,640	-11,329	0,000*	0,932
Ethereum	-11,190	0,000*	0,714	-9,978	0,000*	0,748	-15,624	0,000*	0,070
Ripple	-10,744	0,000*	0,107	-8,975	0,000*	0,170	-14,012	0,000*	0,237

Note: *shows the 1% significance level

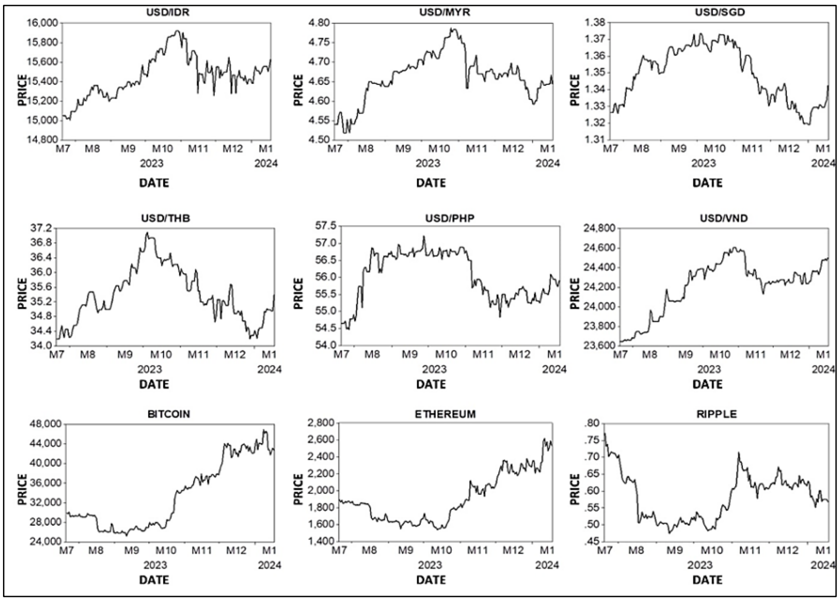

Figure 4: Price Trends in Exchange Rate and Crypto Currency over the Period of 21 July 2023 to 17 January 2024

Figure 4 and 5 illustrates price trend during the observation period, where daily closing prices of each variable continued to fluctuate, with movements that were difficult to predict. These price fluctuations indicate high volatility in the market, which could contribute to increased uncertainty for investors.

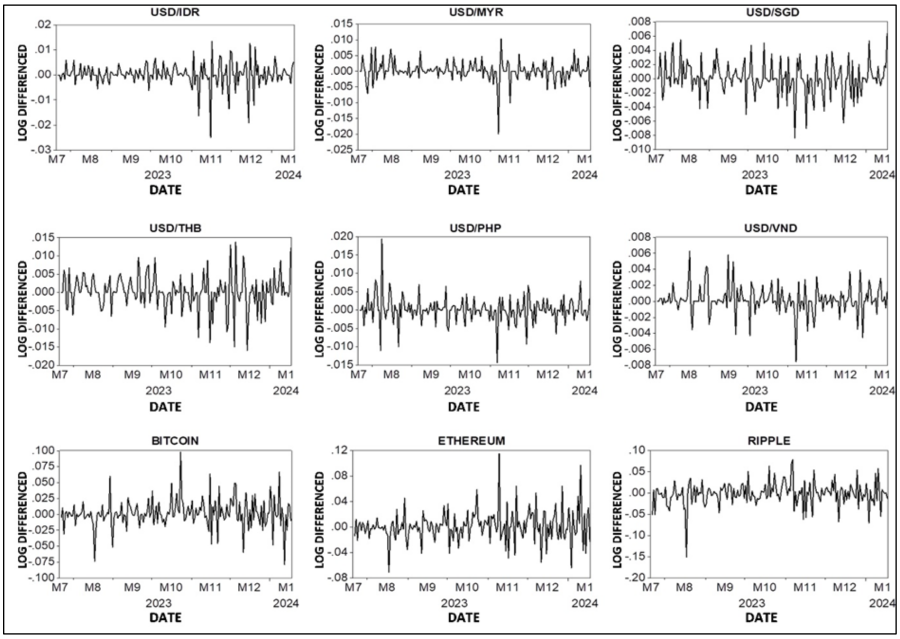

Figure 5: Price Fluctuations in Exchange Rate and Cryptocurrency over the period of 21 July 2023 to 17 January 2024

Table 5: Results Based on the GARCH Models for Entire Study Period

Variables	Model	Log	AIC	α (ARCH)	β (GARCH)	γ (Gamma)
	GARCH (1,1)	-993,728	11,097	0,104 *	0,896 *	-
USD_IDR	GJR-GARCH (1,1)	-992,281	11,092	0,049	0,885 *	0,192 *
	EGARCH (1,1)	-990,304	11,070	0,073	0,943 *	-0,224 *
	GARCH (1,1)	523,537	-5,762	0,265 *	0,691 *	-
USD_MYR	GJR-GARCH (1,1)	529,674	-5,819	0,006	0,732 *	0,380 *
	EGARCH (1,1)	528,149	-5,802	0,656 *	0,309 *	-0,223 *
	GARCH (1,1)	794,972	-8,766	-0,051 **	0,749 *	-
USD_SGD	GJR-GARCH (1,1)	801,920	-8,832	-0,161 *	0,884 *	0,144 *
	EGARCH (1,1)	2.775,735	-30,764	-0,164 *	0,961 *	-0,053 *
	GARCH (1,1)	-412,368	2,243	-0,420	0,450 *	-
USD_THB	GJR-GARCH (1,1)	-225,008	3,190	-0,220	0,670	-11,281 *
	EGARCH (1,1)	-2,104	0,243	-0,341 **	-0,792	-0,282 *
	GARCH (1,1)	-302,127	1,440	-0,158 *	-0.341 *	-
USD_PHP	GJR-GARCH (1,1)	-243,180	5,624	-0,320	0,221	-0,132
	EGARCH (1,1)	125,222	-1,324	-0.551 *	0,112	-0.350 *
	GARCH (1,1)	-2.079,690	23,024	0,121	0,600 **	-
USD_VND	GJR-GARCH (1,1)	-2.079,690	23,035	0,121	0,600	0,050
	EGARCH (1,1)	-1.763,988	19,547	0,094	-0,060	0,091
Bitcoin	GARCH (1,1)	1.244,113	-13,768	0,021 **	-0,996 *	-

	GJR-GARCH (1,1)	-955,122	10,701	0,441 *	0,759 *	-0,175 *
	EGARCH (1,1)	805,283	-8,881	0,308 *	-0,940 *	-0,055 *
	GARCH (1,1)	-654,611	5,424	-0,100 *	0,320 *	-
Ethereum	GJR-GARCH (1,1)	-780,828	8,211	-0,110	0,125	-1,328
	EGARCH (1,1)	-657,717	7,826	0,210	-0,210	0,431 *
	GARCH (1,1)	240,451	-1,799	0,120 *	0,221 *	-
Ripple	GJR-GARCH (1,1)	-99,441	0,670	0,100	0,781	-0,998
	EGARCH (1,1)	221,350	-1,444	-0,221	0,827 *	-0,220

Note: ** refers to 10% significance level, and * refers to 5% significance level

Table 5 shows the results of the GARCH testing on variables in this study. The finding for USD/IDR variable show that in GARCH (1,1) model, α = 0.104 indicates that current volatility is significantly influenced by past shocks. β = 0.896 shows that volatility is quite persistent, but no asymmetry effects are captured. In GJR-GARCH (1,1) model, γ = 0.192* shows presence of asymmetry, where negative shocks have a greater impact on volatility. However, α is not significant, which may suggest that past shock effects are not very strong. In the EGARCH (1,1) model, γ = -0.224* indicates strong asymmetry, where negative shocks have a more significant impact on volatility than positive shocks. β = 0.943* indicates that volatility is highly persistent. Based on AIC values, it can be concluded that EGARCH (1, 1) model is the best due to its lowest AIC value (11.070). The EGARCH model captures asymmetry, where negative shocks have a greater impact on volatility than positive shocks. In the context of USD/IDR, volatility is often higher during negative external shocks, such as global economic instability or monetary policies that cause depreciation of rupiah. This finding is critical for Indonesia, where the economy is sensitive to global financial pressures such as U.S. monetary policy or geopolitical crises. For policymakers, this implies that risk communication strategies should be strengthened during periods of negative global news to stabilize expectations. Currency hedging strategies for import-dependent industries should prioritize protection during downturns, as volatility tends to intensify in such conditions. For the USD/MYR exchange rate, the result indicates that in the GARCH (1, 1) model, past volatility (α = 0.265) significantly influences current volatility, while volatility is quite persistent (β = 0.691), but no asymmetry is captured, suggesting that both positive and negative shocks have similar effects. The GJR-GARCH (1,1) model shows that past volatility is not significant (α = 0.006), but volatility is quite persistent (β = 0.732), and there is a significant asymmetry effect (γ = 0.380), indicating that negative shocks have a greater impact on volatility. The EGARCH (1, 1) model captures significant negative asymmetry (γ = -0.223), where negative shocks have a greater impact on volatility, with volatility dissipating more quickly compared to other models (β = 0.309). Based on the AIC value, the GJR-GARCH (1, 1) model is selected as the most appropriate for modelling USD/MYR volatility, indicating that this exchange rate responds asymmetrically to shocks—particularly, negative news or events have a stronger influence on volatility than positive ones. This result is especially relevant in the context of Malaysia's open economy, which is highly integrated into global trade and sensitive to geopolitical disruptions such as the Red Sea conflict. The significant asymmetry suggests that investor sentiment in Malaysia is more reactive to adverse developments, likely due to concerns over trade route disruptions and commodity price volatility, both of which are critical to Malaysia's economy. For policymakers and investors in the ASEAN-6 region, these findings underline the need for tailored strategies. Central banks might consider pre-emptive communication during global crises to stabilize expectations, while institutional investors should enhance scenario-based risk assessments that account for geopolitical risks. Additionally, export-oriented sectors, which are prominent in Malaysia, may benefit from using currency derivatives not just as a generic hedge, but timed with geopolitical developments, as volatility spikes are more likely during negative news cycles. The analysis of the USD/SGD exchange rate show different volatility behaviours across the models. In GARCH (1, 1) model, ARCH coefficient (α) is negative (-0.051) and significant at 5% level, indicating that short-term volatility shocks have a dampening effect on current volatility. GARCH coefficient (β) of 0.749 indicates strong volatility persistence from previous period to current period. The GJR-GARCH (1, 1) model shows a more negative ARCH coefficient (-0.161) and significant, indicating a greater impact of negative shocks on volatility. The β coefficient of 0.884, which is significant, shows a high level of volatility persistence. The gamma coefficient (γ) is positive and significant (0.144), showing presence of asymmetry, where volatility responds more strongly to negative shocks. The EGARCH (1, 1) model shows similar results with a negative ARCH coefficient (-0.164) and significant, as well as a GARCH coefficient (β) close to one (0.961), indicating very high volatility persistence. The negative gamma value (-0.053) indicates that volatility responds to negative shocks with lower intensity. Among the three models, the EGARCH (1,1) is identified as the best fit for modelling USD/SGD volatility, as indicated by the lowest AIC value (-30.764). This model effectively captures the asymmetric response of volatility to market shocks, particularly in distinguishing between the effects of negative and positive news. Given Singapore's role as a financial hub in ASEAN and its high exposure to global capital flows, this finding is particularly relevant. Volatility in USD/SGD may be more sensitive to global financial shocks, such as interest rate changes in the US or instability in major economies. The EGARCH model's ability to account for such asymmetry enables market participants in Singapore to anticipate disproportionate volatility responses during adverse events. For investors managing crypto or foreign exchange exposures in Singapore, this suggests the need for dynamic hedging strategies, such as using volatility-sensitive instruments like variance swaps or rebalancing crypto-fiat portfolios in anticipation of market stress. Additionally, fintech firms or crypto exchanges operating in Singapore could integrate EGARCH-based volatility forecasts into their algorithmic trading or risk engine models to enhance response mechanisms during macroeconomic shocks. The findings for the USD/THB exchange rate suggest that volatility can be predicted by all three GARCH-type models. The GARCH (1,1) model for USD/THB shows significant results, with a log-likelihood of -412.368 and an AIC of 2.243. The α (ARCH) parameter is negative (-0.420), indicating a relatively slow adjustment of volatility to new shocks—suggesting that the market's reaction to shocks is gradual. Meanwhile, the β (GARCH) value is positive and significant (0.450*), reflecting persistence in volatility, where past volatility contributes to current volatility levels—a typical "memory effect" in financial time series. In the GJR-GARCH (1,1) model, the log-likelihood improves to -225.008, though the AIC increases to 3.190, suggesting a trade-off between fit and complexity. The α value (-0.220) is negative, and the γ parameter (11.281*) is positive and significant, indicating an asymmetric effect, where negative shocks have a greater impact on volatility than positive ones—this captures the leverage effect, which is common in emerging markets like Thailand. Among the models evaluated, the EGARCH (1, 1) model is the most appropriate for capturing USD/THB volatility, as evidenced by the lowest AIC value and significant model parameters. This model effectively captures asymmetric volatility, where negative shocks like geopolitical tensions or domestic political instability trigger a stronger volatility response than positive ones. This characteristic is especially relevant for the Thai Baht, which is often sensitive to external pressures such as changes in global trade flows, tourism trends, or investor sentiment in emerging markets. The ability of the EGARCH model to capture such asymmetries makes it particularly useful in understanding volatility behavior under stress conditions. For instance, during periods of bad news—such as unexpected monetary policy decisions or regional conflicts—volatility tends to rise more sharply, a pattern that symmetric models like GARCH (1, 1) fail to detect. For investors, especially those operating in or exposed to ASEAN-6 markets, the EGARCH (1, 1) model offers valuable insights into managing currency risk in Thailand. It supports the design of responsive hedging strategies that activate when downside risks are detected. For example, corporates with USD-denominated liabilities or revenues can time their hedging instruments in forward contracts or options more effectively, while portfolio managers can rebalance their exposure when signals of volatility asymmetry emerge. Regarding the USD/PHP exchange rate, the analysis indicates that EGARCH (1, 1) is the most effective model in explaining volatility. This is supported by the highest log-likelihood value (125.222) and the lowest AIC (-1.324) among the three models, indicating a better fit and more efficient performance. The α (ARCH) parameter in the EGARCH model is negative and significant (-0.551*), suggesting a quick market response to shocks. Furthermore, the γ parameter (-0.350*) is also significant and negative, confirming the presence of leverage effects, where negative shocks have a larger impact on volatility compared to positive ones. Although the β (GARCH) parameter (0.112) is relatively low, the overall significance of the model makes it the most suitable for capturing the dynamics of volatility in the PHP market. In contrast, the GARCH (1, 1) model, while having a decent fit (log-likelihood of -302.127 and AIC of 1.440), fails to capture asymmetry since it does not include a γ term. Its parameters are significant (α = -0.158*, β = -0.341*), indicating persistence and basic volatility features, but it lacks the ability to detect differing impacts of negative versus positive shocks. The GJR-GARCH (1, 1) model has a lower performance with a higher AIC (5.624) and a less favorable log-likelihood (-243.180). While it includes asymmetry through the γ parameter (-0.132), this value is not statistically significant, and other parameters also lack strong significance, suggesting that this model is less reliable in explaining PHP volatility. This model's strength lies in its ability to capture asymmetric volatility, where negative shocks—such as adverse economic news, political instability, or tightening global financial conditions—lead to a disproportionate increase in volatility compared to positive shocks. From an investment and policy perspective, the adoption of EGARCH (1, 1) as the best-fit model implies that risk management strategies must be more responsive to downside risks. Investors with exposure to the Philippine market—such as multinational corporations, forex traders, or portfolio managers—should be particularly alert to indicators of negative market sentiment. These indicators could trigger volatility spikes, which, if anticipated early, can inform timely hedging strategies using instruments like currency options or dynamic reallocation of assets into more stable regions or currencies. Moreover, for policymakers or financial institutions in the Philippines, the insight from EGARCH modelling provides an analytical foundation for preparing against potential market shocks. This could involve building up foreign reserves, pre-emptively adjusting interest rates, or issuing guidance to market participants. For the USD/VND exchange rate, the analysis reveals that the GARCH (1, 1) model has superior performance with a log-likelihood of -2,079,690. This model is more effective compared to GJR-GARCH (1, 1) and EGARCH (1, 1). Although both alternative models are designed to provide additional information on volatility dynamics, the analysis shows that α and β coefficients in both models are not significant. This inefficacy suggests that GJR-GARCH and EGARCH cannot capture the real volatility behaviour of USD to VND exchange rate, thereby reducing their effectiveness in analysing market fluctuations. In contrast, the GARCH (1, 1) model provides a more stable and consistent contribution to volatility, even though it does not capture leverage effects. The insignificance of asymmetry in both GJR-GARCH and EGARCH models suggests that the standard GARCH (1, 1) model is the most appropriate for modelling USD/VND volatility. Although this model does not capture leverage effects, its superior performance highlights that volatility in the Vietnamese exchange market responds more symmetrically to shocks—possibly reflecting the influence of state interventions or a less liberalized currency regime. This is particularly important for investors and policy analysts, as it indicates that extreme market movements do not disproportionately affect volatility, allowing for more stable volatility forecasting. For investors with exposure to the Vietnamese dong, especially those managing forex positions or engaging in crypto-fiat arbitrage involving VND, the use of the GARCH (1, 1) model enables more consistent and reliable risk estimates. In the context of Vietnam's emerging market dynamics within ASEAN-6, this model supports the development of medium-term risk management strategies—such as gradually adjusting positions rather than aggressive hedging—especially during episodes of regional or global uncertainty. When analyzing Bitcoin volatility, significant differences emerge between the three models. The GARCH (1, 1) model reveals high persistence in volatility (β = 0.938), suggesting that past volatility strongly affects future volatility. However, this model does not account for asymmetric responses to positive and negative shocks. On the other hand, GJR-GARCH (1, 1) model shows a positive γ (0.398), capturing volatility asymmetry, indicating that negative shocks have a greater impact than positive shocks.

The EGARCH (1, 1) model reveals a negative γ (-0.171), confirming that Bitcoin volatility is more affected by negative shocks. The EGARCH model emerges as the most appropriate for modeling Bitcoin volatility, highlighting the importance of asymmetry in the crypto market. Unlike traditional assets, Bitcoin is highly sensitive to negative news—such as regulatory crackdowns or macroeconomic shocks—which can trigger disproportionately large volatility spikes. The EGARCH framework effectively captures this behavior, offering a more realistic view of market dynamics. For crypto investors and portfolio managers, this implies a need for more dynamic and event-driven risk management strategies. Rather than relying solely on historical volatility, market participants should incorporate sentiment analysis, monitor policy developments, and adjust their exposure accordingly. In the ASEAN-6 context, where regulatory clarity varies significantly across countries, this model also helps identify periods of heightened systemic risk, allowing crypto investors to implement more tailored hedging strategies—such as using stablecoins, volatility-index derivatives, or adjusting crypto-fiat allocations to buffer against downside risks. For Ethereum, the GARCH (1,1) model demonstrates strong performance in capturing volatility dynamics. This model yields a log-likelihood of -654.611 and the lowest AIC (5.424) among the three models, suggesting it is the most efficient in balancing model fit and complexity. The GARCH component (β = 0.320*) is statistically significant, indicating that past volatility has a strong and lasting impact on current volatility. This reflects the volatility persistence commonly observed in cryptocurrency markets, particularly during periods of crisis or high speculation. The α (ARCH) parameter is also significant and negative (-0.100*), indicating that volatility adjusts gradually to new information or shocks. In contrast, the GJR-GARCH (1,1) model records a higher AIC (8.211) and a log-likelihood of -780.828, indicating a poorer model fit. While it attempts to account for asymmetry through the γ parameter (-1.328), this value is not statistically significant, suggesting that the model fails to effectively capture the leverage effect, where negative shocks might impact volatility differently from positive ones. Additionally, the GARCH and ARCH components are not significant, further reducing the model's reliability for this dataset. The EGARCH (1, 1) model performs moderately, with a log-likelihood of -657.717 and AIC of 7.826. While its α (ARCH) component is positive (0.210) and β (GARCH) is negative (-0.210), neither is significant. However, the γ parameter (0.431*) is positive and statistically significant, indicating that the EGARCH model successfully captures asymmetric volatility in Ethereum—where negative news has a stronger effect on volatility than positive news. Overall, the GARCH (1, 1) model is the most appropriate for explaining Ethereum's volatility, as it offers the best statistical fit (lowest AIC), significant parameters, and a simple structure that provides clear insights into volatility persistence. For investors, especially in the ASEAN-6 region where crypto markets are growing but remain volatile and lightly regulated, GARCH (1, 1) serves as a practical model for forecasting Ethereum volatility. It supports more robust portfolio decisions by emphasizing the impact of past volatility shocks, aiding in risk-adjusted strategies such as position sizing, volatility-based stop-losses, and identifying volatility clustering periods for better trade execution. Understanding this persistence is critical for navigating the uncertain and fast-moving crypto environment. For Ripple, the GARCH (1,1) model provides the best statistical fit with the lowest AIC (-1.799) and significant α (0.120*) and β (0.221*) values, indicating strong volatility persistence influenced by both recent and past shocks. The EGARCH (1, 1) model also performs well, with a significant β (0.827*) and relatively low AIC (-1.444), capturing persistence and potential asymmetry through its negative γ (-0.220), although the asymmetry is not statistically significant. In contrast, the GJR-GARCH (1, 1) model shows no significant parameters and a higher AIC (0.670), making it the least effective. Among the models tested, the standard GARCH (1, 1) model proves to be the most effective in modeling Ripple's volatility. This model captures the persistence of volatility in the Ripple market, suggesting that current price fluctuations are strongly influenced by past volatility patterns. While more complex models like EGARCH and GJR-GARCH attempt to account for asymmetries, their lack of significant asymmetric components indicates that Ripple's volatility does not respond differently to negative versus positive shocks in a statistically robust way. This implies that Ripple's price movements are more influenced by general market momentum than by directional sentiment. For crypto investors and traders in the ASEAN-6 context, particularly in markets with increasing retail participation and limited derivative instruments, the simplicity and stability of the GARCH (1,1) model offer practical advantages. It supports volatility forecasting for applications such as algorithmic trading, risk budgeting, or deciding entry/exit points based on expected price fluctuation ranges, without relying on complex asymmetric volatility assumptions.

Discussion

The analysis of volatility using the GARCH (1, 1) model and its extensions, such as GJR-GARCH and EGARCH, provides valuable insights for developing investment strategies that aim to minimize risks and maximize returns amid increasing global economic uncertainty. This analysis offers a meaningful understanding of volatility behavior across various financial markets, including currency pairs and cryptocurrency assets. For the USD/IDR exchange rate, the EGARCH (1, 1) model indicates heightened volatility in response to negative shocks, suggesting that markets tend to react more strongly to adverse news or economic uncertainty. This finding is consistent with research showing that Indonesia, as an inflation-targeting economy, experiences persistent asymmetric effects of exchange rate shocks, particularly over the long term (5). The Indonesian rupiah has also been identified as highly responsive to global shocks, especially during the COVID-19 period, with both short-term volatility and long-run contagion effects reflecting fundamental-based transmission risks (2). Moreover, exchange rate volatility in Indonesia is structurally linked to regional financial integration and exposure to external vulnerabilities (3). These findings emphasize the importance of adopting defensive strategies, such as reducing exposure to high-risk assets, employing hedging instruments like currency futures or options, and implementing geographical portfolio diversification to reduce the impact of Indonesia-specific risks. For the USD/MYR exchange rate, the GJR-GARCH (1, 1) model reveals significant asymmetry, where volatility increases more sharply in response to negative shocks compared to positive ones. This is aligned with prior studies highlighting Malaysia’s sensitivity to fundamental contagion, particularly during crisis periods such as the COVID-19 pandemic (2). The prolonged high volatility of the Malaysian ringgit supports the argument that external shocks, especially those related to trade and capital flows, have lasting effects on exchange rate dynamics (2, 3). These findings suggest that investors should exercise greater caution by utilizing derivative instruments such as futures or options to both hedge against risks and take advantage of volatility-based opportunities. In the case of the USD/SGD exchange rate, the EGARCH (1, 1) model provides the best performance in capturing asymmetric volatility, particularly in response to negative shocks. Singapore’s managed floating exchange rate regime has demonstrated sensitivity to both global economic developments and regional contagion. Empirical evidence indicates a relatively quick adjustment toward long-term equilibrium following market disturbances (2). Research also finds that Singapore experiences both short- and long-run volatility during external crises, such as the COVID-19 pandemic (3). Considering Singapore’s role as a major financial hub in Asia, such volatility has significant implications for institutional and retail investors alike. In these conditions, comprehensive risk management approaches are recommended, including the use of derivative contracts and portfolio reallocation into more stable sectors such as infrastructure and utilities to mitigate exposure to currency fluctuations. Regarding the USD/THB exchange rate, the EGARCH (1, 1) model is the most effective in capturing volatility patterns, especially during negative shocks. This supports the view that the Thai market is highly responsive to global uncertainty and external events, often experiencing sharp increases in volatility during periods of financial distress (2). Additionally, studies have emphasized Thailand’s role as a regional transmission channel of volatility, with its exchange rate reflecting and contributing to broader market fluctuations across ASEAN economies (3). Therefore, investors are advised to adopt protective measures, including the use of options and currency futures, to manage risk more proactively in anticipation of macroeconomic or geopolitical developments. For the USD/PHP exchange rate, the EGARCH (1, 1) model also demonstrates strong explanatory power in capturing volatility behavior, particularly the asymmetric impact of negative news on exchange rate movements. This reflects the Philippine market's vulnerability to investor sentiment and global financial shocks (2). The lingering effects of recent crises, such as the COVID-19 pandemic, have intensified this susceptibility, making the peso more reactive to external uncertainty (29). In response, investors should consider monitoring historical volatility trends and applying data-driven strategies to optimize timing in their investment decisions, supported by the use of derivatives to manage potential volatility surges. With regard to the USD/VND exchange rate, the GARCH (1, 1) model is most appropriate in capturing persistent volatility patterns, although it does not exhibit strong asymmetric responses to shocks. This suggests that the Vietnamese dong, while subject to market fluctuations, is relatively stable under directional shocks due to its tightly managed exchange rate regime (3). While this framework may limit the frequency of extreme short-term volatility, long-term risks remain, particularly due to Vietnam's reliance on trade and exposure to external financial disturbances. In this context, investors may find it more beneficial to focus on diversification and macroeconomic trend monitoring rather than speculative trading strategies, using GARCH-based projections to guide portfolio allocations. In the context of cryptocurrency markets, Bitcoin remains a primary focus due to the GJR-GARCH model revealing significant leverage effects. These findings indicate that volatility tends to rise sharply during periods of declining prices, particularly during times of financial stress, such as the COVID-19 pandemic and the Russia–Ukraine conflict (18, 19). These results reinforce the perspective that Bitcoin functions more as a speculative asset than a safe haven, reacting strongly to negative external events (9, 14). Investors may take advantage of this volatility by implementing strategies such as short-selling, trading in derivatives, or utilizing algorithmic systems designed to capitalize on large price movements and improve decision-making during high-volatility periods. Ethereum, in contrast, is best modelled using the GARCH (1,1) framework, which reveals strong volatility persistence with minimal evidence of asymmetry. This indicates that Ethereum's volatility tends to follow a more stable and predictable pattern, particularly under stress. Such behavior aligns with its broader use case as a utility-based platform that supports decentralized applications and smart contracts. Prior studies have identified Ethereum's more stable performance relative to Bitcoin, particularly during periods of heightened global risk (14, 18). These features make Ethereum suitable for long-term investment strategies focused on diversification, periodic portfolio rebalancing, and the use of staking mechanisms to generate passive income. Ripple (XRP) also demonstrates volatility behavior that is best explained by the GARCH (1, 1) model, indicating persistent but symmetrical fluctuations. Although XRP has often been associated with regulatory news and legal developments, the model findings suggest that its volatility is more strongly influenced by historical price trends than by abrupt news-driven asymmetries (10, 30). In this context, technical and historical data analysis can help identify optimal entry and exit points. For investors focused on longer time horizons and systematic risk exposure, XRP presents an opportunity to enhance returns during relatively stable periods without relying on reactive sentiment-based trading strategies. Taken as a whole, these findings show that volatility modelling using GARCH-type approaches offers meaningful insights across both traditional currency and cryptocurrency markets. While Bitcoin presents the most exploitable volatility, it also carries the highest risk exposure. Conversely, assets like Ethereum and Ripple offer more stable patterns that are suitable for strategic positioning. To manage such diverse risk profiles, investors should incorporate derivative instruments, hedging strategies, and portfolio diversification into their decision-making processes. These conclusions contribute to the broader literature on investment risk management and provide practical guidance for navigating the increasingly dynamic landscape of global financial markets.

Conclusion

This study highlights significant findings regarding the volatility and distribution patterns of selected financial variables during the observation period spanning July 21, 2023, to January 17, 2024. Bitcoin demonstrated the highest volatility, reflecting its susceptibility to substantial price fluctuations, while the exchange rate of Singapore Dollar (SGD) showed the lowest volatility, indicating its stability and low-risk profile. The analysis of price distributions revealed that most ASEAN-6 exchange rates were negatively skewed, with the exception of Indonesian Rupiah (IDR), implying a greater likelihood of price decreases. Before Red Sea War event, Philippine Peso (PHP) and Ripple were identified as the most stable variables, while Malaysian Ringgit (MYR) exhibited low volatility but a tendency toward price decreases. After Red Sea War event, a noticeable shift in volatility and distribution patterns was observed. Malaysian Ringgit (MYR) became the second least volatile variable, following Ripple, and transitioned to a positively skewed distribution, suggesting an increased likelihood of price appreciation. This shift indicates that MYR emerged as a safer investment option post-crisis. Overall, the findings emphasize dynamic behavior of financial variables during periods of geopolitical uncertainty and underline the importance of assessing volatility and skewness when evaluating investment risks and opportunities in volatile markets. Based on the analysis, investors are advised to exercise caution when considering high-volatility assets like Bitcoin due to the significant risk of price fluctuations. Instead, prioritizing low-volatility and positively skewed assets such as Malaysian Ringgit (MYR) and Ripple, particularly in post-crisis conditions, could offer more stable and predictable returns. Furthermore, assets like Singapore Dollar (SGD), which exhibit minimal volatility, may serve as safe havens for risk-averse investors seeking to preserve capital during uncertain periods. Diversification across low-risk assets is recommended to mitigate exposure to highly volatile markets.

Abbreviations

AIC: Akaike Information Criterion, ARCH: Autoregressive Conditional Heteroskedasticity, ASEAN: Association of Southeast Asian Nations, GARCH: Generalized Autoregressive Conditional Heteroskedasticity, IDR: Indonesian Rupiah, MYR: Malaysian Ringgit, PHP: Philippine Peso, SGD: Singapore Dollar, THB: Thai Baht, USD: United States Dollar, VND: Vietnamese Dong.

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Author Contributions

All authors contributed equally to this work.

Conflict of Interest

The authors declare no conflict of interest.

Ethics Approval

Not applicable.

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