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Investment volatility during red sea crisis: Study in ASEAN country

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Abstract: The objective of this research is to investigate the volatility of investment instruments, with the aim of providing the best model for predicting investment value. In this topic, the main concepts and theories that underpin the research are presented. Efficient market hypothesis and rational expectations theory stand out, providing a solid basis for understanding the context of the investigation. The methodology adopted for this research GARCH modelling to analysis investment instrument and the impact of its volatility. Data collection was carried out through yahoo finance website and investing website during red sea war event. The research identified optimal GARCH models for different indexes and assets: GARCH (1,1) for JCI, STI, SET, and Bitcoin, E-GARCH (1,1) for KLSE, PSE, and VSE, and GJR-GARCH (1,1) for Gold. It discussed volatility persistence and leverage effects during the Red Sea War, considering model sensitivities, geopolitical impacts, and research limitations. This research's practical and theoretical implications inform financial risk management, highlighting the importance of robust volatility modeling. The findings can enhance portfolio optimization and investment strategies during geopolitical instability. These insights underscore the need for sophisticated approaches to manage financial risks effectively. This research uses advanced GARCH models to analyze volatility during the Red Sea Crisis, revealing asset-specific behaviors under geopolitical stress. The findings improve financial risk management and investment strategies in unstable conditions, enhancing volatility predictions and professional practices.
Keywords: *ASEAN, GARCH, Investment, Red sea crisis, Volatility.*

1. Introduction

Investment plays a critical role in a country's economic growth. Investment market stability and predictability are essential to attract and retain investors, both domestic and international, as it will provide the necessary certainty and confidence for investors to make sustainable and profitable investment decisions. However, global geopolitical conditions often pose challenges which potentially disrupt such stability. One example of a geopolitical crisis that occurred was the Red Sea Crisis, which had a wide impact on global economy, including ASEAN region.

The Red Sea crisis is a geopolitical conflict involving several countries in the region, with implications that go far beyond regional boundaries. This conflict not only disrupts international trade, but also creates uncertainty for investors. Political instability and increasing security threats lead to high market volatility, which in turn influences investment decisions in various sectors of the economy. This condition not only affects countries directly involved in the conflict, but also has an impact on other regions with close economic ties, including ASEAN countries

ASEAN countries with interconnected economies are highly dependent on international trade and are therefore particularly vulnerable to external shocks such as the Red Sea Crisis. Fluctuations in investment flows, exchange rates, and stock markets are some of the impacts of this crisis on the

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ASEAN economy. The following figure explains how stock market fluctuations and gold prices occurred because of the Red Sea War.

Figure 1.
Performance before and after the red sea crisis.
Source: Yahoo Finance.

Figure 1 shows volatility of stock market in ASEAN countries due to Red Sea Crisis. This chart shows the movement of stock indices from various ASEAN countries during the period before and after the Red Sea Crisis. In the chart, the stock indices such as JCI Index (Indonesia), KLSE Index (Malaysia), PSEi (Philippines), STI Index (Singapore), SET Index (Thailand), and VN-Index (Vietnam), experienced significant up-and-down movements, especially at the end of October after the first eruption of Red Sea Crisis. Stock market performance in ASEAN-6 countries often experiences high volatility when events that threaten the global economy occur.

In addition to stock market, global commodities such as gold are also very sensitive to global economic conditions and will fluctuate along with geopolitical uncertainty. When the global economy faces uncertainty or crisis, the price of gold tends to rise because it is considered a safe haven asset by investors. Gold is a commodity that is in demand as an investment even in the conditions of the Red Sea conflict. Likewise, in several events that hit the global economy, gold prices are a commodity whose value has high volatility.

Figure 2.
Bitcoin performance before and after the red sea crisis
Source: Yahoo Finance.

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In addition to the stock market and gold price, Cryptocurrency is also one of the investment assets that is in great demand by investors and is very vulnerable to changes in geopolitical conditions. It can be seen in Figure 2 that one of the cryptocurrency assets, Bitcoin, experienced a sharp increase after the Red Sea Crisis around the end of October. At the end of October 2023 Cryptocurrencies experienced an upswing, with fluctuations experienced until early January 2024. The significant rise in late October 2020 indicates an increase in investor interest and confidence in Bitcoin as a hedge asset during times of crisis.

Based on these phenomena and issues, research was conducted to test whether the red sea crisis had an impact on stock value indices in ASEAN-6 countries, gold prices, and Bitcoin. In addition, this research also analyzed the volatility of stock index values in ASEAN-6 countries, gold prices, and Bitcoin before and after the crisis. Thus, this research is expected to provide valuable insights for readers, especially investors in making investments. This research is expected to enrich the academic literature on the relationship between geopolitical crises and investment volatility in the ASEAN region.

2. Theoretical Framework

Geopolitical events such as the red sea crisis can affect economic conditions globally and trigger unexpected market reactions. The volatile global stock market is characterized by high volatility and increased uncertainty for investors. This turmoil often impacts investor confidence, which can lead to fluctuations in stock indices. In such a situation, it is important for stakeholders to understand the ongoing dynamics to make informed decisions and mitigate the risks. As such, an in-depth analysis of the impact of geopolitical crisis on stock market is essential to assist investors in determining investment strategies. Several previous studies have conducted research related to the impact of geopolitical conditions on a country's stock index(Agustina & Barus, 2023) (Olayungbo et al., 2024)(Mgadmi et al., 2023)(Guo et al., 2021)(Hamil et al., 2023)(Nguyen & Nguyen, 2022)(Truong & Van Vo, 2023)(Hoang Tien et al., 2021)(Alghifary et al., 2023)(Puspitasari, 2024)(Arisandhi & Robiyanto, 2022).

The price of commodities such as gold is one of the investments that is quite sensitive to geopolitical instability. Gold is often considered a safe haven asset, which means investors are likely to turn to gold during times of economic or political uncertainty. When geopolitical tensions arise, demand for gold is likely to increase as investors seek refuge from volatile stock and currency market risks. Gold prices will fluctuate due to the geopolitical crisis due to increasing demand as a safer asset. Therefore, understanding gold price volatility in the context of geopolitical crises is important for investors to make informed decisions and manage the risks associated with gold price volatility. Several previous studies have conducted research related to the impact of geopolitical conditions on global commodity prices such as gold (Agustina & Barus, 2023)(Chemkha et al., 2021)(Kayral et al., 2023)(Daskalakis & Daglis, 2023)(Tetteh & Ntsiful, 2023)(Taera et al., 2023)(Zhang & Mani, 2021)(Nguyen & Nguyen, 2022)(Tunnisa & Darmawan, 2023)(Salikin & Wahab, 2024).

Cryptocurrencies Prices such as Bitcoin are also extremely sensitive to geopolitical instability conditions. Like gold, Bitcoin is often considered a safe haven asset, although it is still relatively new compared to traditional commodities. When geopolitical tensions arise, many investors are looking for alternatives to store their wealth value, and Bitcoin is often acts as a choice due to its decentralized nature and not tied to a particular country's monetary policy. During periods of geopolitical crisis, the demand for Bitcoin can increase significantly. Uncertainty about the stability of a country can encourage investors to shift their assets to Bitcoin as a form of diversification and hedging. This can cause Bitcoin transactions to increase, which leads to bitcoin price fluctuations. Several previous studies have conducted research related to the impact of geopolitical conditions on global commodity prices such as gold(Agustina & Barus, 2023)(Chemkha et al., 2021)(Kayral et al., 2023)(Umar et al., 2021)(Mgadmi et al., 2023)(Guo et al., 2021)(Sarkodie et al., 2022)(Taera et al., 2023)(Zhang & Mani, 2021)(Tunnisa & Darmawan, 2023)(Almeida et al., 2024).

Thus, an analyse of whether the investment instruments included in safe-haven investment are seen in Figure 3.

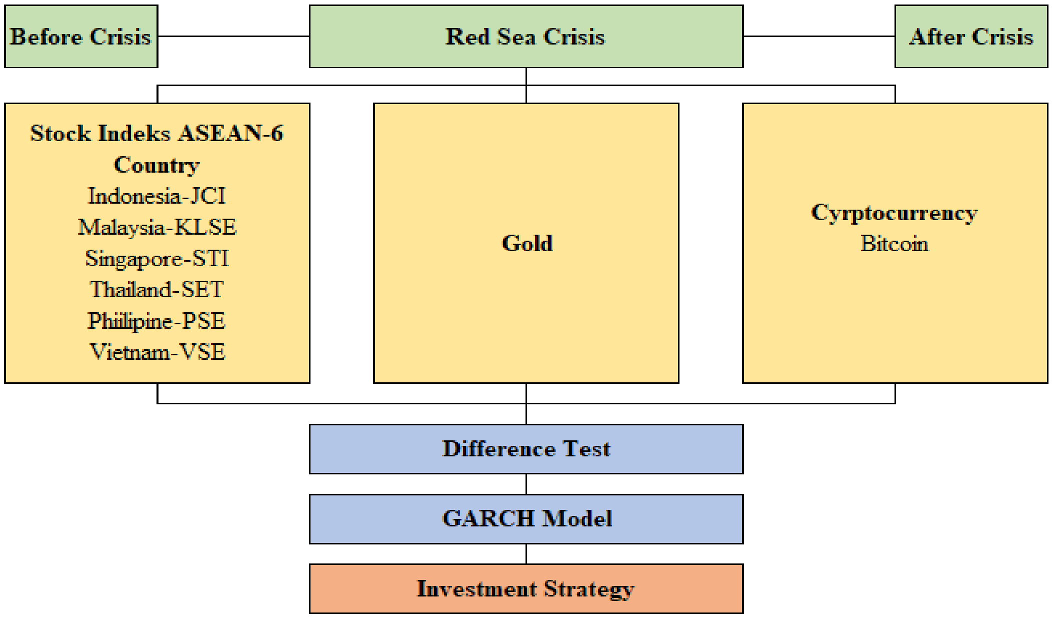

Figure 3.
Theoretical framework.

Based on figure 3, the framework of this research describes differences analysis at stock indices performance in six ASEAN countries (Indonesia-JCI, Malaysia-KLSE, Singapore-STI, Thailand-SET, Philippines-PSE, Vietnam-VSE) on the price of gold and cryptocurrency (Bitcoin) during three periods: before the crisis, during the crisis (referred to as the Red Sea Crisis), and after the crisis. This research uses a difference test and the GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model to analyze the volatility of each of these variables during the red sea war period. The results of this analysis are then used to formulate an optimal investment strategy.

3. Method

This research is quantitative descriptive research with a GARCH analysis model based on impact of the red sea crisis. This research model is used to predict stock index volatility in ASEAN-6 and manage investment portfolios to control investment risks resulting from changes in uncertain economic conditions. The objects of this research are 6 ASEAN countries which have more advanced and larger economies compared to the others, namely Indonesia, Malaysia, the Philippines, Singapore, Thailand, and Vietnam. This research uses secondary data from www.tradingeconomics.com and http://www.finance.yahoo.com The data used in this research was taken 90 days before and after the red sea crisis event, starting from July 21, 2023 until then. January 17, 2024.

The data analysis techniques used in analyzing the data in this research include:

1. Descriptive statistics

This test is used to show the characteristics of the data from this research. This test is to see the research data's mean, median, maximum, and minimum. Descriptive statistics help in looking at the distribution of data and the distribution of data used in this research.

2. Difference Test

This test was carried out to see if there was a significant difference between the conditions before and after the Red Sea crisis. Before conducting a differential test, the researcher conducted a normality

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test first. The normality test aims to find out whether each variable has a normal distribution or not. As for the test, it was carried out by looking at the distribution of data before and after the war. The normality test used Kolmogorov-Smirnov (K-S) statistical analysis. After that, from results of normality test, the type of hypothesis test to be used will be decided. Hypothesis tests are carried out to answer the research question. If the data is distributed normally, One sample t-test will be used. However, if the data is distributed abnormally, one-sample Wilcoxon signed rank test will be used (Agustina & Barus, 2023).

3. GARCH Model

Financial time series often exhibit periods of low volatility followed by periods of high volatility; a phenomenon known as volatility clustering. To model this characteristic in economic and financial time series, ARCH and GARCH models are commonly employed (Bollerslev, 1986).

a. GARCH Model

In financial price volatility modeling, the GARCH family is chosen for its ability to capture dynamic volatility changes and clustering of volatility. Among these models, the one commonly selected is referred to as the GARCH (1,1) model (Karmakar, 2005).

b. GJR-GARCH Model

The GJR-GARCH model was employed to examine asymmetric characteristics in financial market returns. According to this model, it suggests that investors are more anxious about negative returns than they are about positive returns, leading to what is known as the leverage effect (Karmakar, 2005).

c. E-GARCH Model

This model is the exponential GARCH model to account for the asymmetry in the fundamental GARCH model. The E-GARCH model could account for more lags in conditional variance (Nelson1, 1991).

4. Result and Discussion

Based on the closing rates for Stock Indices (JCI, KLSE, SET, STI, PSE, VSE), World Gold, and Crypto Currency (Bitcoin), 90 days before, 90 days after and during the Red Sea War, the research results are as follows:

Table 1.
Descriptive statistic for selected variables.

Statistic/Variables	Bitcoin	Gold	JCI	KLSE	PSE	STI	SET	VSE
Entire period								
Mean	33514.17	1962.036	6986.537	1451.285	6310.842	3180.722	1458.910	57.30315
Median	29908.74	1961.800	6939.890	1451.000	6265.140	3184.300	1431.720	56.97000
Maximum	46970.50	2081.900	7359.760	1501.110	6680.450	3373.980	1576.670	65.47000
Minimum	25162.65	1816.600	6642.420	1413.520	5961.990	3053.360	1357.970	48.47000
Std. Dev.	6821.974	61.98186	154.1577	16.05858	188.4041	75.93907	65.71474	3.907515
Skewness	0.421270	-0.141929	0.681192	0.373443	0.308800	0.433292	0.323565	0.173960
Kurtosis	1.642276	2.450279	2.674506	4.580923	2.234884	2.626672	1.458367	2.004413
Jarque-Bera	19.25605	2.886714	14.79703	23.05607	7.291527	6.714653	21.08203	8.388152
Probability	0.000066	0.236134	0.000612	0.000010	0.026101	0.034828	0.000026	0.015085
Before red sea war								
Mean	27481.11	1912.194	6923.572	1445.229	6315.812	3234.993	1517.117	54.51489
Median	27076.78	1918.450	6922.995	1448.095	6266.340	3218.485	1529.250	53.74000
Maximum	30084.54	1970.500	7016.840	1463.510	6679.130	3373.980	1576.670	58.82000
Minimum	25162.65	1816.600	6852.840	1413.520	6041.040	3136.620	1427.110	48.47000

Statistic/Variables	Bitcoin	Gold	JCI	KLSE	PSE	STI	SET	VSE
Std. Dev.	1397.813	37.77119	43.28175	13.85425	165.3575	57.75065	40.64449	2.204941
Skewness	0.350923	-0.910337	0.392261	-0.992254	0.796269	0.729105	-0.913505	-0.112417
Kurtosis	1.629148	3.222891	2.334073	3.068806	2.639861	2.815348	2.559433	2.530073
Jarque-Bera	8.894336	12.61700	3.971000	14.78628	9.997043	8.101777	13.24524	1.017682
Probability	0.011712	0.001821	0.137312	0.000615	0.006748	0.017407	0.001330	0.601192
After red sea war								
Mean	39600.51	2011.808	7051.060	1457.436	6306.890	3127.352	1401.103	60.11033
Median	40611.11	2007.200	7078.040	1454.380	6260.440	3114.075	1401.560	60.89000
Maximum	46970.50	2081.900	7359.760	1501.110	6680.450	3240.270	1434.590	65.47000
Minimum	29682.95	1932.600	6642.420	1435.330	5961.990	3053.360	1357.970	52.80000
Std. dev.	4200.694	36.40822	194.2941	15.91958	210.5032	48.94090	16.19179	3.186774
Skewness	-0.308301	-0.071936	-0.265987	1.133928	0.076667	0.700155	-0.085054	-0.718397
Kurtosis	2.086262	2.185847	1.783406	3.507667	1.876149	2.554552	2.291383	2.902355
Jarque-Bera	4.556681	2.563289	6.611619	20.25336	4.824574	8.097355	1.991532	7.777165
Probability	0.102454	0.277580	0.036670	0.000040	0.089610	0.017445	0.369440	0.020474

The results of descriptive statistics for selected variables over the entire period (from 21 July 2023 to 17 January 2024) are presented in Table 1. According to standard deviation, Bitcoin was the most volatile with a value of 6821.974, while VSE was the least volatile, with a value of 3.907515. This indicates that Bitcoin was more likely to experience large swings in price than the VSE index. The price distributions of all the variables except Gold were positively skewed, indicating that the probability of price increases was higher than the probability of price decreases. Overall, the VSE Index did not experience much volatility during this period, suggesting that investing in this index has a moderate to low risk. However, the results from the period before the Red Sea Crisis (from 21 July 2023 to 18 October 2023) show that although the VSE index was the least volatile, its price distribution experienced negative skewness. This indicates that before the Red Sea Crisis, the probability of a price decrease was higher than the probability of a price increase. Overall, in the period before the Red Sea Crisis, it is evident that the JCI Index was more stable than the other variables. Nevertheless, the results from the period after the Red Sea Crisis (20 October 2023 to 17 January 2024) show that the KLSE index was the second least volatile variable after the VSE index. The low volatility of this index corresponded with positive skewness, meaning that after the Red Sea Crisis, the probability of a price increase was higher than the probability of a price decrease. Thus, in other words, after this Crisis, investing in the KLSE index became a safe choice for investors with moderate to low risk.

Table 2.
Independent samples Test for difference testing.

Variable	Normality test			Difference testing	
	Before crisis	After crisis	Test	Sig.	Result
JCI index	0,010	0,000	Wilcoxon test	0,000	Significant
KLSE index	0,000	0,000	Wilcoxon test	0,000	Significant
PSE index	0,000	0,001	Wilcoxon test	0,777	No Significant
STI index	0,000	0,000	Wilcoxon test	0,000	Significant
SET index	0,000	0,056	T-test	0,752	No Significant
VSE index	0,006	0,000	Wilcoxon test	0,000	Significant
Gold	0,000	0,018	Wilcoxon test	0,000	Significant

Variable	Normality test			Difference testing	
	Before crisis	After crisis	Test	Sig.	Result
Bitcoin	0,000	0,000	Wilcoxon test	0,000	Significant

Based on Table 2, if the Shapiro-Wilk sig value for either pre and post is above 0.05, then the data is normally distributed, and hypothesis testing is carried out using the independent sample T-Test. Meanwhile, if the Shapiro-Wilk sig value for either pre and post is below 0.05, then the data is not normally distributed, and hypothesis testing is carried out using the Wilcoxon Sign Rank Test. From table 2, it can be explained that the JCI Index, KLSE Index, PSE Index, STI Index, VSE Index, gold, and bitcoin are affected by the wilcoxon test. Meanwhile, the SET Index variable uses a t-test.

Based on the results of difference testing, the variables JCI Index, KLSE index, STI Index, VSE index, gold and bitcoin show the difference between before and after the red sea crisis. Meanwhile, the PSE index and SET Index show that there is no difference between before and after the red sea crisis. From these results, stock indices in Indonesia, Malaysia, Singapore, and Vietnam have experienced a change in sentiment due to the occurrence of the red sea crisis. Similarly, gold and bitcoin also experienced a change in sentiment during the red sea crisis. This shows that the red sea crisis affects global economic conditions, resulting in significant economic disruption due to political and economic uncertainty. However, the PSE index and SET index do not show a difference between before and after the red sea crisis. This happened because investors believed that the impact of the crisis was temporary so that the crisis recovery would take place quickly so that investors remained optimistic and considered that the crisis would not have a long-term impact.

Time series data underwent analysis to detect unit roots. The premise that statistical properties remain consistent over time underpins most statistical tests and methodologies. A stationary time series is essential for modelling and predicting the relationships between variables.

Table 3.
Augmented Dickey–Fuller test results for the selected variables.

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
JCI index	-7.023	0.000*	0.996	-13.937	0.000*	0.537	-9.449	0.000*	0.836
KLSE index	-8.930	0.000*	0.285	-11.890	0.000*	0.869	-12.725	0.000*	0.699
PSE index	-8.126	0.000*	0.741	-11.876	0.000*	0.496	-14.611	0.000*	0.863
STI index	-10.261	0.000*	0.656	-11.088	0.000*	0.445	-15.408	0.000*	0.673
SET index	-11.449	0.000*	0.975	-8.470	0.000*	0.492	-10.326	0.000*	0.907
VSE index	-8.180	0.000*	0.670s	-6.832	0.000*	0.601	-11.616	0.000*	0.992
Gold	-9.059	0.000*	0.545	-8.409	0.000*	0.605	-12.642	0.000*	0.717
Bitcoin	-11.797	0.000*	0.921	-12.099	0.000*	0.640	-11.329	0.000*	0.932

Note: *shows the 1% significance level.

Table 3 shows the results of the augmented Dickey–Fuller (ADF) test for daily closing price returns for selected variables from 21 July 2023 to 17 January 2024. The ADF test was used to determine whether a time series is stationary. A stationary time series is one whose statistical properties do not change over time. The variables taken for this research, included Stock Indices such as JCI, KLSE, SET, STI, PSE, VSE and World Gold & Bitcoin. The probability values of all variables were near zero during the study period. This indicated that all the variables' prices remained stationary during the study period. A unit root null hypothesis was rejected for all log-returns of stock indices because all underlying variables were stationary at the level.

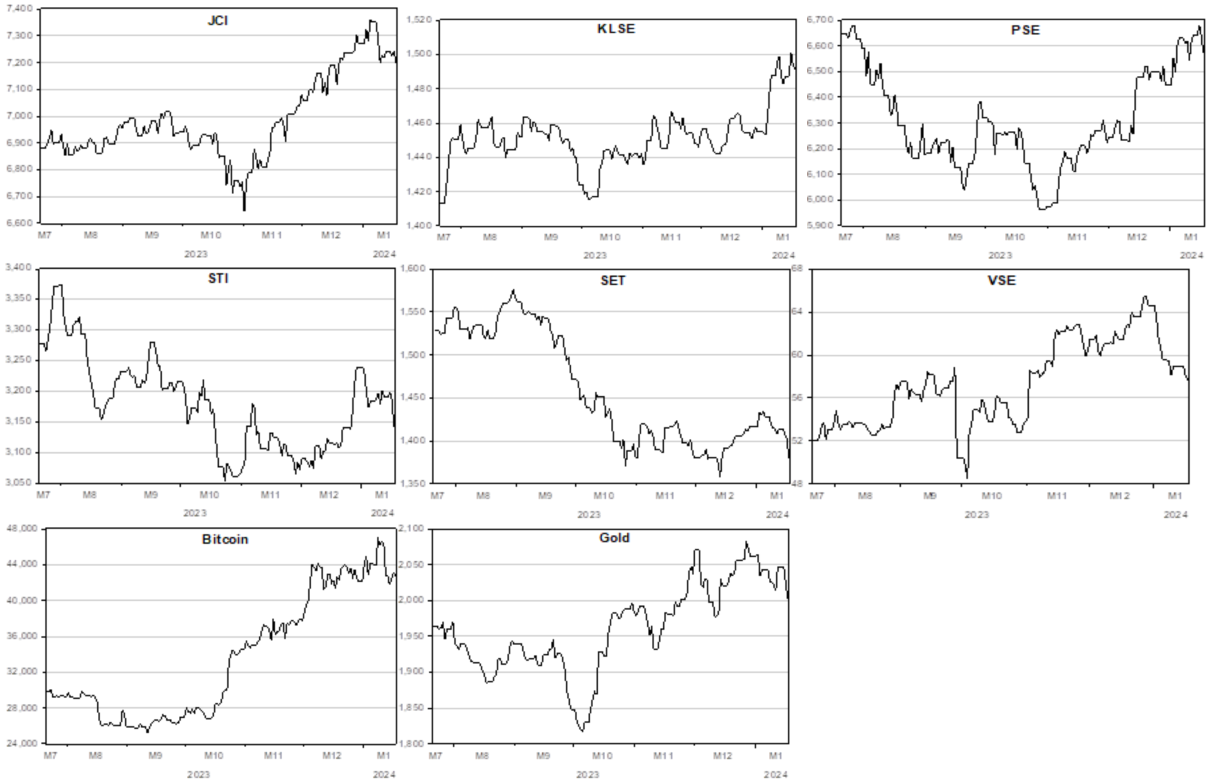
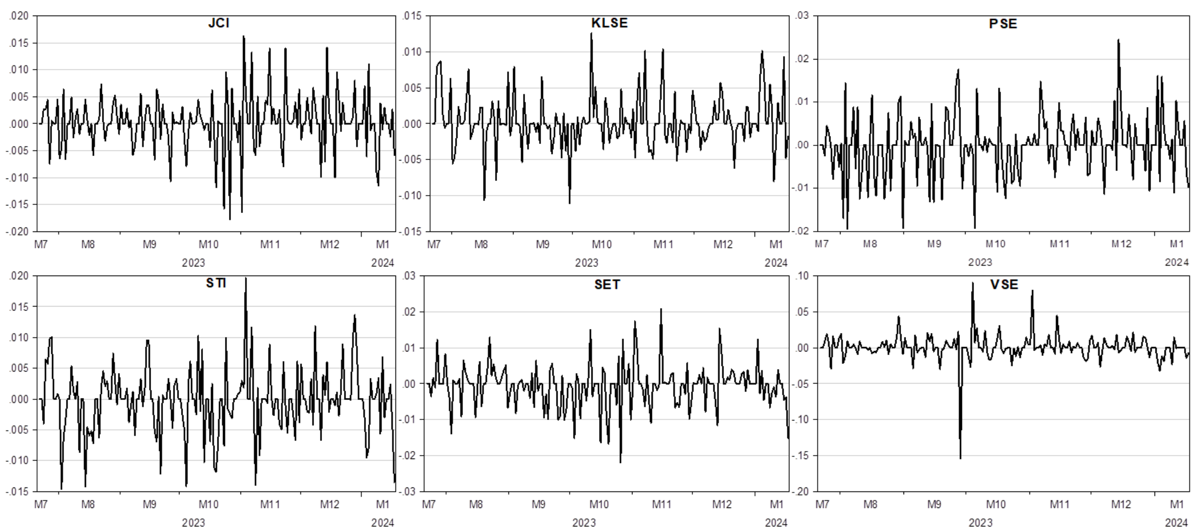


Figure 4.
Price Trends in the Financial Markets over the period of 21 July 2023 to 17 January 2024.



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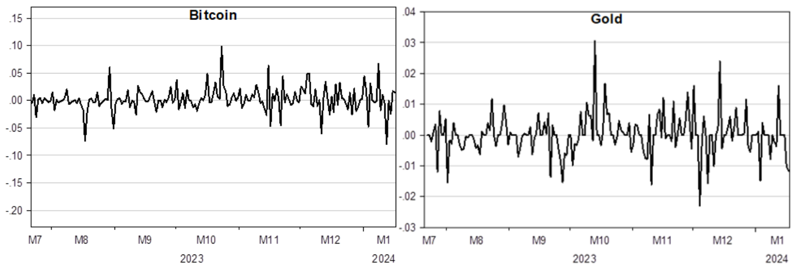

Figure 4.
Price Fluctuations in the Financial Markets over the period of 21 July 2023 to 17 January 2024.

Table 4.
Results based on the GARCH models for entire study period.

Variables	Model	Log	AIC	α (ARCH)	β (GARCH)	γ (Gamma)
JCI index	GARCH (1,1)	-875.012	9.778	-0.049 *	1.043 *	-
	GJR-GARCH (1,1)	-880.314	9.848	-0.093' *	0.720 *	0.435 *
	EGARCH (1,1)	-885.079	9.901	0.289 *	-0.821 *	-0.060
KLSE index	GARCH (1,1)	38.983	-0.378	-0.204 *	-0.846 *	-
	GJR-GARCH (1,1)	-527.641	5.952	-0.065 *	0.584 *	-0.056 *
	EGARCH (1,1)	376.250	-4.114	-0.680 *	0.816 *	0.205 *
PSE index	GARCH (1,1)	-304.368	3.437	0.165 *	-0.631 *	-
	GJR-GARCH (1,1)	-929.260	10.414	0.154 *	0.551 **	-0.144 *
	EGARCH (1,1)	7604.813	-84.431	0.088	-0.859 **	0.110 *
STI index	GARCH (1,1)	-756.038	8.467	-0.079 *	0.550 *	-
	GJR-GARCH (1,1)	-758.570	8.506	-0.001	0.777 *	-0.083
	EGARCH (1,1)	-757.699	8.497	-0.251 **	0.693 *	0.076
SET index	GARCH (1,1)	32.844	-0.299	0.144 *	-0.850 *	-
	GJR-GARCH (1,1)	-635.860	7.143	-0.091 *	0.601 *	0.132 **
	EGARCH (1,1)	-639.233	7.180	0.298 *	-0.762 *	0.077
VSE index	GARCH (1,1)	-257.336	2.915	-0.014	0.592 *	-
	GJR-GARCH (1,1)	-257.999	2.933	0.083	0.594 *	-0.102
	EGARCH (1,1)	-230.315	2.626	1.160 *	-0.131 *	0.113
Gold	GARCH	-706.628	7.907	-0.057 *	0.595 *	-
	GJR-GARCH	-703.429	7.894	-0.033	0.560 *	-0.054
	EGARCHS	-705.561	7.906	0.460 *	-0.450 **	0.003
Bitcoin	GARCH (1,1)	1244.113	-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 *

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

The empirical results with respect to the different GARCH models for study period (21 July 2023 to 17 January 2024) are illustrated in Table 4. Based on Table 4, the AIC (Akaike Information Criteria) values for each selected variables indicated that GARCH (1,1) model was the best-fitted for simulating the price volatility of JCI Index, STI Index, SET Index, and Bitcoin. For KLSE Index, PSE Index, and VSE Index E-GARCH (1,) was the best model for modelling the volatility, while the best model for modelling Gold's volatility was GJR-GARCH (1,1). The outcomes of the GARCH models, used to analyze the effect of the Red Sea Crisis Event on the prices of chosen variables, are shown in Tables 4. Based on the E-GARCH (1, 1) model, JCI Index, KLSE Index, PSE Index, SET Index, and Bitcoin exhibited asymmetric effects at various levels of significance throughout the study period. With respect to the EGARCH model clearly indicated that the prices of JCI Index, KLSE Index, PSE Index, SET Index, and Bitcoin demonstrated significant long-term memory effect and asymmetric behavior during the entire study period with the highest volatility persistence in JCI Index (β = 0.435). This high persistence was likely due to the global financial instability. However, the leverage effect was observed in KLSE Index, PSE Index, and Bitcoin throughout this study period with the highest leverage coefficient in KLSE Index (β = 0.205).

The Red Sea cris, a significant geopolitical conflict, has had profound implications on global financial markets. Geopolitical events often lead to heightened uncertainty, causing substantial fluctuations in asset prices. This increased volatility can be attributed to various factors, including changes in investor sentiment, shifts in economic fundamentals, and alterations in risk perceptions. The influence of price fluctuations in financial assets during economic instability causing by global conflict of various regions has been widely examined in academic research (Agustina & Barus, 2023)(Umar et al., 2021)(Mgadmi et al., 2023)(Hamil et al., 2023)(Truong & Van Vo, 2023)(Puspitasari, 2024). Volatility, a statistical measure of the dispersion of returns for a given security or market index, serves as a crucial indicator of market stability and investor confidence. During periods of geopolitical tension, such as the Red Sea Crisis, the anticipation of potential economic and political repercussions can lead to abrupt market movements. Accurate volatility predictions can aid in developing effective risk management strategies, ensuring market stability, and making informed investment decisions. The GARCH model and its variants, such as GJR-GARCH and EGARCH, are widely used to model and forecast financial market volatility. These models account for time-varying volatility and can capture the persistence and clustering of volatility observed in financial markets. Our study focuses on predicting investment volatility during the Red Sea Crisis event using the GARCH family of models. After analyzing the results, it can be concluded the best-fitting models for each variable, as determined by the lowest AIC values, vary. The GARCH(1,1) model is most suitable for the JCI Index, STI Index, SET Index, and Bitcoin. In contrast, the EGARCH(1,1) model is the best fit for the KLSE Index, PSE Index, and VSE Index. Meanwhile, the GJR-GARCH(1,1) model is the most appropriate for Gold. This indicates that different indices and assets exhibit unique volatility characteristics, necessitating the use of various GARCH-type models to capture their specific behaviors accurately. The results of this analysis offer valuable insights into the behavior of financial markets during periods of geopolitical instability, highlighting the importance of robust volatility modeling in managing financial risk.

The research on predicting investment volatility during the Red Sea Crisis using the GARCH family models has several important implications. It underscores the necessity for sophisticated volatility modeling, like GARCH, EGARCH, and GJR-GARCH, in enhancing risk management and crafting tailored investment strategies. By recognizing the unique volatility characteristics of different assets, investors can optimize their portfolios more effectively during volatile periods. The study also highlights the profound impact of geopolitical events on financial markets, emphasizing the need for policymakers and investors to consider these factors in decision-making processes. Accurate volatility predictions foster market stability and investor confidence, contributing to more informed and resilient financial markets. Additionally, the research advances the field of volatility modeling and offers practical applications for financial institutions, improving their portfolio management practices. Overall, this study provides valuable insights for risk management, investment strategies, and understanding the effects of geopolitical events on market volatility.

5. Conclusion

Based on the research results and discussion, the optimal investment strategy for investors during periods of heightened volatility, such as the Red Sea Crisis, involves a combination of diversification, dynamic asset allocation, and robust risk management techniques. Investors should diversify their portfolios across various asset classes and regions to mitigate risks, while employing hedging instruments like options and futures. Dynamic asset allocation is essential, shifting towards more stable assets such as bonds or gold, especially during increased volatility periods as indicated by the EGARCH model. Conversely, during lower volatility, assets like Bitcoin and the JCI Index, identified by the GARCH(1,1) model, can be prioritized. Risk management through stop-loss orders and adjusting position sizes based on volatility helps protect investments. Tactical investments informed by volatility models, such as favoring gold during geopolitical tensions, can enhance performance. Maintaining a long-term perspective and continuously monitoring and adjusting strategies ensure alignment with market conditions and risk tolerance, enabling investors to effectively navigate and capitalize on market opportunities.

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References
Agustina, A., & Barus, A. C. (2023). Investasi Safe Haven: Dampak Perang Rusia - Ukraina. *Owner*, *7*(3), 2330–2339. https://doi.org/10.33395/owner.v7i3.1523

Alghifary, M. S., Kadji, D., & Hafizah, I. (2023). Islamic and Conventional Stocks' Volatility: Evidence from the Three Waves of Covid-19 Pandemic. *International Journal of Islamic Economics and Finance (IJIEF)*, *6*(1). https://doi.org/10.18196/ijief.v6i1.14838

Almeida, J., Gaio, C., & Gonçalves, T. C. (2024). Crypto market relationships with bric countries' uncertainty – A wavelet-based approach. *Technological Forecasting and Social Change*, *200*. https://doi.org/10.1016/j.techfore.2023.123078

Arisandhi, V. D., & Robiyanto, R. (2022). Exchange Rate, Gold Price, And Stock Price Correlation In Asean-5: Evidence From COVID-19 Era. *Jurnal Manajemen Dan Kewirausahaan*, *24*(1), 22–32. https://doi.org/10.9744/jmk.24.1.22-32

Bollerslev, T. (1986). Generalized Autoregressive Conditional Heteroskedasticity. In *Journal of Econometrics* (Vol. 31).

Chemkha, R., BenSaïda, A., Ghorbel, A., & Tayachi, T. (2021). Hedge and safe haven properties during COVID-19: Evidence from Bitcoin and gold. *Quarterly Review of Economics and Finance*, *82*, 71–85. https://doi.org/10.1016/j.qref.2021.07.006

Daskalakis, N., & Daglis, T. (2023). The Russian War in Ukraine and its Effect in the Bitcoin Market. In *International Journal of Economics and Business Administration: Vol. XI* (Issue 1).

Guo, H., Zhao, X., Yu, H., & Zhang, X. (2021). Analysis of global stock markets' connections with emphasis on the impact of COVID-19. *Physica A: Statistical Mechanics and Its Applications*, *569*. https://doi.org/10.1016/j.physa.2021.125774

Hamil, N. W. B., Zainudin, A. D. Bin, & Wider, W. (2023). Evidence of COVID-19's financial epidemiology on the ASEAN-5 stock indices. *Asian Economic and Financial Review*, *13*(3), 180–191. https://doi.org/10.55493/5002.v13i3.4739

Hoang Tien, N., Jiminez Santural Jose, R., Ehsan Ullah, S., & Vinh Thang, H. (2021). The Impact of World Market on Ho Chi Minh City Stock Exchange in Context of Covid-19 Pandemic. In *Research Article Turkish Journal of Computer and Mathematics Education* (Vol. 12, Issue 14). https://www.investing.com/

Karmakar, M. (2005). Modeling Conditional Volatility of the Indian Stock Markets. *VIKALPA*, *30*(3).

Kayral, I. E., Jeribi, A., & Loukil, S. (2023). Are Bitcoin and Gold a Safe Haven during COVID-19 and the 2022 Russia–Ukraine War? *Journal of Risk and Financial Management*, *16*(4). https://doi.org/10.3390/jrfm16040222

Mgadmi, N., Sadraoui, T., Alkaabi, W., & Abidi, A. (2023). The interconnectedness of stock indices and cryptocurrencies during the Russia-Ukraine war. *Journal of Economic Criminology*, *2*, 100039. https://doi.org/10.1016/j.jeconc.2023.100039

Nelson1, D. B. (1991). Conditional Heteroskedasticity In Asset Returns: A New Approach. In *Source: Econometrica* (Vol. 59, Issue 2).

Nguyen, V. C., & Nguyen, T. T. (2022). Dependence between Chinese stock market and Vietnamese stock market during the Covid-19 pandemic. *Heliyon*, *8*(10). https://doi.org/10.1016/j.heliyon.2022.e11090

Olayungbo, D. O., Zhuparova, A., Al-Faryan, M. A. S., & Ojo, M. S. (2024). Global oil price and stock markets in oil exporting and European countries: Evidence during the Covid-19 and the Russia-Ukraine war. *Research in Globalization*, *8*. https://doi.org/10.1016/j.resglo.2024.100199

Puspitasari, A. (2024). Comparative Analysis of Stock Price Index Before and After The Announcement of Silicon Valley Bank (SVB) Bankruptcy. *AJAR*, 7(01), 1–20. https://doi.org/10.35129/ajar.v7i01.472
Salikin, N., & Wahab, N. A. (2024). *Gold as Safe Haven Strategy During Covid-19 Pandemic: The Case of Bursa Malaysia*. *2*, 2024. https://ejournal.unida.gontor.ac.id/index.php/FICCOMSS
Sarkodie, S. A., Ahmed, M. Y., & Owusu, P. A. (2022). COVID-19 pandemic improves market signals of cryptocurrencies–evidence from Bitcoin, Bitcoin Cash, Ethereum, and Litecoin. *Finance Research Letters*, *44*. https://doi.org/10.1016/j.frl.2021.102049
Taera, E. G., Setiawan, B., Saleem, A., Wahyuni, A. S., Chang, D. K. S., Nathan, R. J., & Lakner, Z. (2023). The impact of Covid-19 and Russia–Ukraine war on the financial asset volatility: Evidence from equity, cryptocurrency and alternative assets. *Journal of Open Innovation: Technology, Market, and Complexity*, *9*(3). https://doi.org/10.1016/j.joitmc.2023.100116
Tetteh, B., & Ntsiful, E. (2023). A comparative analysis of the performances of macroeconomic indicators during the Global Financial Crisis, COVID-19 Pandemic, and the Russia-Ukraine War: The Ghanaian case. *Research in Globalization*, *7*. https://doi.org/10.1016/j.resglo.2023.100174
Truong, L. D., & Van Vo, D. (2023). The asymmetric effects of exchange rate on trade balance of Vietnam. *Heliyon*, *9*(4). https://doi.org/10.1016/j.heliyon.2023.e14455
Tunnisa, I. F., & Darmawan, S. (2023). Comparative performance analysis of bitcoin cryptocurrency, stocks and gold as investments alternative. *Journal of Business and Information Systems (e-ISSN: 2685-2543)*, *5*(2), 234–246. https://doi.org/10.36067/jbis.v5i2.214
Umar, M., Su, C. W., Rizvi, S. K. A., & Shao, X. F. (2021). Bitcoin: A safe haven asset and a winner amid political and economic uncertainties in the US? *Technological Forecasting and Social Change*, *167*. https://doi.org/10.1016/j.techfore.2021.120680
Zhang, S., & Mani, G. (2021). Popular cryptoassets (Bitcoin, Ethereum, and Dogecoin), Gold, and their relationships: Volatility and correlation modeling. *Data Science and Management*, *4*, 30–39. https://doi.org/10.1016/j.dsm.2021.11.001

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