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Volatility Patterns and Reaction to New Shocks: A GARCH-based Analysis of Cryptocurrencies and a Stock Market Index

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Abstract: This study employs various GARCH-family (Generalized Autoregressive Conditional Heteroskedasticity) models to examine the volatility patterns of four cryptocurrencies (Bitcoin, Ethereum, Binance Coin, and Sia Coin) together with a stock market index. The analysis aims to ascertain the differential effects of positive and negative shocks on the volatility levels of these assets. Based on the results, positive news regarding Sia Coin returns typically results in a state of tranquility and less volatility. Conversely, bad news (negative shocks) lead to increased instability in the returns of Bitcoin, Ethereum, Binance Coin, and the Stock Market Index, leading to a state of turmoil in the market.

Keywords: Cryptocurrencies; News; Volatility; Stock Market Index.

1. Introduction

Cryptocurrencies, regarded as a novel type of privately issued currency, have revolutionized the payment system by eliminating the requirement for a middleman, hence enabling the use of currencies in a decentralized manner (Andrikopoulos, Hudson, Akbar, & Saftoiu, 2018). Although they do provide several advantages as a cutting-edge and effective payment method, they also present threats to investors, consumers, businesses, the financial system, and even national security. (Ali, Clews, & Roger Southgate, 2014) suggested the implementation of a decentralized system as a means to eliminate intermediaries and mitigate credit and liquidity risk (Andrikopoulos et al., 2018), Hudson et al. 2018). An asset can be deemed suitable for investment based on its risk profile. When an asset has a negative correlation with another asset, merging the two significantly decreases the risk (Bouri, Molnár, Azzi, Roubaud, & Hagfors, 2017).

Typically, an asset's financial capacity is evaluated by considering its liquidity, sensitivity to changes in other assets, and ability to mitigate risks. One of the assets used for hedging was gold. However, in recent years, there has been a notable increase in the use of virtual currencies (Sami & Abdallah, 2020), such as Bitcoin. Bitcoin is frequently called "Digital Gold" since it is created in a decentralized manner and has minimal connection to traditional assets. Similarly, this applies to the second-largest cryptocurrency in terms of market capitalization, as well as Ethereum's inherent digital token (Félez-Viñas, Foley, Karlsen, & Svec, 2021). Ever since its inception in 2008 by Satoshi Nakamoto (Dyhrberg, 2016), the price of Bitcoin has experienced a significant increase. It was valued at $1.14 US$ on 01/06/2011 and surpassed 900 dollars on 11/01/2014 (Bouoiyour, Selmi, & Tiwari, 2015). By the end of 2015, the overall market capitalization of Bitcoin had surpassed $36 billion (Bouri et al., 2017). Bitcoin's supply expands in a deterministic manner, with the creation of 210 thousand of mined blocks taking place every four years. The inherent emission constraints of Bitcoin provide it with a natural safeguard against inflation. This is why Bitcoin is being rapidly embraced by nations and populations experiencing hyperinflation, such as Argentina and Venezuela (Félez-Viñas et al., 2021).

Bitcoin has experienced a surge in popularity in recent years as more and more companies are accepting it on a regular basis. As more businesses have started accepting cryptocurrency, people are also attributing value to it. Japan and South Korea have officially recognized money as a valid form of payment and legal tender (Bouoiyour et al., 2015); (Mohammed, Hayewa, Shuaibu, & Bunu, 2022). Moreover, Bitcoin serves as a substitute for conventional assets. It is considered a component of a parallel economy (Bouri et al., 2017)due to its ability to offer proof and enable transactions without the need for intermediaries. Bitcoin enhances the infrastructure for money transfer, enabling more efficient and rapid payment processes (Guesmi, Saadi, Abid, & Ftiti, 2019). The remaining sections of the paper are structured in the following manner: Section 1 introduces the topic. Section 2 contains a literature review. Section 3 explains the sources and methodology used in the research. Section 4 delivers the findings and discussion of the research.

2. Literature review

This article expands on earlier empirical research that has identified the relationship between cryptocurrency and the stock market. A number of studies have employed EGARCH and TGARCH models to analyze cryptocurrency volatility, with varying results. For example, (Andrikopoulos et al., 2018) found a causal relationship between returns and volatility for Bitcoin and Litecoin, while Ethereum and Ripple exhibited a causal relationship between volatility and returns. Further research by (Bhatnagar, Taneja, & Rupeika-Apoga, 2023) explored the impact of news shocks on Bitcoin market volatility, finding significant volatility persistence and a strong influence of news events on all cryptocurrencies studied. (Dyhrberg, 2016) explored Bitcoin's capabilities using EGARCH and TGARCH models, suggesting that it could be an effective tool for risk management and suitable for risk-averse investors. These studies highlight the growing interest in understanding cryptocurrency volatility and its potential impact on financial markets. Several key findings have emerged from empirical research that has identified the relationship between cryptocurrency and stock market. (Gupta & Chaudhary, 2022) examined the risk and return of cryptocurrencies, revealing a large spillover effect between Bitcoin and Ethereum due to their high market capitalization. They also observed an asymmetric impact on volatility compared to Litecoin and XRP. (Katsiampa, 2017) investigated the best-fitting conditional heteroscedasticity model for Bitcoin price volatility, concluding that the ACGARCH model provided the most accurate representation of the data.

3. Data and methodology

3.1. Data sources

The sample spans from January 1, 2019, to March 26, 2024. The formula $Rt = log (Pt/Pt\text{-}1)$ is employed to calculate the logarithmic returns based on the daily closing price retrieved from Invasting.com. The MSCI stock market index concluded its trading session over the weekend while cryptocurrency markets continued to operate. In order to ensure simultaneity, we exclude weekend trading, which usually has limited market activity, from our sample.

4. Empirical results

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The Ordinary Least Squares (OLS) regression is not suitable for examining returns and volatility. The GARCH model family is highly successful for measuring time series data, particularly the volatility of returns. Similarly, the EGARCH model is utilized to quantify the existence of long memory and volatility persistence. Additionally, the TGARCH model is employed to identify the response of volatility to positive or negative shocks. The data for this investigation were analyzed using Eviews 12 software (Bhatnagar et al., 2023); (Gupta & Chaudhary, 2022); (Katsiampa, 2017). The models employed in this research comprise the GARCH model, as follows:

$$R_t = \varphi_0 + \sum_{i=1}^{n} \varphi_1 R_{t-i} + \varepsilon_t$$
$$\varepsilon_t \to (0, h_t)$$

R_t: Cryptocurrency and index returns on day t
ε_t: The error term
z_t: The white noise
h_t: The conditional variance

Table 1. GARCH models used in the study

GARCH	$h_t^2 = \alpha_0 + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1}^2$
EGARCH	$log(h_t^2) = \alpha_0 + \alpha\left\lvert\frac{\varepsilon_{t-1}}{h_{t-1}}\right\rvert + \lambda\frac{\varepsilon_{t-1}}{h_{t-1}} + \beta\, log(h_{t-1}^2)$
TGARCH	$h_t^2 = \alpha_0 + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1}^2 + \gamma\varepsilon_{t-1}^2 I_{t-1}$

Source: presented by researchers based on (Katsiampa, 2017), (Gupta & Chaudhary, 2022) studies

4.1. Descriptive statistics

Based on the descriptive statistics data, the average daily mean return of BNB was the greatest, with a value of 0.003361. Following that, Ethereum had a return rate of 0.002319, while SIA and MSCI had the lowest return rates of 0.000963 and 0.000429, respectively. The analysis shows that the standard deviation of SIA returns was the largest, with a value of 0.142265, while the lowest standard deviation was seen in MSCI returns, with a value of 0.011129. The table shows that all variables exhibit leptokurtic distribution. However, variables like R_BTC and R_MSCI display negative skewness, while the others exhibit positive skewness.

Table 2. Descriptive statistics

Statistics	R_BTC	R_ETH	R_BNB	R_SIA	R_MSCI
Mean	0.002140	0.002319	0.003361	0.000963	0.000429
Maximum	1.454068	2.137906	3.103414	1.558828	0.084062
Minimum	-1.434910	-2.011717	-3.045099	-1.354781	-0.104412
Std. Dev	0.069952	0.096325	0.131035	0.142265	0.011129
Skeweness	-0.090074	1.102796	0.437736	0.463612	-1.107993
Kurtosis	270.1451	319.9815	446.4850	27.83674	19.28415
Observation	1362	1362	1362	1362	1362

Source: presented by researchers based on the outputs of Eviews 12 software

4.2. Correlation coefficient

Table 3 displays the coefficient of correlation, which reveals a minor correlation between MSCI returns and the other factors. The correlation between SIA returns and the other variables is moderate, with coefficients of 0.4762, 0.4842, and 0.4614, respectively. Bitcoin, Ethereum, and BNB exhibit a significant positive correlation among them (0.9394, 0.9163, 0.8926), suggesting that these currencies possess the biggest market capitalization. All the correlation coefficients are statistically significant at the 1% level.

Table 3. coefficient of correlation results

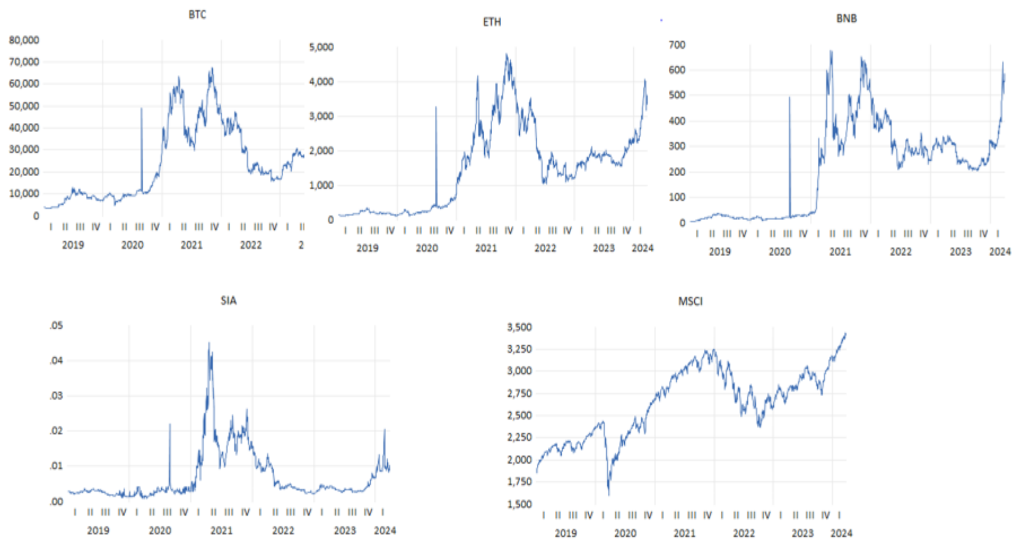
	R_BTC	R_ETH	R_BNB	R_SIA	R_MSCI
R_BTC	1				
R_ETH	0.9394***	1			
R_BNB	0.8926 ***	0.9163***	1		
R_SIA	0.4762***	0.4842***	0.4614***	1	
R_MSCI	0.2074***	0.2025***	0.1402***	0.1501***	1

Source: presented by researchers based on the outputs of Eviews 12 software

4.3. Data price graphs

Figure 1 displays the historical data of cryptocurrency and index prices. A diverse array of fluctuations within each set can be noted, which is a characteristic commonly observed in financial assets.

Fig. 1. Level of cryptocurrencies prices and MSCI index from 1st January 2019 to 26th March 2024

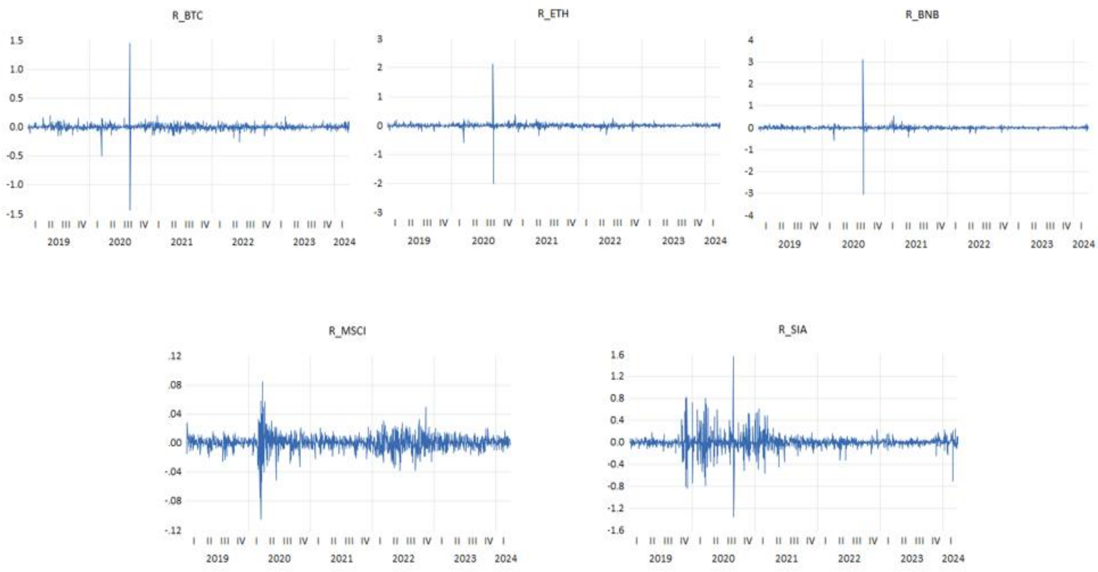


Source: presented by researchers based on the outputs of Eviews 12 software

4.4. Data volatility (returns) graphs

The level of instability experienced from January 2019 to March 2024. Each graph in Figure 2 displays periods of significant volatility and times of relative tranquility, a common characteristic observed in several financial assets.

Fig. 1. Illustrates the volatility in the returns of cryptocurrencies and stock market index from 1st January 2019 to 26th March 2024



Source: presented by researchers based on the outputs of Eviews 12 software

4.5. Stationarity

Prior to estimating the ARMA model, a stationary (unit root) test was conducted on the series to determine whether the variables were stationary or not. The Augmented Dickey-Fuller method was employed for this purpose. The following equation provides the ADF test with both a constant term and a linear trend. The null hypothesis is formulated based on the existence of a unit root in the series.

$$\Delta x_t = c + b_t + \rho x_{t-1} + \sum_{i=1}^{p-1} \pi_i \Delta x_{t-1} + \varepsilon_t$$

Table 4. The unit root test results

Variables	ADF					
	level			1st difference		
	Intercept	Intercept & trend	None	Intercept	Intercept & trend	None
BTC	-0.824	-1.491	0.574	-34.47***	-34.57***	-34.55***
ETH	-1.429	-2.097	-0.230	-34.39***	-34.38***	-34.39***
BNB	-1.453	-2.308	-0.252	-34.44***	-34.43***	-34.43***
SIA	-2.547	-2.566	-1.685*	-31.16***	-31.15***	-31.17***
MSCI	-1.376	-2.309	1.367	-10.74***	-10.74***	-10.67***

Source: presented by researchers based on the outputs of Eviews 12 software

Table 5 displays the findings of the analysis on the stability of the returns in the series. Based on the findings of the panel unit root test displayed in Tables 4 and 5, it can be noted that all price series of the cryptocurrencies possess a unit root and are integrated at order 1, with the exception of SIA. The series is statistically non-stationary at a significance level of 10%. Meanwhile, the return variables remain constant at the I(0) level. When the returns series is stationary, it is possible to replicate the volatility of cryptocurrencies without separating it into short-term and long-term components (Andrikopoulos et al., 2018).

Table 5. The unit root test results

Variables	ADF		
	level		
	Intercept	Intercept & trend	None
R_BTC	-22.93960***	-22.93588***	-22.86516***
R_ETH	-23.84027***	-23.83456***	-23.78816***
R_BNB	-25.93046***	-25.93800***	-25.85650***
R_SIA	-27.72920***	-27.71954***	-27.73509***
R_MSCI	-10.62596***	-10.62207***	-10.56471***

Source: presented by researchers based on the outputs of Eviews 12 software

4.6. ARMA (Box & Jenkins)

According to (Box George, Jenkins Gwilym, Reinsel Gregory, & Ljung Greta, 1976), it is widely recognized that the time series pattern of the ARMA model in the conditional mean can be detected and confirmed by using autocorrelation and partial autocorrelation functions. Analyze the time series behavior of the GARCH model by utilizing the autocorrelation and partial autocorrelation functions for the squared process (Bollerslev, 1986). Table 7 displays the outcomes of utilizing ARMA Maximum Likelihood (OPGBHHH) on a dataset of 1367 return observations. In order to assess the influence of previous returns on variable returns, we employed the ARMA(1,1) model as the most suitable model. Thus, it can be noted that preceding returns had an impact on all variables.

Table 6. ARMA (1,1) Maximum Likelihood (OPG-BHHH) of returns

	R_BTC		R_ETH		R_BNB		R_SIA		R_MSCI	
	Coef	Prob	Coef	Prob	Coef	Prob	Coef	Prob	Coef	Prob
C	0.002	0.179	0.002	0.270	0.003	0.603	0.0009	0.662	0.0004	0.171
AR(1)	0.611	0.000	0.587	0.000	-0.604	0.000	0.367	0.000	-0.9457	0.000
MA(1)	-0.765	0.000	-0.772	0.000	0.830	0.000	-0.652	0.000	0.970	0.000
SIGMASQ	0.004	0.000	0.008	0.000	0.0158	0.000	0.018	0.000	0.0001	0.000

Source: presented by researchers based on the outputs of Eviews 12 software

4.7. Heteroskedasticity test

It is customary to examine the residuals for heteroskedasticity after implementing the ARMA model. To determine the presence of the ARCH effect, we utilize Engle's Lagrange Multiplier test, with the square residual as the dependent variable. The probability in Table 8 is determined using F-statistics. By examining the probability of the Chi-squared statistic, we have determined that heteroskedasticity is present. This means that the variance of all the residuals is not constant. Consequently, the Autoregressive model for the conditional mean needs to be adjusted to include an Autoregressive Conditional Heteroskedasticity model for the conditional variance.

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Table 7. The ARCH effect test results

Heteroskedasticity test : ARCH H0 : there is no ARCH effect in the residuals				
The variables	F-statistics	Prob F (2,1359)	Obs*R-squared	Pro.Chi-square(2)
R_BTC	202.7669	0.0000	313.0739	0.0000
R_ETH	179.2231	0.0000	284.3046	0.0000
R_BNB	183.0997	0.0000	289.1496	0.0000
R_SIA	104.1669	0.0000	181.0055	0.0000
R_MSCI	320.2346	0.0000	436.3774	0.0000

Source: presented by researchers based on the outputs of Eviews 12 software

4.8. GARCH model

Following the completion of ARMA and the heteroskedasticity test, the subsequent task involves analyzing Generalized Autoregressive Conditional Heteroskedasticity (GARCH) as suggested by (Bollerslev, 1986). This method utilizes Maximum Likelihood estimation to evaluate the GARCH regression model. α and β are the coefficients of the ARCH and GARCH terms, respectively. The variable α represents the ARCH effect, which quantifies the reaction to a shock or news in the cryptocurrency market. Beta symbolizes the GARCH phenomenon, which characterizes the enduring nature of volatility. A high ARCH coefficient signifies a heightened responsiveness of volatility to news, while a high GARCH value suggests the existence of prolonged volatility and a slow decay of its effects (Gupta & Chaudhary, 2022). The GARCH (1,1) model was identified as the most suitable for estimating the univariate variance process with the optimal number of lags. All parameter estimates are statistically significant, indicating a substantial presence of ARCH and GARCH effects across all variables. Therefore, the GARCH models are the suitable approach for modeling the volatility of Bitcoin, Ethereum, BNB, SIA, and MSCI.

Table 8. GARCH (1,1) Model

	R_BTC		R_ETH		R_BNB		R_SIA		R_MSCI	
	Coef	Prob	Coef	Prob	Coef	Prob	Coef	Prob	Coef	Prob
C	0.0010	0.000	0.0016	0.000	0.0021	0.000	0.0012	0.000	0	0.000
Mean equation ARCH (α)	0.1478	0.000	0.1456	0.000	0.1410	0.000	0.1381	0.000	0.15	0.003
Variance equation GARCH(β)	0.5978	0.000	0.5956	0.000	0.5910	0.000	0.5851	0.000	0.6	0.000

Source: presented by researchers based on the outputs of Eviews 12 software

4.9. EGARCH model

(Nelson, 1991) presented an alternative model called Exponential GARCH, which is more suited for modeling the conditional variation in asset returns compared to GARCH. This model utilizes a logarithm to allow for both positive and negative values of the conditional variance, thus adopting a natural approach.

Table 9. EGARCH (1,1) Model

	R_BTC		R_ETH		R_BNB		R_SIA		R_MSCI	
	Coef	Prob	Coef	Prob	Coef	Prob	Coef	Prob	Coef	Prob
C	-0.002	0.235	0	0.326	0.011	0.000	-0.001	0.424	0	0.09
AR(1)	-0.216	0.116	1.045	0.000	-0.340	0.000	0.525	0.000	0.189	0.475
MA(1)	0.463	0.000	-0.972	0.000	0.721	0.000	-0.620	0.000	-0.107	0.696
C(4)	-1.673	0.000	-0.583	0.000	-4.290	0.000	-0.152	0.000	-0.560	0.000
C(5)	0.788	0.000	0.442	0.000	1.469	0.000	0.214	0.000	0.225	0.000
C(6)	-0.462	0.000	-0.218	0.000	1.099	0.000	0.069	0.000	-0.139	0.000
C(7)	0.776	0.000	0.944	0.000	0.356	0.000	0.997	0.000	0.959	0.000

Source: presented by researchers based on the outputs of Eviews 12 software

The following equation has three significant dissections: C(5), C(6), and C(7), which indicate the size effect, sign effect, and volatility persistence, respectively. In a broader sense, EGARCH can be written as follows:

EGARCH= Size effect + Sign effect + Volatility persistence

The value of the size effect indicates the shock's impact on volatility. The value of the sign effect represents the relationship between shocks (news) and volatility. The amount of volatility persistence indicates whether the market has been turbulent over a long or short time (Bhatnagar, Taneja et al., 2023). Table 10 demonstrates that AR(1) is statistically significant only for Ethereum and SIA returns. In comparison, MA (1) has a statistically significant probability for all cryptocurrencies but is insignificant for the Stock Market Index.

Furthermore, C(4), C(5), C(6), and C(7) show significant results across all variables, demonstrating that news has a large impact on volatility, with volatility persistence being relatively strong for all cryptocurrencies except Binance Coin. The high levels indicate that if the market is volatile, it will remain so for an extended duration. The findings indicate that both positive and negative news do not have an asymmetric impact on volatility. Specifically, positive news can decrease volatility, while negative news can increase it.

4.10. TGARCH model

The approach presented by (Glosten, Jagannathan, & Runkle, 1993) aims to incorporate nonlinearity in the modeling of conditional variance in time series data. The premise of this is that negative shocks have a more significant influence than positive ones, which is frequently referred to as the leverage effect. Regarding Bitcoin and SIAcoin, the coefficient γ's asymmetric term is negative and statistically significant. This implies that increased volatility is generally linked to positive returns as opposed to negative returns of the same magnitude. Nevertheless, in cases when returns are negative, volatility tends to exhibit a greater increase compared to situations where returns are positive. This is supported by the presence of a positive and statistically significant asymmetric term coefficient γ for Ethereum, Binance Coin, and the Stock Market Index (MSCI).

Table 10. TGARCH (1,1) Model

	R_BTC		R_ETH		R_BNB		R_SIA		R_MSCI	
	Coef	Prob	Coef	Prob	Coef	Prob	Coef	Prob	Coef	Prob
C	0.001	0.003	0	0.000	0.001	0.000	0	0.000	0	0.000
Mean Equation	0.082	0.009	0.108	0.002	6.984	0.000	0.160	0.000	0.055	0.000
Variance equation TGARCH (γ)	-0.03	0.154	1.790	0.000	1.667	0.000	-0.115	0.000	0.193	0.000

Source: presented by researchers based on the outputs of Eviews 12 software

4.11. Comparison of EGARCH and TGARCH

Our objective was to determine the most suitable conditional heteroskedasticity model for the Bitcoin data based on the outcome. Four information criteria, namely Log-likelihood, Akaike (AIC), Schwarz, and Hannan-Quinn, are employed to determine the optimal model for addressing this inquiry. The findings obtained from table (12) are presented below, using the EGARCH and TGARCH models. These findings are evaluated based on four criteria: Log Likelihood, Akaike, Schwarz, and Hannan-Quinn. In general, the EGARCH model appears to be an appropriate tool for measuring the volatility of Bitcoin, Ethereum returns, and the Stock Market Index. The TGARCH model is applicable to both Binance Coin and SIAcoin.

Table 11. Compare between EGARCH and TGARCH

	R_BTC		R_ETH		R_BNB		R_SIA		R_MSCI	
	EGARCH	TGARCH	EGARCH	TGARCH	EGARCH	TGARCH	EGARCH	TGARCH	EGARCH	TGARCH
L-L	1986.5	1922.6	1759.3	1757.0	1649.8	1970.9	1317.9	1324.7	4585.5	4578.9
AIC	-2.902	-2.808	-2.569	-2.566	-2.408	-2.787	-1.926	-1.936	-6.713	-6.703
SC	-2.875	-2.782	-2.542	-2.539	-2.382	-2.760	-1.899	-1.909	-6.686	-6.676
H-Q	-2.892	-2.798	-2.559	-2.555	-2.398	-2.777	-1.916	-1.926	-6.703	-6.693

Source: presented by researchers based on the outputs of Eviews 12 software

5. Conclusion

This paper used models to compare four cryptocurrencies and a stock market index: Bitcoin, Ethereum, Binance Coin and Sia Coin returns plus The Stock Market Index. Moreover, in the research, individual data were used to estimate the model using GARCH family likewise: EGARCH and TGARCH to detect reaction of positive or negative shocks in volatility and applies to measure the presence of long memory and volatility persistence.

After conducting asymmetric testing, we determine that bad news causes Binance Coin returns to become turbulent and volatile. However, the asset Sia coin returns to tend a condition of tranquility and reduce volatility. On the other side, the Bitcoin, Ethereum and Stock Market Index returns, the results imply that negative shocks (bad news) generate larger volatility and the market enter to turbulence state. This asymmetric volatility response highlights the differing behaviors of the cryptocurrencies and the stock market index under the impact of positive and negative shocks. The findings have implications for risk management, portfolio optimization, and investment decision-making in these asset classes.

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Ethics

The authors believe that the publication of this manuscript does not raise any substantial ethical issues.

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Appendices

		R_BTC			
ARMA	Variable	Coefficient	Std. Error	t-Statistic	Prob.
	C	0.002126	0.001583	1.342952	0.1795
	AR(1)	0.611071	0.061312	9.966550	0.0000
	MA(1)	-0.765448	0.052338	-14.62510	0.0000
	SIGMASQ	0.004701	2.61E-05	180.1100	0.0000
GARCH	Variance Equation				
	C	0.001000	0.000171	5.865209	0.0000
	RESID(-1)^2	0.147826	0.036270	4.075698	0.0000
	GARCH(-1)	0.597826	0.068636	8.710141	0.0000
EGARCH	Variance Equation				
	C(4)	-1.673675	0.188950	-8.857791	0.0000
	C(5)	0.788660	0.059623	13.22756	0.0000
	C(6)	-0.462766	0.046774	-9.893760	0.0000
	C(7)	0.776489	0.028890	26.87727	0.0000
TGARCH	Variance Equation				
	C	0.001728	0.000591	2.924958	0.0034
	RESID(-1)^2	0.082177	0.031691	2.593071	0.0095
	RESID(-1)^2*(RESID(-1)<0)	-0.036807	0.025819	-1.425581	0.1540
	GARCH(-1)	0.479064	0.179620	2.667095	0.0077
		R_ETH			
ARMA	C	0.002371	0.002149	1.103368	0.2701
	AR(1)	0.587229	0.047156	12.45297	0.0000
	MA(1)	-0.772781	0.039592	-19.51860	0.0000
	SIGMASQ	0.008796	4.60E-05	191.3228	0.0000

GARCH	Variance Equation				
	C	0.001649	0.000304	5.430543	0.0000
	RESID(-1)^2	0.145630	0.033084	4.401882	0.0000
	GARCH(-1)	0.595630	0.072136	8.256996	0.0000
EGARCH	Variance Equation				
	C(4)	-0.583862	0.047390	-12.32043	0.0000
	C(5)	0.442659	0.019470	22.73509	0.0000
	C(6)	-0.218719	0.015775	-13.86465	0.0000
	C(7)	0.944235	0.007555	124.9883	0.0000
TGARCH					
	C	0.000548	6.23E-05	8.799320	0.0000
	RESID(-1)^2	0.108649	0.035155	3.090543	0.0020
	RESID(-1)^2*(RESID(-1)<0)	1.790244	0.172973	10.34982	0.0000
	GARCH(-1)	0.540827	0.023999	22.53545	0.0000
R_BNB					
ARMA					
	C	0.003344	0.006428	0.520274	0.6030
	AR(1)	-0.604604	0.031160	-19.40297	0.0000
	MA(1)	0.830670	0.027780	29.90158	0.0000
	SIGMASQ	0.015841	9.04E-05	175.1382	0.0000
GARCH	Variance Equation				
	C	0.002177	0.000344	6.331658	0.0000
	RESID(-1)^2	0.141039	0.030157	4.676774	0.0000
	GARCH(-1)	0.591039	0.069261	8.533460	0.0000
EGARCH	Variance Equation				
	C(4)	-4.290989	0.059280	-72.38563	0.0000
	C(5)	1.469847	0.033055	44.46737	0.0000
	C(6)	1.099466	0.028326	38.81454	0.0000
	C(7)	0.356533	0.012449	28.64039	0.0000
TGARCH	Variance Equation				
	C	0.000106	1.98E-05	5.351136	0.0000
	RESID(-1)^2	0.296457	0.040476	7.324309	0.0000
	RESID(-1)^2*(RESID(-1)<0)	1.667191	0.128941	12.92989	0.0000
	GARCH(-1)	0.596236	0.020357	29.28851	0.0000
R_SIA					
ARMA					
	C	0.000937	0.002148	0.436137	0.6628
	AR(1)	0.367921	0.031494	11.68225	0.0000
	MA(1)	-0.652351	0.025420	-25.66308	0.0000
	SIGMASQ	0.018492	0.000221	83.61835	0.0000
GARCH	Variance Equation				

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	C	0.001288	4.51E-05	28.52692	0.0000
	RESID(-1)^2	0.138132	0.006800	20.31328	0.0000
	GARCH(-1)	0.588132	0.011615	50.63482	0.0000
EGARCH	Variance Equation				
	C(4)	-0.152304	0.008136	-18.71889	0.0000
	C(5)	0.214613	0.011040	19.44035	0.0000
	C(6)	0.069457	0.009333	7.442403	0.0000
	C(7)	0.997578	0.001403	711.0059	0.0000
TGARCH	Variance Equation				
	C	4.45E-05	1.07E-05	4.165600	0.0000
	RESID(-1)^2	0.160732	0.012786	12.57099	0.0000
	RESID(-1)^2*(RESID(-1)<0)	-0.115405	0.013076	-8.825930	0.0000
	GARCH(-1)	0.913510	0.004983	183.3233	0.0000
	R_MSCI				
ARMA	C	0.000436	0.000319	1.367528	0.1717
	AR(1)	-0.945730	0.021078	-44.86749	0.0000
	MA(1)	0.970148	0.018933	51.24214	0.0000
	SIGMASQ	0.000123	1.85E-06	66.82888	0.0000
GARCH	Variance Equation				
	C	8.08E-05	2.09E-05	3.862944	0.0001
	RESID(-1)^2	0.150000	0.051532	2.910786	0.0036
	GARCH(-1)	0.600000	0.099093	6.054930	0.0000
EGARCH	Variance Equation				
	C(4)	-0.560807	0.073177	-7.663698	0.0000
	C(5)	0.225578	0.025416	8.875329	0.0000
	C(6)	-0.139943	0.012492	-11.20305	0.0000
	C(7)	0.959360	0.006199	154.7650	0.0000
TGARCH	Variance Equation				
	C	3.08E-06	4.74E-07	6.499764	0.0000
	RESID(-1)^2	0.055184	0.012615	4.374378	0.0000
	RESID(-1)^2*(RESID(-1)<0)	0.193283	0.026710	7.236391	0.0000
	GARCH(-1)	0.819560	0.019518	41.98916	0.0000