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Market volatility in cryptocurrencies: A comparative study using GARCH and TGARCH models

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Abstract Price volatility has a negative connotation, as it is associated with market instability, uncertainty, and loss. When markets swing, investors and traders tend to place additional bets anticipating further swings, resulting in increased price volatility. There are no indices to assess crypto price volatility, but investigating historical price fluctuations provides insights into the rising peaks and depressive troughs that occur at a faster and more extreme rate in crypto prices compared to asset values in mainstream markets. This study employed generalized autoregressive conditional heteroskedasticity (GARCH) as a comparison tool to measure the leverage effect and price volatility among two major cryptocurrencies, Bitcoin and Ethereum, for the period from 2017 to 2021. A unit root test was conducted to determine whether the data should be differenced or regressed, and an autoregressive conditional heteroskedasticity (ARCH) effect test was used to measure the relationships within heteroskedasticity. The study revealed that the prices increased astonishingly over these periods, despite drastic decreases, indicating negative correlations between cryptocurrencies and their volatility.

Keywords: cryptocurrency, cryptocurrency markets, volatility, GARCH model, TGARCH model

1. Introduction

Cryptocurrencies gained traction among millennials, making it a simple asset to invest in and trade. The financial crisis uncovered the confines of existing monetary and payment systems, encouraging investors to look for alternate options. These virtual currencies use a peer-to-peer electronic cash transfer system that allows transactions to process payments online without going through centralized institutions. The increase in the popularity of cryptocurrencies among millennials has made it one of the top assets for investment and trade-in. With the Supreme Court of India lifting the Reserve Bank of India's (RBI) controversial ban on the cryptocurrency trade in the country, cryptocurrency start-ups in India have made significant economic progress (Bouri et al. 2021). India is a dormant beast with a population of more than one billion people. Investments in unregulated digital assets, particularly Bitcoin, have revealed a breath-taking upward trend despite the uncertainty surrounding the future of cryptocurrencies. Reports and historical data from Indian cryptocurrency exchanges indicate(Chaudhary et al. 2020) that more than 10.5 million Indians have invested in this asset class, striking the $10 billion mark. The increasing number of cryptocurrency adopters indicates a drift in the investment paradigm in India, which is traditionally known to invest more frequently in gold and other safer assets. The Taproot upgrade on the bitcoin blockchain has further enhanced scalability, security, and privacy (Abakah et al., 2020) for transactions, bringing its functionality in line with competing block chains such as Ethereum, which already employs programmable smart contracts. This has further enabled bitcoin users to enjoy enhanced wallet functionality and reduced fees for far more complex transactions (Fang et al., 2020). Developers would find a larger toolkit from now on to bring new projects to light that were not previously possible on the bitcoin blockchain

Cryptocurrencies are traded much like stocks, providing a viable alternative to gold and appreciating during uncertain times. It is commonly assumed that their prices are influenced by gold prices, global stock indices, and fear gauges such as the US-EPU (Economic Policy Uncertainty Index) and VIX (Volatile Index) (Schilling and Uhlig 2019). Returns on gold and global stock markets, on the other hand, do not have a negligible impact on Bitcoin prices, but studies have shown that returns on Ripple have a negligible impact on Bitcoin prices (Malladi and Dheeriya 2021). Bitcoin volatility varies dramatically between speculative and stable times, with VIX returns, S&P 500 returns, and mood all influencing Bitcoin volatility (López-Cabarcos, 2021). Furthermore, it has been discovered that the volatility dynamics of crypto markets are sensitive to important news

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(Katsiampa, 2019). The gold price and the S&P 500, on the other hand, are statistically significant in terms of the log-return and volatility of Bitcoin. (Kim et al., 2020). The NVIX (News-based Implied Volatility) had a significant detrimental impact on the long-term volatility of five cryptocurrencies. After adjusting for Realized Volatility1 (RV) and Global Economic Policy Uncertainty (GEPU), the NVIX effect remains substantial (Xia et al., 2023). However, according to research conducted by (Walther el al., 2019), global real economic activity outperforms the other economic and financial navigators and delivers better predictions of realized volatility (RV) for both market rise and decline.

The interrelationships between the conditional correlations of cryptocurrencies and financial market stress in relation to both the US and European financial markets, according to (Akyildirim, 2020), are found to increase significantly during periods of severe financial market stress, indicating that major financial market fears are affecting these new financial products. However, Handika (2020) found no evidence of a significant change in the extent of five cryptocurrencies' spreading mechanisms on Asian exchanges and stock markets and confirmed that cryptocurrencies are statistically insignificant in determining present Asian0financial market change variables, leading to the conclusion that cryptocurrencies pose noosystemic risk to Asian0financial0markets. Bitcoin is the most popular cryptocurrency with the greatest volume of market capital, followed by Ethereum. Gil-Alana et al. (2020) investigated the persistence of volatility in 12 popular cryptocurrencies using fractional integration methods. Each squared return and absolute display exhibit long-term remembrance capacities, according to the results. The order of integration supports the long memory hypothesis (Fousekis&Tzaferi, 2021). However, after considering structural interruptions, studies have shown that the level of persistence in the cryptocurrency0 market has decreased. The presence of volatility persistence means that traders who want to make money on a long-term basis (Cheikh et al., 2020) must use the property of the persistence factor among cryptocurrencies during their valuation as well as forecast models to improve long-term volatility forecasting. Furthermore, Zhang (2021) examined how liquidity risk is priced in connection to cryptocurrency gains and observed a negative association between the two. Furthermore, a detailed examination of three cryptocurrencies revealed no evidence of a significant intertemporal link between liquidity and expected profits.

Interestingly, Gupta and Chaudhary (2022) found an asymmetric impact of Bitcoin and Ethereum compared to that of Litecoin and the XRP. Dangi (2023) observed that there exists a leverage effect in the Bitcoin return series. In contrast, it was found that Bitcoin is not a safe tool for investors in India (Murty et al., 2022). Omane and Alagidede (2021) demonstrated the return-volatility behavior of Bitcoin and Ripple in emerging markets as a result of positive shocks rather than negative shocks in the market. The evidence also showed that Bitcoin is a speculative and better hedging asset due to its high volatility (Subramanian & Rao, 2022). Moreover, volatility in Bitcoin and Ethereum is driven by positive and negative news (Karim et al., 2023). Further evidence suggested that the existence of dynamic ecocorrelation in the cryptocurrency market is due to major events such as government bans and hacker attacks (Demiralay & Golitsis, 2021). Recent evidence has also shown the covolatility between cryptocurrencies and other assets such as commodities, equity, bonds, real estate, and currency markets globally (Velappan, 2024).

Market volatility is a significant component in defining trading strategy and investment decisions, and the dramatic growth in the values of numerous cryptocurrencies over the years has attracted an increasing number of traders (Dutta and Bouri, 2022). Since March 2020, the average daily cryptocurrency trading volume across the largest Indian exchanges has increased by approximately 500%. According to CoinGecko data, the average daily traded volume across the top four Indian cryptocurrency exchanges, WazirX, ZebPay, CoinDCX, and BitBNS, was over $22.4 million on December 16, 2020, up from just under $4.5 million on March 1, 2020. According to Paxful, a major cryptocurrency exchange, Indian investors traded approximately 74.92 million Bitcoins between January 1 and November 14, 2020, up to 347 percent from the previous year. After China, India is the second-largest Bitcoin market in Asia, followed by the US, Nigeria, China, Canada, and the United Kingdom. Inexperienced investors have an eagle’s view of the crucifixion of cryptocurrency for its outrageous volatility, which petrifies them before they obtain a taste from the cryptocurrency market (Bouri et al., 2019). Cryptocurrencies may impact the monetary system of the economy (Trubnikova, 2014), as they have a high degree of relevance to the payment system in addition to their role as an investment tool (Inshyn et al., 2018; Smales, 2022). The monetary system is predominantly governed by inflation, interest rates, and exchange rates (Farhi and Maggiori, 2018), and comparatively, inflation is supposed to have the most vital link with cryptocurrencies compared to the remaining macroeconomic indicators, interest rates and exchange rates. According to (Yen and Cheng, 2021), the economic policy uncertainty index (EPU) of China forecasts cryptocurrency volatility, although changes in the EPU indices of the US, Japan, or Korea have no such influence. Changes in China's EPU index are also adversely correlated with future Bitcoin and Litecoin volatility, showing that Bitcoin and Litecoin act as EPU risk mitigation tools. Under the Chinese government's cryptocurrency policies, changes in China's EPU are unlikely to affect Bitcoin volatility.

Finally, this study employs data for the period ranging from 2017 to 2021. This was selected due to significant market developments and increased adoption of cryptocurrencies during this period, which provides a robust dataset for interpretation. Bitcoin and Ethereum were chosen because they are the leading cryptocurrencies by market capitalization, representing a large portion of market activity and investor interest, thus offering a comprehensive view of the leverage effect and price volatility in the cryptocurrency market.

1.1. Objectives

1. To check the leverage effects among BITCOIN and ETHEREUM.
2. Comparison of GRACH (1, 1) and asymmetric TGARCH.

Data Collection: The data were gathered from coindesk.com for the period 2017-2021. To calculate the returns, we use the daily closing price.

2. Model Selection

2.1. Introduction to traditional GARCH (1, 1) and asymmetric TGARCH models

Financial time series may exhibit asymmetries. The moving average (MA) and autoregressive (AR) models assume that constant conditional variances cannot gauge nonlinear dynamics due to the frequent volatility of financial market data (Nikhil M. N., 2023). In financial time series, linear models cannot explain characteristics such as leverage effects, volatility clustering, long memory, and leptokurtosis (Zivot, 2009). More multifaceted approaches are necessary since linear models are constrained in their flexibility and ability to explain such nonlinear phenomena. However, GARCH (1, 1) cannot be used for understanding the nonlinear dynamics of time series data.

To depict nonlinear patterns as nonconstant volatility, financial time series may exhibit asymmetries (Lithin B M et al., 2023; Nikhil M. N., 2023). This motivates the application of more multifaceted approaches to explain such nonlinear phenomena in time series data. Moreover, the changing conditional variance has garnered the attention of several researchers, particularly in econometric models (Benlagha & Chargui, 2016). Thus, the present study, using a TGARCH specification, explores the asymmetric behavior of cryptocurrencies. Furthermore, it can be used to capture asymmetry, the difference in the impact of positive and negative effects of equal magnitude on conditional volatility, and leverage, which is a negative correlation between return shocks and subsequent volatility shocks (Lithin B M et al., 2023).

2.2. Rationale for choosing asymmetric TGARCH and the leverage effect

In conventional GARCH models, positive and negative error terms are considered to have a symmetric influence on volatility. However, due to a number of factors, including transaction costs, arbitrage restrictions, market frictions, and others, financial time series generally show asymmetrical nonlinear patterns (Aliyev et al., 2020). This suggests that “bad news” or adverse shocks may have a more long-lasting impact on conditional volatility than “good news” or positive shocks of a similar magnitude and is termed the “leverage effect.” The standard GARCH model fails to account for this leverage impact. This necessitates the use of asymmetric TGARCH specifications (Lithin B M et al., 2023;Nikhil M. N., 2023)

Therefore, although this study uses GARCH (1, 1) to study the time series volatility of cryptocurrencies, TGARCH has been employed as an improvement to study the asymptotic behavior of cryptocurrencies, such as the leverage effect, which cannot be accounted for using traditional GARCH (1, 1) (Lithin B M et al., 2023; Nikhil M. N., 2023).

2.3. GARCH (1, 1) and TGARCH specifications

2.3.1. GARCH (standard GARCH model)

The generalized autoregressive conditional heteroskedasticity (GARCH) model is commonly used in analyses to model volatility, estimate value-at-risk (VaR) and predict shortfalls (ESs). Engle introduced the autoregressive conditional heteroskedasticity (ARCH) specification in 1982, and Bollerslev developed it in 1986.

The GARCH (1, 1)0 model is$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2$

where$\sigma_t^2 = conditional\ volatlity$

$\varepsilon_{t-1}^2 = squared\ unexpected\ returns\ for\ the\ previous\ period$; derived from the conditional mean equation; $\omega \geq 0$; $\alpha\ and\ \beta \geq 0$.

2.3.2. Asymmetric TGARCH model

The threshold GARCH (TGARCH) model is another volatility model that is widely used to account for leverage effects. The TGARCH (*m*, *s*) model assumes the form

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{s}(\alpha_i + \gamma_i N_{t-i})\alpha_{t-i}^2 + \sum_{j=1}^{m}\beta_j\,\sigma_{t-j}^2$$

Where, $N_{t-i}\ is\ an\ indicator\ for\ negative\ \alpha_{t-i}\ 1, that\ is$

$$N_{t-i} = \begin{cases} 1\ if\ \alpha_{t-i} < 0, \\ 0\ if\ \alpha_{t-i} > 0 \end{cases}$$

$\boldsymbol{\alpha_i}, \gamma_j, \beta_j$ *are non negative paramters that satisfy similar GARCH model conditions*

The most common method of model selection is Akaike's (1973) information criterion. For decades, the Akaike information criterion (AIC) has been a widely used and well-known method for model selection in a wide range of fields for analyzing actual data. Shibata (1976) demonstrated empirically that the Akaike information criterion (AIC) has the ability to select overparameterized models. Several modifications have been proposed to address this inconsistency. Schwarz (1978) proposed a criterion for models specified in terms of their posterior probability that was compatible (Bayesian approach), popularly known as the Schwarz information criterion (SIC). In our analysis, we use both criteria to select the best-fitting model.

2.3.3. Calculations pertaining to the cryptocurrency daily returns

This study checks the leverage effect between Bitcoin and Ethereum using the GARCH model as a comparison tool. The data were gathered from coindesk.com for the period 2017-2021, and returns were calculated using the daily closing price.

$$R_t = logP_t - logP_{t-1}$$

where R- Returns and P denotes the closing price.

3. Data Analysis and Interpretations

The price fluctuations in the cryptocurrency and conventional markets are largely fuelled by news developments and speculation. However, their impact is overstated in crypto markets due to their limited liquidity compared to that of conventional financial markets, which is a result of crypto markets lacking a robust ecosystem of institutional investors and large trading firms. Intensified volatility and a lack of liquidity generate dangerous combinations since both feed off each other. With the exception of bitcoin, the majority of the other cryptocurrencies lack established and widely adopted derivatives. Crypto prices occasionally exhibit healthy volatility under the influence of day traders and speculators. The figures below depict the price volatility of two major cryptocurrencies, Bitcoin and Ethereum.

Figure 1 represents the prices of Bitcoin and Ethereum (2017-2021). The prices increased astonishingly over the study period, despite drastic decreases in 4 quarters of 2017 and 2nd quarter of 2021. Figure 2 represents the returns of Bitcoin and Ethereum. It is evident that returns are stationary; however, it has been suggested that the unit root test be used to confirm the same.

3.1. Unit root test

A time series variable's unit root status is determined by running it through a unit root test. The series is unstable if there are unit roots. Therefore, the series is not stationary if the p value for z(t) is not significant. The null hypothesis H_0 that the series has a unit root is rejected if z ≤ z 0.05. If there are no unit roots, the series is considered to be stationary. It is important to correctly define the null and alternative hypotheses when testing for unit roots to describe the trend characteristics of the data at hand. The suitable null and alternative hypotheses should take this into account if the observed data do not show an upward or downward trend. The trend properties of the data under the alternative hypothesis determine the form of the test regression used.

Table 1 and Table 2 show the output of the unit root test of Bitcoin and Ethereum, and the section criterion input for both is SIC. The Prob. value being less than 0.05 for both coins, the null hypothesis is rejected, and we conclude that the returns are stationary. Furthermore, this allows us to check for ARCH effects on the returns of Bitcoin and Ethereum.

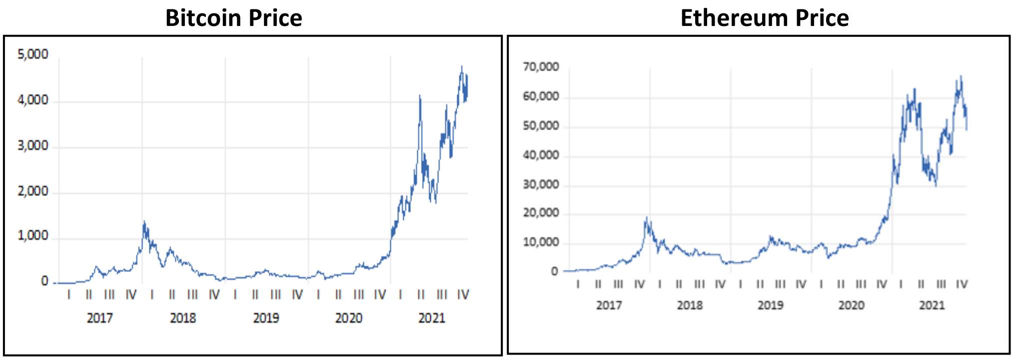

Figure 1 Price analysis of Bitcoin and Etheruem for the period of 2017–2021.

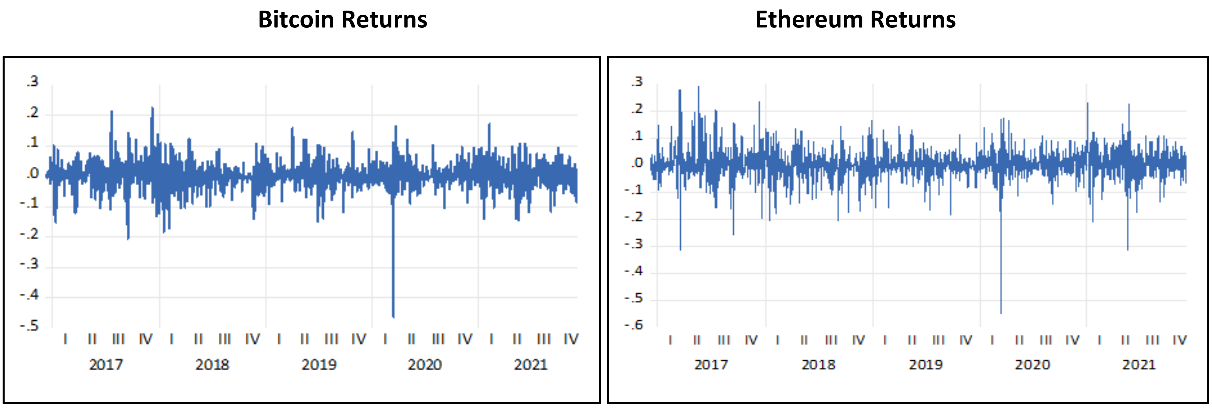

Figure 2 Return analysis of Bitcoin and Ethereum for the period 2017–2021.

3.1.1. Null hypothesis: Bitcoin has a unit root

Table 1 Unit root test for Bitcoin.

Exogenous: Constant			
Lag Length: 0 (Automatic - based on SIC. Maxlag = 24)			
		t-statistics	Prob.*
Augmented Dickey-Fuller test statistics		-43.89106	0.0001
Test critical values:	1% level	-3.433739	
	5% level	-2.862924	
	10% level	-2.567554	

*MacKinnon (1996) one sided p-value

3.1.2. Null hypothesis: Ethereum has a unit root

Table 2 Unit root test for Ethereum.

Exogenous: Constant			
Lag Length: 0 (Automatic - based on SIC. Maxlag = 24)			
		t-statistics	Prob.*
Augmented Dickey-Fuller test statistics		-43.89241	0.0001
Test critical values:	1% level	-3.433739	
	5% level	-2.862924	
	10% level	-2.567554	

*MacKinnon (1996) one sided p-value

3.2. Arch effect test

To analyze and forecast price volatility, the ARCH test enables the identification of a time-varying phenomenon in conditional volatility and recommends diverse models to capture these dynamics. A higher order (nonlinear) of autocorrelation is investigated, as it is perceived to be vital for exploring the time dynamics of the second moments (i.e., conditional variance). The presence of a significant excess kurtosis is not indicative of time-varying volatility, but the reverse is true: a significant ARCH effect identifies time-varying conditional volatility, volatility clustering (or mean reversion), and, as a result, the presence of a fat-tailed distribution (i.e., excess kurtosis > 0).

Table 3 and Table 4 show the results of the ARCH test, with the corresponding probability of the F-statistic being less than .005. We reject the null hypothesis that there are ARCH effects on the returns of Bitcoin and Ethereum.

3.2.1. Null hypothesis: Bitcoin has no arch effect

Table 3 Arch effect test for Bitcoin.

Heteroskedasticity Test ARCH			
F-statistics	13.26966	Prob. F(1.1819)	0.0003
Obs*R-squared	13.18804	Prob. Chi-Square(1)	0.0003

3.2.2. Null hypothesis: Etheruem has no arch effect

Table 4 ARCH effect test for Ethereum.

Heteroskedasticity Test ARCH			
F-statistics	31.24704	Prob. F(1.1819)	0.0000
Obs*R-squared	30.75311	Prob. Chi-Square(1)	0.0000

3.3. Garch model

The GARCH model forecasts the level of volatility at a given time. The proportion of risky versus risk-free assets is adjusted based on whether the predicted volatility value is higher or lower than the target value. It also provides a solution to the issues of the ARCH model. The GARCH model is more parsimonious and much less likely to breach the nonnegativity constraints (Mukhopadhyay et al., 2014). With a GARCH model, one does not need to estimate the number of lags and only needs to estimate a small number of parameters.

Table 5 and Table 6 are the outputs of the GARCH Model for Bitcoin and Ethereum, respectively. The first portion of the tables represents the main equation, and the lower portion represents the variation equations. It is evident from the graph that both the GARCH and ARCH coefficients are statistically significant since their p values are < 0.05 and the Durbin Watson statistical value is close to 2, indicating the absence of autocorrelation.

Table 5 GARCH Model – Bitcoin.

Dependent Variable		Bitcoin		
Sample		08/12/2016 - 07/12/2021		
Garch = C(2)+C(3)*resid(-1)^2+C(4)*garch(-1)				
Variable	Coefficient	Std. Error	z-Statistics	Prob.
C	0.002848	0.000895	3.181112	0.0015
Variance Equation				
C	0.000105	1.181005	8.909055	0.0000
RESID(-1)^2	0.112930	0.010105	11.17579	0.0000
GARCH(-1)	0.837616	0.014750	56.78634	0.0000
R-squared	-0.000166	Mean dependent var		0.002303
Adjusted R-squared	-0.000166	S.D dependent var		0.042226
SE of regression	0.04223	Akaike info criterion		-3.60765
Sum of squared resid	3.24748	Schwarz criterion		-3.59556
Log likelihood	3290.572	Hannan-Quinn criter		-3.60319
Durbin-Watson Stat	2.05702			

Table 6 GARCH Model – Ethereum.

Dependent Variable		Ethereum		
Sample		08/12/2016 - 07/12/2021		
Garch = C(2)+C(3)*resid(-1)^2+C(4)*garch(-1)				
Variable	Coefficient	Std. Error	z-Statistics	Prob.
C	0.002778	0.001230	2.259158	0.0239
Variance Equation				
C	0.000267	3.631205	7.355068	0.0000
RESID(-1)^2	0.128757	0.012451	10.34134	0.0000
GARCH(-1)	0.793426	0.020666	38.39372	0.0000
R-squared	-0.000138	Mean dependent var		0.003440
Adjusted R-squared	-0.000138	S.D dependent var		0.056387
SE of regression	0.056391	Akaike info criterion		-3.043183
Sum of squared resid	5.790648	Schwarz criterion		-3.031091
Log likelihood	2776.340	Hannan-Quinn criter		-3.038722
Durbin-Watson Stat	2.056979			

3.4. TGARCH

It is a volatility model used to handle leverage effects (Glosten et al., 1993) and (Zakoian 1994). The model uses zero as its threshold to separate the impacts of past shocks. The TGARCH model relaxes the linear restriction on the conditional variance dynamics. Questioning the common finding of a high degree of persistence to conditional variance in the GARCH model, Lamoureux and Lastrapes (1990) suggest that such high persistence may be spurious if there are regime shifts in the volatility process.

Table 7 and Table 8 are the outputs of the TGARCH model. The first portion of the tables represents the main equation, and the lower portion represents the variation equations. It is evident that both the GARCH and ARCH coefficients are statistically significant since their respective p values are < 0.05. Furthermore, the leverage coefficient being greater than 0 and its corresponding p values being less than 0.05 confirm the presence of leverage effects in the returns of Bitcoin and Ethereum.

Table 7 TGARCH Model – Bitcoin.

Dependent Variable			Bitcoin	
Sample			08/12/2016 - 07/12/2021	
Garch = C(2)+C(3)*resid(-1)^2+C(4)*resid(-1)<0+C(5)*garch(-1)				
Variable	Coefficient	Std. Error	z-Statistics	Prob.
C	0.002313	0.000951	2.431867	0.0150
	Variance Equation			
C	0.000120	1.332005	9.024810	0.0000
RESID(-1)^2	0.079934	0.010949	7.300936	0.0000
RESID(-1)^2*(RESID(-1)<0)	0.080349	0.010975	7.321194	0.0000
GARCH(-1)	0.822334	0.001543	53.28544	0.0000
R-squared	-0.000000	Mean dependent var		0.002303
Adjusted R-squared	-0.000000	S.D dependent var		0.042226
SE of regression	0.042226	Akaike info criterion		-3.613605
Sum of squared resid	3.246940	Schwarz criterion		-3.598490
Log likelihood	3296.994	Hannan-Quinn criter		-3.608029
Durbin-Watson Stat	2.057362			

Table 8 TGARCH Model – Ethereum.

Dependent Variable			Ethereum	
Sample			08/12/2016 - 07/12/2021	
Garch = C(2)+C(3)*resid(-1)^2+C(4)*resid(-1)<0+C(5)*garch(-1)				
Variable	Coefficient	Std. Error	z-Statistics	Prob.
C	0.002581	0.0012363	2.043114	0.0410
	Variance Equation			
C	0.000277	3.712305	7.446098	0.0000
RESID(-1)^2	0.119604	0.015627	7.653449	0.0000
RESID(-1)^2*(RESID(-1)<0)	0.024657	0.012504	1.972314	0.0486
GARCH(-1)	0.787627	0.021161	37.22127	0.0000
R-squared	-0.000232	Mean dependent var		0.003440
Adjusted R-squared	-0.000232	S.D dependent var		0.056387
SE of regression	0.056394	Akaike info criterion		-3.042631
Sum of squared resid	5.791194	Schwarz criterion		-3.027516
Log likelihood	2776.837	Hannan-Quinn criter		-3.037055
Durbin-Watson Stat	2.056785			

4. Discussion

As reported, the results provide strong evidence against the null hypothesis, i.e., the data are homoscedastic; we conclude that the returns series show heteroscedasticity or that the presence of the ARCH effect is confirmed. Thus, to model this conditional variance, we proceed with the GARCH (1,1) and TGARCH models. Furthermore, we estimate models based on AIC and BIC values. The GARCH model shows that the ARCH term and GARCH term are statistically significant across Bitcoin and Ethereum. This implies that the conditional variance of the bond cryptocurrencies is significantly impacted by the lagged conditional variance and squared disturbances, implying that volatility news of previous time periods impacts the volatility of current days. Furthermore, the sum of the α and β coefficients across the four maturities is less than unity, implying the validity of the GARCH (1,1) model. However, symmetric GARCH models cannot differentiate the impact of the "leverage effect" on the conditional variance of cryptocurrency return data. Hence, we further proceed by applying popular TGARCH models to measure the impact of positive and negative shocks. The results of asymmetric TGARCH models are presented. Based on the AIC and BIC values (lowest values), the TGARCH model is considered in this study. However, the TGARCH model is often superior for predicting volatility in a single phase. The leverage effect refers to the well-established negative relationship between returns and future volatility. This relation is usually explained by the increased leverage ratio that arises from a decrease in the share price of a firm. As the price of a stock decreases, its debt-to-equity ratio increases, increasing the volatility of returns to equity holders (Black & Cox, 1976). A stylized characteristic of financial volatility is that negative shocks (bad news) influence volatility more than positive shocks (good news), where the focus is on equity returns (Aliyev et al., 2020b; Bhatia & Gupta, 2020; Wang et al., 2022). The findings emphasize that negative shocks tend to cause volatility to rise as opposed to positive shocks of equal magnitude. In addition, the results show evidence for high volatility persistence; when it rises, it remains high for a considerable time and returns to its mean only gradually in a euphoric period.

Moreover, long memory qualities and asymmetric impacts are stylized facts likely to result in significant financial outcomes. A time series is regarded as having long memory and asymmetric behavior when its corresponding autocorrelation function is nonintegrable. In reality, the fundamental result of long memory is its nonlinear dependence during the first and second moments (Elder &Serletis, 2008). The results, however, confirm that shocks to the returns may take longer to dissipate, but they are not permanent. If a shock to a given system is lasting, volatility is highly persistent, and the behavior of volatility in the past can be utilized to forecast future volatility. However, normal times with relatively stable pricing may be followed by periods with significant volatility. Because information decays slowly in such markets, old information is more important than new knowledge. This is evidence of so-called long memory behavior. In view of the financial implications of these coefficients, investors can construct future positions in anticipation of this feature. In contrast, low volatility persistence suggests that the shock response function could quickly decrease. Low persistence equates to rapid decay and quick reversion to the mean.

For both investors and policymakers in the cryptocurrency market, the results of this research carry important weight. To be more precise, it is crucial for investors to adopt improved risk management strategies given that there is a noticeable degree of leverage effect and volatility persistence in this market. To this end, it should be noted that in regard to information asymmetry, investors would do better by predicting volatility using negative shocks rather than positive shocks. Therefore, investors can incorporate this asymmetry into their volatility forecasting models to better anticipate and mitigate potential risks. Furthermore, investors should focus on historical data and trends when making their investment decisions rather than relying purely on recent movements because older information is thought to carry more weight. Additionally, it is important to acknowledge that volatility persists for longer periods and does not quickly revert to the mean. For this reason, investors must take a long-term approach when designing their portfolio as well as when anticipating extended periods characterized by unstable markets.

The results of the study should help policymakers create regulations that understand what makes cryptocurrency markets different. An important thing to keep in mind during turbulent market conditions is improving market stability by creating mechanisms that can stabilize it and protect investors, while another area of emphasis is protection against sudden market breakdown in the case of negative news. Furthermore, to reduce the effect of unexpected negative events and increase the transparency of the market, policymakers could consider developing regulations that guide market transparency. In addition, comprehending cryptocurrency volatility’s long-memory characteristics could be used as a basis for formulating regulative measures charged at preventing systematic risks. Most importantly, if regulators take the persistence of volatility into account, then they can create interventions that will support resilience in the markets and lead to more enduring financial steadiness.

Overall, investors should be aware that the volatility of crypto returns is more sensitive to bad news across different types of cryptocurrencies. However, it is important to examine the properties of the yield in both bull and bear periods to better understand how it behaves under different market conditions.

5. Limitations

Although the paper presents an interesting analysis of the leverage effect and price volatility of Bitcoin and Ethereum, there are certain limitations that need to be considered to provide a more complete interpretation of the findings. The first and most obvious limitation is given by the data constraints. The period considered in the paper (2017-2021) is subjectively chosen based on the significant market developments during this time frame. A longer sample period could have provided insights into the long-run dynamics of cryptocurrency returns and could have better characterized the evolving nature of the cryptocurrency market. Additionally, the historical price data on which the analysis is based do not directly capture other relevant variables that may affect cryptocurrency volatility. For instance, the impact of key fundamental variables such as market sentiment and regulatory and macroeconomic factors on cryptocurrency returns may be an avenue for future research.

In addition to the data constraints, the assumptions made on the conditional variance in the GARCH and TGARCH models could introduce bias into the results. These specifications assume that the volatility of Bitcoin and Ethereum follows a specific structure that in practice could be more complex and difficult to characterize, especially in alternative and less liquid markets such as those for cryptocurrencies. For example, the GARCH (1,1) model specifies that the variance is a function of past squared returns and past variances, which could be too simplistic in the case of cryptocurrency markets where the volatility clustering phenomenon of volatility that exhibits large and small bursts that are unconnected and irregularly spaced is thought to be driven by many sources of volatility. The TGARCH model includes an asymmetric specification that accounts for the leverage effect by considering that positive and negative shocks do not have the same impact on volatility. However, this specification still assumes that asymmetries are adequately described by the specifications considered in the paper.

A further potential source of bias could be given by model misspecification. If the models selected in the paper are misspecified and therefore do not correctly represent the data-generating process, the inference on the volatility and leverage effects could be biased. Finally, the analysis considers the case of only two cryptocurrencies (Bitcoin and Ethereum), which cannot perfectly represent the behavior of all other cryptocurrencies that instead may have different volatility patterns and asset price returns and may be subject to different market dynamics.

6. Conclusion

The identities of digital currencies are difficult to establish because they are technology-driven and highly distributed. No one country can be able to effectively manage crypto assets effectively, as technology does not have any borders, resulting in its susceptibility to volatility. The volatility in cryptocurrencies Bitcoin and Ethereum is evident through the GRACH models in our study. Furthermore, the presence of the leverage effect in both cryptocurrencies is confirmed by the leverage coefficient being positive and statistically significant in the TGARCH Model. This indicates a negative correlation between cryptocurrency and its volatility. The presence of the leverage effect is useful for potential investors, as it indicates that a decrease in daily prices will be followed by a decrease in daily prices for a certain time period. This would help potential investors purchase the dips. The GARCH and TGARCH models were found to be statistically significant; however, based on the AIC and SIC criteria, the TGARCH model stands out as the best-fit model for estimating volatility among the given cryptocurrencies. This allows us to conclude that the leverage effect plays a significant role in estimating volatility. The study further concluded that the asymmetry is found to be positive for all cryptocurrencies employed in the study, indicating a higher level of volatility due to negative shocks in the cryptocurrency market compared to positive shocks of equal magnitude.

Ethical considerations

This article conforms to the ethical standards established by the Multidisciplinary Science Journal and abides by the principles outlined in relevant ethical guidelines, including those established by the Committee on Publication Ethics (COPE). The authors also disclose any potential conflicts of interest that may have influenced the research or its findings. Furthermore, the work acknowledges and properly cites the contributions of others, respecting intellectual property rights, and giving appropriate credit to prior research in the field.

Conflict of Interest

The authors of this article assert that they have no conflicts of interest that could potentially impact or be perceived to impact the research and its results.

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References

Abakah, E. J. A., Gil-Alana, L. A., Madigu, G., & Romero-Rojo, F. (2020). Volatility persistence in cryptocurrency markets under structural breaks. *International Review of Economics & Finance*, *69*, 680-691.

Akaike, H. (1973). Maximum likelihood identification of Gaussian autoregressive moving average models. *Biometrika*, *60*(2), 255-265.

Akyildirim, E., Corbet, S., Lucey, B., Sensoy, A., &Yarovaya, L. (2020). The relationship between implied volatility and cryptocurrency returns. Finance Research Letters, 33. https://doi.org/10.1016/j.frl.2019.06.010

Aliyev, F., Ajayi, R., & Gasim, N. (2020a). Modelling asymmetric market volatility with univariate GARCH models: Evidence from Nasdaq-100. Journal of Economic Asymmetries, 22(September 2019), e00167. https:// doi.org/10.1016/j.jeca.2020.e00167

Benlagha, N., &Chargui, S. (2016). Range-based and GARCH volatility estimation: Evidence from the French asset market. Global Finance Journal, 32, 149–165. https://doi.org/10.1016/j.gfj.2016.04.001

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of econometrics*, *31*(3), 307-327.

Bouri, E., Saeed, T., Vo, X. V., &Roubaud, D. (2021). Quantile connectedness in the cryptocurrency market. *Journal of International Financial Markets, Institutions and Money*, *71*, 101302.

Bouri, E., Shahzad, S. J. H., &Roubaud, D. (2019). Co-explosivity in the cryptocurrency market. *Finance Research Letters*, *29*, 178-183.

Cheikh, N. B., Zaied, Y. B., & Chevallier, J. (2020). Asymmetric volatility in cryptocurrency markets: New evidence from smooth transition GARCH models. *Finance Research Letters, 35* https://doi.org/10.1016/j.frl.2019.09.008

Chowdhury, R., Rahman, M. A., Rahman, M. S., & Mahdy, M. R. C. (2020). An approach to predict and forecast the price of constituents and index of cryptocurrency using machine learning. *Physica A: Statistical Mechanics and its Applications*, *551*, 124569.

Demiralay, S., &Golitsis, P. (2021). On the dynamic equicorrelations in cryptocurrency market. *The Quarterly Review of Economics and Finance*, *80*, 524-533.

Dutta, A., & Bouri, E. (2022). Outliers and time-varying jumps in the cryptocurrency markets. *Journal of Risk and Financial Management*, *15*(3), 128.

Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica: Journal of the econometric society*, 987-1007.

Fang, T., Su, Z., & Yin, L. (2020). Economic fundamentals or investor perceptions? The role of uncertainty in predicting long-term cryptocurrency volatility. *International Review of Financial Analysis*, *71*, 101566.

Farhi, E., & Maggiori, M. (2018). A model of the international monetary system. *The Quarterly Journal of Economics*, *133*(1), 295-355.

Fousekis, P., &Tzaferi, D. (2021). Returns and volume: Frequency connectedness in cryptocurrency markets. *Economic Modelling, 95*, 13-20.

Gil-Alana, L. A., Abakah, E. J. A., & Rojo, M. F. R. (2020). Cryptocurrencies and stock market indices. Are they related?. *Research in International Business and Finance*, *51*, 101063.

Glosten, L. R., Jagannathan, R., & Runkle, D. E. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks. *The journal of finance*, *48*(5), 1779-1801.

Gupta, H., & Chaudhary, R. (2022). An empirical study of volatility in cryptocurrency market. *Journal of Risk and Financial Management*, *15*(11), 513.

Handika, R., Soepriyanto, G., &Havidz, S. A. H. (2019). Are cryptocurrencies contagious to Asian financial markets? *Research in International Business and Finance, 50*, 416-429. https://doi.org/10.1016/j.ribaf.2019.06.007

https://doi.org/10.1016/j.econmod.2020.11.013

https://doi.org/10.3390/math8111859

Inshyn, M., Mohilevskyi, L., & Drozd, O. (2018). The issue of cryptocurrency legal regulation in Ukraine and all over the world: a comparative analysis. *Baltic Journal of Economic Studies*, *4*(1), 169-174.

Karim, M. M., Ali, M. H., Yarovaya, L., Uddin, M. H., & Hammoudeh, S. (2023). Return-volatility relationships in cryptocurrency markets: Evidence from asymmetric quantiles and non-linear ARDL approach. *International Review of Financial Analysis*, *90*, 102894.

Katsiampa, P. (2019). An empirical investigation of volatility dynamics in the cryptocurrency market. *Research in International Business and Finance*, *50*, 322-335.

Kim, J, Kim, S,& Kim, S. (2020). On the relationship of cryptocurrency price with US stock and gold price using copula models. *Mathematics, 8*(11), 1-15.

Lamoureux, C. G., & Lastrapes, W. D. (1990). Persistence in variance, structural change, and the GARCH model. *Journal of Business & Economic Statistics*, *8*(2), 225-234.

Lithin B M, Suman Chakraborty, Vishwanathan Iyer, Nikhil M N & Sanket Ledwani (2023) Modelling asymmetric sovereign bond yield volatility with univariate GARCH models: Evidence from India, Cogent Economics & Finance, 11:1, 2189589, DOI:10.1080/23322039.2023.2189589

López-Cabarcos, M. Á., Pérez-Pico, A. M., Piñeiro-Chousa, J., &Šević, A. (2021). Bitcoin volatility, stock market and investor sentiment. are they connected? *Finance Research Letters, 38* https://doi.org/10.1016/j.frl.2019.101399

Malladi, R. K., &Dheeriya, P. L. (2021). Time series analysis of cryptocurrency returns and volatilities. *Journal of Economics and Finance, 45*(1), 75-94. https://doi.org/10.1007/s12197-020-09526-4

Mukhopadhyay, U., Skjellum, A., Hambolu, O., Oakley, J., Yu, L., & Brooks, R. (2016, December). A brief survey of cryptocurrency systems. In *2016 14th annual conference on privacy, security and trust (PST)* (pp. 745-752). IEEE.

Murty, S., Victor, V., & Fekete-Farkas, M. (2022). Is bitcoin a safe haven for Indian investors? A GARCH volatility analysis. *Journal of Risk and Financial Management*, *15*(7), 317.

Nikhil M. N., Suman Chakraborty, Lithin B. M., Sanket Ledwani and Satyakam (2023). Modeling Indian Bank Nifty volatility using univariate GARCH models. Banks and Bank Systems, 18(1), 127-138. doi:10.21511/bbs.18(1).2023.11

Omane-Adjepong, M., &Alagidede, I. P. (2021). Modelling asymmetry and leverage in cryptocurrencies and emerging financial markets. *Economic Papers: A journal of applied economics and policy*, *40*(2), 152-166.

Sapuric, S., Kokkinaki, A., & Georgiou, I. (2020). The relationship between bitcoin returns, volatility and volume: Asymmetric GARCH modeling. *Journal of Enterprise Information Management,* https://doi.org/10.1108/JEIM-10-2018-0228

Schilling, Linda, and Harald Uhlig. 2019. Some simple bitcoin economics. *Journal of Monetary Economics* 106: 16–26.

Schwarz, G. (1978). Estimating the dimension of a model. *The annals of statistics*, 461-464.

Shibata, R. (1976). Selection of the order of an autoregressive model by Akaike's information criterion. *Biometrika*, *63*(1), 117-126.

Smales, L. A. (2022). Investor attention in cryptocurrency markets. *International Review of Financial Analysis*, *79*, 101972.

Subramanian, A., & Rao, B. M. (2022). Diversifying investor's portfolio using bitcoin: An econometric analysis. *Journal of Public Affairs*, *22*(3), e2527.

Trubnikova, E. I. (2014). Cryptocurrency: tool of shadow schemes or monetary system of a free society?. *ВестникСамарскогоуниверситета. Экономика и управление*, *5*(6), 151-158.

Velappan, S. (2024). Co-volatility dynamics in global cryptocurrency and conventional asset classes: a multivariate stochastic factor volatility approach. *Studies in Economics and Finance*.

Walther, T., Klein, T., & Bouri, E. (2019). Exogenous drivers of Bitcoin and Cryptocurrency volatility–A mixed data sampling approach to forecasting. *Journal of International Financial Markets, Institutions and Money*, *63*, 101133.

Wiley. (n.d.). *Analysis of Financial Time Series, Third edition*. O'Reilly Online Learning. Retrieved December 6, 2021, from https://www.oreilly.com/library/view/analysis-of-financial/9781118017098/c03_level1_9.xhtml.

Xia, Y., Sang, C., He, L., & Wang, Z. (2023). The role of uncertainty index in forecasting volatility of Bitcoin: fresh evidence from GARCH-MIDAS approach. *Finance Research Letters*, *52*, 103391.

Yen, K. C., & Cheng, H. P. (2021). Economic policy uncertainty and cryptocurrency volatility. *Finance Research Letters*, *38*, 101428.

Zakoian, J. M. (1994). Threshold heteroskedastic models. *Journal of Economic Dynamics and control*, *18*(5), 931-955.

Zhang, W., & Li, Y. (2021). Liquidity risk and expected cryptocurrency returns. International Journal of Finance and Economics, https://doi.org/10.1002/ijfe.2431

Zivot, E. (2009). Handbook of Financial Time Series. Handbook of Financial Time Series. https://doi.org/10. 1007/978-3-540-71297-8