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Exploring Bitcoin and Litecoin Volatility and Trends

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Abstract

Cryptocurrencies are subject to thorough examination and discourse by numerous media outlets, venture capitalists, financial institutions, banking organizations, market stakeholders, and political entities worldwide. Cryptocurrencies are currently emerging as a new investment class, and this presents an opportunity to explore historically revealed properties of cryptocurrencies. Consumers or investors may use online wallets to buy, store, and trade cryptocurrencies. Cryptocurrencies are not regulated by any government or bank and are designed to replace fiat money. The cryptocurrency market is highly volatile due to its emergent stage. Understanding the dynamics of cryptocurrency "market volatility" is crucial for investors and formulating investment strategies. Volatility is essentially attached to risk and return; as volatility rises, the cryptocurrency market faces greater instability. The volatility inherent in the Bitcoin and Litecoin market is analyzed through a daily return series comprising 3865 observations from January 2014 to July 2024. This study uses symmetric and asymmetric "Generalized Autoregressive Conditional Heteroskedasticity (GARCH)" models to evaluate Bitcoin and Litecoin returns and volatility. The study found a positive "risk premium" in both markets, supporting the hypothesis that volatility correlates with predicted returns. Furthermore, our findings suggest that cryptocurrency return has a "leverage effect," and the effect of news (information) is asymmetric. Negative news has a larger influence on volatility than positive news in Bitcoin returns and has an effect of the same magnitude in Litecoin returns.

Keywords: Bitcoin, Cryptocurrency, GARCH, Litecoin, Return, Volatility.

Introduction

The public's confidence in conventional banking systems was questioned during the economic crisis 2008 (1). Following the financial crisis of 2008, an unidentified individual or group, "Satoshi Nakamoto," unveiled an electronic peer-to-peer network centered on the blockchain technology behind Bitcoin. Bitcoin provides lower-cost transactions and a safe and secure way of exchange over the virtual environment using mathematical algorithms (2). Introduced in 2008, Bitcoin is a decentralized digital currency that became operational in 2009. Cryptocurrency was a reaction to the financial organizations that frequently socialized losses and privatized profits (3). While these cryptocurrencies utilize various algorithmic designs, they share comparable cryptography technologies. Several altcoins were generated to resolve the problem with Bitcoin, including high energy consumption and its limit of up to 21 million coins (4). The expansion of international trade, which accelerated throughout time, affected payment systems. The need for quick, easy, and secure financial transactions is growing along with the expansion of the global economy (5). Cryptocurrency became part of the global economic system after the issuance of regulated futures on bitcoin by the world's most considerable future and options exchange, the Chicago Mercantile Exchange (CME), in 2017 (6). Cryptocurrency is a digital currency based on a cryptographic algorithm that can be used as an alternative online payment form. Cryptocurrency is digital money that is not governed by the government or international law (7). Approximately 20,000 cryptocurrencies have been in circulation since the introduction of Bitcoin (8). Blockchain technology is the underlying technology behind cryptocurrency development (2). Blockchain technology is a revolutionary and promising technology that helps to eliminate fraud, lower security concerns, and increase transparency. Blockchain technology was developed to establish a decentralized ecosystem free from third-party control over transactions and data (9). Blockchain is a decentralized and distributed database that contains a growing number of blocks in chronological order connected via their hash value (2). Despite the rising popular-

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ity of decentralized marketplaces like cryptocurrency exchanges, investors and traders continue to be concerned about their volatility. Cryptocurrencies are volatile, with their value changing dramatically in short periods, leading to a high-risk investment possibility for individuals and groups (10, 11). A favorable correlation between Bitcoin gains and market volatility suggests that cryptocurrencies might serve as a source of security during times of financial crisis. Bitcoin is digital gold among cryptocurrencies (12), can serve as a good investment in times of financial crisis, and might be an essential asset in an investment portfolio (13). Some argue that decentralized markets are inherently more volatile due to a lack of regulation and infrastructure. In contrast, others argue they may be more resistant to economic shocks and market manipulation (13). As a result, comparative market research and volatility trends are required in decentralized and regulated markets to understand their behavior better and identify probable contributing elements to their volatility. Understanding cryptocurrency volatility is an essential hedging or pricing tactic in financial investing. Whether cryptocurrency will be considered a mode of exchange or a financial asset is a matter of much discussion. Our research assumes bitcoin transactions are financial assets used for long-term investment or short-term profit (14-16). Numerous research works have examined the characteristics of asset volatility. Analysis of cryptocurrency volatility and contrast to other financial assets has gained importance because of its surge in popularity. Bitcoin returns remain unaffected by macroeconomic factors (17).

Market Valuation

Since the financial sector's collapse in 2008, cryptocurrencies have gained global interest as a new speculative asset that may be traded. Cryptocurrency price movements have attracted interest throughout the past decade. The bitcoin market has experienced price volatility and the introduction of new currencies (18). Volatility is the uncertainty around the extent of a financial asset's value fluctuations. A "high volatility" indicates that a security's value may be distributed throughout a broader range of values, while a "lower volatility" indicates that the value fluctuates gradually over time (19, 20). The market capitalization of cryptocurrency peaked at $3 trillion at the beginning of 2021 from its invention in 2008. After that, there was a high decline in market capitalization over 2022, and market capitalization reached up to $1 trillion. However, there was a high recovery in 2023, especially in Bitcoin, and the overall cryptocurrency market reached nearly $1.7 trillion (21). Recently, there has been significant growth. In this perspective, examining the cryptocurrency market and ecosystem trends is critical (22). Among many, the top-traded cryptocurrencies include Bitcoin, Ethereum, and "Litecoin," along with Ripple (XRP) (16). Bitcoin is the most popular amid these coins because of its remarkable increase in cryptocurrency users and its popularity among retailers (17). The total number of coins that can be supplied in the market in the case of Bitcoin is 21 million, and the price of Bitcoin has increased by more than 700% in the last five years. The number of Bitcoin exchanges where Bitcoin is traded in standard currencies is over 35, and the daily transaction volume is over 1 million dollars (23).

There has been controversy among previous researchers on the currency worth of cryptocurrencies; most scholars think they are valuable investments (17, 24). Cryptocurrencies, like bonds, equities, and commodities, are seen as investments (10, 23). Although Bitcoin and other cryptocurrencies have grown rapidly, the sector is still relatively new (active trading began in 2013) (25). It is vital to gain insight into how the Bitcoin ecosystem operates. One of the most essential concerns to be addressed is the spillover effects inside the cryptocurrency market and from other financial markets. Through GARCH-M models, we study the price fluctuation of the most prominent cryptocurrencies and evaluate spillovers inside and across other financial markets (26). Cryptocurrency markets are characterized by volatility, unpredictability, and disruption (27). The Bitcoin market is highly speculative (14, 28). Most cryptocurrencies created subsequently exhibit similar price fluctuations. Given the nascent nature of the cryptocurrency industry, it is worth investigating volatility in this market.

Volatility

After forecasting Bitcoin's returns and volatility, academics began to employ several models to determine its returns and volatility. Price volatility is examined promptly in the stock market (29-32), yet the volatility of Bitcoin and Litecoin prices is insufficient to identify. Since cryptocurrency prices have fluctuated dramatically, many scholars are concentrating on this topic.

Time series data is autoregressive, conditional on prior information, and has non-constant variance. Cryptocurrency market volatility is "time-varying" and displays "volatility clustering." Volatility clustering refers to a series with high and low volatility periods. The bitcoin market has experienced price volatility and the introduction of new currencies (18, 33). Volatility is the uncertainty around the extent of a financial asset's value fluctuations. A higher volatility shows that a security's value may be distributed throughout a broader range of values, while a lower volatility indicates that the value fluctuates gradually over time (19, 20). How are cryptocurrency market prices changing? Do returns on cryptocurrencies and uncertainties have a relationship? Does volatility or return spillover occur in the cryptocurrency or other currency markets? The appropriate evaluation methodology is always necessary to assess the risk associated with market performance (34-36). Several ways to estimate volatility have been discussed in the literature, as well as time-varying volatility models. Model development requires understanding of volatility's characteristics (16, 37).

The GARCH approach in mean models examines the relationship between uncertainty and returns for nascent cryptocurrencies to address concerns. The distribution of volatility and uncertainty among various cryptocurrencies is significant (26). Analyzing and forecasting the volatility of financial data has gained popularity among academics, researchers, and others. Volatility analysis is vital in various economic and financial uses, such as portfolio optimization, risk management, and asset pricing (19). Recent studies in behavioral finance have recognized volatility clustering in the stock market using time series analysis. The GARCH model has been recognized as an effective tool for forecasting asset return volatility (38, 39). Investments in cryptocurrency have high risk and high return characteristics. We can evaluate the probability of outcomes by assessing the return variability (16). Volatility features serve as essential for developing different econometric models. Various GARCH models have consistently provided the most predictable results, and the GARCH model has become the standard approach for proving volatility in financial data (40). The volatility of seven cryptocurrencies using various GARCH models was evaluated, and the "Exponential Autoregressive Conditional Heteroskedasticity (EGARCH)" model was considered a robust model for describing the asymmetric nature of volatility (41). Return connectedness in cryptocurrencies increases with both shocks, increasing volatility during significant occurrences (42). Another study examines the dynamics of cryptocurrency's "return and volatility" linkages over the COVID-19 pandemic. They discovered that volatility connection increases significantly over the COVID-19 era, while returns connectivity is most robust over short-term timeframes of one day to one week (43). The price-volume connection in the Bitcoin market was studied, focusing on returns, volatility, and trading volumes. Results of the study show traders become more active when they see significant price rises caused by fresh knowledge about trading volume (15). There was literature regarding Bitcoin and Litecoin technology and progress in its inception, but recently, individuals have been conducting more and more financial studies. Firstly, this study focuses on trends in closing prices of two major and oldest cryptocurrencies, i.e., Bitcoin and Litecoin. Secondly, this study analyzes volatility in the daily returns of these cryptocurrencies with the help of various GARCH models.

Methodology

Autoregressive Conditional Heteroskedasticity (ARCH Model)

The "ARCH model," introduced by Engle R. F. in 1982, is a fundamental tool used in econometrics and finance to analyze "time-varying data" where the series variance or "volatility" is not constant. Unlike models that assume constant variance, the ARCH model methodically integrates volatility variations by defining the error term's conditional variance as a function of prior error terms. The ARCH model is especially relevant in financial markets, where asset returns often exhibit volatility (44).

y_t represents the time series data at time t and ε_t be the error term or innovation at time t, where ε_t is assumed to have a mean of zero.

$$y_t = \mu + \varepsilon_t \quad [1]$$

$$\varepsilon_t = \sigma_t z_t \quad [2]$$

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \alpha_2\varepsilon_{t-2}^2 + \cdots + \alpha_{q-1}\varepsilon_{t-q-1}^2 + \alpha_q\varepsilon_{t-q}^2 = \alpha_O + \Sigma_{i=1}^{q}\alpha\varepsilon_{t-1}^2.. \quad [3]$$

μ is the mean of the series.

σ_t^2 is the conditional variance at the time t.

α_0 is constant

α_0 and α_1 are parameters, with $\alpha_0 > 0$ and $\alpha_1 \geq 0$.

ε_{t-1}^2 are the past squared error terms.

GARCH Model

The "GARCH model" is an extension of the "ARCH model," developed by Bollerslev, T. in 1986. It is extensively used in econometrics and finance to model and forecast time series data with time-varying volatility (45). The "GARCH model" generalizes "the ARCH model" by allowing the "conditional variance" to depend not only on past squared errors but also on "past variances" (46). The GARCH model can extend into various forms, such as GARCH (p, q) models, where q represents the number of "lag variances," and p represents the number of lag squared errors included in the model.

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \ldots + \alpha_q \varepsilon_{t-q}^2 + \beta_1 \sigma_{t-1}^2 + \ldots + \beta_p \sigma_{t-p}^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \, \varepsilon_{t-i}^2 \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \ldots \quad [4]$$

σ_{t-j}^2 (for j=1, 2…, p) are the lagged conditional variances.

α_i (for i=1, 2…, q) are coefficients related with the lagged squared error (with $\alpha_i \geq 0$).

βj (for j=1, 2…, p) are coefficients related to lagged conditional variances ($\beta_j \geq 0$).

Standard GARCH: GARCH (1, 1), or the standard GARCH model, is the most basic form of the GARCH model. The widespread empirical success of the GARCH (1,1) model across various financial markets has cemented its status as the go-to model for volatility forecasting, balancing accuracy and complexity in a way that is both practical and highly effective (45,47,48). Bollerslev's original paper, "*Generalized Autoregressive Conditional Heteroskedasticity*," has had a profound impact on the way economists and financial analysts approach the modeling of time-varying volatility, solidifying its place as a standard in the field (49).

The conditional variance of the GARCH model is given below.

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \quad [5]$$

Stationary is shown by $\alpha_1 + \beta_1 < 1$. The sum $\alpha_1 + \beta_1$ indicates the persistence of volatility. If this sum is close to 1, it suggests that volatility shocks are highly persistent.

The GARCH (1, 1) model suggests that today's volatility (σ_t^2) is affected by both the previous day's volatility (σ_{t-1}^2) and the previous day's squared error (ε_{t-1}^2). The parameters α_1 and $\beta_1$capture the persistence of volatility, with α_1 reflecting the impact of recent shocks and β_1 represents the influence of past volatility.

EGARCH Model: Standard GARCH models suggest that volatility is equally affected by positive and negative error components. Financial time series often display asymmetrical nonlinear patterns due to transaction costs, market frictions, arbitration restrictions, etc. (45). The EGARCH model, introduced by Engle R. F. and Victor NG in 1993, is an addition of the GARCH model that provides a more flexible approach to modeling volatility. Unlike traditional GARCH models, the EGARCH model incorporates an asymmetric response to shocks, allowing it to capture the leverage effect where negative news (information) has a more pronounced impact on volatility compared to positive news (information) (39, 50, 51). The persistence of volatility is modeled by β_1, which reflects the influence of past volatility on current volatility (52).

$$ln\sigma_t^2 = \alpha_0 + \beta_1 \, ln\sigma_{t-1}^2 + \alpha_1 \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \quad [6]$$

Where γ is the coefficient that measures the asymmetry in the effect of shocks on volatility whenever $\gamma \neq 0$.

GARCH in Mean (GARCH-M) Model: In financial markets, the return on an investment can be determined by its volatility. This model expands the fundamental "GARCH framework" in which its "conditional variance" or "standard deviation" determines the conditional mean of a sequence (53). Individuals demonstrating risk aversion generally require a premium before selecting an asset for their investment portfolio (54). The larger the conditional variation of returns, the higher the compensation required for the agent to retain the asset (53, 55).

The mean equation will be

$$y_t = \mu + \lambda \sigma_t^2 + \varepsilon_t \quad [7]$$

The parameter λ is known as the risk premium parameter. A positive λ□ states a positive relation between the return and their volatility.

Threshold GARCH (TGARCH)

One another model commonly utilized to examine leverage effects is the TGARCH model, developed by Zakoian JM (54,56). The TGARCH (1,1) model states conditional variance as follows:

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \gamma D_{t-1} \, \varepsilon_{t-1}^2 \quad [8]$$

D_{t-1} is a dummy variable, which implies

$$D_{t-1} = \{1 \; if \, \varepsilon_{t-1} < 0, \; goodnews \;\; 0 \;\; if \, \varepsilon_{t-1} \geq 0, \; badnews \quad [9]$$

γ is considered as the asymmetry or leverage coefficient. $\gamma > 0$, then there is an asymmetry effect, while γ = 0 is symmetry and collapses with GARCH (1,1). If γ is positive and significant, then negative news (information) has a larger effect on conditional variance (σ_t^2) than positive news (54, 57).

Results and Discussion

Data

Daily time series data is used to model the volatility of Bitcoin and Litecoin returns from January 01, 2014, to July 31, 2024. The data was collected from the Coinmarketcap website. The study is based on 3865 daily observations from closing prices.

Empirical Findings

Basic Statistical and Trend Analysis: Return represents the difference in the natural logarithm of the closing prices between two time periods. Mathematically, it is often expressed as:

$$return = dlog(close) \qquad [10]$$

Where, $dlog(close) = log\ log\ (close_t) - log\ (close_{t-1})$

$close_t$ is the closing price at time t, and $close_{t-1}$ is the closing price at the previous time period or one day before time (t−1).

The graphical representation in Figure 1 delineates the historical closing prices of Bitcoin and Litecoin from 2013 to 2024, underscoring the inherently volatile characteristics of cryptocurrency markets. In the initial years, both cryptocurrencies exhibited relatively stable and modest price levels, with Litecoin demonstrating a marginally superior performance compared to Bitcoin. A notable escalation transpired in 2017, during which both cryptocurrencies attained unprecedented price peaks, particularly Bitcoin, the predominant force in the market then (11). This phenomenon may be attributed to the trade conflict between China and the United States (23).

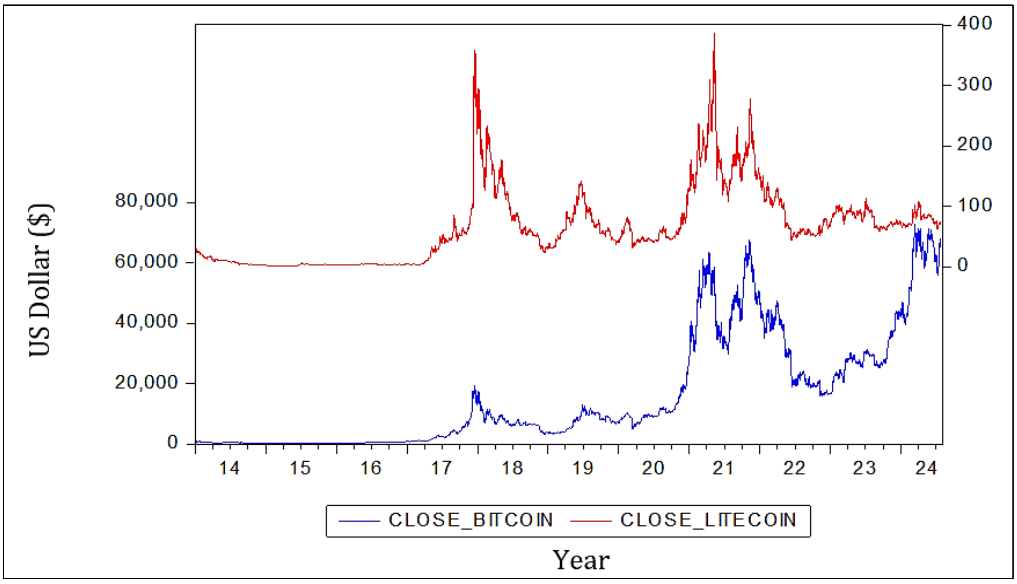

Figure 1: Trends in the Closing Price of Bitcoin and Litecoin

Subsequently, a pronounced decline ensued throughout 2018, primarily due to a cyber breach at Coindesk, Japan's foremost cryptocurrency trading platform, resulting in substantial investor losses and a deterioration of trust within the industry. Numerous nations have instituted restrictions and regulations governing cryptocurrency trading in response to the imperative of curtailing money laundering and financial malfeasance (23). Between 2020 and 2021, another substantial price increase was observed, with Bitcoin attaining new historical peaks and Litecoin exhibiting a similar, albeit modest, upward trajectory. Recent observations indicate that both cryptocurrencies have undergone fewer extreme price fluctuations, with Bitcoin displaying slight stabilization, while Litecoin reflects these trends at diminished price levels. The graph implies a robust correlation between the price trajectories of Bitcoin and Litecoin, with Bitcoin frequently establishing the market trend. This observed pattern of sharp price peaks succeeded by steep declines epitomizes speculative trading behavior and fluctuations in market sentiment, thereby emphasizing the intrinsic volatility of the cryptocurrency domain.

Table 1: Descriptive Statistics

Descriptive Statistics	Close_Bitcoin	Close_Litecoin
Mean	16153.59	65.27004
Median	8151.501	56.64144
Maximum	73083.50	386.4508
Minimum	178.1030	1.157010
Std. Dev.	18973.13	61.73814
Skewness	1.237508	1.399451
Kurtosis	3.443915	5.424841
Jarque-Bera	1018.229	2208.478
Probability	0.000000	0.000000
Sum	62433634	252268.7
Sum Sq. Dev.	1.39E+12	14728016
Observations	3865	3865

The descriptive statistics about the closing prices of Bitcoin and Litecoin elucidate several significant distinctions, as shown in Table 1. The average closing price of Bitcoin is markedly elevated in comparison to that of Litecoin, standing at $16,153.59 juxtaposed with $65.27. This divergence is further illustrated by examining median values: Bitcoin's closing price median is $8,151.50, whereas Litecoin's median is $56.64. Both cryptocurrencies display substantial right skewness, with Bitcoin's skewness calculated at 1.24 and Litecoin's at 1.40, indicating that their respective distributions are elongated to the right, predominantly influenced by a limited number of high values that elevate the average.

The peak closing price for Bitcoin is extraordinarily elevated at $73,083.50, in contrast to Litecoin's maximum closing price of $386.45, accentuating Bitcoin's heightened price volatility. Similarly, the minimum closing prices are recorded at $178.10 for Bitcoin and $1.16 for Litecoin, indicating that while both assets have encountered low price points, Litecoin's minimum value is significantly closer to zero. Bitcoin's standard deviation of $18,973.13 further underscores its greater volatility relative to Litecoin, which possesses a standard deviation of $61.74. The results of the Jarque-Bera test signify non-normality and suggest that the price distributions of both cryptocurrencies are asymmetrical and significantly influenced by extreme values.

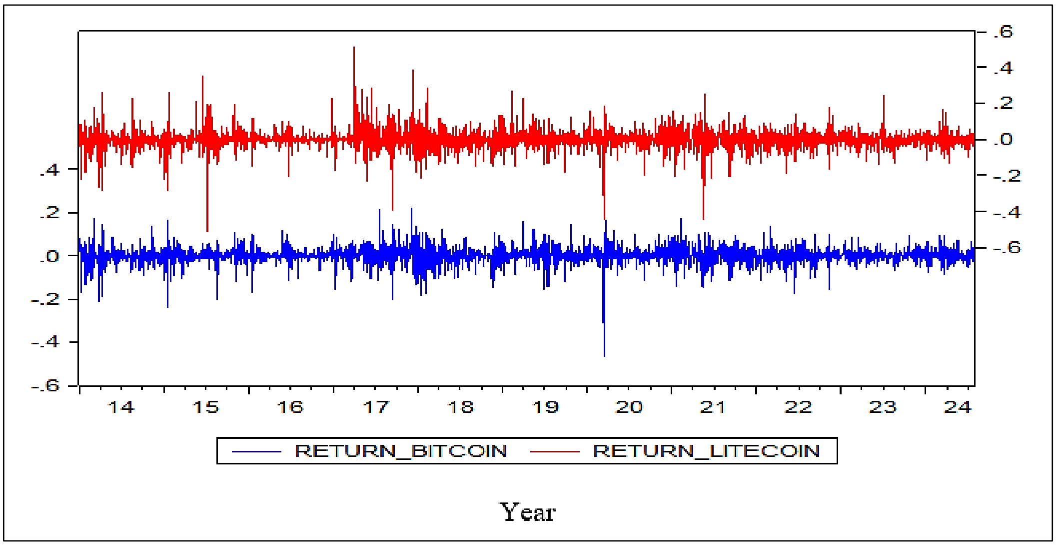

Figure 2: Returns of Bitcoin and Litecoin

The visual depiction (Figure 2) shows how Bitcoin and Litecoin have performed daily, with the blue line representing Bitcoin and the red line for Litecoin. Both cryptocurrencies demonstrate considerable daily variability, signifying "volatility clustering."Large changes in returns follow large changes, and small changes follow small changes. However, Litecoin seems to undergo more pronounced and frequent fluctuations in returns than Bitcoin, implying that it may exhibit greater volatility. The returns for both assets oscillate around a mean of zero, indicating fluctuations of both gains and losses over time. The analogous movement patterns of the two lines suggest a potential correlation between the returns of Bitcoin and Litecoin, although this relationship is not explicitly quantified in the graph.

Unit Root Test:

Data should be stationary for applying the models based on time series analysis. If the series is stationary, it denotes that the data structure within the time series is reliable, meaning that mean, variance, and covariance are consistent over time. The unit root will be checked to check the stationary of data, for which the "Augmented Dickey-Fuller test (ADF)" and "PP test"statistics will be applied (58).

H_0: Data of the return series in non-stationary.

H_1: Data of the return series in stationery.

Table 2: Unit Root Test

	Bitcoin		Litecoin	
Value	ADF	PP	ADF	PP
t-statistics	-63.68043	-63.66156	-63.61371	-63.61371
Prob.*	0.0001	0.0001	0.0001	0.0001
Critical Value				
1%	-2.565561	-2.565561	-2.565561	-2.565561
5%	-1.940906	-1.940906	-1.940906	-1.940906
10%	-1.616644	-1.616644	-1.616644	-1.616644

Table 2 shows that Bitcoin and Litecoin returns display stationarity because the p-value in both cases is less than 0.05.

Heteroskedasticity Test: H_0: There is no heteroskedasticity in the time series data. H_1: There is heteroskedasticity in the time series data. Table 3 presents the results of an "ARCH LM test," which detects "heteroskedasticity" / "homoskedasticity" in time series data, mainly when the variance of the errors (or returns, in this case) changes over time. The p-values linked with the Chi-Square and F-statistic is 0.0000, below the significance level of 0.05. The results strongly show the presence of heteroskedasticity in both the Bitcoin and Litecoin time series. This suggests that the variance of returns for both cryptocurrencies is not constant over time, which is a common characteristic in financial time series data.

Table 3: Heteroskedasticity Test – ARCH LM Test

	F-statistic	Obs*R-squared	Prob. Chi-Square (1)	Prob.F(1,3860)
Bitcoin	56.34522	55.56334	0.0000	0.0000
Litecoin	71.05743	69.80915	0.0000	0.0000

GARCH Model:

Table 4: Estimation Result for Bitcoin Return

Parameter	GARCH (1,1)		EGARCH		GARCH-M		TARCH	
	Coef.	Prob.	Coef.	Prob.	Coef.	Prob.	Coef.	Prob.
Mean equation								
λ	-	-	-	-	0.710837	0.3871	-	-
C	0.001455	0.0059	-	-			-	-
Return (-1)	-0.009596	0.5576	-	-			-	-
Variance equation								
α_0	0.0000571	0.0000	-0.596318	0.0000	0.0000575	0.0000	0.0000611	0.0000
α_1	0.116235	0.0000	0.241466	0.0000	0.116974	0.0000	0.093045	0.0000
β_1	0.852425	0.0000	0.935605	0.0000	0.851462	0.0000	0.847232	0.0000
γ	-	-	-0.041648	0.0000	-	-	0.049332	0.0000
$\alpha_1 + \beta_1$	0.96866		1.177071	0.968436			0.940277	
Regression Statistic								
Log-likelihood	7564.823		7586.041	7565.383			7570.794	
SIC	-3.905863		-3.914710	-3.904015			-3.906817	
AIC	-3.913965		-3.924432	-3.913737			-3.916538	
ARCH-LM Test	0.130865	0.7176	0.279062	0.5973	0.097110	0.7553	0.160945	0.6883

Table 5: Estimation Result for Litecoin Return

Parameter	GARCH (1,1)		EGARCH		GARCH-M		TARCH	
	Coef.	**Prob.**	**Coef.**	**Prob.**	**Coef.**	**Prob.**	**Coef.**	**Prob.**
Mean equation								
λ	-	-	-	-	0.390155	0.4827	-	-
C	-0.000450	0.5740	-	-	-	-	-	-
Return (-1)	-0.009596	0.4597	-	-	-	-	-	-
Variance equation								
α_0	0.000126	0.0000	0.438758	0.0000	0.000127	0.0000	0.000120	0.0000
α_1	0.082486	0.0000	0.171342	0.0000	0.082815	0.0000	0.092030	0.0000
β_1	0.874788	0.0000	0.945645	0.0000	0.874313	0.0000	0.879384	0.0000
γ	-	-	0.023010	0.0000	-	-	-0.024362	0.0000
$\alpha_1 + \beta_1$	0.957274		1.116987		0.957128			
Regression Statistic								
Log-likelihood	6196.154		6190.713		6196.422		6198.581	
SIC	-3.197259		-3.192304		-3.195260		-3.196378	
AIC	-3.205361		-3.202026		-3.204982		-3.206099	
ARCH-LM Test	0.001960	0.9647	0.279062	0.5973	0.000495	0.9823	0.011167	0.9158

Tables 4 and 5 present a comparative examination of four distinct volatility models of the returns of Bitcoin and Litecoin: standard GARCH or GARCH (1, 1), EGARCH, TGARCH, and GARCH-M. Within the GARCH (1, 1) model setting, both ARCH (α_1) and GARCH (β_1) coefficients regarding the return series of Bitcoin and Litecoin are positive and show a significant statistical level at 1%. The importance of the ARCH (α_1) and GARCH (β_1) parameters indicates that historical volatility and returns significantly influence current volatility, thereby confirming that past data plays a crucial role in shaping volatility (26). The cumulative coefficients of ARCH and GARCH, representing the persistence of volatility, are 0.96866 for the Bitcoin return series and 0.957274 for Litecoin, suggesting that current shocks will affect forthcoming returns (23, 59). As the aggregate is below one in both cases, it is evident that the process exhibits mean reversion characteristics. An elevated volatility value signifies the presence of market inefficiencies and the potential for enhanced profits. A market with enduring volatility patterns often faces sharp price alterations, potentially leading to reluctance among risk-averse investors to pursue investment opportunities (60, 61). The process exhibits mean reversion traits, as the aggregate consistently remains below one across all observations. The "ARCH-LM test" statistics reveal that the variance equations for both series are appropriately specified. The model demonstrates efficacy since no ARCH effects are present, as the above statistics corroborated. The GARCH-M (1, 1) specification indicates the existence of a positive risk premium (0.710837 and 0.390155, although not statistically significant), suggesting that the data series reflects a positive association with its underlying volatility. The GARCH-M model incorporates the mean equation component λ, which does not achieve statistical significance (p-values of 0.3871 and 0.4827 for the Bitcoin and Litecoin return series, respectively), indicating that the inclusion of volatility within the mean equation does not materially affect returns. The asymmetric models EGARCH and TGARCH are employed to investigate leverage effects within the returns of Bitcoin and Litecoin throughout the study period (26). The EGARCH model does not impose restrictions on nonnegative parameters, whereas the TGARCH model necessitates that these parameters be positive.

The "E-GARCH (1, 1) model" demonstrates evident GARCH properties and corroborates the presence of "volatility clustering" in the markets for Bitcoin and Litecoin (62). The return series for both cryptocurrencies reveal a positive and statistically significant ARCH coefficient (α_0) at the 1% significance level (41). A significant magnitude of this parameter indicates that the shock substantially affects the volatility of market returns (59). The parameters α_1 for Bitcoin and Litecoin of the two variance equations were determined to be 0.241466 and 0.171342, respectively, whereas the asymmetric coefficients γ were assessed as -0.041648 and 0.02872, respectively.

The asymmetric term (γ) is -0.041648, with a p-value of 0.0000, indicating a leverage effect, implying that adverse shocks (news) exert a more pronounced impact on volatility than positive shocks for Bitcoin returns (63), which is contradictory to the result of the study of Wang, C (2018) (23). Regarding Litecoin returns, the asymmetric term (γ) is 0.023010. It is also highly statistically significant (p = 0.0000), signifying the presence of leverage effects whereby adverse shocks (news) influence volatility in a manner distinct from positive shocks (news). The summation of α_1 and β_1 is 1.177071 and 1.116987 in both instances, slightly exceeding 1, which may imply non-stationarity in variance.

The findings of the TARCH model, as delineated in Tables 4 and 5, indicate that the coefficient associated with the "leverage effect" is statistically significant (64, 65) and positively correlated with Litecoin returns, demonstrating that adverse news has a more profound impact on volatility than equivalent favorable news. Conversely, for Bitcoin returns, the γ coefficient (0.049332), which is statistically significant (p-value = 0.0000), suggests that adverse news has a substantial effect on volatility, albeit through a different mechanism compared to positive news (59), which is contradictory to the result of the study of Wang C (23).

Conclusion

Bitcoin and Litecoin returns and volatility grew significantly between 2017 and 2020-2021. There was some substantial evidence that occurred during that period. The US-China trade war started in 2017–2018, and COVID-19 circulated in 2019–2020, causing global financial problems. Surprisingly, while financial market returns fell during the global crisis, cryptocurrency returns and volatility increased.

In Bitcoin return, the EGARCH model outperforms the others, with the maximum log-likelihood and minimum AIC and SIC values, suggesting a better fit to the data. It captures volatility persistence and asymmetry well. GARCH (1, 1) and GARCH-M models perform similarly but do not account for asymmetric effects, unlike EGARCH and TARCH. TARCH additionally captures asymmetry but with slightly lower fit statistics compared to EGARCH. The TARCH model is the most fitting model for the data of Litecoin return due to its slightly better fit, as confirmed by the highest log likelihood and lowest information criteria values. Furthermore, it efficiently reflects the asymmetry in the data, with significant γ coefficients, signifying that negative shocks have a greater influence on volatility. However, all models are statistically suitable, passing the ARCH-LM test and demonstrating that they accurately reflect the data's volatility structure.

The empirical results of this study are significant for investors, portfolio managers, and a diverse group of market players developing plans to hedge their financial risks, enabling investors to understand volatility and predict projected patterns in the Bitcoin and Litecoin market. Market developments indicate that cryptocurrencies are highly vulnerable to speculation. Investors should be careful that volatility in cryptocurrency returns is particularly susceptible to negative news among different types of cryptocurrencies. To better understand how the return responds to various market situations, looking at its characteristics throughout both "bull and bear" markets is crucial. Investors prioritizing risk and anticipated return should consider currency volatility while making investment choices.

This study only focus on two cryptocurrencies and different GARCH models but in future study can be conducted on other cryptocurrencies i.e. Ethereum, Binance coin, Ripple etc. On the other hand, this study focuses only on the daily closing price and volatility. Still, the effect of news sentiments (i.e., the Musk effect) and macroeconomic variables can be studied in the future.

Abbreviations

ARCH: Autoregressive Conditional Heteroskedasticity, GARCH: Generalized Autoregressive Conditional Heteroskedasticity, EGARCH: Exponential Autoregressive Conditional Heteroskedasticity, GARCH-M: GARCH in Mean, TGARCH: Threshold GARCH.

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