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Unveiling Interconnectedness and Volatility Transmission: A Novel GARCH Analysis of Leading Global Cryptocurrencies

ABSTRACT

The cryptocurrency industry has grown erratically and at an alarming pace during its brief life. It has received massive attention from the practitioners, academicians, and especially media since Bitcoin was introduced in 2009. The current paper investigates the volatility dynamics of five major cryptocurrencies, namely Bitcoin, Ethereum, Litecoin, DASH and Ripple's XRP. It discloses the impact of volatility in the prices of other cryptocurrencies on the Bitcoin's price volatility. The time series of all the cryptocurrencies prices for the period 2016 to 2022 are considered and preliminary analysis highlights that there exists conditional volatility in all the cryptocurrencies which allows us to use the family of GARCH model. The research findings reveal the significant effect of asymmetric past shocks on the current volatility of Bitcoins. Further, the volatility of remaining virtual currencies are also significantly affecting the Bitcoin's current volatility. Therefore, the present study unveils the absence of diversification benefits in the market of virtual assets as significant effect of price volatility of other digital coins has been found on the price volatility of Bitcoins. The practical implication of our study is that the findings offer new information for investors and portfolio managers, who are attracted to invest in or hedging strategies in cryptocurrencies.

Keywords: Bitcoin, Cryptocurrency, Ethereum, Litecoin, DASH, Ripple's XRP, Volatility

JEL classification: C32, C5, G1

INTRODUCTION

The cryptocurrency industry has grown erratically and at an alarming pace during its brief life. It has received massive attention from the practitioners, academicians, and especially media since Bitcoin was introduced in 2009. Now, we have more than 550 cryptocurrencies in the system. Many of the developed and developing nations have adopted some of the cryptocurrencies as their legitimate means of payment (Aziz, 2019; Alvarez *et al.,* 2022). Cryptocurrencies resemble more financial assets rather than currencies (Yermack, 2015; Corbet *et al.,* 2018; Jalal *et al.,* 2021) due to certain characteristics like the volatility feature (Chu *et al.,* 2017; Katsiampa, 2017; Ghorbel & Jeribi, 2021; Doumenis *et al.,* 2021), vulnerability to speculation (Cheah and Fry, 2015; Katsiampa, 2020; Grone *et al.,* 2021), persistence (Caporale *et al.,* 2018; Abakah *et al.,* 2020; Yaya *et al.,* 2021), leverage effects (Phillip *et al.,* 2018; Huang *et al.,* 2022) and, heavy tail behaviour (Chan *et al.,* 2017; Osterrieder and Lorenz, 2017; Gkillas and Katsiampa, 2018; Phillip *et al.,* 2018; Fung *et al.,* 2022). Some studies argue that cryptocurrencies constitute a new investment asset class (Corbet *et al.,* 2018a, 2018b; Ram, 2019; Sterley, 2019).

Due to the ambivalent nature of crypto-assets, understanding the dynamics of their price movement and investigating the volatility connection among them will certainly lead to efficient risk management and optimum portfolio allocation (Almeida & Gonçalves, 2022). It will contribute to comprehend the information transmission process in the cryptocurrency market and also offer valuable information for market participants specially investors, portfolio managers and miners. If the different cryptocurrencies are strongly connected, it results in limiting the benefits of diversification (Huang *et al.,* 2022). If market participants have the knowledge on the information transmission process in the cryptocurrency market, it can be utilized by them to make required changes in their portfolios.

In particular, in order to hedge against the fluctuations in the stock returns, some investors have started investing in cryptocurrencies (Cheong, 2019; Hasan *et al.,* 2023). In scenarios of uncertainties, the knowledge about volatility transmission among cryptocurrencies would certainly guide them to investigate in a suitable cryptocurrency in order to hedge the risk based on their risk appetite. We need to appreciate that the information transmission process of cryptocurrency market may differ from the processes defined for other financial assets since the underlying technology and market environment of cryptocurrencies differ from conventional financial assets like shares, bonds, currency, and derivatives (Aslanidis *et al.,* 2019; Chandra & Iryanto, 2023). Therefore, it is very crucial for the market players to investigate the volatility transmission among the major cryptocurrencies.

It is evident that Bitcoin plays a leading role in the cryptocurrency market and the statistics reflect that most altcoin orders are executed in Bitcoin (Ciaian & Rajcaniova, 2018; Zhang & Mani, 2021). Most of the current studies focus entirely on Bitcoin (Vranken, 2017; Schiling & Uhlig, 2019; Badea & Mungiu-Pupăzan, 2021; John *et al.,* 2022). A scarcity is felt on analyzing other important cryptocurrencies, thus this study investigates four other major cryptocurrencies along with Bitcoin. Moreover, a great deal of literature has focused on the categories or the performance of cryptocurrencies. However, most of literature focuses on Bitcoin only and pays little attention to the relationship, especially volatility connectedness among different cryptocurrencies (Corbet *et al.,* 2018b; Mensi *et al.,* 2021). The reason for this could be expected that the prices of Bitcoin and other cryptocurrencies are interdependent, again due to Bitcoin's dominance, the literature on interlinkages and volatility dynamics within cryptocurrency markets still remains underexplored. The study intends to fill this gap by estimating volatility connectedness among five cryptocurrencies.

The present study, exploring the volatility spillover from four major cryptocurrencies on the most powerful and the oldest cryptocurrency, Bitcoin, complements the existing work on cryptocurrencies. Earlier research has emphasized on either the classification of cryptocurrency or on the reactions of the existing cryptocurrencies to the relevant external shocks. But there is a dearth of research on the volatility interconnectedness among different cryptocurrencies. To the best of our knowledge, this is the first attempt to fill this gap by evaluating the volatility transmission from four major cryptocurrencies on the volatility of Bitcoin.

The present study attempts to provide new information for investors and portfolio managers, who are attracted to invest in or hedging strategies in cryptocurrencies. The structure of this paper is as follows. In section 2, a review of related literature is highlighted. In section 3, we present the research methodology adopted in the study. Section 4 reflects the empirical results of five cryptocurrencies employed in the study and discuss the major findings. In section 5, the study draws conclusion.

REVIEW OF LITERATURE

There is a large body of literature investigating the role of various exogenous variables (financial variables and macro-economic) in understanding and forecasting the volatility of conventional financial assets like equities, bonds, commodities, and currencies (Schwert, 1989; Paye, 2012; Christiansen *et al.,* 2012; Adams *et al.,* 2020; Susanto *et al.,* 2021; Elsayed *et al.,* 2022). With the growing popularity of Cryptocurrencies as a new digital financial asset in the current times, investigating the factors influencing the volatility of cryptocurrencies has become a crucial research topic (Corbet *et al.,* 2018a; Bouri *et al.,* 2020; Ghorbel & Jeribi, 2021; Kyriazis, 2021). It is researched that cryptocurrencies are highly volatile (Chu *et al.,* 2017, Katsiampa, 2017; El-

Khatib & Hatemi-J, 2023) and its volatility is more than that of traditional assets like equities and gold (Klein *et al.,* 2018, Baur *et al.,* 2018b; Zieba *et al.,* 2019; Sonkurt & Altinoz, 2021). Accordingly, investors, portfolio managers and traders are interested in understanding and estimating the variables impacting volatility of cryptocurrencies for applying hedging strategies, minimizing risk and optimizing portfolios.

Earlier studies have used GARCH models to examine the volatility of cryptocurrencies and tried analyzing Bitcoin volatility based only on past returns as conditional information (Katsiampa, 2017; Conrad *et al.,* 2018; Cheikh *et al.,* 2020; Kim *et al.,* 2021). Some other determinants of cryptocurrencies' volatility have also been studied. In one of the research studies, Wavelet approach is used to investigate the variables impacting Bitcoin prices and volatility, Kristoufek (2015). The findings highlight signs of classical currency with supply and price level being the dominant volatility factors. In another study, no exogenous variable was identified to influence price of Bitcoin (Baek & Elbeck, 2015). There are studies that examine the impact of other financial variables and financial assets like gold, commodities, equity market volatility and equity indices on Bitcoin's volatility (Kristoufek, 2015; Bouri *et al.,* 2017b; Baumohl, 2019, Bouri *et al.,* 2018a, b, Corbet *et al.,* 2018a, Demir *et al.,* 2018; Panagiotidis *et al.,* 2018; Dyhrberg, 2016; Bouri *et al.,* 2017a, Charfeddine & Maouchi, 2019). These studies use GARCH models to predict Bitcoin's volatility.

Numerous studies in the past have implored the risk mitigation and diversification benefits of adding the Bitcoin with other traditional assets in a portfolio (Dyhberg, 2016; Bouri *et al.,* 2017; Corbet *et al.,* 2018; Fang *et al.,* 2019; Ji *et al.,* 2019). Only a handful of studies have explored the dynamic linkage across varied cryptocurrencies. For instance, Gandal and Halaburda (2016) contrasted the exchanges rates of various cryptocurrencies and found that the market was dominated primarily by Bitcoin currency. It observed that while other currencies were depreciating vis-à-vis the U.S dollar, bitcoin appreciated inferring that the latter can be used as a financial asset. It is pivotal to note that the external events may cause significant spillover effects across various types of digital currency. Fry and Cheah (2012, 2016) discerned the price movements of Bitcoin and its competitor cryptocurrency, Ripple. The study found that the exogenous shocks such as technical failures, government restrictions created a negative bubble effect between the two currencies. Corbet et al. (2018) further extended the previous research by examining the spillover effects across the most prominent digital currencies, namely, Bitcoin, Litecoin, and Ripple. It also discerned the dynamics of digital currency to that of traditional financial assets such as gold, stocks, bonds etc. and evidenced that the two asset classes are isolated to one another. In addition, the cryptocurrencies are relatively more immune to external disturbances reflecting greater diversification benefits.

The most recent outbreak of the dangerous Covid-19 pandemic coerced the governments of all nations to impose monetarily detrimental lockdowns, subsequently keeping worldwide supply chains in a halt mode (Bouhali *et al.,* 2021). The high financial expenses related with Coronavirus contagion set off outrageous hazard avoidance universally, causing a sharp liquidity crush across the various business sectors followed by a massive fall in the securities' valuations. By employing the spillover indexing technique proposed by Diebold and Yilmaz (2012), Sui et al. (2022) distinguished the topological structure and the volatility association across the major global cryptocurrencies before and after the COVID-19 outbreak. It confirmed the exponential rise in volatility linkage, especially after the occurrence of pandemic conditions, across major crypto players such as Bitcoin, Ripple, Cardano, Litecoin, Stellar and Ethereaum. Sajeev and Afjal (2022) ascertained the contagion effects of digital currencies across India, U.S., London and China. The study indicated negative correlation between the Bitcoin markets of U.S. and China, and positive, but weak, association of Indian market with London. In addition, time-varying analysis evidenced that the Bitcoin market is more affected by the negative market events than the positive incidents. Similar evidence was observed by Balcilar et al. (2022) for Saudi Arabia, U.S., and Thailand implying that such contagion effect is not restricted to regional level, but surpasses the national boundaries.

The current investigation undertakes an examination of the transmission of market fluctuations from four prominent cryptocurrencies to Bitcoin, the most robust and longstanding cryptocurrency. This study serves as a valuable addition to the existing body of research on cryptocurrencies. Previous scholarly work has primarily focused on either categorizing cryptocurrencies or examining the responses of established cryptocurrencies to external shocks (Wu *et al.,* 2018; Katsiampa *et al.,* 2019; Yin *et al.,* 2021; Yarovaya & Zięba, 2022). However, there is a noticeable lack of research on the interconnectedness of volatility among various cryptocurrencies. To the best of our knowledge, this study represents the inaugural effort to address this gap by assessing the transmission of volatility from four major cryptocurrencies to Bitcoin. The objective of this study is to furnish fresh insights for investors and portfolio managers who are attracted to the prospects of investing in or employing hedging strategies within the realm of cryptocurrencies.

RESEARCH METHODOLOGY

Since the incidence of COVID-19 pandemic, the financial turmoil increased the anxiety among households forcing them to look for additional source of income. Bitcoins became massively popular worldwide specially during global lockdown period. Therefore, examining the dynamics of crypto currencies during this time frame is extremely crucial. The present study investigates the volatility dynamics of five major cryptocurrencies, namely Bitcoin, Ethereum, Litecoin, DASH and Ripple's XRP. Secondary data in the form of time series has been collected from the financial year 2016-17 to 2021-22 primarily from the website of Yahoo Finance. Descriptive statistics have been applied to explore the basic tenets of the collected time series. The main objective of the study has been examined using the GARCH model. One faction of econometricians prefers applying the ARIMA model over the ARCH and related models. However, the former is restricted to a mean equation due to which the conditional variance cannot be identified. This limitation has been removed by using the GARCH model which adopts a lagged conditional variance. Daily log returns of all the 5 time series namely Bitcoin, Ethereum, Litecoin, DASH and Ripple's XRP are calculated using the following equation:

$$R_t = \log\left(\frac{P_t}{P_{t-1}}\right) \quad \textbf{Equation (1)}$$

Where, R_t refers to the daily returns during the period t, P_t denotes the closing price at the time t, while, P_{t-1} indicate the closing price during the preceding day. This model desires the data to be normal and stationary. Therefore, Jarque Bera test has been applied to check the normality in the collected data. In addition, unit root test, specifically, Augmented Dickey Fuller test has been applied. Equation (2) depicts the mean equation for developing the GARCH (1,1) model:

$$R_y = C_1 + C_2 * X + \epsilon_1 \quad \textbf{Equation (2)}$$

where, R_y refers to the returns of the dependent variable, C_1 is the constant term, C_2 is the co-efficient of the independent variable X, while the error term is denoted by ϵ_1. Equation (3) shows the variance equation used to apply the GARCH (1,1) model:

$$H_t = C_3 + C_4 * H_{t-1} + C_5 * \epsilon_{2,t-1} \quad \textbf{Equation (3)}$$

where, H_t is the residual term calculated from Equation (2) and is referred as the return volatility of the dependent variable, H_{t-1} indicates the GARCH term and is the volatility in return of the preceding day, and finally $\epsilon_{2,t-1}$ indicates the ARCH term implying the previous day returns and the main factor causing volatility in present returns.

RESULTS AND DISCUSSION

The current study examines the impact of volatility in the returns of other cryptocurrencies on the Bitcoin's return's volatility. The results are discussed in this section.

Descriptive statistics

This section highlights the descriptive and normality of all the time series used in the current research. The results show the mean, median, maximum, minimum, standard deviation, skewness and kurtosis of all the cryptocurrencies namely – BTC, ETH , LTC, DASH , XRP. It also reflects the findings of Jarque-Bera Statistics to check the normal distribution of each time series. The tests have been applied on log returns of cryptocurrencies and the outcomes of the test indicate that none of the time series are not normally distributed.

Unit root test

It is essential to figure out the stationarity of all the time series otherwise the inferences are not considered authentic and hence ineffective. Unit root test, ADF test (Elliot *et al.,* 1996; Dritsaki and Dritsaki-Bargiota, 2005) has been applied. The ADF model is:

$$\Delta Z_t = \alpha_1 + \alpha_{2,t} + \alpha_3 Z_{t-1} + \sum_1^p \beta_i \Delta Z_{t-1} + \epsilon_t \qquad \textbf{Equation (4)}$$

where ADF regression tests for the existence of unit root of Z_t, the logarithmic values of all model variables at time t.

The log-transformed data for the returns of Bitcoin, Ethereum, Litecoin, DASH and Ripple's XRP are tested for stationarity. The results depicted in Table 1 reflects that the p values are less than 0.05, so all the series are stationary. Now, since series are stationary, the next step is to determine the best mean fitting equation through the auto-regressive process.

Table 1: Unit Root Test

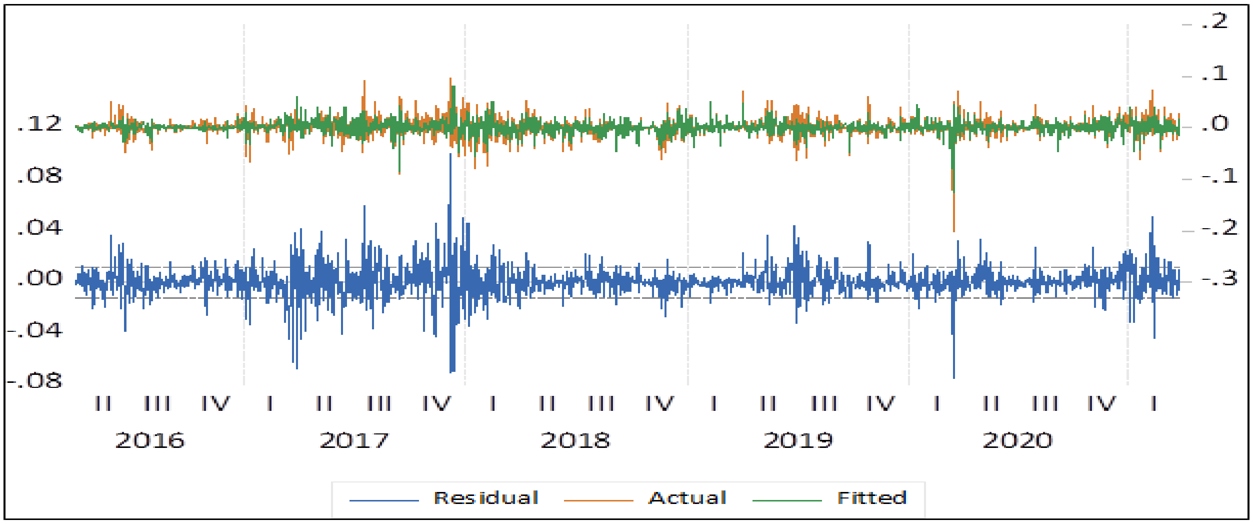
Time series	ADF	Prob.*
LBTC	-43.3296	0.0005***
LETH	-43.0620	0.0005***
LDASH	-43.66983	0.0001***
LXRP	-27.5516	0.0004***
LLTC	-42.5538	0.0001***

Source: Author's own computation.
Note: *** indicate significance at 1% level.

INTERRELATIONSHIP BETWEEN MOVEMENT OF BITCOIN AND THE VOLATILITY OF OTHER VIRTUAL CURRENCIES USING GARCH MODEL

The current study tries to establish a relationship between the volatility of BTC and the volatility of rest of the cryptocurrencies. To examine this volatility relationship and also based on the stationarity nature of the time series, it is suggested to use the GARCH (1, 1) model. It is appropriate to examine the residuals of the dependent variable, in this case, BTC returns to decide which model suits best on the sample of our study. Same has been checked and the resulted graph is as follows:

Figure 1: Heteroscedasticity test



Source: Author's own depiction.

It can be seen that for the period from Year 2017 (III) to Year 2018 (II), the fluctuations are large. So we can say that the period of high volatility is followed by a period of high volatility. It can also be, observed that the period from Year 2018 (III) to Year 2019 (IV) has witnessed small fluctuations. So, we can also say that period of low volatility is followed by a period of low volatility. It can thus be concluded that the period of high volatility is followed by a period of high volatility and period of low volatility is followed by a period of low volatility. This suggests that when residual behaves like this, residual or error term has conditional heteroscedasticity and it is appropriate to introduce the ARCH/GARCH model in the study.

Development of the GARCH (1,1) Model

Mean equation of the GARCH(1,1) model is displayed as follows

$$LBTC = C(1) + C(2)LBTC(-1) \qquad \textbf{Equation (5)}$$

where,

LBTC = log Returns of BTC, Dependent Variable

C(1) = Constant

LBTC(-1) = lag of log Returns of BTC, Independent Variable

Variance Equation can be written as follows:

$$H_t = C(1) + C(2)H_{t-1} + C(3)e_{2(t-1)} + C(4)LDASH + C(5)LETH + C(6)LLTC + C(7)LXRP \quad \textbf{Equation (6)}$$

Where,

H(t) = current day volatility of BTC returns. It is also known as the Garch Term

e 2t-1 explains if the previous day BTC returns is causing today's return. It is also known as the Arch Term

C(3) = Coefficient of LDASH, LDASH = Log returns of DASH, Independent Variable

C(4) = Coefficient of LETH, LETH = Log Returns Of ETH, Independent Variable

C(5) = Coefficient of LTC, LLTC = Log Returns of LTC, Independent Variable

C(6) = Coefficient of XRP , LXRP = Log Returns of XRP, Independent Variable

Table 2: GARCH (1,1) MODEL

Variable	**Coefficient**	**Std. Error**	***z*-statistic**	**Prob.**
Panel A: Mean Equation				
C	0.00111	0.00036	3.05313	**0.00230***
Panel B: Variance Equation				
C	0.00002	0.00000	11.40319	**0.00000***

RESID(-1)^2	0.15567	0.01498	10.39203	**0.00000*** **
GARCH(-1)	0.80522	0.01446	55.67786	**0.00000*** **
LDASH	-0.00018	0.00009	-1.90172	**0.05720***
LETH	-0.00026	0.00009	-2.97102	**0.00300*** **
LLTC	0.00019	0.00009	2.03629	**0.04170** **
LXRP	**-0.00014**	**0.00005**	**-2.84628**	**0.00440** **

Source: Author's own computation.
Note: ***, **, * indicate significance at 1%, 5% and 10% level respectively.

GARCH (1, 1) model using the normal distribution method is applied in this section and Table 2 depicts the results. It can be seen that the ARCH term indicated by as **e2t-1** is not significant at 5% significant level meaning that previous day BTC's returns are not influencing today's BTC's returns volatility. It can also be observed from the table below that the GARCH term is not significant at 5% significant value. It means that the previous day's return's volatility, **Ht-1** in variance equation is not influencing present return's volatility. The values indicate that the ARCH term is not significant as well as the GARCH term is also not significant at 5% significance level respectively so it can be concluded that BTC returns does not impact the volatility of other coins like ETH, XRP , LTC, DASH. The p-value of ETH , LTC , DASH , XRP is not significant at 5% significantlevel and therefore not affecting the returns of BTC.

Model Fit

It is equally important to examine whether the model chosen by the researcher fits best to analyse the relationship. To do so, the study has applied three different tests on the residuals namely, Serial correlation, Heteroscedasticity Test (ARCH) and Normal distribution. The following section gives a detailed analysis of all three tests.

Serial correlation

Table 3: Serial correlation

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	-0.000	-0.000	2.E-06	0.999
		2	-0.016	-0.016	0.4557	0.796
		3	-0.026	-0.026	1.6613	0.646
		4	0.024	0.023	2.6776	0.613
		5	-0.001	-0.001	2.6785	0.749
		6	-0.002	-0.001	2.6829	0.847
		7	0.002	0.003	2.6907	0.912
		8	-0.008	-0.008	2.7991	0.946
		9	-0.010	-0.009	2.9657	0.966
		10	-0.008	-0.008	3.0764	0.980
		11	-0.009	-0.010	3.2159	0.988
		12	-0.005	-0.005	3.2558	0.993
		13	-0.017	-0.017	3.7794	0.993
		14	-0.003	-0.003	3.7971	0.997
		15	0.008	0.008	3.9173	0.998
		16	0.004	0.003	3.9433	0.999
		17	-0.011	-0.010	4.1698	0.999
		18	-0.004	-0.003	4.1926	1.000
		19	-0.012	-0.013	4.4635	1.000
		20	-0.015	-0.016	4.8852	1.000
		21	0.006	0.006	4.9554	1.000
		22	-0.006	-0.008	5.0260	1.000
		23	-0.004	-0.004	5.0521	1.000
		24	-0.008	-0.007	5.1649	1.000
		25	-0.000	-0.001	5.1650	1.000
		26	-0.003	-0.004	5.1854	1.000
		27	-0.012	-0.012	5.4318	1.000
		28	-0.001	-0.001	5.4333	1.000
		29	0.014	0.013	5.7763	1.000
		30	-0.005	-0.006	5.8171	1.000
		31	0.001	0.002	5.8205	1.000
		32	-0.012	-0.013	6.1109	1.000
		33	-0.009	-0.011	6.2674	1.000
		34	-0.011	-0.012	6.5090	1.000
		35	0.007	0.005	6.5915	1.000
		36	0.016	0.015	7.0962	1.000

Source: Author's own calculation.

Serial correlation of the residuals has been applied to examine whether the residuals have serial correlation or not. Thirty-six iterations were selected by the software (Eviews) itself and the results are indicated in the following table. All the probability values are more than .05 so the null hypothesis indicating that there is no serial correlation cannot so this study accepts the Null Hypothesis Hence, it can be concluded that there is no serial correlation which is acceptable for the model to stay fit for analysing the relationship between BTC and ETH, XRP, LTC, DASH.

Heteroscedasticity Test

The results of heteroscedasticity test reveal that the p-value is 0.9988 which is more than 5% significance level so we accept the null hypothesis indicating that there is no heteroscedasticity effect in the residuals or there is no ARCH effect. This result is also good for the model to stay fit.

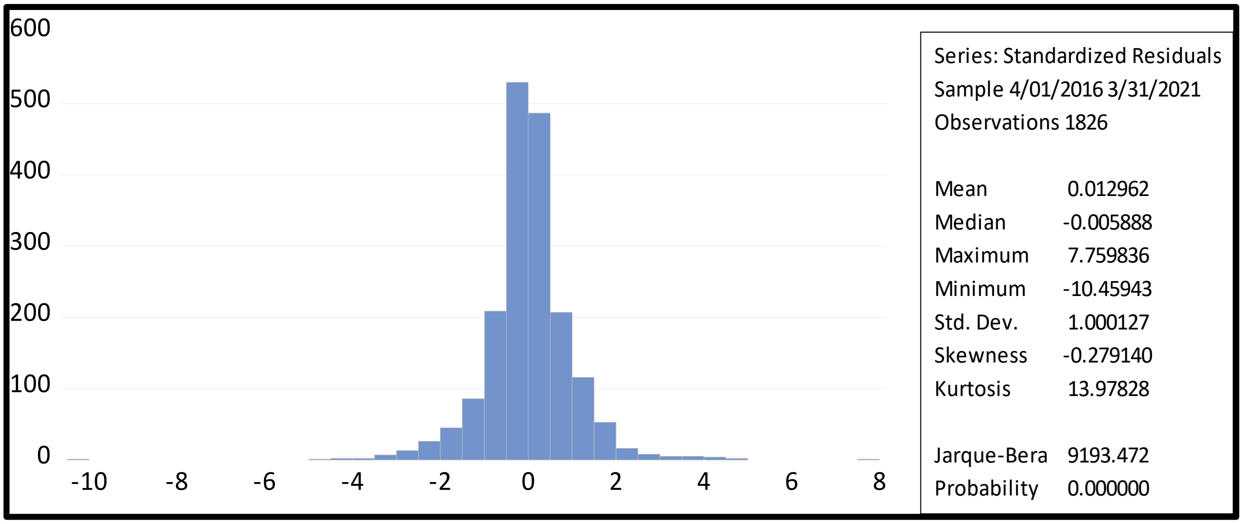
Table 4: Heteroscedasticity test

Parameters	Value
F-statistic	2.13E-06
Obs* R-squared	2.13E-06
Prob. F (1,1823)	0.9988
Prob. Chi-square (1)	0.9988

Source: Author's own calculation.

Normal Distribution Test

Figure 2: Normality Test



Source: Author's own depiction.

The results of the Jarque-Bera test indicated that the p-value is 0.0000000 which is less than .05 so the null hypothesis indicating that the data is not normally distributed which is rejected. This result is not desirable for the model to stay fit.

The current paper recommends that portfolio managers investing in the stock market of various economies may also explore cryptocurrency market as possible destinations to diversify their risk.The findings have substantial implications for institutional investors, policymakers and portfolio managers in the assessment of various investment avenues and finalising the asset allocation. Before expanding investment beyond stock market and entering cryptocurrencies markets for investments, the market participants may capture the findings of our study. and pay attention to the volatility transmissions. Moreover, international portfolio managers, hedgers and arbitragers may be able to assess the volatility linkage between cryptocurrencies effectively.

CONCLUSION

The volatility in Bitcoin prices and other cryptocurrencies is still poorly known, as cryptocurrency market is a largely unexplored field of study. But, as the interest and credibility in cryptocurrencies grows, especially with the establishment of derivatives markets, it's critical to understand the forces that cause fluctuations in the crypto market. The current study examines the connection in the volatility of the major cryptocurrencies namely, Bitcoin , Ethereum , Ripple , Litcoin , Dashcoin of the world. The majority studies in the past agree that the market for virtual assets is heavily dominated by Bitcoins. Due to the incidence of COVID-19 pandemic, the topological structure of the market changed heavily resulting in ever increasing linkage across different digital currencies (Bouhali *et al.,* 2021; Sajeev & Afjal, 2022; Sui *et al.,* 2022). The present study establishes evidence in agreement to the previous studies (Dyhberg, 2016; Fry & Cheah, 2016; Gandal & Halaburda, 2016; Bouri *et al.,* 2017; Corbet *et al.,* 2018; Fang *et al.,* 2019; Ji *et al.,* 2019; Mensi *et al.,* 2021) where the findings reflect that bitcoin's volatility is significantly impacted by three altcoins namely XRP, LTC , ETH and by its own internal shocks. This study is one of the unique studies on cryptocurrencies which would not only help the portfolio managers but also the policy makers and policy regulators. It can be suggested to portfolio managers and investors, both institutional and retail to study the volatility patterns of cryptocurrencies before making any investment decision. As there are less regulationsin the crypto market, this research would help the policy maker in formulating the policies related to cryptocurrencies.

AUTHOR'S CONTRIBUTION

Dr. Silky Vigg Kushwah has taken the initiative to identify the gap in research and has offered insightful guidance for further investigation. Employing her analytical prowess, she has derived pivotal findings crucial to this paper after carefully designing the appropriate research methodology. Dr. Payal Goel, on the other hand, has composed the introduction, drawing from an extensive range of research papers and crafting a comprehensive literature review to establish the objectives. The conclusion of this paper is the culmination of a collaborative endeavor between both authors.

CONFLICT OF INTEREST

The authors of this manuscript affirm their lack of any conflicts of interest.

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