Research Article

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# Interconnectedness and Volatility Dynamics in Major Cryptocurrency Markets: A Study of LTC-USD, BTC-USD, BNB-USD, and ETH-USD

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## Abstract

This study employs an asymmetric VAR(1)-multivariate GARCH(1,1)-BEKK approach to evaluate the returns, shock, and volatility spillovers for BTC-USD, LTC-USD, BNB-USD, and ETH-USD cryptocurrencies. The findings of the current study reveal significant interconnectedness between currencies, and notable complementarity between BTC and ETH. Additionally, LTC and BNB exhibit an inverse impact on BTC and ETH returns, indicating their increasing popularity among investors. The variance equation analysis demonstrates that past shocks/news significantly affect all cryptocurrencies, with lower cross-news effects compared to internal news impacts. In addition, a significant short-term and long-term volatility spillovers are found among the four major cryptocurrency markets. Further, we find a substantial increase in the conditional volatility of the selected cryptocurrencies from April 2022 to November 2022. This research work emphasizes the significance of interconnectedness, and volatility dynamics of cryptocurrencies in portfolio management. Additionally, it provides suggestions for policymaking for effective risk management strategies and regulatory measures in the market.

Keywords: Interconnectedness. Volatility. Cryptocurrency. Spillover. Multivariate GARCH.

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## 1 Introduction

In the worldwide financial background, cryptocurrencies have emerged as an important asset that attracts the interest of investors and decision-makers. Litecoin (LTC), Bitcoin (BTC), Binance (BNB), and Ethereum (ETH) are major cryptocurrencies, each with its special attributes and market dynamics. Understanding the following digital asset's interconnection and volatility dynamics is important for successful portfolio management and policy formulation, as evidenced by its impressive fluctuations and adoption.

In this context, this study tried to analyze the dynamics of volatility and connectivity in cryptocurrency markets, concentrating on pairs of currencies BTC, BNB, LTC, and ETH. It is interesting to shed light on complex relationships that exist among cryptocurrencies. It also investigates how volatility appears at different times, providing insights into the fundamental forces that shape market behaviour. Due to their popularity and market capitalization, which makes

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them illustrative of larger cryptocurrencies, LTC, BTC, BNB, and ETH were considered. With evaluation of daily closing prices obtained from yahoo finance during July 14, 2021, and July 6, 2023, this study aims to study patterns and advancements in the cryptocurrencies structure. This study uses different econometric tools to find notable patterns and linkages in the interconnectedness and the volatility dynamics of cryptocurrency markets. The means of empirical inquiry, the objective of this study is to also provide practical insights that can help in investment decision making and policy initiatives within the swiftly changing cryptocurrency landscape.

The structure of research on cryptocurrencies has been found very significant, with studies delving into several areas related to cryptocurrencies. Study on bitcoin as a possible alternative monetary system has been conducted in large part, as publications discussed by Becker et al.'s (2013) work. In addition, a substantial of research work including works done by Ankenbrand and Bieri's (2018) discussed the ongoing discussion of whether cryptocurrencies belong in the asset or currency class.

In addition, several authors have investigated the spillover effects that cryptocurrencies have on conventional assets with the aim of identifying the speculative character of cryptocurrencies as well as its potential as tools for diversification. Some important contributions to this field of work have been made through Guesmi et al.'s (2019) and Charfeddine, Benlagha, and Maouchi's (2020) in different studies. Moreover, considerable attention has been devoted to the modeling structure and prediction of the volatility of cryptocurrency markets (Gyamerah; Bezerra & Albuquerque, 2017; Catania, Grassi, & Ravazzolo, 2019; Patel et al., 2020; Xiao & Sun, 2020)

The Covid-19 pandemic reignited interest in the financial market and its contagion dynamics, studies that examine how cryptocurrencies and traditional assets interact during crisis period. In a study, Lahmiri and Bekiros's (2020) analyzed the characteristics of 16 worldwide stock markets and 45 cryptocurrencies prior to and after the pandemic, they found significant differences between the two assets during the crisis period. In a similar work, Corbet et al.'s (2019) studied the relationship between Bitcoin risk and Chinese financial market risk, emphasizing increased dependency during the COVID-19 crisis. In some other study, Bouri, Gupta, and Vo's (2022) evaluated the contagion of cryptocurrency markets in reaction to geopolitical concerns, concentrating on the jump component between specific cryptocurrencies markets and geopolitical risk.

The current research on cryptocurrencies discusses a wide range of topics, including systemic risk assessment, financial market dynamics, and environmental implications. In their analysis of the environmental effects of Ethereum and Bitcoin, Cheraghali et al.'s (2024) discuss attention to the fact that proof of work processes produces more carbon emissions than Proof of Stake mechanisms. The study predicts that future halving times may pose a threat to the viability of Bitcoin mining, and highlighting the necessity of responsible innovation and governmental monitoring. (Boubaker et al., 2024) discussed and compared the performance of cryptocurrencies to inflation forecasts in order to study the relationship between the two currencies, which shows that cryptocurrencies, in contrast to gold, are not a dependable hedge against inflation, especially in low-inflation circumstances.

The effects of cyberattacks on cryptocurrency and conventional financial markets are examined in a different study by Cheraghali et al.'s (2024), that finds that these attacks raise trading volumes and volatility in both areas, but as time goes on, its influence on cryptocurrencies is waning while it increases on the financial industry. Finally, Boubaker et al.'s (2024) investigated the use of big data in finance sector, and focus on predicting systemic risk associated with cryptocurrencies. They discover that smaller cryptocurrencies, as Fantom, have a higher tolerance for risk. This provides idea to investors about safe havens, and hedging tactics for market fall. As a whole, the following studies provide insightful information about the complex dynamics of cryptocurrency markets, and how they are interacting with conventional financial structure, especially in turbulent economic times like the COVID-19 crisis. When taken as a whole, these papers provide insightful information about the complex dynamics of cryptocurrency markets and how they interact with conventional financial systems, especially in turbulent economic times like the COVID-19 crisis.

## 2 Research Gap and Objectives

Although a lot of work has been completed with cryptocurrencies, but there is a significant gap in the studies regarding the interconnection and volatility dynamics among major cryptocurrencies. Old research frequently concentrates on specific cryptocurrencies or neglects to thoroughly investigate the connections, among other cryptocurrencies. Furthermore, although the volatility of cryptocurrency markets has been studied in several researches, but little is known about the underlying causes and connections among various cryptocurrencies. Research work that methodically examines the interdependence and volatility patterns among the main cryptocurrencies is therefore desperately needed in order to give investors, portfolio managers, and policymakers useful information.

The primary aim of this study is to evaluate the connectivity among LTC, BTC, BNB, and ETH and the volatility dynamics both within and between these cryptocurrency markets in order to fill this research gap. By completing these tasks, current research work wants to advance knowledge of the complex interactions and dynamics that characterize cryptocurrency markets. In particular, the aim is to determine the degree of dependency between pairings of currencies such as LTC-USD, BTC-USD, BNB-USD, and ETH-USD, as well as to clarify the causes influencing volatility in these markets.

Finally, this study aims to provide insights into the mechanisms driving the behaviour of the bitcoin market through empirical analysis and sophisticated econometric approaches. The objective is to offer valuable information to both regulators tasked with regulating the emerging cryptocurrency ecosystem and investors looking to diversify its portfolios. The study will achieve this by methodically analyzing the interconnection and volatility dynamics of key cryptocurrencies. So, the ultimate goal is to find a significant gap in the literature and add to the continuing discussion on cryptocurrencies, and how they influence financial markets.

## 3 Methods and Data Analysis

Our analysis is based on the closing prices of selected cryptocurrencies at daily frequency sourced from yahoo finance. The sample under study is from 14 July 2021 to 06 July 2023. This study uses “Asymmetric VAR(1)-multivariate GARCH(1,1)-BEKK” model to analyze the mean and volatility spillover among the four major cryptocurrencies. Some preliminary tests precede the application of this model. As follows in any time series analysis, first we test for the stationarity of the variables used in this study using the DF-GLS test, KPSS test and Lee-Strazicich unit root test. Our second step involves analyzing the spillovers between the cryptocurrency returns using the VAR (1) model. Subsequently, we use an LM test to examine whether there are multivariate ARCH effects and time-varying conditional correlations. Figures 1, 2, 3 and 4 depicts that the closing price of all four cryptocurrencies decreased during the sample period. This may be due to the geo-political conditions worldwide, the Russia-Ukraine war, and the regulatory measures adopted in some countries.

The four cryptocurrency returns are depicted in Table 1 and 2 with descriptive statistics and unconditional correlations. Table 1 shows that all four markets, showed small negative average


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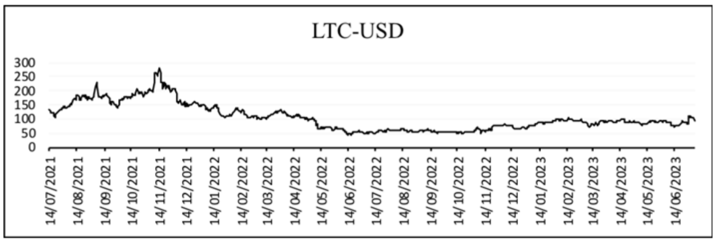


Figure 1. LTC-USD price


Figure 2. BNB-USD price

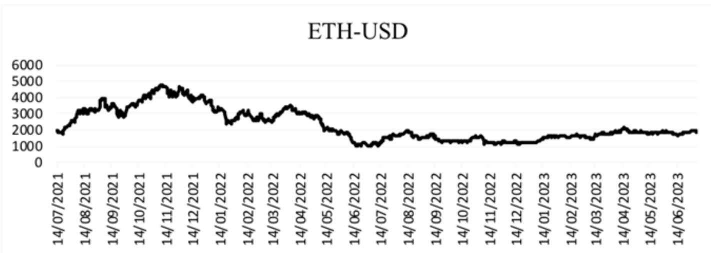


Figure 3. ETH-USD price

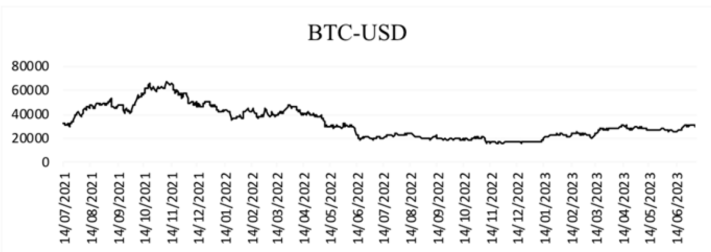


Figure 4. BTC-USD price


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Table 1. Descriptive Statistics of Returns

| | Δltc | Δbtc | Δbnb | Δeth |
|---|---|---|---|---|
| Mean | -0.043601 | -0.012872 | -0.039687 | -0.010507 |
| Std. Dev. | 4.502226 | 3.190355 | 3.636189 | 4.056647 |
| Max. | 24.36499 | 13.57643 | 13.05926 | 16.64878 |
| Min. | -20.90436 | -17.40526 | -20.53705 | -19.18441 |
| Skewness | -0.193735 | -0.368517 | -0.662097 | -0.349931 |
| Kurtosis (excess) | 6.276686 | 6.544531 | 6.947916 | 5.906751 |

Table 2. Unconditional Correlations

| | Δltc | Δbtc | Δbnb | Δeth |
|---|---|---|---|---|
| Δltc | 1 | | | |
| Δbtc | 0.77754524... | 1 | | |
| Δbnb | 0.73633466... | 0.77789908... | 1 | |
| Δeth | 0.79034358... | 0.87371891... | 0.80661304... | 1 |

returns (0.0105% - 0.0436%) over the study period. Further, a measure of standard deviation shows that all four markets depicted high average unconditional volatility (3.1903 - 4.5022) over the study period. It is possible that this is due to the high uncertainty and risk associated the cryptocurrency markets. The BTC returns were the least volatile of all four cryptocurrency returns during the sample period, while the LTC returns were the most volatile. All four currency returns show significant negative skewness that indicates the tendency of realizing frequent large negative daily returns than positive returns. Additionally, evidence suggests a significant excess kurtosis that confirms the leptokurtic distribution of all four cryptocurrency returns. Lastly, Table 2 reveals a very high unconditional correlation between all four cryptocurrency returns during the sample period. Correlation between BTC-USD and ETH-USD is found to be maximum during the sample period.

The analysis undertaken to understand the interlinkages between four major cryptocurrency markets is the focus of this section, which also discusses the results and findings.

All cryptocurrency returns are stationary, as revealed by the unit root test results. To study the mean spillovers between all four cryptocurrency returns, a VAR(1) model is employed. Our next task was to check for the existence of multivariate ARCH effects in the residuals of the VAR (1) model. Table 3 demonstrate that the null hypothesis of the absence of multivariate ARCH effects in the VAR residuals is rejected at a 1% level. The VAR (1)-multivariate GARCH (1, 1) CCC model is used to test for the presence of constant conditional correlation. Table 4 shows that we reject the null hypothesis of constant correlation. This indicates that the endogenous variables have time-varying conditional correlations (TVCCs).

In light of these initial results, this research employs an "Asymmetric VAR (1)-multivariate GARCH(1,1)-BEKK" model to evaluate the interconnection between the mean and volatility of

Table 3. Preliminary Tests. Panel A: Multivariate ARCH effects Test

| Test | Statistic |
|---|---|
| Multivariate ARCH effects | 1335.37 *** |

Table 4. Panel B: CCC-GARCH Test

| Test | Statistic |
|---|---|
| CCC-GARCH Specification | 16.50** |

cryptocurrencies. Below is a description of the empirical model used in this study:

$$\Delta c_t = \alpha + A\Delta c_{t-1} + \varepsilon_t \tag{1}$$

where

$$\Delta c_t = \left(\Delta c_t^{LTC} \Delta c_t^{BTC} \Delta c_t^{BNB} \Delta c_t^{ETH}\right)$$

is a 4 x 1 vector of returns. " $\alpha$ is a 4 x 1 vector of constants while A is a 4*4 matrix of parameters in the VAR (1) model that indicate returns spillovers. The error term $\epsilon_t$ in (1) is a vector of four error terms having an underlying t-distribution with $\frac{\varepsilon_t}{\Omega_{t-1}} \sim t(0, H_t)$ , where $\Omega_{t-1} = \{\varepsilon_{t-1}, \varepsilon_{t-2}, \varepsilon_{t-3}, \ldots\}$ . Further, $\epsilon_t = H_t^{-\frac{1}{2}} \theta_{Z_t}$ such that $\mathbb{E}\left(\varepsilon_t / \Omega_{t-1}\right) = 0$ and $\mathbb{E}\left(\frac{\varepsilon_t \varepsilon_t'}{\Omega_{t-1}}\right) = H_t$ " following Dua and Suri's (2019). In this study, is formulated as follows

$$H_t = \begin{bmatrix} h_t^{LTC} & h_t^{LTC,BTC} & h_t^{LTC,BNB} & h_t^{LTC,ETH} \\ h_t^{BTC,LTC} & h_t^{BTC} & h_t^{BTC,BNB} & h_t^{BTC,ETH} \\ h_t^{BNB,LTC} & h_t^{BNB,BTC} & h_t^{BNB} & h_t^{BNB,ETH} \\ h_t^{ETH,LTC} & h_t^{ETH,BTC} & h_t^{ETH,BNB} & h_t^{ETH} \end{bmatrix} \tag{2}$$

The related variance-covariance equation is given below:

$$H_t = B'B + D'\varepsilon_{t-1}\varepsilon_{t-1}'D + EH_{t-1}E + F\xi_t\xi_t'F \tag{3}$$

where D, E and F are 4 x 4 matrices while B is 4 x 1 upper-triangular matrix. Here, $\xi_{it-1}$ is defined as $\epsilon_{t-1}$ if $\epsilon_{t-1}$ is negative, and 0 otherwise. As per (3), "the conditional variance of each cryptocurrency is influenced by past error terms, past conditional variance, and past shocks caused by negative news from the four markets. The diagonal parameters in matrices D, E, and F show the effects of each market's past shocks, volatilities, and negative shocks on its current conditional variance. Previous shocks, volatilities, and negative shocks on each market's current conditional variance are depicted by the diagonal parameters in matrices D, E, and F. In contrast, the impacts of past shocks, volatilities, and negative shocks of market i on the current conditional variance of market j are shown by the off-diagonal parameters in these matrices ($d_{ij}, e_{ij},$ and $f_{ij}$)" following Chen, Yu, and Gang's (2021)

The method of maximum likelihood is used to estimate (1) and (3), wherein simplex algorithm is used for some initial iterations and then BFGS algorithm is utilized for the remaining observations. It may be noted that our main findings are based on "Asymmetric VAR (1)-multivariate GARCH (1, 1)-BEKK" model. Figures 5, 6, 7 and 8 represent the volatility plots and the conditional correlation plots are presented in Figures from 9 to 12. As shown in Table 7, the diagnostic statistics show the absence of autocorrelation in standardized and squared standardized residuals.

## 3.1 Mean Equation Results

Table 5. Panel A: VAR equations
Estimated Coefficients for Conditional Mean Return Equations

| | $\Delta L^{LTC}_{c,t}$ (j=1) | | $\Delta L^{BTC}_{c,t}$ (j=2) | | $\Delta L^{BNB}_{c,t}$ (j=3) | | $\Delta L^{ETH}_{c,t}$ (j=4) | |
|---|---|---|---|---|---|---|---|---|
| | Coe. | Std. Err. | Coe. | Std. Err. | Coe. | Std. Err. | Coe. | Std. Err. |
| $\alpha$ | -0.0028 | 0.0822 | 0.0483 | 0.0050*** | 0.0065 | 0.0656 | 0.0467 | 0.0071*** |
| $a_{j1}$ | -0.0143 | 0.0334 | -0.0804 | 0.0077*** | -0.0222 | 0.0238 | -0.0969 | 0.0110*** |
| $a_{j2}$ | 0.0362 | 0.0523 | 0.0966 | 0.0063*** | 0.0597 | 0.0377 | 0.0832 | 0.0161*** |
| $a_{j3}$ | 0.0449 | 0.0457* | -0.0611 | 0.0044*** | -0.1119 | 0.0363*** | -0.0755 | 0.0280*** |
| $a_{j4}$ | -0.0835 | 0.04701 | 0.0498 | 0.0118*** | 0.0462 | 0.0675 | 0.0675 | 0.0191*** |

Note: The table shows estimated coefficients for conditional mean return equations. Significance levels are indicated as *** (1%), ** (5%), and * (10%).

Table 6. Panel B: Multivariate GARCH
Estimated Coefficients for Variance Covariance Equations

| | $\Delta ltc$ (j=1) | | $\Delta btc$ (j=2) | | $\Delta bnb$ (j=3) | | $\Delta eth$ (j=4) | |
|---|---|---|---|---|---|---|---|---|
| | Coe. | Std. Err. | Coe. | Std. Err. | Coe. | Std. Err. | Coe. | Std. Err. |
| $b_{1j}$ | 1.9701 | 0.1879*** | | | | | | |
| $b_{2j}$ | 0.9635 | 0.2056*** | 0.8238 | 0.1166*** | | | | |
| $b_{3j}$ | 1.361 | 0.1779*** | 0.2924 | 0.1165*** | 0.3011 | 0.0766*** | | |
| $b_{4j}$ | 1.1572 | 0.1992*** | 0.5443 | 0.1257*** | -0.245 | 0.0682*** | 0.00004 | 0.0984*** |
| $d_{1j}$ | 0.35993 | 0.0548*** | 0.097 | 0.0388** | 0.1981 | 0.0493*** | 0.1162 | 0.0488** |
| $d_{2j}$ | -0.1347 | 0.0948 | 0.1046 | 0.0771 | -0.167 | 0.0868* | -0.2581 | 0.0900*** |
| $d_{3j}$ | 0.109 | 0.0691 | 0.1513 | 0.0406*** | 0.3877 | 0.0543*** | 0.1131 | 0.0517** |
| $d_{4j}$ | -0.0578 | 0.0521 | -0.0873 | 0.0349** | -0.0945 | 0.0421** | 0.2757 | 0.0442*** |
| $e_{1j}$ | 0.7383 | 0.0411*** | -0.0839 | 0.0271*** | -0.1489 | 0.0309*** | -0.1432 | 0.0290*** |
| $e_{2j}$ | 0.1298 | 0.0825 | 0.9204 | 0.0646*** | 0.042 | 0.0684 | 0.0619 | 0.0635 |
| $e_{3j}$ | -0.3224 | 0.0523*** | -0.1661 | 0.0303*** | 0.6938 | 0.0381*** | -0.176 | 0.0389*** |
| $e_{4j}$ | 0.1761 | 0.0326*** | 0.1011 | 0.0237*** | 0.1318 | 0.0241*** | 1.0238 | 0.0260*** |
| $f_{1j}$ | -0.7933 | 0.1186*** | -0.2876 | 0.0669*** | -0.5605 | 0.0897*** | -0.4995 | 0.0810*** |
| $f_{2j}$ | 0.4224 | 0.1549*** | 0.1427 | 0.1127 | 0.5158 | 0.1336*** | 0.0117 | 0.143 |
| $f_{3j}$ | -0.5841 | 0.1410*** | -0.4949 | 0.0869*** | -0.8148 | 0.1122*** | -0.5467 | 0.1096*** |
| $f_{4j}$ | 1.1219 | 0.1325*** | 0.7823 | 0.096*** | 1.0412 | 0.1145*** | 1.1381 | 0.1160*** |

Note:*, **, *** indicate 10%, 5% and 1% LoS respectively.

Table 7. Results of Causality in mean tests for the estimated model

| Conjecture | Null Hypothesis | $\chi^2$-statistic(P-value) | Result |
|---|---|---|---|
| No causality from BTC to LTC | $a_{12} = 0$ | 0.4798 (0.4884) | Do not reject Ho |
| No causality from BNB to LTC | $a_{13} = 0$ | 3.3363 (0.0677) | Reject Ho |
| No causality from ETH to LTC | $a_{14} = 0$ | 0.0025 (0.9598) | Do not reject Ho |
| No causality from LTC to BTC | $a_{21} = 0$ | 108.37 (0.0000) | Reject Ho |
| No causality from BNB to BTC | $a_{23} = 0$ | 191.26 (0.0000) | Reject Ho |
| No causality from ETH to BTC | $a_{24} = 0$ | 17.56 (0.0000) | Reject Ho |
| No causality from LTC to BNB | $a_{31} = 0$ | 0.8721 (0.3503) | Do not reject Ho |
| No causality from BTC to BNB | $a_{32} = 0$ | 2.512 (0.1129) | Do not reject Ho |
| No causality from ETH to BNB | $a_{34} = 0$ | 0.1506 (0.6978) | Do not reject Ho |
| No causality from LTC to ETH | $a_{41} = 0$ | 76.505 (0.0000) | Do not reject Ho |
| No causality from BTC to ETH | $a_{42} = 0$ | 26.598 (0.0000) | Reject Ho |
| No causality from BNB to ETH | $a_{43} = 0$ | 7.241 (0.0071) | Reject Ho |

Table 8. Results of Causality in variance tests for the estimated model

| Conjecture | Null Hypothesis | $\chi^2$-statistic(P-value) | Result |
|---|---|---|---|
| No causality from BTC to LTC | $d_{21} = e_{21} = f_{21} = 0$ | 31.838 (0.0000) | Reject Ho |
| No causality from BNB to LTC | $d_{31} = e_{31} = f_{31} = 0$ | 90.5603 (0.0000) | Reject Ho |
| No causality from ETH to LTC | $d_{41} = e_{41} = f_{41} = 0$ | 61.6283 (0.0000) | Reject Ho |
| No causality from LTC to BTC | $d_{12} = e_{12} = f_{12} = 0$ | 12.658 (0.0054) | Reject Ho |
| No causality from BNB to BTC | $d_{32} = e_{32} = f_{32} = 0$ | 20.143 (0.0001) | Reject Ho |
| No causality from ETH to BTC | $d_{42} = e_{42} = f_{42} = 0$ | 8.665 (0.0340) | Reject Ho |
| No causality from LTC to BNB | $d_{13} = e_{13} = f_{13} = 0$ | 54.63 (0.0000) | Reject Ho |
| No causality from BTC to BNB | $d_{23} = e_{23} = f_{23} = 0$ | 61.869 (0.0000) | Reject Ho |
| No causality from ETH to BNB | $d_{43} = e_{43} = f_{43} = 0$ | 39.469 (0.0000) | Reject Ho |
| No causality from LTC to ETH | $d_{14} = e_{14} = f_{14} = 0$ | 92.1453 (0.0000) | Reject Ho |
| No causality from BTC to ETH | $d_{24} = e_{24} = f_{24} = 0$ | 73.565 (0.0000) | Reject Ho |
| No causality from BNB to ETH | $d_{34} = e_{34} = f_{34} = 0$ | 107.603 (0.0000) | Reject Ho |

The results of the returns equation are shown in Table 5. The presence of significant bi-directional returns spillovers between BTC-USD and ETH-USD is observed. Further, estimates of VAR(1) coefficients (Table 5) shows that BTC-USD returns are positively related to ETH-USD returns. Furthermore, we find that the return of BTC-USD and ETH-USD are significantly affected by the return of the remaining three currencies. According to our results, an increase (decrease) in LTC-USD returns and BNB-USD returns causes a decrease (increase) in BTC-USD and ETH-USD returns.

## 3.2 Variance Equation Results

The coefficient ($d_{ij}$) indicating the own news effect is significant in the variance equation of all cryptocurrencies according to Table 6. Our analysis shows that the cross-news effects for these markets are less pronounced than the own news effects from the previous period. We find that there are bi-directional shock spillovers between BTC-USD and BNB-USD, BTC-USD and ETH-USD, and BNB-USD and ETH-USD. Moreover, we identify cross-news impacts from LTC-USD to BTC-USD, BNB-USD, and ETH-USD.

The GARCH effect ($e_{ij}$), also known as the own previous period volatility effect is significant in the variance equation of all cryptocurrencies, as indicated by the results reported in Table 6. As shown in the table, the own previous period volatility effects ($e_{ij}$) are greater than the cross-volatility effects ( ) . Our findings indicate bi-directional volatility spillovers between BTC-USD and ETH-USD. Our results reveal presence of cross volatility effects from LTC-USD to

BTC-USD, BNB-USD to LTC-USD, and ETH-USD to BNB-USD.

It may be noted from Table 6 that the coefficients ($f_{ij}$) are significant at a 1% significance level. The effect of negative shocks (against positive shocks) on the volatility of all four cryptocurrency markets considered in this study is significant, as suggested. Subsequently, we evaluated causality in mean and variance using estimates of the "Asymmetric VAR (1)-multivariate GARCH (1, 1)-BEKK" model (Table 7 and Table 8). It may be seen from Table 4 that the mean spillovers between BTC-USD and ETH-USD returns are Granger causal-in-mean. Further, the null hypothesis that there are no volatility spillovers (causality in variance) is rejected for all cryptocurrency pairs, as shown in Table 8.

## 3.3 Volatility and Conditional Correlations

The estimated volatility graphs the four crypocurrencies are presented in Figures 5, 6, 7 and 8. Furthermore, Figures from 9 to 14 depict TVCCs between all four cryptocurrency pairs. Our findings indicate that the volatility of the four cryptocurrency rates was considerably high from April 2022 to November 2022. Moreover, we find that while the conditional volatility of LTC was highest, BTC was the least volatile among all four currencies during the sample period. Further, the figures shows that the conditional correlations between all four cryptocurrencies showed considerable variability during the sample period.

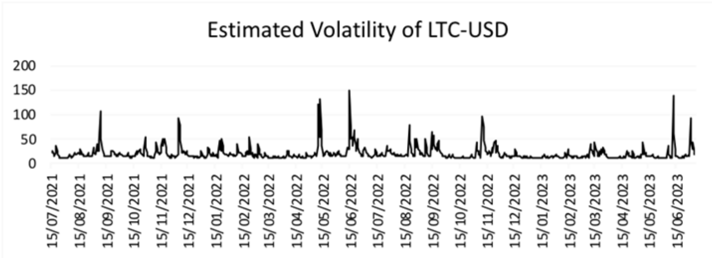


Figure 5. Estimated Volatility of LTC-USD

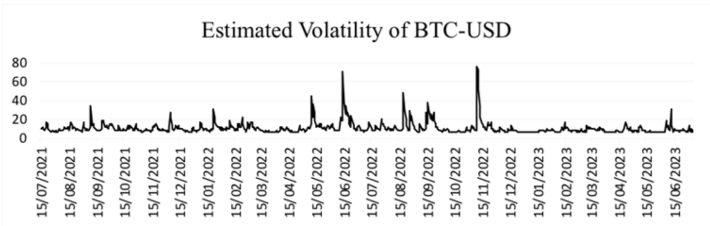


Figure 6. Estimated Volatility of BTC-USD


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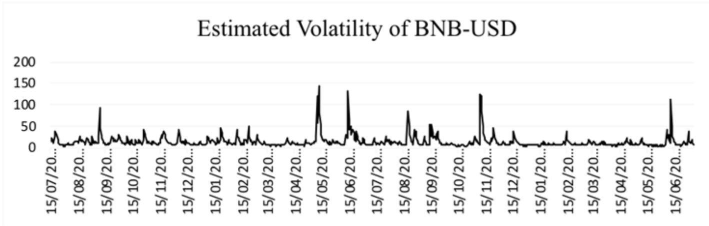


Figure 7. Estimated Volatility of BNB-USD

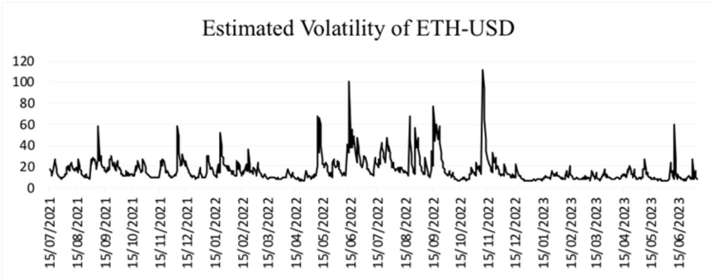


Figure 8. Estimated Volatility of ETH-USD

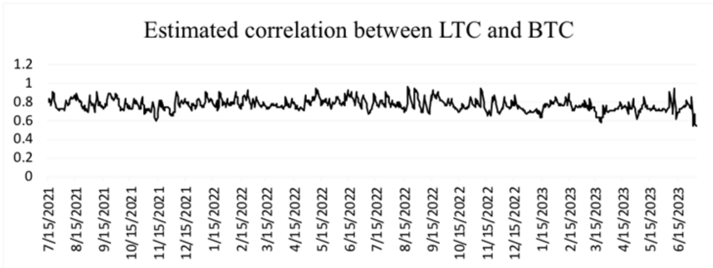


Figure 9. Estimated Conditional Correlation among LTC-USD and BTC-USD

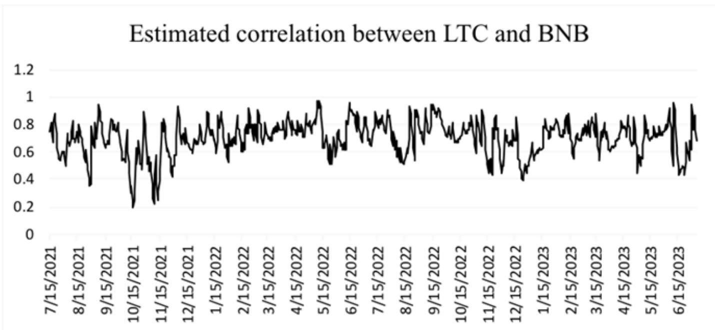


Figure 10. Estimated Conditional Correlation among LTC-USD and BNB-USD

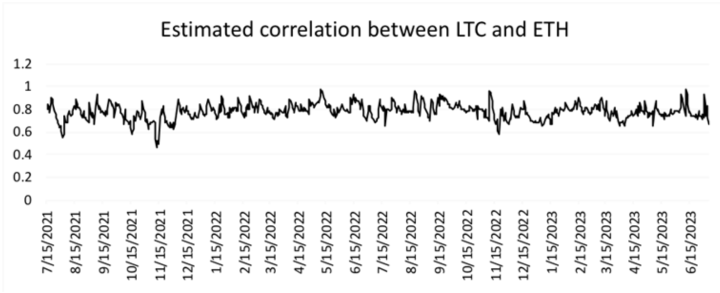


Figure 11. Estimated Conditional Correlation among LTC-USD and ETH-USD

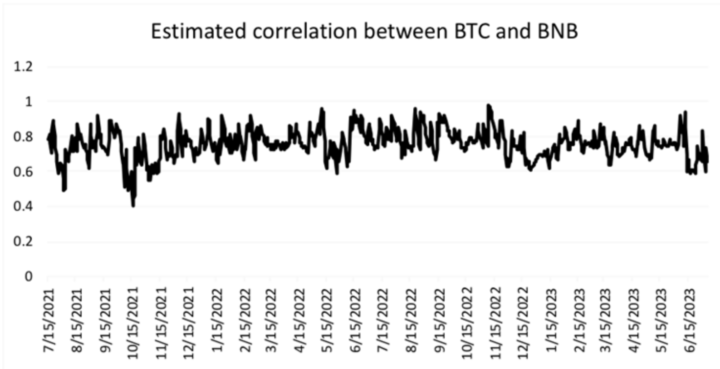


Figure 12. Estimated Conditional Correlation among BTC-USD and BNB-USD

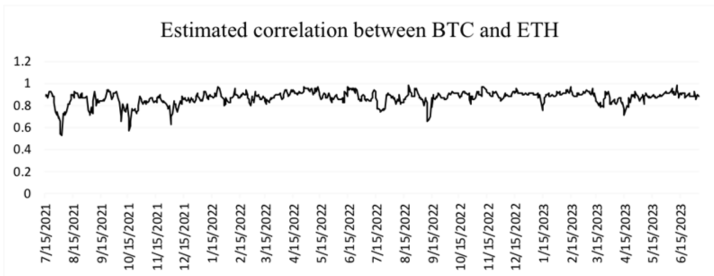


Figure 13. Estimated Conditional Correlation among BTC-USD and ETH-USD

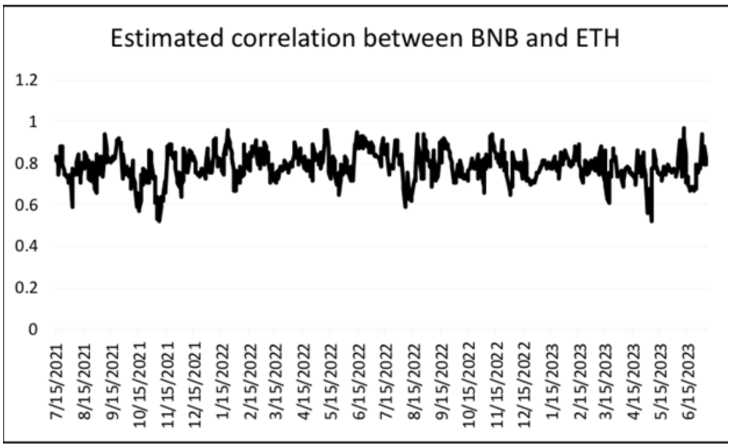


Figure 14. Estimated Conditional Correlation among BNB-USD and ETH-USD

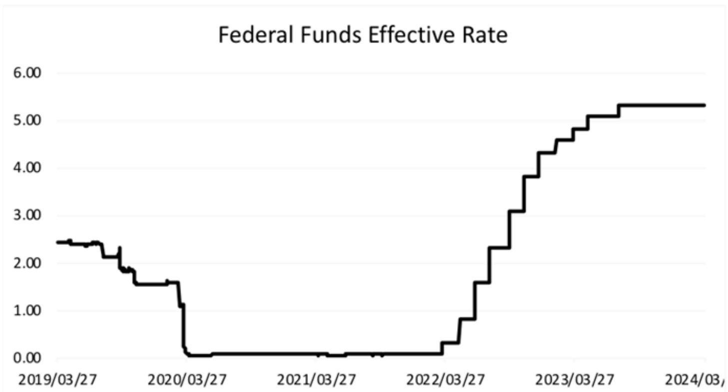


Figure 15. Federal Funds Effective Rate

## 4 Conclusion

The mean and volatility spillovers among LTC-USD, BTC-USD, BNB-USD, and ETH-USD are analyzed by this paper with an "Asymmetric VAR (1)-multivariate GARCH (1, 1)-BEKK" specification. We find that all four selected cryptocurrency markets have significant returns and volatility spillovers, indicating a strong interconnection between these currencies. Further, we find a positive and significant relationship between BTC and ETH which may indicate that these two currencies are complementary. Moreover, our results suggest that returns of LTC and BNB have a significant inverse impact on BTC and ETH. This indicates that these currencies are emerging as popular cryptocurrencies among investors.

The variance equation estimates show that all four cryptocurrencies are greatly impacted by t past shocks/news and these effects are higher than the the cross-news effects. Further, the estimates of the variance equation suggest significant volatility spillovers (short-term and long-term) among the four major cryptocurrencies. Our findings indicate that the volatility of all four cryptocurrencies responds significantly to the negative shocks.

The conditional volatility plots of the selected cryptocurrencies reveal a considerable increase in the conditional volatility of these currencies from April 2022 to November 2022. The Federal Reserve Bank (FED)'s change in monetary policy stance in mid-March 2022 is a possible explanation. To limit the impact of covid catastrophe that hit the U.S. economy, FED adopted an accommodative or expansionary monetary policy in April 2020 in which federal funds effective rates were reduced to almost zero percent (Figure 15). However, as the U.S. inflation rate plunged above acceptable levels in early 2022, FED started with policy tightening measures such as tapering asset purchases and raising the federal fund's effective interest rates in March 2022. This sudden shift in the FED monetary policy possibly caused a sharp downslide and substantial volatility in the cryptocurrency markets during the second and third quarters of 2022.

This study has several implications for portfolio managers, researchers, and policymakers. Our analysis suggests that like other asset markets, viz. exchange rate markets and stock markets, there exists a strong connection between the major cryptocurrencies in terms of mean, shock, and volatility spillovers. So, for optimal portfolio management, it is pertinent for all the portfolio managers, to account for the TVCCs between different cryptocurrencies. Further, the strong spillovers between the cryptocurrencies found in this study have implications for government policymaking.

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