Journal of Commerce & Accounting Research
11 (1) 2022, 69-86
http://publishingindia.com/jcar/

Submitted: 17 September, 2021
Accepted: 13 October, 2021

ASYMMETRIC VOLATILITY AND VOLATILITY SPILLOVER: A STUDY OF MAJOR CRYPTOCURRENCIES

Rajib Bhattacharya*, Arindam Das, Shuvashish Roy*****

Abstract *Cryptocurrencies have recently emerged as a popular asset class, with investors having high risk appetite and speculative attributes. They are not backed by physical assets, such as commodities or real currencies; they are purely speculative assets having high volatility. Regulatory authorities across the globe have conflicting rules regarding cryptocurrencies. Recent studies on volatility of cryptocurrencies have primarily addressed univariate volatility analysis and volatility spillover between cryptocurrencies and other asset classes, mostly stocks and commodities. This study has three objectives. Firstly, it considers six prominent cryptocurrencies, i.e., Bitcoin, Ethereum, Binance Coin, Cardano, Tether, and Ripple, and examines the nature of asymmetrical volatility in them using EGARCH and TGARCH techniques. Secondly, it examines whether there are volatility spillovers between the cryptocurrencies as well as from one of the most popular global fear indices, i.e., CBOE volatility index, using dynamic conditional correlation (DCC). Thirdly, it further measures the total and directional volatility spillover among the cryptocurrencies using the Diebold-Yilmaz index. This study has found that Ethereum and Ripple may be used to construct a portfolio. There exists long-term volatility spillover among all the cryptocurrencies; however, there is no short-term spillover of volatility. Volatility of Binance Coin, Cardano, and Ripple influence and are influenced the most by volatilities of other cryptocurrencies.*

Keywords: *Cryptocurrency, Volatility Spillover, EGARCH, TGARCH, Dynamic Conditional Correlation (DCC), Diebold-Yilmaz Index*

INTRODUCTION

The concept of cryptocurrencies originated in 2008. Since then cryptocurrencies have had an interesting journey till date, marked with controversies and stellar growth in their prices (Bigmore, 2018). The sentiments of the investors and the regulatory authorities in countries all over the world are also polarised. Some regulatory authorities, such as central banks and governments have legalised the use of cryptocurrencies, while some have banned it. Cryptocurrencies are the most preferred asset class for some investors, while some consider it to be a pure gamble. Cryptocurrencies came into existence with the emergence of Bitcoin in 2008. Bitcoin was both a financial as well as a technological revolution. It was based on three technologies, i.e., encryption methodology, block-chain technology, and the Internet (Granot, 2018). The most important characteristic of cryptocurrencies, which the investors try to address and resolve, is the volatility of prices. This high volatility stems from the fact that most of the cryptocurrencies are purely digital assets. They are not backed by any physical asset like commodities or real currency. Hence, their prices depend solely on their supply and demand positions. Investing in cryptocurrencies does not require expertise which is needed to invest in markets like stocks, bonds, commodities, foreign exchange, derivatives, real estate, and so on. Thus, investing in cryptocurrencies is largely speculative in nature. There occurs sudden inflow of money when investors expect short-term gains due to a fear of losing out when there is price appreciation (Baur & Dimpfl, 2018). When the actual performance of cryptocurrencies falls short of their short-term expectations, the market experiences a sudden outflow of money when investors cash out and the prices fall. The patience required in investors in other financial markets is often lacking in cryptocurrencies. This causes comparatively higher volatility in cryptocurrencies. As

* Associate Professor, Globsyn Business School, Kolkata, West Bengal, India. Email: rajib.learner@gmail.com
** Professor, Department of Commerce, The University of Burdwan, Golapbag, Burdwan, West Bengal, India. Email: arindam_dasbu@yahoo.co.in
*** Financial Advisor, Hazrat Khajar Bashir Unani Ayurvedic Medical College & Hospital Foundation, Jamalpur, Bangladesh. Email: shuvashishroy@gmail.com

many cryptocurrencies have emerged and have become popular with the investors, they often switch from one cryptocurrency to another. This causes volatility in both the cryptocurrencies involved, resulting in volatility spillover between cryptocurrencies. Moreover, cryptocurrencies are traded in the market just like other financial assets, and provide a feasible alternative investment to such other assets. They have empirically exhibited appreciating trends in prices during times of uncertainty affecting markets of other financial assets. Thus, volatility in other financial assets and that of cryptocurrencies are related. Spillover patterns is a measure of contagion risk as well (Koutmos, 2018). This has made investors in cryptocurrencies, along with potential investors, study and assess the complex dynamics of volatility of cryptocurrencies. This study focuses on the volatility spillover between six major cryptocurrencies, vis-à-vis one of the most popular global volatility indices, i.e., CBOE VIX. The findings of this study will be useful to investors regarding their investment decisions about cryptocurrencies.

SURVEY OF CONTEMPORARY LITERATURE

The study of academic literature on volatility modelling and volatility spillover of cryptocurrencies has been carried out considering the period 2018 and thereafter to have a contemporary backdrop of the current study.

Baur and Dimpfl (2018) examined the asymmetric volatility of 20 cryptocurrencies. Their study found that the asymmetry in cryptocurrencies are different from that of the stock market, as, in cryptocurrencies, positive shocks increase the volatility more than the negative shocks. Koutmos (2018) measured volatility spillovers among 18 cryptocurrencies and inferred that volatility spillover from Bitcoin was the most prominent. His findings indicated a prominent interdependency between cryptocurrencies. Yi and Wang (2018) studied total connectedness of eight cryptocurrencies and found them to be varying periodically. Their findings inferred that Bitcoin was a significant source of connectedness, but not the most prominent one. They also found that some less-traded cryptocurrencies, such as Maidsafe Coin, also caused strong volatility shocks to other cryptocurrencies. Bouri et al. (2018) examined the volatility spillover between Bitcoin and stocks, commodities, currency, and bonds markets, both in bullish and bearish markets, on the basis of daily data from 19 July 2010 to 31 October 2017. Their study revealed a relation between Bitcoin and the commodities markets. The study provided empirical evidence that Bitcoin transmits less volatility than it receives. Katsiampa et al. (2019) examined the interactions between volatilities of different cryptocurrencies. They found that the shocks from Bitcoin lasted the most. They found that an asymmetric BEKK model provided the best fit. The study further inferred that time-varying conditional correlations existed in the case of the selected cryptocurrencies, which proved that cryptocurrency markets were interdependent. ERTUĞRUL (2019) worked on the ARCH/GARCH and EGARCH-TGARCH models on the volatility of Bitcoin and Ripple. They found that the TGARCH provided the best predictive accuracy. Palamalai & Maity (2019) examined the volatility spillover effects across eight cryptocurrencies as per market capitalisation by using a vector error correction approach, as well as the diagonal BEKK multivariate GARCH model. Their study detected evidence of interdependence and volatility co-movements among different cryptocurrency-pairs. The study further pointed out the existence of limited opportunities for the short-term portfolio diversification benefits regarding the eight cryptocurrencies selected for the study. Dangi (2020) studied the dynamics of volatility of Bitcoin, Bitcoin Cash, Ethereum, EOS, Stellar, Tether, XRP, and Litecoin for the period July 2017 to March 2019. The study used GARCH family models and confirmed the presence of highly persistent volatility. Abahah et al. (2020) analysed the persistence of volatility in Bitcoin, Bytecoin, Bitshare, Ether, Dash, Monero, Nem, Ripple, Siacoin, Litecoin, Tether, and Stellar. The study considered the possibility of structural breaks. The study revealed a reduction in persistence of volatility in the cryptocurrencies considered for the study. Ma et al. (2020) studied the applicability of a Markov regime-switching mixed-data sampling model to better the predictive accuracy of the realised variance of Bitcoin. They found that high volatility is enhanced by jump occurrences. Jimoh & Benjamin (2020) examined the inter-relatedness between stock market prices and foreign exchange rates, and Ethereum and Bitcoin prices in Nigeria. Their study was based on monthly data from August 2015 to December 2019. They used the GARCH and EGARCH methods, along with Granger causality tests. They found that the stock market was comparatively more influenced by the volatility of Bitcoin and Ethereum prices, rather than the exchange rates in the Nigerian markets. Their study also revealed evidence of a one-way causality from Ethereum and Bitcoin to the stock market index. Kayral (2020) considered daily closing prices from 10 January 2015 to 10 January 2018 of Ethereum, Bitcoin, and Ripple, and detected the presence of ARCH effects in their prices. They used GARCH (1,1), EGARCH (1,1), TGARCH (1,1), APARCH (1,1), CGARCH (1,1), and ACGARCH (1,1) models. The study found that the most appropriate model was EGARCH for Ethereum and Bitcoin. The APARCH (1,1) model was found to the best one for Ripple. The study could not detect any leverage effect in Ethereum and Bitcoin. Sensoy et al. (2021) examined the returns and volatility of certain important cryptocurrencies, among which they inferred that

Bitcoin, Litecoin, and Ethereum were the most important ones. They found that spillovers existed between them. The cryptocurrencies considered in their study exhibited different volatility clustering patterns. This indicates that the spillover patterns between them could also have been different. Malladi and Dheeriya (2021) opined that Bitcoin and Ripple were the most important cryptocurrencies. They found that the prices of cryptocurrencies are partly determined by the fear indices, e.g., the VIX. They could not, however, find any evidence that returns on Ripple caused any change in prices of Bitcoin. Yin et al. (2021) used GARCH models to examine the effect of stocks from crude oil on long-term volatility of cryptocurrency prices. They considered Bitcoin, Ethereum, and XRP. Their study revealed that an adverse oil market shock made the cryptocurrencies more attractive. Huang and Huang (2021) found that cryptocurrencies have varying volatility dynamics. Siu (2021) studied the impacts of long memory in conditional volatility using GARCH-type models. Gradojevic and Tsiakas (2021) used high-frequency (one-minute) data on Bitcoin, Ethereum, and Ripple, against the US dollar, to assess the probability of high or low volatility of one time period being propagated to the succeeding time period. They found that from longer to shorter time periods, the cascading effect of volatility was symmetric, whereas from shorter to longer horizons, the same was found to be asymmetric. The findings were similar for all the three cryptocurrencies considered by them, and across various time periods. Yaya et al. (2021) tested volatility persistence in 12 cryptocurrencies, both during the pre-crash and post-crash time periods. The volatility was found to be high, especially post the crash. Persistence of volatility was found to be shorter during the pre-crash time period. Fasanya et al. (2021) assessed the volatility spillovers between certain prominent cryptocurrencies. Their study was on daily data for the period 10 August 2015 to 15 April 2018. The study used the Diebold and Yilmaz spillover technique. Substantial differences among behaviours regarding volatility spillover was exhibited over time. Evidence found by the study confirmed interdependence among portfolios made up of different cryptocurrencies. Ftiti (2021) used high-frequency data to model the volatility of Ethereum, Bitcoin, Ripple, and Classic, with emphasis on the pandemic period from April 2018 to June 2020. They used heterogeneous autoregressive models and inferred that the extended heterogeneous autoregressive model, which encompassed positive and negative semi-variances, was the best applicable model. Hsu et al. (2021) examined volatility spillovers between currency and gold markets and cryptocurrency markets, and used the diagonal BEKK model, considering daily data from 07 August 2015 to 15 June 2020. Their study revealed that volatility spillovers were significantly different between extreme and normal market conditions. The study revealed significant co-volatility spillover between the cryptocurrency market and traditional currency or gold markets.

The survey of contemporary academic literature revealed that the studies on volatility spillover between cryptocurrencies have been limited. The growing importance of cryptocurrencies as an asset class for investment, the changing dynamics of their volatility patterns, and a skewed use of the GARCH family of techniques for predictive accuracy of volatility of cryptocurrencies have prompted this study on short-term and long-term volatility spillover between the most prominent cryptocurrencies.

ANALYSIS AND INTERPRETATION

Selection of the cryptocurrencies for the study has been done on the basis of market capitalisation as on 19th August 2021 (Trentina & Schmidt, 2021). The selected cryptocurrencies are given in Table 1.

Table 1: Cryptocurrencies Selected for the Study along with Their Ticker Symbols and Market Capitalisations

Cryptocurrencies	Ticker Symbols	Market Capitalisation as on 19 August 2021
Bitcoin	BTC	More than USD 856 Billion
Ethereum	ETH	More than USD 357 Billion
Binance Coin	BNB	More than USD 70 Billion
Cardano	ADA	More than USD 69 Billion
Tether	USDT	More than USD 64 Billion
Ripple	XRP	More than USD 52 Billion

Source: Trentina & Schmidt, 2021.

The daily closing prices in USD have been sourced from https://www.cboe.com/tradable_products/vix/ (accessed on 20th August 2021). The selected cryptocurrencies have been referred to hereafter in the paper by their ticker symbols. Investment decision in cryptocurrencies, just like any other asset class, is taken against the backdrop of the anticipated market condition of other asset classes, primarily the stock market. The sentiment about the future condition of the stock market is reflected in the volatility index. Hence, the most popular volatility index in the global scenario, i.e., the CBOE volatility index (CBOE VIX), has also been considered in the study.

This index is a 30-day anticipated volatility of the American stock market and is computed on the basis of mid-quote real-time prices of the S&P 500 Index call and put options. This index has been chosen as it ranks among the most globally recognised measures of volatility and is reported by financial media across the world; it is closely followed by market players as a significant daily market sentiment indicator. Considering stock market volatility index in the context of studying volatility spillover between cryptocurrencies has literature support (Malladi & Dheeriya, 2021). The daily

CBOE VIX data have been sourced from https://in.investing.com/, accessed on 20th August 2021, and has been dubbed as CIX henceforth in the paper.

The window for this study is from 23 January 2018 to 28 August 2021, to have the maximum number of data points for all the six selected cryptocurrencies and CBOE VIX. The number of data points was 1,314 daily closing prices/values. The price movements of the selected six cryptocurrencies vis-à-vis the movement of CBOE VIX over the selected period for the study, are shown in Chart 1.

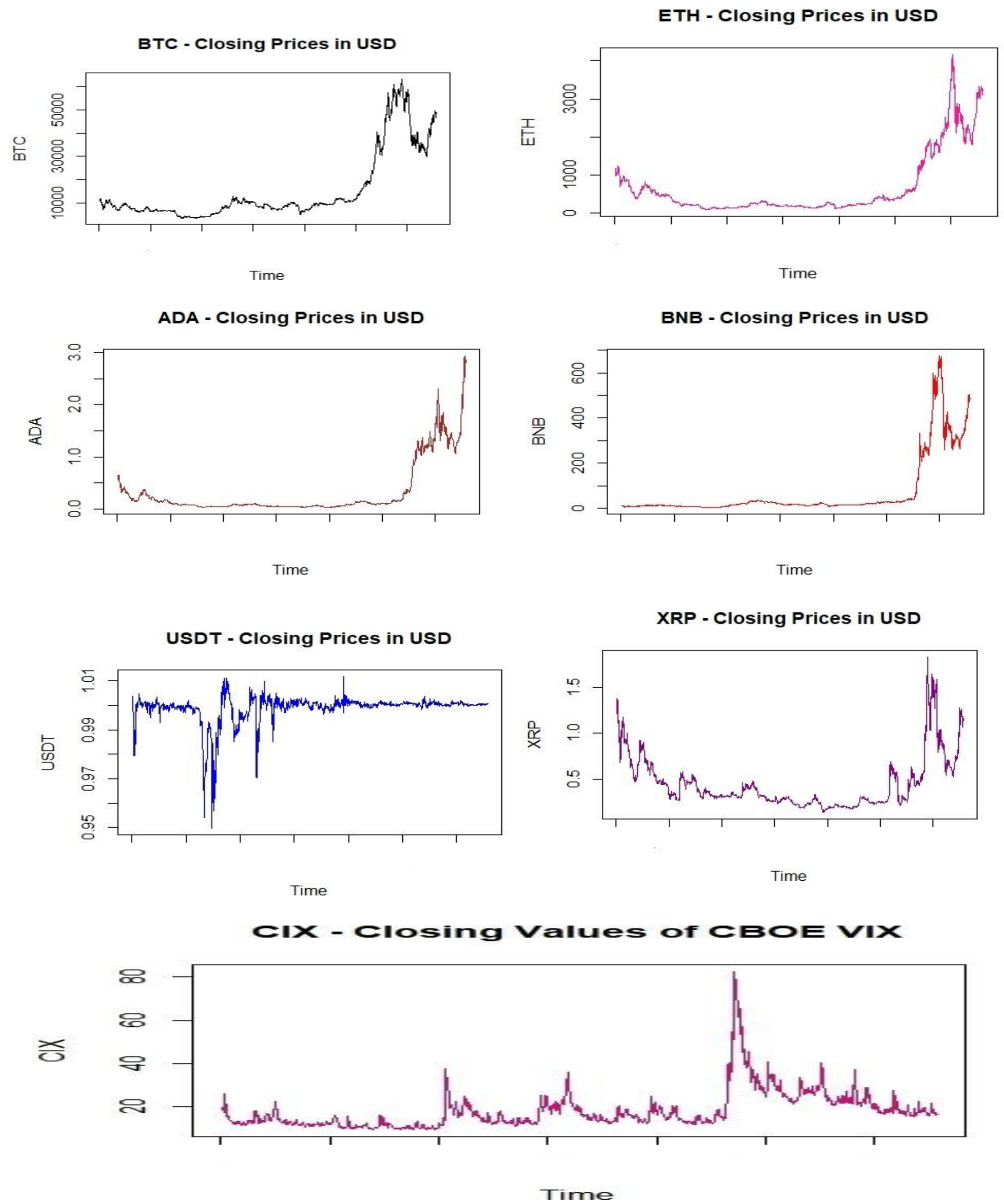


Chart 1: Closing Prices of Cryptocurrencies and Closing Values of CBOE VIX

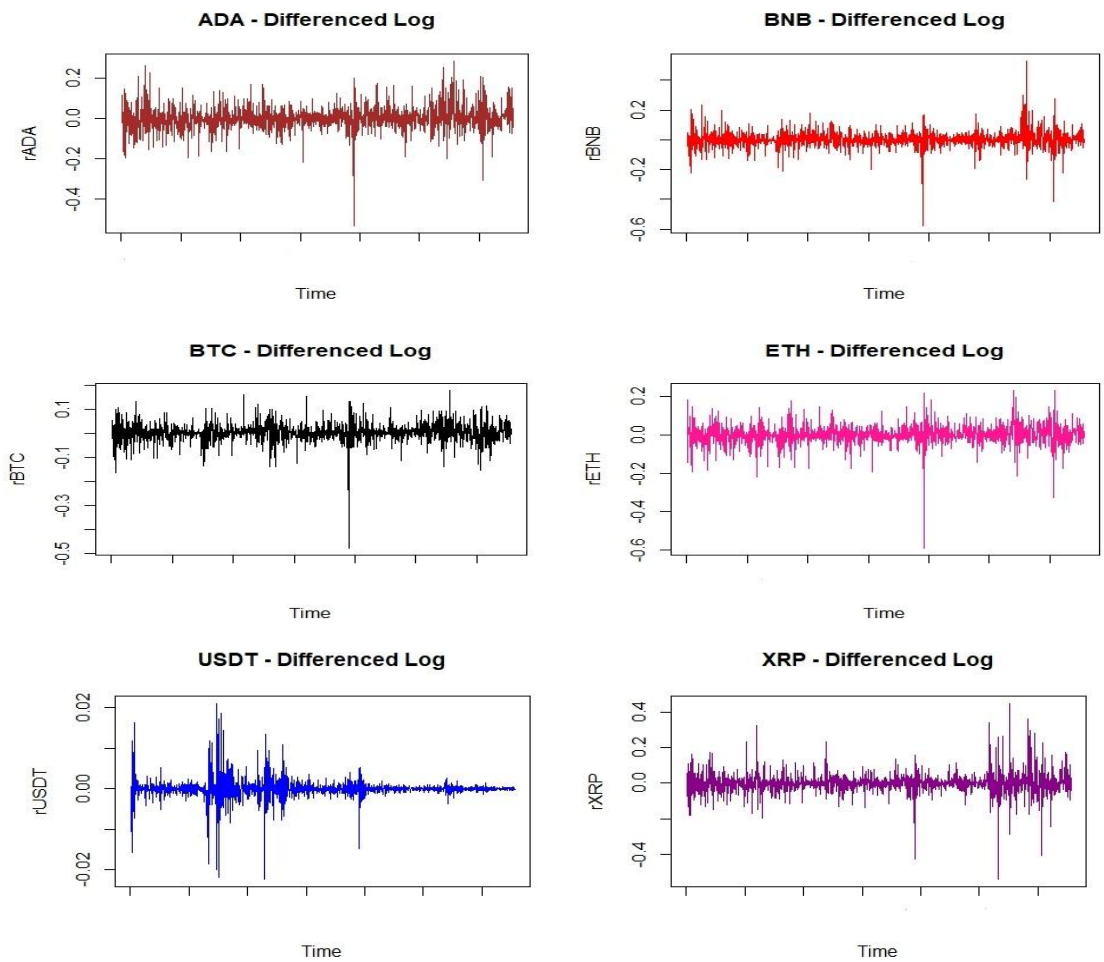
As all the series contain either price data or index data, log-difference of all the series are taken for analysis. The log-differenced series are recoded as rBTC, rETH, rBNB, rADA, rUSDT, rXRP, and rCIX, respectively. The log-differenced series are tested for stationarity by the Augmented Dickey-Fuller (ADF) test, the results of which are given in Table 2.

Table 2: Augmented Dickey-Fuller Test Results (p-Values against 5% Level of Significance)

Series	ADF	Constant Model		Trend Model	
		Test Statistic	Critical Value	Test Statistic	Critical Value
rBTC	0.01	−39.7316	−2.864192	−39.7984	−3.415689
rETH	0.01	−40.7657		−40.9001	
rBNB	0.01	−39.7024		−39.7280	
rADA	0.01	−39.3252		−39.3786	
rUSDT	0.01	−44.4810		−44.4534	
rXRP	0.01	−37.4674		−37.5281	
rCIX	0.01	−41.8048		−41.7872	

Source: Authors' own calculations.

The absolute values of the test statistic (Z-Tau) in the ADF test (both with and without trends) have been found to be higher than the critical values at 5% level of significance; hence, all the series are found to be stationary. Accordingly, the null hypotheses of non-stationarity in the data series is rejected. All the series are, thus, found to be eligible for application of time series modelling techniques. Chart 2 shows the selected log-differenced series.



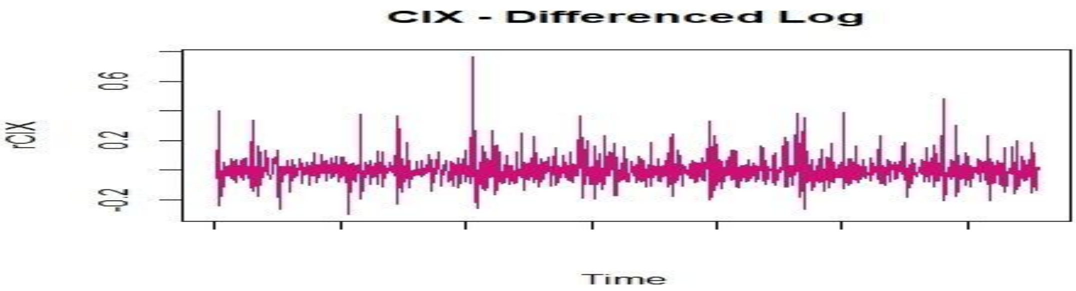


Chart 2: Log-Differenced Closing Prices of Cryptocurrencies and Log-Differenced Closing Values of CBOE VIX

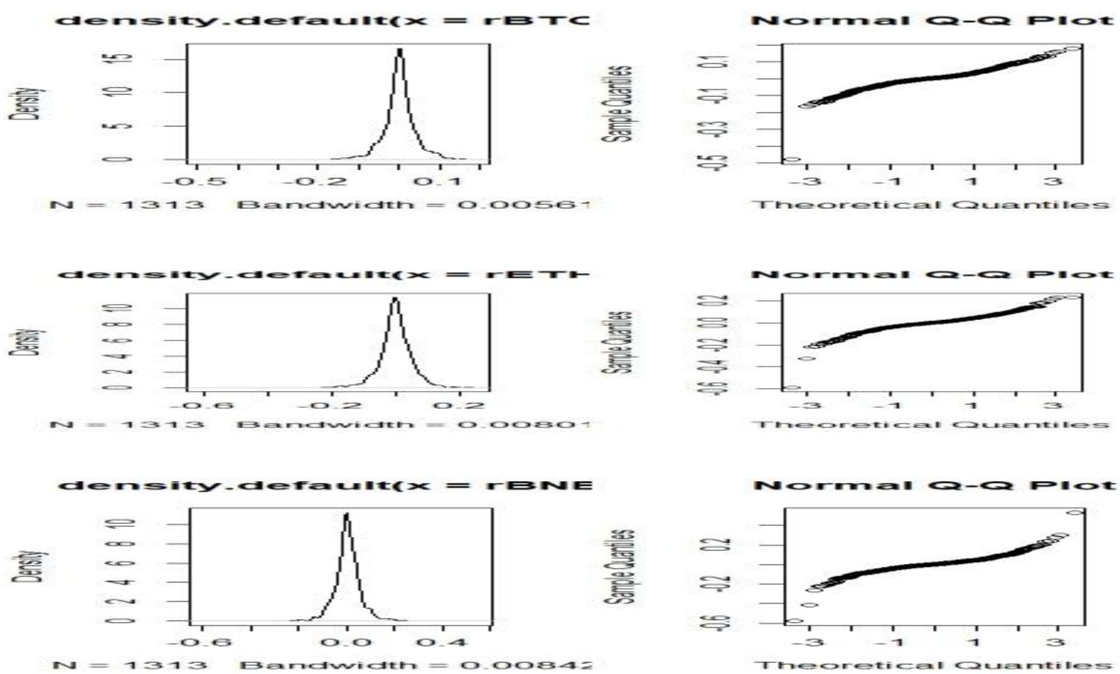
The plots exhibit visual evidence of the presence of volatility clusters, which are tested statistically through ARCH modelling. The descriptive statistics of the log-differenced stationary series are presented in Table 3.

Table 3: Descriptive Statistics of the Log-Differenced Series of Closing Cryptocurrency Prices and Closing CBOE VIX Values

Series	Mean	Median	Standard Deviation	Skewness	Kurtosis
rBTC	0.0011465	0.0013644	0.0406976	−1.2594361	16.3466518
rETH	0.0009000	0.0013990	0.0543203	−1.2156593	13.3226930
rBNB	0.0027010	0.0015280	0.0596532	−0.2835896	15.0772748
rADA	0.0012290	0.0007373	0.0624909	−0.2903784	5.9434194
rUSDT	−0.0000018	0.0000000	0.0025889	−0.3615178	25.0544765
rXRP	−0.0001341	0.0000000	0.0631245	0.0862258	12.5888864
rCIX	−0.0001263	−0.0071749	0.0843467	1.5128123	8.8047459

Source: Authors' own calculations.

The density plots and the Q-Q plots of the stationary time series are contained in Chart 3, which exhibit symmetry but leptokurtic distributions.



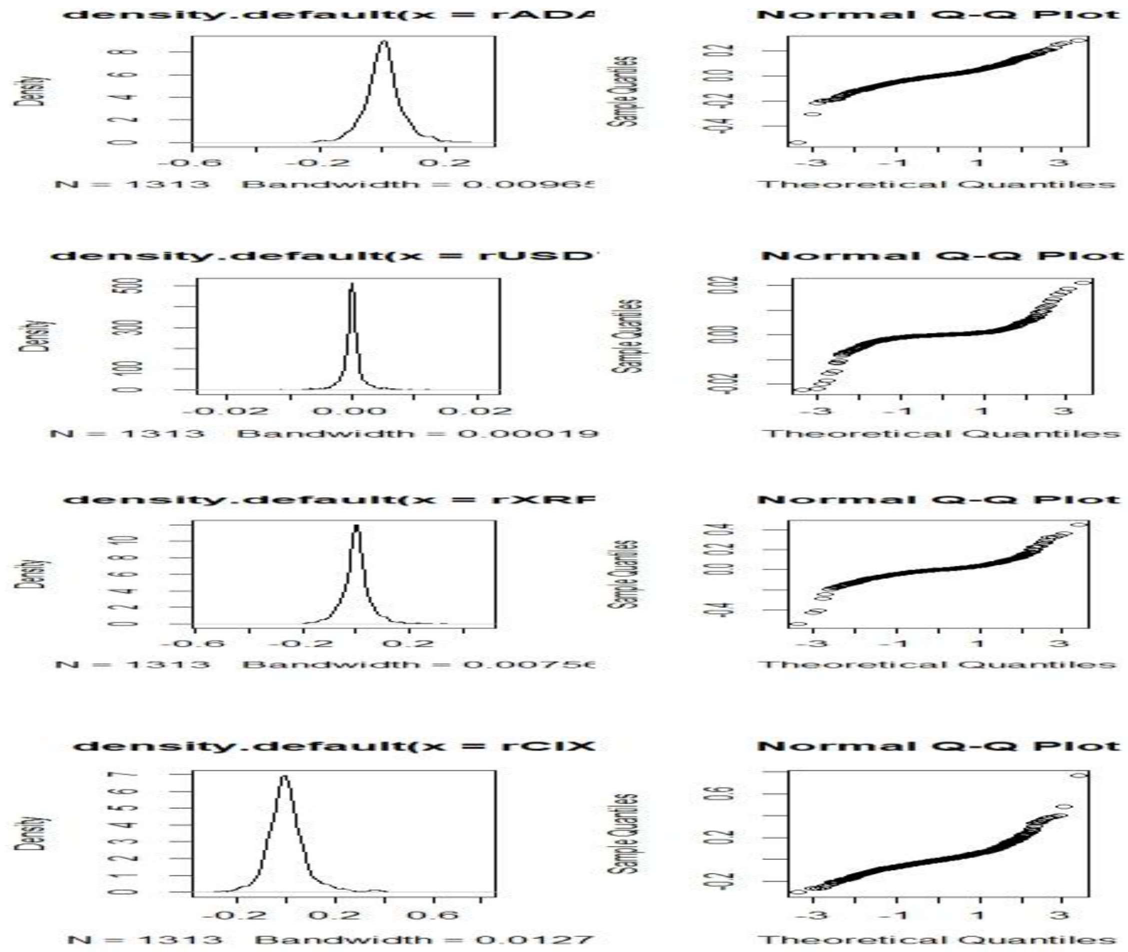
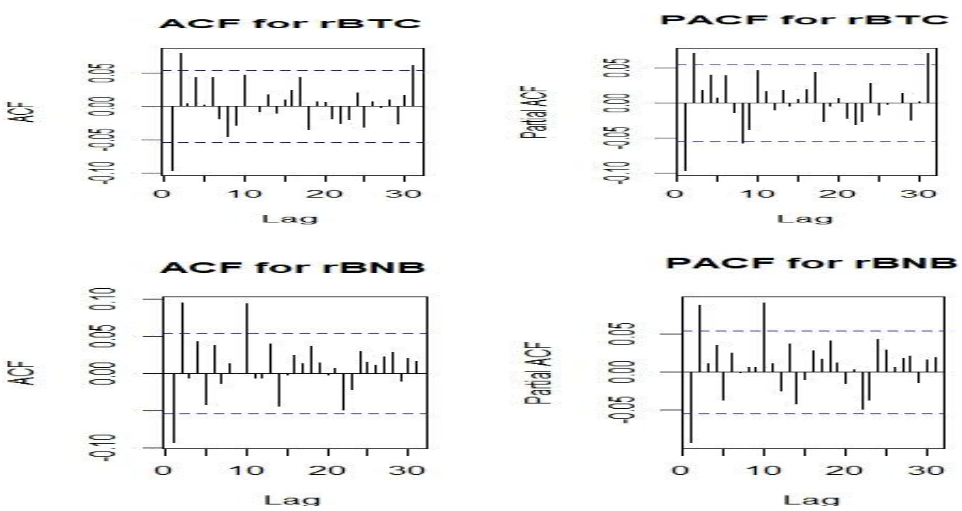


Chart 3: Density Plots and Q-Q Plots of the Log-Differenced Series

The leptokurtic distributions indicate a deviation from the Gaussian distribution of the data; however, such phenomena have been proved to be conducive to GARCH modelling (Carnero et al., 2004). The skewness of all the log-differenced series are within the range of ±2, which is an acceptable range for conformity with Gaussian distribution (Trochim & Donnelly, 2006; Field, 2000, 2009; George & Mallery, 2010; Gravetter & Wallnau, 2014). The ACF and PACF charts for all the series are shown in Chart 4.



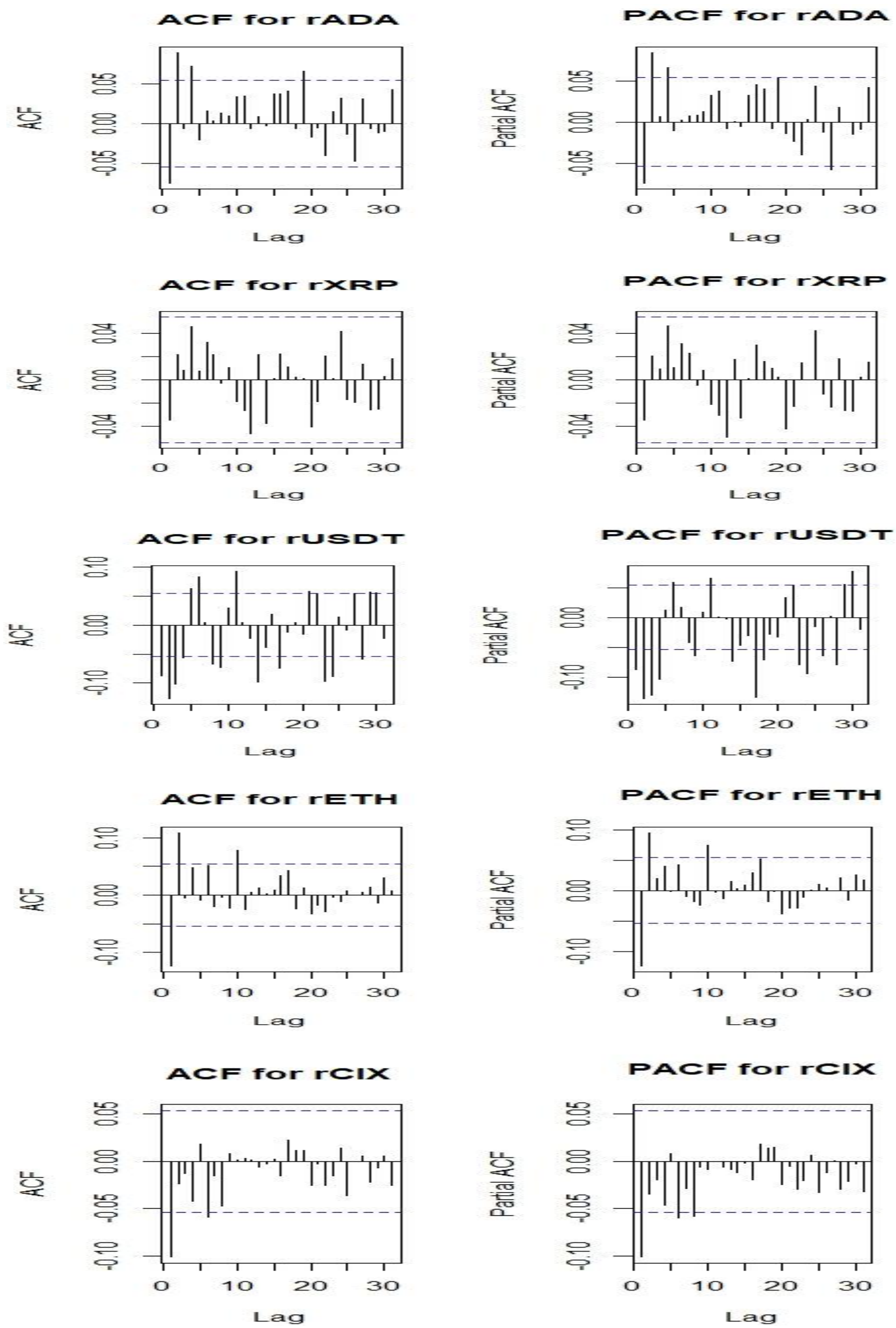


Chart 4: ACF and PACF Plots of the Log-Differenced Series

Based on the lag levels and the corresponding statistical significance of autocorrelations and partial autocorrelations, along with the pattern of decay thereof, the ARMA orders of the corresponding log-differenced series have been determined, which are shown in Table 4.

Table 4: ARMA Orders of the Log-Differenced Series

Series	ARMA Order
rBTC	(0,2)
rETH	(5,0)
rBNB	(2,2)
rADA	(3,0)
rUSDT	(5,2)
rXRP	(0,0)
rCIX	(1,1)

Source: Authors' own calculations.

The log-differenced series were subjected to the test for determination of the respective GARCH orders, and to test whether there are any ARCH effects in them. The results of the tests are presented in Table 5.

Table 5: GARCH Order and ARCH Test Results

Series	GARCH Order	p-Value of ARCH Test
rBTC	(1,1)	0.07679
rETH	(1,1)	0.0005718
rBNB	(1,1)	3.912e−14
rADA	(1,1)	4.787e−05
rUSDT	(1,1)	2.2e−16
rXRP	(1,1)	3.711e−09
rCIX	(1,1)	4.96e−06

Source: Authors' own calculations.

It was observed that there was no ARCH effect in the log-differenced BTC series as the p-value was more than the level of significance, i.e., 0.05, and the null hypotheses could not be rejected due to lack of sufficient statistical evidence. Hence, the series rBTC was discarded for further analysis. All the other series conformed to the GARCH (1,1) model. Initially, the model fit for all the log-differenced series, except rBTC, was done using the standard GARCH model. The estimates of the parameters of the standard GARCH (1,1) models of the log-differenced series are shown in Table 6.

Table 6: Estimates of the Parameters of the GARCH Equations with Corresponding p-Values within Parentheses

Parameters	rETH	rBNB	rADA	rUSDT	rXRP	rCIX
M	0.001544 (0.297311)	0.002928 (0.16823)	0.001014 (0.527937)	−0.000001 (0.91281)	0.001903 (0.12285)	−0.001346 (0.11207)
Ω	0.000184 (0.000358)	0.000168 (0.00015)	0.000345 (0.00055)	0.000000 (0.99613)	0.000415 (0.000001)	0.001668 (0.00000)
A	0.091689 (0.000001)	0.169290 (0.000000)	0.111686 (0.000011)	0.093993 (0.00000)	0.408289 (0.00000)	0.209312 (0.003054)
B	0.849436 (0.000000)	0.801753 (0.000000)	0.805232 (0.000000)	0.896231 (0.00000)	0.590711 (0.00000)	0.562258 (0.000000)
$\alpha + \beta$	0.941125 i.e. < 1	0.971043 i.e. < 1	0.916918 i.e. < 1	0.990224 i.e. < 1	0.99900 i.e. < 1	0.77157 i.e. < 1
Sign Bias (p-value)	0.1852	0.3636	0.5469	0.83360	0.9237	0.6351
Negative Sign Bias (p-value)	0.5601	0.2153	0.9277	0.02969	0.5159	0.2153
Positive Sign Bias (p-value)	0.9662	0.7026	0.9764	0.78870	0.9712	0.8584
Half-Life (no. of periods)	11.4231	23.58858	7.991298	70.56088	692.6729	2.672858

Source: Authors' own calculations.

The overall mean (μ) was found to be statistically insignificant for all the series. However, the constant term (Ω) was found to be significant for all the series, except rUSDT. The ARCH and GARCH coefficients, i.e., (α & β) are found to be significant for all the series. The corresponding sums of α & β are found to be less than one for all the series. The significance of the ARCH term (α) proved that the models constructed could capture the effect of all the news on the returns in all the series. The significance of the GARCH term (β) proved the persistence of volatility in each of the series. The measure of volatility persistence in the number of days is found to be the least in ADA and the highest in XRP. The standard GARCH equations are shown in Table 7.

Table 7: The Standard GARCH Models ($\delta_t^2 = \Omega + \alpha_1 * \varepsilon_{t-1}^2 + \beta_1 * \delta_{t-1}^2 + \varepsilon_t$)

Log-Differenced Series	GARCH (1,1) Equations
rETH	$\delta_{t\text{-}rETH}^2 = 0.000184 + 0.091689 * \varepsilon_{t-1}^2 + 0.849436 * \delta_{t-1}^2 + \varepsilon_t$
rBNB	$\delta_{t\text{-}rBNB}^2 = 0.000168 + 0.169290 * \varepsilon_{t-1}^2 + 0.801753 * \delta_{t-1}^2 + \varepsilon_t$
rADA	$\delta_{t\text{-}rADA}^2 = 0.000345 + 0.111686 * \varepsilon_{t-1}^2 + 0.805232 * \delta_{t-1}^2 + \varepsilon_t$
rUSDT	$\delta_{t\text{-}USDT}^2 = 0.093993 * \varepsilon_{t-1}^2 + 0.896231 * \delta_{t-1}^2 + \varepsilon_t$
rXRP	$\delta_{t\text{-}XRP}^2 = 0.000415 + 0.408289 * \varepsilon_{t-1}^2 + 0.590711 * \delta_{t-1}^2 + \varepsilon_t$
rCIX	$\delta_{t\text{-}CIX}^2 = 0.001668 + 0.209312 * \varepsilon_{t-1}^2 + 0.562258 * \delta_{t-1}^2 + \varepsilon_t$

Source: Authors' own calculations.

However, no leverage effect could be captured, as the p values of the sign bias, positive sign bias, and the negative sign bias for all the series were found to be more than the level of significance of 5%. This is evidenced by the symmetrical news impact curves for the models of all the series. This phenomenon is natural for GARCH models (Engle & NG, 1993), as the news impact curve function in the GARCH model is quadratic, with centre at $\varepsilon_{t-1} = 0$. The important GARCH plots, including the news impact curves for all the log-differenced series, are presented in the following charts.

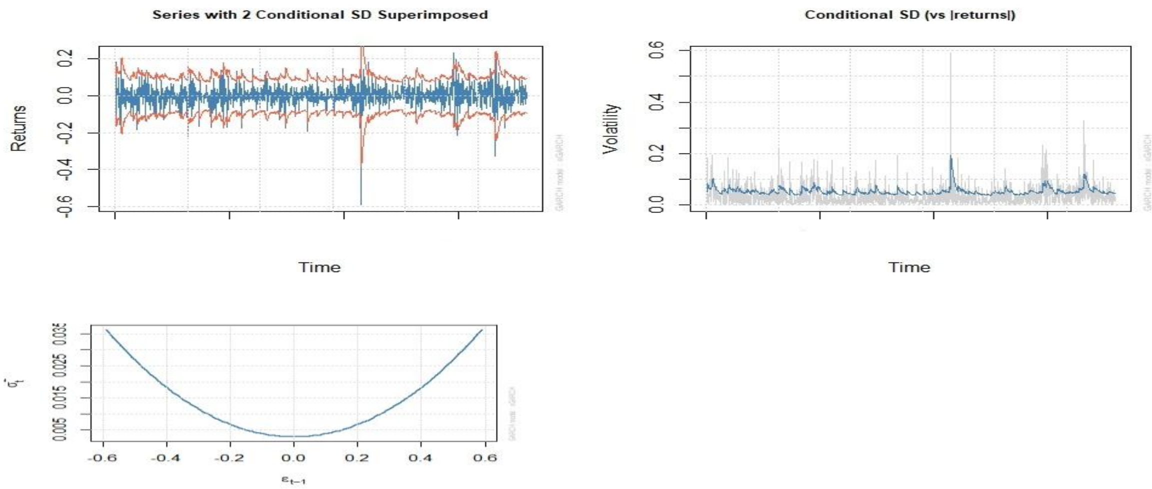


Chart 5: rETH Series with Two Conditional SD Superimposed, Conditional SD vs. Returns and the News Impact Curve

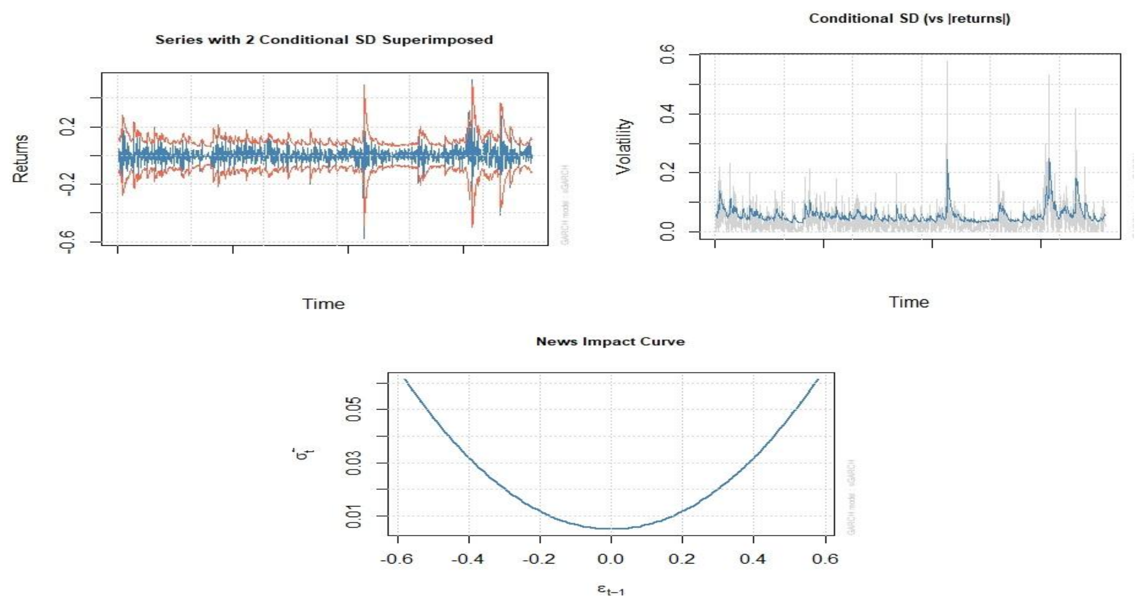


Chart 6: rBNB Series with Two Conditional SD Superimposed, Conditional SD vs. Returns and the News Impact Curve

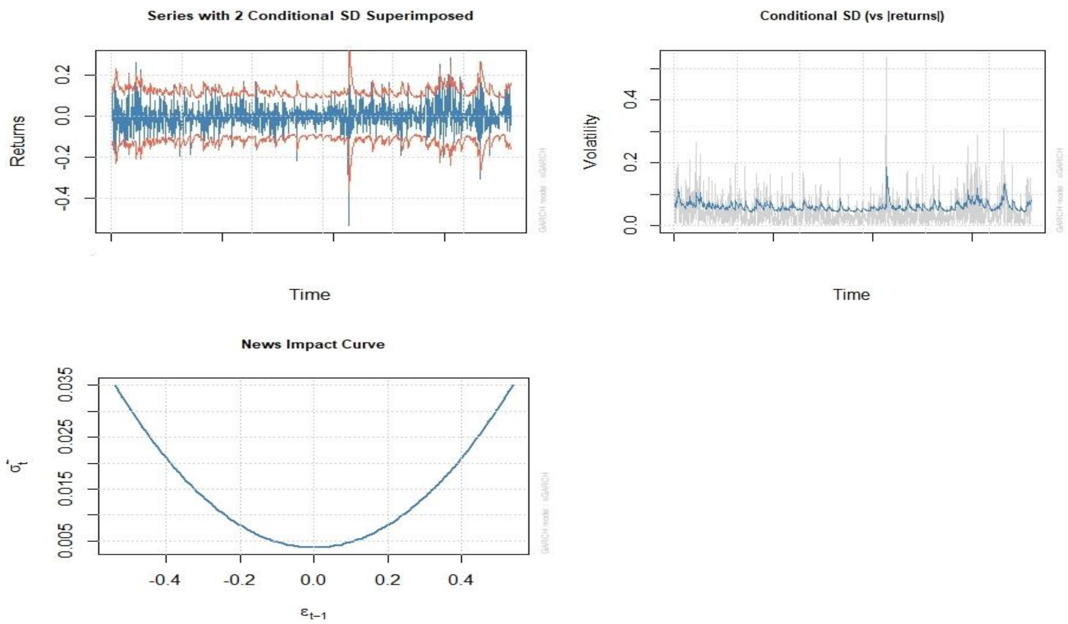


Chart 7: rADA Series with Two Conditional SD Superimposed, Conditional SD vs. Returns and the News Impact Curve

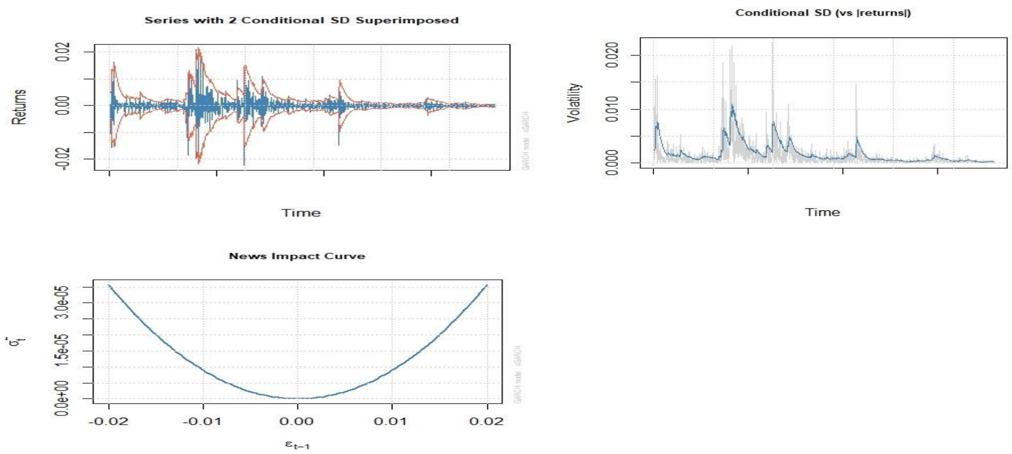


Chart 8: rUSDT Series with Two Conditional SD Superimposed, Conditional SD vs. Returns and the News Impact Curve

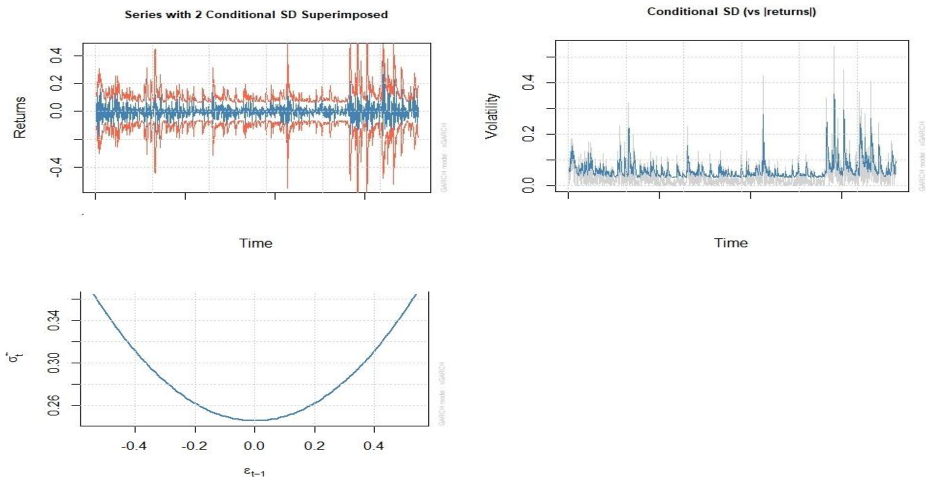


Chart 9: rXRP Series with Two Conditional SD Superimposed, Conditional SD vs. Returns and the News Impact Curve

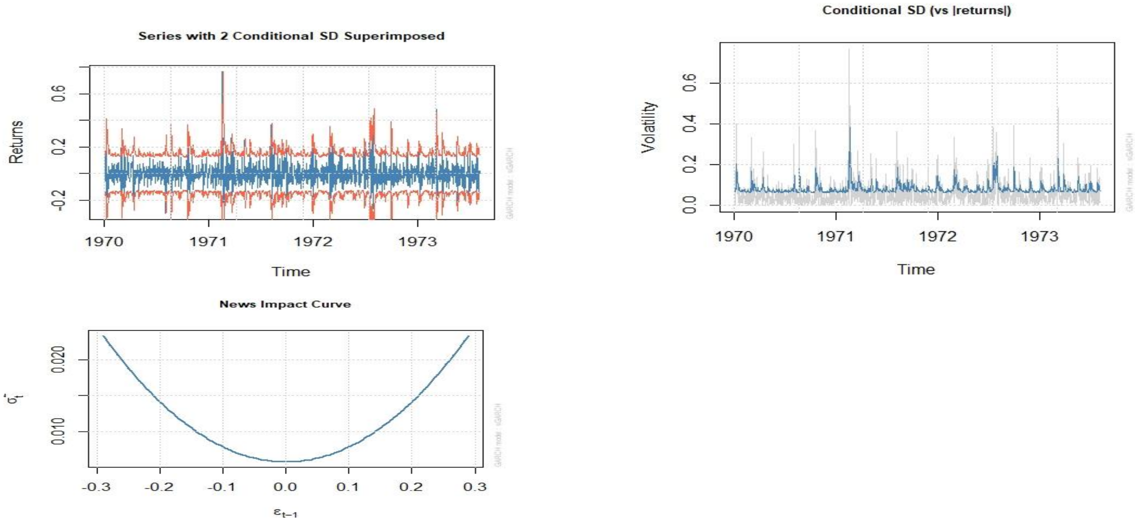


Chart 10: rCIX Series with Two Conditional SD Superimposed, Conditional SD vs. Returns and the News Impact Curve

However, positive news and negative news are intuitively supposed to have different levels of shocks to the series. Other factors remaining constant, negative return shocks have been empirically found to generate more volatility than positive return shocks (Engle & NG, 1993). This asymmetric impact of good and bad news on volatility is better captured by the EGARCH model than the GARCH model (Engle & NG, 1993; Ali, 2013), as the EGARCH news impact curve is an exponential function. This phenomenon has been tested for its presence on all the log-differenced series in this study, by fitting an EGARCH (1,1) model as well as a TGARCH (1,1) model to each of them. Only the leverage effect is tested in both the methods by focusing on the significance of the asymmetry (γ) term in the EGARCH and TGARCH models of the series. The results are shown in Table 8.

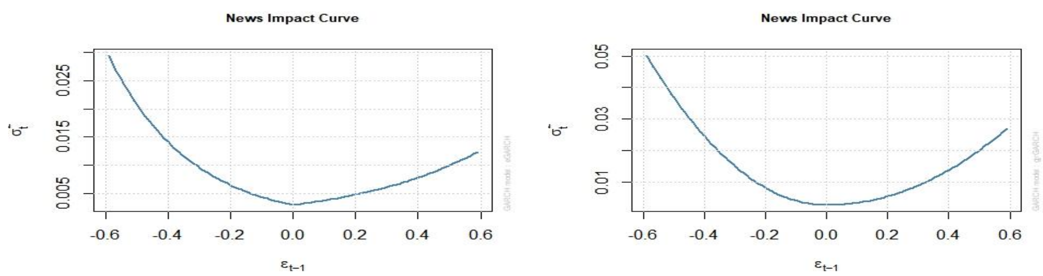
Table 8: Estimates of the Asymmetry (γ) Parameters of the EGARCH and TGARCH Models with Corresponding p-Values within Parentheses

Parameters	rETH	rBNB	rADA	rUSDT	rXRP	rCIX
γ (EGARCH)	0.184981 (0.000002)	0.286204 (0.000000)	0.231395 (0.000000)	0.319834 (0.000000)	0.506274 (0.000000)	0.035840 (0.068687)
γ (TGARCH)	0.067066 (0.0450989)	0.068706 (0.025489)	0.049731 (0.146650)	0.014512 (0.36627)	−0.024722 (0.741532)	−0.405262 (0.00000)

Source: Authors' own calculations.

It was observed from the contents of Table 8 that the TGARCH model indicates a significant asymmetry only in the case of rETH, rBNB, and rCIX, whereas the EGARCH model indicates asymmetry in all the series, with a negligible value in rCIX. The news impact curves of the series under EGARCH and TGARCH are presented in Chart 11.

EGARCH TGARCH



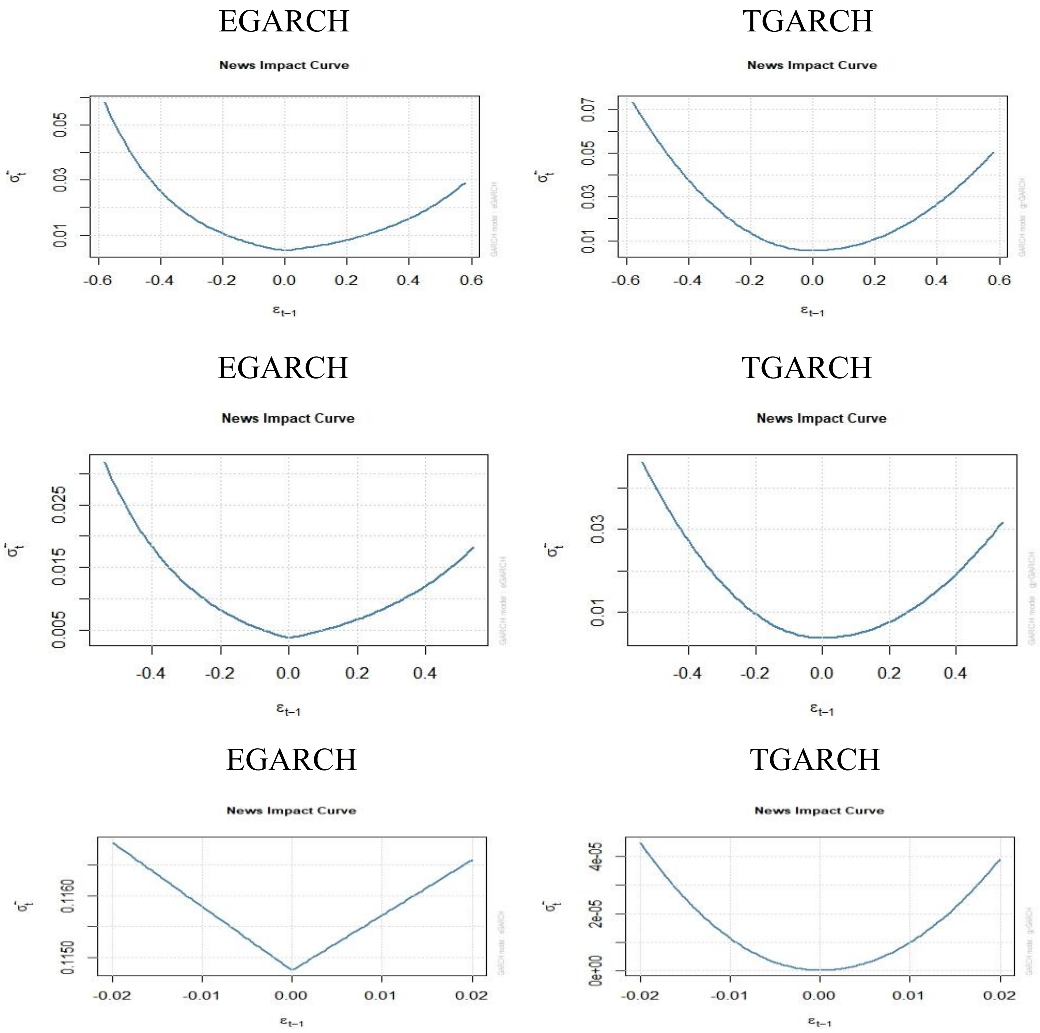


Chart 11: News Impact Curve Plots under EGARCH and TGARCH rETH Series

The study has further examined the short-term and long-term volatility spillover between cryptocurrencies, as well as CBOE VIX. Accordingly, a comparatively new multivariate GARCH model – the dynamic conditional correlation (DCC) approach – is applied, taking two cryptocurrencies at a time, i.e., considering the bivariate GARCH approach. The results of the application of DCC approach on the log-differenced series of the cryptocurrencies are presented in Table 9.

Table 9: α DCC and β DCC Parameters for Bivariate Volatility Spillovers between the Log-Differenced Series

Volatility Spillover between	Estimates with Corresponding p-Values within Parentheses		
	α DCC	β DCC	α DCC + β DCC
rETH & rBNB	0.035440 (0.000005)	0.963994 (0.000000)	0.999434
rETH & rADA	0.033020 (0.01153)	0.965162 (0.000000)	0.998182
rETH & rUSDT	0.039357 (0.256859)	0.959974 (0.000005)	0.999331
rETH & rXRP	0.018118 (0.000388)	0.965882 (0.000000)	0.984000
rBNB & rADA	0.061119 (0.000007)	0.921720 (0.000000)	0.982839
rBNB & rUSDT	0.004061 (0.494213)	0.764505 (0.001607)	0.768556
rBNB & rXRP	0.077240 (0.000006)	0.905024 (0.000000)	0.982264
rADA & rUSDT	0.004263 (0.484717)	0.778057 (0.000000)	0.782320
rADA & rXRP	0.047846 (0.000030)	0.941113 (0.000000)	0.988959
rUSDT & rXRP	0.010223 (0.403613)	0.579837 (0.002222)	0.590060

Source: Authors' own calculations

The α DCC and the β DCC terms denote the short-term and long-term volatility spillover between the two concerned cryptocurrencies. It is observed that the long-term volatility spillovers between all the possible pair-wise combinations of the cryptocurrencies are significant at 5% level. The short-term volatility spillover is also significant in all the possible pairs of cryptocurrencies, except the pairs involving rUSDT. No short-term volatility is observed between rUSDT and any of the other four cryptocurrencies. The pair-wise DCC plots are shown in Chart 12.

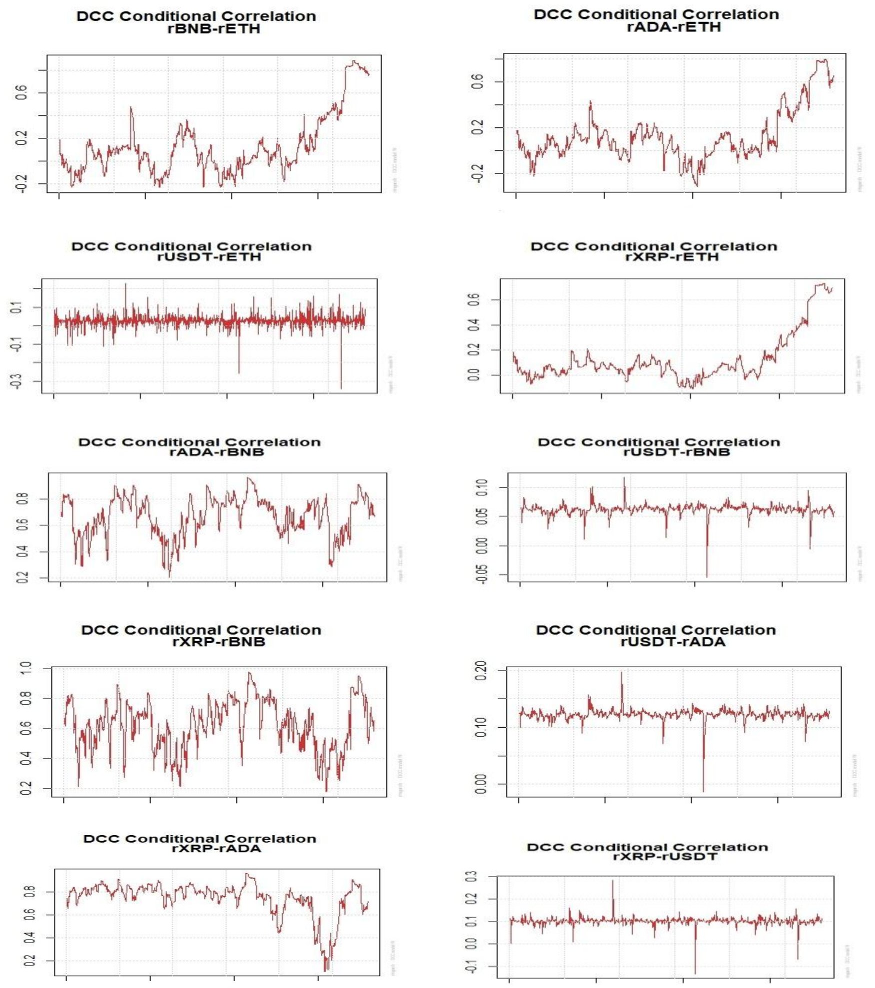


Chart 12: Pair-Wise DCC Plots of the Selected Cryptocurrencies

The study has also examined whether there are any short-term or long-term volatility spillovers from the CBOE VIX, i.e., one of the most popular global fear indices to the cryptocurrencies considered in the study. The DCC approach is applied and the α DCC and β DCC estimates so obtained are presented in Table 10.

Table 10: α DCC and β DCC Parameters for Bivariate Volatility Spillovers from Log-Differenced CIX to Other Log-Differenced Series

Volatility Spillover from rCIX to	Estimates with Corresponding p-Values within Parentheses		
	α DCC	β DCC	α DCC + β DCC
rETH	0 (0.999951)	0.930155 (0.074882)	0.930155
rBNB	0 (0.999891)	0.920794 (0.000018)	0.920794
rADA	0 (0.999317)	0.918419 (0.000013)	0.918419
rUSDT	0.016817 (0.000008)	0.868207 (0.999999)	0.885024
rXRP	0 (0.999014)	0.919975 (0.000000)	0.919975

Source: Authors' own calculations.

It is observed that there was significant long-term volatility spillover from CBOE VIX to BNB, ADA, and XRP. Short-term volatility spillover is found to be significant from CBOE VIX to only USDT. Thus, no significant volatility spillover from CBOE VIX is observed to ETH (both short- and long-term). Short-term volatility spillover is not found from CBOE VIX to BNB, ADA, and XRP. Long-term volatility spillover from CBOE VIX to USDT is found to be insignificant. The DCC plots from CBOE VIX to the cryptocurrencies considered in the study are shown in Chart 13.

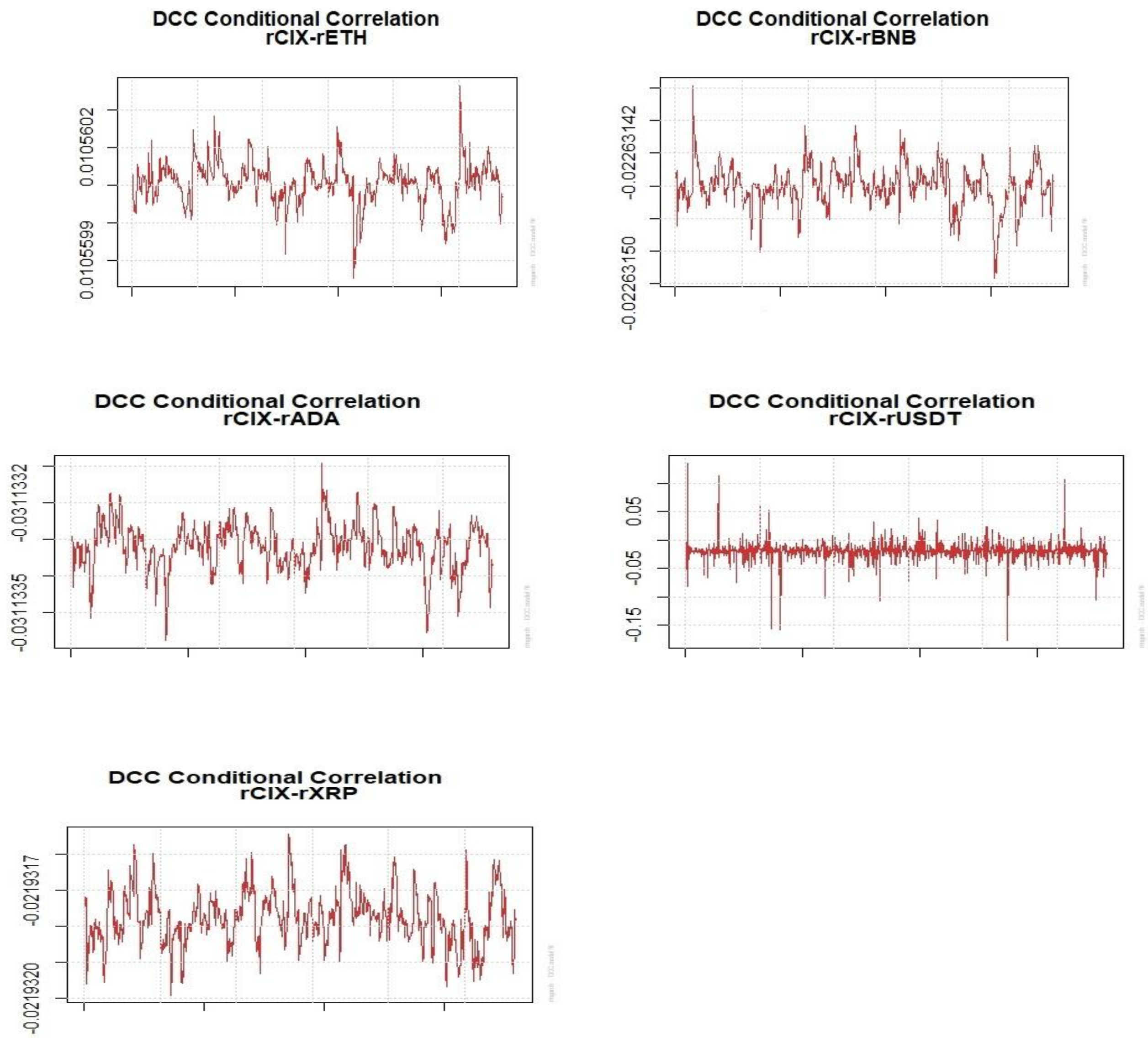


Chart 13: Pair-Wise DCC Plots of CIX with Cryptocurrencies

To have a deeper insight into the volatility spillover between cryptocurrencies, it becomes imperative to have an idea about the total and directional volatility spillover between them. The Diebold and Yilmaz (2012) approach offers a simple measure of the total and directional volatility spillover between assets, through utilisation of the generalised vector autoregressive technique, which yields decomposition of variances not affected by ordering. The connectedness between the cryptocurrencies using the Diebold-Yilmaz technique is shown in Table 11.

Table 11: Table of Connectedness between Cryptocurrencies

	Series with Corresponding Values					From
	rETH	rBNB	rADA	rUSDT	rXRP	
rETH	91.87	2.69	2.46	0.07	2.91	1.63
rBNB	1.66	56.58	22.80	0.40	18.56	8.68
rADA	1.58	21.33	52.65	0.98	23.46	9.47
rUSDT	0.05	1.66	2.69	94.62	0.98	1.08
rXRP	1.74	18.24	24.50	0.37	55.15	8.97
TO	1.01	8.78	10.49	0.36	9.18	29.82

Source: Authors' own calculations.

An analysis of Table 11 reveals that 29.82%, i.e., about 30%, of the total changes in the five cryptocurrency prices is caused by the mutual influence of the cryptocurrency prices on one another. The 'from' column in the table shows that BNB, ADA, and XRP have comparatively higher values than EH and USDT. Thus, BNB, ADA, and XRP are more influenced by other cryptocurrencies, and ETH and USDT are comparatively less affected. Similarly, an analysis of the total of the 'to' column reveals that BNB, ADA, and XRP show comparatively higher values than ETH and USDT. This indicates that BNB, ADA, and XRP have higher influence on the prices of other currencies, compared to ETH and USDT.

Major Findings and Policy Implication

A vast majority of the studies on volatility spillover regarding cryptocurrencies are on the spillover between cryptocurrencies and other asset classes, mainly stocks and commodities. This paper has focused on examining the asymmetry of the volatility of the cryptocurrency prices, along with the volatility spillover between the cryptocurrencies. Moreover, as cryptocurrency prices are characterised by high volatility, volatility spillover to the cryptocurrency prices from one of the most popular global fear indices, the CBOE VIX, has been studied.

Asymmetry in volatility is found to be most prominent in ETH, BNB, and CIX, as they were confirmed by both the EGARCH and TGARCH models. Thus, investors can expect a higher volatility in these cryptocurrencies in case of an adverse news in the market regarding them. This information will allow the speculators in cryptocurrencies to take up appropriate positions in response to the news regarding the cryptocurrencies in the market, whether favourable or adverse.

The dynamic conditional correlation analysis between the cryptocurrencies has pointed out the existence of long-term volatility spillover between all the five cryptocurrencies. However, short-term volatility spillover is not found in the cryptocurrency pairs involving USDT. Thus, short-term portfolio of cryptocurrencies may be constituted by investors taking USDT as one of the cryptocurrencies.

Volatility spillover from CBOE VIX is found in long-term to BNB, ADA, and XRP only. Short-term volatility spillover from CBOE VIX is found only in USDT. Thus, the interconnectedness between the investor sentiment in stock markets and the cryptocurrency prices is found to exist with BNB, ADA, and XRP in the long term, and with USDT in the short run. This insight will be of assistance to those investors who wish to build their portfolio with stocks as well as cryptocurrencies. A long-term portfolio created with stocks and cryptocurrencies may include ETH and USDT, and a short-term portfolio created with stocks and cryptocurrencies may include ETH, BNB, ADA, and XRP.

The Diebold-Yilmaz technique brought out some important implications for portfolio construction with cryptocurrencies only. While constructing the portfolio, the general effort is given to constituent assets which are uncorrelated (to the extent possible). If there is a significant volatility spillover between assets, such assets should not be used to build up a portfolio. The results of this study show that BNB, ADA, and XRP have comparatively more influence on other cryptocurrencies. These three cryptocurrencies are also comparatively more influenced by other cryptocurrencies. Hence, ETH and XRP are more suitable for building up portfolios.

CONCLUSION

From the major findings, it may be concluded that asymmetry in volatility is found in ETH, BNB, and CIX; there exists long-term volatility spillover in all the selected five cryptocurrencies along with the interconnectedness between the investor sentiment in stock markets and the cryptocurrency prices in the BNB, ADA, and XRP in the long term, and USDT in the short run. To take more informed decisions about investing in cryptocurrencies and to create short-term or long-term portfolios with cryptocurrencies exclusively or with other asset classes, e.g., stocks, a clear understanding of univariate, as well as multivariate volatility of cryptocurrencies is essential. This study generates some insight in this context. The findings of this study would help investors in cryptocurrencies in this context. However, as the dynamics of volatility of cryptocurrencies is itself dynamic and the regulatory bodies are coming up with new rules and policies regarding cryptocurrencies, the findings of this study may be corroborated with similar studies involving a larger window and a greater number of cryptocurrencies. Moreover, other techniques of the GARCH family, i.e., IGARCH, CGARCH, APARCH, Markov-switching GARCH, and other methods like Diagonal BEKK model, may be used, to have a deeper insight into the complex dynamics of the univariate and multivariate volatilities of cryptocurrencies.

REFERENCES

Abakah, E. J. A., Gil-Alana, L. A., Madigu, G., & Romero-Rojo, F. (2020). Volatility persistence in cryptocurrency markets under structural breaks. *International Review of Economics & Finance, 69,* 680-691. doi:https://doi.org/10.1016/j.iref.2020.06.035

Ali, Ghulam. (2013). EGARCH, GJR-GARCH, TGARCH, AVGARCH, NGARCH, IGARCH and APARCH Models for Pathogens at Marine Recreational Sites. *Journal of Statistical and Econometric Methods, 2*(3), 57-73.

Allen, D., McAleer, M., Powell, R., & Singh, A. (2017). Volatility spillover and multivariate volatility impulse response analysis of GFC news events. *Proceedings of the 2017 International Conference on Economics, Finance and Statistics (ICEFS 2017).* doi:https://doi.org/10.2991/icefs-17.2017.9

Baur, D. G., & Dimpfl, T. (2018). Asymmetric volatility in cryptocurrencies. *Economics Letters, 173,* 148-151. doi:https//doi.org/10.1016/j.econlet.2018.10.008

Bigmore, R. (2018). A decade of cryptocurrency: From bitcoin to mining chip. Retrieved July 16, 2021, from https://www.telegraph.co.uk/technology/digital-money/the-history-of-cryptocurrency/

Bouri, E., Das, M., Gupta, R., & Roubaud, D. (2018). Spillovers between Bitcoin and other assets during bear and bull markets. *Applied Economics, 50*(55), 5935-5949. doi:https//doi.org/10.1080/00036846.2018.1488075

Carnero, M. A., Pena, D., & Ruiz, E. (2004). Persistence of Kurtosis in GARCH and stochastic volatility models. doi:10.1093/JJFINEC/NBH012. Retrieved September 3, 2021, from https://core.ac.uk/download/pdf/29429136.pdf

Dangi, V. (2020). Volatility dynamics of cryptocurrencies' returns: An econometric study. *IUP Journal of Applied Finance, 26*(1), 5-30.

Diebold, F., & Yilmaz, K. (2009). Measuring financial asset return and volatility spillovers, with application to global equity markets. *Economic Journal*, *119*(534), 158-171.

Diebold, F., & Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting*, *28*(1), 57-66.

Engle, Robert F., & Ng, Victor K. (1993). Measuring and testing the impact of news on volatility. *The Journal of Finance, 48*(5), 1749-1778.

ERTUĞRUL, H. M. (2019). Kripto Paralarin Volatilite Dinamiklerinin İncelenmesi: Garch Modelleri Üzerine Bir Uygulama. *Journal of Management & Economics Research, 17*(4), 59-71. doi:https//doi.org/10.11611/yead.555713

Fasanya, I. O., Oyewole, O., & Odudu, T. (2021). Returns and volatility spillovers among cryptocurrency portfolios. *International Journal of Managerial Finance, 17*(2), 327-341. doi:https//doi.org/10.1108/IJMF-02-2019-0074

Field, A. (2000). *Discovering statistics using SPSS for windows.* London-Thousand Oaks-New Delhi: Sage publications.

Field, A. (2009). *Discovering statistics using SPSS. London: SAGE.*

Ftiti, Z., Louhichi, W., & Ben Ameur, H. (2021). Cryptocurrency volatility forecasting: What can we learn from the first wave of the COVID-19 outbreak? *Annals of Operations Research*, 1-26. doi:https://doi.org/10.1007/s10479-021-04116-x

George, D., & Mallery, M. (2010). *SPSS for windows step by step: A simple guide and reference, 17.0 update* (10a ed.). Boston: Pearson.

Gradojevic, N., & Tsiakas, I. (2021). Volatility cascades in cryptocurrency trading. *Journal of Empirical Finance, 62,* 252-265. doi:https://doi.org/10.1016/j.jempfin.2021.04.005

Gravetter, F., & Wallnau, L. (2014). *Essentials of statistics for the behavioral sciences* (8^{th} ed.). Belmont, CA: Wadsworth.

Hsu, S. H., Sheu, C., & Yoon, J. (2021). Risk spillovers between cryptocurrencies and traditional currencies and gold under different global economic conditions. *North American Journal of Economics & Finance, 57*(C). doi:https://doi.org/10.1016/j.najef.2021.101443

Huang, J.-Z., Huang, Z. J., & Xu, L. (2021). Sequential Learning of cryptocurrency volatility dynamics: Evidence based on a stochastic volatility model with jumps in returns and volatility. *Quarterly Journal of Finance, 11*(2), 1-37. doi:https://doi.org/10.1142/S2010139221500105

Jimoh, S. O., & Benjamin, O. O. (2020). The effect of cryptocurrency returns volatility on stock prices and exchange rate returns volatility in Nigeria. *Acta Universitatis Danubius: Oeconomica, 16*(3), 200-213.

Katsiampa, P., Corbet, S., & Lucey, B. (2019). High frequency volatility co-movements in cryptocurrency markets. *Journal of International Financial Markets, Institutions & Money, 62,* 35-52. doi:https://doi.org/10.1016/j.intfin.2019.05.003

Kayral, İ. E. (2020). En Yüksek Piyasa Değerine Sahip Üç Kripto Paranin Volatilitelerinin Tahmin Edilmesi. *Journal of Financial Researches & Studies / Finansal Arastirmalar ve Calismalar Dergisi*, *11*(22), 152-168. doi:https://doi.org/10.14784/marufacd.688447

Koutmos, D. (2018). Return and volatility spillovers among cryptocurrencies. *Economics Letters, 173,* 122-127. doi:https://doi.org/10.1016/j.econlet.2018.10.004

Lobato, I., & Velasco, C. (2004). A simple test of normality for time series. *Econometric Theory, 20,* 671-689. doi:10.1017/S026646664204030

Lundbergh, S., & Terasvirta, T. (2002). Evaluating GARCH models. *Journal of Econometrics, 110,* 417-435.

Ma, F., Liang, C., Ma, Y., & Wahab, M. I. M. (2020). Cryptocurrency volatility forecasting: A Markov regime-switching MIDAS approach. *Journal of Forecasting, 39*(8), 1277-1290. doi:https://doi.org/10.1002/for.2691

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

Palamalai, S., & Maity, B. (2019). Return and volatility spillover effects in leading cryptocurrencies. *Global Economy Journal, 19*(3), 1-20. doi:https://doi.org/10.1142/S2194565919500179

Sensoy, A., Silva, T. C., Corbet, S., & Tabak, B. M. (2021). High-frequency return and volatility spillovers among cryptocurrencies. *Applied Economics, 53*(37), 4310-4328. doi:https://doi.org/10.1080/00036846.2021.1899119

Siu, T. K. (2021). The risks of cryptocurrencies with long memory in volatility, non-normality and behavioural insights. *Applied Economics, 53*(17), 1991-2014. doi:https://doi.org/10.1080/00036846.2020.1854669

Trentina, K., & Schmidt, J. (2021, August). Top 10 cryptocurrencies. Retrieved August 20, 2021, from https://forbes.com/advisors/investing/top-10-cryptocurrencies

Trochim, W. M., & Donnelly, J. P. (2006). *The research methods knowledge base* (3rd ed.). Cincinnati, OH: Atomic Dog.

Urbina, J. (2013). Financial spillovers across countries: Measuring shock transmissions. Munich Personal RePEc Archive Paper No. 75756. Retrieved from https://mpra.ub.uni-muenchen.de/75756/

Xiao, X. & Huang, J. (2018). Dynamic connectedness of international crude oil prices: The Diebold-Yilmaz approach. *Sustainability, 10*, 3298. doi:https://doi.org/10.3390/su10093298

Yaya, O. S., Ogbonna, A. E., Mudida, R., & Abu, N. (2021). Market efficiency and volatility persistence of cryptocurrency during pre- and post-crash periods of Bitcoin: Evidence based on fractional integration. *International Journal of Finance & Economics, 26*(1), 1318-1335. doi:https://doi.org/10.1002/ijfe.1851

Yi, S., Xu, Z., & Wang, G.-J. (2018). Volatility connectedness in the cryptocurrency market: Is Bitcoin a dominant cryptocurrency? *International Review of Financial Analysis, 60,* 98-114. doi:https://doi.org/10.1016/j.irfa.2018.08.012

Yin, L., Nie, J., & Han, L. (2021). Understanding cryptocurrency volatility: The role of oil market shocks. *International Review of Economics & Finance, 72,* 233-253. doi:https://doi.org/10.1016/j.iref.2020.11.013

WEB RESOURCES

https://www.cboe.com/tradable_products/vix/ accessed on 20 August 2021

https://www.forbes.com/advisor/investing/top-10-cryptocurrencies/ accessed on 20 August 2021

https://in.investing.com/ accessed on 20 August 2021

https://www.telegraph.co.uk/technology/digital-money/the-history-of-cryptocurrency/ accessed on 16 July 2021