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Volatility in Cryptocurrency Market – Before and During Covid-19 Pandemic

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Abstract

This paper aims to measure the nature of volatility in the cryptocurrency market before and during Covid-19 pandemic period. To achieve this goal, the Wald test, Granger Causality and Generalized Autoregressive Conditional Heteroskedasticity (1,1) have been applied considering the daily US dollar dominated closing prices of 15 leading cryptocurrencies and volatility index (VIX- CBOE) from 1 January, 2019 to 5 June, 2020. The presence of structural breaks in all the selected cryptocurrencies is observed which result in erroneous forecasting in cryptocurrency market. The small size of cryptocurrency market hinders the risk diversification. It is further noticed that cryptocurrencies are exposed to the systematic bubble risks and therefore it is very unpredictable. Inclusion of cryptocurrencies in the portfolio along with conventional instruments like stocks, bonds, precious metals, commodities, and paper currencies may gear up the overall return on investment and increase the possibility of risk diversification if necessary investment precautions are taken.

Keywords

Covid-19, cryptocurrency, GARCH, Granger causality, return spillover, structural break

Introduction

We live in such a world where seldom we need to touch physical notes or coins. We perform most of our day to day transactions like payment for groceries, utilities, DTH bills, and Uber bills through online using different types of currencies. Apart from conventional currencies, the usage of cryptocurrencies is increasing at a faster rate (Brandvold, Molnár, Vagstad & Valstad, 2015). Cryptocurrency is such a medium of exchange, where there exist no physical coins or notes. In this system, the transactions between the trading partners are recorded online and authenticated by a third party known as miner. The historical transactions are recorded in a very secured electronic ledger system known

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as blockchain. Due to having world-wide acceptances, high security and low transaction costs, cryptocurrencies are now being popular among the people (Polasik, Piotrowska, Wisniewski, Kotkowski & Lightfoot, 2015). Unlike traditional currencies, precious metals and commodities, cryptocurrencies have become an important financial asset in our daily life. People invest in different cryptocurrencies to perform daily transactions as well as to gain profit over the period. Due to price speculations, investment in cryptocurrencies is not free from risk. In portfolio management, risk can be reduced through proper diversification. Although investment in cryptocurrencies is being popular day by day, most of the people are at their early stage of knowledge on cryptocurrencies and the prices of cryptocurrencies are subject to severe conjectures (Alvarez-Ramirez, Rodriguez & Ibarra-Valdez, 2018). Since, at present there are 5563[2] different cryptocurrencies in the world, investors can diversify the risk of investment by adding desired cryptocurrencies in their portfolios. The risk-return tradeoff of cryptocurrencies is not as same as that of stocks, bonds, paper currencies and precious metals. These are free from macro-economic, commodities, currencies and common stock market related factors. Liu and Tsyvinski (2018) observed that the returns of cryptocurrencies can be forecasted only by studying the factors related to cryptocurrency markets. They also noticed the presence of strong time-series momentum effect which helps investors to predict cryptocurrency returns. With the increasing trend of popularity of cryptocurrency, analyzing the nature of volatility has become an important research topic. Till date, no research has been found focusing on the nature of volatility in this highly sensitive market during Covid-19 pandemic. This study attempts to measure the volatility in cryptocurrency market before and during Covid-19 pandemic considering the top 15 cryptocurrencies with four specific objectives. First, checking the presence of structural breaks among the selected cryptocurrencies. Second, verification of cryptocurrency volatility spillovers. Third, measuring the causal relationship among the cryptocurrencies and forth, analyzing the volatility behavior pattern of cryptocurrencies before and during Covid-19 pandemic period.

The paper continues as follows. Section 2 focuses on previous findings. Section 3 describes data and research methods. Section 4 presents the empirical results and section 5 concludes the paper.

Literature Review

Cryptocurrency is a kind of money managed by computer in the form of public ledger. The first concept of cryptocurrency came to the light in 2008 through an article entitled "Bitcoin: A Peer-to-Peer Electronic Cash System" written by Satoshi Nakamoto (2008). Basically, the Bitcoin was invented as an alternative option of conventional currencies but people started treating it as a speculative investment sector (Baur, Hong & Lee, 2018). With the advancement of digital technology, the usage of digital currencies is also getting momentum. People

[2] https://coinmarketcap.com/

now shop online from different parts of the world. While making payment, security becomes a real concern for them. Cryptocurrency eliminates this problem by ensuring appropriate security through the application of blockchain technology (Takaishi, 2018).

Financial economists have been doing research on the relationship between volatility and the asset prices for a long time. Guo and Savickas (2008) studied volatility in foreign exchanges, Cao and Han (2013) studied volatility in equity & option market, Fuertes, Miffre and Fernandez-Perez (2015) studied volatility in commodity market. While, Hou and Loh (2016) studied impact of unconventional volatility on the expected returns of stocks, Chung, Wang and Wu (2019) studied volatility in the bond market. Such studies on digital currency is equally important as cryptocurrency got its position beside these conventional assets and has made this market very risky through severe price fluctuations (Corbet, Lucey, Urquhart & Yarovaya, 2019). Koutmos (2018) checked the interrelations among the cryptocurrencies by applying conditional variance analysis. Brauneis and Mestel (2018) studied price discovery among the cryptocurrencies. Chu, Chan, Nadarajah, and Osterrieder (2017) established volatility modeling considering seven most popular cryptocurrencies and observed that the model can successfully measure the value at risk. Brauneis and Mestel, (2018) extended their scope of study considering several cryptocurrencies beyond Bitcoin and observed a negative linkage between efficiency and liquidity. With the surge of liquidity, cryptocurrencies become less foreseeable. Platanakis, Sutcliffe and Urquhart (2018) contributed by testing the performance of naïve and optimal diversification in a portfolio considering four cryptocurrencies. They found a very insignificant opportunity for naïve and optimal diversifications minimizing the scope of risk aversion. This study will add significant literature by measuring the states of volatility in cryptocurrency market before and after the announcement of any such crisis like Covid-19 pandemic. Bouri, Lucey and Roubaud (2019) tested the volatility shocks of leading cryptocurrencies by checking the temporary and permanent associations. There has not been found any study on the analysis of return spillovers in the cryptocurrency market. This study will fill the gap by measuring the return spillover among the leading cryptocurrencies by applying Granger causality method. At the initial stage, the only cryptocurrency was Bitcoin, over the last decade, many other cryptocurrencies emerged and thus people got a break to diversify the Bitcoin centric risk in their portfolios (Canh, Wongchoti, Thanh & Thong, 2019). Therefore, it is essential to know the price dynamics and the interlinks among the available cryptocurrencies. This study will bridge this gap by verifying the presence of structural breaks among the cryptocurrencies.

Although there are many literatures on the volatility of cryptocurrencies in separate forms, no study focuses on the volatility spillover, structural breaks and systematic risk analysis with special focus on Covid-19 pandemic all together considering daily closing prices of leading 15 cryptocurrencies. The above review motivates to develop the following hypotheses:

H_1: there is no presence of structural breaks in cryptocurrency market

H_2: the volatility in cryptocurrency market does not spillover

H_3: cryptocurrency X does not Granger cause cryptocurrency Y

H_4: the volatility behavior pattern in cryptocurrency market does not change

Research Methods

Data and Sources

This study uses the dollar dominated daily closing prices of 15 different cryptocurrencies namely Bitcoin, Zcash, Ethereum, Litecoin, Stellar, Monero, Dash, Nem, Tether, Eos, Binance, Cardano, Tron, Neo and Iota and volatility index (VIX) of CBOE-traded from 1 January, 2019 to 5 June, 2020. All the data have been collected from the website of yahoo finance. To avoid noises due to price fluctuations and trading activities, the procedure of Katsiampa (2017) has been followed by converting the closing prices of each cryptocurrency to logarithmic form. The stationarity of data, has been verified through Augmented Dickey Fuller (ADF) and Phillips-Perron (PP) unit root test models.

Estimation of Structural Breaks and Volatility Spillover

To know the price changing pattern of cryptocurrencies, this study assumes unknown break date for each cryptocurrency. It is assumed that each cryptocurrency is an equation of constant as below:

$$Cryto_t=\alpha_0+\varepsilon_t \qquad (1)$$

Where, Cryto is the log value of daily closing prices of each cryptocurrency, t is the date, α is the coefficient and ε is the residual term. Applying the Wald test on equation 1, the break date of each cryptocurrency is to be determined. To understand the price behavior in cryptocurrency market, it is essential to know the break date.

Granger-causality Test

It is assumed that variable ‘a’ can predict the behavior of variable ‘y’ if ‘a’ contains any such information of ‘y’ (Granger, 1969). There exist Granger causality between the variables if they are cointegrated and move in the same directions. This study applies Toda-Yamamoto (1995) approach to test the Granger causality between the cryptocurrencies. The lag length and maximal order (p+m) are required to know to create VAR models for the data as follows:

$$Y_t=a_o+\sum_{i=1}^{p+m} a_i Y_{t-i}+\sum_{i=1}^{p+m} b_i X_{t-i}+u_t \qquad (2)$$

$$X_t=c_o+\sum_{i=1}^{p+m} c_i X_{t-i}+\sum_{i=1}^{p+m} d_i Y_{t-i}+v_t \qquad (3)$$

To test the Granger causality using Wald test, the desired null hypothesis is, variable X does not Granger cause (≠>) variable Y:

$$H_0:\sum_{i=1}^{p} b_i=0; H_0:\sum_{i=1}^{p} b_i \neq 0$$

And Y does not Granger cause X:

$$H_0:\sum_{i=1}^{p} d_i=0; H_0:\sum_{i=1}^{p} d_i \neq 0$$

Rejection of null hypothesis indicates presence of Granger causality.

Generalized Autoregressive Conditional Heteroskedasticity (GARCH)

To examine the volatility of cryptocurrency market before and during Covid-19 pandemic period, the returns have been calculated as follows:

$$r_{t,m}=(\ln r_{t,m}-\ln r_{t,m-1})x100$$

Where, $r_{t,m}$ is the daily return of cryptocurrency and VIX on trading day t. The volatility of the cryptocurrency market has been measured following the procedure of Bollerslev (1986) and Engle (2002):

$$r_t=\alpha_t+\sum_{j=1}^{t}\sigma r_{t-j}+c_t+\sum_{j=1}^{t}\eta b_{t-j}+dj_t+\sum_{j=1}^{t}\gamma v_{t-j}+u_t \qquad (4)$$

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

Where, r_t is the returns of cryptocurrencies, c_t is the cryptocurrencies, and v_t is the VIX at time t. σ, η and γ refer to lagged returns of daily closing prices of cryptocurrency's daily volatility. The mean equation (Eq. 5) shows volatility impact on the cryptocurrency returns while variance equation (Eq. 6) shows long-term average volatility.

$$y_t=\mu_1+C_2\lambda_t+e \qquad (5)$$

Where, y_t is the first-difference of the closing price of cryptocurrency at time t, λ_t is volatility index at time t, μ is the mean constant, and e is the error term.

$$H_t=\omega_3+C_4\beta_{t-1}+C_5\alpha_{t-1}+e \qquad (6)$$

Where, H_t is the variance of the residual (error term) derived from Eq. (5), β_{t-1} is the previous day's residual variance, known as garch term, α_{t-1} is the previous period's squared residual derived from Eq. (5), known as Arch term, ω is the variance constant e is the error term. Since World Health Organization (WHO) officially announced Covid-19 as a pandemic on 11 March 2020[3], the period prior to that is taken as pre-Covid-19 (M1) and the period after the announcement is considered as during-Covid-19 (M2) period.

Empirical Findings

Table 1 shows the descriptive summary of sample data. The average value and standard deviation of Bitcoin are the highest whereas that of Tron has the lowest. Kurtosis values indicate that series are platykurtic and the skewness values show that series are symmetric around the mean.

Table 2 exhibits the correlation matrix between the variables. The pairwise correlation shows both positive and negative relations among the variables.

[3] WHO/Europe | Coronavirus disease (COVID-19) outbreak

Zcash, Ethereum and Litecoin have relatively strong correlations with other cryptocurrencies. The volatility has weak negative relations with all except Bitcoin.

Figure 1 shows the diagram of log of daily closing prices of 15 cryptocurrencies for the specified period. The figure shows that out of 15 cryptocurrencies, the prices of 12 fell on the same date.

Table 1. Summary Statistics

	Bitcoin	*Zcash*	*Ethereum*	*Litecoin*	*Stellar*	*Monero*	*Dash*	*Nem*	*Tether*	*EOS*	*Binance*	*Cardano*	*Tron*	*NEO*	*IOTA*	*VIX*
Mean	7649.57	53.15	183.12	63.93	0.08	65.23	92.65	0.05	1.00	3.74	19.10	0.05	0.02	10.12	0.27	15.92
SD	2373.49	19.06	48.41	25.51	0.03	16.16	31.85	0.02	0.01	1.33	7.37	0.02	0.01	2.49	0.08	4.05
Kurt	-0.87	1.02	-0.10	0.65	-0.75	-0.20	-0.06	0.34	12.37	0.72	-0.27	-0.21	-0.35	1.31	0.16	3.67
Skew	-0.35	1.03	0.68	1.09	0.52	0.64	0.77	1.11	1.37	1.13	0.45	0.90	0.62	1.01	0.50	1.56
Min	3359.99	24.94	103.13	29.95	0.03	33.01	39.87	0.03	0.97	1.85	5.57	0.02	0.01	5.38	0.11	9.15
Max	12936.45	114.08	334.21	141.63	0.14	117.42	178.69	0.10	1.05	8.51	38.82	0.10	0.04	19.49	0.51	37.32
Obs.	522	522	522	522	522	522	522	522	522	522	522	522	522	522	522	522

Source: The author.

Table 2. Correlation Matrix

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	Bitcoin	1.00															
2	Zcash	0.25	1.00														
3	Ethereum	0.76	0.71	1.00													
4	Litecoin	0.51	0.85	0.79	1.00												
5	Stellar	-0.20	0.78	0.36	0.60	1.00											
6	Monero	0.72	0.78	0.90	0.90	0.46	1.00										
7	Dash	0.31	0.93	0.74	0.89	0.74	0.83	1.00									
8	Nem	0.24	0.92	0.71	0.86	0.82	0.78	0.91	1.00								
9	Tether	-0.44	-0.13	-0.34	-0.28	0.19	-0.34	-0.21	-0.07	1.00							
10	EOS	0.28	0.86	0.70	0.92	0.75	0.81	0.94	0.88	-0.20	1.00						
11	Binance	0.71	0.70	0.85	0.93	0.41	0.93	0.78	0.73	-0.39	0.81	1.00					
12	Cardano	0.23	0.87	0.70	0.82	0.81	0.75	0.89	0.86	-0.16	0.89	0.71	1.00				
13	Tron	-0.06	0.87	0.45	0.71	0.90	0.56	0.80	0.86	0.05	0.80	0.50	0.79	1.00			
14	NEO	0.57	0.78	0.83	0.79	0.47	0.82	0.76	0.73	-0.26	0.75	0.76	0.75	0.62	1.00		
15	IOTA	0.07	0.84	0.54	0.76	0.88	0.63	0.83	0.87	0.08	0.84	0.57	0.80	0.91	0.61	1.00	
16	VIX	0.06	-0.12	-0.18	-0.07	-0.20	-0.01	-0.17	-0.14	-0.06	-0.16	-0.04	-0.24	-0.09	-0.17	-0.14	1.00

Source: The author.

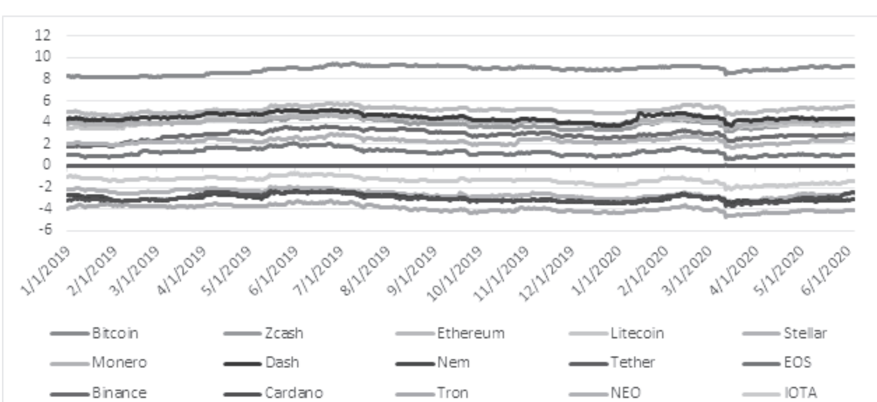


Figure 1. Log of Daily Closing Prices of 15 Cryptocurrencies
Source: The author.

To test the stationarity of the variables, both Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests have been applied. It is observed (Table 3) that all the variables are significantly stationary at level.

Table 3. Unit Root Test Results

	Augmented Dickey-Fuller		Phillips-Perron	
	T-stat	p value	T-stat	p value
Bitcoin	-26.5884	0.000	-26.4183	0.000
Zcash	-24.4916	0.000	-24.4423	0.000
Ethereum	-27.4536	0.000	-27.1127	0.000
Litecoin	-26.4009	0.000	-26.3842	0.000
Stellar	-22.4056	0.000	-22.4021	0.000
Monero	-25.8012	0.000	-25.6574	0.000
Dash	-20.5503	0.000	-20.5527	0.000
Nem	-25.3563	0.000	-25.2267	0.000
Tether	-22.7752	0.000	-22.7752	0.000
Eos	-28.1076	0.000	-27.7958	0.000
Binance	-24.7464	0.000	-24.6633	0.000
Cardano	-25.2408	0.000	-25.1114	0.000
Tron	-24.1288	0.000	-24.2034	0.000
Neo	-23.5335	0.000	-23.5227	0.000
Iota	-24.7195	0.000	-24.6941	0.000
VIX	-23.8778	0.000	-23.9586	0.000
Test critical values				
1% level	-3.4427		-3.4427	
5% level	-2.86688		-2.86688	
10% level	-2.56967		-2.56967	

Source: The author.

Table 4 shows the results of structural break tests for 15 cryptocurrencies. The coefficient of test statistics indicates unstable nature of prices over the period. Figure 2 clearly indicates that the cryptocurrencies have breaks in their price series and most of the breaks occur on the same date. Presence of systematic structural break in any asset, limits the possibility of risk diversification. Therefore, the first hypothesis cannot be rejected.

Table 4. Structural Break Test

Coin	Test Stat	Break date	Critical value			p-value
			1%	5%	10%	
Bitcoin	30.7703	3/12/2020	4.949133	4.443649	4.193627	0.01
Zcash	27.19269	3/12/2020	4.949133	4.443649	4.193627	0.01
Ethereum	31.8616	3/12/2020	4.949133	4.443649	4.193627	0.01
Litecoin	29.12275	3/12/2020	4.949133	4.443649	4.193627	0.01
Stellar	24.0752	3/12/2020	4.949133	4.443649	4.193627	0.01
Monero	29.4896	3/12/2020	4.949133	4.443649	4.193627	0.01

(Table 4 Continued)

(Table 4 Continued)

Dash	22.61693	1/15/2020	4.949133	4.443649	4.193627	0.01
Nem	26.86593	5/16/2019	4.949133	4.443649	4.193627	0.01
Tether	43.22562	5/15/2019	4.949133	4.443649	4.193627	0.01
Eos	31.2005	3/12/2020	4.949133	4.443649	4.193627	0.01
Binance	28.4806	3/12/2020	4.949133	4.443649	4.193627	0.01
Cardano	27.94773	3/12/2020	4.949133	4.443649	4.193627	0.01
Tron	26.44035	3/12/2020	4.949133	4.443649	4.193627	0.01
Neo	25.94118	3/12/2020	4.949133	4.443649	4.193627	0.01
Iota	26.77105	3/12/2020	4.949133	4.443649	4.193627	0.01

Source: The author.

It is observed that except Dash, Nem and Tether which break on 15 January 2020, 16 May 2019 and 15 May 2019 respectively, other 12 cryptocurrencies break on the same date on 12 March 2020. The presence of structural breaks in cryptocurrencies indicates that there is a possibility of huge forecasting errors and models may be unreliable thus the market remains volatile (Antoch, Hanousek, Horváth, Hušková & Wang, 2019).

The results of these models and that of previous structural breaks are in same direction and clearly indicate that the cryptocurrency market is exposed to the systematic bubble risks. Since cryptocurrency market is not monitored by any such central bank, it is free from any sort of measures. Investors may enjoy potential hedge benefits as this market is volatile and free from measures of any central monitoring body. Su, Li, Tao and Si (2017) recommend to use Bitcoin as an important option for hedging against market-centric risk, while this study recommends to add other cryptocurrencies such as Litecoin, Eos, Tron, Binance, Ethereum, Monero, Cardeno and Iota along with Bitcoin in that chart.

To test the Granger causality between the variables, appropriate lag selection is required as all VAR models contain constant. Table 5 shows lag order selection criterion based on the AIC, SC and HQ. Though, SC and HQ recommend 0 lag, this study applies 2 lags as it is recommended by AIC.

Table 5. Lag Selection Criterion

Lag	AIC	SC	HQ
0	-84.1055	-83.97328*	-84.05369*
1	-84.34608*	-82.0978	-83.4648
2	-84.1403	-79.7761	-82.4297
3	-83.8223	-77.342	-81.2822
4	-83.468	-74.8717	-80.0985
5	-83.0255	-72.3132	-78.8266
6	-82.6725	-69.8442	-77.6442

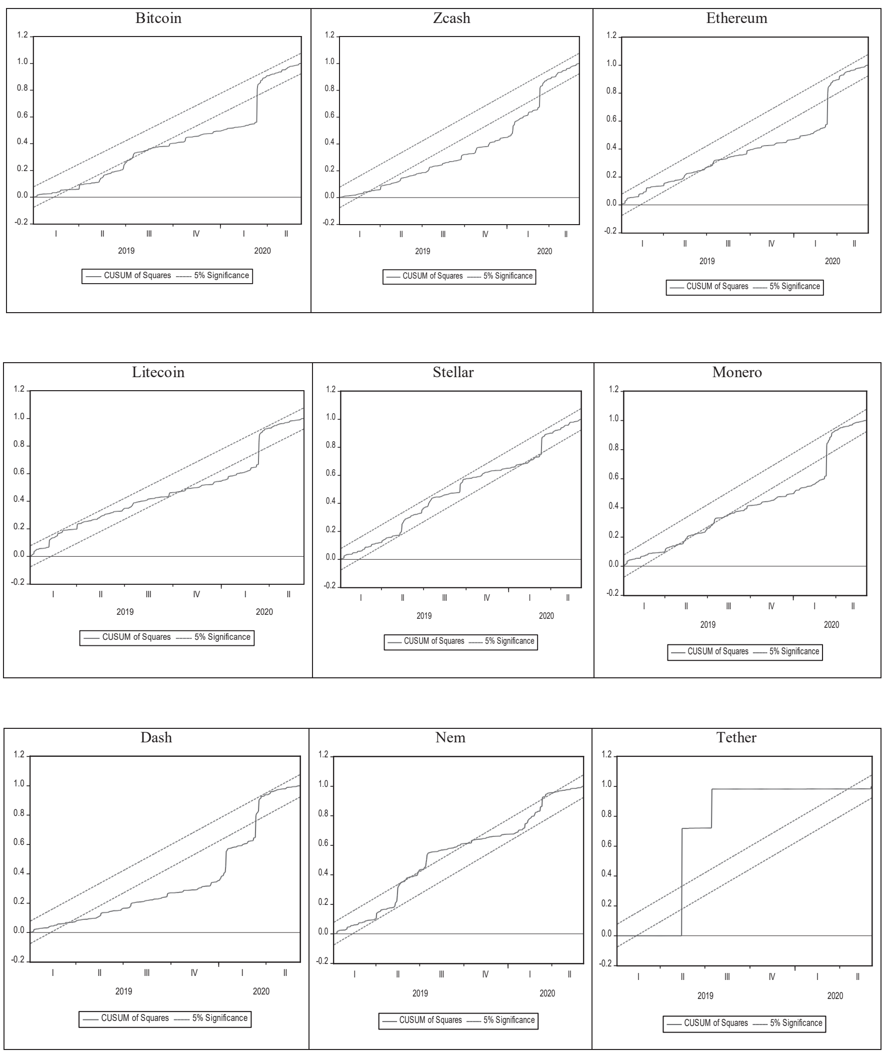
(Table 5 Continued)

(Table 5 Continued)

7	-82.2574	-67.3131	-76.3997
8	-81.9279	-64.8676	-75.2408

* indicates lag order selected by the criterion, AIC: Akaike information criterion, SC: Schwarz information criterion and HQ: Hannan-Quinn information criterion.

Source: The author.



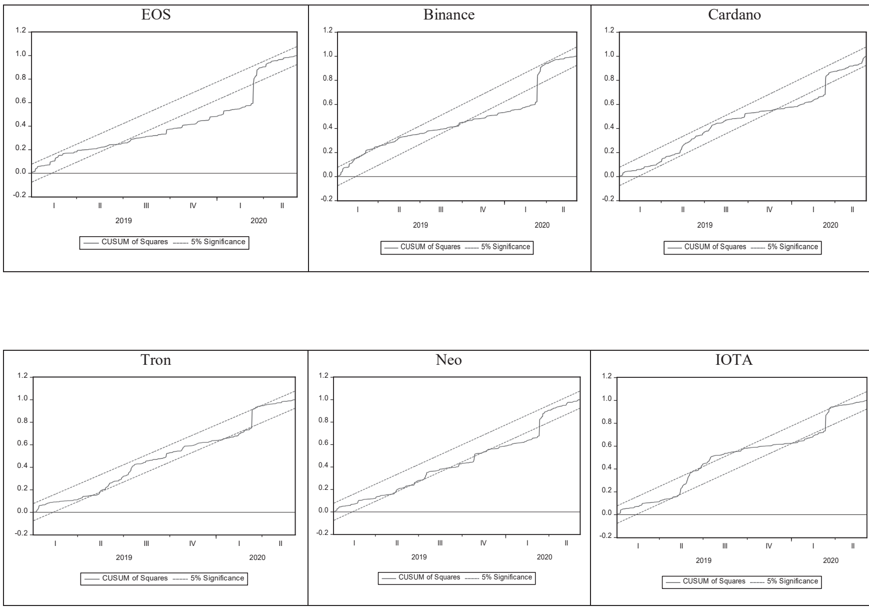
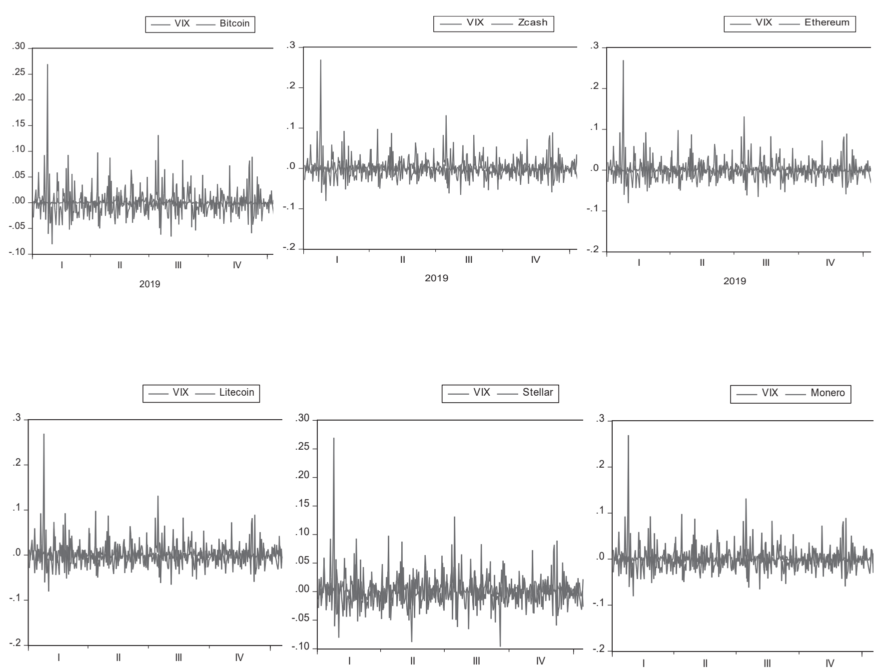


Figure 2. Group of Structural Break Tests
Source: The author.



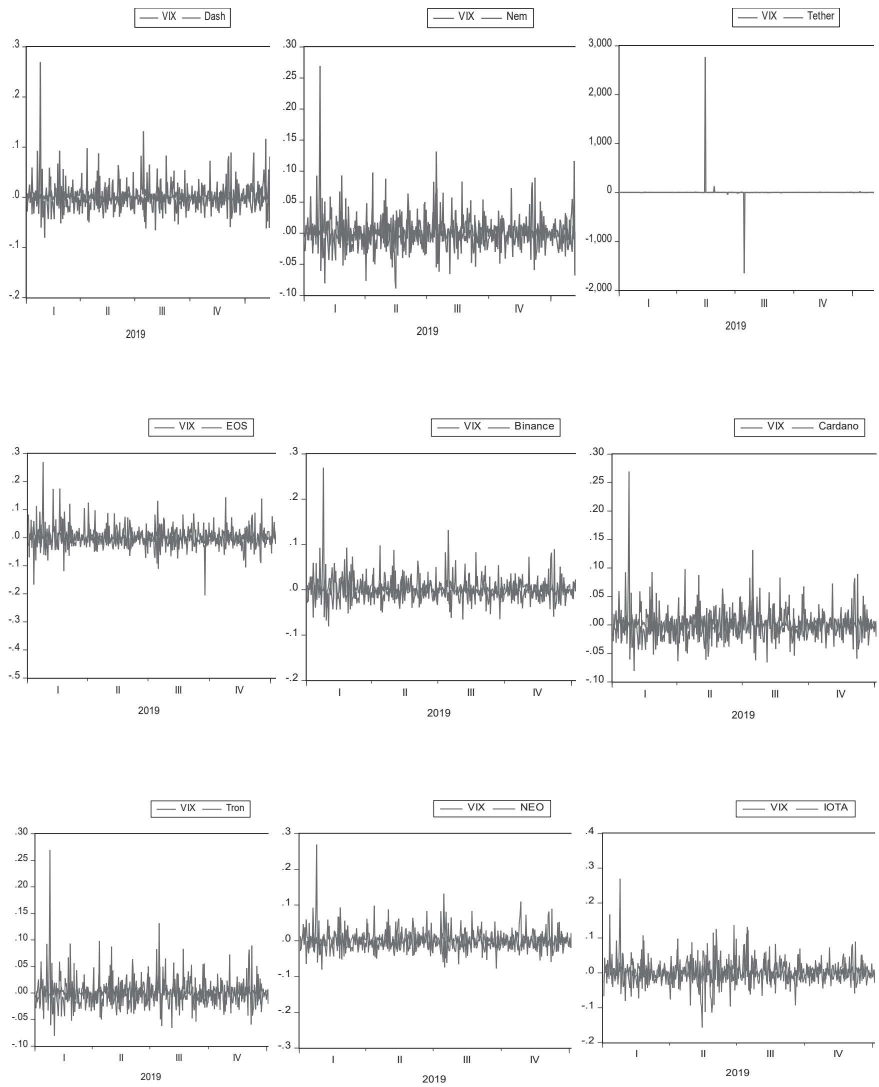


Figure 3. Dynamic Correlation between Selected Cryptocurrencies and the VIX

Source: The author.

Figure 3 shows the sign of having dynamic correlations between VIX and the 15 cryptocurrencies from January 2019 to June 2020. Throughout the period, several times the correlations have gone up and come down. Significant variations are noticed at the beginning of 2019 and the first quarter of 2020 which give signals of higher correlations between implied volatility and the returns of corresponding cryptocurrencies thus leading to the possibility of return spillover. Therefore, the second hypothesis cannot be accepted.

Table 6. Results of Granger-Causality Tests

Null hypothesis	F-stat	P-value	Decision	Null hypothesis	F-stat	P-value	Decision
zcash ≠>bitcoin	5.797	0.003	Rejected	nem ≠>stellar	2.065	0.128	Accepted
bitcoin ≠>zcash	0.931	0.395	Accepted	stellar ≠>nem	3.426	0.033	Rejected
ethereum ≠>bitcoin	0.206	0.814	Accepted	tether ≠>stellar	2.787	0.063	Accepted
bitcoin ≠>ethereum	2.264	0.105	Accepted	stellar ≠>tether	7.968	0.000	Rejected
litecoin ≠>bitcoin	0.137	0.872	Accepted	eos ≠>stellar	7.907	0.000	Rejected
bitcoin ≠>litecoin	5.074	0.007	Rejected	stellar ≠>eos	1.829	0.162	Accepted
stellar ≠>bitcoin	0.452	0.637	Accepted	binance ≠>stellar	3.848	0.022	Rejected
bitcoin ≠>stellar	11.947	0.000	Rejected	stellar ≠>binance	0.716	0.489	Accepted
monero ≠>bitcoin	1.019	0.362	Accepted	cardano ≠>stellar	2.032	0.132	Accepted
bitcoin ≠>monero	2.106	0.123	Accepted	stellar ≠>cardano	0.814	0.444	Accepted
dash ≠>bitcoin	2.266	0.105	Accepted	tron ≠>stellar	1.882	0.153	Accepted
bitcoin ≠>dash	9.822	0.000	Rejected	stellar ≠>tron	1.474	0.230	Accepted
nem ≠>bitcoin	0.837	0.434	Accepted	neo ≠>stellar	1.106	0.332	Accepted
bitcoin ≠>nem	2.032	0.132	Accepted	stellar ≠>neo	0.125	0.882	Accepted
tether ≠>bitcoin	1.332	0.265	Accepted	iota ≠>stellar	0.602	0.548	Accepted
bitcoin ≠>tether	5.164	0.006	Rejected	stellar ≠>iota	0.843	0.431	Accepted
eos ≠>bitcoin	0.606	0.546	Accepted	dash ≠>monero	3.066	0.048	Rejected
bitcoin ≠>eos	0.860	0.424	Accepted	monero ≠>dash	3.824	0.023	Rejected
binance ≠>bitcoin	0.145	0.865	Accepted	nem ≠>monero	1.895	0.151	Accepted
bitcoin ≠>binance	4.471	0.012	Rejected	monero ≠>nem	0.984	0.374	Accepted
cardano ≠>bitcoin	0.079	0.924	Accepted	tether ≠>monero	1.076	0.342	Accepted
bitcoin ≠>cardano	1.884	0.153	Accepted	monero ≠>tether	2.877	0.057	Accepted
tron ≠>bitcoin	1.496	0.225	Accepted	eos ≠>monero	1.945	0.144	Accepted
bitcoin ≠>tron	7.596	0.001	Rejected	monero ≠>eos	0.365	0.695	Accepted
neo ≠>bitcoin	1.688	0.186	Accepted	binance ≠>monero	0.306	0.736	Accepted
bitcoin ≠>neo	4.033	0.018	Rejected	monero ≠>binance	2.690	0.069	Accepted
iota ≠>bitcoin	0.957	0.385	Accepted	cardano ≠>monero	0.693	0.501	Accepted
bitcoin ≠>iota	0.825	0.439	Accepted	monero ≠>cardano	0.601	0.549	Accepted
ethereum ≠>zcash	0.421	0.657	Accepted	tron ≠>monero	2.858	0.058	Accepted
zcash ≠>ethereum	7.366	0.001	Rejected	monero ≠>tron	5.344	0.005	Rejected
litecoin ≠>zcash	0.334	0.716	Accepted	neo ≠>monero	0.686	0.504	Accepted
zcash ≠>litecoin	1.578	0.207	Accepted	monero ≠>neo	1.892	0.152	Accepted
stellar ≠>zcash	0.090	0.914	Accepted	iota ≠>monero	0.678	0.508	Accepted
zcash ≠>stellar	2.679	0.070	Accepted	monero ≠>iota	0.027	0.974	Accepted
monero ≠>zcash	0.457	0.633	Accepted	nem ≠>dash	3.708	0.025	Rejected
zcash ≠>monero	6.287	0.002	Rejected	dash ≠>nem	1.954	0.143	Accepted
dash ≠>zcash	2.751	0.065	Accepted	tether ≠>dash	1.409	0.245	Accepted
zcash ≠>dash	11.262	0.000	Rejected	dash ≠>tether	2.508	0.082	Accepted
nem ≠>zcash	1.099	0.334	Accepted	eos ≠>dash	4.359	0.013	Rejected
zcash ≠>nem	6.281	0.002	Rejected	dash ≠>eos	7.914	0.000	Rejected
tether ≠>zcash	0.124	0.884	Accepted	binance ≠>dash	1.421	0.242	Accepted
zcash ≠>tether	3.070	0.047	Rejected	dash ≠>binance	1.128	0.324	Accepted
eos ≠>zcash	0.770	0.463	Accepted	cardano ≠>dash	2.259	0.106	Accepted
zcash ≠>eos	7.616	0.001	Rejected	dash ≠>cardano	0.715	0.490	Accepted
binance ≠>zcash	0.236	0.790	Accepted	tron ≠>dash	0.803	0.449	Accepted
zcash ≠>binance	2.137	0.119	Accepted	dash ≠>tron	0.561	0.571	Accepted
cardano ≠>zcash	0.105	0.900	Accepted	neo ≠>dash	1.171	0.311	Accepted

(Table 6 Continued)

(Table 6 Continued)

zcash $\nRightarrow$ cardano	4.023	0.019	Rejected	dash $\nRightarrow$ neo	1.453	0.235	Accepted
tron $\nRightarrow$ zcash	0.537	0.585	Accepted	iota $\nRightarrow$ dash	0.355	0.701	Accepted
zcash $\nRightarrow$ tron	4.219	0.015	Rejected	dash $\nRightarrow$ iota	3.564	0.029	Rejected
neo $\nRightarrow$ zcash	0.307	0.736	Accepted	tether $\nRightarrow$ nem	27.810	0.000	Rejected
zcash $\nRightarrow$ neo	5.456	0.005	Rejected	nem $\nRightarrow$ tether	10.664	0.000	Rejected
iota $\nRightarrow$ zcash	1.017	0.362	Accepted	eos $\nRightarrow$ nem	1.182	0.308	Accepted
zcash $\nRightarrow$ iota	5.628	0.004	Rejected	nem $\nRightarrow$ eos	1.009	0.365	Accepted
litecoin $\nRightarrow$ ethereum	0.042	0.959	Accepted	binance $\nRightarrow$ nem	0.272	0.762	Accepted
ethereum $\nRightarrow$ litecoin	4.419	0.013	Rejected	nem $\nRightarrow$ binance	1.258	0.285	Accepted
stellar $\nRightarrow$ ethereum	3.442	0.033	Rejected	cardano $\nRightarrow$ nem	1.381	0.252	Accepted
ethereum $\nRightarrow$ stellar	8.173	0.000	Rejected	nem $\nRightarrow$ cardano	0.383	0.682	Accepted
monero $\nRightarrow$ ethereum	0.413	0.662	Accepted	tron $\nRightarrow$ nem	1.129	0.324	Accepted
ethereum $\nRightarrow$ monero	0.637	0.529	Accepted	nem $\nRightarrow$ tron	2.142	0.119	Accepted
dash $\nRightarrow$ ethereum	2.321	0.099	Accepted	neo $\nRightarrow$ nem	0.480	0.619	Accepted
ethereum $\nRightarrow$ dash	5.622	0.004	Rejected	nem $\nRightarrow$ neo	0.847	0.429	Accepted
nem $\nRightarrow$ ethereum	0.518	0.596	Accepted	iota $\nRightarrow$ nem	3.340	0.036	Rejected
ethereum $\nRightarrow$ nem	0.575	0.563	Accepted	nem $\nRightarrow$ iota	1.571	0.209	Accepted
tether $\nRightarrow$ ethereum	3.868	0.022	Rejected	eos $\nRightarrow$ tether	2.125	0.121	Accepted
ethereum $\nRightarrow$ tether	6.675	0.001	Rejected	tether $\nRightarrow$ eos	1.036	0.356	Accepted
eos $\nRightarrow$ ethereum	2.477	0.085	Accepted	binance $\nRightarrow$ tether	2.202	0.112	Accepted
ethereum $\nRightarrow$ eos	0.313	0.731	Accepted	tether $\nRightarrow$ binance	0.688	0.503	Accepted
binance $\nRightarrow$ ethereum	0.465	0.629	Accepted	cardano $\nRightarrow$ tether	10.064	0.000	Rejected
ethereum $\nRightarrow$ binance	2.379	0.094	Accepted	tether $\nRightarrow$ cardano	1.572	0.209	Accepted
cardano $\nRightarrow$ ethereum	0.338	0.713	Accepted	tron $\nRightarrow$ tether	5.759	0.003	Rejected
ethereum $\nRightarrow$ cardano	1.270	0.282	Accepted	tether $\nRightarrow$ tron	1.478	0.229	Accepted
tron $\nRightarrow$ ethereum	2.851	0.059	Accepted	neo $\nRightarrow$ tether	6.537	0.002	Rejected
ethereum $\nRightarrow$ tron	8.273	0.000	Rejected	tether $\nRightarrow$ neo	1.194	0.304	Accepted
neo $\nRightarrow$ ethereum	0.447	0.640	Accepted	iota $\nRightarrow$ tether	12.052	0.000	Rejected
ethereum $\nRightarrow$ neo	2.991	0.051	Accepted	tether $\nRightarrow$ iota	1.610	0.201	Accepted
iota $\nRightarrow$ ethereum	1.146	0.319	Accepted	binance $\nRightarrow$ eos	0.446	0.641	Accepted
ethereum $\nRightarrow$ iota	0.134	0.875	Accepted	eos $\nRightarrow$ binance	4.698	0.010	Rejected
stellar $\nRightarrow$ litecoin	1.430	0.240	Accepted	cardano $\nRightarrow$ eos	0.775	0.461	Accepted
litecoin $\nRightarrow$ stellar	3.612	0.028	Rejected	eos $\nRightarrow$ cardano	3.379	0.035	Rejected
monero $\nRightarrow$ litecoin	0.992	0.371	Accepted	tron $\nRightarrow$ eos	3.373	0.035	Rejected
litecoin $\nRightarrow$ monero	0.235	0.791	Accepted	eos $\nRightarrow$ tron	10.184	0.000	Rejected
dash $\nRightarrow$ litecoin	0.497	0.609	Accepted	neo $\nRightarrow$ eos	2.563	0.078	Accepted
litecoin $\nRightarrow$ dash	2.962	0.053	Accepted	eos $\nRightarrow$ neo	7.789	0.001	Rejected
nem $\nRightarrow$ litecoin	1.066	0.345	Accepted	iota $\nRightarrow$ eos	1.060	0.347	Accepted
litecoin $\nRightarrow$ nem	0.187	0.830	Accepted	eos $\nRightarrow$ iota	0.334	0.716	Accepted
tether $\nRightarrow$ litecoin	1.871	0.155	Accepted	cardano $\nRightarrow$ binance	1.487	0.227	Accepted
litecoin $\nRightarrow$ tether	1.721	0.180	Accepted	binance $\nRightarrow$ cardano	1.146	0.319	Accepted
eos $\nRightarrow$ litecoin	6.879	0.001	Rejected	tron $\nRightarrow$ binance	0.161	0.851	Accepted
litecoin $\nRightarrow$ eos	1.255	0.286	Accepted	binance $\nRightarrow$ tron	4.843	0.008	Rejected
binance $\nRightarrow$ litecoin	1.444	0.237	Accepted	neo $\nRightarrow$ binance	0.854	0.426	Accepted
litecoin $\nRightarrow$ binance	1.981	0.139	Accepted	binance $\nRightarrow$ neo	2.145	0.118	Accepted
cardano $\nRightarrow$ litecoin	1.327	0.266	Accepted	iota $\nRightarrow$ binance	0.664	0.515	Accepted
litecoin $\nRightarrow$ cardano	0.873	0.418	Accepted	binance $\nRightarrow$ iota	0.775	0.461	Accepted
tron $\nRightarrow$ litecoin	2.123	0.121	Accepted	tron $\nRightarrow$ cardano	1.436	0.239	Accepted
litecoin $\nRightarrow$ tron	8.241	0.000	Rejected	cardano $\nRightarrow$ tron	4.424	0.012	Rejected

(Table 6 Continued)

(Table 6 Continued)

neo ≠>litecoin	3.244	0.040	Rejected	neo ≠>cardano	0.119	0.888	Accepted
litecoin ≠>neo	3.225	0.041	Rejected	cardano ≠>neo	2.028	0.133	Accepted
iota ≠>litecoin	0.552	0.576	Accepted	iota ≠>cardano	0.270	0.763	Accepted
litecoin ≠>iota	0.108	0.898	Accepted	cardano ≠>iota	0.115	0.891	Accepted
monero ≠>stellar	4.247	0.015	Rejected	neo ≠>tron	2.501	0.083	Accepted
stellar ≠>monero	0.741	0.477	Accepted	tron ≠>neo	0.113	0.894	Accepted
dash ≠>stellar	0.824	0.439	Accepted	iota ≠>tron	0.690	0.502	Accepted
stellar ≠>dash	0.864	0.422	Accepted	tron ≠>iota	3.108	0.046	Rejected
				iota ≠>neo	0.007	0.993	Accepted
				neo ≠>iota	0.136	0.873	Accepted

Source: The author.

The results of Granger causality in Table 6 shows that most of the cryptocurrencies does not Granger cause each other. When, Bitcoin Granger causes Zcash, the Litecoin, Steller, Dash, Tether, Binance, and Tron move in uni-directional way; when Zcash Granger causes Ethereum, the Dash, Nem, Eos, Cardano, Neo, and Iota move in uni-directional way. On the other hand, although Ethereum Granger causes the Steller, Dash, Tether, and Tron, Litecoin Granger causes the Steller, Eos in uni-directional way. The bi-directional relation is observed between Litecoin and Neo, Dash and Monero, Eos and Dash, and finally between Tron and Eos. The absence of predictability and unidirectional links among the cryptocurrencies indicate that crypto-traders can gain by studying portfolio implications (Platanakis & Urquhart, 2019) and mastering the investment techniques (Faria & Venora, 2018). Bouri and Roubaud (2019) observed the similar results for Bitcoin which strategically governs the interconnections among the smaller cryptocurrencies in the long-run. So, the third hypothesis cannot be rejected. The positive volatility changes between VIX and cryptocurrencies are further observed in Table 7. The table shows two scenarios namely before announcement of Covid-19 as pandemic (M1) and during pandemic (M2) side by side. It is observed that during pandemic period, with respects to the VIX, significant elevations in volatility is noticed for Nem, Neo, Monero, Tether, Cordano and the Iota. The positive and significant impact of arch and garch on returns of cryptocurrencies throughout the period implies that the information and volatility of previous day are repeated in the returns and volatility on the following day. This trend of cryptocurrency market authenticates that there is volatility transition over the period. As the volatility exists in the cryptocurrency market, investors may ensure significant benefits by including cryptocurrencies in their portfolios and can diversify the overall risk. Therefore, the fourth hypothesis is accepted. While most of the previous studies observed lack of correlations between VIX and cryptocurrencies, Akyildirim, Corbet, Lucey, Sensoy and Yarovaya (2019) observed presence of correlation between VIX and cryptocurrencies using 30 minutes data.

Table 7. GARCH (1,1) Estimation Results

	Bitcoin		Litecoin		*Dash*		*Eos*		*Tron*	
	M1	M2	M1	M2	M1	M2	M1	M2	M1	M2
	Mean Equation									
μ	0.000 (0.000)	0.000 (0.001)	0.000 (0.001)	0.002 (0.002)	0.000 (0.000)	0.001 (0.001)	-0.001*** (0.000)	0.002 (0.011)	0.000 (0.001)	0.000 (0.005)
λ	0.005 (0.007)	-0.020 (0.054)	0.010 (0.021)	0.052 (0.094)	-0.002 (0.013)	-0.019 (0.090)	0.034 (0.061)	0.104 (0.513)	-0.009 (0.021)	-0.012 (0.237)
	Variance Equation									
ω	0.000*** (0.000)	0.000 (0.000)	0.000*** (0.000)	0.000 (0.000)	0.000*** (0.000)	0.000 (0.000)	0.003*** (0.000)	0.001 (0.001)	0.000*** (0.000)	0.000 (0.000)
α	0.132*** (0.037)	0.021 (0.041)	0.146*** (0.042)	0.386*** (0.196)	0.235*** (0.064)	0.525*** (0.204)	-0.033*** (0.005)	0.080 (0.105)	0.137*** (0.044)	0.150 (0.301)
β	0.580*** (0.124)	0.628 (0.700)	0.514*** (0.115)	0.700*** (0.145)	0.584*** (0.116)	0.675*** (0.097)	-0.912*** (0.021)	0.744*** (0.213)	0.721*** (0.084)	0.600 (0.507)
	Zcash		*Stellar*		*Nem*		*Binance*		*Neo*	
	M1	M2	M1	M2	M1	M2	M1	M2	M1	M2
	Mean Equation									
μ	0.000 (0.000)	0.002 (0.001)	0.001 (0.001)	-0.002 (0.003)	0.001 (0.001)	0.000 (0.001)	0.001 (0.001)	0.000 (0.009)	0.000 (0.001)	0.006*** (0.003)
λ	0.016 (0.017)	-0.039 (0.065)	-0.011 (0.024)	-0.075 (0.139)	-0.013 (0.017)	-0.049*** (0.011)	0.010 (0.027)	-0.006 (0.423)	0.041 (0.037)	-0.199 (0.130)
	Variance Equation									
ω	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000 (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000 (0.001)	0.000*** (0.000)	0.000 (0.000)
α	0.295*** (0.063)	0.948*** (0.199)	0.219*** (0.067)	0.051 (0.123)	0.292*** (0.048)	-0.060*** (0.011)	0.163*** (0.042)	0.150 (0.309)	0.185*** (0.048)	1.058*** (0.262)
β	0.451*** (0.078)	-0.014*** (0.053)	0.637*** (0.091)	0.704 (0.523)	0.627*** (0.039)	1.113*** (0.019)	0.693*** (0.051)	0.600 (0.469)	0.488*** (0.113)	0.400*** (0.081)
	Ethereum		*Monero*		*Tether*		*Cardano*		*Iota*	
	M1	M2	M1	M2	M1	M2	M1	M2	M1	M2
	Mean Equation									
μ	0.000 (0.000)	0.003 (0.002)	0.000 (0.000)	0.003*** (0.001)	-3.857 (82.738)	-3.406*** (0.315)	0.000 (0.001)	-0.006*** (0.003)	0.002 (0.002)	-0.007*** (0.004)
λ	0.006 (0.015)	0.052 (0.085)	0.021 (0.016)	0.010 (0.068)	-236.138 (910.726)	-232.761*** (28.101)	-0.008 (0.025)	-0.046 (0.146)	0.021 (0.049)	-0.116 (0.190)
	Variance Equation									
ω	0.000 (0.000)	0.000 (0.000)	0.000*** (0.000)	0.000 (0.000)	11720.30 (11975.45)	6.279 (7.354)	0.000*** (0.000)	0.000 (0.000)	0.000*** (0.000)	0.000 (0.000)
α	0.046 (0.035)	0.342*** (0.184)	0.124*** (0.045)	0.461*** (0.206)	-0.003*** (0.002)	14.092*** (3.297)	0.148*** (0.042)	0.380*** (0.221)	0.121*** (0.028)	0.515*** (0.249)
β	0.626*** (0.276)	0.715*** (0.162)	0.635*** (0.129)	0.747*** (0.108)	0.561 (0.445)	0.003 (0.008)	0.717*** (0.076)	0.661*** (0.198)	0.832*** (0.033)	0.723*** (0.107)

Note: μ-constant, λ-VIX, ω-constant, α-ARCH effect, β-GARCH effect. *, ** and *** denote the significance level at 10%, 5% and 1%. Standard errors are in parentheses. M1-before-covid and M2-during-covid scenario.

Source: The author.

Policy Implications

As volatility measures the degree of risk associated with investment, knowing the level of volatility is very important be it low volatile items like gold, bonds and commodities or highly volatile items like stocks and cryptocurrencies. There are a few reasons behind the categorization of cryptocurrency market as a volatile market. First, the market size is very small and the cryptocurrency mechanism is even not clear to many people. Second, this market is not regulated by any organized body like central bank or government of a country. The absence of authority to regulate the price movement is responsible for significant price movement which is ultimately dictated by the so-called faith of investors on currencies. Third, the investors do not require any legal documents like trade license, tax-payers identification number, and passport to engage themselves in currency trading process like stock market, money market or real estate. Forth, due to frequent price fluctuations, people do not want to consider cryptocurrency as one of the secured investment options. The speculative nature of this market discourages the long-term investors out of this market.

To handle the volatility in cryptocurrency market, investors should take long position ignoring day trading. To enhance the liquidity and salability of the asset, more investors should join the market with necessary knowledge on the same. Organized exchanges should include cryptocurrencies on their trading list like Chicago Mercantile Exchange and The Chicago Board Options Exchange to enhance its acceptability and credibility. Governments of different countries may allow transactions through cryptocurrencies like USA, Canada, Australia, Finland, Belgium, Germany to eliminate paper-currency based frauds. Formation of a verified exchange traded fund for the crypto may encourage people to invest in this highly potential option. However, based on above analysis, this study suggests that the expansion of cryptocurrency market may offer an important viable financial asset option to the investors along with the traditional products like stocks, bonds, commodities, and traditional currencies.

Conclusion

Being a relatively new asset, cryptocurrencies encounter high volatility and are not correlated to other conventional assets like shares, bonds, and gold. To understand the nature of volatility of cryptocurrency market, before the announcement of Covid-19 and during the pandemic period, four specific objectives have been justified. This study has observed the presence structural breaks in all the 15 cryptocurrencies which make the market unpredictable. There is a positive dynamic correlation among the cryptocurrencies which ensures the possibility of return spillover among the currencies. There exists both uni and bi-directional relationship among the cryptocurrencies. Analyzing the nature of volatility in the crypto-market, it is recommended to include cryptocurrencies as one of the important investment components along with traditional stocks, bonds, precious metals, commodities, and paper currencies in the portfolio to stimulate the returns at the same time to reduce the overall portfolio risks. This paper considered only 15 cryptocurrencies ranging data from January 2019 to June 2020. Since at present we are passing through the second wave of the Covid-19 pandemic, potential researchers may analyze the impact of the Covid-19 on the volatility in cryptocurrency market considering death cases, confirm cases and other Covid-19 variables covering the whole Covid-19 pandemic period.

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