Evaluating the Return Volatility of Cryptocurrency Market: An Econometrics Modelling Method

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Abstract: Cryptocurrency is the blockchain financial technology used for transactions in financial institutions and exchanges. Bitcoin has attracted much coverage from investors and commentators as it represents the maximum market capitalization on a crypto-currency exchange. The study aims to determine the correlation between the daily log–returns and to understand the tendencies in the cryptocurrency market instability of Bitcoin, Litecoin, XRP, Nxt, Dogecoin, Vertcoin, DigiByte, DASH, Counterparty, and MonaCoin. The correlation among the selected cryptocurrencies exists in the study. The analysis is focused primarily upon reference information from the preserved servers of cryptocurrency websites and finance.yahoo.com. This research assesses regular details on the Logarithmic return of Bitcoin, Litecoin, XRP, Nxt, Dogecoin, Vertcoin, DigiByte, DASH, Counterparty, and MonaCoin for a timeframe spanning from October 01st, 2014, to April 30th, 2020. From 131 cryptocurrencies, we considered only 10 Cryptocurrencies due to the availability of data after October 2014. Where there was insufficient information, there were average results determined from preceding and succeeding data. Findings demonstrate that there is GARCH modelling of cryptocurrencies against Bitcoin. Litecoin, XRP, Nxt, Dogecoin, Vertcoin, DigiByte, DASH, Counterparty, and MonaCoin; variability values throughout the duration had a significant effect on the updates from Bitcoin returns. We believe that it helps create information and resources that are valuable to practitioners and scholars who research and form cryptocurrency markets in the future.

Keywords: Blockchain; Bitcoin; Counterparty; Cryptocurrency; Dash; DigiByte; Dogecoin; Litecoin; MonaCoin; Vertcoin; XRP

1 Introduction

Financial Technology (FinTech) is the blending together of economics, engineering, marketing as well as strategic business planning in an integrated form. Moreover, FinTech innovations also build upon emerging technologies or indeed unique businesses [1]. Over the past ten years, FinTech has observed the remarkable expansion of cryptocurrencies. One of the latest technology phenomena is cryptocurrencies [2]. A cryptocurrency is a digital resource that can be used for trading in which coin possession documents are held in the public ledger or computerized archive, use solid encryption to protect transaction record entries, and allows for the digital monitoring of the establishment and transition of coin possession [3] [4] which constituents the framework of digital transactions. Their underlying technologies offer solutions in various kinds of business processes. The regulations of extended distribution chains based on and vulnerable to fraud are considered from the management of supply chains to the protection of said supply chains. Bitcoin was the first designed decentralized cryptocurrency based on blockchain technology [5]. Then, it was developed further based on different financial dimensions [6] [7].

Cryptocurrency is named 'digital gold' [8]. As Bitcoin establishes the largest cryptocurrency sector capitalization, it has received great attention from investors and analysts [9]. Subsequently, several cryptocurrencies developed, such as: Litecoin, XRP, Nxt, Dogecoin, Vertcoin, DigiByte, Dash, Counterparty, MonaCoin, FairCoin, MaidSafeCoin, Monero, NavCoin, Bytecoin, BitShares, I/O Coin, Stellar, Syscoin, GameCredits, Ubiq, Verge, Blocknet, Nexus, Tether, NEM, Ethereum, Siacoin, Factom, Augur, Decred, PIVX, Lisk, DigixDAO, Steem, Waves, Ardor, Ethereum Classic, Stratis, Neo, NoLimitCoin, SingularDTV, Zcoin, Zcash, Lykke, Golem, Obyt, Wings, Komodo, FirstCoin, Melon, Nano, Ark, TaaS, Edgeless, iExec RLC, Gnosis, Aragon, Qtum, Basic Attention Token, Horizen, Aeternity, Metaverse ETP, Veritaseum, Quantum Resistant Ledger, MobileGo, IOTA, SONM, Bancor, FunFair, TenX, Status, EOS.IO, AdEx, Storj, MCO, Gas, Metal, Populous, OmiseGO, Civic, Ethos, Particl, Bitcoin Cash, Binance Coin, district0x, Dentacoin, 0x, HyperCash, VeChain, Waltonchain, Loopring, Neblio, TRON, ATBCoin, Chainlink, Kyber Network, Substratum, Kin, SALT, Cardano, Bitcoin Gold, Exchange Union, ICON, QASH (QASH-USD), etc [10].

The need for this study is to create information and resources that are valuable to practitioners and scholars who research and form the cryptocurrency market. The importance of the study also focused on the policy maker of the cryptocurrency market. The objectives of the study are to find the correlation between the daily log-returns of Bitcoin, Litecoin, XRP, Nxt, Dogecoin, Vertcoin, DigiByte, DASH, Counterparty, and MonaCoin, as well as to understand the tendencies in cryptocurrency market instability. Cryptocurrencies are electronic financial instruments that the encrypted blockchain infrastructure ensures ownership and exchanges of ownership. The increase of the market value of cryptocurrencies and associated increasing worldwide attractiveness opens up an amount of business and industrial economic challenges and concerns [11]. These analytical aspects explore the key developments in a scientific study concerning cryptocurrencies and discuss the offerings of the chosen mechanisms to literature in neoclassical and behavioral theories. Socio-economic, corruption, and environmental issues are of special significance. There are arguments to support the control of the economy [12] [13]. Cryptocurrencies may serve certain valuable roles and bring economic benefits and, although this may counter the original libertarian argument behind cryptocurrencies, it is a move towards enhancing social security. Cryptocurrencies are electronic financial instruments that ensure ownership and sharing of ownership through the cryptographic blockchain network. Growth in the market valuation of cryptocurrency and rising global influence poses a range of threats and problems for enterprises and industries. The analysis explores major developments in cryptocurrency scientific studies and examines both neoclassical and behavioral theories' contribution to literature in the context of financial management [14] [15] [16] [17] [18] [19].

How are the market values of cryptocurrencies changing? Do cryptocurrency returns and uncertainty have interconnectedness? Do the cryptocurrency markets or other currencies have any returns or volatility spillovers? Accessing the risk of market performance always requires the proper method of assessment [20] [21]. In response to concerns, the GARCH method in mean models analyses the relationship concerning uncertainty and returns of emerging cryptocurrencies. It helps to research spillovers upon these blockchain monetary and financial markets. In general, the distribution of fluctuations, as well as uncertainty among the most relevant cryptocurrencies, is highly relevant [22]. The instability of such cryptocurrencies as well as the impact that occurs mostly on three major digital cryptocurrencies of Bitcoin, Ethereum, and Ripple. In the utilization of GARCH models, the consequences including downturns throughout the returns of all these three aforementioned cryptocurrencies, are analysed. Many cryptocurrencies support Bitcoin, Ethereum, and Ripple, so there are no market volatility capabilities in troubled times for major financial instruments [23].

This study aims to find the correlation between the daily log-returns of Bitcoin, Litecoin, XRP, Nxt, Dogecoin, Vertcoin, DigiByte, DASH, Counterparty, and MonaCoin. It also evaluates the cryptocurrency market instability tendencies of Bitcoin, Litecoin, XRP, Nxt, Dogecoin, Vertcoin, DigiByte, DASH, Counterparty, and MonaCoin.

2 Literature Framework

Various research contributions have explored the asymmetrical essence of US stock returns and the heterogeneous impact on stock return volatility [24]. The financial convergence of global economies as a study-relevant subject has been examined. There is also a greater concern in emerging markets amid significant developments in capital markets worldwide [25]. The purpose of this examination was to explore the financial angle from an international perspective of portfolio diversification, the convergence of existing US and emerging Asian stock markets before and after the recent financial crisis. Moreover, we clarified why Bitcoin, a modern innovative asset class, has drawn exceptional global interest. Cryptocurrency features heavy uncertainty, intense instability, and market disruption [26]. A price-taking mechanism was suggested; based on the stochastic jump volatility model and compared this to the versatile jump-taking model that creates a non-affine structure [27]. Both models' validation effects affirm the effect on simulation choices and the study of the expected variance curve of jumps and co-jumps. It was demonstrated that a significant share of price jumps are simultaneously and significantly affecting the volatility jumps. Moreover, the pioneering work into BTC alternatives was included in the report; validating the significance of swings on crypto-currency futures markets as illustrated by the proposed price structure [28].

It was realised that the investigation of the best model of conditional heteroscedasticity, in terms of value for money, like bitcoin. The strongest model was the AR-CGARCH model which emphasized the value of both the short-term and long-lasting aspects of the conditional variance [29]. Furthermore, the exploration was carried out of static as well as dynamic communication between eight standard cryptocurrencies. Subsequently, the findings revealed the cyclical fluctuation of their relationship and showed a strong trend upwards since 2016. An input network connects 52 cryptocurrencies to their VARs using the LASSO-VAR technique. The 52 cryptocurrencies were shown to be tightly intertwined with each other, so a cryptocurrency "mega-cap" was more prone to trigger unpredictable shocks to others [30]. Nevertheless, certain unnoticeable cryptocurrencies do have small volatility net transmitters and a low volatility share than others. Moreover, the complexities of cryptocurrencies are still not being explored, as recent research indicates Bitcoin, the most common cryptocurrency, reveals several different stylized details such as background and heteroskedasticity. This statement incorporates all of these characteristics into a common formula to calculate cryptocurrencies on various characteristics with market financial conditions. Subsequently, comprehension of these assets allows determining their investability [31]. This showed that in fact, cryptocurrencies had many peculiar properties including leveraging impact and the spread of errors.

On the other side, the interpretation of Granger causality factors in the context of a co-quantile causal response to the trade rate and uncertainty of the crypto-monetary industry. The regular results of seven big cryptocurrencies reveal that Granger’s trading rate generates negative and positive returns from all under-research cryptocurrencies [32]. Nevertheless, the Granger amount stagnant factors in the return volatility of three cryptocurrencies at low volatility. However, the latter result only applies to square returns used as a volatility proxy and not GARCH volatility. Moreover, the continuing pace and uncertainty of Bitcoin's price and the impact of the systemic split because of the advent of Bitcoin as a global financial fund. Strong evidence was found that favored permanent shocks and a lack of a medium reversal using parametric and semi-parametric techniques [33]. It also showed structural improvements in Bitcoin's structure. For certain instances, a proof-of-mean reversal has been identified upon analysis of fundamental splits in the level sequence. The functional consequences of inefficiency and its value for consumers and investors in the Bitcoin industry were addressed. There are many issues in the corporate governance framework, market discipline and in building an efficient, competitive market in many developing countries [34]. Moreover, the poverty-stricken citizens' access to public healthcare systems is worse in many countries, irrespective of whether they are developed or developing countries [35] [36].

The use of the GARCH-MIDAS model for the analysis of cryptocurrencies' long-term and short-term volatility elements has produced a significant outcome. Possible causes of Bitcoin uncertainty and risk factors on the US financial exchange and global economic activity were also regarded. Also, observed was volatility on the S&P 500 had a significant and very relevant impact on Bitcoin's longer-term volatility. The conclusion was unusual for co-movements of volatility across financial markets. There was a significant beneficial impact on the long-term Bitcoin price with the S&P 500 Risk Premia Rates Carry Index. Finally, the Baltic Dry Index, as well as long-term Bitcoin volatility, have a clear and positive correlation [37]. These findings revealed that the value of Bitcoin is strongly correlated with foreign economic operations. In general, results have been used to construct improved Bitcoin long-term volatility forecasts. Subsequently, the assessment of Bitcoin return volatility has used 3 GARCH methods. The latest technology permits simulation of clustering, distorting as well as leptokurtic distribution impact. The Standard Inverse Gaussian (NIG) distributive correctly represented leptokurtosis as well as skewness in both GARCH methods according to the student's t-distribution as well as standard error distribution. The TGARCH model defined asymmetrical shocks on the bitcoin market as the best models. In other terms, investors react differently to the same volume of positive and negative news. Based on the analytical findings, TGARCH-NIG was the strongest way to predict variance in Bitcoin's return sequence [38]. In general, the NIG distribution in model GARCH will be suitable because most cryptocurrencies are leptokurtic distribution. Similarly, the presence of ups and downs of Bitcoin log-return was realised with GARCH unpredictability patterns and Markov-GARCH (MSGARCH) method switches. Assessed by forecasting, the Value at Risk (VaR) was compared MSGARCH with the standard GARCH criteria. In Bayesian probability, the system specifications were calculated and the VaR forecasts were assessed. The clear proof was observed of improvements in the GARCH cycle and showed that whenever forecasting the VaR, MSGARCH methods exceeded single-state parameters [39]. Additionally, several empirical tests were considered, as well as, a trade-simulation method on behalf of the day-of-week impact on the cryptocurrency market. Economies, in terms of regulatory reforms, are more open to non-South Asian economies and not open to each other [40]. However, reforms have had varying degrees of impact on market structure depending on the country and the sector [41] [42]. Moreover, Economies are largely dependent on skilled and knowledge-intensive workers [43]. Sustainable development is a major common concern for the future of countries in the Asia-Pacific region [44].

Systematic research on seven global cryptocurrencies on systemic splits and instability spillovers highlights the unique outcomes. Several tests and models have also shown in these common cryptocurrencies structure splits are uniformly present; changing from smaller to greater cryptocurrencies. There were volatility spillovers with clear positive associations between cryptocurrencies. The results demonstrate the extent of the strengths of diversification within the cryptocurrency market itself [45]. Moreover, the implementation of three BEKK-pair bivariate models of three cryptocurrencies, the conditional instability dynamics along with associations and conditional correlations have been studied. Although the unpredictable price of cryptocurrencies was found to depend on its previous shocks and instability, proof for the two-way impact propagation in the middle of three cryptocurrency impact spillovers was identified [46]. Furthermore, in the examination of both US as well as EU capital markets, the cryptocurrencies are analysed through VIX as well as VSTOXX for their interaction with the demand fluctuation of the wide spectrum. The findings revealed time-variable positive connections between cryptocurrencies' conditional associations and financial market tension [47]. Moreover, during times of intense stock market tension, these similarities have risen dramatically, suggesting that the contagion of major expectations of the financial sector affects these emerging financial products [48].

The GARCH-MIDAS system application for daily, weekly, and monthly volatility forecasts for cryptocurrencies and the cryptocurrency Index CRIX has been introduced. As the main exogenous volatility generators in cryptocurrency markets based on prevention efficiency. We found that the economic activity grubs all the other currencies under the review of financial factors. It also showed that for both bull and bear markets. The economic operation provides superior volatility forecasts. The average mix of projections often contributes to small failure functions. It suggested that the quality of knowledge on exogenous variables changes over time average methodology diversifies the influence of individual drivers [49]. Likewise, it is established that the risk-return deal for occurrences is separate from that for financial instruments. Some common stock and macroeconomic variables are not vulnerable to cryptocurrencies [50]. However, factors that are unique to cryptocurrency markets will forecast the return of cryptocurrency. In particular, the time series shows that there is a clear trend that investor interest measures strongly forecast cryptocurrency returns.

In the context of measuring the trade barriers in financial services in BRICS countries as per the General Agreement on Trade in Services (GATS), it is realised that China is the most open, followed by Brazil, Russia, South Africa, and India. More interestingly, based on commitments, China is the most open in financial services among the BRICS countries, and India the most restricted [51]. Moreover, the special problem with the new trend of cryptocurrency was realised. Cryptocurrencies are digital financial instruments of which encrypted blockchain infrastructure ensures ownership as well as exchanges of ownership. The increase of cryptocurrencies' significance on the market, as well as increasing global popularity, opens up an amount of business and industrial economic challenges and concerns [52]. This explores the key developments in a scientific study concerning cryptocurrencies and discusses the contributions of the chosen works to the literature in both neoclassical and behavioural theories. The socio-economic and environmental issues are of significance. Furthermore, cryptocurrencies may serve certain valuable roles and bring forth economic benefits. While the initial liberal reasoning behind cryptocurrency may be contradictory, it seems to be a logical move to enhance social security [53]. Additionally, the function of price overreactions in the crypto-currency sector in the 2013-2018 case of BitCoin was analysed and realised that the theories concerning whether or not Bitcoin price patterns concern awareness of the extent of overreactions are not periodic [54]. However, market convergence of 12 prominent cryptocurrencies between the 8th of August, 2015 and the 28th of February, 2019 occurred. This showed the average return equi-correlation was time-varied based on the dynamic equi-correlation (DECO) model. It grew from the latter year to early 2019 and stayed reasonably strong, despite global uncertainty in 2016-2017 [55]. This result suggested that greater penetration into the cryptocurrency industry was a continuing and enduring trend, following the rapid price declines in the cryptocurrency sector in 2018.

Table 1
Summary of Literature Review on Cryptocurrencies

Author	Year	Summary of the study
Hou et al. [26]	2020	Cryptocurrency features heavy uncertainty, intense instability, and market disruption.
Akyildirim et al. [47]	2020	Time-variable positive connections between cryptocurrencies' conditional associations and financial market tension
Giudici et al. [52]	2020	The increase of cryptocurrencies' significance on the market, as well as increasing global popularity, opens up an amount of business and industrial economic challenges and concerns.
Bouri et al. [55]	2020	The average return equi-correlation was time-varied based on the dynamic equi-correlation (DECO) model.
Bouri et al.. [28]	2019	Validating the significance of swings on crypto-currency futures markets as illustrated by the proposed price structure.
Bouri et al. [33]	2019	Favored permanent shocks and a lack of a medium reversal using parametric and semi-parametric techniques

Gyamerah, S. A. [38]	2019	TGARCH-NIG was the strongest way to predict variance in Bitcoin's return sequence
Ardia et al. [39]	2019	Improvements in the GARCH cycle and showed that whenever forecasting the VaR, MSGARCH methods exceeded single-state parameters
Canh et al. [45]	2019	The extent of the strengths of diversification within the cryptocurrency market itself.
Katsiampaa et al. [46]	2019	The unpredictable price of cryptocurrencies was found to depend on its previous shocks and instability, proof for the two-way impact propagation in the middle of three cryptocurrency impact spillovers was identified.
Walther et al. [49]	2019	The quality of knowledge on exogenous variables changes over time average methodology diversifies the influence of individual drivers.
Caporale et al. [54]	2019	The function of price overreactions in the crypto-currency sector in the 2013–2018 case of BitCoin was analysed and realised that the theories concerning whether or not Bitcoin price patterns concern awareness of the extent of overreactions are not periodic.
Yi et al. [230]	2018	An input network connects 52 cryptocurrencies to their VARs using the LASSO-VAR technique.
Phillip et al. [31]	2018	Certain unnoticeable cryptocurrencies do have small volatility net transmitters and a low volatility share than others.
Bouri et al. [32]	2018	The interpretation of Granger causality factors in the context of a co-quantile causal response to the trade rate and uncertainty of the crypto-monetary industry.
Conrad et al. [37]	2018	The Baltic Dry Index, as well as long-term Bitcoin volatility, have a clear and positive correlation
Liu, Y., and Tsyvinski, A. [50]	2018	Some common stock and macroeconomic variables are not vulnerable to cryptocurrencies.
Katsiampa, P. [29]	2017	The strongest model was the AR-CGARCH model which emphasized the value of both the short-term and long-lasting aspects of the conditional variance.

(Source: Authors, literature reviews from the duration of 2017 to 2020)

3 Research Methods

Based on the synthesis of the literature, the researcher has framed the following hypothesis of the study:

H1: The logarithmic returns performances of Bitcoin, Litecoin, XRP, Nxt, Dogecoin, Vertcoin, DigiByte, DASH, Counterparty, and MonaCoin aren’t stationary.

H2: The returns of Litecoin, XRP, NXT, Dogecoin, Vertcoin, DigiByte, DASH, MonaCoin, and Counterparty cryptocurrencies have no impact on Bitcoin's return

In order to address the hypothesis, the researchers propose the time frame analysis, logarithmic return assessment, and econometric method for the research.

3.1 Time Frame and Information

The analysis was focused primarily upon reference information from the preserved server of cryptocurrency websites and finance.yahoo.com. This research assesses regular details on the Logarithmic return of Bitcoin (BTC), Litecoin (LTC), XRP, Nxt (NXT), Dogecoin (DOGE), Vertcoin (VTC), DigiByte (DGB), DASH, Counterparty (XCP), and MonaCoin (MONA) for the timeframe spanning from October 01, 2014, to April 30th, 2020. From 131 cryptocurrencies, we have considered only 10 cryptocurrencies because of the availability of data after October 2014. Where there was insufficient information, there were average results from the preceding date and subsequent dates. The regularly updated ending amounts were used for the period.

3.2 Calculation of Logarithmic Return Time Frame and Information

Earning daily Return (R) announced by the cryptocurrency market indicators have been calculated by exponential deviation, i.e.,

$$R = ln\,(S_p/(S_{p-1})/t \times 100\% \qquad (1)$$

Whereas Sp and Sp-1 are closing figures at the period of "p" and "p-1" for daily price return.

3.3 Econometric Method

In the Econometric Method, the assumptions were tested using the Testing of Stationary and Assessment of Generalized Auto-Regressive Conditional Heteroscedasticity.

A) Testing of Stationary:

Null hypothesis check from Phillips–Perron

$$\rho = 1\ in\ \Delta y_r = (\rho - 1)\, y_{r-1} + e_r \qquad (2)$$

Whereas Δ y_r a process was generating data and y_{r-1} endogenous test equation.

B) Assessment of Generalized Auto-Regressive Conditional Heteroscedasticity

The model is primarily used to study information and has been demonstrated to measure uncertainty in the cryptocurrency market. Instability systematically implies clear correlation coefficients in measured returns and can be observed by heteroscedasticity checking.

The regular equity return for the GARCH (1, 1) method is following [51] [52]:

$$\Upsilon_p = \beta + \beta_1 \Upsilon_{p-1} + \mathcal{E}_p \tag{3}$$

The coefficient of variation is presented by

$$S_p = \omega + \alpha_1 \mathcal{E}_{p-12} + \beta_1 S_{p-1} \tag{4}$$

Whereas $\omega > 0$, α_1, $\beta_1 S_{p-1}$, Sp is the contingent variable, and S_{p-1} is determined based on previous data.

The analysis and findings are deliberated using the above approach to fulfil the objectives and confirm the hypothesis of the study. The limitations of the study are time boundaries, little available information on cryptocurrencies, and not well-established markets around the world. There are more than 131 cryptocurrencies that are transacting in the market from where we have taken only 10. So, for future researchers, there are more opportunities for further study on this topic.

4 Analysis and Results

The analysis, results, and findings of the study are deliberated with the capitalization of the cryptocurrency market, correlation analysis, unit root assessment, GARCH framework forecasts with spillover uncertainty, and moving average results.

4.1 Capitalisation of the Cryptocurrency Market

Market capitalization simply defines the current share price multiplied by the total number of existing shares. In cryptocurrency terms, this means the current price of coin times the total number of coins on the market, often referred to as ‘circulating supply’. The analysis for capitalization of the cryptocurrency market is as below.

Table 2

Capitalisation of the Cryptocurrency Market

Cryptocurrency	Market cap (USD $)	Circulating Supply	Max. Supply	Price (Bitcoin)	Price (USD $)
Bitcoin (BTC)	170,379,150,961	18,366,300	21,000,000	1.00	9,276.75
Litecoin (LTC)	2,972,748,239	64,674,643	84,000,000	0.00493	45.96
XRP	9,539,609,515	44,112,853,111	99,990,976,125	0.0000232	0.21625
Nxt (NXT)	12,119,720	998,999,942	1,000,000,000	0.0000012	0.01213

Dogecoin (DOGE)	315,816,192	124,454,164,575	124,685,906,295	0.0000002	0.00253
Vertcoin (VTC)	16,067,160	54,631,397	84,000,000	0.0000316	0.29410
DigiByte (DGB)	293,778,769	13,110,607,127	21,000,000,000	0.0000025	0.02274
Dash (DASH)	738,286,705	9,480,742	18,900,000	0.00839	77.87
Counterparty (XCP)	2,657,779	2,615,338	2,615,391	0.0001101	1.02
MonaCoin (MONA)	88,341,735	65,729,675	76,421,850	0.000144	1.34

(Source: Authors, data collected from the website of respective cryptocurrency, as of 7 May 2020)

The above table represents total observations, mean, median, minimum, maximum, standard deviation, standard error, skewness, kurtosis, confidence level at 95%, and 99%, as well as Jarque–Bera Normality test for p-value.

4.2 Correlation Analysis

The correlation analysis is a statistical method used to evaluate the strength of the relationship between two quantitative variables. A high correlation means that two or more variables have a strong relationship with each other. The following table shows correlation analysis for cryptocurrencies.

Table 3

Correlation Analysis

Crypto currencies	BTC	LTC	XRP	NXT	DOGE	VTC	DGB	DASH	XCP	MONA
BTC	1									
LTC	0.64	1								
XRP	0.37	0.39	1							
NXT	0.52	0.45	0.34	1						
DOGE	0.54	0.52	0.43	0.48	1					
VTC	0.35	0.32	0.24	0.36	0.38	1				
DGB	0.40	0.33	0.29	0.34	0.41	0.26	1			
DASH	0.53	0.45	0.29	0.38	0.39	0.27	0.31	1		
XCP	0.31	0.24	0.20	0.24	0.28	0.23	0.24	0.23	1	
MONA	0.32	0.27	0.19	0.23	0.21	0.14	0.19	0.26	0.19	1

(Source: Authors, calculated at MS Excel with data analysis tools)

The table shows the correlation for log-returns (daily) of Bitcoin (BTC), Litecoin (LTC), XRP, Nxt (NXT), Dogecoin (DOGE), Vertcoin (VTC), DigiByte (DGB), DASH, Counterparty (XCP), and MonaCoin (MONA) in percentage from October 2014 to April 2020.

4.3 Unit Root Valuation

The unit root assessment tests whether a time series variable is non-stationary and possesses a unit root. The null hypothesis is generally defined as the presence of a unit root, and the alternative hypothesis is either stationarity, trend stationarity, or explosive root. The following table shows the unit root assessment using the Phillips-Perron Test.

Table 4
Phillips-Perron Test

Crypto Currencies	*Methods*	*Test Statistic*	*Interpolated Dickey-Fuller Critical Value*			*Mac Kinnon P-Value*
			1%	*5%*	*10%*	
Bitcoin (BTC)	Z(rho)	-2129.639	-20.700	-14.100	-11.300	0.0000
	Z(t)	-45.925	-3.430	-2.860	-2.570	
Litecoin (LTC)	Z(rho)	-2128.869	-20.700	-14.100	-11.300	0.0000
	Z(t)	-45.285	-3.430	-2.860	-2.570	
XRP	Z(rho)	-2330.725	-20.700	-14.100	-11.300	0.0000
	Z(t)	-45.378	-3.430	-2.860	-2.570	
NXT	Z(rho)	-2230.811	-20.700	-14.100	-11.300	0.0000
	Z(t)	-46.684	-3.430	-2.860	-2.570	
Dogecoin (DOGE)	Z(rho)	-1993.032	-20.700	-14.100	-11.300	0.0000
	Z(t)	-42.769	-3.430	-2.860	-2.570	
Vertcoin (VTC)	Z(rho)	-2010.474	-20.700	-14.100	-11.300	0.0000
	Z(t)	-45.783	-3.430	-2.860	-2.570	
DigiByte (DGB)	Z(rho)	-2156.288	-20.700	-14.100	-11.300	0.0000
	Z(t)	-45.477	-3.430	-2.860	-2.570	
DASH	Z(rho)	-2125.379	-20.700	-14.100	-11.300	0.0000
	Z(t)	-45.800	-3.430	-2.860	-2.570	
Counterparty (XCP)	Z(rho)	-2359.022	-20.700	-14.100	-11.300	0.0000
	Z(t)	-55.742	-3.430	-2.860	-2.570	
MonaCoin (MONA)	Z(rho)	-1939.964	-20.700	-14.100	-11.300	0.0000
	Z(t)	-43.652	-3.430	-2.860	-2.570	

(Source: Authors, Calculated at Stata for Phillips–Perron Test with Logarithmic Return)

The designed ADF information for Bitcoin (-45.925), Litecoin (-45.285), XRP (-45.378), NXT (-46.684), Dogecoin (-42.769), Vertcoin (-45.783), DigiByte (-45.477), DASH (-45.800), Counterparty (-55.742) and MonaCoin (-43.652), therefore, the null hypothesis H1 had already been rejected, all of these are lower than the average critical value (-3.430, -2.860 and -2.570) at interpolated Phillips–Perron test Critical Values of 1%, 5% and 10%, accordingly. According to hypothesis 1, the logarithmic returns performances of Bitcoin, Litecoin, XRP, Nxt, Dogecoin, Vertcoin, DigiByte, DASH, Counterparty, and MonaCoin aren't stationary, which has been rejected. The assumption for H1 is the information seems to have a unit root.

4.4 GARCH Framework Forecasts with Spillover Uncertainty

The GARCH framework can be estimated by the following equation:

$$GARCH = C\,(2) + C\,(3) \times RESID\,(-1)2 + C\,(4) \times GARCH\,(-1) + C\,(5) \times GARCH\,(-1) + C\,(6) \times GARCH\,(-1) + C\,(7) \times GARCH\,(-1) + C\,(8) \times GARCH\,(-1) + C\,(9) \times GARCH\,(-1) + C\,(10) \times GARCH\,(-1) + C\,(11) \times GARCH\,(-1) + C\,(12) \times GARCH\,(-1) + C\,(14) \times BTC\,(-1) \quad (5)$$

Firstly, the method uses dummy variables to cover the entire duration of the dataset. The GARCH method is considered for Litecoin, XRP, Nxt, Dogecoin, Vertcoin, DigiByte, DASH, Counterparty, and MonaCoin returns for the whole period. Meanwhile, a conditional sequence of updates also collected from Bitcoin returns affects performance on contemporary values and affects their data which was also observed furthermore by the output of a perpetual sequence. Data was collected from 10/1/2014 to 4/30/2020, the observable sample number considered for the analysis is 2,039, the method used is ARCH family regression with Gaussian Distribution, Wald chi^2 is 19094.28, log-likelihood is 4715.721, and Prob > chi^2 is 0.0000.

Table 5
ARCH Family Regression

BTC		Coefficient	OPG Standard Error	z	P>|z|	[95% Confidence Interval]	
BTC	*LTC*	0.2974525	0.007656	38.85	0.000	0.2824471	0.312458
	XRP	0.0314102	0.0092545	3.39	0.001	0.0132717	0.0495487
	NXT	0.1030547	0.0045366	22.72	0.000	0.0941631	0.1119464
	DOGE	0.082712	0.0087737	9.43	0.000	0.065516	0.0999081
	VTC	0.0116342	0.0048807	2.38	0.017	0.0020682	0.0212002
	DGB	0.0338306	0.0041816	8.09	0.000	0.0256347	0.0420265
	DASH	0.1175871	0.0072455	6.23	0.000	0.1033862	0.131788
	XCP	0.0118775	0.0044567	2.67	0.008	0.0031426	0.0206124
	MONA	0.0299818	0.0053793	5.57	0.000	0.0194385	0.0405251
	_cons	0.0007671	0.0004187	1.83	0.067	-0.000054	0.0015878

ARCH	*Arch L1*	0.2230476	0.0175169	12.73	0.000	0.1887152	0.2573801
	Garch L1	0.7357927	0.0163834	44.91	0.000	0.7036818	0.7679035
	_cons	.0000405	3.69e-06	10.97	0.000	0.0000332	0.0000477

(Source: Authors, Calculated at Stata for ARCH family regression with Logarithmic Return)

Litecoin returns have an estimated coefficient of 0.2974525 and an Outer Product Gradient Standard Error of 0.007656, and a p-value of 0.000. XRP returns have estimated a coefficient of 0.0314102 and an Outer Product Gradient Standard Error of 0.0092545 and a p-value of 0.001. Nxt returns have estimated a coefficient of 0.1030547 and an Outer Product Gradient Standard Error of 0.0045366 and a p-value of 0.000. Dogecoin returns have estimated a coefficient of .082712 and an Outer Product Gradient Standard Error of .0087737 and a p-value of 0.000. Vertcoin returns have estimated a coefficient of 0.0116342 and an Outer Product Gradient Standard Error of 0.0048807 and a p-value of 0.017. DigiByte returns have estimated a coefficient of 0.0338306 and an Outer Product Gradient Standard Error of 0.0041816 and a p-value of 0.000. DASH returns have estimated a coefficient of 0.1175871 and an Outer Product Gradient Standard Error of 0.0072455 and a p-value of 0.000. Counterparty returns have estimated a coefficient of 0.0118775 and an Outer Product Gradient Standard Error of 0.0044567 and a p-value of 0.008. MonaCoin returns have estimated a coefficient of 0.2974525 and an Outer Product Gradient Standard Error of 0.0053793 and a p-value of 0.000. Thus, H2 differed at $\alpha = 0.05$ point, as p-value lesser than 0.05, and all cryptocurrencies return variability value throughout the duration had a significant effect on the updates from Bitcoin returns.

The ARCH, as well as GARCH (α as well as β) coefficients, remain relevant, showing that data impact on return variability is persistent. In the duration (0.2230476), the ARCH parameter ($\alpha1$) is stable. The large GARCH parameter level ($\beta1$) for the duration (0.7357927) suggests that throughout the time, the uncertainty in return distributions is strong. The spike in the value of the cryptocurrency market is often discussed in the press. The large valuation of α, as well as β, suggests that the cryptocurrency market has evolved fast. A very long time is taken before the knowledge impact on the contingent variability is lost. The complete ARCH, as well as GARCH ($\alpha1+\beta1$) i.e. (0.2230476+0.7357927 = 0.9588403) equations, are practically unique on behalf of either duration that suggests a lower variance of cryptocurrency performance. Therefore, GARCH (1,1), $(\alpha_1+\beta_1)<1$, has a stationary state. A stationary validation of the information via the ADF method is performed to prevent false regression. The sufficient number of lags is calculated using Akaike Data Parameters. According to the hypothesis 2, the returns of Litecoin, XRP, NXT, Dogecoin, Vertcoin, DigiByte, DASH, MonaCoin, and Counterparty cryptocurrencies have no impact on Bitcoin's return, which has been also rejected. The significant effect exists on Bitcoin's return.

4.5 Moving Average Results

A moving average is an analysis tool that smooths out data by creating a constantly updated average value. The average is taken over a specific period for all variables. The following graphs illustrate the moving average results for all cryptocurrencies under the study. It includes the assessment of moving averages for Bitcoin, LTC, XRP, NXT, DOGE, VTS, DGB, DASH, XCP and Mona.

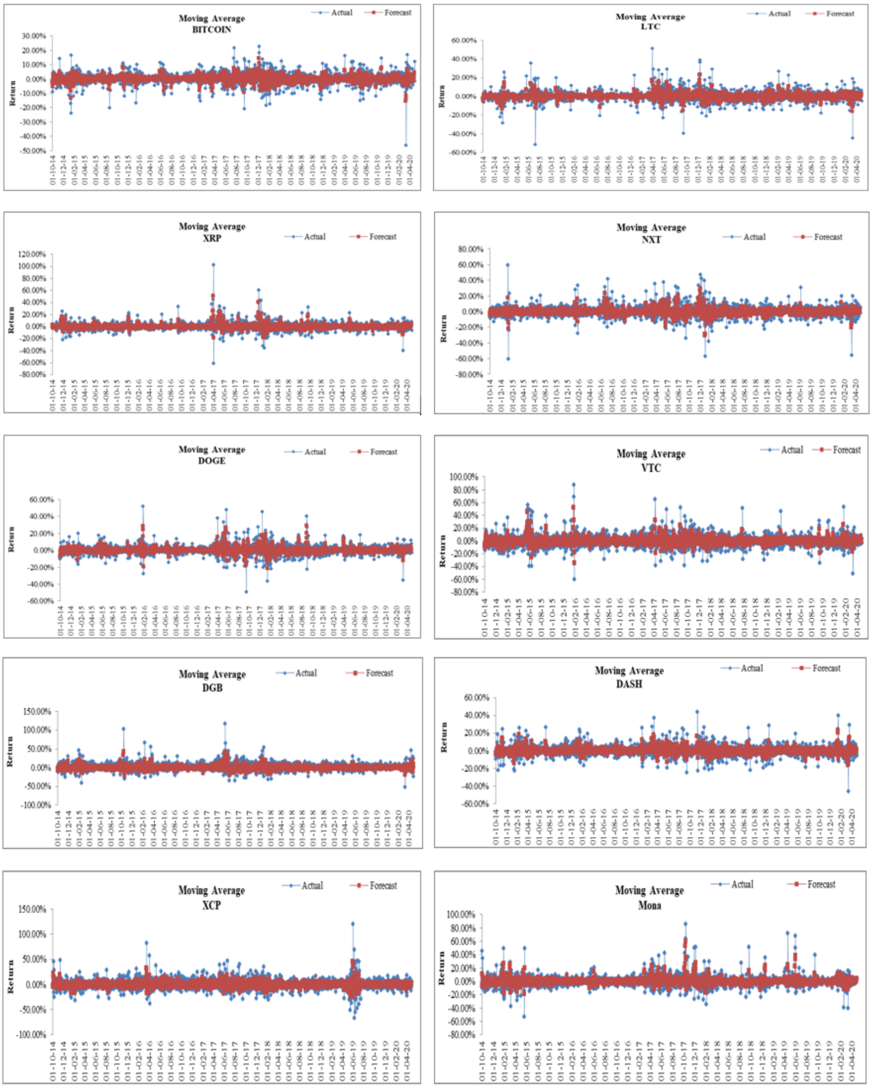

Figure 1

Moving Average of Bitcoin, Litecoin, XRP, Nxt, Dogecoin, Vertcoin, DigiByte, DASH, Counterparty, and MonaCoin returns (Source: Authors, all the figures created using Microsoft Excel)

Conclusions

This paper highlights the scientific contribution in the domain of cryptocurrencies by emphasising the study of Bitcoin with the consequences for other cryptocurrencies. The most important aspect of the study is the assessment of GARCH-effects on Bitcoin, Litecoin, XRP, Nxt, Dogecoin, Vertcoin, DigiByte, DASH, and MonaCoin. We have noticed that the ten pairs of cryptocurrencies had similarities however the average movement for return forecasts offer clear proof supporting the success of cryptocurrency market growth and further reinforce conclusions from previous analyses on cryptocurrency interdependencies. The XRP, Nxt, Dogecoin, Vertcoin, DigiByte, DASH, Counterparty, and MonaCoin returns variability value throughout the duration had a significant effect on the updates from Bitcoin returns. Moreover, Litecoin, returns have estimated a coefficient of 0.2974525 with Outer Product Gradient Standard Error of 0.007656 and a p-value of 0.000. Thus, H2 was rejected as p-value lesser than 0.05, and Litecoin returns variability value throughout the duration had a significant effect on the updates from Bitcoin returns. Both ARCH and GARCH coefficients (α and β) remain important and indicate a persistent effect of data on return variability. The parameter ARCH ($\alpha 1$) is constant in length (0.2230476). The high amount of GARCH parameters ($\beta 1$) for the period (0.7357927) shows that unsafe returns are substantial over time. There was also talk in the press about the difference in the valuation of the cryptocurrency sector. The strong estimation of α and β shows that the cryptocurrency industry is growing rapidly. The dependence on dependent volatility requires more time before the information is lost. The bitcoin crisis will influence other cryptocurrencies, according to the hypothesis test.

The boom of cryptocurrency technologies and many others in additional fields shows that it has a strong potential to improve productivity and accountability in certain transactions. While we learn from previous practice, hysteria is likely to decrease with time as the advantages are evident and practical. In several cases, blockchain may not be advantageous as compared to traditional major competition. In the future, the focus should be on the ways to make innovative use of technology to enhance financial systems and processes improvement should be taken into consideration how the various parties' interests could be developed fairly (in particular the balance of social, economic as well as environmental considerations); how projects are supported, and individuals as well as businesses. We hope that this particular issue will help us to understand cryptocurrencies and their problems. We also believe that it helps create information and resources that are valuable to practitioners and scholars who research. This may change and become something very different from what we now see, but cryptocurrencies are certainly already capable of innovation in financial efficiency and economic growth. We just need the training to utilize this invention correctly.

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