Article title: How Blockchain Network Factors and Market Forces Determine Bitcoin Returns
Authors: Adedeji Daniel Gbadebo[1]
Affiliations: Department of Accounting Science, Walter Sisulu University, Mthatha, Eastern Cape, South Africa[1]
Orcid ids: 0000-0002-1929-3291[1]
Contact e-mail: gbadebo.adedejidaniel@gmail.com

DOI: 10.14293/S2199-1006.1.SOR-.PPASACK.v2
Preprint first posted online: 25 December 2022
Keywords: Bitcoin, Bitcoin Price, Bitcoin Network Factor, Bitcoin Market Forces, VAR/VECM

How Blockchain Network Factors and Market Forces Determine Bitcoin Returns

Gbadebo Adedeji Daniel
gbadebo.adedejidaniel@mail.com
Department of Accounting Science
Walter Sisulu University, Mthatha
Eastern Cape, South Africa

Abstract
The creation of distributed ledgers technologies spirals secured peer-to-peer interactions that pave way for the invention of Bitcoin. Since its invention, the price of Bitcoin has exhibited excessive volatility and has attracted increasing attentions. The study considers the isolated influence of network activities, mining (technology) and market information as fundamental drivers of bitcoin prices. A long-term equilibrium and short-term dynamic relationship is confirmed amongst endogenous system's variables in the VEC Model. This suggests that any deviation from the equilibrium dynamics due to perturbations of market forces (bitcoin supply and trade volume), mining information (network difficulty, Hashrate and transaction fees) as well as the network activity (confirmed payments and users adoptions) would be minimised. The model explains that the cointegration relationship has a reverse adjustment effect on bitcoin return. This justifies why Bitcoin price, and by implication the return, continues to experience different massive run-up, spiky protrusions, resistance, reversals, strong supports and consolidations in the short. Amongst others, the study recommends that there should be increase in regulation to curb excessive fluctuations that can cause significant loss to the returns and discourage digital investors.

Keywords: Distributed ledgers, Bitcoin, VECM, Market information, Mining information, Network activity

JEL Codes: C10; G15, G17

1. Motivation

The thrust of this study is to explore the determinants of bitcoin returns in the cryptocurrency markets. Bitcoin, the first decentralized financial currency, applies blockchain technology network to permit anonymous and irreversible transactions. The digital currency and asset has gained global attention from investors and regulators in the financial markets (Liu, & Tsyvinski, 2021; Liang, Zhang, Li & Ma, 2020; Aalborg, Molnar, & Erik de Vries, 2018). There has been significant increase in the number institutional involvement in cryptocurrency since the launching of bitcoin future options after the establishment of Bitcoin futures contracts by the Chicago Board Options Exchange in December 2017 (Catania, Grassi, & Ravazzolo, 2019).

Previous studies focused on bitcoin price nexus with traditional assets (Matkovskyy & Jalan, 2019), speculative bubbles (Baur, Hong, & Lee, 2018), mining technology (Kjærland, Khazal et al., 2018; Li & Wang, 2016), market volatility (Hung, Liu & Yang, 2020; Troster et al., 2018), time-of-day periodicities of trading (Wang, Liu, & Hsu, 2020); survey of bitcoin Exchange (Jeon, Samarbakhsh, & Hewitt, 2020), predictability of returns (Philippas, Rjiba, Guesmi, & Goutte, 2019), technical indicators (Huang, Huang, & Ni, 2019) and the determinants of price fluctuations (Sovbetov, 2018; Julio, 2017). Corbet, Meegan et al. (2018) discover bitcoin speculative bubbles with non-predictable fundamental value equals to zero. Matkovskyy and Jalan (2019) suppose bitcoins riskiness over traditional assets makes risk averse investors to evade the cryptocurrency in periods of financial depression.

A major issue confronting stakeholders is how to understand what determines bitcoin price. Some attempts have been made to categorize the factors that determine bitcoin pricing as internal and external. Researched recognise the internal factors include supply and demand for bitcoin (transaction cost) [Ji, Bouri, Kristoufek, & Lucey, 2019, Aalborg et al., 2018], bitcoins adoptions [Liu, & Tsyvinski, 2021]; coins circulation (hash rate) and mining difficulty [Guizani & Nafti, 2019; Kjærland et al., 2018; Julio, 2017]. Our paper attempt to demonstrate the relative importance of the internal and market factors in the determination of the daily bitcoin price returns.

The external factors as political considerations, which includes legalization (adaptation) [Murphy, 2015; Cvetkova, 2018], restrictions (ban) [Schueffel, & Hammer, 2020]; cryptocurrency market influences like as cryptocurrency market (capitalization) [Sovbetov, 2018; Poyser, 2019], cryptocurrency withdrawal [Ji, Bouri, Kristoufek, & Lucey, 2019]; bitcoin attractiveness [das Neves, 2020, Guizani &Nafti, 2019; Sovbetov, 2018; Ciaian, Rajcaniova & Kancs, 2014], investor's sentiments [Poyser, 2019]; market trends and speculations [Blau, 2018;

Lansky, 2016], as well as the macro-financial, which include stock markets (global market spill overs and volatility) [Liang et al., 2020], macroeconomic (financial development) [Guizani & Nafti, 2019]; exchange rates [Ji et al., 2019]; financial assets and commodities as gold price [Liu, & Tsyvinski, 2021; Deniz, 2019; Kjærland et al., 2018]; macroeconomic news [Guizani & Nafti, 2019]; and the social media attention [Liu, & Tsyvinski, 2021; Luu & Huynh, 2019; Kjærland et al., 2018], including information demand (google search) [Aalborg et al., 2018] and Twitters tweets [Shen, Urquhart & Wang, 2019].

This study attempts to model the combined impact of internal and external factors, in the determination of bitcoin price. The paper does not consider market spill-over effects from traditional asset, foreign exchange rate, commodity markets and other external factors which influence on bitcoin prices have been inconsistent (Liang et al., 2020; Aalborg et al., 2018; Yechen, Dickinson & Jianjun, 2016; Wang, Xue, & Liu 2016). The bitcoin market has distinct features which necessitated an isolated consideration. The market is traded twenty-four hours and seven days a week, unlike the stock market that is off during weekends and holidays. The market trades freely without constraint on its upper-lower bound for trading, whereas some financial markets regulate these bounds. This means that bitcoin has high volatility tendencies which permits unrestricted price pump.

The study examines the issue with the multivariate estimation with focus on unifying the influence of identified determinants. The study considers the isolated influence of market information, network activities and mining information as three distinct bitcoin price drivers. Understanding the interconnectedness of the price drivers is key to describe the relationships amongst internal determinants, and to inform whether bitcoin price in different markets (or Bitcoin exchanges) reacts to the efficacy and influence from its production, advancement in technology and incessant adoptions.

The study finds the existence of a long-term equilibrium and short-term dynamic relationship amongst the endogenous system's variables in the VEC Model. The contribution supposes that identified deviation from the equilibrium dynamics due to perturbations of market forces (bitcoin supply and trade volume), mining information (network difficulty, Hashrate and transaction fees) as well as the network activity (confirmed payments and users adoptions) would be minimised. The model explains that the cointegration relationship has a reverse adjustment effect on bitcoin return. The rest of the paper is underscores. Section two is literature review, while section three provides the models and methodology adopted. Section four presents the results, and section five is the conclusions.

2. Material Review

There exist plethora of literature on cryptocurrency but only a handful focused on the determinants of bitcoin returns. Liu, & Tsyvinski. (2021) links between risks and returns of bitcoin. BitPremier (2020) computed bitcoin volatility index. Ji et al. (2019) investigated realized volatility connectedness among Bitcoin exchange markets. Luu and Huynh (2019) explained spillover risks on bitcoin and cryptocurrency. Karkkainen (2018) considered the price discovery in the bitcoin futures and cash. Corbet et al. (2018) analysed links amongst alternative cryptocurrencies. Julio (2017) analysed bitcoin price volatility. Dwyer (2015) investigated the economics and financial characteristics of cryptocurrencies. Ciaian et al. (2014) revealed the economics of bitcoin price formation.

Some studies applied weekly or monthly data periodicity [Ji et al., 2019; Poyser, 2019; Aalborg et al., 2018; Kjærland et al., 2018; Yechen, et al., 2016], while some others [Table 1] applied daily or hourly data periodicities to investigate on the determinate of bitcoin prices and returns. Each author applied unique frameworks in addressing established hypotheses, research questions, and focus on different aspects of the cryptocurrency and obtained varying results. Ji et al. (2019) established that amongst other hypothesize variables, asset withdrawal provides more volatility in BTC price for individual exchanges than the transaction volume. Aalborg et al. (2018) considered the effect of trade volume, Google searches for “Bitcoin”, and Chicago Board Options Exchange (CBOE) volatility (VIX) index on the volatility of BTC price. They discovered that trade volume positively affect the BTC volatility. Poyser (2019) employed the Bayesian structural method to investigate the effect of gold, stock index and investor’s sentiments (ISEN) on BTC price volatility. They found that the Bitcoin price volatility relates positively with stock index, countries’ search trend differentials, USD/Euro rate, while negatively associated with Yuan/USD rate, ISEN and gold price. Yechen et al. (2016) examined how economic factors such as, US dollar index, custom price index, federal funds rate, Dow jones industry average and gold price influence bitcoin price.

Table 1: Summary of empirical reviews

Name	Data	Methodology	Variable	Remarks
Liu, & Tsyvinski. (2021)	18/07/2010 15/11/2017	VAR	Return, User adoptions, Google search, Aggregate and Individual stock return	User adoptions and Google search determines, as well as both forecast the expected cryptocurrency returns.
Liang et al. (2020)	01/01/2013 31/08/2019	(GARCH-MIDAS)	Price, VIX, Global Economic Policy Uncertainty index (GEPU) Gold volatility Index (GVZ), Google Trends, Geopolitical Risk	Provide strong evidence that GVZ variable display the strongest predictability for Bitcoin volatility.
Deniz (2019)	28/02/2013 23/07/2019	VAR	Price, Gold, Brent oil	Oil and Gold prices do not determinate BTC price
Guizani and Nafti (2019)	19/12/2011 06/02/2018	ARDL	Price, Bitcoin Supply and demand, Macroeconomic and Financial development, Mining difficulty, Stock, EUR/USD rate	The Supply and demand, Attractiveness, Number of wallet addresses, Mining difficulty have impact on BTC price, while transaction volume, Stock, EUR/USD rate and financial development do not
Luu and Huynh (2019)	08/09/2015 04/01/2019	VAR SVAR	Price, news and moving patterns	Check the important of bad news on the spillover risks amongst cryptocurrencies. Found that Ethereum is independent but Bitcoin is the spillover effect recipient.
Sathyanarayana and Gargesa (2019)	01/09/2013 31/03/2018	VAR GARCH EGARCH	Price, USD, GBP, Euro, Yen and CHF	The GARCH and EGARCH tests shows leverage effect. The last phase decomposition capture the variance explained by prominent global currencies on Bitcoin. USD and GBP share long run relationship with Bitcoin.
Shen et al. (2019)	04/09/2014 31/08/2018	Granger causality, VAR	Returns, investor attention and trading volume and realized volatility, number of tweets	Tweets is a significant driver of next day returns, trading volume, and realized volatility.
Ji et al., (2019)*	11/13/2017 05/31/2019	VAR	Volatility, Bitcoin exchanges, volume, Transaction, Asset withdrawal convenient on Exchanges	The ability for investors to withdraw asset impacts more on the volatility through various bitcoin exchange more than trading volume
Kjærland et al. (2018)	01/01/2013 20/02/2018	ARDL	Price, Hashrate, Google searches, S&P500, VIX, Oil, Gold, Volume	The Google searches and S&P500 have positive and significant effect on BTC price volatility.
Erdas, & Caglar (2018)**	24/11/2013 08/07/2018	Asymmetric Causality Test	Price, Gold, Brent oil, US dollar, S&P500 index, BIST 100 indexes,	The result shows correlation between BTC price and S&P500 index. There exist undetermined links between bitcoin price and other variables.
Sovbetov (2018)**	01/2010 31/2018	ARDL	Price, Trading volume, Market capitalization, Attractiveness, Stock market	The transaction volume and volatility have significant impact on price. The S&P500 index in the long run has a weak positive impact on price.
Karkkainen (2018)	13/12/2017 16/05/2019	VAR VECM	Price, Hasbrouck's information share and Gonzalo-Granger component, trading volume	The intraday prices show that the futures are leading the price discovery process at varying frequencies, even with low trading volumes.
Yechen (2017)	09/2011 03/2016	VECM	Price, Custom price index (CPI), US dollar index (USDI), Dow Jones (DJIA) industry average, Federal funds rate (FFR), Gold price	The CPI, DJIA, FFR, USDI, Gold have a negative effect on Bitcoin price. The price of gold does not affect bitcoin price. Bitcoin because the value of bitcoin is not only determined by its supply and demand.
Li, and Wang (2016)	01/01/2011 31/12/2014	ARDL	Price, market conditions, trading volume, economic fundamentals, mining technology	In the short run, Bitcoin price is influenced by market conditions, while in long run, the price is more sensitive to fundamentals and less of technology.
Wang et al. (2016)	01/01/2011 30/04/2016	VAR	Price, WTI crude oil price, stock price index, oil price and daily trading volume	The short-run shows that oil price and BTC trading volume have little influence on price while stock price index has larger impact on it. In the long run, stock price index and oil price have negative effect on bitcoin price.
Kristoufek (2015)	14/09/2011 28/02/2014	Wavelet	Price, Gold, Search engine, Financial Stress Index	Show interconnections and differentiate between short-term and long-term connections. Concludes bitcoin exhibits unique asset possessing properties of both speculative and traditional assets.

Note: * Study employ hourly, ** Study employ daily/weekly/monthly.

3. Methodology

3.1 Data information

Bitcoin The price increased almost 2000 percent reach above USD19,500 on December 18, 2017. With about 28,750 percent returns on investment since July 5, 2018, bitcoin price hits daily average all-time high of about USD 64,863.31 on April 14, 2021. The price has fallen about 40 percent to USD 40,044.54 in June, 2021. Figure 1 shows the daily price of bitcoin from 30 June 2018 to 1 July, 2021. The figure shows bitcoin experience massive run-up, spiky protrusions, resistance, reversals, strong supports and consolidations. It depicts high volatility and validate a sign for nonstationary trend of the daily price of bitcoin over time as would be expected for such financial asset. The prices show evidence of upward movement and strong tendency of co-movement with erratic swings, particularly following the launching of the bitcoin futures options trading by the CME Group, Hence, the data is split into two partition to clarify two trend episodes for the basic statistics.

Source: Author (Blockchain.com's data)

Figure 2 (Panel A– C) display the trajectories of daily Bitcoin returns, with a trend smoothed line using 'loess' for different measures: ΔP_t, $P_t\ (P_{t-1})^{-1}$ and $\mathrm{Ln}[P_t\ (P_{t-1})^{-1}]$, respectively. The figures depict volatility but validate sign for stationarity which is not surprising for a return series. Each figure shows that the returns displayed a mean reversing trend and a cointegrated daily closing time series of over time. The plots of $\mathrm{Ln}[P_t\ (P_{t-1})^{-1}]$ mimics $P_t\ (P_{t-1})^{-1}$ except for the range its assumed and clustering between approximately -0.4 and 0.2, with non-surprising a relatively more smoother striations. The plot of $P_t\ (P_{t-1})^{-1}$ assumes values within positive quadrant, since it is a relative measure of returns.

Seven internal and market determinants of bitcoin returns are identified. These are categorized into three groups: Market Information (total bitcoin supply and trade volume on exchanges), Mining Information (network difficulty, Hash-rate, and total transaction fees) and

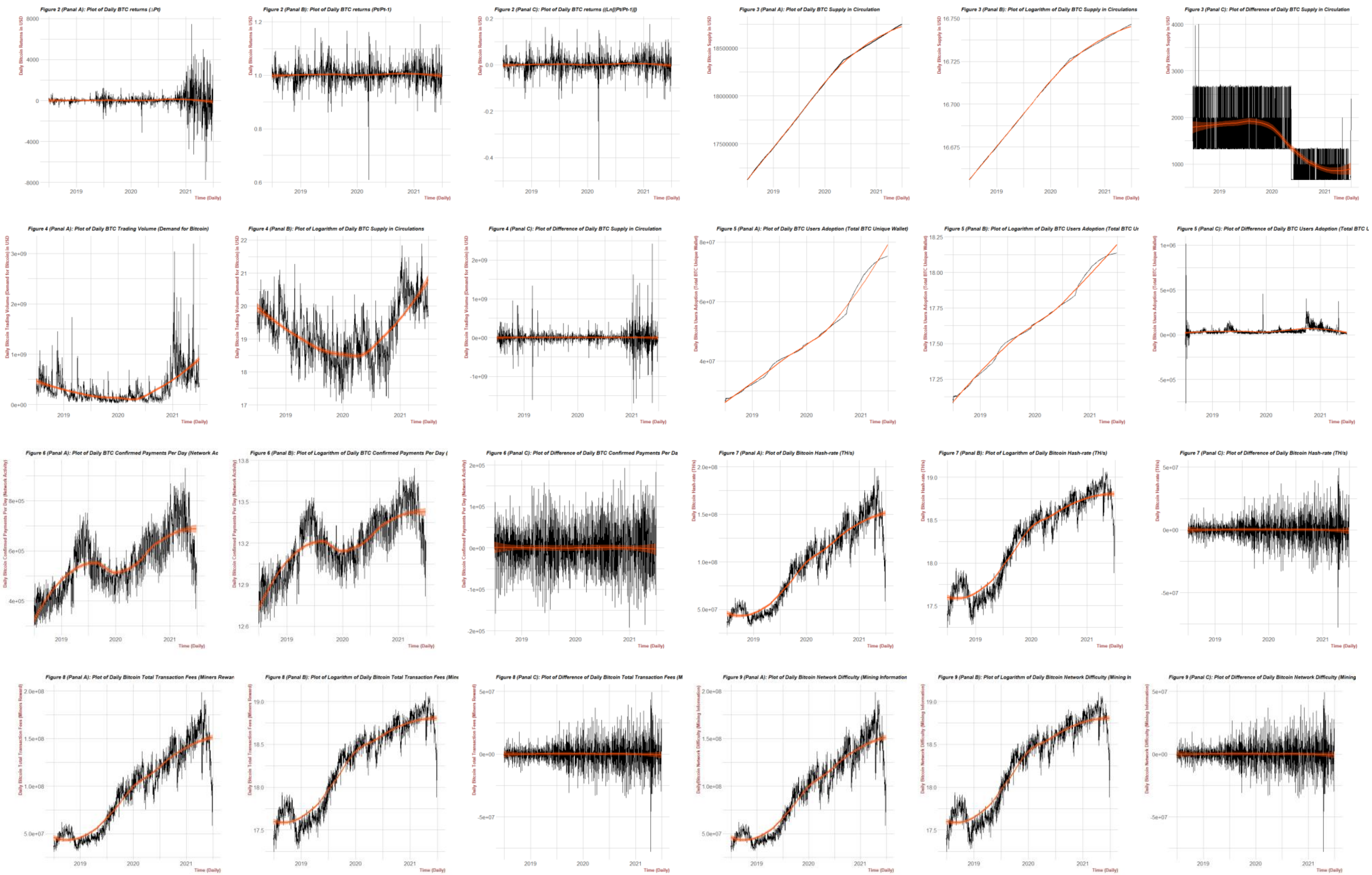
Network Activity (Confirmed Payments and users adoptions). This grouping follows regular classification by major exchanges (Blckchain.com, 2021). Unlike some studies [Liang et al., 2020; Arman, 2018; Aalborg et al., 2018; Kjærland et al., 2018; Yechen, 2016], this paper does not include any stock market and external variable whose data is not available for all, including weekends and non-trading perios, unlike bitcoin that is traded every moment. They are not applied to avoid smoothing of the information for unavailable data.

The paper adopts the mining information and Blockchain technology factors in line with some studies (Guizani & Nafti, 2019; Kjærland et al., 2018). Hashrate is the speed for which computer complete an operation in the Bitcoin coding. It is a measure of the estimated Tera-hashes per second (TH/s) which network execute in last 24 hours. The mining difficulty is a comparative index of how difficult in mining new bitcoin block on the blockchain. The Hash of current blocks [$Hash$] is obtained as a function, $Hash = f(\theta_{t-1}, \rho, \Phi)$, where θ is the hash, ρ is coin mining difficulty, and Φ is the random key. And the total transaction fees the aggregate bitcoin value of all transaction fees paid to miners as rewards for mining bitcoin.

In the cryptocurrency markets changes in Bitcoin prices is explained by the supply-demand constraints (Guizani & Nafti, 2019). This suppose both measures as market information, in the determination of bitcoin returns. The total number of mined BTCs currently in circulation on the network is used as proxy for the supply of bitcoin, while the trading volume aggregated in USD amount on major exchanges is used as proxy for the demand. I include the Users Adoption proxy by the unique wallet, and the confirmed payments daily as network information proceed by Blockchain DLT. The user's adoption represents the total bitcoin unique wallet obtained from Blockchain. An increase in amount of wallets indicates new users adopting crypto usage. The number of confirmed payments is the aggregative amount of verified payments proceed on the Blockchain.

For all the attendant determinants, each corresponding plots [Figure 3 – 6 (Panel A – C)] show the time series in linear scale, $x_{j,t}$ (Panel A), logarithmic scale, $\text{Ln}[x_{j,t}]$ (Panel B), and difference scale, $\Delta x_{j,t}$ (Panel C). The plots displays pattern among the series. The logarithm plots exhibit mirror reflections of thee corresponding linear trajectories, except for its smoother striations. The bitcoin supply series and users adoptions display linear pattern, indicating the presence of positive autocorrelation. Generally, financial time series are often trended and not stationary. The original series appear explosive, while the difference series clustered and are obviously mean reversing.

Figure:



The empirical investigation examines monthly frequency series between 2015:M1 to 2022:M6. The data is sourced from the Blockchain, and the bitcoin series used is the USD denominated unweighted average of monthly closing market prices. Before estimation, logarithm scaling is applied on each series. Since the price of financial asset would normally be expected to be nonstationary, the study adopts the return series (Liang et al., 2020; Kjærland et al., 2018; Wang et al., 2016). The bitcoin returns is computed using the ratio of each month current closing price to the previous closing one. Logarithemic normalization preserve cointegration relationship, while the heteroscedasticity is eliminated in the source sequence. Table 2 shows a summary descriptions and references for each data employed.

Table 2: Summary descriptions for data

S/N	Data		Unit	Classification	Description	Reference
1	BTCRn_t	Intraday Returns	USD	Currency/ Asset	Natural logarithm of the ratio of current closing price to previous day closing.	Liu, & Tsyvinski. (2021), Shen et al. (2019), Arman (2018).
2	SupBTC_t	Total Bitcoin Supply	BTC	Market Information (BTC Supply)	The total number of mined BTCs currently in circulation on the network	Ji et al. (2019), Guizani and Nafti (2019), Ciaian et al.(2014).
3	TrVOL_t	Trade Volume	USD	Market Information (BTC Demand)	The aggregated USD amount of trading volume on identified major exchanges.	Ji et al. (2019), Shen et al. (2019), Guizani and Nafti (2019), Wang et al. (2016).
4	NETDiF_t	Network Difficulty	Index	Mining Information	A comparative index of how difficult to mine new bitcoin block on the blockchain.	Guizani & Nafti (2019), Kjærland et al. (2018), Julio (2017)
5	HASHr_t	Hash-rate	TH/s	Mining Information	An internal measure of the estimated Tera-hashes per second which network is execute in last 24 hours.	Guizani & Nafti (2019), Kjærland et al. (2018), Julio (2017)
6	TRANFe_t	Total Transaction Fees	BTC	Mining Information (Reward System)	The aggregate bitcoin value of all transaction fees paid to miners, excluding Coinbase block rewards.	Ji et al. (2019), Aalborg et al. (2018)
7	NcPAY_t	Confirmed Payments	Pay-ments	Network Activity	The total number of verified payments/day process on Blockchain.	Authors
8	WALLet_t	Users Adoption	Walle ts	Network Activity	Total BTC unique wallet obtained from Blockchain. An increase in amount of wallets indicates new users adopting crypto usage.	Liu, & Tsyvinski (2021)

Table 3: Descriptive statistics (information) of variables

	Deterministic Statistics						Normality	
$x_{j,t}$	$\bar{x}_j$	$\bar{x}_{Max}$	$\bar{x}_{Min}$	$x_{1\sigma}$	β_1	β_2	$\mathrm{JB}_{(\beta_1,\beta_2)}$	$\mathrm{Pr.}[\mathrm{JB}_{(\beta_1,\beta_2)}]$*
Prior to Futures Options [2015:M1–2019M12]								
BTCRn_t	0.001	0.162	-0.150	0.036	0.021	6.717	324.20	0.000
SupBTC_t	16.68	16.71	16.65	0.017	0.008	1.798	33.919	0.000
TrVOL_t	19.06	21.27	17.04	0.750	-0.080	2.712	12.553	0.003
NETDiF_t	29.68	30.25	29.25	0.314	0.609	1.938	61.304	0.000
HASHr_t	17.85	18.60	17.24	0.334	0.502	1.985	47.770	0.000
TRANFe_t	3.484	5.432	2.300	0.677	0.983	3.227	91.852	0.000
NcPAY_t	13.08	13.53	12.59	0.192	0.004	2.566	14.414	0.001
WALLet_t	17.39	17.64	17.07	0.166	-0.133	1.616	46.578	0.000
Posts Futures Options [2020:M1–2022M:9]								
BTCRn_t	0.003	0.175	-0.497	0.045	-2.441	31.46	18554	0.000
SupBTC_t	16.73	16.74	16.75	0.009	-0.320	2.124	26.166	0.000
TrVOL_t	19.35	21.88	17.27	0.956	0.071	2.249	13.003	0.002
NETDiF_t	30.53	30.85	30.24	0.155	0.147	2.045	22.222	0.000
HASHr_t	18.67	19.16	17.88	0.180	-0.204	2.981	14.704	0.001
TRANFe_t	4.207	5.710	2.358	0.697	-0.365	2.329	21.875	0.000
NcPAY_t	13.32	13.74	12.81	0.171	-0.127	2.501	6.9841	0.030
WALLet_t	17.90	18.13	17.64	0.167	0.046	1.462	52.827	0.000
Full Sample Information [2015:M1–2022M:9]								
BTCRn_t	0.002	0.175	-0.497	0.041	-1.588	24.981	22545	0.000
SupBTC_t	16.70	16.74	16.65	0.027	-0.338	1.770	90.078	0.000
TrVOL_t	19.25	21.88	17.04	0.868	0.135	2.592	10.938	0.004
NETDiF_t	30.09	30.85	29.25	0.489	-0.283	1.577	107.27	0.000
HASHr_t	18.25	19.16	17.24	0.487	-0.308	1.687	96.063	0.000
TRANFe_t	3.836	5.710	2.300	0.776	0.244	1.911	65.100	0.000
NcPAY_t	13.20	13.74	12.59	0.218	-0.154	2.533	14.276	0.001
WALLet_t	17.63	18.37	17.07	0.304	0.027	1.941	51.422	0.000

The result of normality test of significant for each data, to verify whether each data is normally distributed using the Jarque-Bera (JB_{β_1,β_2}) test, with the test statistics $JB_{\beta_1,\beta_2} = f(\beta_1,\beta_2) = [n6^{-1}(\beta_1{}^2 + 4^{-1}(\beta_2 - 3)^{-1})]$, where n is degrees. $JB_{\beta_1,\beta_2}$is always nonnegative, and the more distance from 0 signals non-normal distribution. *Probability value for the Jarque-Bera statistics. If β_1 = 0, the distribution is symmetric and if β_2 < 3, the distribution is platykurtic, if β_2 = 3, mesokurtic or normal and if β_2 > 3, leptokurtic.

The computation shows the average of the log of the returns ($\bar{x}_1$) is almost same in all samples. The post CME Options has the highest standard deviation ($x_{1\sigma}$), whereas the lowest is prior to the official launching of the future options. The returns series (BTCRn_t) is leptokurtic (β_2 >3) for all data periods. The distribution of the data for transaction fees for the sample set prior to the launch of the futures options is mesokurtic or normal (β_2= 3.027). The distribution for other attendant determinants of bitcoin returns are platykurtic, having β_2<3. All the distribution are symmetric ($\beta_1 \neq 0$). Except for the users adoptions (WALLet_t), all series for the prior to futures options periods are positively skewed, and for the full sample all series except trading volume, transaction fees and number of unique wallets are left-skewed.

The network and mining information variables almost mimic the behaviour of the distribution of the bitcoin return series. The bitcoin associated determinants are likely to have gain values as much as how the Bitcoin movements fascinate many attentions (das Neves, 2020, Guizani &Nafti, 2019; Sovbetov, 2018). The probability values for the Jarque Bera statistics indicate that all the variables are not normally distributed at the 1% level, rejecting the normality null. There is positive correlation between bitcoin returns and all determinant fundamentals, as well as between bitcoin. As expected, the Hashrate is proportionally correlated with mining difficulty and the bitcoin rice returns. As the Hashrate increases, the underlying Bitcoin algorithm adjusts the mining difficulty for the bitcoin supply to align on a programmed path.

Table 4 show a long-run covariance (LRCOV) [Bartlett Kernel method] between all variables, while Table 5 present the (ordinary) Pearson correlation and ordinary covariance coefficients. The LRCOV provides trends between data analogous to low-pass filtered series, which are designed to extract variability that trails periods longer than the sample span. The result (Table 5) shows that aside trading volume, there is positive long-run co-movement between the returns and all other series. The degree of movement in the trends and long run is weak and could simply be a sign that other factors beyond Blockchain technology and its internal factor would influence prices and returns evolution of the cryptocurrency over-time.

Table 4: Centred Long-run Covariance [Bartlett Kernel, Newey-West fixed bandwidth = 7.0000]

$x_{j,t}$	BTCRn_t	SupBTC_t	TrVOL_t	NETDiF_t	HASHr_t	TRANFe_t	NcPAY_t	WALLet_t
BTCRn_t	0.0016	0.0002	-0.001	0.0012	0.0030	0.0153	0.0041	0.0027
SupBTC_t	0.0002	0.0052	0.0127	0.0898	0.0874	0.0821	0.0296	0.0568
TrVOL_t	-0.0010	0.0127	3.9773	0.2765	0.1774	1.2893	0.2138	0.3713
NETDiF_t	0.0012	0.0898	0.2765	1.6596	1.6087	1.2352	0.4584	0.9734
HASHr_t	0.0030	0.0874	0.1774	1.6087	1.6095	1.1786	0.4705	0.9443
TRANFe_t	0.0153	0.0821	1.2893	1.2352	1.1786	3.7668	0.8519	0.9803
NcPAY_t	0.0041	0.0296	0.2138	0.4584	0.4705	0.8519	0.2725	0.3434
WALLet_t	0.0027	0.0568	0.3713	0.9734	0.9443	0.9803	0.3434	0.6412

Three methods are common for computing the LRCOV amongst variables. The prewhitened kernel method; the parametric and the nonparametric kernel approach. The estimates for the non-parametric kernel estimator 'Bartlett kernel' as well as a real-valued bandwidth defined by the function of T are presented. The Bartlett kernel method has a renowned history which the bandwidth and kernel important determinants of the finite-sample properties of the LRCOV. In obtaining these estimators, the data is pre-whitened by 'centering' (subtracting off the means) prior to computation of the kernel covariance estimator.

Source: Author (2022)

Table 4: Pearson Correlation (information) for all variables

	$x_{j,t}$	Centered								Uncentered							
		BTCRn_t	SupBTC_t	TrVOL_t	NETDiF_t	HASHr_t	TRANFe_t	NcPAY_t	WALLet_t	BTCRn_t	SupBTC_t	TrVOL_t	NETDiF_t	HASHr_t	TRANFe_t	NcPAY_t	WALLet_t
Correlations	BTCRn_t	1.000								1.000	0.039	0.039	0.039	0.039	0.054	0.040	0.039
	SupBTC_t	0.028	1.000								1.000	0.999	0.999	0.999	0.980	0.999	0.999
	TrVOL_t	0.004	0.076	1.000								1.000	0.998	0.998	0.982	0.999	0.999
	NETDiF_t	0.008	0.963	0.093	1.000								1.000	0.999	0.981	0.999	1.000
	HASHr_t	0.020	0.940	0.056	0.969	1.000								1.000	0.982	0.999	0.999
	TRANFe_t	0.081	0.554	0.348	0.468	0.444	1.000								1.000	0.982	0.982
	NcPAY_t	0.069	0.711	0.145	0.618	0.631	0.763	1.000								1.000	0.999
	WALLet_t	0.031	0.981	0.201	0.942	0.916	0.596	0.745	1.000								1.000
Covariances	BTCRn_t	0.001								0.001	0.026	0.030	0.048	0.029	0.008	0.021	0.028
	SupBTC_t	0.000	0.000								279.1	320.8	502.9	305.0	64.10	220.6	294.7
	TrVOL_t	0.000	0.001	0.753								369.5	578.0	350.5	73.89	253.6	338.8
	NETDiF_t	0.000	0.012	0.039	0.238								906.1	549.6	115.6	397.4	531.0
	HASHr_t	0.000	0.012	0.023	0.230	0.237								333.4	70.18	241.0	322.1
	TRANFe_t	0.002	0.011	0.234	0.177	0.167	0.601								15.31	50.77	67.80
	NcPAY_t	0.000	0.004	0.027	0.065	0.067	0.129	0.047								174.3	232.9
	WALLet_t	0.004	0.008	0.053	0.139	0.135	0.140	0.049	0.092								311.2

Both the Centered ($\rho_{x_1x_2}$) and Uncentered correlation ($\rho^*_{x_1x_2}$) coefficients (*Pearson correlation coefficients)* are measure of linear correlation between two sets of data, $x_i$and x_j. The centered correlation obtained from the set of paired data $(x_{1,1}, x_{2,1})$, $(x_{1,2}, x_{2,2})$, …, $(x_{1,n}, x_{2,n})$ consisting of n pairs, is defined as $\rho_{x_1x_2} = \sum_i^n (x_{1,t} - \bar{x}_1)(x_{2,t} - \bar{x}_2)\left[\sqrt{(x_{1,t} - \bar{x}_1)^2}\sqrt{(x_{2,t} - \bar{x}_2)^2}\right]^{-1}$. For the sample means ($\bar{x}_i$ and $\bar{x}_j$) are set to zero (0) in computing the Uncentered correlation coefficients. Both correlation coefficients lie between -1 and $+1$.

3.2. Methods

The study analyses the relationship between endogenous time-series using the VAR/VECM. The VECM is applied as a restricted VAR, if the series are nonstationary and cointegrated. Previous studies use VAR/VECM to explain price volatility spill-over (Luu & Huynh, 2019), as well as the determinants of price and returns (Giudici & Abu-Hashish, 2018; Karkkainen, 2018; Wang et al., 2016; Yechen et al., 2016). Giudici and Abu-Hashish (2018) use VAR model to show the evolution of bitcoin prices based on price, Gold, Oil, SP500; USD/YUAN and USD/EUR. Karkkainen (2018) applies VAR/VECM to show that the futures markets are leading the bitcoin price discovery. Wang et al. (2016) explain how WTI crude oil price, stock price index, oil price and trading volume cause fluctuations of bitcoin price. Yechen et al. (2016) use VECM to verify how factors such as dollar index, Custom price index, Dow jones average, gold price and Federal Funds affect bitcoin price.

Theoretical time-series of vector autoregression uses VAR only on stationary data leading to loss of information about long-run among the integrated series. VECM modifies the VAR by accommodating whether the (nonstationary) level regressions are dependable (cointegrated), hence captures the role for deviations from the long-run equilibrium. The resulting VAR from the VECM representation has more efficient coefficient estimates, since it adopts the co-integration restriction information into the specifications. The process is considered in the following steps.

First, the study completes a time-series' unit root testing. The pre-test verifies the stochastic characterization of data generating process of the time series, identifying whether the series are stationary or integrated. Assume $z_t\ [y_t, x_t]$ is the sets of variables, where, $y_t\ (x_t)$ is the dependent variable (regressors), the study presents statistics for each series of z_t. The Augmented-Dickey-Fuller (ADF) used to verify stationarity for the z_t is:

$$z_t = a_0 + \varphi z_{t-1} + \sum_{i=1}^{p-1} \delta_i \Delta z_{t-i} + \Omega_t;\ i = 1, 2, \ldots, p-1. \qquad (1)$$

$\delta_i = -\sum_{j=i+1}^{p-1} \varphi_j$ and a_0, Ω_t and p are drift, Gaussian noise, and lag length, respectively. The test statistics [$\tau_\mu = \hat{\varphi}_T - 1/se(\hat{\varphi}_T)$, where $se(\hat{\varphi}_T)$ is $\hat{\varphi}_T'$'s standard error] is computed with least squares. The test is conducted with a null of non-stationarity ($H_0\colon \varphi = 1$) and alternative ($H_1\colon \varphi > 1$). z_t is denoted as $l(0)$ [$l(1)$ or $l(d)$] for level [differenced] stationary (d is order of integration.

Second, the study selects the system's optimal lag needed for the cointegration test parameterisation. Optimal lag selection is crucial because if the lag applied is too little, the residual will not be white noise hence the model may inaccurately estimate the actual error. The Akaike Information Criteria (*A1C*), specified in (2), is applied to select optimal lag.

$$AlC(p,q) = \log \hat{\sigma}^2 + 2(p+q)T^{-1} \tag{2}$$

T is number of observations and $\hat{\sigma}^2$ is covariance matrix of residual. Both p and q are different orders, *m* is maximum possible lag (upper bound). To select optimal lag, AIC sets two upper bounds (p_{m} ; q_{m}) for the orders $[\varphi(B); \theta(B)]$. $B^j x_t \equiv x_{tj}$ θ=-ψ; $\psi_j = \varphi^j$ and ψ = weight of the 1st-Order Moving Average [MA(1)]. AIC select orders p_1 and q_1 such that $AlC(p_1, q_1) = \min AlC(p,q)$, where ($p \in \overline{p}$; $q \in \overline{q}$) and $\overline{p} = \{0, 1, \dots, p_{\mathrm{m}}\}$ and $\overline{q} = \{0, 1, \dots, q_{\mathrm{m}}\}$.

Third, the system cointegration is confirmed to establish if there is long-run equilibrium between a dependent variable and its associated regressors. The Johansen (1988) test, which applies the Maximum Likelihood Estimation (MLE) for a cointegrated system, is employed. The test use both the Trace and Maximum eigenvalue to determine the rank r of the cointegrating space of matrix $\boldsymbol{\pi}$. The Trace [Maximum eigenvalue]'s null hypothesis of no co-integrating vectors [$H_0 = rank(\boldsymbol{\pi}) = r$] is tested against the alternative hypothesis of at least one co-integrating vector [H_1: r >0]. Trace statistic (η_r) and Maximum eigenvalue (ζ_λ), where $\lambda_{i+1}, \dots, \lambda_n$ are the $n + r$ smallest squared canonical correlations between x_{t+k} ($k = 1, 2, \dots, n$) and x_t:

$$\eta_r = T \textstyle\sum_{i=r+1}^{n} \ln(1 - \lambda_i) \tag{3}$$

$$\zeta_\lambda = T \ln|(1 - \lambda_{r+1})| \tag{4}$$

The estimated eigenvalues need to be larger than the critical values, for the null to be rejected.

Fouth, if cointegration exists, the VECM is estimated to offer valuable short-run dynamics for the established co-integrating relations. Otherwise, the unrestricted VAR is represented for the differenced series. The *n*-dimension multivariable cointegrated $VAR(p)$ model is:

$$\boldsymbol{A}(B)\mathbf{x}_t = \boldsymbol{c} + \boldsymbol{u}_t \tag{5}$$

$E(\boldsymbol{u}_t) = 0$; $E(\boldsymbol{u}_t \boldsymbol{u}_s) = \Omega_p, \forall\, t = s, E(\boldsymbol{u}_t \boldsymbol{u}_s) = 0, \forall\, t \neq s$. Assume $\mathbf{x}_\mathrm{t} \sim l(1)$ *and* $\Delta\mathbf{x}_\mathrm{t} \sim l(0)$ are cointegrated with rank r and $\boldsymbol{\Pi} = \beta\alpha'$ (product of 2 $n \times r$ matrices, α, β), and $\boldsymbol{\Pi}$ is the long-run matrix. Applying Beveridge-Nelson Decomposition[1] $[i.e., \Delta\mathbf{x} = c + \Phi(B)\Delta\mathbf{x}_{-1} + \Pi\boldsymbol{y}_{-1} + u]$ and imposes restrictions due to the existence of integrated but co-integrated data, the VECM is:

$$\Delta\mathbf{x} = c + \sum_{i=1}^{p} \Phi_\tau \Delta\mathbf{x} + \beta\alpha'\mathbf{x} + u_t \tag{6}$$

[1] $\boldsymbol{A}(B) = (l_l - \boldsymbol{A}B) - \boldsymbol{\Phi}(B)B\nabla$, Where $A = \sum_{i=1}^{p} \boldsymbol{A_i}$, $\Phi(B) = \sum_{i=1}^{p-1} \Phi_i B^{i-1}$; $\Phi_i = -\sum_{j=i+1}^{p} A_j$.

Where, c is the matrix of exogenous constant, β is the matrix of cointegration vectors and α is a matrix that indicates how each difference series responds to perturbations in the long run equilibrium where $\alpha^{'}\mathbf{x}.\boldsymbol{\Pi} = \beta\alpha'$, Φ_{τ} is the parameter matrices of the lagged stationary difference. The matrix $\alpha^{'}\mathbf{x}$ contains the r stationary error corrections known as Granger's Representation Theorem. The VECM includes the estimated long run relationship between the $l(1)$ and $l(0)$ series, and makes adjustments to the short-run effects. The method is appropriate since it incorporates non-statistical a priori information used in determining inter-dependencies and dynamic relationships.

4. Results

4.1. Stationarity Test

The stochastic characterization of the variables is reported in Table 6. The ADF test rejects the null of nonstationary at the level of 5% significance for the returns. Hence, except for the return series [BTCRn_t] the evidence shows the all original series are non-stationary (Figure 2 [Panel A−C]). The first difference is stationary, signifying that the time series with initially large variance has tendency to converge. All variables are integrated [$\mathrm{x}_t \sim I(1)$], except the returns series [$I(0)$]. In cryptocurrency market, unprecedented Bitcoin price vagaries are connected to response from spill-overs emanating from continuous mining activities, network activities and users infiltrations. Since price is not Ponzi, it would always retract making returns mean-reversing.

Table 6: ADF stationarity test

Levels $[\mathrm{x}_t]$	τ_{ADF}	$[ADF_\alpha]$ 1%	5%	Prob	Difference $[\Delta\mathrm{x}_t]$	τ_{ADF}	$[ADF_\alpha]$ 1%	5%	Prob
BTCRn_t	-4.04*	-3.43	-2.86	0.00	$\Delta\mathrm{BTCRn}_t$	-21.17	-3.43	-2.86	0.00
SupBTC_t	-1.02	-3.43	-2.86	0.85	$\Delta\mathrm{SupBTC}_t$	-21.50	-3.43	-2.86	0.00
TrVOL_t	-1.52	-3.43	-2.86	0.60	$\Delta\mathrm{TrVOL}_t$	-21.70	-3.43	-2.86	0.00
NETDiF_t	-1.07	-3.43	-2.86	0.73	$\Delta\mathrm{NETDiF}_t$	-30.16	-3.43	-2.86	0.00
HASHr_t	-2.47	-3.43	-2.86	0.11	$\Delta\mathrm{HASHr}_t$	-13.26	-3.43	-2.86	0.00
TRANFe_t	-1.76	-3.43	-2.86	0.40	$\Delta\mathrm{TRANFe}_t$	-10.27	-3.43	-2.86	0.00
NcPAY_t	-0.66	-3.43	-2.86	0.85	$\Delta\mathrm{NcPAY}_t$	-50.50	-3.43	-2.86	0.00
WALLet_t	-1.19	-3.43	-2.86	0.51	$\Delta\mathrm{WALLet}_t$	-45.91	-3.43	-2.86	0.00
$\mathbf{BTCRn}_t$	-3.86**	-3.96	-3.41	0.00	$\boldsymbol{\Delta}\mathbf{BTCRn}_t$	-18.86	-3.96	-3.41	0.00
$\mathbf{SupBTC}_t$	-1.09	-3.96	-3.41	0.79	$\boldsymbol{\Delta}\mathbf{SupBTC}_t$	-21.50	-3.96	-3.41	0.00
$\mathbf{TrVOL}_t$	-1.57	-3.96	-3.41	0.68	$\boldsymbol{\Delta}\mathbf{TrVOL}_t$	-21.69	-3.96	-3.41	0.00
$\mathbf{NETDiF}_t$	-2.81	-3.96	-3.41	0.19	$\boldsymbol{\Delta}\mathbf{NETDiF}_t$	-30.15	-3.96	-3.41	0.00
$\mathbf{HASHr}_t$	-2.67	-3.96	-3.41	0.25	$\boldsymbol{\Delta}\mathbf{HASHr}_t$	-13.30	-3.96	-3.41	0.00
$\mathbf{TRANFe}_t$	-2.34	-3.96	-3.41	0.41	$\boldsymbol{\Delta}\mathbf{TRANFe}_t$	-10.26	-3.96	-3.41	0.00
$\mathbf{NcPAY}_t$	-1.13	-3.96	-3.41	0.92	$\boldsymbol{\Delta}\mathbf{NcPAY}_t$	-50.54	-3.96	-3.41	0.00
$\mathbf{WALLet}_t$	-2.92	-3.96	-3.41	0.16	$\boldsymbol{\Delta}\mathbf{WALLet}_t$	-45.90	-3.96	-3.41	0.00

ADF (non-stationary null) compare with the alternative (stationary null) is rejected if $\tau_{ADF} > \alpha_{ADF}$. ADF_α: MacKinnon (1996) one-sided p-values. $\Delta\mathrm{x}_t$ is first difference. *Stationary at 1% significance. **Stationary at 5% significance. The '**Bold**' figures are test with intercept without Time Trend.

4.2. Optimal lag and Cointegration Tests

Table 7 presents the different lag selection tests. The various information criteria and in particular, the AIC with highest absolute value (-17.999) suggests 3 lags for parameterization of the Johansen test. Table 8 reports the outcome of the trace and maximum-eigenvalue tests. The procedure starts with testing for zero cointegrating vectors and eventually accepts the first null that is not rejected. The test rejects the null hypothesis of non-existence and existence of only one cointegration vector. However, two co-integrating combinations are significant (i.e. two unit roots were rejected). For the Trace test statistics ($\eta_r = 18.773$) and maximum-eigenvalue statistics ($\zeta_\lambda = 13.114$) are lower than the critical value (29.797 and 21.132, respectively) at *r* = 2, hence, the null of at most two co-integrating vector could not be rejected. The existence of long run relationship amongst the variables is intuitive. Technology and market factors motivate fluctuation in volume and price of bitcoin. As more users adopt the blockchain, and more coins are mined, more institutions enter the market with large capital, the price and returns of bitcoin would increase.

Table 7: VAR lag order selection criteria

	Lag Length			
Criteria	0	1	2	3
FPE	0.001	0.0000	0.0000	0.00001*
AIC	0.901	-16.973	-17.948	-17.999*
SC	0.920	-16.692	-17.012*	-16.930
HQ	0.908	-16.870	-17.605	-17.656*

*Indicates lag order selected. LR (Sequential modified LR test statistic) (each test at 5% level).
FPE (Final prediction error), AIC (Akaike information criterion), SC (Schwarz information criterion), HQ (Hannan-Quinn information criterion)

Table 8: Unrestricted cointegration rank test

Test	Hypothesized No. of CE(s)	Test Statistics	Critical Value (0.05)	Prob. Value	Test Decision
Trace	*n - 5 = r = 0**	279.03	125.61	0.000	Rejected
Statistics	*n - 4 = r = 1**	104.18	95.754	0.000	Rejected
	n - 3 = r = 2	18.773	29.797	0.509	Not rejected
$[\eta_r = T\sum_{i=r+1}^{n} \ln(1\ \lambda_i)]$	*n - 2 = r = 3*	5.6592	15.495	0.735	Not rejected
	n - 1 = r = 4	0.2065	3.8412	0.650	Not rejected
Maximum	*n - 5 = r = 0**	174.8	46.231	0.000	Rejected
Eigenvalue	*n - 4 = r = 1**	93.59	40.078	0.000	Rejected
$[\zeta_\lambda = T \ln\lvert(1\ \lambda_{r+1})\rvert]$	*n - 3 = r = 2*	13.11	21.132	0.442	Not rejected
	n - 2 = r = 3	5.454	14.265	0.684	Not rejected
	n - 1 = r = 4	0.206	3.8413	0.650	Not rejected

Trace test [Max-eigenvalue] indicates 4 cointegrating equations (C.E.) at the 0.05 level.
* denotes rejection of the hypothesis at the 0.05 level.

4.3. The VEC Model [VECM]

Since at least one of $\mathbf{x}_{j,t}$ is non-stationary, and there is cointegration, the VECM which ensure the log (differenced) stationary level regressions are trustworthy ('cointegration') is estimated. The standardized cointegration equation reflects the relationship between the bitcoin returns, bitcoin supply in circulations, trading volume, network difficulty, hash-rate, transaction fees, confirmed payments and users adoptions with 2 lags and 4 co-integrating relationship. From the outcome, the VECM is more adequate, hence the insertion of the error correction terms (ECT) to perform the system's long-term adjustments. The VECM is estimated with a deterministic trend included in the cointegration relation and use to make statistical inference with respect to the cointegration rank. In equation (6), c is the (8 × 1) vector of exogenous constant, β is a (8 × 2) matrix of the 2 cointegration vectors and α is a (8 × 2) matrix that indicates how each difference series responds to perturbations in the long run equilibrium, where $\alpha'\mathbf{x}.\boldsymbol{\Pi} = \beta\alpha'$, Φ_τ is the (8 × 8) parameter matrices of the lagged stationary difference. The estimation is executed using the cointegrating restriction. The results offers the relationship between bitcoin return and market factors, mining and network activities.

Table 9 reports the cointegration matrix' coefficients [β_1,β_2] of the error correction component. Recall that the coefficient of adjustment $\alpha_1[\alpha_2]$ applies to the cointegration matrix β_1 [β_2]. As would be seen, the coefficient of log bitcoin returns is in positive β_1 indicative that an increase of BTCRn_{t-1}, not complemented by systemic change in other attendant variables that would neutralize the increase will generates a positive error but pressure a decline in the variation in returns ($\Delta\mathrm{BTCRn}_t$), since its interactive adjustment coefficient, α_1, is negative. The same can be infer for (e.g., transaction volume. number of confirm payment and users adoption). However, for the variable (network difficulty, total transaction fees, Hash-rates at $\mathrm{t}-1$), whose coefficient is negative in β_1, and any increase of at current month value of the variable, without any change in in other systemic variables, would generate force such that that in the next period the change in return would increase due to the correspond negative adjustment coefficient, α_1. Since adjustment's coefficient α_2 corresponds to the cointegration matrix β_2, the outcome suppose thatβ_2 is negative in coefficients for Hashrate, confirm pay and users adoption. By implication, any sudden increase or drift in an of these variables [NETDiF_{t-1}, NcPAY_{t-1}, WALLet_{t-1}] would results in a negative error which interacted with correspond negative adjustment coefficient, α_2, would pressure increase of the next period the change in return.

Table 10 is the outcome of the VECM regressions' coefficient, which also include the adjustment coefficients of the error correction term [α_1,α_2]. The model indicates that the cointegration relationship has a reverse adjustment effect on bitcoin return. If the last period return far exceeds the equilibrium constraint, the error correction would supposedly make current return to decline. This explains the why the price, and by implication the return experience different massive run-up, spiky protrusions, resistance, reversals, strong supports and consolidations in the short run. Both the adjustment coefficient of the EC term are negative in the change in return equation and significance 0.05 level and is negative in the price equation, This supposes that any deviation from the equilibrium dynamics due to perturbations in of market forces (total bitcoin supply and trade volume on exchanges), mining Information (network difficulty, Hashrate, and total transaction fees and network activity (confirmed payments and users adoptions) would be minimized with the correction proposed by the α_1, for the period after (Engle & Granger, 1987). While α_1 contributes around 78%, α_2 offers 22% to the long-term dynamics.

As observed from the VECM regression [Table 10], both marker factors (bitcoin supply and trading volume) positively impact variation in bitcoin return. The mining activities has both positive (network difficulty, and total transaction fees) and negative effect (Hash-rate) as well as the network activities of number of confirmed payments impact the returns variation positively, while the users adoptions affect the deviations in return negatively. Except for coefficients of network difficulty and users adoption, all the model's coefficients are significant.

The market forces offer the highest increment factors affecting variation in current monthly returns. The elasticity of bitcoin returns to trading volume is the highest been 0.668. This supposes that the return is much sensitive to increase bitcoin demand for various speculative, trading purposes. A 1% increase in bitcoin trading volume would lead to a 0.668% increase in the variation in current monthly returns. When bitcoin supply increase by 1%, one would expect variation in current monthly bitcoin return to increase changes 0.112%. The output is very intuitive, in sense that generally, one would expect the market forces to have greater impact on price, and by implication returns in returns. The transaction fees offers the lower incremental impact. A 1% increase in transaction fee would be accompanied in the period after by a monthly increase of 0.016% of the current bitcoin returns. Also, a 1% increase in bitcoin users adoption would lead to a 0.173% decrease in the variation in current monthly returns. Intuitively, excessive adoption of an assets may pressure down the price, and consequently, a fall in returns.

Table 9: Cointegration Matrix (β)'s Coefficients

Variable	β_1 Coeff.	β_σ	t-stat	β_2 Coeff.	β_σ	t-stat
BTCRn_{t-1}	1.000	-	-	-	-	-
SupBTC_{t-1}	-	-	-	1.000	-	-
TrVOL_{t-1}	0.002	0.0016	(1.118)	0.009*	0.0011	(8.220)
NETDiF_{t-1}	-0.112*	0.0015	(-6.754)	0.077*	0.0125	(6.709)
HASHr_{t-1}	-0.088*	0.0138	(-6.380)	-0.073*	0.0096	(-7.531)
TRANFe_{t-1}	-0.016*	0.0032	(-5.129)	0.007*	0.0022	(3.269)
NcPAY_{t-1}	0.089*	0.0167	(5.333)	-0.007	0.0117	(-0.592)
WALLet_{t-1}	0.092*	0.0173	(5.309)	0.031**	0.0121	(-2.525)

*, **, *** indicates statistical significance at 1%, 5% or 10%.

Table 10: VECM regressions' Coefficient

ETC:	ΔBTCRn_t	ΔSupBTC_t	ΔTrVOL_t	ΔNETDiF_t	ΔHASHr_t	ΔTRANFe_t	ΔNcPAY_t	ΔWALLet_t
c	-0.003	0.000	0.094	0.000	-0.012	0.021	0.016	0.001
	(-0.850)	(39.98)	(2.756)	(0.248)	(-1.411)	(1.479)	(1.815)	(10.58)
ΔBTCRn_{t-1}	0.089**	0.000	0.078	0.016	-0.327	0.283	0.213	-0.002
	(2.135)	(1.470)	(0.258)	(1.396)	(-4.468)	(2.174)	(2.721)	(-1.274)
$\Delta\text{SupBTC}_{t-1}$	0.196**	-0.279	-1168.4	8.177	150.2	-263.0	-119.6	-3.933
	(1.979)	(-9.549)	(-3.127	(0.571)	(1.658)	(-1.634)	(-1.239)	(-2.495)
ΔTrVOL_{t-1}	0.668***	0.000	-0.332	0.000	0.014	-0.040	-0.013	0.000
	(1.604)	(4.051)	(-13.45)	(0.037)	(2.370)	(-3.763)	(-2.104)	(-0.602)
$\Delta\text{NETDiF}_{t-1}$	0.043	0.000	0.559	0.243	-0.136	1.352	0.177	-0.005
	(0.559)	(0.223)	(0.729)	(8.285)	(-0.733)	(4.095)	(0.892)	(-1.432)
ΔHASHr_{t-1}	-0.063*	0.000	-0.131	0.008	-0.324	0.031	-0.037	0.000
	(-5.469)	(-2.737)	(-1.142)	(1.850)	(-11.69)	(0.620)	(-1.264)	(0.833)
$\Delta\text{TRANFe}_{t-1}$	0.016*	0.000	1.281	0.001	-0.007	0.039	-0.119	0.000
	(3.236)	(-0.753)	(25.84)	(0.457)	(-0.580)	(1.831)	(-9.277)	(-0.942)
ΔNcPAY_{t-1}	0.070*	0.000	0.341	-0.003	0.237	1.685	-0.131	0.000
	(5.848)	(-1.683)	(2.855)	(-0.744)	(8.193)	(32.78)	(-4.247)	(0.990)
$\Delta\text{WALLet}_{t-1}$	-0.173	-0.001	0.560	-0.067	0.624	-1.514	-6.650	-0.196
	(-0.244)	(-1.916)	(0.079)	(-0.247)	(0.365)	(-0.499)	(-3.654)	(-6.594)
α_1	-2.716	0.000	-0.103	-0.022	0.206	-0.824	0.218	0.000
	(-22.21)*	(1.102)	(-1.817)	(-1.827)	(5.445)	(-0.432)	(-1.236)	(1.039)
α_2	-0.199	-0.001	-2.433	-0.058	0.651	-0.673	-0.328	-0.005
	(-3.473)*	(-25.04)	(-4.255)	(-2.650)	(4.688)	(-2.731)	(-2.219)	(-2.194)
Statistics								
$\bar{R}^2$	0.831	0.631	0.786	0.211	0.763	0.650	0.653	0.473
F-stat	269.02	94.25	201.37	15.61	176.72	102.47	103.73	49.913

*, **, *** indicates statistical significance at 1%, 5% or 10%.

The diagnostic examination [Table 11] confirms adequacy of the VECM regression. The VEC serial Correlation show that the LM statistic fail to reject the null of no serial correlation for both lag 1 and 2, amongst system's residuals at the significance level of 5%. The residuals is not heteroscedastic as the Breusch-Pagan-Godfrey test is insignificant with p-values (0.826), which is more than 0.05 level, supposing the test cannot reject the null. The Jarque-Bera statistic indicates that the normality null of distributed stochastic errors is insignificant and the residuals are not multivariate normal. This would not pose any problem since stability is confirmed for the VECM, given that the obtained Eigen values are contained within the unit circle. This is expected since the significance of the variables indicate that the long-run estimates will be stable, and the short-run dynamics are sustained to the convergence long-run cointegrating equation. Lastly, the Theil inequality coefficient for variation in bitcoin returns forecast 0.0976 (Figure 5.4) is small and distance from 1, indicative that the VEC model is good fit and capable of generating better forecasts.

Table 11: Robustness tests

	Serial Correlation		Heteroskedasticity		Normality [Joint] Test	
Lags ⟹	1	2				
LM-Stat	3.7051	2.2522	$\mathcal{X}^2$-stat[a].	0.8931	JB-stat. (Joint)	1685*
	(0.116)	(0.185)		(0.621)		0.000
			$\mathcal{X}^2$-stat[b].	5049.4		
				(0.000)		

[a] VEC Residual Heteroskedasticity Tests excludes Cross Terms (only levels and squares).
[b] VEC Residual Heteroskedasticity Tests includes Cross Terms. *, **, *** indicates statistical significance at 1%, 5% or 10%.
JB-stat. – Jarque-Bera statistics is join test, which combines both the skewness and kurtosis tests.

Table 11: Forecast Evaluation

Variable	RMSE	MAE	MAPE	Theil
ΔBTCRn_t	0.0640	0.0450	1373.5	0.0976
ΔSupBTC_t	17.985	17.980	99.999	0.2499
ΔTrVOL_t	29.938	29.931	99.999	0.1637
ΔNETDiF_t	12.989	12.989	99.990	0.4993
ΔHASHr_t	16.700	16.700	99.994	0.1241
ΔTRANFe_t	3.4457	3.4311	99.973	0.3104
ΔNcPAY_t	19.493	19.466	99.998	0.3314
ΔWALLet_t	17.623	17.621	99.994	0.1666

RMSE: Root Mean Square Error; MAE: Mean Absolute Error; MAPE: Mean Absolute Percentage Error; Theil: Theil inequality coefficient

5. Conclusions

In the cryptocurrency market, unprecedented price and return shocks are connected to responses from change in mining information (such as network difficulty, Hash-rate, and total transaction fees), network actions (including the numbers of confirmed payments and user's adoptions) and market forces (such as the total bitcoin supply and trade volume on exchanges). The existence and changes in these factors trigger different protrusions which may cause persistent fluctuations in Bitcoin price and return. This paper supposes that these factors are major determinants that explain sporadic variations in bitcoin returns. Through the VECM equations, which can interpret long term and short term dynamics, the study recovers the effects of considered factors on the dynamics of Bitcoin returns. Similar to previous studies (Guizani & Nafti, 2019; Kjærland et al., 2018), the evidence established a long run equilibrium relationship between bitcoin returns and all identified non-stationary markets and network factors.

Based on the outcome, the study propose some recommendations. First, there should be increase in regulation to curb excessive fluctuations that can cause significant loss to the returns and discourage digital investors. Second, stakeholders in the markets should ensure campaigns to encourage more user's adoption and institutional acceptance. The study has few limitations, as it does not include any stock market and other external variables that may have influence on the bitcoin markets (Liang et al., 2020; Aalborg et al., 2018; Kjærland et al., 2018). We suggest that future research may consider this as well asinclude sensitivity check to verify possible influence of data periodicity on the outcomes.

Funding

The research has no funding.

Conflicts of Interest

The authordeclares no conflicts of interest.

References

Aalborg H. A., Molnar, P., & Erik de Vries, J. (2018). What can explain the price, volatility and trading volume of Bitcoin? *Finance Res Letters*. https://doi.org/10.1016/j.frl.2018.08.010.

Baur, D. G., Hong, K., & Lee, A. D. (2018). Bitcoin: Medium of exchange or speculative assets? *Journal of International Financial Markets, Institutions and Money*, 54, 177–189. https://doi.org/10.1016/j.intfin.2017.12.004 .

BitPremier (2020). The bitcoin volatility index. https://www.bitprmier.com/volatility-index. Accessed October 15, 2022.

Blau, B. M. (2018). Price dynamics and speculative trading in Bitcoin. Research in International Business and Finance. 43(2018), 15-21. http://dx.doi.org/10.1016/j.ribaf.2017.07.183.

Blockchain.com (2021) (https://www.blockchain.com/charts/market-price.

Catania, L., Grassi, S., & Ravazzolo, F. 2019. Forecasting cryptocurrencies under model and parameter instability. *International Journal of Forecasting*, 35, (2), 485–501. https://doi.org/10.1016/j.ijforecast.2018.09.005.

Ciaian, P., Rajcaniova, M., & Kancs, A. (2014). The economics of bitcoin price formation. http://arxiv.org/pdf/1405.4498. Accessed October 16, 2022.

Corbet, S., Meegan, A., Larkin, C., Lucey, B., & Yarovaya, L. 2018. Exploring the dynamic relationships between cryptocurrencies and other financial assets. *Economics Letters*, 165, (C), 28–34, https://doi.org/10.1016/j.econlet.2018.01.004.

Cvetkova, I. (2018). Cryptocurrencies Legal Regulation, *BriCs Law Journal*, 5(2), 128–153. https://doi.org/10.21684/2412-2343-2018-5-2-128-153.

das Neves, R. H. (2020). Bitcoin pricing: impact of attractiveness variables. *Financial Innovation*, 6:21. https://doi.org/10.1186/s40854-020-00176-3.

Deniz, A. E., & Teker, D. (2019). Determinants of Bitcoin prices. *Press Academia Procedia* 10, 17–21 http://doi.org/10.17261/Pressacademia.2019.1136.

Dwyer, G. P. 2015. The economics of Bitcoin and similar private digital currencies. *Journal of Financial Stability*, 17(April), 81–91. https://doi.org/10.1016/j.jfs.2014.11.006.

Engle R. F., & Granger, C. W. J. (1987). Cointegration and error correction: representation, estimation and testing. *Econometrica* 55 (2), 251–276. https://doi.org/10.2307/1913236

Kjærland , F., Khazal, A., Krogstad, E., Nordstrøm, F. B., & Oust, A. (2018). An analysis of bitcoin's price dynamics. *Journal. Risk Financial Mgt.* 11(4), 63; https://doi.org/10.3390/jrfm11040063.

Giudici, P., & Abu-Hashish, I. (2018). What determines bitcoin exchange prices? A network VAR approach, *Finance Research Letters*, https://doi.org/10.1016/j.frl.2018.05.013.

Guizani, S., & Nafti, K. (2019). The determinants of bitcoin price volatility: An investigation with ARDL model. *Procedia Comp Sci.*, 164, 233–238. https://doi.org/10.1016/j.procs.2019.12.177.

Huang J., Huang, W., & Ni, J. (2019). Predicting Bitcoin returns using high-dimensional technical indicators. *J. Finance Data Sci.* 5(3),140–155. https://doi.org/10.1016/j.jfds.2018.10.001.

Hung, J., Liu, H., & Yang, J. J. (2020). Improving the realized GARCH's volatility forecast for Bitcoin with jump-robust estimators. *North American Journal of Economics and Finance* 52 (2020) 10116. https://doi.org/10.1016/j.najef.2020.101165

Jeon, Y., Samarbakhsh, L., & Hewitt, K. (2020). Fragmentation in the Bitcoin market: Evidence from multiple coexisting order books. *Finance Research Letters*. https://doi.org/10.1016/j.frl.2020.101654.

Ji, Q., Bouri, E., Kristoufek, L., & Lucey, B. (2019). Realised volatility connectedness among Bitcoin exchange markets, *Finance Research Letters*, https://doi.org/10.1016/j.frl.2019.101391.

Julio C. S. (2017). Analyzing bitcoin price volatility. University of California, Berkeley, https://www.econ.berkeley.edu/sites/default/files/Thesis_Julio_Soldevilla.pdf.

Karkkainen, T. (2018). Price discovery in the bitcoin futures and cash. SSRN, http://dx.doi.org/10.2139/ssrn.3243969.

Kjærland F., Khazal A., Krogstad E. A., Nordstrøm G. B., & Oust A. (2018). an analysis of bitcoin's price dynamics. *Journal of Risk and Fin. Mgt.*, 11, 63. https://doi.org/10.3390/jrfm11040063.

Kristoufek, L. (2015). What are the main drivers of the bitcoin price? Evidence from wavelet coherence analysis. PLoS ONE 10(4): e0123923. https://doi.org/10.1371/journal.pone.0123923.

Lansky, J. (2016). Analysis of cryptocurrencies price development Acta *Informatica Pragensia* 5(2):118-137, https://doi.org/10.18267/j.aip.89.

Li, X, & Wang, C. A., 2016. The technology and economic determinants of cryptocurrency exchange rates: The case of Bitcoin, *Decision Support Systems* 95, https://doi.org/10.1016/j.dss.2016.12.001

Liang, C., Zhang, Y., Li, X., & Ma, F. (2020). Which predictor is more predictive for Bitcoin volatility? And why? *Int. J, Fin Econ.*, 1–15. https://doi.org/10.1002/ijfe.2252.

Liu, Y., & Tsyvinski, A. 2(021). Risks and returns of cryptocurrency. *The Review of Financial Studies*, 34(6), 2689–2727. https://doi.org/10.1093/rfs/hhaa113.

Luu, T., & Huynh, D. (2019). Spillover risks on cryptocurrency markets: A look from VAR-SVAR granger causality and Student's-t Copulas. https://doi.org/10.3390/jrfm12020052

Matkovskyy, R. & Jalan, A. (2019). From financial markets to bitcoin markets: A fresh look at the contagion effect. *Finance Res. Letters 31*, 93–97. https://doi.org/10.1016/j.frl.2019.04.007.

Erdas, M. L, & Caglar, A. E. (2018). Analysis of the relationships between Bitcoin and exchange rate, commodities and global indexes by asymmetric causality test. *Eastern Journal of European Studies*, 9, 27–45, https://ejes.uaic.ro/articles/EJES2018_0902_ERD.pdf

Murphy, E. V. (2015). Bitcoin: Questions, answers, and analysis of legal issues. *Congressional Research Service 7-5700*. https://sgp.fas.org/crs/misc/R43339.pdf

Philippas, D., Rjiba, H., Guesmi, K., & Goutte, S. (2019). Media attention and Bitcoin prices. *Finance Res Letter*, 30, 37–43. https://doi.org/10.1016/j.frl.2019.03.031

Poyser, O. (2019). Exploring the dynamics of Bitcoin's price: a Bayesian structural time series approach. *Eurasian Econ Rev*, 9, 29–60. https://doi.org/10.1007/s40822-018-0108-2.

Sathyanarayana, S., & Gargesa, S. (2019). Modeling cryptocurrency (bitcoin) using vector autoregressive model. SDMIMD J. of Mgt. https://doi.org/10.18311/sdmimd/2019/23181.

Schueffel, P. and Hammer, H. (2020). Regulations and bans – what threatens crypto, bitcoin & co. *Blockchain in Financial Markets*. https://morethandigital.info/en/central-bank-digital-currency-cbdc-digital-money-for-our-central-banks/.

Shen, D., Urquhart, A. and Wang, P. (2019) Does Twitter predict Bitcoin? *Economics Letters*, 174, 118–122, https://doi.org/10.1016/j.econlet.2018.11.007.

Sovbetov, Y. (2018): factors influencing cryptocurrency prices: Evidence from Bitcoin, Ethereum, Dash, Litcoin, and Monero. *Journal of Economics and Financial Analysis*, 2(2), 1-27. https://mpra.ub.uni-muenchen.de/id/eprint/85036.

Troster, V., Tiwari, A.K., Shahbaz, M. & Macedo, D.N. (2018). Bitcoin returns and risk: a general GARCH and GAS analysis. Finance Res. Lett Article in Press. https://doi.org/10.1016/j.frl.2018.09.014

Wang, J., Xue, Y., & Liu, M. (2016). An Analysis of Bitcoin Price Based on VEC Model. International Conference on Economics and Management Innovations (ICEMI 2016). https://doi.org/10.2991/icemi-16.2016.36

Wang, J.N., Liu, H, C., & Hsu, Y. T. 2020. Time-of-Day Periodicities of Trading Volume and Volatility in Bitcoin Exchange: Does the Stock Market Matter? Finance Research Letters 34:101243. https://doi.org/10.1016/j.frl.2019.07.016

Yechen, Z., Dickinson, D., & Jianjun, L. (2016).What Influences Bitcoin's Price? A VEC Model Analysis. Proceedings of the Fourth European Academic Research Conference on Global Business, Economics, Finance and Bankin, Zurich, Switzerland. July 7-9.