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BANKING & FINANCE | RESEARCH ARTICLE

BTC price volatility: Fundamentals versus information

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Abstract: This paper offers a plausible response to "what explains the sporadic volatility in the price of Bitcoin?" We hypothesized that market "fundamentals" and "information demands" are key drivers of Bitcoin's unpredictable price fluctuation. We adopt the transfer-function [Autoregressive Distributed Lag, ARDL] model and its Bounds testing approach to verify how the volatility of the price of Bitcoin responds to its transaction volume, cryptocurrency market capitalisation, world market equity index and Google search. We found the existence of long-run cointegration relation and observed that all the variables except the equity index positively explain the volatility of Bitcoin price. The result established evidence that market fundamentals drive erratic swing in Bitcoin price than information.

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PUBLIC INTEREST STATEMENT

In recent times, finance experts, researchers and regulators are concerned about the cryptocurrency "Bitcoin" and the incessant erratic swings in its price. This paper offers an explanation to what may cause the sporadic volatility in the price of Bitcoin. Unlike typical financial assets, such as commodities, bonds, stocks, for which price swings are largely determined by fundamentals (of demand and supply), the volatility of Bitcoin price is affected by information search on social network. Hence, we employed the ARDL model and its Bounds testing approach to confirm how the volatility of Bitcoin price response to fundamentals as Bitcoin transaction volume and price, as well as other factors as world market equity index and the information (Google) search. We found strong evidence that fundamentals drive erratic swing in Bitcoin price than information.

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Subjects: Economics; Corporate Finance; Investment & Securities
Keywords: Bitcoin price volatility; Bitcoin market fundamentals; information demand; ARDL
Jel classification: C10; G15; G17

1. Introduction

BTC, a portmanteau for "Bitcoin", is a burgeoning technological innovation and the first decentralized finance (DeFi) digital money invented by a person (or group) under the pseudonym Satoshi. The cryptocurrency relies on peer-to-peer (P2P) transactions, anonymity, and transparency, as well as employs interface integrated with social networks and hardware tokens. Like traditional money, BTC serves as medium of payments, exchange for alternative cryptocurrencies or fiat currencies but remained uncoordinated by monetary policy of the Reserve Banks (Aalborg et al., 2018; Mikhaylov, 2020).

BTC is likewise considered as an investment product. Kurka (2019) argued that the turbulence in stock and commodity markets motivates investors to seek alternative investment. The Bitcoin's lack of correlation with traditional assets makes it an attractive option in its fast developing market. With recent formal launch of Bitcoin standardize futures in regulated exchanges, some institutional investors and experts now deliberate BTC as a safe haven or a hedge option (Hughes et al., 2019; Kharpal, 2020). The huge investment in Bitcoin drives significant increases in the number of established decentralized exchange (DEX) that serve as platforms for trading the coins (Kristoufek, 2018). These platforms and market are largely dominated by technology enthusiasts, liberalist traders (Silva et al., 2019), and, fraudsters taking advantages of unsophisticated P2P participants.

The BTC transactions are managed on an open-source system "Blockchain" which applies sophisticated protocol to generate, record, and verify transactions (Smales, 2019). There are 21 million BTCs assumed to be configured in its algorithm's reserve and an estimated 84% have been mined. The supply is projected to have lost about 20% tokens, which unlike fiat money cannot be reprinted or return to circulation (Nathan, 2019). The limited supply, irrecoverable loss and increase in transaction have implications for its swings. Since inception the price of BTC has swing with unpredictable ups and downs movements meted with strong resistance, supports, breakthrough, jumps, consolidations, and corrections in different price episodes. The price of bitcoin increase by over 2000%, and reportedly peaked around $19,400 in December, 2017. By July 2018, it has declined to $12,500 and stood at $7200 in December 2019. The volatility continues and the price has experience massive run-up, reversal and consolidates around $40,000 in July 2021.

The extreme volatility of BTC price has attracted much growing interests among experts. Economists suppose that Bitcoin and its fundamentals differ from those of convention assets as stocks, bonds or foreign exchanges because Bitcoin is not a corporation. There is no known balance sheets, at least at the moment, to review before making decision to invest in Bitcoin, "stablecoins" or alternative DeFi assets. Hence, the volatility of Bitcoin is influenced by factors such as the supply-demand for Bitcoin, as much as spillover of alternative cryptocurrencies. As noted by Guizani and Nafti (2019), the excessive fluctuation in Bitcoin price is occasioned by increase demand, short-term noises, news shock, sophisticated traders trend chasers), naïve traders, and speculators. Some empirical evidence attributed the fluctuation in BTC price to simply supply-demand fundamentals, its returns (Dufour & Engle, 2000; Jain & Jiang, 2014; Julio, 2017; Guizani & Nafti, 2019) and information search on Bitcoin (Kjærland et al., 2018).

In this paper, we attempt to respond to the pertinent issue on "what explains erratic swings in BTC price?" We provide more insights to this incessant debates by dichotomizing the drivers of Bitcoin price volatility into market "fundamentals" and "information demand". The paper advance literature in empirical finance by analyzing within the framework of dynamic modelling that market forces such as price, volume and network search for the word "bitcoin" are the factors that explains the volatility

in the price of Bitcoin. The rest of the study is organized such that sections 2, 3, 4, 5, and 6, respectively, present the BTC price trends, empirical review, methodology, results and conclusions.

2. BTC price trends

The BTC price has sporadically increase and associated with high volatility. In 2009, BTC trades for almost nothing as there was no exchange for the coin. In 6 February 2010 the first official Bitcoin Exchange was launched. As reported (Bitcoinwiki, 2014) in March 2010, a user could not sell 10,000BTCs auction for $50. On 22 May 2010 Bitcoin was first sold online at $0.0025—an historic purchase of Domino's pizza for 10,000BTCs at $25. By July 12, the price increased to $0.008, and later rose 1000% from $0.008 to $0.08 by July 17. In January 2011, the price rose to $0.30, and became par with the US dollar in February. The price rose to $31.50 on June 8, and declined to $11.00 in July and $5.27 at the end of December, 2011.

In 2012, the price which started at $5.27 grew to $7.38 by January 9, crashed later to $3.80, and consolidated around $13.30 gaining about 154% in December. In March 2013 the first Bitcoin regulation was issued by the US Financial Crimes Enforcement Network (FinCEN) as guidelines for persons administering or exchanging Bitcoin. Within few weeks, the BTC market capitalisation reached $1bn and Bitcoin moves above $500. BTC hits $770 in January 2014 but fell to $314 at December, 2014 and to $434 at end of 2015.

In 2016, the price spiked to $998, and experience spectacular increase up to $2800 in August, 2017. The price protruded over 1350% to a peak of $19,783.06 on 17 December 2017, making some institutional investors like the US Chicago Board Options Exchange] to launched Bitcoin futures and began to offered daily contracts on Bitcoins futures. The unprecedented spike decreased about 45% to begin at $13,412.44 on 1 January 2018. By October 31, bitcoin price has declined to $6,300. The price could not hold on the $6,000 rally during a low volatility era, hence fall to $4,000 in November. The BTC price steadily rose to $8721 by May 29 and later to $12,500 in July. In 2019, BTC price which started with $3700 steadily rose and stood at $7200 by December 31. The increase and volatility continues and by November 2020, as reported (CME Group, 2021; Finance.yahoo.com, 2021; Reuter Staff, 2017), the price rallied above $18,000 gaining all losses from previous peak.

Since mid-2020, the role of information tweet in influencing the price of bitcoin price has been more pronounced. The September's announcement by Canton of Zug (Switzerland) to accept tax payments and Elon Musk's tweet to accept bitcoin for Tesla's car purchase caused bitcoin price to skyrocket beyond previous 2017 peak (Browne, 2021). Tesla's purchase of bitcoins of USD $1.5 billion and announced plans to accept BTC for vehicle payment on 8 February 2021 pushed the bitcoin price to $44,141 (Li, 2021). Bitcoin worth over $62,000 USD in both February 2021 and April 2021 due to events and information which involve Tesla and Coinbase announcements. In same period, the Bitcoin market capitalisation reached its all-time high of over $1 trillion, and had since decline roughly around $600 billion in June 2021. At the moment, the price has revolved around $40,000.00 in late July, 2021.

Figure A1(a–f) represents plots for the observed daily Bitcoin price (01\0115–11\01\21), and for two different episodes (01\0115–30\06\19) and (01\0719–11\01\2021), as well as, for the first difference and for log daily price and log-difference price. The plots show that the price follows a nonlinear pattern. Bitcoin volatility reached about 8% in a 90 days span between October 2017 and January of 2018. This is twice its volatility in a 28-day period from 17 December 2019 to 13 January 2020.

3. Empirical review

Most empirical literature on Bitcoin focus on: BTC price formation, relationship between BTC and financial market assets, BTC as speculative bubbles, BTC shares in cryptocurrency market with alternative crypto-asset, BTC time-of-day periodicities of trading, and the estimation of BTC price

volatility. Some papers discuss factors that drive BTC price as macroeconomic and financial development (Pyo & Lee, 2020); technology (Kjærland et al., 2018; Li & Wang, 2017) and the market efficiency (Nadarajah & Chu, 2017).

On relation with traditional assets, some studies (Bouri et al., 2018; Kurka, 2019; Smales, 2019) claim BTC holdings doe not serve as a safe haven for global assets, while Bouoiyour and Selmi (2015) support that BTC serves as a safe haven, and hedges for oil price fluctuation. Matkovskyy and Jalan (2019) argued that during financial crisis, risk-averse investors avoid Bitcoins as it is considered riskier than other assets. Ji et al. (2019) argued that the attractiveness of Bitcoin is a major determinant of other cryptocurrencies. Some authors (Baur et al., 2018; Cheah & Fry, 2015; Corbet et al., 2018) claimed that BTC is a speculative bubbles as its fundamental value cannot be estimated or is equal to zero. Goutte et al. (2019) and Jeon et al. (2020) provided a survey on the mechanisms of BTC exchange and crypto-finance, while Troster et al. (2018) analysed the implications of volatility for the BTC market. Some studies (Acharya et al., 2018; Baur et al., 2019; Eross et al., 2019; Koopman et al., 2005; O'Hara, 2015) focused on time-of-day periodicities of trading in Exchanges. Urquhart (2018) focused on the examination of price clustering, while some studies (Hung et al., 2020; Troster et al., 2018) focused on the estimation of volatility models.

Available evidence (Aalborg et al., 2018; Cebrián-H & Jiménez-Rodríguez, 2021; Guizani & Nafti, 2019; Ji et al., 2019; Kjærland et al., 2018; Liang et al., 2020; Poyser, 2017; Wijk, 2013) discuss the determinants of BTC price (BTCV) volatility. Wijk (2013) analysed the impact of macroeconomic- and financial development factors on BTCV. He checks the impact of exchange rates, oil price and market indices as Equity index, Dow-Jones index and Nikkei index on price volatility. The results shows negative effects for oil price and Nikkei index, but positive effects both Equity index and DJ index on BTC price variability.

Poyser (2017) applied the Bayesian structural approach to analyse the effect of investor's sentiments, gold, and stock index on BTC price volatility. The results showed that the volatility relates positively with USD/Euro rate, stock index and difference among countries' search trends, while negatively associated with gold price, investor's sentiment and Yuan/USD rate. Yechen et al. (2017) applied a Vector error correction on monthly data to explain how BTC price volatility depends on custom price index, US dollar index, Dow jones index, Federal funds rate and gold price. They found that all variables have a long-term influence. Trade volume has positive effect on BTC volatility price. The US dollar index is the biggest influencer, while gold is the least.

Kjærland et al. (2018) applied the Autoregressive Distributed Lag (ARDL) model and generalized autoregressive conditional heteroscedasticity (GARCH) approach to examine BTC price volatility. They identified that technological factor "Hashrate" is immaterial in modelling BTC price dynamics, and verify the effect of Google searches, returns on S&P 500, volatility (VIX) index, oil price, gold price and BTC transaction volume on BTC prices. The Google searches and returns on S&P 500 have positive and significant effect on BTC price volatility, while VIX, oil, gold, and volume to be insignificant. Aalborg et al. (2018) analysed the effect of transaction volume, VIX index and Google searches for "Bitcoin" on the prediction of volatility of BTC price. They applied realized volatility computed from high-frequency data and found that the autoregressive model is suitable for BTC volatility. The trading volume variable shows a positive effect on the volatility model.

Ji et al. (2019) explained the system of BTC exchanges relative to their common dynamics. They considered the connectedness measures based on the daily realised volatility of BTC price. They hypothesized that the positions of specific exchanges within the cryptocurrency network connectedness seems to be driven by individual's exchange's unique characteristics. The paper employed high-frequency data that results reveal that while Binance exchange ranks is weak, the exchange "Coinbase" leads the crypto market. The paper concluded that asset withdrawal explains more of the price volatility amongst individual exchanges than the trade volume.

Guizani and Nafti (2019) explain the reason for excessive BTC price volatility. The paper employs the ARDL and the Granger causality on daily time series to dynamically explain how number of BTC addresses, attractiveness indicator, mining difficulty, transaction volume, stock and EUR/USD rate, macroeconomic and financial development affect Bitcoin price volatility. The result suggests that the number of addresses and the mining difficulty have a significant impact on the BTC price volatility. The stock, the exchange rate, transaction volume and the macroeconomic and financial development do not determine the price of the BTC in the short- and long term.

Liang et al. (2020) applied GARCH-MIDAS model to analyse the impact of VIX, Google Trends, and GPR on bitcoin price and provide strong evidence that Google Trends exhibits strongest predictability for Bitcoin volatility over other competing predictors. Cebrián-H and Jiménez-Rodríguez (2021) applied GARCH and multivariate GARCH (MGARCH) between 1 January 2011 and 31 December 2018 to consider the role of Gold, Brent oil, exchange rates, S&P500, Nikkei 225, VISA and MasterCard transaction, Riot Blockchain, Nvidia on bitcoin prices. He discovered that there exist conditional correlation between the volatility of VISA, MasterCard, Riot Blockchain, Nvidia and Bitcoin, but not with the traditional assets as oil and gold.

4. Data and methodology

4.1. The data

The data for this study are obtained from four sources: www.Google.trends.com, www.bitcoincharts.com; www.nasdaq.com; and www.Blockchain.com. In line with some studies (Aalborg et al., 2018; Ji et al., 2019; Kjærland et al., 2018; Yechen et al., 2017), we applied monthly data between 2013M6 and 2021M6. The bitcoin price adopted is the simple unweighted average of monthly closing price. We focused on the periods for which the volume of bitcoin transaction was considerably increased (Kjærland et al., 2018), and the digital coin has gained attractions. Prior to June 2013, the attraction and transactions volume of bitcoin were relatively low (Guizani & Nafti, 2019).

Unlike some studies (Dwyer, 2015; Kjærland et al., 2018; Wang et al., 2019) that considered blockchain technology factor such as “Hash Rates” as determinant of bitcoin prices volatility, we focus solely on the effects of markets fundamental and information demand for the cryptocurrency. In sum, we employ Bitcoin price, Transaction volume, World market equity index, Cryptocurrency market capitalization, Information demands and the Bitcoin price volatility. The variables are in log form in accordance with analogous Bitcoin study by Pyo and Lee (2020). The logarithmic transformations are done to ensure that the cointegration relationship is preserved while the heteroscedasticity is eliminated series. We discuss each variable in details.

4.1.1. Market fundamentals

The supply and demand for Bitcoin, like other assets in the financial market and foreign exchange market are the two main market fundamentals of price formations. Li and Wang (2017) notes that the demand indicator for BTCs have greater implication for its fluctuation than its reserves fixed supply. We follow some theoretical models on a positive relation between price volatility and trading volume in the financial markets. The common ones amongst these models are “mixture of distributions” models. Taylor (2017), “asymmetric information” models and “differences in opinion” models. According to the “asymmetric information” models, investors submit trades based on available private information. As noted by Bian, Chan and Selgin (2015) as informed investors increase trade volume, volatility increases due to information generated. The literature on the “differences in opinion” approach propound that relatively homogeneous beliefs drives excess price-volatility and excess volume, in relation to a more stable value of the asset.

Unlike asymmetric information, the proponents of the approach establishe that volatility-volume connection depends on who generates the volume, and why they are trading. Informed traders tend to buy and sell within a relatively stable range of prices about the equilibrium value. Bian found that a positive volatility-volume relation is driven by the public investors in the futures

markets for assets. For Bitcoin volatility-volume relation, found that the ability for investors to withdraw asset impacts more on the volatility through various Exchanges and trading volume. Both theoretical and empirical studies have focused on investigating the sources volatility-price relation and intraday price variations (Jiang et al., 2019). These models are based on market microstructure that explore the mechanics of price formation and its relevance to market volatility. The model suggests that traditional volatility models can be augmented with the time-series of the daily price.

Jiang et al. (2019) used a panel VAR estimation to examine the importance of price impact resulting from the order book predicting stock volatility. They found that the price impact at the daily level is a major determinant of stock volatility dynamics. When the traditional volatility models was augmented with the time-series of daily price impact, the volatility becomes more accurately predicted at the one-day ahead forecasting horizon. The inclusion of the price variable is needful as it as well helps improve the robustness of the model. Hence, as with some recent notable studies (Guizani & Nafti, 2019; Kjærland et al., 2018), we use BTC transaction volume (TVOL) and BTC price (BTCP) as proxies for its fundamentals. We expect both BTCP and TVOL to have positive impact on Bitcoin price volatility.

4.1.2. Market capitalisation

The market capitalization is a major factor that affects cryptocurrencies. Market capitalization is obtained by multiplying the total number of Bitcoins in circulation by its own price. Lansky (2016) considered the role of market capitalisation in in influencing the price of major cryptocurrencies. Yhlas (2018) applied an index of market capitalisation for 50 selected top coins. We would expect that a higher market capitalisation would provide a good chance for traders to get hands over higher profits. We use MCAP as proxies for cryptocurrencies market capitalization.

4.1.3. World market (equity) index

Some papers explain how volatility in globally asset markets transfer between markets and countries. These authors (Aalborg et al., 2018; Cebrián-H & Jiménez-Rodríguez, 2021; Guizani & Nafti, 2019; Julio, 2017) incorporate financial development index or world market index—an indication of overall global state of markets, which is expected to stimulate demand, hence causes increase in volatility. Some studies applied the Equity index as Dow-Jones (DJ) index (Liang et al., 2020; Wijk, 2013; Yechen et al., 2017) and Nikkei 225 (Cebrián-H & Jiménez-Rodríguez, 2021; Poyser, 2017; Wijk, 2013), but we incorporate the Morgan Stanley Capital International (MSCI)'s All Country World Index proxy as ACWI. The ACWI is a capitalization-weighted index, covering over 3,000 stocks, that measures global equity performance capturing both developed and emerging markets. We expect the ACWI to have positive higher impact on Bitcoin price volatility.

4.1.4. Information demands

Information shock causes BTC price to spike beyond values consistent with fundamentals within minutes of disclosure. Some empirical studies (Kjærland et al., 2018; Li & Wang, 2017; Poyser, 2017) considered how BTCV is affected by social network, news and search queries. Luu and Huynh applied VAR and SVAR to confirm the role of 'bad news and moving patterns on the spillover risks amongst cryptocurrency markets. While Pak and Paroubek (2010) and Abraham et al. (2018) focus on twitter tweets as a major source of information demand, we work in line with studies (Liang et al., 2020) that focus on Google search. In line with these authors, we verify how frequency of queries for the word "bitcoin" on Google-Trend explains erratic swings in its price. The Google Trend reports the amount of search queries relative to the total amount of Google searches over time. This method generates values that are normalized on a scale from zero to 100.

We favour the use of Google trend for two reasons. First, although both Google trend and Twitter tweets show strong correlation with bitcoin prices but unlike Google trend tweets may fluctuate with prices in a different directions Abraham et al. (2018). The Google search is established to exhibit strongest predictability for Bitcoin volatility over other competing search predictors (Liang

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Table 1. Summary of variables

	Variable	Proxy	Abbreviate	Apriori	Reference
1	Bitcoin price	BTC time series	BTCP	+	Kjærland et al. (2018), Guizani and Nafti (2019)
2	Bitcoin demand	BTC transaction volume	TVOL	+	Guizani and Nafti (2019)
3	Market capitalisation	Market Capitalisation	MCAP	+	Lansky (2016), Yhlas (2018)
4	World market index	MSCI-ACWI index	ACWI	+	Yechen et al. (2017)
5	Information demands	Google-trend	IFOD	+	Poyser (2017), Kristoufek (2018)
6	Bitcoin price volatility	BTC price realised volatility	BTCV	NA	Adkins (2019), Boyte-White (2020)

NA: Not Applicable, BTCV is the dependent variable.

et al., 2020). Second, as reported (Clement, 2020) Google accounted for 87.35% of global market shares of search engine as of January, 2018. We expect high information search (IFOD) to have positive impact on Bitcoin price volatility.

4.1.5. Bitcoin price volatility

We adopt the historical volatility to compute the realised volatility for each month of our data span using available daily bitcoin price. Historical volatility is measured by applying 'summing squared daily returns within each month. This method which applies the daily data $BTCP_{d,t}$ to compute volatility reduces the possibility of error of approximations and gives the accurate representation and serves as guide for investors and analysts (Boyte-White, 2020). To obtain the volatility we first compute the daily BTCP returns series with $BTCR_{d,t} = \left(BTCP_{d,t}/BTCP_{d,t-1}\right)$ and use same calculate the realised volatility as summing squared daily returns within a 21-day time horizon defined as: $BTCV_{m,t} = \sum_{t=1}^{n=21} \left[BTCR_{d,t}\right]^2$.

Table 1 presents a summary of variables for the empirical model.

4.2. The methodology

This study estimates the relationship between the volatility of bitcoin prices and their attendant (explanatory) variables. As applied in previous studies (Bariviera, 2017; Guizani & Nafti, 2019; Kjærland et al., 2018; Lahmiri et al., 2018), we adopt a Transfer-function—the Autoregressive Distributed Lag, (ARDL) model which regresses the lag(s) of BTCV on contemporaneous BTCV. This model helps to apply monthly data to examine the short- and long-run factors that influence prices of cryptocurrencies between 2013:M6 and 2021M6. Kjærland et al. (2018) employed the ARDL to show how the technological "Hashrate", Google searches and BTC return influence Bitcoin price volatility. Guizani and Nafti (2019) adopted same to show how the number of BTC addresses, transaction volume and stocks drive BTC price volatility. The ARDL is considered as the major workhorse in dynamic single-equation estimation. We apply the ARDL, as well as its (cointegration) Bounds test to analyse how bitcoin market Fundamentals and Information demands explain the erratic fluctuations in BTC prices. We summarise our estimation procedure in five steps.

First, we present statistics and verify the stochastic property of the data generating process (DSG) with a unit root test for each time series (z_t). We apply Augmented–Dickey–Fuller (ADF); Elliott–Rothenberg–Stock (ERS)'s DF–GLS, & Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test.

The ADF test verifies the stationarity by assuming that z_t follows a DGP as:

$$z_t = a_0 + \varphi z_{t-1} + \sum_{i=1}^{p-1} \delta_i \Delta z_{t-i} + \Omega_t \tag{1}$$

($\delta_i = -\sum_{j=i+1}^{p-1} \varphi_j; i = 1, 2, \cdots, p-1$). Where, p is lag length, and Ω_t is Gaussian white noise. The equation is estimated with least square and test statistics,$\tau_\mu = \hat{\varphi}_T - 1/se(\hat{\varphi}_T)$ is computed, and, $se(\hat{\varphi}_T)$isstandarderrorof$\hat{\varphi}_T$. The unit root null $H_0 : \varphi = 1$ (of non-stationarity) tested against the alternative, φ>1 is rejected if τ_μ>ADF_α, critical value generated by Dickey–Fuller from a limiting distribution.

The DF–GLS test is based on quasi-differencing of intercept, $d(1|\alpha)$ and trend $d(t|\alpha)$ regressors. The approach regresses $d(z_t|\alpha)$ on $d(1|\alpha)$ and $d(t|\alpha)$ to obtain the intercept, $\hat{\beta}_0(\alpha)$ and trend, $\hat{\beta}_1(\alpha)$ estimates, as well as the detrended series, $z_t^d = z_t - \hat{\beta}_0(\alpha) - \hat{\beta}_1(\alpha)t$. The DF-GLS assumes that the DGP for z_t^d with which we obtain the test statistic, τ_τ is:

$$z_t^d = \varphi z_{t-1}^d + \sum_{i=1}^{p-1} \Delta z_{t-i}^d + a_t \tag{2}$$

The test null, $\varphi = 1$ tested (presence of unit root) against the alternative $\varphi = \bar{\varphi}$<1 is rejected, if the test statistics (τ_τ)>ERS_α, critical value provided by ERS (1996).

KPSS test assumes that the DGP for z_t follows a ARIMA$(0,1,1)$ process defined as:

$$\Delta z_t = \theta_0 + a_t - \theta a_t - 1 \tag{3}$$

We obtain the test statistics, $\tau_\eta = T^{-2} \sum_t^T \hat{S}_t^2 / \hat{\sigma}_\ell^2$; $e_t = z_t - \hat{\beta}_0 - \hat{\beta}_1 t$ and $\hat{S}, = \sum_{i=1}^{t} e_i$. $\hat{\sigma}_\ell^2$ is a consistent estimator of the long-run variance, σ^2.[1] The test null, $\theta = 1$, $\tau_\eta = 0$, is check under the alternative τ_η>0 and is rejected if the test statistics, τ_η>$KPSS_\alpha$, critical value reported.

In order to estimate the ARDL model, we apply the Akaike's information criteria (*A1C*) to select optimal lag.

$$AIC(p, q) = \log\hat{\sigma}^2 + 2(p+q)T^{-1} \tag{4}$$

The AIC selects optimal lag by setting two different upper bounds (p_m and q_m) for the orders of $\varphi(B)$ and $\theta(B)$. Where, $\theta = -\psi; \psi_j = \varphi^j$ and ψ is weight of a linear filter or first-order moving average, *MA(1)*. The B is lag operator B, such that $B^j x_t \equiv x_{tj}$. With $\bar{p} = \{0, 1, \ldots, p_m\}$ and $\bar{q} = \{0, 1, \ldots, q_m\}$, AIC select orders p_1 and q_1 such that,

$$AIC\ (p_1, q_1) = \min AIC(p, q)(p \in \bar{p};\ q \in \bar{q}) \tag{5}$$

Where, p and q are two different orders, m is maximum possible lag (upper bound), and $\hat{\sigma}^2$ is covariance matrix of residual and T is number of observation.

Second, we estimate the ARDL model that shows how, y_t is explained by its own pasts y_{t-i} and current, x_t and past, $x_{t-i}$of the explanatory variables. The general $ARDL(p, s_1, \ldots, s_m)$ is:

$$y_t = \beta_0 + \sum_j^m \beta_j x_{j,t} + \sum_{i=1}^p \varphi_i y_{t-i} + \sum_j^m \tilde{\beta}_{j,i} x_{j,t-i} + a_t \tag{6}$$

The estimates of the long-run relationship between y_t and x_t (denoted as, $\hat{\theta}_j$) from (6)[1] is: $\hat{\theta}_j = \hat{\beta}_j / (1 - \Sigma_{i=1}^p \hat{\varphi}_i)$. In estimating (6) we ignores the "*I(1)*-ness" of the series and estimate the nonstationary series with least squares (Pesaran & Shin, 1999).

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Third, once we estimate (6), the next step is to verify if a long-run (equilibrium or cointegration) relationship exists amongst the $I(0)$ or $I(1)$ variables. We apply the ARDL (Cointegration) Bounds test procedure developed by Pesaran and Shin (1999), Pesaran et al. (2001), and Pesaran et al. (2001) introduce two (bounds) tests for cointegration: an *F*-test on the joint null that the coefficients on the level variables are jointly equal to zero or a *t*-test on the lagged level dependent variable. In order to rule out the possibilities of degenerate cases and obtain valid conclusion, both the *F* and *t*- test work under the that assumption the dependent variable is *I(1)*. We adopt the *F*-test for our study. The bounds test check for cointegration by estimating (a reparameterised) regression for Δy_t:

$$\Delta y_t = \beta_0 + \varphi_i y_{t-i} + \sum_{j=1}^{m} \varphi_i^* \Delta y_{t-i} + \sum_{j=1}^{m} \beta_j x_{j,t-i} + \sum_{j=0}^{m} \gamma_{j,i}(B)\Delta x_{j,t-i} + \alpha_t \tag{7}$$

The test null $\left(H_0 : \ \varphi = \beta_j = 0, j = 1 to m\right)$is no cointegration exist. We estimate (8) to compute the statistic, $F_m$and compare with critical value bound (C.V.B.). Pesaran et al. (2001) propose two sets of C.V.B. consistent to the polar cases of all variables being purely $I(0)$ or $I(d)$, where *d* is order of integration. If F_m > Upper C.V.B., the null is rejected (cointegration exists) and vice versa.

Fourth, if cointegration exist we next estimate the Cointegrating equation and Long run coefficients. To obtain the cointegrating regression, the *ARDL* is transformed to include the error correction mechanism *(ECM)* term, $ec_t = y_t - \theta_0 - \sum_{j=1}^{m} \theta_j x_{j,t}$:

$$\Delta y_t = \beta_0 + \sum_{j=1}^{m} \varphi_i^* \Delta y_{t-i} + \sum_{j=1}^{m} \beta_j x_{j,t-i} + \sum_{j=0}^{m} \gamma_{j,i} \Delta x_{j,t-i} - \mu ECM_{t-1} + \varepsilon_t \tag{8}$$

Equation (8) gives estimates for short- and long-run dynamics. The model expresses the current change in the endogenous variable, Δy_t as a linear function of the current change in the exogenous variable Δx_t and a proportion of the previous error from the long-run "equilibrium", ECM_{t-1}. The β_j'*s* denote the long-run coefficients which represent the equilibrium effects of the x_t on change in the dependent variable, Δy_t. The $\gamma_{j,i}$'s are the short-run coefficients which account for fluctuations that are not determined by deviations from the long-run equilibrium. The (sign and) absolute value of μ indicates the speed of adjustment. The *t*–statistic test on coefficients of the short run, $\gamma_{j,i}$shows the impact of each variables on the dependent variable in the short run. We apply the least squares to estimate our models using the coefficient covariance method of HAC.

Fifth since the ARDL equation comprises of $I(1)$ variable(s), as argued by Borensztein et al. (1998), it is required to check for heteroscedasticity and the serial correlation. To test the stability of the long run parameters estimates, we use the Cumulative Sum (CUSUM) and the Cumulative Sum of Square (CUSUMSQ) tests. This same procedure was relied on by Pesaran and Pesaran (Pesaran et al., 2001) to test the stability of the long-run coefficients. We check for existence of two significant structural breakpoints using the Chow break point test. The first in December, 2017, when the Chicago Board Options Exchange (CBOE) launched bitcoin futures contracts and the second is January, 2020, when the Chicago Mercantile Exchange (CME) Group, the world's largest derivatives exchange launch Bitcoin Options on its Bitcoin futures contracts.

5. The results

5.1. Descriptive statistics

Tables 2 and Tables 3 present the descriptive statistics and the covariance-correlation matrix, respectively. The result shows that the log of bitcoin price has a mean of 3.328 and a standard deviation of 0.768. Aside the bitcoin price and transaction volume, all the logarithmic distribution for other variables are asymmetric (positively skewed). The excess kurtosis for the price volatility and other variables aside the ACWI (with value slightly less than 2) suggests leptokurtic distribution for all series. The probability values for the Jarque Bera statistics for all variables show that all the series are not

Table 2. Descriptive statistics

z_t	BTCV	BTCP	TVOL	MCAP	ACWI	IFOD
Mean	0.022	3.328	13.351	10.472	6.809	4.234
Std. Dev.	0.066	0.768	0.922	0.648	0.247	1.326
Skewness	7.244	−0.286	−0.085	0.198	0.998	0.541
Kurtosis	61.320	52.270	15.121	12.791	1.982	11.884
Jarque-Bera	1594.67	13.474	23.240	40.811	18.095	9.758
Prob. (Jarque-Bera)	0.000	0.001	0.000	0.000	0.000	0.008

Source: Authors' calculation.

Table 3. Covariance—correlation matrix

z_t	BTCV	BTCP	TVOL	MCAP	ACWI	IFOD
BTCV	0.4316*					
	1.0000					
BTCP	0.2833*	0.5836*				
	0.5646	1.0000				
TVOL	0.4877*	0.4685*	0.8419*			
	0.8092	0.6683	1.0000			
MCAP	0.6086*	0.4570*	0.4289*	0.4160*		
	0.4364	0.9276	0.7248	1.0000		
ACWI	0.3029*	1.1293*	1.1424*	0.1103*	0.0604*	
	0.7585	0.6884	0.6314	0.6959	1.0000	
IFOD	0.9438*	0.8024*	0.9636*	0.7215*	0.2318*	1.7400*
	0.8919	0.7963	0.7962	0.8481	0.7148	1.0000

Source: Authors' calculation. The * are the covariance values.

normally distributed, hence rejecting the normality null. This validate reported asymmetry and a sign for nonstationary, which would be confirmed by the unit root tests.

In Table 3, there is high positive correlation between bitcoin price volatility and fundamentals, as well as between volatility of price and information, in line with findings by Bariviera (2017), Cebrián-H and Jiménez-Rodríguez (2021), and Cebrián-H and Jiménez-Rodríguez (2021) establish conditional correlation between the volatility of Bitcoin and attendant variables as MasterCard, Riot Blockchain, Nvidia index. The bitcoin determinants (price, volume, market capitalisation, equity index, information demands) are likely to have gain values as much as the bitcoin attract attentions.

5.2. Unit root test

Table 4 presents the unit root test results. The unit root test applied Equations (1)–(3) to obtain τ_μ, τ_τ, and τ_η, respectively. The results indicate that aside two of the variables (bitcoin price volatility and the world market equity index), there is enough evidence to conclude at 1 percent significance level that other series (z_t) are differenced stationary and *I(1)*. For both ADF and DF-GLS test protocols, the null are accepted, while with the KPSS tests, the nulls of stationarity is rejected. The evidence supports that first differenced (Δz_t) are stationary for ADF and DF-GLS. This is not surprising as we would normally expect volatility, which is an offshoots of differencing not to be trended even for large swings. In the cryptocurrency market, unprecedented volatility are connected to reactions to information shocks. The existence of such headline-making bitcoin

Table 4. Stochastic property of series (unit root tests)

Test Type		ADF H_0: Non-stationarity			DF-GLS H_0: Non-stationarity			KPSS H_0: Stationarity		
	z_t	τ_μ	ADF_α	Pr.[τ_μ]	τ_τ	ERS_α	Pr.[τ_τ]	τ_η	$KPSS_\alpha$	Pr.[τ_η]
Intercept without Time Trend	BTCV	−4.25*	−3.13	0.00	−0.57	−2.89	0.46	0.12	0.15	0.12
	BTCP	−1.57	−3.13	0.17	−0.12	−2.89	0.65	0.43	0.15	0.00
	TVOL	−3.11	−3.13	0.26	0.21	−2.89	0.60	0.29	0.15	0.00
	MCAP	−2.21	−3.13	0.30	0.84	−2.89	0.24	0.81	0.15	0.00
	ACWI	−5.15*	−3.13	0.04	−0.60	−2.89	0.07	0.41	0.15	0.00
	IFOD	−2.56	−3.13	0.09	−2.11	−2.89	0.66	0.22	0.15	0.00
	ΔBTCV	−7.67	−3.13	0.00	−8.69	−2.89	0.00	0.01	0.15	0.11
	ΔBTCP	−9.56	−3.13	0.00	−12.5	−2.89	0.00	0.09	0.15	0.08
	ΔTVOL	−7.22	−3.13	0.00	−15.4	−2.89	0.00	0.09	0.15	0.51
	ΔMCAP	−6.55	−3.13	0.00	−4.12	−2.89	0.00	0.12	0.15	0.26
	ΔACWI	−5.90	−3.13	0.00	−5.57	−2.89	0.00	0.06	0.15	0.25
	ΔIFOD	−9.5	−3.13	0.00	−4.97	−2.89	0.00	0.03	0.15	0.15
Intercept with Time Trend	BTCV	−4.42	−3.43	0.01	−0.47	−3.48	0.77	0.76	0.22	0.16
	BTCP	−0.21	−3.43	0.24	−0.22	−3.48	0.58	0.54	0.22	0.00
	TVOL	−1.82	−3.43	0.25	−1.21	−3.48	0.78	0.69	0.22	0.00
	MCAP	−1.17	−3.43	0.16	−0.95	−3.48	0.67	0.23	0.22	0.00
	ACWI	−6.84	−3.43	0.00	−0.60	−3.48	0.55	0.39	0.22	0.00
	IFOD	−2.91	−3.43	0.30	−2.81	−3.48	0.24	0.43	0.22	0.00
	ΔBTCV	−18.50	−3.43	0.00	−14.25	−3.48	0.00	0.02	0.22	0.89
	ΔBTCP	−18.69	−3.43	0.00	−12.46	−3.48	0.00	0.15	0.22	0.71
	ΔTVOL	−20.15	−3.43	0.00	−12.38	−3.48	0.00	0.09	0.22	0.87
	ΔMCAP	−13.30	−3.43	0.00	−11.91	−3.48	0.00	0.12	0.22	0.81
	ΔACWI	−12.26	−3.43	0.00	−29.18	−3.48	0.00	0.09	0.22	0.64
	ΔIFOD	−21.54	−3.43	0.00	−15.92	−3.48	0.00	0.23	0.22	0.82

The critical values ADF_α, ERS_α and $KPSS_\alpha$ are reported at 1 percent levels. The asterisk* shows series stationary at level form.ADF_α : MacKinnon (1996) one-sided p-values; ERS_α : Elliott-Rothenberg-Stock (1996); $KPSS_\alpha$: Kwiatkowski-Phillips-Schmidt-Shin (1992); *Nonstationary at level; **Stationary at level form.

Table 5. Model selection criteria for BTCV

Model	LogL	AIC*	BIC	HQ	$\bar{R}^2$	Specification
11,500	141.7363	−2.8115	−2.5120	−2.6906	0.3059	ARDL(1, 1, 3, 0, 0, 0)
11,495	142.2196	−2.8004	−2.4736	−2.6685	0.3046	ARDL(1, 1, 3, 0, 1, 0)
11,375	142.1490	−2.7989	−2.4721	−2.6670	0.3036	ARDL(1, 1, 4, 0, 0, 0)
8375	142.1172	−2.7982	−2.4714	−2.6663	0.3031	ARDL(2, 1, 3, 0, 0, 0)
11,475	141.8453	−2.7924	−2.4656	−2.6604	0.2990	ARDL(1, 1, 3, 1, 0, 0)
11,499	141.7894	−2.7912	−2.4644	−2.6592	0.2982	ARDL(1, 1, 3, 0, 0, 1)
8250	142.7688	−2.7907	−2.4367	−2.6478	0.3042	ARDL(2, 1, 4, 0, 0, 0)
10,875	141.7363	−2.7900	−2.4632	−2.6581	0.2974	ARDL(1, 2, 3, 0, 0, 0)
11,370	142.6286	−2.7877	−2.4337	−2.6448	0.3021	ARDL(1, 1, 4, 0, 1, 0)
8370	142.5392	−2.7858	−2.4318	−2.6428	90.3008	ARDL(2, 1, 3, 0, 1, 0)

Source: Authors' calculation.

news triggers temporary protrusions which are reverse during massive sell-out, and retractions, hence constraining prices not to persistently diverge overtime.

5.3. Lag selection and ARDL model

We apply the *A1C* defined by (4) to determine the lag length. Table 5 presents the best ten (10) models obtained from an iteration process which estimates approximately 11,575 independent equations for BTCV models. From the iterations the AIC select a lag length of 3 from which an ARDL (1, 1, 3, 0, 0, 0) which has highest AIC value (−2.8115) would be selected.

From the general ARDL $(p, s_1, \ldots, s_m)$ in (6), the specific ARDL(1, 1, 3, 0, 0, 0) that analyses if the pasts of bitcoin price volatility, $BTCV_{t-i}$ and contemporaneous and pasts of BTCP, TVOL, WMEI and IFOD significantly explain the exogenous current value of BTCV is (10) to be estimated is:

$$BTCV_t = \beta_0 + \beta_1 BTCP_t + \beta_2 TVOL_t + \beta_3 MCAP_t + \beta_4 ACWI_t + \beta_5 IFOD_t + \varphi_i BTCV_{t-i} + \tilde{\beta}_{1,1} BTCP_{t-i} + \sum_{i=1}^{m=3} \tilde{\beta}_{2,i} TVOL_{t-i} + a_t \quad (9)$$

Table 6 reports the coefficients of (10) alongside estimates for scaled (standardised and elasticity) coefficients, as well as their accompanying confidence intervals. The result shows the volatility of bitcoin price would be expected to increase by approximately 0.7% when markets fundamentals (prices and volume vagaries) and information are not drivers of price swings. As would be expected bitcoin prices, transaction volume and market capitalisation are properly signed and significant in line with finding by Kjærland et al. (2018), and the information demands is well signed and significant similar to finding by Poyser (2017). However, the all country world index was signed contrary to positive expectation and is not significant. This is contrary to findings by Wijk (2013) who shows that the Dow jones index has positive effects on BTC price variability, and Yechen et al. (2017) who established that both trade volume and Dow Jones index have positive influence on bitcoin price volatility.

All month-pasts bitcoin price volatility, bitcoin price and transactions volume in the parsimonious model have negative effects on its contemporaneous price volatility value and not significant, except for the previous bitcoin price. This indicates that the past play lesser roles in influencing the contemporaneous value bitcoin price volatility. The significance of one-month pasts in previous prices imply that its effect on contemporaneous price volatility has not waned away.

The results provide adequate evidence that we both price and volume (market fundamentals) explain more of the bitcoin price volatility than information. As would be seen a 1% change in the price of bitcoin and volume lead to approximately 0.241% and 0.04% change, respectively, in the volatility of price, as against the 0.002% occasioned by information demands. The accompanying confidence intervals for estimates are also properly signed within acceptable positive ranges. All standardise coefficient maintain their earlier signs validating that bitcoin price and volume exert greater swings on volatility than information search. The overall model is highly significant at 1% and the predictive power ($\bar{R}^2$) of 90% is high. The purpose of this paper is to examine the response of Bitcoin price volatility to market fundamentals and information, test of significance of the overall model is important rather than predictive ability of the model through fundamentals and information.

5.4. ARDL cointegration (bounds) test

The bounds test check for cointegration amongst variables in (7) with a reparameterised regression. The estimation process eliminate all insignificant lags. Using the AIC the conditional ARDL(1, 1, 3, 0, 0, 0) is selected from all possible test equations. The results reported in Table 7 show that the F-statistic (18.679) is greater than the *I*(1) bounds, hence provides strong evidence to reject the no cointegration null. We conclude that there is existence of long run relationship amongst BTCV and BTCP, TVOL, MCAP, ACWI, and IFOD.

The test equation for the ARDL bounds testing estimated with least squares is:

$$\Delta BTCV_t = \alpha_0 + \varphi_i BTCV_{t-i} + \gamma_{1,1}\Delta BTCP_{t-i} + \sum_{i=0}^{m=2}\gamma_{2,i}\Delta TVOL_{t-i} + \beta_1 BTCP_{t-1} + \beta_2 TVOL_{t-1} + \beta_3 MCAP_{t-1} + \beta_4 ACWI_{t-1} + \beta_5 IFOD_{t-1} + \varepsilon_t \tag{10}$$

$$\begin{aligned}\Delta BTCV_t = {} & 0.760 + 1.074 BTCV_{t-i} \\ & + 0.230\Delta BTCP_{t-i} + 0.039\Delta TVOL_t + 0.038\Delta TVOL_{t-1} + 0.033\Delta TVOL_{t-2} \\ & + 0.044 BTCP_{t-1} - 0.015 TVOL_{t-1} - 0.048 MCAP_{t-1} \\ & - 0.030 ACWI_{t-1}\ 0.004 IFOD_{t-1}\end{aligned} \tag{11}$$

5.5. The short run coefficients

Equation (8) provides the general ARDL-ECM equation. With re-parameterization, the short-run model estimated is (12). The result is reported in Table 8.

$$\Delta \mathrm{BTCV_t} = \varphi_1^{*}\Delta BTCV_{t-i} + \gamma_{1,1}\Delta BTCP_{t-i} + \sum_{0}^{2}\gamma_{2,j}\Delta TVOL_{t-i} + \gamma_{3,1} MCAP_{t-1} + \gamma_{4,1} ACWI_{t-1} + \gamma_{5,1} IFOD_{t-1} - \mu \mathrm{ECM_{t-1}} + \varepsilon_t \tag{12}$$

The short-run dynamics show that the changes in current and pasts price of bitcoin, transaction volume, market capitalisation and information are rightly signed. Aside changes in the equity market index (ACWI) which was wrongly signed contrary to short run expectations, and the change in the one month past of the transaction volume, all the changes in the contemporaneous variables and the changes in their pasts are significant at 5%. This indicates bitcoin price, transaction volume, and information demands explain changes in the volatility of bitcoin price in the short run. The findings correspond with earlier study by Kjærland et al. (2018) which applied realized volatility for bitcoin price to identify the role of technological factor "Hashrate", market fundamentals as transaction volume and Google search on bitcoin price swings. However, the finding contradicts report by Guizani and Nafti (2019) that stock index, transaction volume, and financial development do not determine the price of the BTC in the short- and long term.

Table 6. ARDL model coefficients, scaled coefficients and confidence interval (C.I.)

		$BTCV_t$				Scaled Coefficients		95% C.I.		99% C.I.	
Variables	**Parameters**	**Estimates**	**Std. Error**	**t-statistic**	***p*-value**	**Standardized**	**Elasticity**	**Low**	**High**	**Low**	**High**
C	θ_0	0.708	0.331	2.139	0.035	NA	32.625	0.049751	1.365881	−0.16445	1.580082
$BTCP_t$	θ_1	0.241	0.044	5.414	0.000	2.556	37.543	0.152279	0.329116	0.123498	0.357897
$TVOL_t$	θ_2	0.040	0.018	2.200	0.031	0.550	24.472	0.003816	0.075586	−0.00787	0.087266
$MCAP_t$	θ_3	0.054	0.028	1.913	0.059	0.492	26.301	0.11065	0.002142	0.12901	0.020499
$ACWI_t$	θ_4	−0.014	0.037	−0.380	0.705	−0.050	−4.364	−0.08659	0.058825	−0.11026	0.082492
$IFOD_t$	θ_5	0.022	0.010	2.219	0.023	0.048	0.486	0.01718	0.0261	0.01557	0.038493
$BTCV_{t-1}$	φ_1	−0.066	0.101	−0.655	0.514	−0.066	−0.067	−0.26595	0.134178	−0.33107	0.1993
$BTCP_{t-1}$	$\tilde{\theta}_{1,0}$	−0.194	0.043	−4.525	0.000	−2.091	−29.928	−0.27876	−0.10853	−0.30647	−0.08083
$TVOL_{t-1}$	$\tilde{\theta}_{2,1}$	−0.015	0.022	−0.674	0.502	−0.205	−9.172	−0.05887	0.029062	−0.07318	0.043372
$TVOL_{t-2}$	$\tilde{\theta}_{2,2}$	−0.006	0.020	−0.281	0.780	−0.076	−3.431	−0.04516	0.033992	−0.05804	0.046873
$TVOL_{t-3}$	$\tilde{\theta}_{2,3}$	−0.034	0.017	−2.002	0.049	−0.456	−20.865	−0.06782	−0.00022	−0.07883	0.010781
$\bar{R}^2$					0.899						
Durbin-Watson stat					1.958						
F-statistic					5.076						
p- (F-statistics)					0.000						

ARDL Equation: $BTCV_t = \theta_0 + \theta_1 BTCP_t + \theta_2 TVOL_t + \theta_3 MCAP_t + \theta_4 ACWI_t + \theta_5 IFOD_t \cdot + \varphi_i BTCV_{t-i} + \tilde{\theta}_{1,1} BTCP_{t-i} + \sum_{i=1}^{m=3} \tilde{\theta}_{2,i} TVOL_{t-i} \cdot + a_t.$

Table 7. ARDL (cointegration) bounds test

C.B.V. (5%)	I(0) Bound	I(1) Bound
10%	2.26	3.35
5%	2.62	3.79
2.50%	2.96	4.18
1%	3.41	4.68
F_m	18.679	m = 5

Test Equation: $\Delta BTCV_t = \alpha_0 + \varphi_i BTCV_{t-i} + \gamma_{1,1}\Delta BTCP_{t-i} + \sum_{i=0}^{m=2}\gamma_{2,i}\Delta TVOL_{t-i} - \theta_1 BTCP_{t-1} - \theta_5 IFOD_{t-1} \cdot + \varepsilon_t$
$+ \theta_2 TVOL_{t-1} + \theta_3 MCAP_{t-1} + \theta_4 ACWI_{t-1}$

Since the short-run dynamic effects are sustained to the long-run, the significant *t*-tests for the fundamentals variables (prices and volume), as well as the information search indicate that their long-run coefficients will be stable. The error correction term is rightly signed, being negative and highly significant, hence substantiate the result of the bounds test for cointegration. Approximately 40% of disequilibria from the preceding month's shock converge to the long-run equilibrium in the contemporary month.

5.6. Long run coefficients

The parameter estimates ($\hat{\theta}_j$) of the long-run relationship of ARDL(1, 1, 3, 0, 0, 0) of bitcoin price volatility is defined as $\hat{\theta}_j = [\hat{\beta}_j/(1-\hat{\varphi}_1^*)$, j = 0 to 5]. Table 9 presents the long run coefficients obtained by normalizing the BTCV equation of (10). The results shows the long run effect of price of bitcoin, transaction volume, market capitalisation, world market equity index and Google search for the bitcoin.

The result shows that all the cryptocurrency market fundamentals, bitcoin price, transaction volume, and market capitalisation as well as the information search for Bitcoin positively affect Bitcoin in long run. A significant positive long run coefficient of transaction volume on a bitcoin exchange reduce the risk of it failing suggesting that trade volume would likely provide ability to explain the price volatility of bitcoin. Similar to the short run and the ARDL model, we found again that both BTC price and volume explain more of the BTC price volatility than information

Table 8. ARDL cointegrating (short-run) equation

Variable	Coefficient		Std. Error	*t*-Stat.	Prob.
$\Delta BTCV_{t-1}$	φ_1^*	0.019	0.008	2.371	0.000
$\Delta BTCP_t$	$\gamma_{1,1}$	0.241	0.044	5.414	0.000
$\Delta TVOL_t$	$\gamma_{2,0}$	0.040	0.018	2.200	0.031
$\Delta TVOL_{t-1}$	$\gamma_{2,1}$	0.006	0.020	0.281	0.780
$\Delta TVOL_{t-2}$	$\gamma_{2,2}$	0.034	0.017	2.002	0.049
$\Delta MCAP_t$	$\gamma_{3,1}$	0.054	0.028	2.091	0.041
$\Delta ACWI_t$	$\gamma_{4,1}$	−0.014	0.037	−0.380	0.705
$\Delta IFOD_t$	$\gamma_{5,1}$	0.024	0.010	2.412	0.039
ECM_{t-1}	μ	−0.401	0.018	2.200	0.001

$\varepsilon_t = BTCV - (0.0441 * BTCP - 0.0139 * TVOL$
$- 0.0509 * MCAP - 0.0130 * ACWI + 0.0023 * IFOD + 0.6641)$

Source: Authors' calculation.

Table 9. Long-run coefficients for BTCV

Variable	Coefficient ($\hat{\theta}_i$)		Std. Error	t-Stat.	Prob.
C	$\hat{\theta}_0$	0.664	0.300	2.214	0.030
$BTCP_t$	$\hat{\theta}_1$	0.044	0.020	2.248	0.027
$TVOL_t$	$\hat{\theta}_2$	0.029	0.010	2.928	0.000
$MCAP_t$	$\hat{\theta}_3$	−0.051	0.026	−1.948	0.055
$ACWI_t$	$\hat{\theta}_4$	−0.013	0.034	−0.381	0.704
$IFOD_t$	$\hat{\theta}_5$	0.021	0.009	2.332	0.004

*Confidence interval (C.I.) was constructed without including the intercept as a predictor.

Source: Authors' calculation.

(demands). A 1% increase in Bitcoin price and transactions volume lead to respectively, 0.44% and 0.29% increase in Bitcoin price volatility, all things being equal, while a 1% increase in information search leads 0.21% increase in Bitcoin price swings.

This findings support earlier position of Guizani and Nafti (2019) bitcoin price long-run position. We found that the world market index, which is supposed to stimulate demand has negative long-run effect on BTC price volatility. This may be attributed to the fact that the period covers has not recognised institution and regulation of the digital currency. Except for coefficient of world market index, $\hat{\theta}_4$, all other long-run coefficients are significant at 5%. As noted (Briere et al., 2015), a significance coefficient of world market index is an indication that there is protection to investors who want to limit their risk exposure. There is at least 97% confidence that bitcoin price, transaction volume, market capitalisation and information explains the volatility of Bitcoin price in the long run.

5.7. Robustness test

We assess the appropriateness of the ARDL model by conducting some residual checks to verify their randomness. We examined the structural stability of the long-run coefficients alongside the short-run dynamics. Our results confirm the adequacy of the estimation. Table 10 presents the result of the same robustness tests.

The Breusch-Pagan-Godfrey test is not significant and hence support evidence that there is absence of heteroscedasticity. In addition, the Breusch-Godfrey test is not significant providing no basis to reject the no serially correlation null. With a *p*-value (0.526) the normality null of distributed stochastic errors is not rejected. The CUSUM plot in Figure A1 1(a) indicates structural stability in the long run coefficients. The model passes all the statistic diagnostic tests except the

Table 10. Diagnostic test

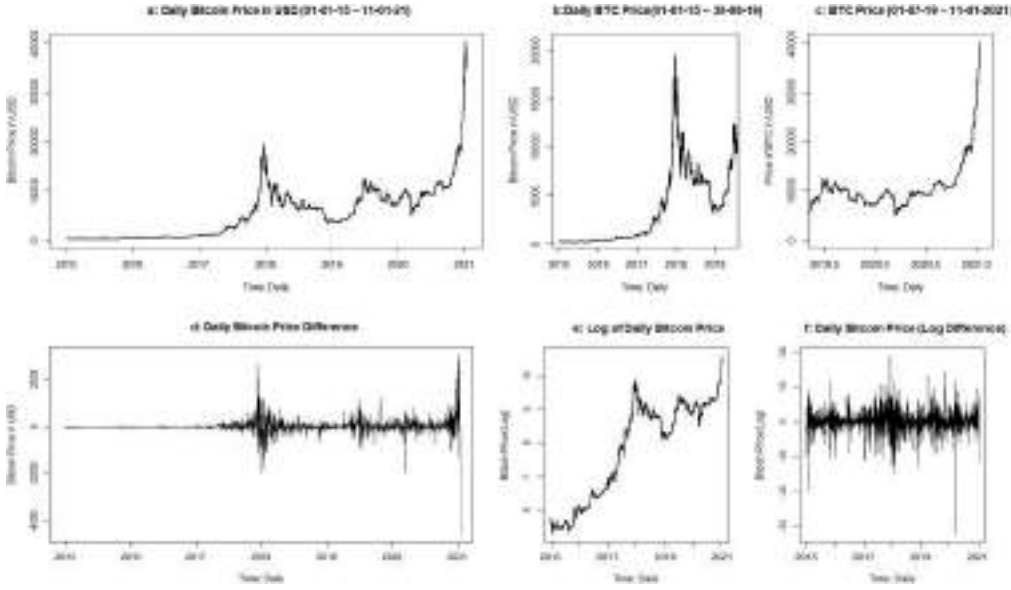
	Breusch-Pagan-Godfrey (Heteroskedasticity Test)	Breusch-Godfrey (Serial Correlation LM Test)
Statistics	**Null(H_0): No ARCH effect**	**Null(H_0): No serially correlated**
Obs. R^2	23.3618	19.2850
F-statistic	0.7450	0.5613
Prob.(F)	0.4712	0.5726
Prob.(Chi-Square)	0.0095	0.5260

Source: Authors' calculation.

Table 11. The chow breakpoint test

	Null: No breaks at specified breakpoints	
Statistics	**Break 1: 2017M12**	**Break 2: 2020M1**
F-statistic	2.162398	0.887659
Log likelihood ratio	26.83272	11.95435
Wald Statistic	23.78638	9.764244
Prob. F(11,72)	0.0261	0.5562
Prob. Chi-Square(11)	0.0049	0.3671

Figure 1. CUSUM and CUSUMSQ plots.



and CUSUMSQ test CUSUM plot Figure 1, which exceeded the upper bound red line a little but still reliable, since heteroscedasticity and serial correlation are absence.

Table 11, Chow breakpoints test examines two significant structural breaks in the data. The first is the month when the CBOE launched Bitcoin Futures contracts on 10 December 2017, (point 2017M12) over the post-Bitcoin Futures periods 2018M1–2021M6. And the second is the month when CME Group launch Bitcoin Options on its Bitcoin Futures contracts on 3 January 2020, which is point 2021M1 over the post-Bitcoin Options periods 2020 M2–2021M6. The break point test was significant for the first break, an indication that there was a break point when CBOE launched Bitcoin Futures contracts in 2017. The second break point test support the null of no break on January 2020 when the CME Group launch Bitcoin Options.

6. Conclusions

This paper supposes that market fundamentals and information demands are drivers of sporadic volatility in the price of Bitcoin. In effects, we checked the influence of price, transaction volume, world equity market index, market capitalisation and Google search on the volatility of Bitcoin price. Similar to Guizani and Nafti (2019), we observed a long-run equilibrium relationship between BTC price volatility and attendant variables. We could not establish evidence that the volatility of

bitcoin price could be influenced under world market index. The results indicate that while the volatility of BTC price response positively to market fundamentals [in line with Kjærland et al. (2018)] and information search on BTC [similar to Poyser (2017)], the fundamentals exert more influence on price fluctuations than search.

We make three recommendations based on the outcome of this study. First is that stakeholders in the cryptocurrency markets should embark on campaigns to encourage more institutional acceptance. Second is that there should be increased regulation in order to curb excessive swings that may significantly affect funds invested in Bitcoin. Third is there should be establishment of a Bitcoin insurance in form of a Decentralised Insurance Product (DIP) that would assure investors of the safety of funds invested in Bitcoin.

This study opens rooms for future research. We limited our focus on the determinants of Bitcoin price volatility. We do not distinct Bitcoin as money or an asset, rather we considered bitcoin in this paper as both a product in a currency exchange market or a security in an asset market. Future research may make distinctions. There may be need to investigate the role of data frequency on the outcome. Future research may focus on infra-monthly data to confirm the sensitivity of Bitcoin price volatility to data periodicity.

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Note

1. $\tilde{\beta}_{j,i}$ is an input polynomial lag expressed as:-

$$\tilde{\beta}_j(B) = \tilde{\beta}_{j,0} + \tilde{\beta}_{j,1}B + \tilde{\beta}_{j,2}B^2 + \ + \tilde{\beta}_{j,s_{j-1}}B^{s_j-1} = -\sum_{l=i+1}^{s_j}\beta_{j,l}\text{-}$$

$\hat{\beta}_j = \hat{\beta}_{j,0} + \ldots + \hat{\beta}_{j,s_j}$; and $\varepsilon_t = \varphi^{-1}(B)a_t$Let
$\theta_0 = \varphi^{-1}(1)\mathcal{B}_0$; $\theta_j = \varphi^{-1}(1)\mathcal{B}_j(1)$;
$\tilde{\theta}_j(B) = \varphi^{-1}(B)\left(\tilde{\beta}_j(B) - \tilde{\varphi}(B)\varphi^{-1}(1)\mathcal{B}_j(1)\right)$.

Competing interests
The author declare not competing interest.

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No potential conflict of interest was reported by the author(s).

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Appendix A

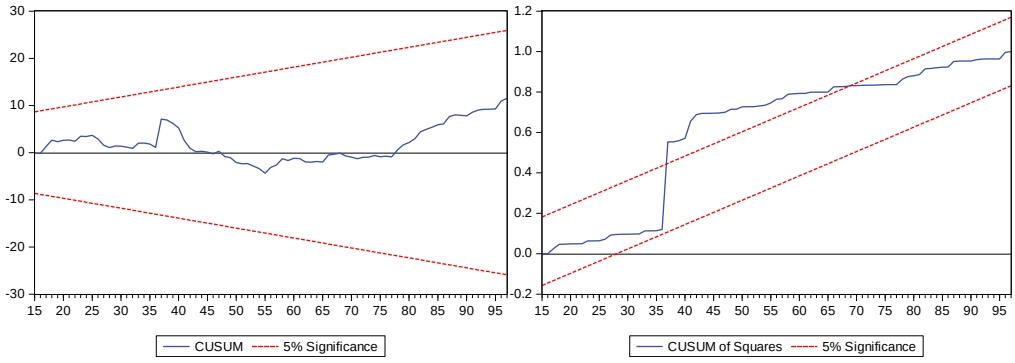


Figure A1. (a) Daily Bitcoin price inUSD (01-01-15–11-01-21). (b) Daily BTC price (01-01-15–30-06-19). (c) BTC price (01-07-19–11-01-2021). (d) Daily bitcoin price difference. (e) Log of daily bitcoin price. (f) Daily bitcoin price (log difference).

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