Bitcoin's return volatility and uncertainty shocks

Bruno Ferreira Frascaroli*

July 16, 2019

Abstract

This paper investigates how Bitcoin's (BTC) return volatility is affected by its own innovative aspects, by the main global financial market indicators, and by shocks on volatility and uncertainty. The strategy was first estimate structural break tests to find significative regime switching in BTC returns. Next conditional volatility parameters are estimated from multivariate perspective using the DCC-MGARCH model. At this stage, the Standard & Poor 500 index, China's SSEC stock index and the price of gold were used to estimate the quasi-covariances and quasi-correlations matrices. In the last step it was also estimated impulse response functions to understand how BTC returns are affected by risk and uncertainty shocks coming from distinct sources. It was found that there are many factors and uncertainty surrounding the BTC market microstructure and indicators of a speculative bubble from the end of 2017 to mid-2018.

Keywords: Bitcoin; Innovation; Drivers; Return volatility; Uncertainty.

Resumo

Este artigo investiga como a volatilidade de retorno do Bitcoin (BTC) é afetada por seus próprios aspectos inovadores, pelos principais indicadores do mercado financeiro global e por choques na volatilidade e incertezas. A estratégia foi primeiramente a estimar testes de quebra estrutural para encontrar mudanças de regime nos retornos de BTC. Na etapa seguinte foram estimados os parâmetros de volatilidade condicional a partir de uma perspectiva multivariada, usando o modelo DCC-MGARCH. Nessa etapa, o índice Standard & Poor 500, o índice de ações SSEC da China e o preço do ouro foram utilizados para estimar as matrizes de quase-covariâncias e quase-correlações. Na última etapa, também foram estimadas funções de impulso resposta para entender como os retornos do BTC são afetados por choques de risco e incerteza provenientes de fontes distintas. Verificou-se que existem muitos fatores e incertezas em torno da microestrutura de mercado do BTC e indicadores de uma bolha especulativa do final de 2017 até meados de 2018.

Palavras-chave: Bitcoin; Inovação; Drivers; Volatilidade nos retornos; Incerteza.

JEL Code: E51, G23, C58.

Área 8: Microeconomia, Métodos Quantitativos e Finanças.

*Department of Economics, Federal University of Paraíba, Cidade Universitária - João Pessoa/PB - Brazil, ZIP Code: 58051-900 Fax: +55 83 3216-7453, Telephone: +55 83 3216-7453. Email: frascaroli.b@gmail.com.

1 Introduction

Some postindustrial events highlight how the worldwide economy is changing. This is evidenced by massive investments on the production of intangible goods, such as information, services, values, symbols, and aesthetics, which has been accelerated by portable technology, such as the smartphone, along with financial innovation (World Economic Forum, 2015). Hence, instruments of exchange have materialized as digital payment methods, also known as fintechs, e.g., as digital wallets, such as PayPal, Google Wallet, MoneyGram, Apple Pay, and Venmo. This payments' ecosystem also includes cryptocurrencies, which are similar to other e-commerce tools. Examples such as Bitcoin (BTC), bKash (Bangladesh), NEO (China), mPesa (Kenya), and Auroracoin (Iceland), Coinbase – which link bank accounts or credit cards to cryptocurrencies, suggest that cash is following the path of information goods.

This fintechs make new business profitable by introducing less bureaucratic and costly protocols to process information (Baur and Dimpfl, 2018; Luther, 2016b). Merge of technologies are also observed as the Gemini, which is a regulated cryptocurrency exchange, and the creation of the BitLicense[1] in 2015. In April 2017 BTC was recognized as a currency by Japan. In October of the same year, the US Commodity Futures Trading Commission (CFTC) approved LedgerX as the first company to serve as a clearinghouse for cryptocurrencies using swaps. In March 2018, Germany also recognized BTC as a currency. Lagarde (2017) forecasts the end of the current state of the art of banking and the popularization of cryptocurrency, calling this dollarization 2.0.

These events were followed by the launching BTC futures contracts on December 10, 2017 by the Chicago Board Options Exchange (CBOE) (Baur and Dimpfl, 2019). Eight days later, the Chicago Mercantile Exchange & Chicago Board of Trade (CME Group) initiated similar operations. In this sense, besides being the first cryptocurrency, BTC has the higher disruptive impact among the more of 1,634 known cryptocurrency. However, this complex ecosystem of cryptocurrencies is contestable, since there are 1,634 non-BTC entrants to date competing in the market (White, 2015). It is a digital token with the highest daily trading volume on the financial markets, an open source accounting system, with a ledger that resides on thousands of computers.

Although, the adoption of cryptocurrencies depends on a special type of network externality where the degree of utility gained by an individual (node) depends on the number of users (other nodes) of the same good, i.e., the network matters (Catalini and Gans, 2017). The blockchain, which keeps track of all BTC transactions, has been making possible new smart-contract applications (Fanning and Centers, 2016). Part because it is not possible to duplicable BTC by its users Miller (2014) and this make possible to introduce continuous competition in this market (Lo and Wang, 2014; White, 2015). Nonetheless, BTC is often diffuse and too opaque for regulators as well, which affects its price, brings volatility and also evidence of an speculative bubble from end of 2017 to mid-2018 (Corbet et al, 2018a).

Rumors, hack attacks, and other orthogonal events suggests that BTC price formation depends on multivariate events, and that there are much uncertainty in this market (Fang et al, 2019). The role of information technology, new understandings of BTC behavior and applications, which also includes its acceptance as payment method, are among their first obstacles. Facing so many simultaneously events, this paper provides multivariate empirical evidence of how distinct sources of volatility, risk and uncertainty shocks affect BTC returns. The main global financial market indicators were used to assemble new evidence on some previous univariate contributions such as Lo and Wang (2014), Ciaian et al (2016), Frascaroli and Pinto (2016), Urquhart (2016), Chan et al (2017), Scaillet et al (2017), Ardia et al (2018), Baur and Dimpfl (2018), Blau (2018), Li et al (2015), Peng et al (2018), Zargar and Kumar (2018), Silva et al (2019) and Zargar and Kumar (2019).

The Standard & Poor's 500 index (S&P500), China's main stock index (SSEC) and the price of gold (XAU) (Klein et al, 2018) are used. Such findings will be important to understand what are the sources of BTC volatility and how markets could deal with it. The empirical strategy is composed of four steps which tries to control the

[1] A BitLicense is a business license issued by the New York State Department of Financial Services (NYSDFS) to regulate businesses limited to activities involving New York or a New York resident that make use of virtual currency activities.

findings considering distinct sources of volatility, risk and uncertainty shocks. Thus, the first step is to estimate the structural breaks in BTC returns, considering historical events that may have affected its dynamics. Second, the univariate volatility parameters of BTC returns are estimated. Third, a multivariate empirical investigation to track BTC return volatility is detailed. In the fourth step, BTC conditional volatility and estimated residuals were used as inputs in a vector autoregressive framework to simulate impulse response shocks coming from distinct sources, including uncertainty.

This paper is divided into five sections in addition to this brief section 1. section 2 describe the literature review. Next, section 3 provides the empirical strategy. Sample planning and treatment are detailed in section 4. The empirical findings obtained are discussed in section 5, and section 6 delivers summary and conclusions.

2 Literature

BTC is the name of the cryptocurrency, its units, and the payment network on which the digital tokens are stored, traded and moved. The domain name bitcoin.org was registered on 18 August, 2008 developed by Satoshi (2008). The first protocol was put in practice with BTC using peer-to-peer (P2P) technology to run decentralized value trade through a collective trust agreement process by using independent computer networks. This allows BTC trading be validated using algorithms, where each computer works simultaneously as a server and a user, i.e., such network enables operations without the strict need for third parties. In this framework, miners are one of the most important components as their computers are tasked to process new transactions coming onto the blockchain ledger and constantly updating it (Corbet et al, 2018b).

This makes BTC resembles mineral-types of money because its supply theoretically expands according to a known stochastic process, in which a hash[2] function can map variable-length data and return fixed-length data. The mining structures compete to receive the payout in synthetic commodity money every ten minutes, making BTC similar to electronic money (Selgin, 2015). They are forced to search for a number, based on prime number algorithms created to be deflationary by nature, i.e., the core protocol itself is in charge of preventing new issues. Thus, they could be efficient from the point of view of inflation (Rogoff, 2014), besides enable more secure, agile and customized financial services.

Hence, while anyone can use computers to mine BTC, only specialized hardware is capable of winning this race. Such decentralized, globally distributed and competitive network system make sure that the blockchain be trustworthy. This also because the system allows each network node to hold a copy of the blockchain itself (Luther, 2016a). It means that each BTC user can have as many public keys as desired, but at least two keys: one public and one private. The public key identifies the user on the network and uses a digital signature algorithm called ECDSA (Nair and Cachanosky, 2017). As the public key assigns a hash to each new information, it is possible to confront the transaction to the trader's public key, eliminating the possibility of double spending (Chakravorti et al, 2016).

This open source transparency is one of the most important factors of BTC market microstructure because allows data scientists and researchers worldwide to collaborate in a digital platform innovation[3]. However, while it is possible to verify in the blockchain the traded amounts of BTC at any time, it is not possible to directly identify users involved in the transactions. This makes cryptocurrencies able to support criminal activities[4], ransom and Ponzi schemes (Foley et al, 2018). Fanusie and Robinson (2018) found that a quarter of

[2]A hash is a unique data identifier consisting of 64 characters, in a one-way function. Thus, each block mined informs the next block's hash (Paar and Pelzl, 2010).

[3]One example is the Airfox, a Boston-based mobile financial services company, which is using the blockchain to provide a cheaper, easier (through an app), and much more modern alternative to credit access in Brazil.

[4]Locky Ransomware attack12, the OneCoin scheme and the Silk Road website, which was mainly used to traffic narcotics in 2013, and AlphaBay, shut down in July 2017, are also examples of this misuse of cryptocurrencies (Fanusie and Robinson, 2018).

all transactions went into Europe (2015-16), which hosted 38% to 57% of all illicit transactions, while Gandal et al (2018) identified episodes of suspicious trading activity and frauds.

Moreover, these risks are increased by hack attacks, such as that against Mt. Gox, a popular Japanese exchange company that has been hit more than 150,000 times by hackers and declared in February 2014 that 750,000 BTC had been stolen. Another attack was registered in August 2016, against the major BTC exchange Bitfinex, when nearly 120,000 BTC were stolen. This approximately $65 USD million theft caused a 10% drop in BTC price, and all transactions on the virtual exchange were suspended. It took one week for the security breach to be investigated and transactions reestablished. This also characterize a vulnerability, since approximately 40% of the world's total BTC is owned by 1,000 users, e.g., more than $100 million BTC per person on average.

Empirical evidence has point out that BTC returns follow non-normal distribution, exhibit heavy tails (Chan et al, 2017), is subject to jumps (Scaillet et al, 2017) and regime changes (Ardia et al, 2018; Silva et al, 2019). On the other hand, while 60% of BTC is mined by five entities, F2Pool, AntPool, BW.COM, BTCC Pool and ViaBTC, Choi et al (2018) found that network limit the ability of arbitrages in this market. They also indicate that the BTC premia are positively related to transaction costs, confirmation time in the blockchain, and to BTC return volatility. Concerning such volatility, there is evidence of long memory (Peng et al, 2018; Zargar and Kumar, 2018, 2019), asymmetry distribution (Baur and Dimpfl, 2018), and volatility transmission among cryptocurrencies (Yi et al, 2018).

Furthermore, the recent remarkable increase in BTC prices at the end of 2017 and its fall in first six months of 2018 has raised the question of whether it has just experienced one of history's biggest speculative bubbles. Blanchard and Watson (1982) highlight that bubbles have mostly been accompanied by volatility in international events. The questions addressed here are important puzzles, which reinforce risks and uncertainties around BTC. Thus, a business that makes use of cryptocurrencies needs to carefully consider its risks (Grant and Hogan, 2015; Choi et al, 2018). Thus, is necessary to identify global drivers and uncertainty sources of BTC price formation and access its valuation.

3 Empirical strategy

3.1 Dynamic conditional correlation multivariate GARCH model

The estimation of volatility from autocorrelations, the mean and the variance of BTC returns comes from the pioneering contributions of Bollerslev (1982) and Bollerslev (1986). In addition to estimating structural changes that affect BTC price dynamics, a dynamic specification of the MGARCH is used to estimate BTC conditional volatility and to identify the drivers of its quasi-covariances and quasi-correlations. The multivariate framework provides information about other stochastic processes important to predicting BTC returns and volatility. Engle (2002) developed the DCC-MGARCH, wherein R_t follows a GARCH (1,1) process. The parameters of R_t are not standardized to be correlations and are called quasi-correlations. To maintain parsimony, all correlations are constrained to follow the same dynamics.

The DCC-MGARCH is significantly more flexible and does not introduce a much larger number of parameters for the number of stochastic processes. It utilizes weighted nonlinear combinations of time-variant univariate GARCH. The diagonal elements of H_t are modeled using univariate GARCH. The remaining elements are estimated by nonlinear functions based on the terms resulting from the diagonal:

$$h_{ij,t} = \rho_{ij,t} + \sigma_{i,t}\sigma_{j,t}{}^{1/2} \tag{1}$$

where the terms $h_{ii,t}$ and $h_{jj,t}$ characterize the GARCH process, and $\rho_{ij,t}$ represents the dynamic process (Engle, 2002). The DCC-MGARCH can be written using a DVECH (1,1) as follows:

$$R_t = diag\ Q_t^{-1/2}\ Q_t\ diag Q_t^{-1/2} \tag{2}$$

$$Q_t = (1-\lambda_1-\lambda_2)R + \lambda_1 \tilde{\varepsilon}_{t-1}\tilde{\varepsilon}'_{t-1} + \lambda_2 Q_{t-1} \tag{3}$$

where D_t. y_t is a dependent variable vector of order $mx1$, C is a parameter matrix of order mxk, x_t is an independent variable vector that may contain lags of y_t, $H_t^{1/2}$ is the Cholesky factor of the time-variant conditional covariance matrix H_t, v_t is a vector of order $mx1$, which is a vector of zero mean and i.i.d. with unit variance, and D_t is a diagonal conditional variance matrix, which in this case has a (4 x 4) dimension.

$$B = \begin{bmatrix} \sigma_{1,2}^2 & 0 & \dots & 0 \\ 0 & \sigma_{1,2}^2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \sigma_{1,2}^2 \end{bmatrix} \tag{4}$$

where each $\sigma_{i,t}^2$ evolves corresponding to a univariate GARCH, given as follows:

$$\sigma_{i,t}^2 = s + \sum_{j=1}^{p} \alpha_j \varepsilon_{i,t-j}^2 + \sum_{j=1}^{q} \beta_j \sigma_{i,t-j}^2 \tag{5}$$

or when the constant term is added:

$$\sigma_{i,t}^2 = exp(\gamma_i z_{i,t}) + \sum_{j=1}^{p} \alpha_j \varepsilon_{i,t-j}^2 + \sum_{j=1}^{q} \beta_j \sigma_{i,t-j}^2 \tag{6}$$

where γ_i is a $1xp$ parameter vector, z_i is a $px1$ vector of independent variables including a constant term, α_j are ARCH parameters, and β_j are GARCH parameters. The conditional quasi-correlation matrix is:

$$R_t = \begin{bmatrix} 1 & \rho_{12,t} & \cdots & \rho_{1m,t} \\ \rho_{12,t} & 1 & \cdots & \rho_{2m,t} \\ \vdots & \vdots & \ddots & \vdots \\ \rho_{1m,t} & \rho_{2m,t} & \cdots & 1 \end{bmatrix} \tag{7}$$

where $\tilde{\varepsilon}_{t-1}$ is a $mx1$ vector of standardized residuals, $D_t^{-1/2}\tilde{\varepsilon}_t$, λ_1 and λ_2 are parameters that drive the quasi-correlation dynamics, λ_1 and λ_2 are non-negative and meet condition $0 \leq (\lambda_1+\lambda_2) < 1$.

When Q_t is stationary, the matrix R is the weighted average of the covariance matrix of the standardized residuals $\tilde{\varepsilon}_t$. It is denoted by $\bar{R}$ and the unconditional average of Q_t, described by $\bar{Q}_t$. Because $Q_t \neq R_t$, R does not represent the correlation matrix or the unconditional average of Q_t. For this reason, the parameters in R are called quasi-correlations. Alternatively, the estimator developed by Tse and Tsui (2002) assumes the VECH-diagonal form. This means that Equation 5 also applies to the conditional covariance terms in which $\sigma_{i,t}^2$ is replaced by $\sigma_{i,t-j}$, and $\varepsilon_{i,t}^2$ is replaced, for instance, by $\varepsilon_{i,t}$ for $1 \leq i \leq j \leq K$. Therefore, considering their contribution, it is also assume that the time-varying conditional correlation matrix ε_t is generated from the recursion:

$$\Gamma_t = (1-\theta_1-\theta_2)\Gamma + \theta_1\Gamma_{t-1} + \theta_2\Psi_{t-1} \tag{8}$$

where $\Gamma = \{\rho_{ij}\}$ is a time-invariant KxK matrix, also defined as a positive parameter matrix, with unit diagonal elements; and Ψ_{t-1} is a KxK matrix whose elements are functions of the lagged ε_t. The parameters θ_1 and θ_2 are free of the non-negative condition, since it was fit a univariate EGARCH in first step of estimations. Tse and Tsui (2002) point out that Γ_t is a weighted average of Γ, Γ_{t-1} and ψ_{t-1}. If ψ_{t-1} and Γ_0 are well-defined correlation matrices, Γ_t will also be a well-defined correlation matrix. They propose considering the following specification for $\Psi_{t-1} = \psi_{ij,t}$:

$$\psi_{ij,t-1} = \frac{\sum_{h=1}^{M} \varepsilon_{i,t-h}\varepsilon_{j,t-h}}{\sqrt{\left(\sum_{h=1}^{M} \varepsilon_{i,t-h}^2\right)\left(\sum_{h=1}^{M} \varepsilon_{j,t-h}^2\right)}} \tag{9}$$

Hence, ψ_{t-1} is the sample correlation matrix of $\{\varepsilon_{t-1}, ..., \varepsilon_{t-M}\}$.

The fitted models EGARCH (p,q), introduced by Nelson (1991), and the Glosten-Jagannathan-Runkle GARCH (GJR-GARCH) model (Glosten et al, 1993) do not need the non-negativity constraint of the parameters for the variance be not negative. Thus, unlike the symmetric GARCH (p,q), these functional forms provide better fit. The EGARCH conditional variance in logarithmic form is expressed as:

$$ln\, h_t = \alpha_t + \sum_{j=1}^{q} \beta_j lnh_{t-j} + \sum_{l=1}^{p} \theta_l \left[\theta_l \zeta_{t-l} + \gamma_l \left(|\zeta_{t-l}| - \sqrt{\frac{2}{\pi}}\right)\right] \tag{10}$$

with $h_t = \sigma_t^2$ and $\zeta_t = \frac{\varepsilon_t}{\sqrt{h_t}}$. Note that the term h_t depends on both sides of Equation 10 and the ε_t sign. The process in question has stationary covariance if, and only if, $\sum_{j=1}^{q} \beta_j < 1$. Otherwise, the GJR-GARCH could be specified as:

$$h_t^2 = \omega + \sum_{l=1}^{q} \left(\alpha_l \eta_{t-l}^2 + \gamma_l I_{t-l} \eta_{t-l}^2\right) + \sum_{j=1}^{p} \beta_j \delta_{t-j}^2 \tag{11}$$

It is assumed that the impact of η_t^2 on the conditional variance h_t^2 is distinct depending on whether η_t is positive or negative. Hence, I_{t-l} is a dummy variable, i.e., assumes 1, if $\eta_{t-l} < 0$, or 0, if otherwise, $\eta_{t-l} \geq 0$. If $\gamma_1 = ... = \gamma_q = 0$, it implies that the shocks impact curve is symmetric, i.e., past positive and negative shocks equally impact current volatility. Thus, the null hypothesis of no leverage effect is easy to test in the GJR functional form. Following Baur and Dimpfl (2018), the asymmetric specification adopted by both functional forms, also allows volatility to respond more quickly to positive returns. It eliminates the possible consequence of the leverage effect, i.e., an unexpected BTC price drop increases volatility more than an analogous unexpected price increase.

3.2 Impulse response function simulations

This paper also uses BTC conditional volatility, the conditional quasi-correlations and the estimated residuals as inputs on a vector autoregressive framework (Sims, 1980) to simulate the impulse responses' shocks. Thus, from an adaptation of Jurado et al (2015) and Scotti (2016), shocks coming from risk and uncertainty measures were simulated to understand how the selected drivers affects the BTC returns. The unrestricted VAR model is described in its simplest form in terms of lagged variables:

$$y_t = \sum_{l=1}^{p} \Phi_l y_{t-l} + \varepsilon_t \tag{12}$$

where Φ_l for $l = 1, 2, ..., p$ is a matrix $k \times k$ of the BTC covariate parameters, and ε_{it} is the vector of errors i.i.d. Hence, this term is used to simulate the shocks through impulse response functions (IRFs).

4 Data sample design and processing

The used data were obtained from Datastream and covers the period from September 13, 2011, to June 19, 2018. The daily logarithmic returns of global financial indexes' total sample has 2,472 interpolated observations of BTC, S&P500, SSEC and XAU. The S&P500 representing the US stock market index reflects potential startups that could develop new technologies from blockchain. This indicator is composed of 500 large companies listed on the NYSE/NASDAQ that together represent approximately 80% of US market capitalization. China's main stock index (SSEC Composite Index) represents Asia, identified as the global leader in BTC trading services since 2015-16, hosting over half of total transactions (Fanusie and Robinson, 2018). They justifies that the SSEC has performed a role similar to that of the S&P500 in BTC price formation.

Similar to mineral-type commodities, the BTC price depends on the miners' marginal costs (Selgin, 2015). Thus, considering this synthetic money aspect of BTC, the price of gold (XAU) was also used to track the multivariate volatility. Figure 3 and Figure 4 in the Appendix A exhibits the trajectories of BTC (USD$/BTC) and the logarithmic returns of the selected variables. To test structural changes in BTC returns the Chow test, developed by (Chow, 1960), was used to control the results.

5 Empirical findings

The results of Chow tests performed are in Table 4 in the Appendix A. They reveal that the hack attack against Bitfinex was statistically significant and initiate a new regime for BTC returns. Thus, it was set the regime 1 for the period of September 13, 2011, to July 7th, 2016, with 1,783 observations. The regime 2 refers to the period from August 8, 2016, to June 19, 2018, with 680 observations. Moreover, the descriptive statistics regards the used variables are illustrated in Table 1. The columns at right corresponds to the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP) and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests.

Table 1: Descriptive statistics and unit root tests of the logarithmic returns of the period of all sampled variables

Variable	Mean	Median	Min.	Max.	Stand. Dev.	Skewness	Kurtosis	ADF	PP	KPSS
BTC	0.0040	0.0021	-0.3109	0.36147	0.0482	0.1198	11.3614	-48.6257	-48.6587	0.1948
S&P500	0.0004	0.0002	0.04332	-0.0375	0.0065	-0.2119	8.7394	-47.2649	-47.7470	0.1030
SSEC	0.0001	0.0004	0.0576	-0.0763	0.0102	-0.9755	14.010	-43.9245	-43.9784	0.1170
XAU	-0.0001	-0.0001	0.0480	-0.0542	0.0076	-0.3421	10.1015	-47.3667	-47.4520	0.1471

Source: Authors' elaboration using selected data from br.investing.com.

All returns are stationary, since the null hypothesis is rejected at 1% for ADF and PP and not rejected for the KPSS test. The maximum daily return of BTC was 36.14%, which occurred on 16 April 2013, while its minimum was -31.09% observed on 18 August 2012. The sample revealed skewness and kurtosis, with attention to SSEC data. Excess kurtosis postulates platykurtic series, which are commonly present in financial time series. This strengths the argument for selecting a model capable of measuring volatilities from a multivariate perspective, in opposite to univariate analysis. Several models with different estimators and specifications were tested, including a set of functional forms ARFIMA (p,d,q) for testing long memory volatility (Peng et al, 2018; Zargar and Kumar, 2018, 2019), but results suggested no improvements.

Following Ardia et al (2018), the stochastic processes also pointed for two different regimes better described by the ARMA (2,1) EGARCH (1,1) (regime 1) and ARMA (1,1) GJR-GARCH (2,1) (regime 2), respectively. It was confirmed by the log-likelihood and the serial correlation (ARCH test) for both regimes. The null hypothesis is no ARCH, which was rejected according to Table 5 in Appendix A. The estimation of the MGARCH model follows two steps. First, the univariate EGARCH and GJR-GARCH are estimated for each of four variables.

Second, the multivariate model and proceed to the diagnosis tests were performed. The best fit for both of the regimes was using the estimator developed in Tse and Tsui (2002). This estimator considers a constant in the variance parameter ($Const_{\sigma^2}$) for the second regime, which does not depend on time t and was significative at a 95% confidence level.

The results of the univariate estimations are summarized in Table 6 in Appendix A. The parameter α is from ARCH model, while β_i are GARCH parameters, θ_i are EGARCH parameters, and γ is the GJR parameter specification, respectively. They presented strong convergence, i.e., the estimators are asymptotically consistent. The sampled mean of squared residuals was used to start recursion, and these were obtained through the sandwich formula, i.e., robust standard errors. This univariate model estimate that a volatility innovation in response to ε_{t-1} increases, indicated by the negative parameter α for regime 1, while it diminish as consequence of the positive parameter α for regime 2.

The parameter β, for instance, illustrates high volatility for regime 1 (close to unity), while for regime 2 $\beta_2 > \beta_1$ indicates that volatility is falling over time. Positive shocks in long run BTC return volatility increases it by more than negative shocks for regime 1. Similar to Baur and Dimpfl (2018), this is illustrated by the asymmetry parameter θ_2, which is different from zero at a 99% confidence level. The asymmetry parameter γ for regime 2 is not different from zero at a 99% confidence level. Table 2 summarizes the results of the DCC-MGARCH, considering regimes 1 and 2, respectively:

Table 2: Results of the MGARCH models

	Regime 1			Regime 2		
Parameter	Value	t	Prob.	Value	t	Prob.
ρ_{21}	0.02408	70.61	0.0000	-0.00752	-0.2243	0.8226
ρ_{31}	-0.23239	-1187	0.0000	-0.03266	-3.9063	0.0651
ρ_{41}	-0.19233	-666.2	0.0000	0.01797	0.5432	0.5872
α (ARCH)	0.00873	9.140	0.0000	0.01302	0.2912	0.7710
β (GARCH)	0.99125	1008	0.0000	0.0000	0.00	1.0000
Degr. of freedom	2.90914	54.27	0.0000	3.68762	20.06	0.0000
Log-likelihood	22287.2			Log-Likelihood	2629.74	

Source: Authors' elaboration using selected data from br.investing.com.

The parameters ρ_{ij} reveal the quasi-correlation described in Equation 7. By assuming BTC=1, S&P500=2, SSEC=3 and XAU=4, the parameters for regime 1 were $\rho_{21} = 0.02408$, $\rho_{31} = -0.23239$, and $\rho_{41} = -0.19233$, while for regime 2, they were $\rho_{21} = -0.00752$, $\rho_{31} = -0.03266$, and $\rho_{41} = 0.01797$, respectively. The estimated parameters underlines that the degree of interdependence between BTC return volatility was evidenced in regime 1, where all quasi-correlation parameters were statistically significant at a 99% confidence level. However, it changes dramatically for the very recent regime (regime 2), where only SSEC was statistically significant at a 90% confidence level. Other changes in relation to regime 1 were observed, as the parameters α and β, which become not statistically significant for the second one.

Such outcomes indicates that the effects of shocks on BTC return volatility at time t when the shock occurs, and volatility's persistence, are only significative for the first regime. Moreover, the estimations are also in line with Ciaian et al (2016) for regime 2, since they did not reveal significant conditional variance parameters for any of the selected variables. Similar to Klein et al (2018), the estimated dynamic conditional correlation of BTC for regime 1 presented a positive signal for the S&P500 and a negative signal for the SSEC and the XAU. The parameters for regime 2 seem to emphasize that BTC volatility follows a less interdependent trajectory, mainly characterized by heavy uncertainty around BTC events. Table 3 exhibits the results of the best fit for both of regimes:

Table 3: Goodness-of-fit models

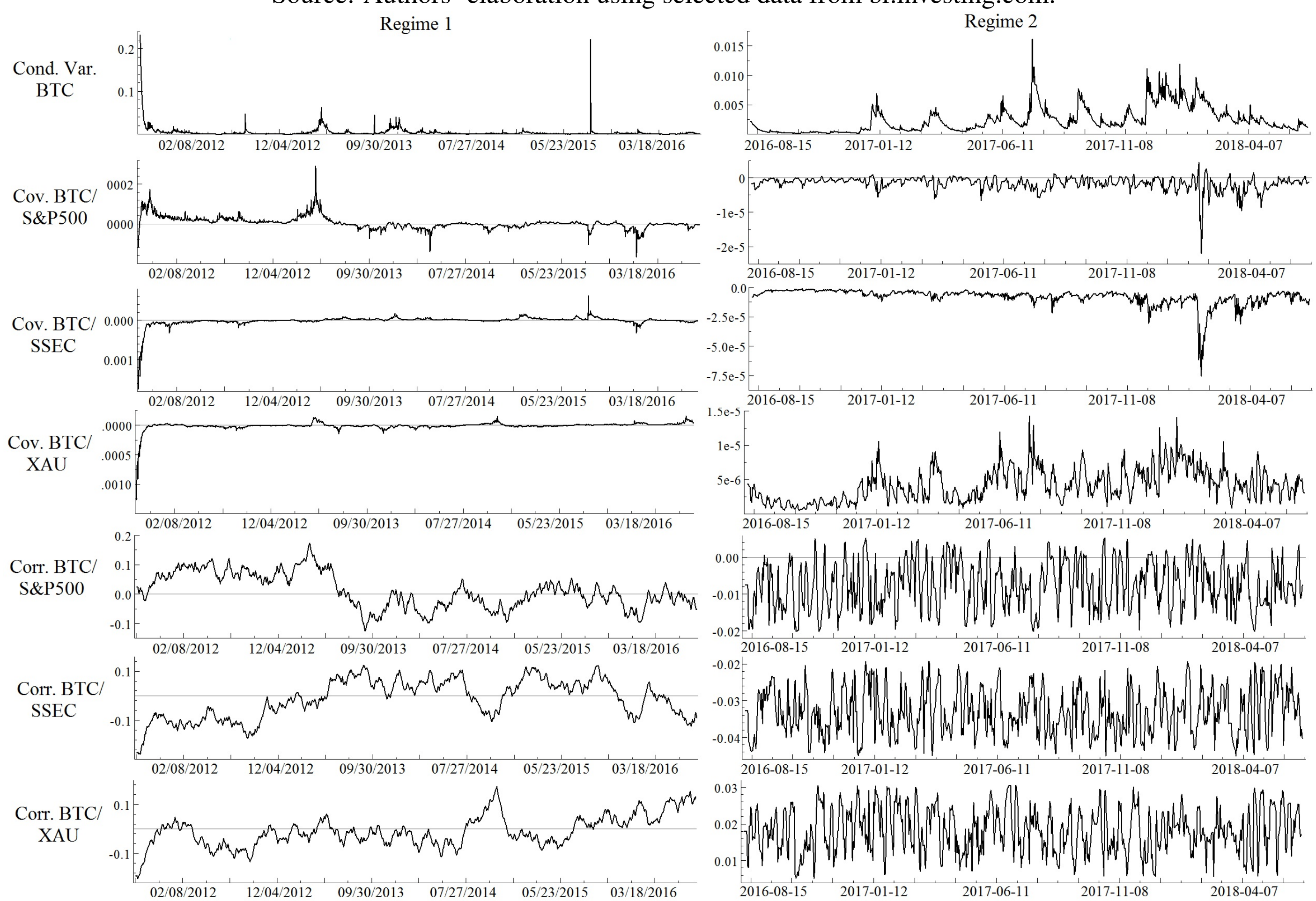
Regimes	AIC	SBC	Shibata	HQ
Regime 1	-25.00025	-24.88625	-25.00109	-24.95815
Regime 2	-27.81970	-27.57393	-27.82521	-27.72458

Source: Authors' elaboration using selected data from br.investing.com.

The goodness-of-fit criteria were based on the Akaike Information Criterion (AIC), the Schwartz Bayesian Criterion (SBC), and the Shibata and Hannan-Quinn (HQ). The less the values of these statistics are, the better the model fits the data. Table 7 and Table 8 in Appendix A exhibit the normality tests and the autocorrelation tests on the returns' residuals and the squares of the returns' residuals, respectively. Thereafter, autocorrelation tests (Q statistic) of the returns' residuals and squared returns' residuals were performed. They suggested that the models completely corrected residual autocorrelation. Figure 1 shows the DCC-MGARCH estimations for BTC conditional variance, conditional covariances and correlation for S&P500, SSEC and XAU.

Figure 1: DCC-MGARCH conditional variance of BTC and the conditional covariances and correlation of the variables used for regimes 1 and 2

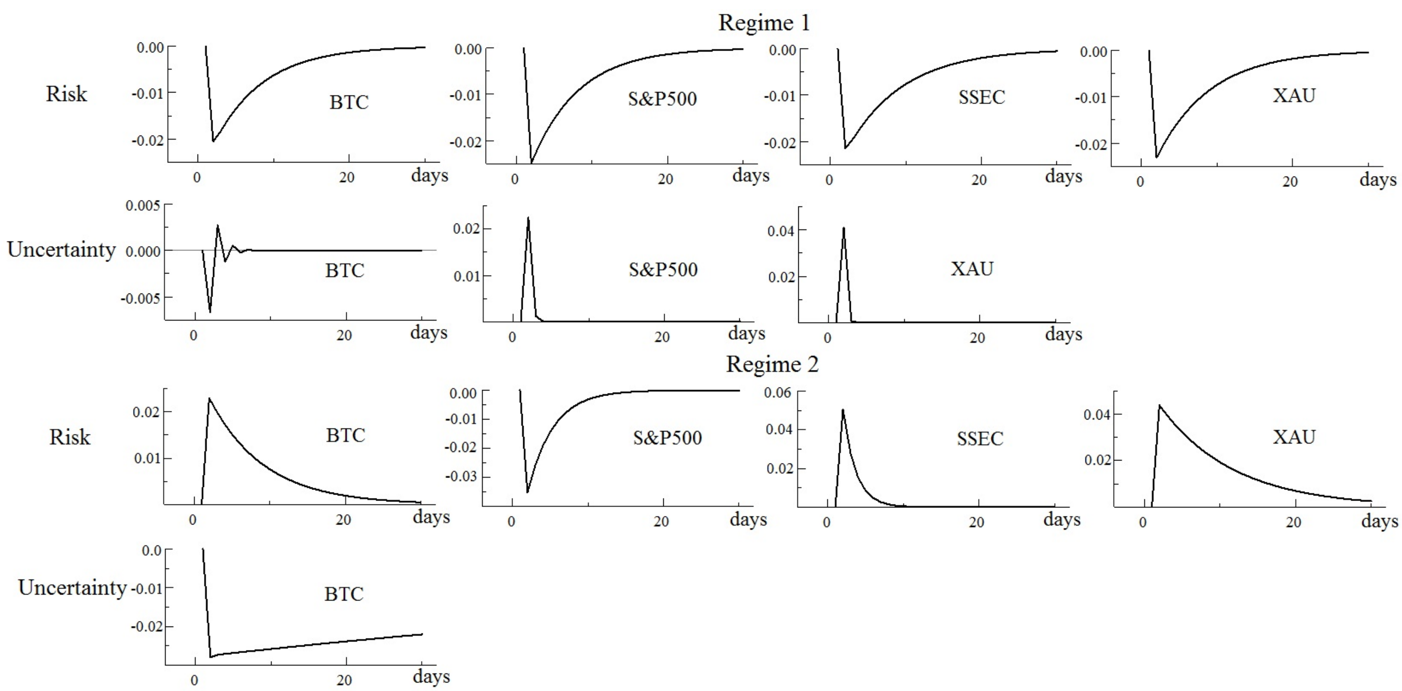
Source: Authors' elaboration using selected data from br.investing.com.



Great volatility cluster for the conditional variance of BTC during mid-2012 to 2013 was observed for regime 1. In addition, the conditional covariances suggests a positive-to-negative relation of BTC with the S&P500, while the opposite is observed regarding the SSEC and XAU. The quasi-correlations reveal a similar positive-to-negative relation with S&P500 and negative-to-positive relations with SSEC and XAU. Regime 2 indicates completely distinct trajectories, with various conditional volatility clusters since mid-2017 to mid-2018. The conditional covariances point to a negative relation between the BTC and the S&P500 and SSEC and a positive relation with XAU. This regime is also characterized by high volatility of all series, mainly the quasi-correlations. They presented as negative for the S&P500 and positive for SSEC and XAU.

There is still no information about how the BTC returns are affected by other shocks beyond information provided by the GARCH-type models. Hence, it was used unrestricted VAR framework to estimate IRFs, which consists of positive orthogonal shocks of 3% on the term ε_{it} from Equation 12. For this purpose, the conditional variances and the estimated residuals obtained in step 3 were used. It was consider predictions 30 days ahead for BTC, SP&500, SSEC and XAU on the BTC returns. The IRFs are illustrated in Figure 2:

Figure 2: Impulse response functions of a positive shock of 3% in the residuals of BTC; the effects of S&P500, SSEC and XAU risks and uncertainty on BTC returns



Source: Authors' elaboration using selected data from br.investing.com.

On the top part of the figure are the estimated responses for first regime, and below these are the estimated responses for regime 2. The estimated responses to risks represent the shocks of the conditional variances of each variable. Uncertainty consists of shocks coming from sources that were not explained by the GARCH-types of models. The estimated residuals from step 3 were used as proxies for this purpose. All shocks have instantaneous, short and transitory effects on BTC returns, whose predictions are indicate on the horizontal axis. All shocks coming from risk presented as being approximately -2% on BTC returns for regime 1, while for regime 2, they are positive for BTC (2.2%), SSEC (5%) and XAU (4.3%) and negative for S&P500 (-3.5%).

Shocks coming from uncertainty point to oscillatory effects from BTC for regime 1; positive from the S&P500 (2.3%) and XAU (4%) and not statistically significant from the SSEC (-3.0%). This paper found empirical evidence based on univariate approaches that asymmetry parameter for regime 2 was not statistically significant, and that volatility is falling over time. However, according to VAR, they were negative for BTC (-3%) and not statistically significant for other sources. The outcomes also suggests that the highest effect among estimated shocks comes from BTC uncertainty. The volatility tends to rise in response to negative news for BTC prices, making excess returns lower than expected. Otherwise, volatility tends to fall in response to good news, making excess returns higher than expected, i.e., a negative correlation between BTC returns and changes in return volatility.

It was difficult to fit any covariates to predict BTC returns and to find evidence to support any quasi-correlation. In addition, the most relevant cluster of volatility found aftermath from May 19, 2015, indicates a regime changing in BTC returns. The IRFs also register an instantaneous, strong and transitory effect coming from BTC uncertainty, also in line with the evidence found in White (2015), Urquhart (2017), Corbet et al (2018b) and Li et al (2015). This makes uncertainty coming from own BTC price formation important to explain its returns, while other sources of shocks were statistically nonsignificant. While in regime 1 BTC return volatility is also explain by financial global indicators, in regime 2 such volatility mainly depends on its own market microstructure.

Moreover, distinct from other assets, BTC return is affected depending on how such technology is consumed. Combined, the increasing demand for anonymity in the international financial system and derivatives collateralization issued by CME, CBOE and LedgerX, could had accelerated BTC speculation in short-term, while has potential to split volatility in long-term, as found by Baur and Dimpfl (2019). BTC prices appreciated more than thirty times in sixteen months from US$604.10 (August 5th, 2016) to US$19,187.00 (December 14th, 2017). According to multivariate analysis, there is clear signals of a BTC speculative bubble from the end of 2017 to mid-2018. All uncertainty distancing BTC prices from the forces that affect an ordinary asset's fundamental aspects, such as earnings per share, the discounted present value and expectations about the future.

6 Summary and conclusions

Fintechs reflect macroeconomic changes by allowing to individuals to access fully transparent financial services governed by open source algorithms. One of the main advantages of this distinct ecosystem is to create incentives for those who maintain and check all of the information in the network. Blockchain as financial innovation and new type of decentralized, globally distributed and competitive network allows startups to collaborate without permission from other network users. Nonetheless, the success of BTC as well as of other fintechs depends, in turn, on which effect will prevail in terms of their utilization in businesses: that from the underground economy or that from the aboveground economy.

However, government announcements, rumors, hack attacks, etc., may turn out to be a distraction and generates more uncertainty and speculative market behavior concerning a still under-developed system. On the other hand, if the regulatory frameworks of countries do not follow the evolution of cryptocurrency and create the appropriate economic incentives, BTC and other fintechs will become largely worthless. To better understand how the threats against this new ecosystem materialize into volatility and uncertainty, some empirical evidence provided indicates that BTC returns appear to follow two regimes.

BTC return volatility was estimated using dynamic conditional heteroskedasticity models, and the outcomes of quasi-correlations and quasi-covariances between volatilities demonstrated high volatility, subject to uncertainty shocks, mainly from the end of 2017 to mid-2018. Meanwhile, this information technology framework with publicly available usage data does not require oversight by any monetary authority. Since these algorithms could be permanently and continuously audited, this characteristic should be better explored to reduce its return volatility.

These last events could toward possible equilibrium: If the CME and CBOE, in addition to LedgerX, fully collateralize their operations, then a number of startups will be able to bring institutional investments without increasing volatility. Competition among altcoins could lead to hybrid monetary arrangements with private and government monies issuers. Thus, this paper propose investigations on algorithm regulation, their costs and benefits. Thereby, it also could help to decrease the risk and uncertainty surrounding cryptocurrency.

References

Ardia D, Bluteau K, Rüede M (2018) Regime changes in Bitcoin GARCH volatility dynamics. In: Finance Research Letters, DOI https://doi.org/10.1016/j.frl.2018.08.009

Baur DG, Dimpfl T (2018) Asymmetric volatility in cryptocurrencies. Economics Letters 173:148 – 151, DOI https://doi.org/10.1016/j.econlet.2018.10.008

Baur DG, Dimpfl T (2019) Regime changes in Bitcoin GARCH volatility dynamics. In: Journal of Futures Markets, DOI https://doi.org/10.1002/fut.22004

Blanchard O, Watson M (1982) Bubbles, rational expectations and financial markets. NBER Working Papers 0945, National Bureau of Economic Research, Inc, URL https://EconPapers.repec.org/RePEc:nbr:nberwo:0945

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

Bollerslev T (1982) Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. Econometrica pp 987–1007

Bollerslev T (1986) Generalized autoregressive conditional heteroskedasticity. Journal of Econometrics 31(1):307–327

Catalini C, Gans JS (2017) Some simple economics of the Blockchain. In: Rotman School of Management Working Paper Nº 2874598 - MIT Sloan Research Paper Nº 5191-16, DOI http://dx.doi.org/10.2139/ssrn.2874598

Chakravorti B, Chaturvedi RS, Mazzotta B (2016) The countries that would profit most from a cashless world. In: Harvard Business Review, URL https://hbr.org/2016/05/the-countries-that-would-profit-most-from-a-cashless-world

Chan S, Chu J, Nadarajah S, Osterrieder J (2017) A statistical analysis of cryptocurrencies. Journal of Risk and Financial Management 10(12):1–23, DOI http://dx.doi.org/10.3390/jrfm10020012

Choi KJ, Lehar A, Stauffer R (2018) Bitcoin microstructure and the Kimchi premium. In: SSRN Papers, DOI http://dx.doi.org/10.2139/ssrn.3189051

Chow GC (1960) Tests of equality between sets of coefficients in two linear regressions. Econometrica 28(3):591–605, URL http://www.jstor.org/stable/1910133

Ciaian P, Rajcaniova M, d'A Kancs (2016) The economics of BitCoin price formation. Applied Economics 48(19):1799–1815, DOI 10.1080/00036846.2015.1109038

Corbet S, Lucey B, P M, Vigne S (2018a) Bitcoin Futures—What use are they? Economics Letters 172:23 – 27, DOI https://doi.org/10.1016/j.econlet.2018.07.031

Corbet S, Lucey B, Yarovaya L (2018b) Datestamping the Bitcoin and Ethereum bubbles. Finance Research Letters 26:81 – 88, DOI https://doi.org/10.1016/j.frl.2017.12.006

Engle R (2002) Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. Journal of Business & Economic Statistics 20(3):339–350

Fang L, Bouri E, Gupta R, Roubaud D (2019) Does global economic uncertainty matter for the volatility and hedging effectiveness of Bitcoin? International Review of Financial Analysis 61:29 – 36, DOI https://doi.org/10.1016/j.irfa.2018.12.010

Fanning K, Centers DP (2016) Blockchain and its coming impact on financial services. Journal of Corporate Accounting & Finance 27(5):53–57, DOI https://www.doi.org/10.1002/jcaf.22179

Fanusie YJ, Robinson T (2018) Bitcoin laundering: an analysis of illicit flows into digital currency services. In: Memorandum, Elliptic and Center on Sanctions and Illicit Finance (CSIF) - Foundation for Defense of Democracies (FDD), URL https://info.elliptic.co/thank-you-whitepaper-fdd-bitcoin-laundering?submissionGuid=8cdafc4b-96eb-4e36-aaed-7259e18e195e

Foley S, Karlsen JR, Putnins TJ (2018) Sex, drugs, and Bitcoin: How much illegal activity is financed through cryptocurrencies? DOI http://dx.doi.org/10.2139/ssrn.3102645

Frascaroli BF, Pinto TC (2016) Aspectos inovativos do Bitcoin, microestrutura de mercado e volatilidade de retornos [Innovative aspects of Bitcoin, market microetructure and volatility returns]. Revista Brasileira de Economia de Empresas 18(2):49–70, URL https://portalrevistas.ucb.br/index.php/rbee/article/view/6778/4699

Gandal N, Hamrick JT, Moore T, Oberman T (2018) Price manipulation in the Bitcoin ecosystem. Journal of Monetary Economics In Press, DOI https://doi.org/10.1016/j.jmoneco.2017.12.004

Glosten LR, Jagannathan R, Runkle DE (1993) On the relation between the expected value and the volatility of the nominal excess return on stocks. The Journal of Finance 48(5):1779—1801, DOI https://doi.org/10.2307/2329067

Grant G, Hogan R (2015) Bitcoin: risks and controls. Journal of Corporate Accounting & Finance 26(5):29–35, DOI https://www.doi.org/10.1002/jcaf.22060

Jurado K, Ludvigson SC, Ng S (2015) Measuring uncertainty. American Economic Review 105(3):1177—-1216, DOI http://dx.doi.org/10.1257/aer.20131193

Klein T, Thu HP, Walther T (2018) Bitcoin is not the New Gold – A comparison of volatility, correlation, and portfolio performance. International Review of Financial Analysis 59:105 – 116, DOI https://doi.org/10.1016/j.irfa.2018.07.010

Lagarde C (2017) Central banking and Fintech — A brave new world? In: Speech in Bank of England Conference, URL https://www.imf.org/en/News/Articles/2017/09/28/sp092917-central-banking-and-fintech-a-brave-new-world

Li Z, Tao R, Su C, Lobonţ O (2015) Does Bitcoin bubble burst? Quality & Quantity 35(2):1–15, DOI https://doi.org/10.1007/s11135-018-0728-3

Lo S, Wang JC (2014) Bitcoin as money? In: Current Policy Perspectives, Federal Reserve Bank of Boston, US, Nº 14-4, URL https://www.bostonfed.org/-/media/Documents/Workingpapers/PDF/cpp1404.pdf

Luther WJ (2016a) Cryptocurrencies, network effects, and switching costs. Contemporary Economic Policy 33(3):553–571, DOI https://doi.org/10.1111/coep.12151

Luther WJ (2016b) Reframing financial regulation: enhancing stability and protecting consumers. Peirce, H. and Klutsey, B. Eds., Arlington, VA: Mercatus Center at George Mason University, chap Regulating Bitcoin: on what grounds? Rethinking Financial Markets Regulation, pp 391–415

Miller M (2014) The ultimate guide to Bitcoin. Pearson Education

Nair M, Cachanosky N (2017) Bitcoin and entrepreneurship: breaking the network effect. The Review of Austrian Economics 30(3):263–275, DOI https://doi.org/10.1007/s11138-016-0348-x

Nelson DB (1991) Conditional heteroskedasticity in asset returns: a new approach. Econometrica 59(2):347–370, DOI https://doi.org/10.2307/2938260

Paar C, Pelzl J (2010) Understanding cryptography: a textbook for students and practitioners. Springer, Berlin, Heidelberg, DOI https://doi.org/10.1007/978-3-642-04101-3

Peng Y, Albuquerque PHM, de Sa JMC, Padula AJA, Montenegro MR (2018) The best of two worlds: Forecasting high frequency volatility for cryptocurrencies and traditional currencies with support vector regression. Expert Systems With Applications 97(May):177–192, DOI https://doi.org/10.1016/j.eswa.2017.12.004

Rogoff K (2014) Costs and benefits to phasing out paper currency. In: NBER Macroeconomics Annual Conference 2014, URL https://scholar.harvard.edu/files/rogoff/files/c13431.pdf

Satoshi N (2008) Bitcoin: a peer-to-peer electronic cash system. Tech. rep., Bitcoin Organization

Scaillet O, Treccani A, Trevisan C (2017) High-frequency jump analysis of the Bitcoin market. In: Swiss Finance Institute, Research Paper Series Nº 17-19, URL https://papers.ssrn.com/sol3/Delivery.cfm/SSRN_ID2992637_code623849.pdf?abstractid=2982298&mirid=1

Scotti C (2016) Surprise and uncertainty indexes: Real-time aggregation of real-activity macro–surprises. Journal of Monetary Economics 82:1–19, DOI https://doi.org/10.1016/j.jmoneco.2016.06.002

Selgin G (2015) Synthetic commodity money. Journal of Financial Stability 17:92–99, DOI https://doi.org/10.1016/j.jfs.2014.07.002

Silva PVJG, Klotzle MC, Pinto ACF, Gomes LL (2019) Volatility estimation for cryptocurrencies using markov-switching garch models. In: International Journal of Financial Markets and Derivatives, URL https://www.inderscience.com/info/ingeneral/forthcoming.php?jcode=ijfmd

Sims C (1980) Macroeconomics and reality. Econometrica 48(1):1–48

Tse YK, Tsui AKC (2002) A Multivariate Generalized Autoregressive Conditional Heteroscedasticity model with time-varying correlations. Journal of Business & Economic Statistics 20(3):351–362, DOI https://www.doi.org/10.1198/073500102288618496

Urquhart A (2016) The inefficiency of bitcoin. Economics Letters 148(C):80–82, DOI http://dx.doi.org/10.1016/j.econlet.2016.09.019

Urquhart A (2017) Price clustering in Bitcoin. Economics Letters 159:145 – 148, DOI https://doi.org/10.1016/j.econlet.2017.07.035

White LH (2015) The market for cryptocurrencies. Cato Journal 35(2):383–402, URL https://object.cato.org/sites/cato.org/files/serials/files/cato-journal/2015/5/cj-v35n2-13.pdf

World Economic Forum (2015) The future of financial services: how disruptive innovations are reshaping the way financial services are structured, provision and consumed. Tech. rep., World Economic Forum

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

Zargar FN, Kumar D (2018) Informational inefficiency of Bitcoin: A study based on high-frequency data. In: Research in International Business and Finance, DOI https://doi.org/10.1016/j.ribaf.2018.08.008

Zargar FN, Kumar D (2019) Long range dependence in the Bitcoin market: A study based on high-frequency data. Physica A 515:625—-640, DOI https://doi.org/10.1016/j.physa.2018.09.188

Appendix A

Figure 3: Trajectories of all sampled variables

Source: Authors' elaboration using selected data from br.investing.com.

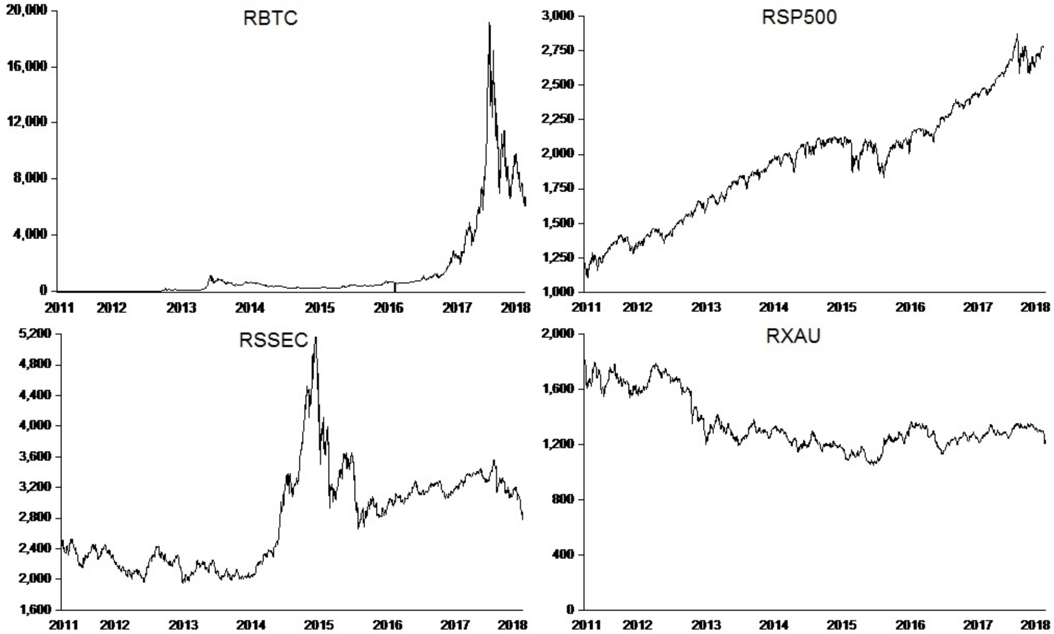


Figure 4: Logarithmic returns of all sampled variables

Source: Authors' elaboration using selected data from br.investing.com.

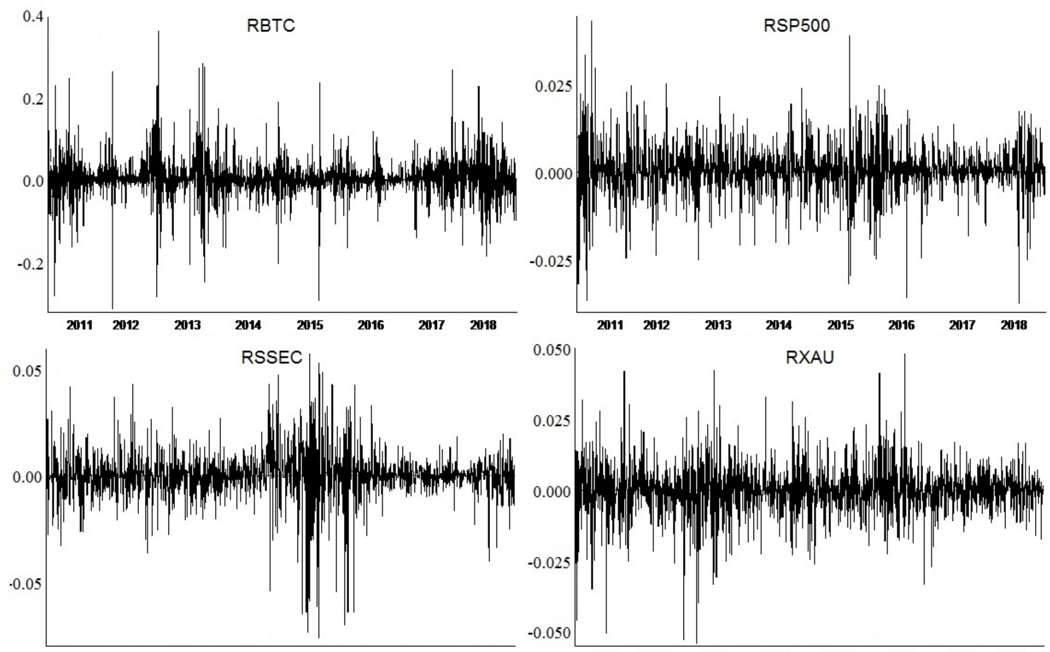


Table 4: Chow test

Unrestricted Model			Dummy Model		
Statistic	Value	Prob.	Statistic	Value	Prob.
S&P500	0.00314	0.874	S&P500	0.00596	0.763
SSEC	0.03875	0.050	SSEC	-0.034815	0.079
XAU	0.02089	0.288	XAU	0.02182	0.267
Const.	1233.235	0.000	Const.	1202.168	0.000
			D1	77.2118	0.014
BTC Param.	P>|t|		BTC Param.	P>|t|	
F(3, 2466)	1.66		F(4, 2465)	2.75	
Prob > F	0.1743		Prob > F	0.0266	

Source: Authors' elaboration using selected data from br.investing.com.

Table 5: ARCH test BTC

Model	Lags	F Statistic	Value	Prob.
Regime 1	1-2	F(2,1773)	0.10083	0.9401
	1-5	F(5,1767)	0.20144	0.9868
Regime 2	1-2	F(2,673)	0.01308	0.9870
	1-5	F(5,667)	0.20144	0.9619

Source: Authors' elaboration using selected data from br.investing.com.

Table 6: Results of the univariate GARCH model estimations

Regime 1 - EGARCH					Regime 2 - GJR-GARCH				
Param.	BTC	S&P500	SSEC	XAU	Param.	BTC	S&P500	SSEC	XAU
AR(1)	-0.19639	0.12541	0.15551	-0.82867	AR(1)	0.99987	-0.44778	0.36191	0.55604
	(-2.031)	(0.2570)	(1.193)	(-4.495)		(232.3)	(-1.639)	(0.9191)	(1.655)
	[0.0424]	[0.7972]	[0.2331]	[0.0000]		[0.0000]	[0.1017]	[0.3584]	[0.0984]
AR(2)	-0.04580	0.01936	0.07997	0.01352	MA(1)	-0.98913	0.42232	-0.22953	-0.47990
	(-1.101)	(1.125)	(2.708)	(0.4344)		(-190.5)	(1.490)	(-0.6685)	(-1.478)
	[0.2711]	[0.2608]	[0.0068]	[0.6641]		[0.0000]	[0.1367]	[0.5041]	[0.1397]
MA(1)	0.27903	-0.13118	-0.05682	0.85782	α	0.18418	-0.02914	-0.02476	-0.04195
	(3.143)	(-0.2703)	(-0.4442)	(4.908)		(2.877)	(-1.194)	(-0.6449)	(-5.886)
	[0.0017]	[0.7870]	[0.6570]	[0.0000]		[0.0041]	[0.2328]	[0.5192]	[0.0000]
α	-0.50798	-0.42881	-0.49930	-0.33231	β_1	0.33091	0.23872	0.02232	1.61627
	(-3.012)	(-4.236)	(-4.682)	(-1.720)		(1.544)	(1.195)	(0.3733)	(26.06)
	[0.0026]	[0.0000]	[0.0000]	[0.0857]		[0.1231]	[0.2326]	[0.7091]	[0.0000]
β	0.99294	0.99525	0.99602	0.99545	β_2	0.48416	0.55887	0.75631	-0.76141
	(326.6)	(1055.0)	(1432.0)	(0.00094)		(2.480)	(3.422)	(2.211)	(-11.60)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]		[0.0134]	[0.0007]	[0.0273]	[0.0000]
θ_1	0.02909	-0.22405	-0.00809	-0.04964	γ	0.02969	0.26680	0.28457	0.02881
	(0.3219)	(-5.835)	(-0.2041)	(-1.459)		(0.4574)	(1.982)	(0.6470)	(3.307)
	[0.7476]	[0.0000]	[0.8383]	[0.1447]		[0.6475]	[0.0479]	[0.5179]	[0.0010]
θ_2	0.53270	0.50546	0.45513	0.36940	$Const_{\sigma^2}$	0.22410	2.32761	2.85806	4.62889
	(6.348)	(4.631)	(4.675)	(3.266)		(1.471)	(2.493)	(0.5293)	(3.526)
	[0.0000]	[0.0000]	[0.0000]	[0.0011]		[0.1417]	[0.0129]	[0.5968]	[0.0005]
Log–likelihood	3171.17	6388.56	5585.33	5876.36	Log–likelihood	1244.03	2736.73	2649.76	2629.75

Source: Authors' elaboration using selected data from br.investing.com.
Note: t-statistics are in () and P-values are in [].

Table 7: Normality tests for the MGARCH

		Regime 1			Regime 2		
Variable	Statistic	t-Test	t	p-Value	t-Test	t	p-Value
BTC	Skewness	-2.1132	36.428	0.00000	0.10550	1.1265	0.25997
	Excess kurtosis	26.185	225.82	0.00000	2.2869	12.227	0.00000
	Jarque-Bera	52178	-	0.00000	149.67	-	0.00000
S&P500	Skewness	-0.17422	3.0033	0.00267	-0.90481	9.6607	0.00000
	Excess kurtosis	5.3205	45.885	0.00000	6.7817	36.257	0.00000
	Jarque-Bera	2108.5	-	0.00000	1397.9	-	0.00000
SSEC	Skewness	-0.17518	3.0199	0.00253	-0.79308	8.4678	0.00000
	Excess kurtosis	5.8004	50.023	0.00000	6.3307	33.846	0.00000
	Jarque-Bera	2504.4	-	0.00000	1588.1	-	0.00000
XAU	Skewness	-0.22193	3.8257	0.000130	-0.48148	5.1408	0.00000
	Excess kurtosis	8.0276	69.231	0.00000	3.1328	16.749	0.00000
	Jarque-Bera	4375.3	-	0.00000	304.80	-	0.00000

Source: Authors' elaboration using selected data from br.investing.com.

Table 8: Q-Statistics on residuals and squared standardized residuals

Variable		Q-stat	P-Value	Variable		Q-stat	P-Value
			Regime 1				
			Residuals				
BTC	(Q5)	12.7740	0.025591	SSEC	(Q5)	3.29294	0.65492
	(Q10)	31.3497	0.000514		(Q10)	10.2344	0.42017
	(Q20)	59.5027	0.00001		(Q20)	18.3058	0.56727
S&P500	(Q5)	2.49033	0.77795	XAU	(Q5)	7.04440	0.21736
	(Q10)	13.8320	0.18079		(Q10)	10.3579	0.40967
	(Q20)	28.7602	0.09259		(Q20)	12.7887	0.88627
			Squared standardized residuals				
BTC	(Q5)	0.21792	0.99891	SSEC	(Q5)	10.1660	0.07067
	(Q10)	1.78122	0.99776		(Q10)	23.6681	0.00853
	(Q20)	3.17029	0.99999		(Q20)	45.6143	0.00091
S&P500	(Q5)	17.1197	0.00428	XAU	(Q5)	11.3682	0.04455
	(Q10)	61.3462	0.00000		(Q10)	17.0446	0.07338
	(Q20)	113.181	0.00000		(Q20)	41.7052	0.00302
			Regime 2				
			Residuals				
BTC	(Q5)	5.39559	0.36953	SSEC	(Q5)	11.8298	0.03720
	(Q10)	9.33507	0.50063		(Q10)	13.7376	0.18530
	(Q20)	14.3783	0.81081		(Q20)	19.9326	0.46216
S&P500	(Q5)	5.86778	0.31930	XAU	(Q5)	5.82143	0.32399
	(Q10)	12.6252	0.24539		(Q10)	8.91005	0.54066
	(Q20)	28.6521	0.09484		(Q20)	27.5010	0.12175
			Squared standardized residuals				
BTC	(Q5)	0.999512	0.96260	SSEC	(Q5)	1.11482	0.95278
	(Q10)	5.00174	0.89106		(Q10)	5.65041	0.84373
	(Q20)	15.9604	0.71908		(Q20)	23.9812	0.24322
S&P500	(Q5)	1.39110	0.92528	XAU	(Q5)	6.92023	0.22664
	(Q10)	11.1518	0.34582		(Q10)	25.0213	0.00531
	(Q20)	22.4099	0.31869		(Q20)	56.2945	0.00003

Source: Authors' elaboration using selected data from br.investing.com.

Table 9: Results of the VAR models estimations for risks and uncertainty

Regime 1					Regime 2				
Param.	BTC	S&P500	SSEC	XAU	Param.	BTC	S&P500	SSEC	XAU
BTC(-1)	0.03213	0.03158	0.03165	0.03163	BTC(-1)	-0.01558	-0.01555	-0.01570	-0.01587
	(1.36)	(1.33)	(1.33)	(1.33)		(-0.404)	(-0.403)	(-0.407)	(-0.412)
	[0.1755]	[0.1832]	[0.1823]	[0.1826]		[0.6865]	[0.6869]	[0.6841]	[0.6807]
Risk(-1)	-0.02058	-0.02363	-0.02147	-0.0221	Risk(-1)	0.23462	-17.9183	25.5298	221.379
	(-0.858)	(-0.930)	(-0.907)	(-0.912)		(0.295)	(-0.327)	(0.561)	(0.743)
	[0.3912]	[0.3526]	[0.3643]	[0.3621]		[0.7681]	[0.7437]	[0.5749]	[0.4580]
Const.	0.00392	0.00385	0.00386	0.00386	Const.	0.00399	0.00502	0.00375	-0.001433
	(3.32)	(3.29)	(3.29)	(3.29)		(1.52)	(2.20)	(1.63)	(-0.173)
	[0.0009]	[0.0010]	[0.0010]	[0.0010]		[0.1297]	[0.0279]	[0.1026]	[0.8624]
F(4,3550)	3766.36	7591.92	10400.9	9389.75	F(4,1352)	349.876	165.153	68.1965	449.168
	[0.0000]**	[0.0000]**	[0.0000]**	[0.0000]**		[0.0000]**	[0.0000]**	[0.0000]**	[0.0000]**
Normality	40855	0.00000	0.00001	0.00001	Normality	612.60	2223.8	2387.4	464.28
test $\chi^2(4)$	[0.0000]**	[0.0000]**	[0.0000]**	[0.0000]**	test $\chi^2(4)$	[0.0000]**	[0.0000]**	[0.0000]**	[0.0000]**
Log–likelihood	8885.13	10091.64	10430.66	10319.71	Log–likelihood	4794.76	7459.95	7188.12	8916.66
BTC(-1)	0.03894	0.03232	0.03272	0.03001	BTC(-1)	0.26488	-0.01503	-0.01684	-0.01523
	(0.210)	(1.36)	(1.38)	(1.27)		(0.515)	(-0.389)	(-0.436)	(-0.395)
	[0.8341]	[0.1728]	[0.1680]	[0.2051]		[0.6066]	[0.6971]	[0.6630]	[0.6929]
Uncert.(-1)	-0.006654	0.2246	-0.05510	0.40331	Uncert.(-1)	0.00319	-0.10010	-0.22232	-0.26891
	(-0.0358)	(1.34)	(-0.541)	(2.90)		(1.03)	(-0.284)	(-0.673)	(-0.785)
	[0.9714]	[0.1792]	[0.5885]	[0.0038]		[0.3015]	[0.7764]	[0.5009]	[0.4328]
Const.	0.003766	0.00369	0.003772	0.003826	Const.	-0.28056	0.00459	0.00456	0.00455
	(3.23)	(3.16)	(3.23)	(3.28)		(-0.547)	(2.57)	(2.55)	(2.55)
	[0.0013]	[0.0016]	[0.0013]	[0.0010]		[0.5848]	[0.0105]	[0.0109]	[0.0111]
F(4,3550)	504.478	2.86268	0.83771	3.44647	F(4,1352)	+∞	1.18136	0.345582	0.29223
	[0.0000]**	[0.0221]*	[0.5010]	[0.0081]**		[0.0000]**	[0.3172]	[0.8472]	[0.8831]
Normality	9131.2	9131.2	3034.9	2665.0	Normality	192.54	485.07	445.68	360.95
test $\chi^2(4)$	[0.0000]**	[0.0000]**	[0.0000]**	[0.0000]**	test $\chi^2(4)$	[0.0000]**	[0.0000]**	[0.0000]**	[0.0000]**
Log–likelihood	10152.92	9157.89	8271.34	8834.17	Log–likelihood	+∞	3766.12	3712.25	3739.66

Source: Authors' elaboration using selected data from br.investing.com.

Note: t-statistics are in ( ) and P-values are in [ ]. Significant outcomes at a 1% level are shown by two stars ** and at a 5% by one star *.