Economics Letters 172 (2018) 97–101

Contents lists available at ScienceDirect

Economics Letters

journal homepage: www.elsevier.com/locate/ecolet

Liquidity uncertainty and Bitcoin's market microstructure

Dimitrios Koutmos

Worcester Polytechnic Institute, 100 Institute Road, Worcester, MA 01609, USA

HIGHLIGHTS

- This paper provides a novel measure for the liquidity uncertainty of Bitcoin.
- This measure is constructed using bid–ask spread data.
- It proceeds to test whether Bitcoin's liquidity uncertainty can be explained.
- Market microstructure variables underlying Bitcoin serve as explanatory variables.
- A regime-switching regression approach is used to capture low and high uncertainty.

ARTICLE INFO

Article history:
Received 10 April 2018
Received in revised form 25 August 2018
Accepted 28 August 2018
Available online 31 August 2018

JEL classification:
C58
G12
G17

Keywords:
Bitcoin
GARCH
Liquidity
Market microstructure
Markov regime-switching

ABSTRACT

This paper provides a novel measure of liquidity uncertainty for Bitcoin using bid–ask spread data from Bitfinex — one of the largest and most liquid Bitcoin exchanges. This measure can be used to analyze liquidity developments in Bitcoin exchanges or to gauge the immediacy associated with buying or selling Bitcoin. It then proceeds to identify what aspects of Bitcoin's market microstructure can explain the time series behavior of this liquidity uncertainty. The estimation results are based on a Markov regime-switching model that captures episodes of high and low liquidity uncertainty for Bitcoin over the period from October 2013 to March 2018.

© 2018 Elsevier B.V. All rights reserved.

1. Introduction

Liquidity and marketability are among the central attributes of financial instruments that are perceived as desirable for at least two reasons; first, they instill confidence among individuals and institutions, who can transact such instruments efficiently across time. Second, they allow a central bank to provide monetary stability through policymaking tools that impact the inflows or outflows of such instruments on the balance sheets of financial institutions, thereby affecting asset–liability mismatches and, consequently, lending behaviors and individual borrowing and spending tendencies.

While both these reasons are relevant to conventional currencies and other assets, policymakers have questioned how they apply to cryptocurrencies such as Bitcoin. First, Bitcoin prices are too volatile relative to other currencies, thereby eroding any chance Bitcoin has of being accepted as a mainstream medium of exchange among individuals and institutions (Lo and Wang, 2014). Second, since Bitcoin is independent of the authority of the state or central bank (and therefore its protection), the incentive to hijack it rises along with its growing acceptance and use (Gandal et al., 2018; Velde, 2013).

The private sector, on the other hand, is embracing this new technology at an increasing rate while the number of businesses accepting Bitcoin as some form of payment is steadily rising.[1] Among other microstructure characteristics shown in Fig. 1, the price and trading activity underlying Bitcoin have particularly risen astronomically in recent years and bear no resemblance to the growth patterns observed in conventional asset classes. Nascent academic literature has focused on explaining or forecasting Bitcoin's price behavior (Cheah et al., 2018; Ciaian et al., 2016; Katsiampa, 2017; Khuntia and Pattanayak, 2018; Koutmos, 2018; Nadarajah and Chu, 2017; Symitsi and Chalvatzis, 2018; Urquhart,

E-mail address: DKoutmos@WPI.edu.

https://doi.org/10.1016/j.econlet.2018.08.041
0165-1765/© 2018 Elsevier B.V. All rights reserved.

[1] A list of companies that accept Bitcoin as payment is available online here: https://99bitcoins.com/who-accepts-bitcoins-payment-companies-stores-take-bitcoins/. Prominent companies, such as Bloomberg, Expedia, Gap, JC Penney, Microsoft, Subway, to name but a few, are on the list.

2017). The emerging consensus is that, unlike conventional asset classes, Bitcoin's prices cannot be explained on the basis of economic fundamentals.

When compared to studies which try to explain Bitcoin's price behavior, however, there is little discussion pertaining to Bitcoin's market microstructure or its liquidity risks (Phillip et al., 2018; Wei, 2018). Since Bitcoin is a distinct asset, it is conceivable that its microstructure is driven by an investor and clientele base that is very different from what can be found in the market exchanges for traditional financial instruments. We should therefore begin focusing on the technical and economic dimensions underlying its market microstructure in order to gain important insights into this new asset.

Our lack of understanding of Bitcoin's market microstructure, yet, its increasing popularity in the face of policymakers' dire warnings, impel the motivation for this paper. Thus far, Bitcoin's unruly price volatility is an attribute that may diminish its liquidity and marketability—central features that demarcate mainstream currencies. Yet, its popularity among businesses and individuals is on the rise.

In light of the aforementioned, this paper posits the following question: "*How can we measure Bitcoin's liquidity uncertainty and what are its market microstructure determinants?*" In the first part of the analysis, it uses an ARMA-GARCH framework to construct a time series that represents the uncertainty associated with Bitcoin's bid–ask spreads. This time series captures the degree of liquidity uncertainty for Bitcoin and is advantageous in that it can be re-constructed using bid–ask spread data from other Bitcoin exchanges. In the second part, it explores which of the economic and technological characteristics of its microstructure can help to explain this liquidity uncertainty. A Markov-regime switching framework is used to show findings for periods of low versus high liquidity uncertainty.

2. Data & preliminary methods

2.1. Measuring liquidity uncertainty

The degree of asset liquidity is inferable by measuring, among other features, the cost of immediacy. An investor seeking to trade faces a certain tradeoff: They may wait for a favorably perceived price in order to trade, or, they may choose to trade immediately at prevailing bid and ask prices. Quoted ask prices include a premium for immediate buying while bid prices include a discount required for immediate selling. All else remaining constant, a rising bid–ask spread reflects a rising cost in immediacy and a deterioration in liquidity conditions while volatility in this spread reflects liquidity uncertainty.

Thus far, empirical tests of Bitcoin argue that its relatively high price volatility inhibit its liquidity and marketability, thus reducing the possibility that it can become a mainstream medium of exchange. Nonetheless, tests of Bitcoin have yet to explicitly examine or model its liquidity characteristics.

This paper suggests that the volatility associated with its bid–ask spreads can serve as a measure of the liquidity uncertainty of Bitcoin. It therefore fits an ARMA-GARCH model on daily quoted bid–ask spreads, Q, obtained from Bitfinex—one of the largest and most liquid Bitcoin exchanges[2]:

$$Q_t = \beta_0 + \beta_1 Q_{t-1} + \beta_2 Q_{t-2} + \varepsilon_t - \varphi \varepsilon_{t-1}$$

$$\sigma^2_{Q,t} = \alpha_0 + \alpha_1 \varepsilon^2_{t-1} + \alpha_2 \sigma^2_{Q,t-1} \tag{1}$$

Unlike classical asset pricing tests that typically decompose a time series into its expected and unexpected components using some ARMA-type model of the predicted values and the residuals, respectively, the ARMA-GARCH framework in Eq. (1) allows for a novel alternative to measuring uncertainty. This is because it extracts the conditional variance of the residual rather than only using the residual itself to measure uncertainty. This is an attractive feature for measuring the uncertainty of a given time series because, as Becker and Sy (2005) argue, it is based on more information and naturally has a forward-looking property for forecasting uncertainty rather than only observing when uncertainty happens (as is the case with the residual being used by itself).

Fig. 2 shows a time series plot of the liquidity uncertainty measure estimated from Eq. (1). The sample range is from October 9, 2013 until March 21, 2018 and the frequency is daily. Since it includes weekends (Bitcoin trades on weekdays and weekends), there are a total of 1625 observations.

As shown in Fig. 2, periods of high liquidity uncertainty are associated with the Mt. Gox debacle (2013–14), the hacking of Bitfinex (summer of 2016), China's ban of cryptocurrencies (fall of 2017) and South Korea's threat to shut down cryptocurrency exchanges (winter of 2017), to name but a few events. The probability of being in a high liquidity uncertainty state is shown in gray and discussed further in Section 3.

2.2. Market microstructure explanatory variables

Transparency is a central feature in Bitcoin's market microstructure with data available to the public on the various characteristics underlying its growing ecosystem.[3] For the aforementioned sample period, this paper uses the following microstructure variables to explain liquidity uncertainty for Bitcoin:

- *(i). Price.* The price of Bitcoin (BTC), expressed as USD/BTC.
- *(ii). RVol.* Range volatility estimate for Bitcoin using its intraday high (H_t) and low (L_t) price within day t and computed as follows: $\ln(H_t) - \ln(L_t)$.
- *(iii). Volume.* The trading volume (in BTC).
- *(iv). Size.* The total market capitalization for Bitcoin (in USD).
- *(v). Addrs.* The total number of unique Bitcoin addresses. These addresses, like an email or physical address, represent a possible destination for a Bitcoin payment. To receive Bitcoin payment, this is the only information that needs to be provided to the payor.
- *(vi). Fees.* The total value of fees that Bitcoin miners earn (in BTC).
- *(vii). Hash.* The number of giga hashes per second (billions of hashes per second) which the Bitcoin network is performing to stay operational. This is a technological unit of measurement of the processing power for the Bitcoin network.

While Fig. 1 shows a time series plot of the variables in their raw form, Table 1 shows transformations performed for each variable to ensure their stationarity, along with their expected signs in explaining liquidity uncertainty. A correlation matrix of the transformed explanatory variables is shown in Table 2, along with their respective pairwise correlations to the liquidity uncertainty (*LiqUnc*) time series that is estimated from Eq. (1).

[2] Unit root tests (not reported for brevity) reject the null of a unit root in Bitcoin's bid–ask spreads. Given their stationarity, this permits fitting an ARMA-GARCH in order to estimate liquidity uncertainty. The data used are publicly available online: https://data.bitcoinity.org. Various lag structures are considered for the ARMA-GARCH framework, yet, produce qualitatively analogous findings (available upon request). The findings reported in Table 3 are based on a ARMA(2,1)-GARCH(1,1), which describes the data well.

[3] The explanatory variables used in this paper to explain Bitcoin's liquidity uncertainty are available online at https://www.quandl.com. Information and real-time data updates are available at https://blockchain.info. More definitions of the explanatory variables used here along with other aspects of Bitcoin's market microstructure are available at https://bitcoin.org/en. The explanatory variables used herein represent all the major available microstructure variables downloadable through Quandl.

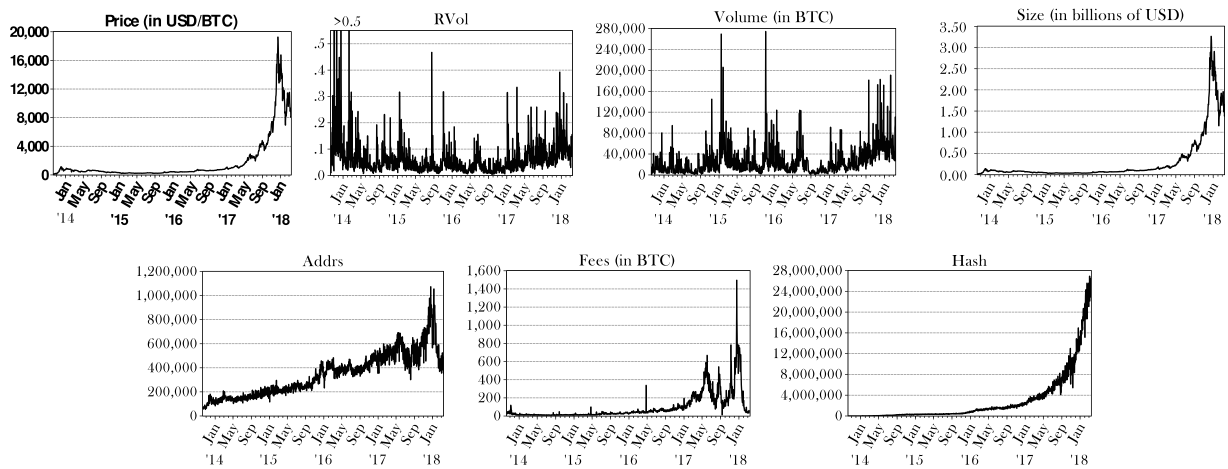

Fig. 1. Time series plots of explanatory variables (in raw levels).

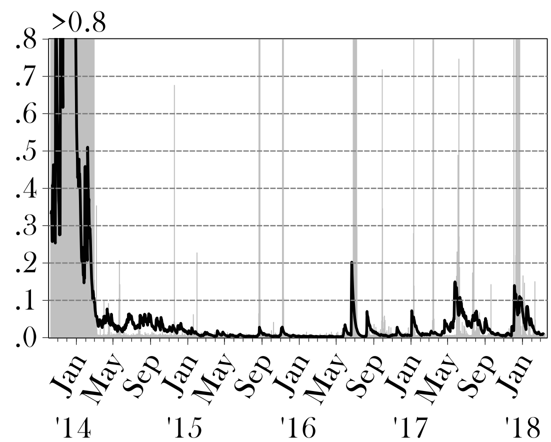

Fig. 2. Time series plot of liquidity uncertainty where the shaded region denotes the probability of the high uncertainty regime, $P(s_t = 2)$.

Table 1
Explanatory variables of the model.

Variable	Transf.	Expected sign	Description
Price	Δln	−	Price of Bitcoin (USD/BTC)
RVol	Level	+	Range volatility between high and low price
Volume	ln	−	Trading volume (in BTC)
Size	Δln	−	Total market capitalization for Bitcoin (in USD)
Addrs	Δln	−	Total number of unique Bitcoin addresses
Fees	Δln	+/−	Total transaction fees (in BTC)
Hash	Δln	+/−	Bitcoin hash rate

This table lists the explanatory variables used to explain liquidity uncertainty in Bitcoin. The first column abbreviates the variables, which are in their raw form, while the second column identifies the transformation performed to ensure stationarity; *ln* and *Δln* denote the natural logarithm and first-difference of the natural logarithm, respectively, while *level* denotes the level of the data series (no transformation). The third column indicates the expected sign of each variable while the last column provides a description of the untransformed data series.

3. Analytical framework

Using the aforementioned explanatory variables, this paper posits the following Markov regime-switching model to explain the time series behavior of Bitcoin's liquidity uncertainty (*LiqUnc*):

$$\begin{aligned} LiqUnc_t &= b_0 + b_{1,s_t}\Delta\ln(Price) + b_{2,s_t}RVol \\ &\quad + b_{3,s_t}\ln(Volume) + b_{4,s_t}\Delta\ln(Size) \\ &\quad + b_{5,s_t}\Delta\ln(Addrs) + b_{6,s_t}\Delta\ln(Fees) \\ &\quad + b_{7,s_t}\Delta\ln(Hash) + \varepsilon_{S_t} \end{aligned} \tag{2}$$

To capture periods of low and high liquidity uncertainty, respectively, each of the coefficients can take different values depending on the regime state, s_t, whereby ε_{S_t} is a vector of disturbances assumed to be normally distributed with a state-dependent variance of σ_S^2:

$$\begin{aligned} &\mathbb{A}_{s_t} = \begin{cases} b_{0,1} & \text{if } s_t = 1 \\ b_{0,2} & \text{if } s_t = 2 \end{cases} \qquad \mathbb{B}_{s_t} = \begin{cases} b_{1,1} & \text{if } s_t = 1 \\ b_{1,2} & \text{if } s_t = 2 \end{cases} \\ &\mathbb{C}_{s_t} = \begin{cases} b_{2,1} & \text{if } s_t = 1 \\ b_{2,2} & \text{if } s_t = 2 \end{cases} \qquad \mathbb{D}_{s_t} = \begin{cases} b_{3,1} & \text{if } s_t = 1 \\ b_{3,2} & \text{if } s_t = 2 \end{cases} \\ &\mathbb{E}_{s_t} = \begin{cases} b_{4,1} & \text{if } s_t = 1 \\ b_{4,2} & \text{if } s_t = 2 \end{cases} \qquad \mathbb{F}_{s_t} = \begin{cases} b_{5,1} & \text{if } s_t = 1 \\ b_{5,2} & \text{if } s_t = 2 \end{cases} \\ &\mathbb{G}_{s_t} = \begin{cases} b_{6,1} & \text{if } s_t = 1 \\ b_{6,2} & \text{if } s_t = 2 \end{cases} \qquad \mathbb{H}_{s_t} = \begin{cases} b_{7,1} & \text{if } s_t = 1 \\ b_{7,2} & \text{if } s_t = 2 \end{cases} \end{aligned} \tag{3}$$

The evolution of the unobservable state variables in Eqs. (2) and (3) follow a two-state Markov chain:

$$\begin{aligned} &\Pr(s_t = 1 | s_{t-1} = 1) = p_{11} \qquad \Pr(s_t = 2 | s_{t-1} = 1) = p_{12} \\ &\Pr(s_t = 1 | s_{t-1} = 2) = p_{21} \qquad \Pr(s_t = 2 | s_{t-1} = 2) = p_{22} \end{aligned} \tag{4}$$

whereby $p_{11} + p_{12} = p_{21} + p_{22} = 1$. The notations $\Pr(\cdot)$ and $p(\cdot)$ respectively represent the discrete probability set and a probability density function (Hamilton, 1988). Estimated values for p_{11}, p_{12},

Table 2
Correlation matrix of explanatory variables.

	$\Delta\ln(Price)$	RVol	$\ln(Volume)$	$\Delta\ln(Size)$	$\Delta\ln(Addrs)$	$\Delta\ln(Fees)$	$\Delta\ln(Hash)$
$\Delta\ln(Price)$		−0.3264	−0.0509	0.5656	−0.0099	0.0002	−0.0164
RVol	−0.3264		0.1419	−0.0285	0.0158	−0.0250	0.0221
$\ln(Volume)$	−0.0509	0.1419		−0.0165	0.0223	0.0363	−0.0163
$\Delta\ln(Size)$	0.5656	−0.0285	−0.0165		0.0406	0.0326	−0.0293
$\Delta\ln(Addrs)$	−0.0099	0.0158	0.0223	0.0406		0.3095	0.1971
$\Delta\ln(Fees)$	0.0002	−0.0250	0.0363	0.0326	0.3095		0.0945
$\Delta\ln(Hash)$	−0.0164	0.0221	−0.0163	−0.0293	0.1971	0.0945	
LiqUnc	0.0495	0.1094	−0.0495	0.0673	−0.0171	−0.0260	0.0252

This table shows pairwise correlations between each of the explanatory variables used to explain liquidity uncertainty (*LiqUnc*) in Bitcoin. A description of each variable is provided in Table 1. The last row shows the pairwise correlations between *LiqUnc* and each of the explanatory variables.

p_{21} and p_{22} denote respective transition probabilities from going from one regime state to another.[4]

4. Empirical results

Estimating Eq. (2) using the regime-switching framework shows that periods of high liquidity uncertainty ($s_t = 2$), which are shaded in Fig. 2, correspond with the aforementioned adverse events that really tested Bitcoin's ecosystem. The Mt. Gox debacle (2013–14) shows the period when liquidity uncertainty was the highest for Bitcoin investors to a degree yet unseen in recent years despite cryptocurrencies being outright banned in China. Fig. 2 thus shows evidence of a distinct low and high liquidity uncertainty regime and this is important because there may be heterogeneity in the explanatory nature of the coefficients in Eq. (2).

Table 3 shows the results for the low ($s_t = 1$) and high ($s_t = 2$) liquidity uncertainty regimes, respectively.[5] Of the seven explanatory variables, for $s_t = 1$, two show a positive and significant relation to liquidity uncertainty (Bitcoin returns and range volatility) while three show a negative and significant relation (trade volume, market capitalization and transaction fees, respectively). Arguably the most unforeseen result is the positive sign for Bitcoin returns (b_1). This finding contrasts sharply with the positive relation between returns and liquidity conditions that typically manifests for traditional asset classes. Nonetheless, it shows that as Bitcoin prices rise, so does the cost of immediacy whereby Bitcoin sellers quote ask prices with large premiums for immediate buyers while quoted bid prices include large discounts for immediate selling. Since this bid–ask behavior is not as pronounced for conventional assets, this feature currently poses a likely impediment for Bitcoin in becoming a mainstream currency.

For $s_t = 1$, the remaining significant coefficients are rather consistent with what is observable for conventional assets; rising intraday volatility is associated with more liquidity uncertainty while rises in trade volume and market capitalization, respectively, are associated with less liquidity uncertainty. Interestingly, as transaction fees rise this is associated with declining uncertainty, possibly because miners perform tasks that grow Bitcoin's ecosystem such as verifying transactions or discovering new Bitcoins.

Table 3
Estimation results.

	Low uncertainty regime ($s_t = 1$)		High uncertainty regime ($s_t = 2$)	
Intercept	0.3512^{**}	(35.126)	0.6687	(0.531)
$\Delta\ln(Price)$	0.0047^{**}	(20.517)	0.0150	(0.140)
RVol	0.8469^{**}	(39.462)	0.5511^{**}	(5.727)
$\ln(Volume)$	-0.0386^{**}	(−33.835)	−0.0337	(−0.255)
$\Delta\ln(Size)$	-0.0017^{**}	(−8.912)	0.0111	(0.823)
$\Delta\ln(Addrs)$	0.0000	(0.779)	−0.0035	(−0.826)
$\Delta\ln(Fees)$	-0.0001^{**}	(−2.305)	−0.0014	(−0.502)
$\Delta\ln(Hash)$	0.0045	(0.643)	0.0026	(0.435)

This table shows coefficient results for Eq. (2) when estimated using the regime-switching framework in Eqs. (3) and (4). For the low ($s_t = 1$) and high ($s_t = 2$) liquidity uncertainty regimes, significance at the 5% and 1% level is denoted by the asterisk (*) and (**), respectively. Test statistics are in parentheses.

In the high liquidity uncertainty regime ($s_t = 2$), there is a deterioration in explanatory power across coefficients, with the exception of range volatility. This lack of significance carries implications for empirical testing of Bitcoin prices or other aspects of its ecosystem. Specifically, this shows that empirical tests of Bitcoin need to consider the possibility of multiple regimes within the time series behavior of its prices or other microstructure characteristics. This finding echoes the conclusions by Li and Wang (2017, p.59), who argue that "…it will be necessary to revisit the model (of Bitcoin prices) at some future time and consider the possibility of multiple regime changes in exchange rate dynamics…".

5. Conclusions

This paper seeks to answer the following question: "*How can we measure Bitcoin's liquidity uncertainty and what are its market microstructure determinants?*" It contributes to our understanding of Bitcoin by, first, constructing a measure of liquidity uncertainty and, second, testing whether various characteristics of its market microstructure can statistically explain this uncertainty. As the mystery creator Satoshi Nakamoto proclaims, we do not know in the future what the volume for Bitcoin will be. However, by further exploring its liquidity and market microstructure characteristics, we will be in a better position to see why this currency is gaining such popularity and whether or not it has the ability to become a mainstream currency.

References

Becker, T., Sy, A., 2005. Were bid–ask spreads in the foreign exchange market excessive during the Asian crisis?. IMF Working Paper No. 05/34, International Monetary Fund.

Cheah, E.T., Mishra, T., Parhi, M., Zhang, Z., 2018. Long memory interdependency and inefficiency in Bitcoin markets. Econom. Lett. 167, 18–25. http://dx.doi.org/10.1016/j.econlet.2018.02.010.

Ciaian, P., Rajcaniova, M., Kancs, D.A., 2016. The economics of Bitcoin price formation. Appl. Econ. 48, 1799–1815. http://dx.doi.org/10.1080/00036846.2015.1109038.

[4] Refer to Hamilton (1990) for a more elaborate discussion on the estimation of Markov regime-switching models. Transition probabilities and other such estimates are available upon request.

[5] Several robustness results are also available upon request which show that the findings in Table 3 generally hold when using bid–ask spread data from Bitstamp, another popular Bitcoin exchange. In addition, variance decompositions of the coefficients in Eq. (2) for the low ($s_t = 1$) and high ($s_t = 2$) liquidity uncertainty regimes reveal the following (results not tabulated but available upon request). For $s_t = 1$, the variables that explain most of the variation in *LiqUnc* (ordered from highest to lowest) are $\Delta\ln(Size)$, *RVol*, and $\Delta\ln(Price)$, respectively. For $s_t = 2$, they are $\ln(Volume)$, $\Delta\ln(Price)$, and *RVol*, respectively. These preliminary findings reveal heterogeneity in variance decomposition proportions across liquidity uncertainty regimes and make for interesting future research.

Gandal, N., Hamrick, J.T., Moore, T., Oberman, T., 2018. Price manipulation in the Bitcoin ecosystem. J. Monet. Econ. 95, 86–96. http://dx.doi.org/10.1016/j.jmoneco.2017.12.004.

Hamilton, J.D., 1988. Rational-expectations econometric analysis of changes in regime: An investigation of the term structure of interest rates. J. Econom. Dynam. Control 12, 385–423. http://dx.doi.org/10.1016/0165-1889(88)90047-4.

Hamilton, J.D., 1990. Analysis of time series subject to changes in regime. J. Econometrics 45, 39–70. http://dx.doi.org/10.1016/0304-4076(90)90093-9.

Katsiampa, P., 2017. Volatility estimation for Bitcoin: A comparison of GARCH models. Econom. Lett. 158, 3–6. http://dx.doi.org/10.1016/j.econlet.2017.06.023.

Khuntia, S., Pattanayak, J.K., 2018. Adaptive market hypothesis and evolving predictability of Bitcoin. Econom. Lett. 167, 26–28. http://dx.doi.org/10.1016/j.econlet.2018.03.005.

Koutmos, D., 2018. Bitcoin returns and transaction activity. Econom. Lett. 167, 81–85. http://dx.doi.org/10.1016/j.econlet.2018.03.021.

Li, X., Wang, C.A., 2017. The technology and economic determinants of cryptocurrency exchange rates: The case of Bitcoin. Decis. Support Syst. 95, 49–60. http://dx.doi.org/10.1016/j.dss.2016.12.001.

Lo, S., Wang, J.C., 2014. Bitcoin as money?. Current Policy Perspectives No. 14-4, Federal Reserve Bank of Boston.

Nadarajah, S., Chu, J., 2017. On the inefficiency of Bitcoin. Econom. Lett. 150, 6–9. http://dx.doi.org/10.1016/j.econlet.2016.10.033.

Phillip, A., Chan, J., Peiris, S., 2018. A new look at cryptocurrencies. Econom. Lett. 163, 6–9. http://dx.doi.org/10.1016/j.econlet.2017.11.020.

Symitsi, E., Chalvatzis, K.J., 2018. Return, volatility and shock spillovers of Bitcoin with energy and technology companies. Econom. Lett. 170, 127–130. http://dx.doi.org/10.1016/j.econlet.2018.06.012.

Urquhart, A., 2017. Price clustering in Bitcoin. Econom. Lett. 159, 145–148. http://dx.doi.org/10.1016/j.econlet.2017.07.035.

Velde, F., 2013. Bitcoin: A primer. Chicago Fed Letter No. 317, Federal Reserve Bank of Chicago.

Wei, W.C., 2018. Liquidity and market efficiency in cryptocurrencies. Econom. Lett. 168, 21–24. http://dx.doi.org/10.1016/j.econlet.2018.04.003.