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Isolated Islands or Communicating Vessels? – Bitcoin Price and Volume Spillovers Across Cryptocurrency Platforms*

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Abstract

The aim of this research is to investigate interdependencies between leading cryptocurrency exchanges (American, European and Japanese ones). We examine price and volume spillovers of daily frequency, to answer the question whether these platforms are integrated one with another or whether they form different isolated clusters. The results show that the big exchanges are indeed closely linked one to another. However, the magnitude of spillovers is higher in the case of prices, compared to volume. We also find that the analysed markets react with the same intensity to the price shocks coming from the other markets as to their own shocks. They are, however, more isolated in terms of volume spillovers.

1. Introduction

In 2008 a person or a group of people under the pseudonym Satoshi Nakamoto introduced bitcoin, currently the most popular cryptocurrency, alongside an electronic payment system, which is based on cryptography, instead of trust. This system allows two parties to make transactions without a trusted third party (Nakamoto, 2008). Due to the original purpose of its use, the question arises whether bitcoin can act as a form of money. There seems to be a consensus – bitcoin, similarly to other cryptocurrencies, does not fulfil the three functions of money – a medium of exchange, store of value and unit of account. The low level of its acceptance limits its usage as a medium of exchange. Due to the high volatility of its prices, it is unsuitable to store any value. It also does not serve as a unit of account because of the high price volatility and the low level of acceptance (European Central Bank, 2015, p. 23). Moreover, many bitcoin holders do not consider it as a form of money or a tool used to settle payments but as an investment vehicle. Some authors show that it should be treated rather as a speculative asset or a hedging one (see the Literature Review section). As a result, the investment infrastructure facilitating bitcoin and other cryptocurrency trading has been

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growing rapidly in recent years. According to CoinMarketCap.com, as of the beginning of September 2018, there were 218 platforms, commonly called exchanges, which enabled bitcoin trading (CoinMarketCap, 2018) – converting it to other cryptocurrencies or to fiat money, and the other way round. Nevertheless, the real number of such venues might be higher.

Pieters and Vivanco (2017) analysed eleven cryptocurrency platforms and studied the characteristics of bitcoin price dynamics. The authors concluded that, depending on the analysed platform, bitcoin has different price variations and fluctuations. The study was further extended by Matkovskyy (2018) who compared the euro, the U.S. dollar and the British pound sterling centralized and decentralized bitcoin cryptocurrency markets. He found that these two groups of platforms differed in terms of return volatility and interdependency. In this article, we further analyse the diverse ecosystem of cryptocurrency platforms, contributing to a better understanding of the bitcoin market.

The aim of this research is to determine any possible interdependencies between selected bitcoin markets based on daily data from the end of June 2015 to May 2019. Our main research question is: *whether the analysed markets are connected one with another or whether they are rather isolated and not prone to exogenous shocks.* We estimate the magnitude of the price and volume spillovers and analyse their dynamics, as the timespan of our data sample encompasses the biggest crash in this market in 2017/2018. We employ the methodology developed by Diebold and Yilmaz (2009, 2010) and Diebold and Yilmaz (2012), which so far has been applied by various scholars to analyse many different markets.

We set the following research questions:

1. Are volume spillovers weaker, compared to price spillovers? Although investors may use various bitcoin platforms for arbitrage purposes and thus affect their liquidity, the exchanges may serve different groups of investors who do not move their capital between platforms.
2. Did the magnitude of spillovers intensify at the turn of years 2017/2018 when the bitcoin price reached its all-time high and subsequently slumped?
3. Do cryptocurrency exchanges react in the same manner to shocks coming from other platforms as to their own shocks?
4. Are spillovers between the markets which enable trading bitcoin in the same currency stronger than spillovers coming from the markets where investors use various currencies to trade bitcoin?

According to our results, the biggest cryptocurrency platforms are interrelated one with another. Nevertheless, the interdependencies are indeed weaker when volume spillovers are concerned (Question 1). The magnitude of price spillovers did not change to a great extent throughout the analysed period and volume spillovers started to intensify at the beginning of 2017 (Question 2). Generally, the analysed markets react with the same intensity to the price shocks coming from the other markets as to their own shocks, and react stronger to their own volume shocks (Questions 3). The fiat currencies seem to play only a small role in the case of price spillovers. When volume spillovers are considered, BitFlyer, which enables trading bitcoin in the Japanese yen, is the most isolated. In the case of the remaining platforms, the fiat currencies seem to have less impact on the development of volume spillovers than the trade volume (Question 4).

The remainder of the paper is organised as follows. First, we discuss the results obtained by other authors who analysed the bitcoin market. Next, we describe the data and methodology employed in this study. In sections 4 and 5, we present the results of price and volume spillovers, respectively. The last section contains the concluding remarks.

2. Literature Review

The literature on bitcoin has been growing, with the academic community looking at this cryptocurrency from various perspectives. Many researchers consider bitcoin as an investment tool. Some of them concentrate on its speculative character, due to the substantial volatility of its prices and the purpose of its use (Yermack, 2015; Baur, Hong and Lee, 2018). According to Cheah and Fry (2015), bitcoin is vulnerable to speculative bubbles. One of them was detected by the authors in 2013. On the contrary, Blau (2018) does not find that in 2013 it was speculative trading that had driven the massive increase and the subsequent slump in bitcoin prices. He also does not find the evidence that the speculative trading contributed to the increase of volatility of the bitcoin price at that time.

Investors may appreciate the diversification properties of bitcoin, which stem from the negative or low correlation with other asset classes, such as stocks, bonds, commodities, real estate, and use it to reduce the risk of their portfolio (Pandey and Wu 2014; Briere *et al.* 2015; Azzi *et al*. 2017; Baur *et al.* 2017). Bouri, Gupta, *et al.* (2018) show, however, that relationships of bitcoin with other asset classes are complex (asymmetric, nonlinear and quantiles-dependent) and that it is possible to estimate bitcoin price movements using gold prices and values of the aggregate commodity index.

The facts that bitcoin is a homogeneous, fully fungible asset and that there is a multitude of bitcoin trading platforms, raise significant research questions related to bitcoin price settlement, the contribution of particular platforms to the price discovery process as well as to interdependencies between these markets. Despite the importance of these issues, the related literature is rather limited. There are a few exceptions, however, which generally highlight the significance of the largest platforms in this field. Bitcoin price discovery is the subject of research of Brandvold *et al.* (2015) who, using unobserved components price discovery model, find that smaller exchanges are less informative. Furthermore, they ascertain that these platforms frequently follow the market with a lag. The authors focus on seven bitcoin exchanges which, at that time, were responsible for 90% of bitcoin trade volume and which were among the ten largest bitcoin marketplaces. The analysis shows that between April 2013 and February 2014 Mt.Gox and BTC-e were the market leaders with the most significant contribution to price discovery. Brandvold *et al.* also emphasize that the information share of particular markets is dynamic and evolves over time. This is further confirmed by the analysis of Pagnottoni, Baur and Dimpfl (2018) who carry out the study for a more recent time span – from January 2014 to March 2017. The authors analyse the six most important platforms in terms of bitcoin trade volume. They create a ranking of the markets according to the price discovery contribution, based on the Hasbrouck's and Gonzalo and Granger's information share measures. They find that two Chinese platforms – OKCoin, followed by Btcn, were more informative than the other considered markets. The authors stress, however, that their analysis is affected by the decision of the Chinese government to close the platforms on mainland China by the end of September 2017. Giudici and Abu-Hashish (2018) propose a correlation network model, which is an extended vector autoregressive model, to describe the correlation structure between bitcoin prices sourced from eight different markets which jointly accounted for approximately 60% of the total daily bitcoin trade volume at the time of the analysis. The authors identify high interrelations among bitcoin prices from scrutinized exchanges between May 2016 and April 2018. They also find that markets that are larger and/or more connected, drive the prices on the other exchanges. Moreover, they identify Bitfinex and Bitstamp as the leaders in price setting in the bitcoin market. Symitsi and Chalvatzis (2018) confirm the substantial role in price discovery of Bitfinex, and the marginal role of BTC-e, in comparison to four other analysed exchanges. Kliber (2018) studies the transmission of price, information and liquidity shocks among different cryptocurrencies traded in Bitfinex, documenting the existence of a strong co-movement among them.

Kroeger and Sarkar (2017) discover that the amount of price discovery on every exchange and the speed of arbitrage is connected with the frictions present in the market. They identify differences between bitcoin prices expressed in the U.S. dollar from six exchanges between 2015 and August 2016. Pieters and Vivanco (2017) find significant deviations in bitcoin prices among eleven different markets, which constituted 26% of global bitcoin trade volume between June 2014 and July 2015. They ascribe these differences to the market characteristics and discover that prices in the markets that do not require customer identification to open an account are more prone to deviate from the representative market price, compared to the markets which identify their customers.

Another stream of research focuses on shock transmissions and spillovers. Kurka (2017) analyses the transmission of shocks between bitcoin and the representatives of traditional asset classes. He finds that the level of connectedness between bitcoin and other analysed investment vehicles is negligible. The exception is gold, which absorbs shocks from the bitcoin market. Symitsi and Chalvatzis (2018) identify significant return spillovers coming from technology and energy stocks to bitcoin. In the short run, the cryptocurrency in question is affected by volatility spillovers from technology companies, whereas in the long run bitcoin exerts an influence on the volatility of energy companies. Moreover, shock spillovers between bitcoin and stock indices are asymmetric and bidirectional. Bouri *et al.* (2018) find that bitcoin volatility can be predicted based on the volatility of the other analysed traditional asset classes and that bitcoin absorbs more volatility than it transmits. The patterns of spillovers exhibit some differences in the bear and bull markets.

Apart from studying price spillovers, we are also interested in linkages among different platforms in terms of liquidity. In our study, we approximate it with trade volume (measured in the number of bitcoins traded). Liquidity is one of the most significant factors affecting investment decisions. Therefore, it has been also studied in the case of the bitcoin market. Loi (2017) shows that between 2014 and 2015 Bitfinex was the most liquid platform, compared to Bitstamp, BTC-e, HitBTC and itBit. The analysis of Dimpfl (2017) suggests that bitcoin liquidity depends on the time of the day and is the highest at the time when a respective stock market is open. The patterns were the most distinct for American and European markets, whereas in Chinese markets the trade volume was more uniformly distributed throughout the day. Brauneis and Mestel (2018) and Wei (2018) examine large sets of different cryptocurrencies and conclude that as liquidity increases, prices become less predictable. Eventually, Będowska-Sójka *et al.* (2019) show that high volatility in cryptocurrency markets contributes to the increase of their liquidity, which means that it is high volatility that attracts investors to these markets.

3. The Data

We analysed the data covering the period from June 24th, 2015 to May 26th, 2019, sourced from the website bitcoinity.org. The selection of platforms, the exchange rates with fiat currencies and the starting point of the analysis depended on trade volume and data availability. In the latter case, we also took into consideration the fact that the bitcoin system is dynamic, and its features change very often (Thies and Molnár, 2018). The investigated set of platforms consists of five entities, described in Table 1. They significantly differ in terms of the number of offered cryptocurrencies – Bitfinex is an indisputable leader with 137 different cryptocurrencies, followed by Kraken with 20.

Table 1 Basic Characteristics of the Analysed Cryptocurrency Platforms

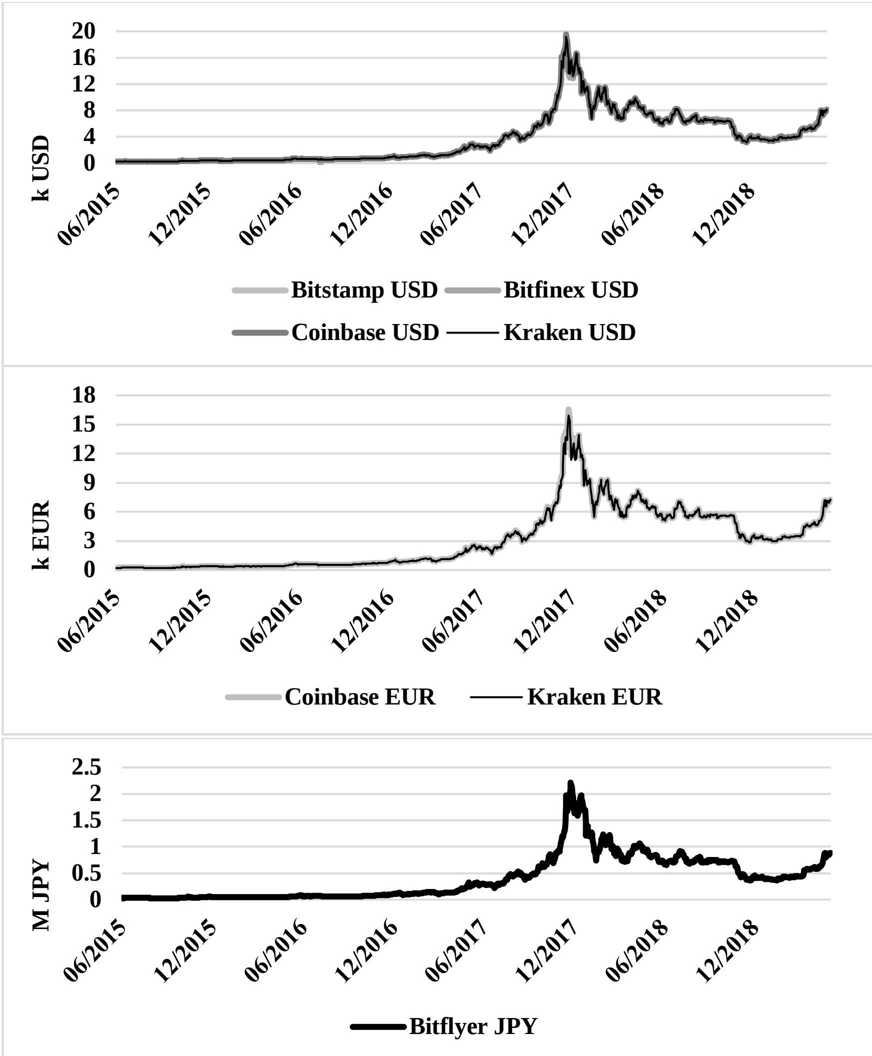
Name	*Headquarters*	*Year of foundation*	*Nº of cryptocurrencies in the offer*	*Accepted fiat currencies*
Bitfinex	Hongkong	2012	137	EUR, GBP, JPY, USD
BitFlyer	Japan, Tokyo	2014	7	JPY
Bitstamp	UK, London	2011	5	EUR, USD
Coinbase	USA, San Francisco	2012	10	EUR, GBP, USD
Kraken	USA, San Francisco	2011	20	CAD, EUR, GBP, JPY, USD

Source: Bitfinex (2019a, 2019b), BitFlyer (2019a, 2019b), Bitstamp (2019a, 2019b, 2019c), Bloomberg (2019), Coinbase (2019a, 2019b), Kraken (2019a, 2019b).

As shown in Figure 1, the dynamics of bitcoin prices quoted on the analysed platforms in different fiat currencies is similar. However, the statistics presented in Table 2 reveal some differences among the prices. In May 2017, the growth of bitcoin prices started to accelerate. The prices achieved their all-time high in December 2017 and subsequently started to decline. The revival in the bitcoin market could be observed in March 2019, when the prices started to rise again.

Figure 2 presents the daily volume on the analysed exchanges. We may observe that it is very volatile. This is in line with the high standard deviations presented in Table 2, containing the descriptive statistics of the log-changes of the daily trade volume.

Figure 1 Bitcoin Prices on Different Platforms



As Figure 2 shows, the markets scrutinised in this study differ in terms of volume, even within one platform – e.g. bitcoin trading on Kraken is much more intense in the euro than in the U.S. dollar. Therefore, we suspect that other factors (apart from the exchange rate between traditional currencies, e.g. EUR/USD) may affect the bitcoin price formation with regards to different traditional currencies on the same platform and may impact spillovers.

In the case of missing information about the price or volume, we imputed the observations with the mean of the neighbouring values. Observations equalled to zero were also treated as missing ones. Next, we calculated log-returns of prices and for the sake of consistency, we repeated the procedure for volumes. Thus, the VARs and spillover indices, described in the next sections, are computed for log-returns of the raw data.

Figure 2 Bitcoin Trade Volume on Different Platforms

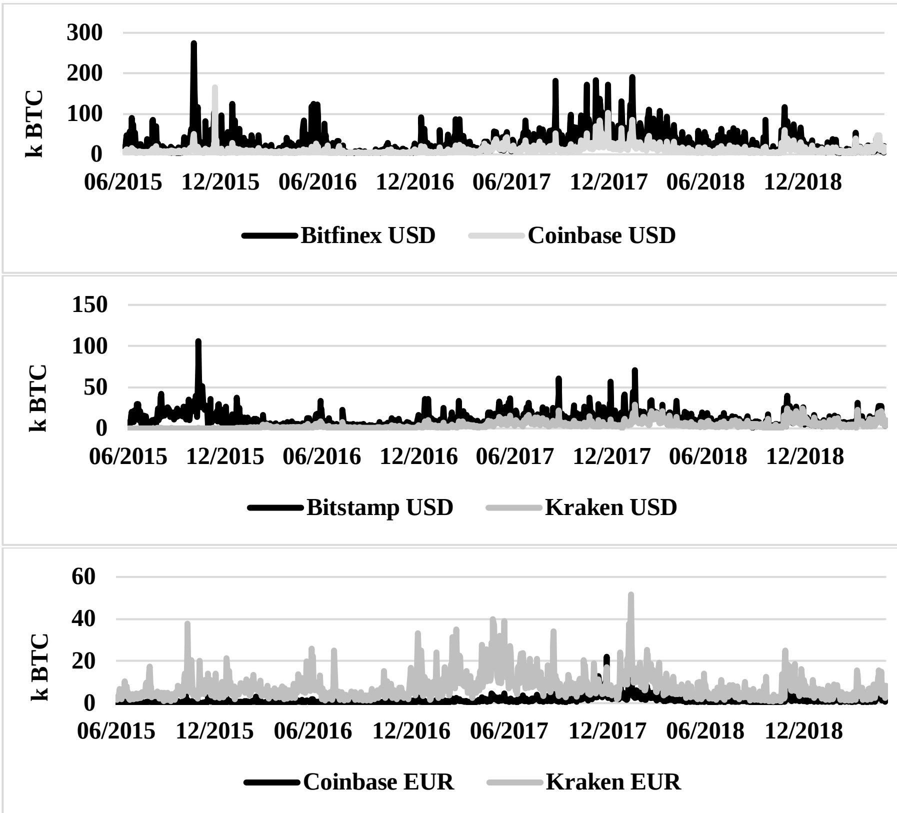


Table 3 contains the descriptive statistics for daily logarithmic returns of close prices. Several approaches to approximate the daily bitcoin price can be found in the literature. Some authors analyse the Bitcoin index from Coindesk. This was impossible in our case, as the index does not distinguish between exchanges. Instead, it provides an aggregated price from selected trading platforms. Another approach is to use the daily weighted prices. In our case, such a price was not available for Bitfinex (USD) and Coinbase (USD). Therefore, we decided to use the daily closing price for these platforms (as in e.g. Urquhart, 2017), knowing the limitation of the approach (different time in different countries and possible different trade intensity).

Table 2 Descriptive Statistics of the Log-Changes of Daily Trade Volume (in Number of Bitcoins) in the Analysed Period

Fiat currency	*Name of the platform*	*Mean*	*Std. dev.*	*Min*	*Median*	*Max*
USD	Bitfinex	0.0002	0.5846	-1.7789	-0.0360	2.2313
	Bitstamp	0.0002	0.5373	-1.6554	-0.0221	2.4178
	Coinbase	0.0009	0.4604	-2.7105	-0.0176	3.2033
	Kraken	0.0062	0.6938	-4.2631	-0.0271	5.1751
EUR	Coinbase	0.0021	0.5922	-4.8929	-0.0325	3.1352
	Kraken	0.0009	0.4961	-1.4628	-0.0212	1.9360
JPY	BitFlyer	0.0073	0.5398	-3.4965	-0.0109	7.9154

Table 3 Descriptive Statistics of Daily Logarithmic Returns in the Analysed Period

Fiat currency	*Name of the platform*	*Mean*	*Std. dev.*	*Min*	*Median*	*Max*
USD	Bitfinex	0.0025	0.0326	-0.1891	0.0019	0.1571
	Bitstamp	0.0025	0.0322	-0.1653	0.0020	0.1604
	Coinbase	0.0025	0.0323	-0.1624	0.0019	0.1956
	Kraken	0.0025	0.0323	-0.1530	0.0021	0.1657
EUR	Coinbase	0.0025	0.0324	-0.1660	0.0022	0.1982
	Kraken	0.0025	0.0322	-0.1723	0.0023	0.1628
JPY	BitFlyer	0.0023	0.0332	-0.1993	0.0018	0.2277

4. The Model

The Spillover Index proposed by Diebold and Yilmaz (2009) is based on vector autoregression model (further: VAR) and Cholesky decomposition of the forecast error variance. Let us assume that the system of variables can be described using VAR model of the following form:

$$\boldsymbol{y}_t = \boldsymbol{\Phi}\boldsymbol{y}_{t-1} + \boldsymbol{\epsilon}_{\mathbf{t}}. \tag{1}$$

In our case $\boldsymbol{y}_t$ is composed of the log-changes of the bitcoin prices on the analysed platforms (and in the later cases: of the log-volume changes). If the system is covariance-stationary, then there is a MA-representation of it, of the following form:

$$\boldsymbol{y}_t = \boldsymbol{\Theta}(L)\boldsymbol{\epsilon}_t, \tag{2}$$

where: $\boldsymbol{\Theta}(L) = (\mathbf{I} - \boldsymbol{\Phi}L)^{-1}$. We can re-write it also as:

$$y_t = \mathbf{A}(L)\mathbf{u}_t, \tag{3}$$

where $A(L) = \mathbf{\Theta}(L)\mathbf{Q}_t^{-1}, \mathbf{u_t} = \mathbf{Q_t}\boldsymbol{\epsilon}_\mathbf{t}$, $\mathrm{E}(\mathbf{u_t}\mathbf{u_t'}) = \mathbf{I}$, and $\mathbf{Q_t^{-1}}$ is the unique lower triangle Cholesky factor of the covariance matrix of $\boldsymbol{\epsilon}_{\boldsymbol{t}}$.
If we consider a 1-step ahead forecast:

$$\mathbf{y_{t+1,t}} = \mathbf{\Phi}\mathbf{y_t} \tag{4}$$

the corresponding 1-step ahead forecast error vector is:

$$\mathbf{e}_{t+1,t} = \mathbf{y}_{t+1} - \mathbf{y}_{t+1,t} = \mathbf{A}_0\mathbf{u}_{\mathrm{t+1}} = \begin{bmatrix} a_{0,11} & \cdots & a_{0,1k} \\ \cdots & \cdots & \cdots \\ a_{0,k1} & \cdots & a_{0,kk} \end{bmatrix} \begin{bmatrix} u_{1,t+1} \\ \cdots \\ u_{k,t+1} \end{bmatrix}, \tag{5}$$

while the covariance matrix is:

$$E\left(\mathbf{e_{t+1,t}}\mathbf{e'_{t+1,t}}\right) = \mathbf{A_0}\mathbf{A'_0}. \tag{6}$$

The spillover index (in the case of the 1-step ahead forecast) is defined as:

$$S = \frac{\sum_{i,j=1}^{k} a_{0,ij}^2}{trace(\mathbf{A_0}\mathbf{A'_0})} \cdot 100, i \neq j. \tag{7}$$

The idea is as follows. Variance decomposition allows us to split the forecast error into parts attributable to shocks from different variables, particularly – own shocks (own variance shares) and shocks from other variables (cross variance shares). The total spillover is the ratio of the sum of cross variance shares divided by the total forecast error variation: $trace(\mathbf{A_0}\mathbf{A'_0})$.

The main drawback of this approach is that it requires *a priori* knowledge about the possible strength of influence between the variables in the system, as the decomposition method is vulnerable to the ordering of variables. The solution is to check all possible permutation of variables and compute the average spillover measure (see: Kloessner and Wagner, 2012).

Another solution is to use another method of variance decomposition, which was proposed by Diebold and Yilmaz (2012). In this approach the authors use a generalized VAR framework and, in this way, eliminate the possible dependence of results on ordering (see: Koop, Pesaran and Potter, 1996 and Pesaran and Shin, 1998). In this approach the shocks are not orthogonalized, and thus the sum of contributions to variance is not necessarily equal to one.

The *H*-step-ahead forecast error variance decomposition θ_{ij}^h is constructed as follows:

$$\theta_{ij}^g(H) = \frac{\sigma_{ii}^{-1} \sum_{h=0}^{H-1} (\mathbf{e}_i'\mathbf{A_h}\mathbf{\Sigma}\mathbf{e}_j)^2}{\sum_{h=0}^{H-1} (\mathbf{e}_i'\mathbf{A_h}\mathbf{\Sigma}\mathbf{A_h}'\mathbf{e}_j)^2}, \tag{8}$$

where $\mathbf{\Sigma}$ is the variance matrix of $\boldsymbol{\epsilon}$, σ_{ii}- the standard deviation of the error term for the *i*-th equation and $\mathbf{e}_i$ is a selection vector with 1 on the *i*-th place and 0 otherwise. The sum of the elements of each row of the variance decomposition table – as already mentioned – does not equal one. Therefore, the values are normalized through division by the sum of all the elements in the row:

$$\tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)}. \tag{9}$$

Now, by construction $\sum_{j=1}^{N} \tilde{\theta}_{ij}^{g}(H) = 1$ while $\sum_{ij=1}^{N} \tilde{\theta}_{ij}^{g}(H) = N$. Eventually, the **total spillover index** is constructed as:

$$S^{g}(H) = \frac{\sum_{i,j=1;i\neq j}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{ij=1}^{N} \tilde{\theta}_{ij}^{g}(H)} \cdot 100 = \frac{\sum_{i,j=1;i\neq j}^{N} \tilde{\theta}_{ij}^{g}(H)}{N} \cdot 100. \tag{10}$$

Based upon this definition we can construct also:

- **Directional spillover** index (decomposition of total spillovers into coming *from* or *to* a particular source):
    - Received by market *i* from other markets: $S_{i\cdot}^{g}(H) = \frac{\sum_{j=1;i\neq j}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{j=1}^{N} \tilde{\theta}_{ij}^{g}(H)} \cdot 100$
    - Transmitted from market *i* to other markets: $S_{\cdot i}^{g}(H) = \frac{\sum_{j=1;i\neq j}^{N} \tilde{\theta}_{ji}^{g}(H)}{\sum_{j=1}^{N} \tilde{\theta}_{ji}^{g}(H)} \cdot 100$
- **Net spillover** index: $S_{i}^{g} = S_{\cdot i}^{g}(H) - S_{i\cdot}^{g}(H)$
- **Pairwise spillover** index: $S_{ij}^{g} = \left(\frac{\tilde{\theta}_{ij}^{g}(H)}{\sum_{k=1}^{N} \tilde{\theta}_{ik}^{g}(H)} - \frac{\tilde{\theta}_{ji}^{g}(H)}{\sum_{k=1}^{N} \tilde{\theta}_{jk}^{g}(H)}\right)$.

In order to compute price and volume spillovers we utilize a package frequency Connectedness written by Krehlik (see: Barunik and Krehlik, 2018 and Krehlik, 2018). We calculate rolling spillovers of price and volume, using the window of 120 daily observations. To overcome the problem of over-parametrization and instability of the parameters, we use the bootstrap procedure, as suggested in Choi and Shin (2018). For each window of 120 observation we generate 500 VAR-bootstrap samples and for each one we compute the overall spillover index. We present 90% confidence intervals taking 5% and 95% quantile from each sample. The value of the spillover index is approximated by the median taken from each bootstrap sample.

5. Results

In Figures 3 and 4 we can observe the dynamics of the overall spillover indices during the investigated period, for the changes of prices and volume respectively. The indices were calculated for the window of 120 observations (about four months), taking into account one-step forecast horizon.

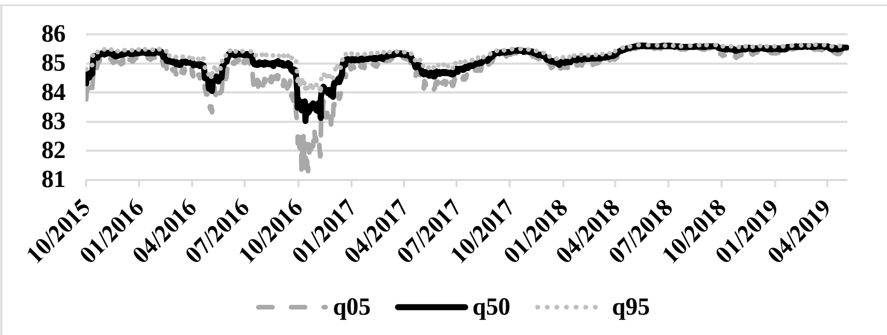
The analysis of the dynamics of the indices allowed us to answer the first and the second research questions. First of all, we observe significant differences in the behaviour of the two indices and the lower magnitude of volume spillovers, compared to price ones (Question 1). The values of price spillovers (Figure 3) oscillated around

85% over the whole period, except for the two drops: in the first and the second half of 2016. Volume spillovers started from the low level of approximately 60% and grew steadily up to May 2017. At this time, the index reached a relatively stable value of about 80%. Therefore, we find that the values of price spillovers were higher than the values of volume spillovers.

Bitcoin units are homogeneous – they have the same properties, no matter where they are traded. Therefore, it might be expected that the law of one price would not be violated. On the other hand (see the Literature Review section), cryptocurrency platforms differ in terms of price discovery. Thus, some frictions limiting the arbitrage can occur. The fact that we analyse the biggest and the most liquid bitcoin platforms might explain the relatively high values of the overall price spillover index. The shift in the overall index for volume in May 2017 may suggest that investors move their capital between bitcoin markets more freely and may be also a sign of the presence of institutional investors who specialise in arbitrage.

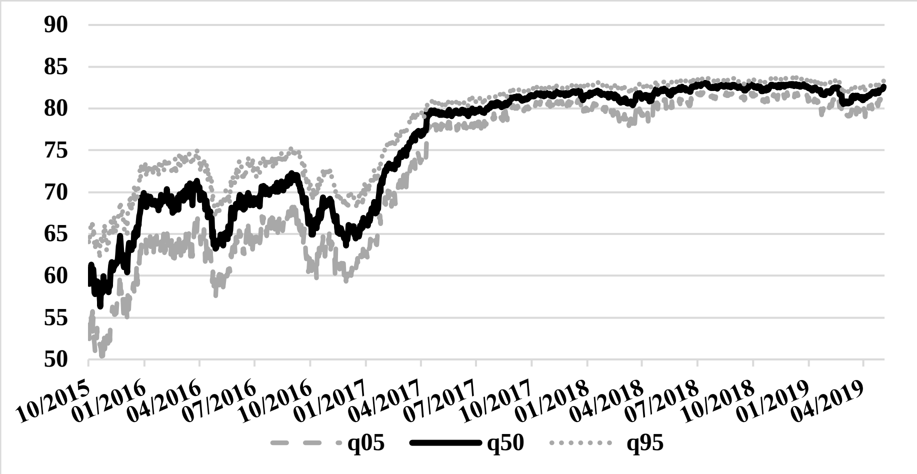
With regards to Question 2, we find that the values of the overall spillover indices did not change to a great extent in the event of the biggest bitcoin boom and the slump at the turn of years 2017/2018. The values of the overall spillover index for volume changed more than the magnitude of overall price spillovers throughout the analysed period.

Figure 3 90% Confidence Interval of Daily Price Spillovers – The Overall Spillover Index (Rolling Window of 120 Observations)



Notes: q05, q50 and q95 denote respectively the 5%, 50% (median) and 95% quantile of the bootstrap distributions.

Figure 4 90% Confidence Interval of Daily Volume Spillover – The Overall Spillover Index (Rolling Window of 120 Observations)



Notes: q05, q50 and q95 denote respectively the 5%, 50% (median) and 95% quantile of the bootstrap distributions.

To investigate the nature of price fluctuations in detail and answer Question 3 and 4, formulated in the introduction, we analyse the results in Tables 4 and 5. They constitute a decomposition of the overall spillover indices, respectively for price and volume.

In Table 4, for instance, we find that innovations to returns on BitFlyer (JPY) are accountable for 13.55% of the error variance in one-step ahead forecasts of the returns on Bitstamp (USD). At the same time, the innovations to returns on the latter platform had a slightly greater share in the error variance of the forecasts of the returns on BitFlyer (JPY) – 14.25%.

Generally, the price interdependencies among the platforms are strong. Moreover, the reaction of the markets to the impulses coming from other markets is almost the same as the reaction to their own impulses. Price interdependencies among the markets which enable bitcoin trading in the same traditional currencies (the euro and the U.S. dollar) are slightly higher than spillovers among the market quoting bitcoin in different fiat currencies. Nevertheless, the differences are not very high. It is also worth noting, that in the case of BitFlyer (JPY) the fraction of the forecast error variance due to its own shocks (15.14%) is slightly higher compared to the fraction of any other analysed market. Innovations from BitFlyer (JPY) account for 11.60% of the error variance in one-step ahead forecasts of the returns on the other analysed markets. This suggests that BitFlyer (JPY) is slightly more isolated than the markets enabling trading bitcoin in the euro and the U.S. dollar.

Table 4 Overall Price Spillover Table

	BitFlyer JPY	*Bitstamp USD*	*Bitfinex USD*	*Kraken USD*	*Coinbase USD*	*Coinbase EUR*	*Kraken EUR*	*FROM OTHERS*
BitFlyer JPY	**15.14**	14.25	13.92	14.11	14.23	14.16	14.21	12.12
Bitstamp USD	13.55	**14.66**	14.31	14.51	14.46	14.14	14.38	12.19
Bitfinex USD	13.45	14.55	**14.85**	14.48	14.37	13.99	14.31	12.16
Kraken USD	13.47	14.54	14.27	**14.71**	14.43	14.16	14.43	12.18
Coinbase USD	13.58	14.52	14.19	14.46	**14.64**	14.28	14.33	12.19
Coinbase EUR	13.63	14.34	13.95	14.31	14.41	**14.76**	14.60	12.18
Kraken EUR	13.54	14.41	14.11	14.42	14.30	14.45	**14.78**	12.17
TO OTHERS	11.60	12.37	12.11	12.33	12.31	12.17	12.32	**85.21**

Notes: In the table we present the values of spillovers between each pair of the markets. The values in each row correspond to the fraction of the forecast error variance due to the shock coming from the respective market (which name is in a given column). The values in bold print on the main diagonal are the "own" spillovers, i.e. the fraction of the forecast error variance due to own shocks. The column FROM OTHERS was computed as a sum of values in a given row minus the reaction to own shocks and divided by the number of markets included in the system. The values in this column are interpreted as a fraction of total spillover received by the given market. The row TO OTHERS was computed analogously. It is interpreted as a percentage contribution of each market to spillovers sent to the whole system. The total value of spillover is given as a sum of all values in column FROM OTHERS (or row TO OTHERS).

Volume spillovers (Table 5) behave differently from price spillovers. The markets are less prone to volume-change impulses sent by the other markets – as compared to price spillovers (the reaction to own shocks is much stronger than the reaction to shocks from others). It is particularly visible in the case of BitFlyer (JPY), which may result from the fact that bitcoin is quoted in a different fiat currency there. A similar phenomenon can be noticed in the case of Kraken (USD) and Coinbase (EUR). The trade volume in these fiat currencies on these platforms was smaller in the analysed period, in comparison to other scrutinised markets (Figure 2). This may imply that in the case of the platforms where trade in different fiat currencies is allowed, the smaller the volume, the more isolated the market is, regardless of the currency. The value for Bitfinex (USD) is also relatively high, taking into account the large trade volume of this platform. It might be a result of the missing data for the particular week when the exchange was offline. It was due to the hacking attack on Bitfinex on August 2nd, 2016 when more than 60 million USD was stolen (Higgins, 2016).

Table 5 Overall Volume Spillover Table

	BitFlyer JPY	Bitstamp USD	Bitfinex USD	Kraken USD	Coinbase USD	Coinbase EUR	Kraken EUR	FROM OTHERS
BitFlyer JPY	**34.73**	12.13	11.23	7.76	12.17	8.86	13.12	9.32
Bitstamp USD	7.89	**23.00**	14.70	11.05	15.66	11.28	16.43	11.00
Bitfinex USD	7.86	15.60	**25.62**	11.03	14.68	9.45	15.76	10.63
Kraken USD	5.93	13.26	12.39	**30.54**	13.43	9.05	15.40	9.92
Coinbase USD	7.98	15.46	13.90	11.12	**22.74**	13.15	15.66	11.04
Coinbase EUR	7.17	13.70	11.08	8.80	16.31	**27.97**	14.97	10.29
Kraken EUR	8.20	15.91	14.50	12.51	15.36	11.86	**21.65**	11.19
TO OTHERS	6.43	12.29	11.12	8.89	12.52	9.09	13.05	**73.39**

To sum up, it can be noticed that in the case of price spillovers the exchanges react in the same manner to the shocks coming from other platforms as to their own shocks. When volume spillovers are considered, internal shocks are more important than the external ones (Question 3). Moreover, price spillovers among the markets that enable trading bitcoin in the same fiat currencies, are slightly stronger than spillovers among the markets that quote bitcoin in different traditional currencies. However, the differences are not very high. In the context of volume spillovers, BitFlyer is the most isolated market. The results imply that the magnitude of volume spillovers is shaped to a greater extent by trade volume than by the type of the fiat currency (Question 4).

Figures A1 and A2 in the *Appendix* (on the website of this journal) depict net price and volume spillovers respectively. They enable us to identify further whether a market acts as a source or as a receiver of spillovers, as well as to observe their changes over the sample period. Net spillovers fluctuate more than overall spillover indices. BitFlyer (JPY) is the most pronounced example of a shock receiver in the analysed sample. This platform absorbed more shocks (both price and volume) than it transmitted, almost throughout the entire period. This tendency started to change at the end of 2018 (in the case of price spillovers) and at the beginning of 2019 (volume spillovers). At that time, these values oscillated around 0. Bitstamp (USD), by contrast, is the most significant source of price and volume spillovers. Nevertheless, the magnitude of spillovers generated by this market was decreasing throughout the sample period.

As a robustness check, we added to the sample one more platform, which has also a relatively high trade volume (but smaller than the exchanges analysed in the previous step), Gemini. It has not been used in the first phase of the analysis, because the data from this platform on bitcoinity.org were available starting from October 8th,

2015. Thus, we could either exclude it from the study or shorten the analysed period. We decided for the first solution.

Including Gemini in the shorter sample, we calculated the values of overall price and volume spillovers once again. The results are presented in Tables A1 and A2 in the *Appendix* (on the website of this journal). The main conclusions have not changed – again, the reaction to the price impulses from other exchanges is almost the same as the reaction to own impulses of the markets. Moreover, BitFlyer (JPY) and platforms with lower trade volume – Kraken (USD), Coinbase (EUR), Gemini (USD) – are more isolated in terms of volume spillovers, compared to the most liquid European and American markets considered in this article.

6. Conclusions

In the article we explore the relationships among the main platforms enabling trading bitcoin in the euro, the U.S. dollar and the Japanese yen. To investigate the interdependencies between bitcoin price and volume in different markets, we computed the spillover index of Diebold and Yilmaz (2012). The analysis of interrelationships shows that both price and volume are closely linked among the main markets.

The results allowed us to answer the research questions stated in the introductory section. First, we document that volume spillovers are indeed weaker, compared to price spillovers. Second, there is no evidence (at the aggregated level) that spillovers intensified at the turn of the years 2017/2018, when the biggest bitcoin bubble burst. The overall price spillover index was rather stable over the analysed period. In the case of volume spillovers, the values increased at the beginning of 2017. Third, the magnitude of the reaction of the markets to their own price shocks is comparable to the reaction to impulses coming from the other platforms. Nevertheless, for volume spillovers the internal shocks are more important than the external ones. Fourth, price spillovers between the markets which enable trading bitcoin in the same traditional currency are slightly higher than spillovers between the markets quoting bitcoin in different fiat currencies. However, the differences are not very high. In the case of volume spillovers, BitFlyer – which enables trading bitcoin in the Japanese yen – is the most isolated. With regards to the remaining platforms, trade volume seems to be a more important factor shaping the magnitude of volume spillovers, than the type of the fiat currency.

The cryptocurrency market has developed rapidly for the last ten years, offering new possibilities to investors. It is still a relatively new concept, so its characteristics change over time, as it is also presented in this article. The analysis of spillovers between various trading platforms that operate in this highly fragmented market is crucial for understanding how the cryptocurrency market functions as a whole. Moreover, the results can be of interest to investors who wish to diversify their portfolio with bitcoin or look for any arbitrage opportunity in the cryptocurrency market. Previous studies document that cryptocurrency platforms differ in terms of bitcoin price discovery. We contribute to the literature by showing how the impulses spill among main bitcoin markets. When an arbitrageur knows which markets generate the impulses and which ones absorb them, s(he) may use this knowledge to build an investment strategy and place appropriate orders in the markets that react with a lag.

REFERENCE

Azzi G, Bouri E, Hagfors LI, Molnár P, Roubaud D (2017): On the Hedge and Safe Haven Properties of Bitcoin: Is it Really More Than a Diversifier? *Finance Research Letters*, 20:192-198.

Barunik J, Krehlik T (2018): Measuring the Frequency Dynamics of Financial Connectedness and Systemic Risk. *Journal of Financial Econometrics*, 16(2): 271–296.

Baur DG, Hong KH, Lee AD (2018): Bitcoin: Medium of Exchange or Speculative Assets? *Journal of International Financial Markets, Institutions and Money*, 54: 177–189.

Będowska-Sójka B, Hinc T, Kliber A (2019): Causality Between Volatility and Liquidity in Cryptocurrency Market. *Working Paper*.

Blau BM (2018): Price Dynamics and Speculative Trading in Bitcoin. *Research in International Business and Finance*, 43:15–21.

Bouri E, Das M, Gupta R, Roubaud D (2018): Spillovers Between Bitcoin and other Assets during Bear and Bull Markets. *Working Paper*, University of Pretoria, Department of Economics.

Bouri E, Gupta R, Lahiani A, Shahbaz M (2018): Testing for Asymmetric Nonlinear Short- and Long-Run Relationships Between Bitcoin, Aggregate Commodity and Gold Prices. *Resources Policy*, 57:224–235.

Brandvold M, Molnár P, Vagstad K, Valstad OC (2015): Price Discovery on Bitcoin Exchanges. *Journal of International Financial Markets, Institutions and Money*, 36:18–35.

Brauneis A, Mestel R (2018): Price Discovery of Cryptocurrencies: Bitcoin and Beyond. *Economics Letters*, 165:58–61.

Briere M, Oosterlinck K, Szafarz A (2015): Virtual Currency, Tangible Return: Portfolio Diversification with Bitcoin. *Journal of Asset Management*, 16:365-373.

Cheah ET, Fry J (2015): Speculative Bubbles in Bitcoin Markets? An Empirical Investigation into The Fundamental Value of Bitcoin. *Economics Letters*, 130:32–36.

Choi JE, Shin DW (2018): Bootstrapping Volatility Spillover Index. *Communications in Statistics - Simulation and Computation* (online first version).

Diebold FX, Yilmaz K (2009): Measuring Financial Asset Return and Volatility Spillovers, with Application to Global Equity Markets. *The Economic Journal*, 119: 158–171.

Diebold FX, Yilmaz K. (2010): Errata to Measuring financial asset return and volatility spillovers, with application to global equity markets. *Economic Journal* 120: F354 – F355.

Diebold FX, Yilmaz K (2012): Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting*, 28(1): 57–66.

Dimpfl T (2017): Bitcoin Market Microstructure. https://ssrn.com/abstract=2949807 (accessed: 07.02.2019).

European Central Bank (2015): Virtual Currency Schemes – a Further Analysis. European Central Bank, Frankfurt.

Giudici P, Abu-Hashish I (2018): What determines bitcoin exchange prices? A network VAR approach. *Finance Research Letters*, in press, corrected proof, available online in 2018.

Hileman G, Rauchs M (2017): Global Cryptocurrency Benchmarking Study. https://www.jbs.cam.ac.uk/fileadmin/user_upload/research/centres/alternative-finance/downloads/2017-global-cryptocurrency-benchmarking-study.pdf (accessed: 07.02.2019).

Kliber A (2018): Price, Liquidity and Information Spillover within the Cryptocurrency Market. The Case of Bitfinex. *Safe Bank*, 73 (4): 62-79.

Kloessner S, Wagner S (2012): Exploring All VAR Orderings for Calculating Spillovers? Yes, We Can! - A Note on Diebold and Yilmaz (2009). *Journal of Applied Econometrics*, 29(1): 172–179.

Koop G, Pesaran MH, Potter SM (1996): Impulse response analysis in nonlinear multivariate models. *Journal of Econometrics*, 74(1): 119–147.

Krehlik T (2018): Package ‘frequencyConnectedness’. https://cran.r-project.org/web/packages/frequencyConnectedness/frequencyConnectedness.pdf (accessed: 07.02.2019).

Kroeger A, Sarkar A (2017): The Law of One Price, https://www.philadelphiafed.org/-/media/bank-resources/supervision-and-regulation/events/2017/fintech/resources/law-of-one-bitcoin-price.pdf?la=en (accessed: 07.02.2019).

Kurka J (2017): Do Cryptocurrencies and Traditional Asset Classes Influence Each Other? *IES Working Paper*. No. 29/2017, Charles University in Prague, Institute of Economic Studies (IES), Prague.

Loi H (2017): The Liquidity of Bitcoin. *International Journal of Economics and Finance*, 10(1):13–22.

Matkovskyy R (2019): Centralized and decentralized bitcoin markets: Euro vs USD vs GBP. *The Quarterly Review of Economics and Finance*, 71:270–279.

Nakamoto S (2008): Bitcoin: A Peer-to-Peer Electronic Cash System. https://bitcoin.org/bitcoin.pdf (accessed: 07.02.2019).

Pagnottoni P, Baur DG, Dimpfl T (2018): Price Discovery on Bitcoin Markets. *IRTG 1792 Discussion Paper 2018-014*.

Pandey VK, Wu CY (2014): The Value of Bitcoin in Enhancing the Efficiency of an Investor’s Portfolio. *Journal of Financial Planning*, 27:44–52.

Pesaran MH, Shin Y (1998): Generalized Impulse Response Analysis in Linear Multivariate Models. *Economics Letters*, 58(1):17–29.

Pieters G (2016): Bitcoin Reveals Exchange Rate Manipulation and Detects Capital Controls, Working Paper.

Pieters G, Vivanco S (2017): Financial Regulations and Price Inconsistencies Across Bitcoin Markets. *Information Economics and Policy*, 39:1–14.

Symitsi E, Chalvatzis KJ (2018): Return, Volatility and Shock Spillovers of Bitcoin with Energy and Technology Companies. *Economics Letters*, 170:127–130.

Urquhart A (2017): Price Clustering in Bitcoin. *Economics Letters*, 159:145–148.

Thies S, Molnár P (2018): Bayesian Change Point Analysis of Bitcoin Returns. *Finance Research Letters,* 27: 223-227.

Wei WC (2018): Liquidity and Market Efficiency in Cryptocurrencies. *Economics Letters*, 168:21–24.

Yermack D (2015): Is Bitcoin a Real Currency? An Economic Appraisal. In: Lee DKC (eds): *Handbook of Digital Currency. Bitcoin, Innovation, Financial Instruments, and Big Data*, Elsevier, San Diego.

Internet sources

Bitfinex, 2019a, https://support.bitfinex.com/hc/en-us/articles/213892209-What-is-Bitfinex- (accessed: 30.05.2019).

Bitfinex, 2019b, https://www.bitfinex.com/stats#data (accessed: 30.05.2019).

Bitflyer, 2019a, https://bitflyer.com/en-jp/company (accessed: 30.05.2019).

Bitflyer, 2019b, https://bitflyer.com/en-jp/ex/Home (accessed: 30.05.2019).

Bitstamp, 2019a, https://www.bitstamp.net (accessed: 30.05.2019).

Bitstamp, 2019b, https://www.bitstamp.net/about_us/ (accessed: 30.05.2019).

Bitstamp, 2018c, https://www.bitstamp.net/news/ (accessed: 30.05.2019).

Bloomberg, 2019, Company Overview of iFinex Inc. (BVI), https://www.bloomberg.com/research/stocks/private/snapshot.asp?privcapId=309312629 (accessed: 30.05.2019).

Coinbase, 2019a, https://www.coinbase.com/about (accessed: 30.05.2019).

Coinbase, 2019b, https://pro.coinbase.com/trade/BTC-USD (accessed: 30.05.2019).

CoinMarketCap, 2018, 24 Hour Volume Rankings (All Exchanges) https://coinmarketcap.com/exchanges/volume/24-hour/all/ (accessed: 05.09.2018).

Higgins S, 2016, The Bitfinex Bitcoin Hack: What We Know (And Don't Know), https://www.coindesk.com/bitfinex-bitcoin-hack-know-dont-know (accessed: 22.11.2018).

Kraken, 2019a, https://www.kraken.com/en-us/about (accessed: 30.05.2019).

Kraken, 2019b, https://www.kraken.com/prices, (accessed: 30.05.2019).