No 4(73) 2018

ISSN 2544-7068

BEZPIECZNY BANK

BANKOWY FUNDUSZ GWARANCYJNY

SAFE BANK is a journal published by the Bank Guarantee Fund since 1997. It is devoted to issues of financial stability, with a particular emphasis on the banking system.

All articles published in “SAFE BANK” are reviewed.
All articles present the opinions of the authors and should not be construed to be an official position of BFG

PUBLISHER

Bankowy Fundusz Gwarancyjny
ul. Ks. Ignacego Jana Skorupki 4
00-546 Warszawa

SECRETARY

Ewa Teleżyńska
Telephone: 22 583 08 78
e-mail: redakcja@bfg.pl

DOM WYDAWNICZY ELIPSA

Desktop publishing:
Dom Wydawniczy ELIPSA
ul. Inflancka 15/198, 00-189 Warszawa
tel. 22 635 03 01, e-mail: elipsa@elipsa.pl,
www.elipsa.pl

Safe Bank 4 (73) 2018

DOI: 10.26354/bb.4.4.73.2018

Agata Kliber*
ORCID: 0000-0003-1996-5550

Price, Liquidity and Information Spillover within the Cryptocurrency Market. The Case of Bitfinex[1]

Abstract

The aim of the research was to investigate price, liquidity and information spillover within the cryptocurrency market. Since from the introduction of bitcoin, many other cryptocurrencies have emerged, there appears a question, whether the market is and will be dominated by Bitcoin, while other cryptocurrencies are only marginal and follow the price, liquidity and overall dynamics of Bitcoin, or can they be possibly used to portfolio diversification. The article contributes also to the debate on the possibility of contagion across the cryptocurrency market. By measuring and quantifying the spillovers of prices, information and liquidity among the cryptocurrencies, we try to investigate the strength of influence of the separate currencies on the whole system. The following cryptocurrencies traded in Bitfinex were taken it account: Bitcoin, Ether, Litecoin, Dashcoin and Monero. All the prices were expressed in US dollars. The period of the study covers one year, from May 2017 to May 2018. Liquidity was measured by Volume over Volatility measure, while information inflow through volume traded. Volume of spillovers were computed according to the methodology proposed by Diebold and Yilmaz. The study suggest strong co-movement across the currencies and high and relatively stable value of spillover indices.

Key words: Cryptocurrencies, Bitcoin, DASH, Ether, Litecoin, Monero, spillover index, liquidity

JEL: G11, G15, G19

* PhD, Poznan University of Economics and Business, Department of Applied Mathematics.

1 The study is supported by the interdepartmental grant of Poznan University of Economics and Business: *The Future of money – cryptocurrencies, local currencies and cashless society* and the research grant: 2017/25/B/HS4/01546 *The measurement of liquidity and the dynamics of the transaction process.*

Przenoszenie zmian cen, płynności i informacji między kryptowalutami na przykładzie giełdy BitFinex

Streszczenie

Celem artykułu jest zbadanie przenoszenia zmian cen, płynności i informacji pomiędzy kryptowalutami (na przykładzie giełdy BitFinex), w celu odpowiedzi na pytanie, czy rynek kryptowalutowy jest i będzie zdominowany przez Bitcoina, a inne kryptowaluty tylko naśladują jego zachowanie. Zbadane zostało zachowanie cen (wyrażonych w dolarach), płynności i przepływu informacji następujących kryptowalut: Bitcoin, Ether, Litecoin, Dashcoin i Monero. Okres badania objął rok (od maja 2017 do maja 2018). Jako miarę płynności przyjęto Volatility over Volume, a przepływ informacji aproksymowany był wielkością transakcji. Do zbadania siły zarażania wykorzystano metodykę indeksu przenoszenia (*spillover index*) zaproponowaną przez Diebolda i Yilmaza. Na podstawie wyników stwierdzono silną współbieżność kryptowalut, silne powiązania i relatywnie stałe wielkości przenoszenia.

Słowa kluczowe: kryptowaluty, Bitcoin, DASH, Ether, Litecoin, Monero, indeks przenoszenia, płynność

1. Introduction

Bitcoin was created by pseudonymous software developer Satoshi Nakamoto in 2009, as an electronic payment system based on mathematical proof. The idea was to produce a means of exchange, independent of any central authority. Although Bitcoin uses the concept of a blockchain, it has no monopoly on this technology. Other people can also create their own cryptocurrencies and their own blockchains.

Over the years Bitcoin has become very popular, however it has some drawbacks (high transaction fees, large amount of energy consumption, anonymity problems, etc.). For this and more other reasons, alternative cryptocurrencies have been designed. Some of the most popular altcoins include Ether, Litecoin, Dash, Monero and others. Accordng to coinmarketcap[2] at the moment of writing this article there has been over 1600 cryptocurrencies. Bitcoin still has the highest capitalization from all of them.

In the article we deal with the question whether the altcoins can be treated as an alternative investment to the investment in Bitcoin or do they just mimic its behaviour. In other words: is it possible to diversify the portfolio including altcoins in it or are all the cryptocurrencies the parts of one big market? Many researchers (see the literature review section) showed that Bitcoin should not be associated with “new gold”, nor alternative currency, but as it is typically uncorrelated with stock market, it can be possibly used to hedge market risk (e.g. Dhyrberg 2016). As the market of cryptocurrencies explodes, the question of whether any other cryptocurrency can be an alternative is worth to tackle. Therefore, the degree of

[2] https://coinmarketcap.com/all/views/all/

interdependence among the cryptocurrencies need not to be studied, to analyse and understand the degree of contagion risk within this market.

In order to answer the question we analyse the spillover of prices, volume and information across the aforementioned cryptocurrencies within one exchange – Bitfinex. There are many exchanges of cryptocurrencies and the choice of Bitfinex was motivated by the fact that it is most liquid by the volume of trading of Bitcoin against the US dollar (see e.g. Kliber et al. 2018). According to the statistics provided by bitcoinity.org, over the period 2016–2018 it was ranked the first, when it comes to market share of Bitcoin transaction in US dollars (32.38%), bitcoin trading volume in US dollars (39.56%), as well as a number of trades per minute in US dollars (47 which amounted to 26.83% market share). Through analyzing the spillovers we can decide whether the other altcoins are tied to Bitcoin and follow its dynamics or are they separated one from another and react to their own shocks rather to the shocks in Bitcoin prices. The results of the analysis suggest clearly that Bitcoin dominates the market and its shocks influence the prices and information in the market the most. However, when it comes to liquidity, it appears that the dominating currencies are the ones where transactions are performed faster – here: DASH (Dash transactions are confirmed in 4 seconds, while sending the Bitcoin to someone can take even 10 minutes).

The article is structured as follows. In the next section we present the dynamics of prices and volume in the charts and give the descriptive statistics of data. Subsequently, we present the model of spillover index. The results are discussed in the last section.

2. Literature review

The literature on Bitcoin and properties of its price behaviour managed to emerge together with the growth of its popularity. The first research papers concentrated on studying Bitcoin bubbles (Cheach and Fry 2015; Fry and Cheach 2016), property of its volatility (e.g. Katsiampa 2017; Bouri et al. 2017a; Conrad et al. 2018) and its role in financial markets – wheter it can be treated as a safe haven, hedge or diversifier (Bouri et al. 2017b; Bouri et al. 2017c; Corbet et al. 2018). Later on, the researchers started to ask themselves a question with what kind of financial asset can Bitcoin be associated. Dhyrberg (2016) claimed that Bitcoin possessed similarities to both currency and gold and could be possibly used as a medium of exchange and a hedging asset. On contrary, Kim et al. (2018), as well as Klein et al. (2018) showed that Bitcoin should not be treated as a "new gold", and the behavior of its volatility resembles gold only in asymmetric response of variance to the news, while Baur et al. (2018) concluded that Bitcoin should not be associated neither with medium of exchange, nor with alternative currency – as it is mainly used for speculation.

The literature concerning another cryptocurrencies emerged a little later and its boom is dated to the second half of 2018. Some of the research concentrate on price discovery in the cryptocurrency market, studying its efficiency. Zhang et al. (2018) confirmed its inefficiency (as a whole) and correlation with Dow Jones Industrial Average. Brauneis and Mestel (2018) found that Bitcoin is the most efficient of the cryptocurrencies and that the efficiency is linked to liquidity (approximated by the Bid-Ask spread of Corwin and Schultz 2012). The result was corroborated by Wei (2018).

On contrary, Yi et al. (2018) who studied the volatility connectedness between cryptocurrencies stated that Bitcoin is not the clear leader – although it became one in the period 2017–2018. Zięba and Śledziewska (2018) analyzing demand shocks in cryptocurrency market concluded that Bitocoin indeed plays one of the most important roles in the cryptocurrency market, while other cryptocurrencies form clusters. However, demand shocks in Bitcoin prices are not contagious to other cryptocurrencies, and thus the conclusions drawn from the analysis of Bitcoin should not be generalized to the whole market of cryptocurrencies. Vidal-Tomas et al. (2018) found out that smallest digital currencies are herding with the largest ones (which suggests that the investors base their decisions on the behaviour of the main cryptocurrencies) – but as the rest of the crypto-market does not herd with Bitcoin, the latter should not be associated with clear leadership. Koutmos (2018) reached slightly different conclusions claiming that over the period 2015–2018 Bitcoin was a clear leader when it comes to price and volatility transmission. Zhang et al. (2019) – studying correlation among Bitcoin, Ether, Litecoin and Ripple – concluded that all four cryptocurrencies exhibited moderately positive correlations between each other. From the fact that the strongest correlations corresponded to Bitcoin (which may be due to the fact that Bitcoin accounts for the largest share of the total cryptocurrency market capitalization) the authors derive suggestion that any movement in the price of Bitcoin will almost certainly cause a knock on effect on the overall cryptocurrency market. Yet, another result was obtained by Dimpfl and Peter (2018) who – based on group transfer entropy – concluded that bitcoin is not the dominating cryptocurrency when information process leadership is concerned.

Yi et al (2018) as well as Koutmos (2018) utilize the spillover measure of Diebold and Yilmaz (2009 and 2010) to assess the interconnectedness of the cryptocurrencies. In this case our research is similar to their approach. However, our study in a sense extends the results of the authors. To compute the spillover index we do not take into account the volatility, but only returns, as well as volume and liquidity. The spillovers are interpreted respectively as price, information and liquidity spillovers.

The use of trading volume as an approximation of information can cause some serious doubts. Although it is used as a proxy for information flow in the case of stocks[3], such usage in the case of cryptocurrencies requires explanation. In the

[3] The relevance of the trading volume in stock trading is already well-established. The decisions of buying and selling are mainly prompted by the belief of bidders and askers that they can affect the price of the stock which they consider as underpriced(overpriced). The trading volume (or number of transactions themselves – see Jones et al. 1994) can act as a proxy for the flow of information

literature more and more popular proxy for investors' sentiment is their Internet activity measured e.g. by Google Trends, Tweets, Yahoo Search Engine and others (see e.g. Bollen et al. 2011; Bordino et al. 2012). The authors show that there is strong and positive correlation between trading volume and the number of queries about the same stock. Similar relationships have been found in the case of Bitcoin. For instance, Matta et al. (2018) showed that search volumes can predict trading volumes of Bitcoin. Yet, more explicit evidence that trading volume can be used as a proxy for information arrival provided Balciclar et al. (2017). The researchers showed that Bitcoin trading volume can predict returns, but not volatility of its price. More precisely: when the market is functioning around the normal (median) mode, volume can indeed predict returns, and provide investors in the Bitcoin market with valuable predictive information.

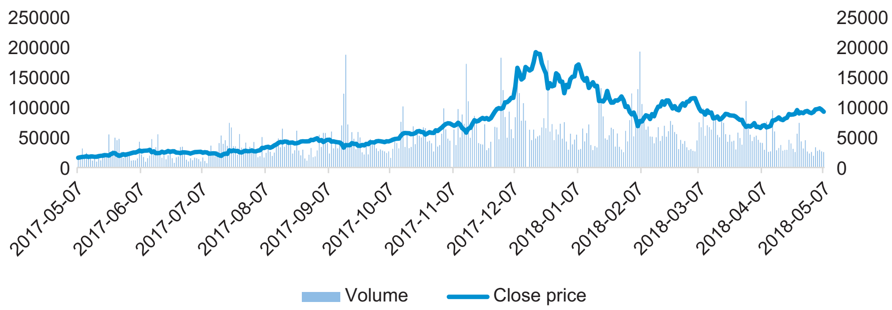
We concentrate only on the last year: 2017 to 2018 and on the most liquid exchange platform – Bitfinex. Our findings concerning price spillovers confirm the results obtained by other authors (i.e. that Bitcoin was the leading cryptocurrency in the case of shock transmission). However, when it comes to information spillover it is the Litecoin, which is the least influenced by other information, while the influence of Bitcoin and Ether is comparable. Eventually, when it comes to liquidity spillovers – although liquidity of Bitcoin seems to be most isolated from the shocks coming from the liquidity of the rest of the cryptocurrencies, this is DASH that contributes the most to the whole system. Such results can be possibly explained by the speed of the transactions.

3. Data

We take into account the dynamics of prices and volume of the five cryptocurrencies over one year time: from May 2017 to May 2018. The data is presented in Figures 1 to 5. The prices and volume were downloaded from the Bitfinex platform. We observe that all of them exhibited enormous growth at the end of 2017 and all the prices started to decline at the beginning of 2018. There are, however, differences when it comes to the volume of transactions. We assume that through analyzing the volume of transaction, we can capture the information arriving into the market (see previous paragraph for explanation).

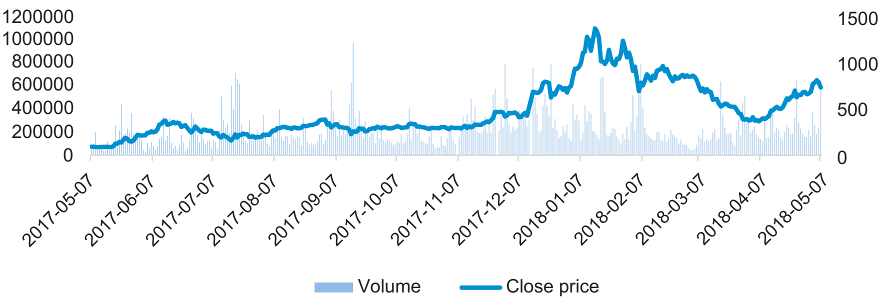
among them. Large trading volumes are associated with a large amount of news which tend to impact the price (see: Jennings et al. 1981, Karpoff, 1987, Jones et al. 1994, Easley et al. 2016, Graczyk and Queiros, 2017, Będowska-Sójka 2014 and many others).

Figure 1. Dynamics of daily prices and volume of BTCUSD over the period May 2017 – May 2018



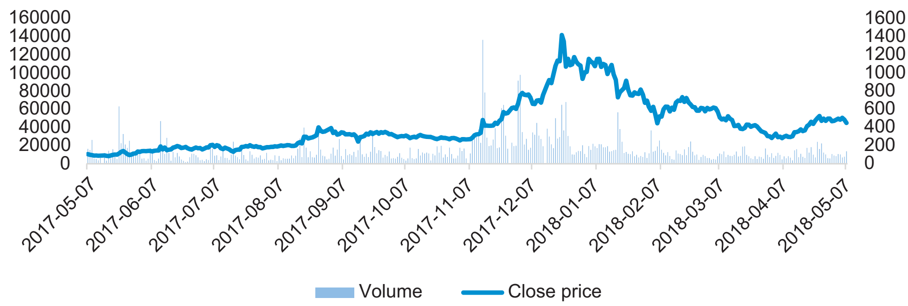
Source: Own computations based on Bitfinex data.

Figure 2. Dynamics of daily prices and volume of ETHUSD over the period May 2017 – May 2018



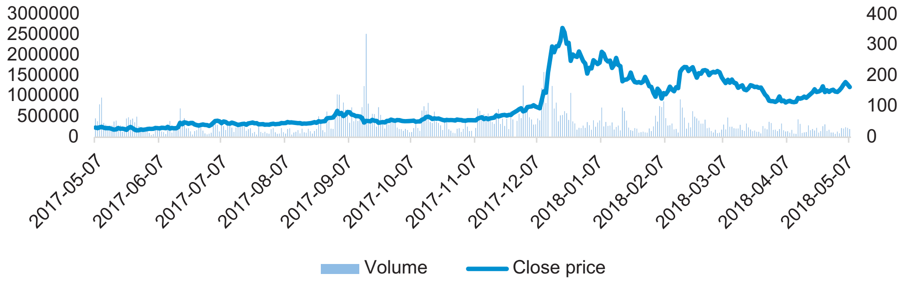
Source: Own computations based on Bitfinex data.

Figure 3. Dynamics of daily prices and volume of DSHUSD over the period May 2017–May 2018



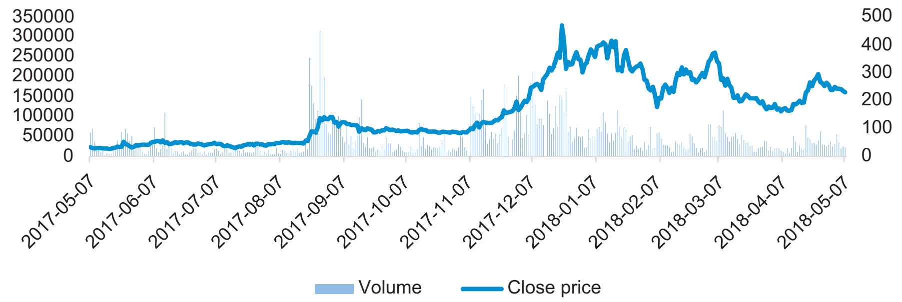
Source: Own computations based on Bitfinex data.

Figure 4. Dynamics of daily prices and volume of LTCUSD over the period May 2017–May 2018



Source: Own computations based on Bitfinex data.

Figure 5. Dynamics of daily prices and volume of XMRUSD over the period May 2017–May 2018



Source: Own computations based on Bitfinex data.

Apart from price and information spillovers, we include in our analysis also liquidity spillovers. In the literature there are many proxies used to measure liquidity (see e.g. Goyenko 2009 Marshall et al. 2018 or Będowska-Sójka 2018 for the review of the proxies). In this study we use *volume over volatility* (further: VoV). The measure was introduced by Fong et al. in 2017 (Fong et al. 2017). The volume over volatility is calculated as follows:

$$VoV_t = \frac{\ln\left(\frac{H_t}{L_t}\right)}{\sqrt{volume_t}}, \tag{1}$$

where H_t denotes highest price over the trading day, L_t – the lowest price over the day, $\ln(\cdot)$ is a natural logarithm, while $volume_t$ is the volume observed during the day t. The idea of the indicator is as follows: a given level of volume of liquid instruments causes lower distortions in price and lowers the absolute returns more than the one of the illiquid instruments.

Table 1. Descriptive statistics of data

	Number of observations	Minimum	Maxi-mum	Range	Median	Mean	Std.dev
dVolBTC	362	-118709.100	135769.40	254478.500	-1378.591	35.584	26589.010
dPrice_BTC	362	-20.566	23.313	43.879	0.595	0.482	5.700
VoV_BTC	363	0.000	0.001	0.001	4.01E-04	4.27E-04	1.68E-04
dVolDSH	362	-63368.460	113982.60	177351.000	-527.426	-7.694	13660.150
dPrice_DSH	362	-23.145	34.852	57.997	0.403	0.398	7.428
VoV_DSH	363	0.000	0.002	0.002	9.20E-04	9.88E-04	3.92E-04
dVolETH	362	-657766.100	553241.30	1211007.000	-8691.751	1653.779	144079.200
dPrice_ETH	362	-22.531	29.345	51.876	0.298	0.572	6.968
VoV_ETH	363	0.000	0.001	0.001	2.09E-04	2.32E-04	1.10E-04
dVolLTC	362	-1705938.000	1278362.0	2984300.000	-10654.750	-716.396	230240.500
dPrice_LTC	362	-28.361	37.300	65.661	0.256	0.460	7.855
VoV_LTC	363	0.000	0.001	0.001	2.00E-04	2.15E-04	9.36E-05
dVolXMR	362	-230342.500	230085.80	460428.300	-323.815	-103.465	35883.390
dPrice_XMR	362	-28.985	42.425	71.410	0.062	0.535	8.188
VoV_XMR	363	0.000	0.004	0.004	6.20E-04	6.84E-04	3.61E-04

Source: Own computations.

In Table 1 we present descriptive statistics of data. We included in the table the prices changes of each cryptocurrency, the changes of volume and the level of liquidity. Transformation of prices and volume was necessary, as the data proved to be non-stationary, according to the ADF test (see Appendix for details). As the null hypothesis of the ADF test was rejected in the case of VoV (i.e. we rejected the null about the unit root), we leave the measure unchanged (i.e. in levels instead of changes) over the whole analysis.

4. Model

Spillover index proposed by Diebold and Yilmaz (2009, 2010) is based on vector autoregression model (further: VAR) and Cholesky decomposition of forecast error variance. Let us assume that the system of variables can be described using VAR model of the following form:

$$y_t = \Phi y_{t-1} + \epsilon_t. \tag{2}$$

In our case y_t is composed of the changes of five currencies' prices (and in the later cases: of volumes and liquidities of the currencies). If the system is covariance-stationary, then there exist a MA-representation of it, of the following form:

$$y_t = \Theta(L)\epsilon_t, \tag{3}$$

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

$$y_t = \mathrm{A}(L)\mathrm{u}_t, \tag{4}$$

where $\mathrm{A}(L) = \Theta(L)\mathrm{Q}_t^{-1}$, $\mathrm{u}_t = \mathrm{Q}_t\epsilon_t$, $\mathrm{E}(\mathrm{u}_t\mathrm{u}_t') = \mathrm{I}$, and Q_t^{-1} is the unique lower triangle Cholesky factor of the covariance matrix of ϵ_t.

If we consider a 1-step ahead forecast:

$$y_{t+1,t} = \Phi y_t. \tag{5}$$

The corresponding 1-step ahead forecast error vector is:

$$e_{t+1,t} = y_{t+1} - y_{t+1,t} = A_0 u_{t+1} = \begin{bmatrix} a_{0,11} & \dots & a_{0,1k} \\ \dots & \dots & \dots \\ a_{0,k1} & \dots & a_{0,kk} \end{bmatrix} \begin{bmatrix} u_{1,t+1} \\ \dots \\ u_{k,t+1} \end{bmatrix}, \tag{6}$$

while the covariance matrix is:

$$E(\mathrm{e}_{t+1,t}\mathrm{e}'_{t+1,t}) = \mathrm{A}_0\mathrm{A}'_0. \tag{7}$$

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

$$S = \frac{\sum_{i,j=1}^{k} a_{0,ij}^2}{trace(A_0 A_0')} \cdot 100, i \neq j. \tag{8}$$

The idea is as follows. Variance decomposition allows us to split the forecast error to 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: $trace(\mathrm{A}_0\mathrm{A}'_0)$.

The main drawback of the approach is that it requires the *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). Such an approach was applied in this research. To check the robustness of the results, we include also comparison of the average spillover to the minimal and maximal ones. The latter are computed for such an ordering of variables, where the contribution of each to the system is the smallest or the highest, respectively. To compute the spillover index and spillover tables the R package called fastSOM was used (Kloessner and Wagner 2016).

5. Results

In Tables 2 to 4 we present the average daily spillover value of prices, liquidity and information among the cryptocurrencies within the investigated year, while in Table 5 the contribution of each cryptocurrency to the spillover index in the case when the minimum, average and maximum value of the index is taken into account. What we observe is that the information spillover index was the lowest, amounting to 51% (with minimal spillover amounting to 20%, and maximum to 64%), while the price and volatility spillover indices were comparable and both exceeded 61% (with minimal spillover amounting to 26 and maximal to 72% in the case of price spillover, and 36 and 71%, respectively, in the case of the liquidity spillover).

Table 2. Price spillovers (average) over the period May 2017–May 2018 – average

Contribution to:	Contribution from:					Total:
	dPriceBTC	dPriceDSH	dPriceETH	dPriceLTC	dPriceXMR	
dPriceBTC	**59.70**	9.30	9.55	11.85	9.60	100.00
dPriceDSH	23.06	**39.100**	11.590	11.29	14.96	100.00
dPriceETH	22.843	19.48	**31.04**	13.28	13.36	100.00
dPriceLTC	23.34	16.18	16.81	**31.03**	12.65	100.00
dPriceXMR	20.23	22.68	14.04	13.17	**29.88**	100.00
Total:	149.18	106.74	83.03	80.61	80.45	–
Contribution excluding own:	*89.48*	67.634	51.99	49.58	50.57	**61.85**

Source: Own computations.

Let us concentrate first on price spillovers. We observe that almost 60% of the variance of the one-step-ahead forecast error of the Bitcoin price change can be attributed to the unexpected change of Bitcoin price. The shares of the influence of the unexpected change of the prices of DASH, Ether and Monero in explaining the forecast error of the Bitcoin price change are comparable and amount to 9%. The influence of Litecoin is slightly higher and amounts to almost 12%. When we look at the altcoins we notice that the influence of the own price change on the variance of the forecast error is in all the cases much lower than in the case of the Bitcoin and varies between 30% (Monero) to 40% (DASH). In the case of DASH, Ether and Litecoin the influence of the Bitcoin price seems to be the highest (apart from the "own" influence), oscillating around

23%, while in the case of Monero; DASH influence exceeds slightly the influence of Bitcoin, which can be explained by the fact that both altcoins are the so called private-coins. However, when we take a look at the last row of the table, we observe that the value of the "contribution to others" is the highest in the case of the Bitcoin. The second most influential cryptocurrency seems to be DASH.

Table 3. Information spillovers (average) over the period May 2017–May 2018 – average

Contribution to:	Contribution from:					Total:
	dVolBTC	dVolDSH	dVolETH	dVolLTC	dVolXMR	
dVolBTC	**56.68**	8.98	17.09	10.48	6.76	100.00
dVolDSH	36.03	**30.76**	16.81	7.91	8.49	100.00
dVolETH	22.28	6.63	**57.19**	9.59	4.31	100.00
dVolLTC	15.22	3.07	15.82	**63.79**	2.10	100.00
dVolXMr	17.61	10.79	25.59	8.58	**37.43**	100.00
Total:	147.82	60.24	132.50	100.34	59.10	–
Contribution excluding own:	*91.137*	29.480	75.312	36.555	21.663	50.830

Source: Own computations.

In Table 3 we present the information spillovers across the market. The results differ slightly from the previous case. Still, we observe that when it comes to "Contribution excluding own", the information coming from Bitcoin is still the most influential. However, when we analyse the decomposition of forecast error variance of separate cryptocurrencies, we can see that it is the Litecoin, which is the least influenced by other information (almost 64% of the forecast error variance can be explained by the "own" change), while the influence of Bitcoin and Ether is comparable (around 15%). In the case of the Bitcoin, only about 57% of the forecast error variance can be contributed to the "own" change, while 17% to the change of the volume of Ether, 10% to the change of the volume of Litecoin, 9% – to the change of DASH and 7% – to the change of Monero. The dominance of the influence of the change of Bitcoin volume over the influence of any other altcoin change is observed when we analyse the decomposition of the forecast error of DASH and Ether. However, in the case of Monero the share of the influence of the Ether volume change (26%) is already higher than the influence of the Bitcoin volume change (18%).

Eventually, when it comes to liquidity spillovers (Table 4), we observe yet another pattern. Although liquidity of Bitcoin seems to be most isolated from the shocks coming from the liquidity of the rest of the cryptocurrencies (almost 64% of forecast error variance can be attributed to the "own" shocks), yet when we look at the amount of contribution of each cryptocurrency to the whole system, this is DASH that contributes the most. It is also the second most immune cryptocurrency when it comes to the reaction to the shocks (56% of the forecast error variance is explained by own shocks) and is most influenced by the Bitcoin liquidity shocks (almost 14%). However, the influence of the Bitcoin liquidity shock is weaker than the influence of the DASH liquidity shocks in the case of the Ether, Litecoin and Monero. Such results can be possibly explained by the speed of the transactions' as already mentioned. Dash transactions are confirmed in 4 seconds, while sending the Bitcoin to someone can take even 10 minutes (Rutnik 2018).

Table 4. Liquidity spillovers (average) over the period May 2017–May 2018 – average

Contribution to:	Contribution from:					Total:
	VoVBTC	VoVDSH	VoVETH	VoVLTC	VoVXMR	
VoVBTC	**63.73**	7.92	9.30	11.04	8.00	100.00
VoVDSH	13.59	**55.56**	9.11	10.69	11.04	100.00
VoVETH	25.28	30.04	**20.62**	13.31	10.75	100.00
VoVLTC	25.01	31.42	13.53	**19.04**	11.00	100.00
VoVXMr	16.13	25.68	10.67	13.38	**34.15**	100.00
Total:	143.75	150.61	63.23	67.46	74.95	–
Contribution excluding own:	80.018	*95.050*	42.610	48.421	40.800	**61.380**

Source: Own computations.

Table 5. Percentage contribution of separate cryptocurrencies to the price, information and spillover indices

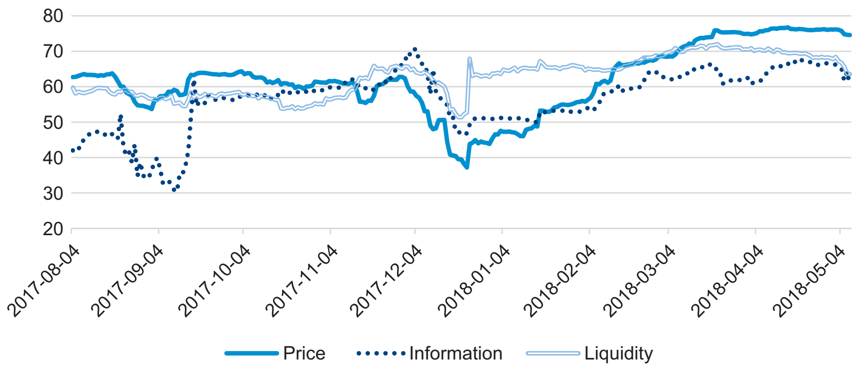
	Price spillover			Information spillover			Liquidity spillover		
	Minimum	Average	Maximum	Minimum	Average	Maximum	Minimum	Average	Maximum
BTC	69.555	**28.933**	24.552	41.689	**35.860**	33.183	35.370	**26.073**	23.793
DSH	23.658	**21.871**	21.293	0.824	**11.600**	13.976	60.646	**30.971**	24.941
ETH	5.157	**16.811**	18.520	30.523	**29.633**	28.212	1.563	**13.884**	16.716
LTC	1.488	**16.033**	17.747	7.026	**14.383**	16.607	0.088	**15.777**	18.496
XMR	0.143	**16.352**	17.888	19.937	**8.524**	8.022	2.333	**13.294**	16.054
sum	100	100	100	100	100	100	100	100	100
Spillover value	26.495	**61.850**	72.17	19.555	**50.830**	63.705	36.197	**61.380**	71.385

Note: Minimum/maximum denotes the spillover index computed for such ordering of variables, when contribution of each to the whole system was the smallest/the highest. We bolded the average spillover values.

Source: Own computations.

Eventually, in Table 5 we summarize the contribution of separate cryptocurrencies to the price, information and liquidity spillover indices, when the average spillover is compared to the two extremes: minimum and maximum spillover values. The minimum (maximum) spillover index is computed for such ordering of variables, when the minimal (maximal) contribution of each to the whole system is taken into account (Kloessner and Wagner 2012 and 2016). What we can notice is that in the analysed period the contribution of Bitcoin to price and information spillovers was always the highest, while the contribution of DASH dominated in the case of liquidity spillover one.

Figure 6. Price, information and liquidity spillovers over the period May 2017–May 2018. Average spillover value over 3-months period



Source: Own computations.

At the end, we plotted the changes of spillover indices computed using rolling-window over 3-months period. We observe that the pattern of information spillover behaved differently from the remaining two indices up to October 2017, as if information had not spread freely over the market before Autumn 2017. Next, the spillover level remained on almost constant level and fell at the beginning of 2018, when first decline of the prices after the constant growth have been observed. The first to recover has been liquidity – the index grew to the previous level almost immediately, while the price and information spillover indices required some time to return to the previous levels. What is interesting, at the end of the analysed period the price spillover index has been constantly growing and exceeded the remaining ones. This can support the thesis that at the moment the prices of cryptocurrencies follow strictly one another, and that the possible moment when this pattern had broken was the moment of the falling prices.

6. Conclusions

In the article we analyse price, liquidity and information spillovers across five top-popular cryptocurrencies: Bitcoin, DASH, Ether, Litecoin and Monero in Bitfinex exchange and over the period: May 2017 – May 2018. We compute spillover table according to the methodology proposed by Diebold and Yilmaz (2009, 2010), and to avoid the problems emerging from the variables ordering, we apply the solution of Kloessner and Wagner (2012). Based on the results we can conclude that in the analysed period Bitcoin had the leading role in price formation in the market. However, when it comes to liquidity spillover (measured by VoV), the leading one seems to be DASH – probably due to much faster transaction processing algorithm, as well as due to the increasing need of anonymity in the Internet (DASH and Monero are the leading privacy-oriented altcoins). Eventually, when it comes to information spillovers, measured by the volume traded, we observed the leading role of Bitcoin again, but also increasing role of Litecoin and Ether. This result partially confirms the finding of Zięba and Śledziewska (2018) that not all cryptocurrencies follow strictly Bitcoin, but tend to form kind of clusters within which they influence one another.

At the end we estimated the price, liquidity and information spillover indices computed by rolling-window approach for 3-months period and for one-step ahead forecast. We observe that at the beginning of the period information spillover was much smaller than the spillover of prices and liquidity. However, together with the sharp growth of the currencies' prices, the level of all kind of spillovers grew and stabilized oscillating around 60–65%. At the beginning of 2018, together with the first downfall of the prices, also the spillover level diminished, but over the year returned and even exceeded the previous level. The fastest reaction has been observed in the case of liquidity spillover index.

The aim of the analysis was to verify whether the prices, volume and liquidity of the cryptocurrencies move together or are they separated one from another and could be possibly used to diversify portfolio. The very high level of spillover index indicates a high level of co-movement, which can be possibly distorted only during some hectic investors' behaviour – e.g. the one that leaded to the fall of the Bitcoin price at the beginning of 2018. As such events are rather unpredictable, we should state that the cryptocurrencies are closely linked one to another, constitute one market and can be used as substitutes rather than diversifiers.

Our results corroborate the finding of Koutmos (2018) and Yi et al. (2018). The latter – analyzing volatility connectedness among eight cryptocurrencies – found that in the period from 2017 to April 2018 Bitcoin became a net transmitter of volatility shocks to other cryptocurrencies, which may be due to the heat of the Bitcoin market in 2017. Yi et al. (2018) explain this phenomenon speculating that the price of Bitcoin can be perceived as an indicator of market attitude towards the cryptocurrency market as a whole, and affect the performance of the market itself. Yet another explanation is of behavioral nature. The fact that Bitcoin is gradually accepted by the public, and perceived as a representative of cryptocurrencies, may cause people believe that this cryptocurrency should eventually win the "winner-takes-all" race against other ones (Yi et al. 2018).

The implication of the research is that due to the high interconnectedness among the cryptocurrencies, the investors who wish to diversify their portfolios (see also: Bouri et al. 2017) do not have to necessary stick to Bitcoin. However, due to the specific role of the Bitcoin in the market, they should closely monitor its price, as the changes of Bitcoin price may affect the dynamics of the other cryptocurrencies.

At the end we want to stress the fact that the results were obtained for the Bitfinex platform, ranked one when it comes to the number and liquidity of Bitcoin transaction in US dollars. Thus, as Bitcoin dominates the exchange, we could have expected that the results would suggest its clear leadership in the market. As the total domination of Bitcoin has not been confirmed, we can suppose that the results can be generalized to more exchanges. However, further investigation is needed to answer the question definitely.

Appendix

1 Results of ADF test

Table 6. P-values of the ADF test

	Bitcoin	Dashcoin	Ether	Litecoin	Monero
dPrice	0.01	0.01	0.01	0.01	0.01
dVol	0.01	0.01	0.01	0.01	0.01
VoV	0.013	0.01	0.037	0.046	0.01

Note: Null hypothesis: data has unit rot.

Source: Own computations using R package tseries (Trappletti and Hornik 2018).

References

Balciclar M., Bouri E., Gupta R., Roubaud D. (2017), *Can volume predict Bitcoin returns and volatility? A quantiles-based approach*, "Economic Modelling", Vol. 64: 74–61.

Baur D.G., Hong K., Lee A.D., *Bitcoin: Medium of exchange or speculative assets?*

"Journal of International Financial Markets, Institutions and Money" 2018, Vol. 54: 177–189.

Będowska-Sójka B. (2014), *Wpływ informacji na ceny instrumentów finansowych. Analiza danych* śróddziennych, Wydawnictwo Uniwersytetu Ekonomicznego w Poznaniu, Poznań.

Będowska-Sójka B. (2018), *The coherence of Liquidity Measures. The Evidence from the Emerging Market*, "Finance Research Letters" 10.1016/j.frl.2018.02.014.

Bollen J., Mao H., Zeng X. (2011), *Twitter mood predicts the stock market*, "Journal of Computational Science", Vol. 2(1): 1–8.

Bordino I., Battiston S., Caldarelli G., Cristelli M., Ukkonen A., Weber I. (2012), *Web search queries can predict stock market volumes*, "PloS one", Vol. 7(7): e40014, 1–17.

Bouri E., Azzi G. Dhyrberg A. (2017a), *On the return-volatility relationship in the Bitcoin market around the price crash of 2013*, "Economics E-Journal", Vol. 11(2): 1–16.

Bouri E., Gupta R., Tiwari A.K., Roubaud D. (2017b), *Does bitcoin hedge global uncertainty? Evidence from wavelet-based quantile-in-quantile regressions*, "Finance Research Letters", Vol. 23: 87–95.

Bouri E., Molnár P., Azzi G., Roubaud D., Hagfors L.I. (2017c), *On the hedge and safe haven properties of bitcoin: Is it really more than a diversifier?* "Finance Research Letters", Vol. 20: 192–198.

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

Cheah E.-T., Fry J. (2015), *Speculative bubbles in bitcoin markets? An empirical investigation into the fundamental value of bitcoin*, "Economics Letters", Vol. 130: 32–36.

Conrad C., Custovic A. (2018), Ghysels E., *Long- and short-term cryptocurrency volatility components: A GARCH-MIDAS analysis*, "Journal of Risk and Financial Management", Vol. 11, (2): 23–35.

Corbet S., Lucey B., Urquhart A., Yarovaya L. (2018), *Cryptocurrencies as a financial asset: A systematic analysis*, "International Review of Financial Analysis" (in press), https://doi.org/10.1016/j.irfa.2018.09.003

Diebold F.X., Yilmaz K. (2009), *Measuring financial asset return and volatility spillovers, with application to global equity markets*, "Economic Journal", Vol. 199(534): 158–171.

Diebold F.X., Yilmaz K. (2010), *Errata to Measuring financial asset return and volatility spillovers, with application to global equity markets*, "Economic Journal", Vol. 120: F354–F355, doi: 10.1111/j.1468-0297.2010.02386.x

Dimpfl T., Peter F.J. (2018), *Group transfer entropy with an application to cryptocurrencies*, "Physica A: Statistical Mechanics and its Applications", (in press), https://doi.org/10.1016/j.physa.2018.10.048

Dhyrberg A.H. (2016), *Bitcoin, gold and the dollar – A GARCH volatility analysis*, "Finance Research Letters", Vol. 16: 85–92.

Easley D., De Prado M.L., O'Hara M. (2016), *Discerning Information from Trade Data*, "Journal of Financial Economics", Vol. 120(2): 269–286.

Fong K.Y.L., Holden C.W., Tobek O. (2017), *Are Volatility Over Volume Liquidity Proxies Useful For Global Or US Research*, Kelley School of Business Research Paper No. 17-49.

Fry J., Cheah E.-T. (2016), *Negative bubbles and shocks in cryptocurrency markets*, "International Review of Financial Analysis", Vol. 47: 343–35.

Goyenko R.Y., Holden C.W., Trzcinka C.A. (2009), *Do Liquidity Measures Measure Liquidity?*, "Journal of Finacial Economics", Vol. 92(2): 153–181.

Jennings R.H., Starks L., Fellingham J. (1981), *An Equilibrium Model of Asset Trading with Sequential Information Arrival*, "Journal of Finance", Vol. 36(1): 143–61.

Jones M.C., Kaul G., Lipson M.L. (1994), *Transactin, Volumes and Volatility*, "The Review of Financial Studies", Vol. 7, No. 4: 631–651.

Karpoff J.M. (1987), *The relation between price changes and trading volume: a survey*, "The Journal of Financial and Quantitative Analysis", Vol. 22: 109–126, doi: 10.2307/2330874

Katsiampa P. (2017), *Volatility estimation for Bitcoin: A comparison of GARCH models*, "Economic Letters", Vol. 158: 3–6.

Klein T., Thu H., 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.

Kloessner S., Wagner S. (2016), *fastSOM: Calculation of Spillover Measures*. R package version 1.0.0., URL: http://CRAN.R-project.org/package=fastSOM

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", Vol. 29(1): 172–179.

Kliber A., Marszałek P., Musiałkowska I, Świerczyńska K. (2018), *Bitcoin: Safe Haven Hedge or Diversifier? Perception of Bitcoin in the Context of a Country's Economic Situation*, presented at 25th EBES Conference, May 23–25,, Berlin.

Koutmos D. (2018), *Return and Volatility Spillovers Among Cryptocurrencies*, "Economic Letters", Vol. 173: 122–127.

Marshall B.R., Nguyen N.H., Visaltanachoti N*., Do Liquidity Proxies Measure Liquidity Accurately in ETFs?*, "Journal of International Financial Markets, Institutions and Money", Vol. 55: 94–111.

Matta M., Lunescu M.I., Marchesi M. (2015), *The Predictor Impact of Web Search Media on Bitcoin Trading Volumes*, "Proceedings of the 7th International Joint Conference on Knowledge Discovery, Knowledge Engineering and Knowledge Management", DOI: 10.5220/0005618606200626

Pavlus J. (2018), *Świat Bitcoina*, Świat Nauki, Vol. 2(318): 32–37.

Rutnik M. (2018), *What is Dash – a Short Guide*, "Android Authority", 18.02, https://www.androidauthority.com/what-is-dash-820943/

Vidal-Tomas D., Ibanez A.M., Farinos J.E. (2018), *Herding in the Cryptocurrency Market: CSSD and CSAD Approaches*, "Finance Research Letters" (in press), https://doi.org/10.1016/j.frl.2018.09.008

Trapletti A., Hornik K. (2018), *tseries: Time Series Analysis and Computational Finance*. R package version 0.10-44.

Wei W.C. (2018), *Liquidity and market efficiency in cryptocurrencies*, "Economics Letters", vol. 168(C): 21–24.

Yi S., Xu Z., Wang G.-J. (2018), *Volatility connectedness in the cryptocurrency market: Is Bitcoin a dominant cryptocurrency?*, "International Review of Financial Analysis", Vol. 60: 98–114.

Zhang W., Wang P., Li X., Shen D. (2018), *The inefficiency of cryptocurrency and its cross-correlation with Dow Jones Industrial Average*, “Physica A: Statistical Mechanics and its Applications”, vol. 510(C): 658–670.

Zhang W., Chan S., Chu J., Nadarajah S. (2019), *Stylized Facts for High Frequency Currency Data*, “Physica A: Statistical Mechanics and its Applications”, vol. 513(1): 598–612.

Zięba D., Śledziewska K. (2018), *Are demand shocks in Bitcoin contagious?*, Working Papers 17, Faculty of Economic Sciences, University of Warsaw.