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Do Cryptocurrencies and Traditional Asset Classes Influence Each Other?

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IES Working Paper: 29/2017



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Do Cryptocurrencies and Traditional Asset Classes Influence Each Other?

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Abstract:

Large stream of literature studies interconnectedness among various assets that are relevant in current global markets. Transmission of shocks between cryptocurrencies and traditional asset classes is, however, not understood at all, but should not be ignored due to increasing influence of cryptocurrencies in recent years. In this paper, we study how shocks between the most liquid representatives of the traditional asset classes including commodities, foreign exchange, stocks, financials, and cryptocurrencies are being transmitted. Generally, we document very low level of connectedness between the main cryptocurrency and other studied assets. The only exception is gold which receives substantial amount of shocks from cryptocurrency market. Our findings are important since we show that cryptocurrencies play role in global markets, and the results could also be useful in portfolio diversification schemes. Moreover, we find significant positive asymmetry in spillovers between the studied assets, which is in contradiction to previous studies conducted on assets from a single asset class.

Keywords: cryptocurrencies, volatility, connectedness, asymmetric effects, realized semivariance

JEL: C38, C58, E49

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1 Introduction

Rapid development of cryptocurrencies attracted lot of attention in recent research (Brandvold, Molnár, Vagstad, and Valstad, 2005; Bouri, Jalkh, Molnár, and Roubaud, 2017; Urquhart, 2016; Katsiampa, 2017; Urquhart, 2017; Nadarajah and Chu, 2017). Although the role of cryptocurrencies can still be disputed, they are certainly subject of rising awareness, and must be taken into account as a valid economic phenomenon. While connectedness of stock markets has been lively topic of research in the past decades (Kanas, 2000; Yang and Doong, 2004; Mensi, Beljid, Boubaker, and Managi, 2013), there is no study examining connectedness between cryptocurrencies and traditional assets. In this paper, we contribute to the literature by examining asymmetric volatility spillovers between the most liquid cryptocurrency, Bitcoin, and most liquid representatives of the traditional asset classes including foreign exchange, stocks, financials and commodities.

Interconnectedness of financial markets has been important topic in center of research agenda since the 1990s (e.g., Forbes and Rigobon, 2002; Gande and Parsley, 2005). Researchers felt it was a key to understand crises periods, which became a central topic especially after the Asian crisis. Among many studies, Diebold and Yilmaz (2009, 2012) provided a simple quantitative measure of markets interdependence that quickly became popular among researchers. Diebold and Yilmaz (2009, 2012) noted that the spillover index can be obtained by looking at variance decompositions estimated on a system of studied assets.

In our work, we follow this strand of literature, and measure directional spillovers between main representatives of cryptocurrencies, and traditional asset classes in the framework developed by Diebold and Yilmaz (2012). We employ realized variance (Andersen, Bollerslev, Diebold, and Labys, 2001; Barndorff-Nielsen, 2002), developed as a non-parametric estimator of variance based on intraday data. An extension of this framework allowing for asymmetric response of volatility to positive and negative returns, which is a widely documented stylized fact about volatility (e.g., Black, 1976; Pindyck, 1984)¹, was proposed by Barndorff-Nielsen, Kinnebrock, and Shephard (2010). The basic idea is to separately consider the part of variation caused by positive returns, realized positive semivariance (RS^+), and the part of variation caused by negative returns, realized negative semivariance (RS^-).

Since asymmetric behavior of stock markets is well documented stylized fact, information may transmit asymmetrically as well. This has been noted by Barunik, Kočenda, and Vácha (2015, 2016, 2017), who developed a quantitative measure of spillover asymmetry that fits well into the popular framework of Diebold and Yilmaz (2012). Using this strand of literature, we also look how shocks to negative and positive volatility transmit between studied assets. Hence we uncover asymmetric connectedness between main cryptocurrency market and traditional assets. This contributes to current literature by exploring the position cryptocurrencies hold relative to assets traditionally traded on financial markets.

2 Methodology

Before proceeding to the empirical results, we need to introduce the key concepts used to obtain them. Nowadays, we are able to measure connectedness across markets by employing a directly implementable measure of volatility spillovers developed by Diebold and Yilmaz (2009, 2012). Although the range-based daily or even lower frequency estimators of volatility provide consistent

¹ There are several hypotheses explaining such phenomenon. According to the leverage effect hypothesis (Black, 1976; Christie, 1982), decline in prices (i.e. negative returns) raises financial leverage, which increases volatility due to higher overall riskiness of stocks. In addition, Pindyck (1984) and French, Schwert, and Stambaugh (1987) point out the presence of time-varying risk premia on financial markets, which are a cornerstone to the volatility feedback effect hypothesis. When volatility is included in the pricing mechanism, its increase causes the required return on equity to increase and prices to fall.

estimates, using realized measures of volatility in spillover framework brings several advantages. Firstly, it enables us to better understand dynamics of the transmission mechanisms. Secondly, it allows measuring of asymmetries in volatility transmission using methodology proposed by Baruník, Kočenda, and Vácha (2016). We begin by description of realized volatility measures in the next subsection, then we continue with Diebold and Yilmaz (2009, 2012) spillover indices, and lastly we show how Baruník, Kočenda, and Vácha (2016) combine these two concepts to obtain measures of spillover asymmetry.

2.1 Realized measures of volatility

Andersen, Bollerslev, Diebold, and Labys (2001) and Barndorff-Nielsen (2002) propose a non-parametric measure of variance based on high-frequency observations of prices. Consider log-prices p_t evolving through time over a horizon $[0 \leq t \leq T]$ according to a continuous time stochastic process, which consists of a continuous component and pure jump component,

$$p_t = \int_0^t \mu_s ds + \int_0^t \sigma_s dW_s + J_t,$$

where μ is a locally bounded and predictable drift component, σ is a strictly positive volatility process, and all components are subject to common filtration \mathfrak{F} . Then the quadratic variation of such process is

$$[p_t, p_t] = \int_0^t \sigma_s^2 ds + \sum_{0 < s \leq t} (\Delta p_s)^2,$$

where $\Delta p_s = p_s - p_{s-}$ are jumps, if present. Andersen, Bollerslev, Diebold, and Labys (2001) and Barndorff-Nielsen (2002) propose to estimate quadratic variation as a sum of squared returns from given time horizon, naming such measure realized variance (RV). Let p_0, \dots, p_n , the intraday log-prices, be equally spaced over a time interval $[0, t]$, and intraday log-returns be defined as $r_i = p_i - p_{i-1}$, then

$$RV = \sum_{i=1}^n r_i^2.$$

It can be shown that RV converges in probability to $[p_t, p_t]$ as $n \rightarrow \infty$. Barndorff-Nielsen, Kinnebrock, and Shephard (2010) further propose decomposition of RV into realized semivariance (RS), which allow us to measure volatility coming from positive and negative returns separately. In this paper, realized positive (RS^+) and negative (RS^-) semivariance is employed in a following way;

$$RS^+ = \sum_{i=1}^n I(r_i > 0) r_i^2,$$

$$RS^- = \sum_{i=1}^n I(r_i < 0) r_i^2.$$

Realized semivariance contains all components included in realized variance, hence $RV = RS^+ + RS^-$. Barndorff-Nielsen, Kinnebrock, and Shephard (2010) show that as $n \rightarrow \infty$, each RS converges to $\frac{1}{2} \int_0^t \sigma_s^2 ds$ plus the sum of jumps due to volatility of respective sign.

Thus, realized semivariance enables us to examine discrepancies in movements in tails of volatility distribution. We can use negative semivariance as a proxy for bad volatility, and positive semivariance as a proxy for good volatility (Segal, Shaliastovich, and Yaron, 2015), thus, it allows us to observe different effects of good and bad volatility.

2.2 Volatility spillovers

A quantitative measure of volatility spillovers was defined by Diebold and Yilmaz (2009). It is based on forecast error variance decomposition (FEVD), which is a part of Vector Autoregressive (VAR) framework. FEVD records how much of the H-step ahead forecast error variance of variable i is due to innovations of variable j . Therefore, it can serve as a directly implementable measure of volatility spillovers. The simplicity of implementation was appealing, however, the new methodology suffered from few drawbacks. Firstly, FEVD from the standard VAR framework might be dependent on variable ordering, due to relying on Cholesky-factor identification of VARs. Secondly, it was only

able to measure total spillovers. Diebold and Yilmaz (2012) presented an improvement to spillover methodology accounting for both of these shortcomings. The variance decomposition was newly based on generalized VAR framework, where FEVD is invariant to variable ordering. Furthermore, it allows us to measure also directional, not only total spillovers.

Measure of spillovers used in this paper follows directly from a generalized VAR model FEVD, as proposed by Diebold and Yilmaz (2012). Consider vector $\mathbf{RV}_t = (\mathbf{RV}_{1t}, \dots, \mathbf{RV}_{Nt})'$ containing RVs of N assets, then the covariance-stationary VAR model of order p reads;

$$\mathbf{RV}_t = \sum_{i=1}^p \boldsymbol{\rho}_i \mathbf{RV}_{t-i} + \boldsymbol{\varepsilon}_t;$$

where $\boldsymbol{\varepsilon}_t \sim \mathcal{N}(\mathbf{0}, \boldsymbol{\Sigma}_\varepsilon)$ is a vector of independently, identically distributed disturbances, and $\boldsymbol{\rho}_i$ are coefficient matrices for $i=1, \dots, p$. Each invertible VAR process has its moving average representation,

$$\mathbf{RV}_t = \sum_{i=0}^{\infty} \boldsymbol{\varphi}_i \boldsymbol{\varepsilon}_{t-i},$$

where the $N \times N$ coefficient matrices $\boldsymbol{\varphi}_i$ can be obtained recursively as $\boldsymbol{\varphi}_i = \sum_{j=1}^p \boldsymbol{\rho}_j \boldsymbol{\varphi}_{i-j}$, with $\boldsymbol{\varphi}_0 = \mathbf{I}_n$ and $\boldsymbol{\varphi}_i = \mathbf{0}$ for $i < 0$. The infinite moving average representation is necessary for the computation of variance decomposition, which in Diebold and Yilmaz (2012) follows from generalized VAR framework proposed by Koop, Pesaran, and Potter (1996) and Pesaran and Shin (1998). This framework does not use orthogonalized shocks, instead, it allows for correlation and accounts for it by using the observed distribution of errors while assuming normality.

2.2.1 Total spillovers

Own variance shares are defined as fractions of the H-step-ahead variance forecast error of variable i, that are due to shocks to variable i for $i=1, \dots, N$. *The cross variance shares – spillovers –* are defined as fractions of the H-step-ahead variance forecast error of variable i, that are due to shocks to variable j, for $i, j=1, \dots, N$, $i \neq j$. H-step-ahead FEVD generalized matrix for each H consists of $N \times N$ elements ω_{ij}^H such that

$$\omega_{ij}^H = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' \boldsymbol{\varphi}_h \boldsymbol{\Sigma}_\varepsilon e_j)^2}{\sum_{h=0}^{H-1} (e_i' \boldsymbol{\varphi}_h \boldsymbol{\Sigma}_\varepsilon \boldsymbol{\varphi}_h' e_j)},$$

where $\boldsymbol{\Sigma}_\varepsilon$ is the variance matrix for the vector $\boldsymbol{\varepsilon}_t$, σ_{jj} is the standard deviation of the error term in j -th equation, e_j is a vector of zeros with 1 at the j -th place, and $\boldsymbol{\varphi}_h$ are moving average coefficients from the forecast at time t. As the shocks are not orthogonalized, the row sums do not have to be equal to 1. Hence, each element needs to be normalized by the row sum;

$$\hat{\omega}_{ij}^H = \frac{\omega_{ij}^H}{\sum_{j=1}^N \omega_{ij}^H}.$$

Note that by construction, $\sum_{j=1}^N \hat{\omega}_{ij}^H = 1$ and $\sum_{i,j=1}^N \hat{\omega}_{ij}^H = N$, thus contributions of both own and cross variance shares are normalized by the total forecast error for variable i, $i=1, \dots, N$. For the sake of clarity, we multiply every element of the matrix by 100, such that

$$\tilde{\omega}_{ij}^H = 100 \cdot \frac{\omega_{ij}^H}{\sum_{j=1}^N \omega_{ij}^H} = 100 \cdot \hat{\omega}_{ij}^H.$$

Now, $\sum_{j=1}^N \tilde{\omega}_{ij}^H = 100$ and $\sum_{i,j=1}^N \tilde{\omega}_{ij}^H = 100 \cdot N$. The *total spillover index* is then defined simply as

$$S^H = \frac{1}{N} \sum_{\substack{i,j=1 \\ i \neq j}}^N \tilde{\omega}_{ij}^H.$$

The sum contains all cross-variance elements from FEVD.

2.2.2 Directional spillovers

The total spillover index gives us a basic idea about the overall magnitude of shocks that is transmitted across variables. However, by ignoring individual elements of the variance decomposition matrix, we would be losing large part of the information. Every element is an indicator of interaction between individual variables. Based on that, Diebold and Yilmaz (2012) formalize a measure of directional spillovers to, and from, variable i . Spillovers received by asset i from all other assets are measured as

$$S_{i\leftarrow\cdot}^H = \frac{1}{N} \sum_{\substack{j=1 \\ i \neq j}}^N \tilde{\omega}_{ij}^H.$$

Spillovers transmitted by variable i to all other variables are measured as

$$S_{i\rightarrow\cdot}^H = \frac{1}{N} \sum_{\substack{j=1 \\ i \neq j}}^N \tilde{\omega}_{ji}^H.$$

2.2.3 Net spillovers and net pairwise spillovers

Using the directional spillover measures, we can obtain net spillovers for asset i , such that

$$S_i^H = S_{i\rightarrow\cdot}^H - S_{i\leftarrow\cdot}^H.$$

Sign of this measure indicates, if asset i is the net giver (positive sign), or net receiver (negative sign) of shocks in the system. If we are particularly interested in mutual interaction of two variables, then we call for *net pairwise spillovers*

$$S_{ij}^H = \frac{1}{N} (\tilde{\omega}_{ij}^H - \tilde{\omega}_{ji}^H).$$

2.3 Asymmetric spillovers

Diebold and Yilmaz (2009, 2012) use daily or weekly range-based volatility estimators to measure spillovers. While the range-based estimators provide efficient spillover estimates, employing realized volatility measures enables us to conduct more detailed spillover analysis. The decomposition of RV into RS^+ and RS^- provides us with natural proxies of upside and downside risk. We are able to measure spillovers coming from good and bad volatility by letting RS^+ and RS^- enter the spillover analysis separately, and then test whether they are of the same magnitude.

As volatility is documented to be propagated in an asymmetric way, it is natural to expect such phenomenon to be present also in volatility spillovers. Baruník, Kočenda, and Vácha (2016) propose a measure of spillovers considering spillovers from good and bad volatility separately, creating positive and negative total spillover indices (S^+, S^-), and directional spillovers due to positive returns ($S_{i\leftarrow\cdot}^+, S_{i\rightarrow\cdot}^+$), and negative returns ($S_{i\leftarrow\cdot}^-, S_{i\rightarrow\cdot}^-$). When we estimate spillovers, we take the vector of RVs $\mathbf{RV}_t = (\mathbf{RV}_{1t}, \dots, \mathbf{RV}_{Nt})'$, and then proceed as described in the above subsection. Spillovers coming from positive volatility are estimated in the same manner, only the vector $\mathbf{RV}_t = (\mathbf{RV}_{1t}, \dots, \mathbf{RV}_{Nt})'$ is substituted by the vector $\mathbf{RS}_t^+ = (\mathbf{RS}_{1t}^+, \dots, \mathbf{RS}_{Nt}^+)'$, which contains positive realized semivariances of N assets. To estimate spillovers coming from negative volatility, vector $\mathbf{RS}_t^- = (\mathbf{RS}_{1t}^-, \dots, \mathbf{RS}_{Nt}^-)'$ containing realized negative semivariances of N assets is used, instead of $\mathbf{RV}_t = (\mathbf{RV}_{1t}, \dots, \mathbf{RV}_{Nt})'$. Index H is left off in the above definitions to ease notation, however, remains a valid parameter for estimation of asymmetric spillovers.

Estimation of spillovers due to positive and negative returns, i.e. positive and negative spillovers, lets us test hypotheses about asymmetries in volatility transmission mechanism. Under the null hypothesis we assume the spillovers are symmetric. Rejection of the null is evidence for different reaction of assets to good and bad volatility of other assets. Testing will be based on comparing the magnitude of positive and negative spillovers. Our hypotheses on spillover asymmetry are;

$$H_0^1 : S^+ = S^- ; \text{ against } H_A^1 : S^+ \neq S^-$$

$$H_0^2 : S_{i\leftarrow}^+ = S_{i\leftarrow}^- ; \text{ against } H_A^2 : S_{i\leftarrow}^+ \neq S_{i\leftarrow}^-$$

$$H_0^3 : S_{i\rightarrow}^+ = S_{i\rightarrow}^- ; \text{ against } H_A^3 : S_{i\rightarrow}^+ \neq S_{i\rightarrow}^-$$

2.3.1 Spillover asymmetry measure

Baruník, Kočenda, and Vácha (2016) also introduce *Spillover Asymmetry Measure (SAM)*, which is a tool to simplify quantification of spillover asymmetry; $SAM = S^+ - S^-$. SAM measures the direction and the magnitude of asymmetry between spillovers from RS^+ and RS^- . When SAM is equal to zero, then spillovers from RS^+ are of the same magnitude as spillovers from RS^- . When SAM is positive, then positive spillovers are larger than negative spillovers, and the opposite is true, when it is negative.

2.3.2 Directional SAM

Apart from asymmetry of total spillover index, we are interested in spillover asymmetries for the individual assets. Baruník, Kočenda, and Vácha (2016) define SAM for spillovers transmitted to asset i from all other assets as

$$SAM_{i\leftarrow} = S_{i\leftarrow}^+ - S_{i\leftarrow}^-$$

SAM for spillovers transmitted from asset i to all other assets is defined in a similar fashion;

$$SAM_{i\rightarrow} = S_{i\rightarrow}^+ - S_{i\rightarrow}^-$$

When $SAM_{i\rightarrow}$ ($SAM_{i\leftarrow}$) takes the value of zero, spillovers from (to) asset i from RS^+ are of the same magnitude as spillovers from (to) asset i from RS^- . When $SAM_{i\rightarrow}$ ($SAM_{i\leftarrow}$) is greater than zero, then positive spillovers prevail among spillovers from (to) asset i , and vice versa when $SAM_{i\rightarrow}$ ($SAM_{i\leftarrow}$) is lower than zero.

3 Empirical Results

We study connectedness of cryptocurrencies and the major traditional asset classes; foreign exchange, commodities, stocks, financials represented by the most liquid assets from each class. The complete set of assets is listed in Table 1. Due to high volatility of Bitcoin, which could misrepresent the whole analysis, we rescaled returns of all variables such that

$$\tilde{r}_{i,n} = \frac{r_{i,n} - \text{mean}(r_n)}{sd(r_n)}$$

for $n = \{1, \dots, 7\}^2$. The sample period is from June 2011 to December 2015, which corresponds to time for which it is meaningful to track Bitcoin price changes. After deleting days with low trading activity and weekends for Bitcoin, the resulting number of observations is 1124. Bitcoin prices were obtained from bitcoincharts³.

Table 1. Set of assets entering spillover analysis.

Class	Representatives
Cryptocurrencies	Bitcoin
Foreign exchange	EUR/USD forex, JPY/USD forex
Commodities	Gold, Crude oil
Stocks	S&P 500 stock index
Bonds	US 2-year T-note

² Rescaled volatility time series are graphically presented in the Appendix.

³ <https://bitcoincharts.com/charts/bitstampUSD#rg10zig5-minztgSzm1g10zm2g25zv>

3.1 Overall connectedness

Throughout our spillover analysis, we use horizon $h=10$, VAR model with number of lags $p=2$ ⁴, and rolling window of 200 days when dynamics is in question⁵. Table 2 presents spillovers measured for the whole sample period, we are mostly interested in the bottom row and the last column. They represent volatility transmitted by asset i to all other assets, and volatility received by asset i from all other assets, respectively. By subtracting these two numbers we arrive at net spillovers. The largest net giver is S&P 500, while gold is on the opposite side of the spectrum. Bitcoin does not display interconnectedness with any of the assets, with the exception of gold. Shocks from Bitcoin are transmitted to the market for gold, however, the reversed causality does not hold. To be able to better understand this relationship, we examined the dynamics of Bitcoin to gold volatility transmission mechanism. The results are striking (see Figure 1).

High amount of volatility transmitted from Bitcoin to gold is caused solely by a period starting with a sudden steep spike around quarter of 2013 and ending at the beginning of 2014. The exact date of this sudden change is April 12 2013, which is only 2 days after the first significant Bitcoin price crash (61% decline from the peak of 266\$ per BTC)⁶. Exchanges trading Bitcoin were not able to cope with increased demand, which caused large problems with transaction processing. Delays in transaction completion resulted in substantial panic and subsequently a drastic price decline, as cryptocurrencies were almost completely unexplored territory then. The corresponding timing of the spillover increase and Bitcoin price crash is evident from Figure 1, where these two time-series are plotted next to each other.

Table 2. Total spillovers

	Bitcoin	EURO	JPY	Crude Oil	Gold	S&P 500	T-note	$i \leftarrow \cdot$
Bitcoin	92,66	0,43	1,36	1,14	0,95	1,56	1,89	1,05
EURO	1,08	55,26	8,18	15,29	3,63	13,82	2,74	6,39
JPY	0,94	12,13	70,70	3,00	5,26	6,57	1,40	4,19
Crude Oil	0,13	8,46	1,89	66,08	1,18	17,83	4,43	4,85
Gold	3,65	7,70	6,28	4,15	65,20	12,20	0,82	4,97
S&P 500	1,20	7,43	4,50	10,29	4,11	71,63	0,85	4,05
T-Note	0,46	6,50	2,49	7,23	1,17	2,99	79,16	2,98
$i \rightarrow \cdot$	1,07	6,09	3,53	5,87	2,33	7,85	1,73	28,47

Investors in Bitcoin and gold are connected by a certain degree of doubts about the current monetary system. That is why it is likely that large part of panicking investors in Bitcoin quickly switched to gold in time of distress. Importantly, faith in Bitcoin was restored shortly after the first crash, which led investors to switch back from gold to Bitcoin, and triggered negative returns on markets for gold. Such mechanism would explain how the volatility spills over between these two markets, and also why these spillovers are driven exclusively by negative volatility, which we will elaborate on in the next subsection. Increased spillovers are present solely during 2013, the year with largest volatility spikes (see Figure 6, Appendix A). In 2011, when volatility was also substantial, Bitcoin was not relevant enough to notably increase volatility on other markets.

Limited connectedness to volatility in other markets makes Bitcoin a candidate to be an efficient diversifier. Such potential is in accordance with Bouri, Jalkh, Molnár, and Roubaud (2017), whose

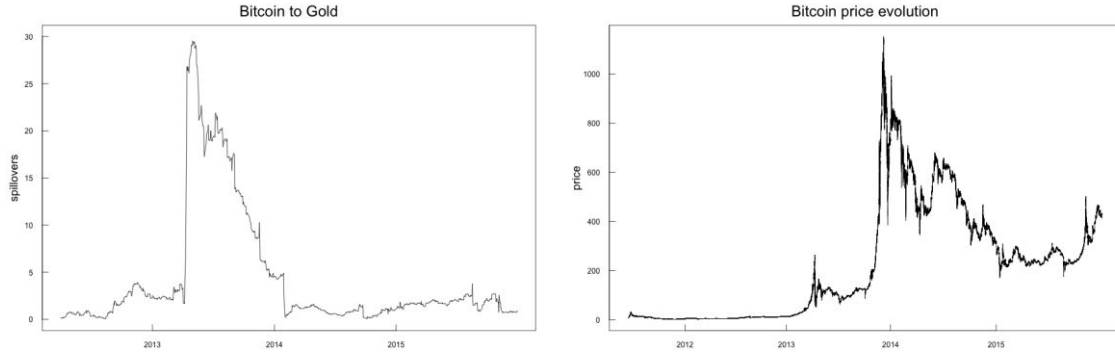
⁴ As a robustness check, we tried models with different values of forecast horizon and number of lags. The results did not qualitatively change, hence our analysis is robust to changes in parameters. Results available upon request.

⁵ Points from $t-199$ to t are included in each of such windows.

⁶<https://www.forbes.com/sites/timothylee/2013/04/11/an-illustrated-history-of-bitcoin-crashes/#adeb73940397>

results support role of Bitcoin as a diversifier, for certain periods of time even as a hedge or safe-heaven to commodities. According to our results, the diversifying feature of Bitcoin could be applied to a broader class of assets. To confirm that low contribution of Bitcoin to total spillovers is robust, we present the evolution of total spillover index with and without Bitcoin in the set of assets (see Figure 7, Appendix A). There is no significant difference between the two lines. The index is even higher, when Bitcoin is excluded, which shows its contribution to shock transmission is negligible in total⁷.

Figure 1. Spillovers from Bitcoin to gold (left), dynamics of Bitcoin price (right).



Volatility is one of the most commonly used risk measures. Hence spillovers contain information about how market participants perceive the overall riskiness of markets, and how homogeneous their beliefs are. However, spillover estimation for the whole period provides only a snapshot of the situation, we must turn to examination of spillovers on a rolling window to capture the dynamics of such beliefs. Dynamics of Total spillover index (solid line) and TED spread (dashed line) are depicted in Figure 2. Spillovers may be interpreted as an indicator of expectations about overall riskiness in the economy, while TED spread is a widely recognized indicator of credit risk, it shows beliefs of lenders about the risk of default on interbank loans. Thus, theoretically, these two indicators should display similar evolution in time. The end of 2013 sees both TED spread and spillovers decrease substantially, arguably due to stabilization of financial markets following the global financial crisis. For most of the examined period both indicators co-move in quite a balanced way. From the economic perspective, Figure 2 confirms we can perceive spillovers of volatility also as the spillovers of risk.

3.1.1 Asymmetric connectedness

Spillover asymmetry is a very popular topic, recently it was examined for stock markets (Baruník, Kočenda, and Vácha, 2016), foreign exchange markets (Baruník, Kočenda, and Vácha, 2017), or petroleum markets (Baruník, Kočenda, and Vácha, 2015). The prevailing result in all papers is negative spillover asymmetry of larger or lower magnitude. Whereas these papers concentrate on assets from single class, we include assets from different classes, therefore, it will be interesting to observe how it affects the results. We use the spillover asymmetry measure defined in section 2.3.1 to test for asymmetries. Recall, that SAM is formulated as difference between positive and negative spillovers. To ease testing, we can reformulate the hypotheses in terms of SAM

$$H_0^1 : SAM = 0 ; \text{ against } H_A^1 : SAM \neq 0.$$

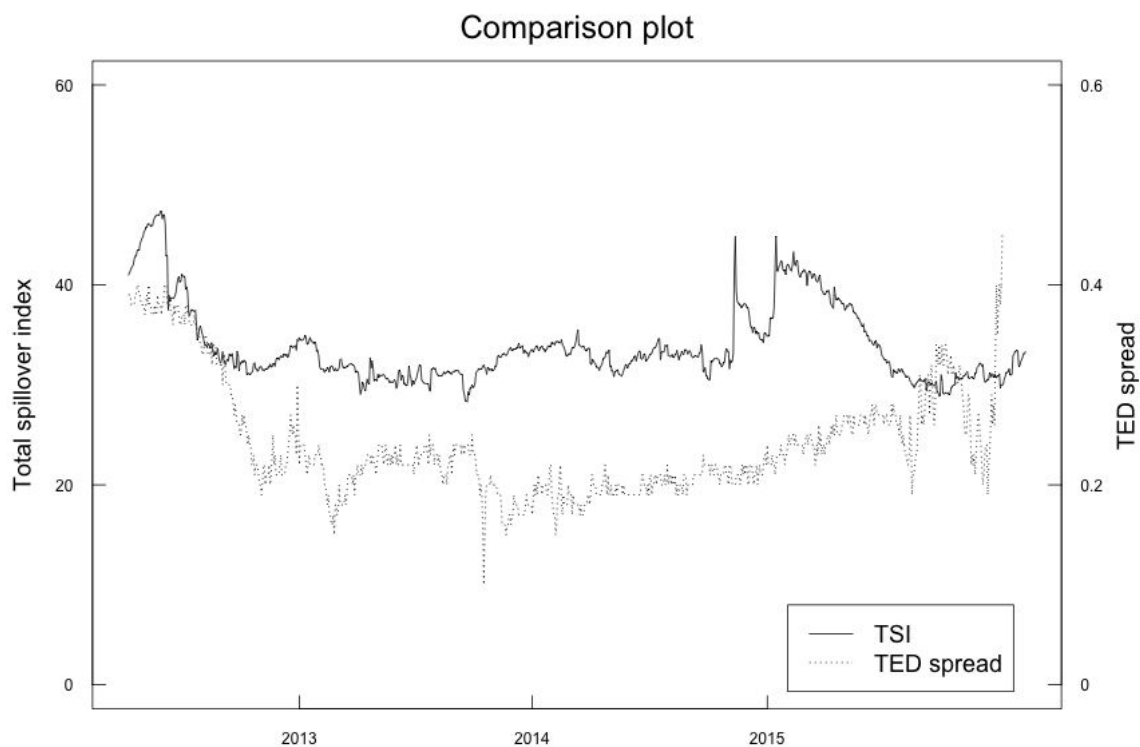
$$H_0^2 : SAM_{i \leftarrow} = 0 ; \text{ against } H_A^2 : SAM_{i \leftarrow} \neq 0.$$

$$H_0^3 : SAM_{i \rightarrow} = 0 ; \text{ against } H_A^3 : SAM_{i \rightarrow} \neq 0.$$

We use bootstrapped confidence intervals to test hypotheses of symmetrical spillovers. Departures from zero may also be caused by VAR estimation error, or discretization error from construction of realized measures. Thus, we take into account only asymmetries falling outside the confidence bands. While bootstrapping the standard errors and constructing the confidence intervals, we followed methodology used in Baruník, Kočenda, and Vácha (2016). The resulting 95 percent confidence interval is (-2.7585, 2.9741).

⁷ On the other hand, when any other asset is dropped, the index decreases significantly.

Figure 2. Comparison of Total Spillover Index on 200-days rolling samples against TED spread

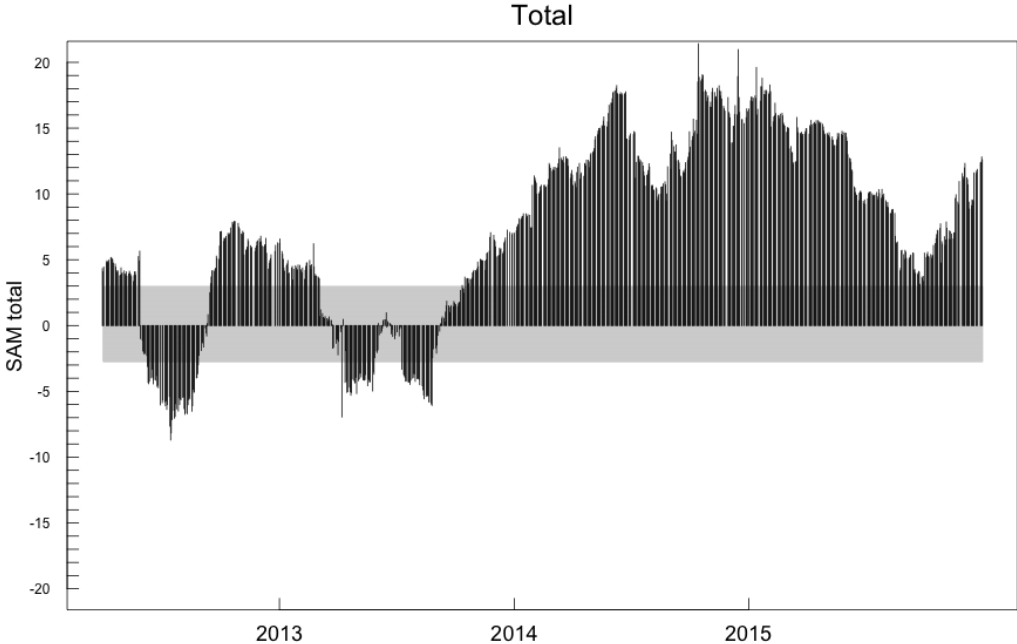


Symmetric response of the total spillovers index can be rejected. Figure 3 shows that until 2013 SAM oscillates between positive and negative values, and it is on the edge of statistical significance. Since then, the asymmetry becomes largely significant. The source of asymmetric behavior is positive volatility, which is contradictory to previous results (e.g., Baruník, Kočenda, and Vácha, 2017). As noted above, this may be due to presence of different asset classes in our dataset. Secondly, the selected time interval could play its role, as spillover asymmetry may be interpreted as an indicator of prevailing mood on examined markets. Positive asymmetry means optimistic traders dominate the market, negative spillover asymmetry indicates prevalence of pessimistic traders. Our interval is from mid-2011 to the end of 2015, as opposed to 2008 – 2016 used in Baruník, Kočenda and Vácha (2017). Spillover asymmetries observed during crises, are more likely to be negative, than asymmetries observed post-crises.

3.1.2 Asymmetric connectedness at the individual markets level

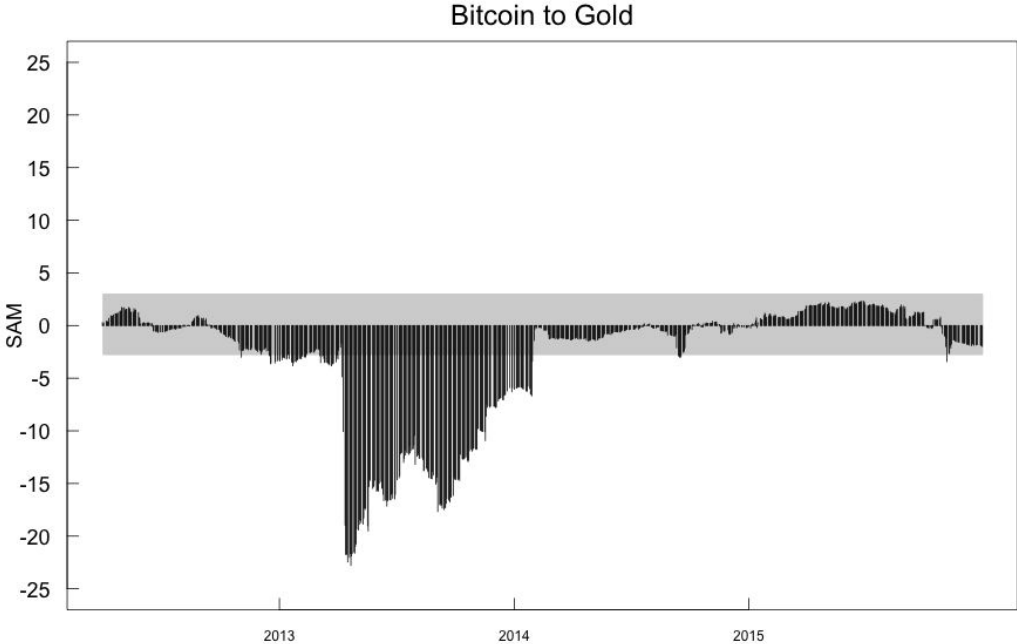
While SAM measures asymmetry of aggregate spillovers, $SAM_{i \rightarrow}$ ($SAM_{i \leftarrow}$) measures asymmetry in spillovers from (to) asset i to (from) all other assets. Measuring spillovers on rolling samples then allows us to capture the dynamics of $SAM_{i \rightarrow}$ and $SAM_{i \leftarrow}$. Disintegration into individual assets reveals sources of the observed asymmetry. Figure 5 displays $SAM_{i \rightarrow}$ in panel a and $SAM_{i \leftarrow}$ in panel b. In terms of spillovers transmitted to others, the only significant asymmetries are displayed by S&P 500 and T-note. Both assets are givers of positive spillovers. Asymmetries in received spillovers are present for EURO, Japanese YEN, and T-note. The latter two are receivers of positive spillovers, when the asymmetry is significant. On the other hand, EURO is subject to largely negative spillovers in the beginning of the observed period, which likely reflects impacts of the European debt crisis.

Figure 3. Dynamics of spillover asymmetry for total spillovers. Shaded band represents 95% confidence interval obtained by bootstrap.



In the previous subsection, we detected large amount of volatility transmitted from Bitcoin to gold. Let us uncover, if it is driven by spillovers from positive or negative volatility. Figure 4 depicts asymmetries in this relationship. The period of significant asymmetry exactly corresponds to the period of increased spillovers in Figure 1, and evidently gold receives mainly negative spillovers from Bitcoin. It is a real-world example of sudden financial distress on market for cryptocurrency being transmitted to a traditional asset. It is evidence that cryptocurrencies can influence other assets, and interact with other markets. It is still too early to assume anything, but our results indicate that cryptocurrencies may play a certain role, negative or positive, in global financial markets of the future.

Figure 4. Dynamics of SAM for spillovers from Bitcoin to gold.



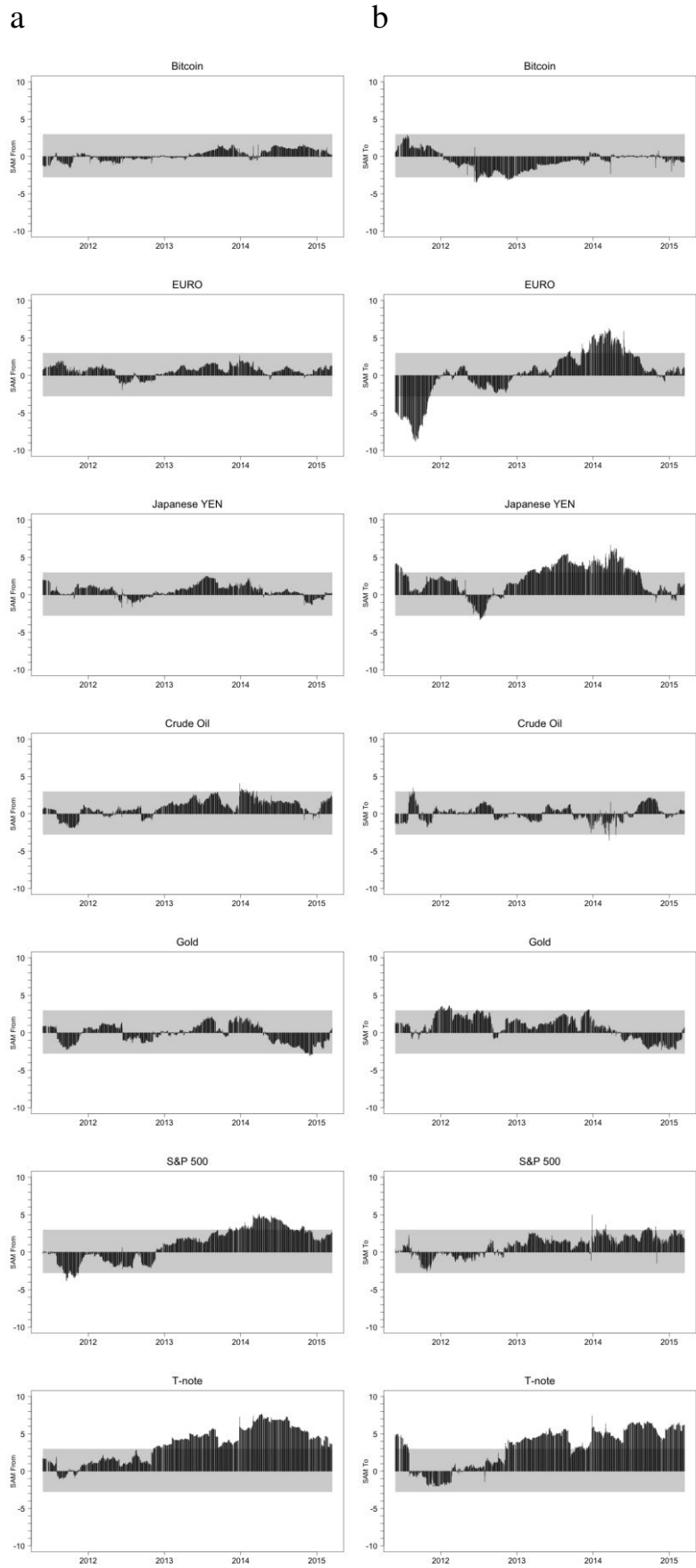


Figure 5: Panel (a) SAM for spillovers from individual assets. Panel (b) SAM for spillovers to individual assets

4 Conclusion

We combine several recently developed concepts to assess the interconnectedness between cryptocurrencies and traditional asset classes. Specifically, we use realized measures of volatility proposed by Andersen, Bollerslev, Diebold, and Labys (2001) and Barndorff-Nielsen (2002), and insert them into volatility spillovers methodology developed by Diebold and Yilmaz (2012). Moreover, we explore asymmetries in volatility transmission mechanisms using approach developed by Baruník, Kočenda, and Vácha (2016), which is based on spillover methodology (Diebold and Yilmaz, 2012), but employs realized semivariances (Barndorff-Nielsen, Kinnebrock, and Shephard, 2010) that enable us to consider volatility coming from negative and positive returns separately.

We selected the most liquid cryptocurrency, Bitcoin, and the most liquid representatives of traditional asset classes including foreign exchange, commodities, stocks and financials. Then, using the above described methodology, we assessed connectedness between these assets, and asymmetries in the potential transmission mechanisms. Analysis of spillover asymmetries provided contradictory results to previous studies conducted on assets from a single class (e.g., Baruník, Kočenda, and Vácha; 2016, 2017). In our case, total spillovers are driven significantly by positive volatility for most of the studied period. The same applies for individual assets, as only one of them displays significant negative asymmetry for an extended time period. The reason behind this could be the examined period, as sign of spillover asymmetry indicates the prevailing mood on markets in question. Hence, including only post-crisis years pushes SAM towards positive figures. Another possible explanation is stabilization by including different asset classes.

The role and relevance of cryptocurrencies to financial markets is largely disputed. Most of our results do not support Bitcoin as an instrument relevant to other markets, as the level of connectedness to other assets is negligible. However, we provide empirical evidence that situation in the market for Bitcoin can influence situation in a market for other assets. Our results show a large spike in spillovers to gold after a price crash on markets for Bitcoin. Sudden disruption triggered a stream of negative spillovers of substantial magnitude from Bitcoin to gold. Hence, by transmission of its shocks to gold, Bitcoin proves it might be a more relevant phenomenon for financial markets than previously believed.

References

- Andersen, T., Bollerslev, T., Diebold, F., Labys, P., 2001. The distribution of realized stock return volatility. *Journal of Financial Economics* 61 (1), 43-76.
- Barndorff-Nielsen, O.E., 2002. Econometric analysis of realized volatility and its use in estimating stochastic volatility models. *Journal of Royal Statistical Society: Series B (Statistical Methodology)* 64 (2), 253-280.
- Barndorff-Nielsen, O., Kinnebrock, S., Shephard, N., 2010. Measuring downside risk-realized semivariance. In: *Volatility and Time Series Econometrics: Essays in Honor of Robert F. Engle*. Oxford: Oxford University Press.
- Baruník, J., Kočenda, E., Vácha, L., 2015. Volatility Spillovers Across Petroleum Markets. *The Energy Journal* 77, 309-329.
- Baruník, J., Kočenda, E., Vácha, L., 2016. Asymmetric connectedness on the U.S. stock market: Bad and good volatility spillovers 27. *Journal of Financial Markets*, 55-78.
- Baruník, J., Kočenda, E., Vácha, L., 2017. Asymmetric volatility connectedness on the forex market. *Journal of International Money and Finance* 77, 39-56.
- Black, F., 1976. Studies of stock price volatility changes. In: *Proceedings of the 1976 Meetings of the American Statistical Association, Business and Economical Statistics Section*, pp. 177-181.
- Bouri, E., Jalkh, N., Molnár, P., Roubaud, D., 2017. Bitcoin for energy commodities before and after the December 2013 crash: diversifier, hedge or safe haven? *Applied Economics* 49 (50), 5063-5073.
- Brandvold, M., Molnár, P., Vagstad, K., Valstad, O.C.A., 2015. Price discovery on Bitcoin exchanges. *Journal of International Financial Markets, Institutions and Money* 36, 18-35.
- Christie, A., 1982. The stochastic behavior of common stock variances: value, leverage and interest rate effects. *Journal of Financial Economics* 10 (4), 407-432.
- Diebold, F., Yilmaz, K., 2009. Measuring Financial Asset Return and Volatility Spillovers, with Application to Global Equity Markets. *The Economic Journal* 119 (534), 158-171.
- Diebold, F., Yilmaz, K., 2012. Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting* 28 (1), 57-66.
- Forbes, K., Rigobon, R., 2002. No Contagion, Only Interdependence: Measuring Stock Market Comovements. *Journal of Finance* 57 (5), 2223-2261.
- French, K., Schwert, G., Stambaugh, R., 1987. Expected stock returns and volatility. *Journal of Financial Econometrics* 19 (1), 3-29.
- Gande, A., Parsley, D., 2005. News Spillovers in the Sovereign Debt Market. *Journal of Financial Economics* 75 (3), 691-734.
- Kanas, A., 2000. Volatility Spillovers Between Stock Returns and Exchange Rate Changes: International Evidence. *Journal of Business Finance & Accounting* 27 (3-4), 447-467.
- Katsiampa, P., 2017. Volatility estimation for Bitcoin: A comparison of GARCH models. *Economics Letters* 158, 3-6.
- Koop, G., Pesaran, M., Potter, S., 1996. Impulse response analysis in nonlinear multivariate models. *Journal of Econometrics* 74 (1), 119-147.
- Mensi, W., Beljid, M., Boubaker, A., Managi, S., 2013. Correlations and volatility spillovers across commodity and stock markets: Linking energies, food, and gold. *Economic Modelling* 32, 15-22.
- Nadarajah, S., Chu, J., 2017. On the inefficiency of Bitcoin. *Economics Letters* 150, 6-9.
- Pesaran, M., Shin, Y., 1998. Generalized impulse response analysis in linear multivariate models. *Economic Letters* 58 (1), 17-29.
- Pindyck, R., 1984. Risk, inflation, and the stock market. *American Economic Review*, 334-351.
- Segal, G., Shaliastovich, I., Yaron, A., 2015. Good and bad uncertainty: Macroeconomic and financial market implications. *Journal of Financial Economics* 117 (2), 369-397.

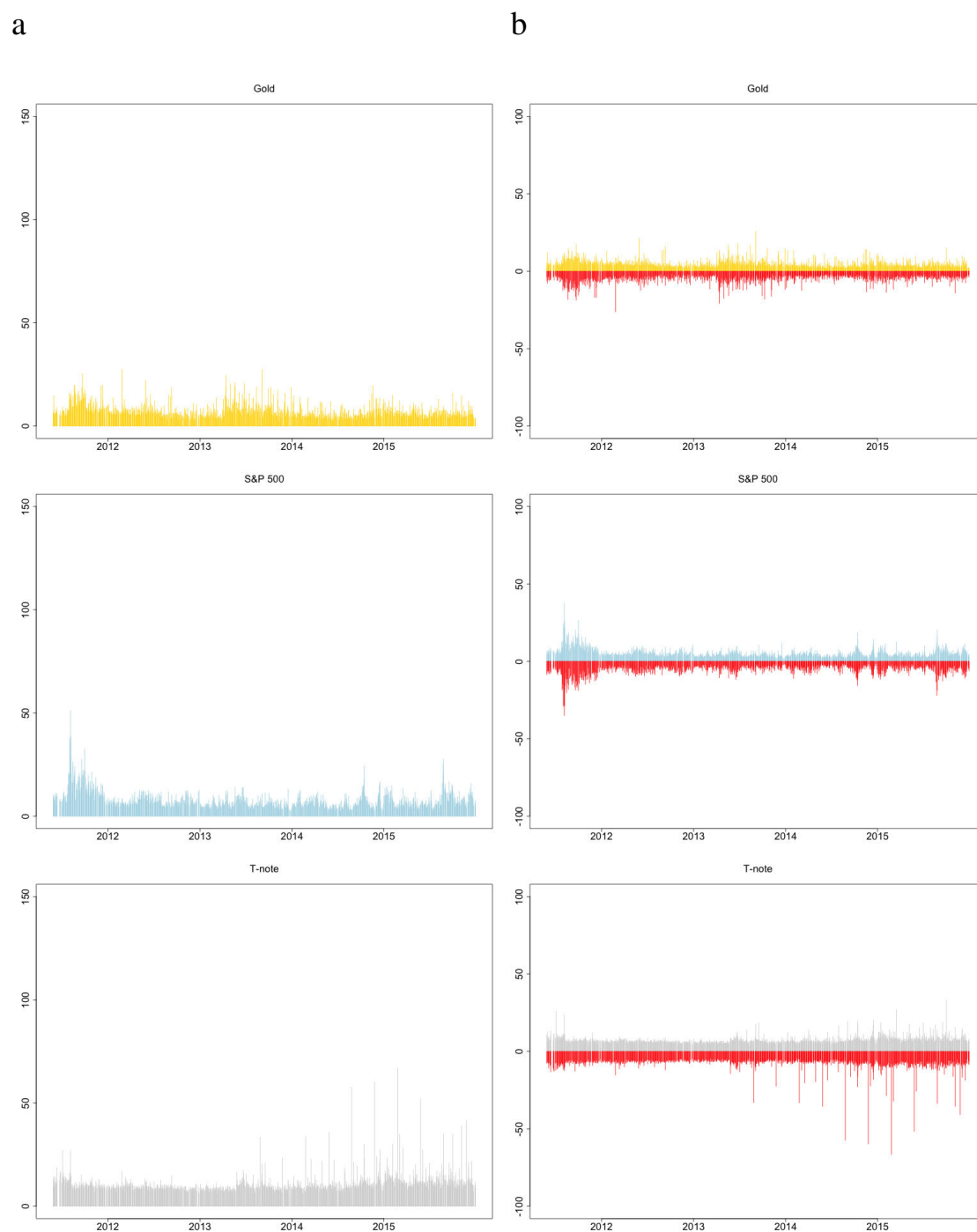
Urquhart, A., 2016. The inefficiency of Bitcoin. *Economics Letters* 148, 80-82.

Urquhart, A., 2017. Price clustering in Bitcoin. *Economics Letters* 159, 145-148.

Yang, S.-Y., Doong, S.-C., 2004. Price and Volatility Spillovers between Stock Prices and Exchange Rates: Empirical Evidence from the G-7 Countries. *International Journal of Business and Economics* 3 (2), 139-153.

A Additional Figures.

Figure 6. Rescaled volatility series. Panel (a): \sqrt{RV} . Panel (b): $\sqrt{RS^+}$ and $-\sqrt{RS^-}$ (in red)



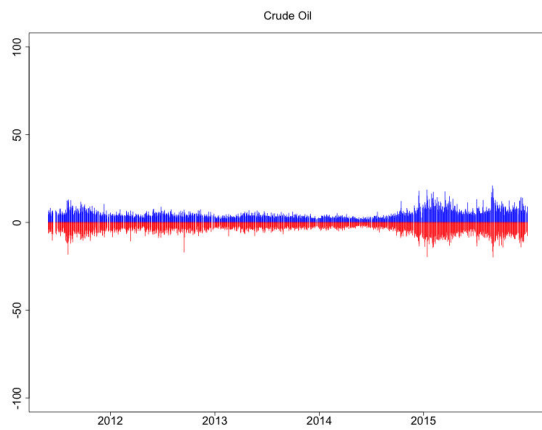
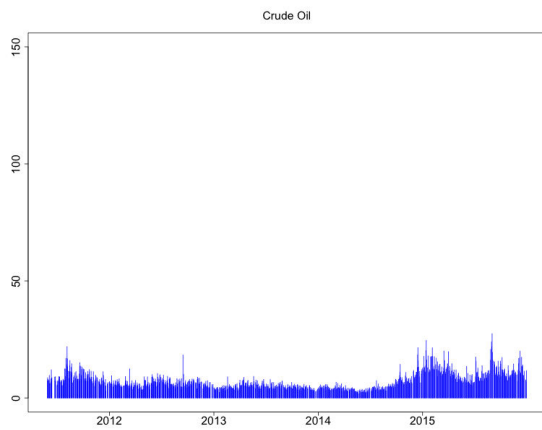
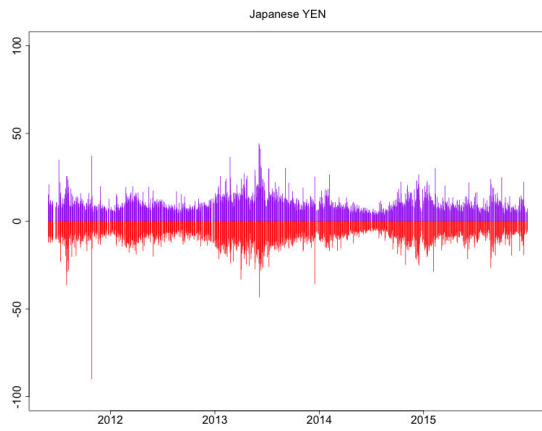
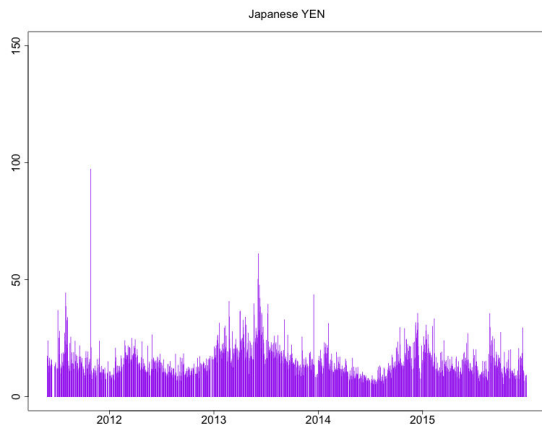
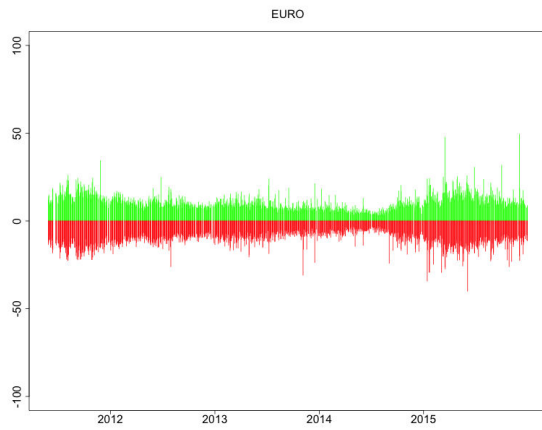
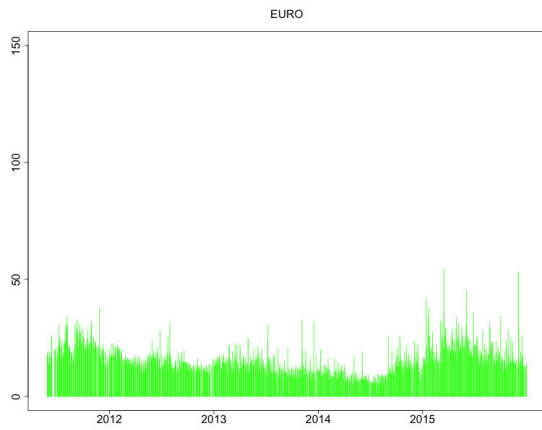
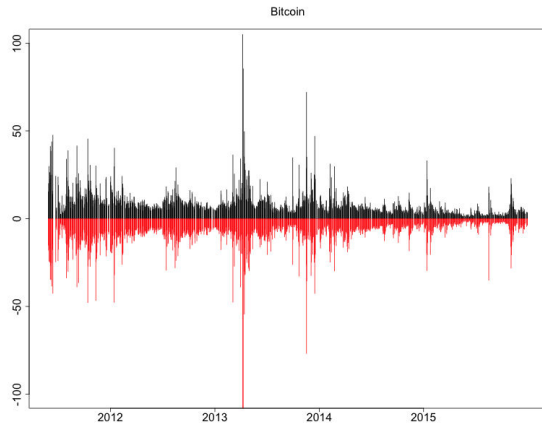
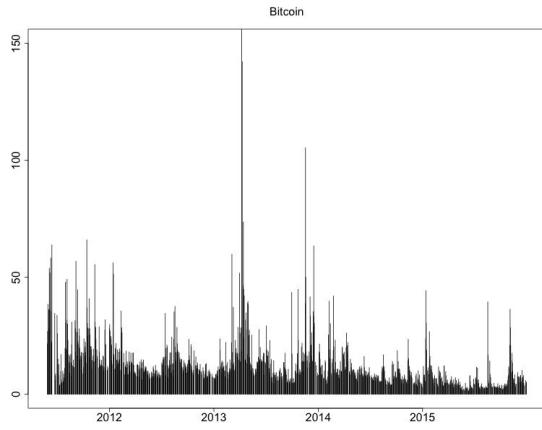
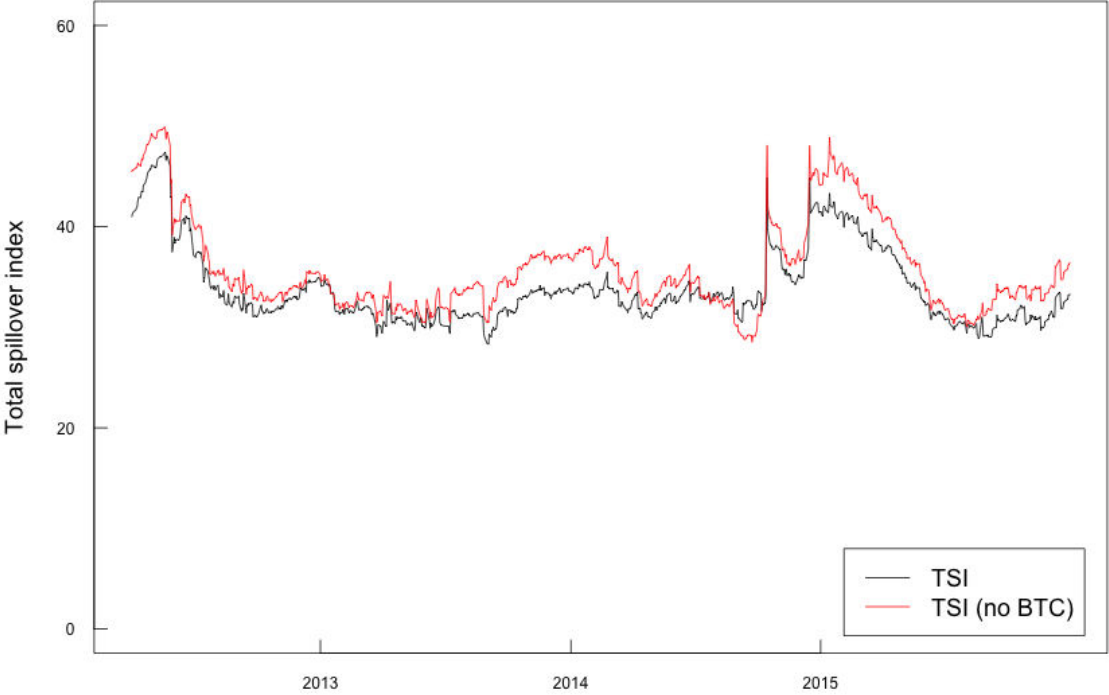


Figure 7. Total spillover index with Bitcoin included in set of assets (black) and excluded from the set of assets (red)



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