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Title Page

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Abstract

We analyse, in the time and frequency domains, the relationships between three popular cryptocurrencies and a variety of other financial assets. We find evidence of the relative isolation of these assets from the financial and economic assets. Our results show that cryptocurrencies may offer diversification benefits for investors with short investment horizons. Time variation in the linkages reflects external economic and financial shocks.

Keywords: Cryptocurrencies, bitcoin, litecoin, time varying, spillovers

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We wish to thank Thomas Kreilik, Institute for Economic Studies, Charles University Prague, for help with the r Package FreqencyConnect

Exploring the Dynamic Relationships between Cryptocurrencies and Other Financial Assets [1]

Abstract

We analyse, in the time and frequency domains, the relationships between three popular cryptocurrencies and a variety of other financial assets. We find evidence of the relative isolation of these assets from the financial and economic assets. Our results show that cryptocurrencies may offer diversification benefits for investors with short investment horizons. Time variation in the linkages reflects external economic and financial shocks.

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1. Introduction

Cryptocurrency markets have recently experienced increased growth leading to some suggesting that they may be seen as a new category of investment assets. For the period from October 2016 to October 2017 the market capitalisation of the oldest and best known, Bitcoin, increased from 10.1 to 79.7 billion, while the price jumped from 616 to 4800 US dollars. Cryptocurrencies high returns may be a rational response to their high volatility (Katsiampa [2017]; Vandezande [2017]). They are characterised by anonymity (Bariviera et al. [2017]), and are prone to speculative bubbles (e.g.,Cheah and Fry [2015a]). Bubbles may in turn spread contagion and weaken financial stability (Yarovaya et al. [2016]). Therefore, it is crucial to identify the patterns of information transmission across cryptocurrencies markets and other asset classes.

Facing this, there has been a growth in papers that analyse cryptocurrencies as investment assets. Recently, the focus of the research has expanded from the technical aspects and stylised facts of cryptocurrency markets (e.g. Dwyer [2015]; Bariviera et al. [2017]) to hedging and safe haven properties of cryptocurrencies (e.g.

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Bouri et al. [2017];Bouri et al. [2017]), return-volume relationships (e.g. M. et al. [2017]), speculation (e.g., Yermack, 2013; Glaser et al., 2014; Blau [2017]) and market efficiency (e.g., Urquhart [2016]; Bariviera [2017]). The majority of these papers, however, focused solely on Bitcoin, omitting other cryptocurrencies. In this note we examine return and volatility transmission across three cryptocurrencies and a variety of other financial assets. To our knowledge, this is the first such study.

We contribute in two ways. First, we provide empirical evidence on the patterns of return and volatility transmission using the Diebold and Yilmaz [2012] methodology. Second, we employ the Barunik and Krehlik [2015] methodology to estimate unconditional connectedness between markets in the time-frequency domain. Our findings provide the evidence on connectedness between markets in short-, medium-, and long-run. We show that cryptocurencies are relatively isolated from market shocks and are decoupled from popular financial assets.

Our paper is organized as follows. Section 2 provides a brief introduction to the area of cryptocurrencies. Section 3 presents our data and some preliminary statistics, Section 4 briefly presents the econometric framework and Section 4.1 discusses the findings. Section 5 concludes the paper.

2. Cryptocurrencies

A number of strands inform our analysis. Vandezande [2017] discussed the risks and regulatory complexities and gaps associated with cryptocurrencies . A conclusion is that itis increasingly important to analyse the current behaviours of major cryptocurrencies in relation to other assets to equip policy makers and regulatory bodies on the role of the cryptocurrencies as an investment asset.

Second, there is a small but growing literature on cryptocurrency price dynamics. Cheah and Fry [2015b] claimed that cryptocurrencies are prone to substantial speculative bubbles. More recently, Blau [2017] argued that the high volatility of the Bitcoin is not related to high speculative activity. The volatility of the cryptocurrencies has been also analysed by Katsiampa [2017], Fry and Cheah [2016], and Pieters and Vivanco (2017). The ambiguity of the results exemplifies the debates about whether cryptocurrencies is a speculative investment asset or a currency. Urquhart [2016] notes that Bitcoin is an inefficient market. cryptocurrencies barely manage to fulfil the traditional characteristics of a money.(Bariviera et al. [2017]). Third, despite extensive research on the economics of cryptocurrencies, there remains a relative dearth on their interlinkages to other assets. A number of papers ([Dyhrberg, 2016b], [Dyhrberg, 2016a], [Bouri et al., 2017], [Bouri et al., 2017] and [Bouri et al., 2017] Dyhrberg [2016a]) have analysed the ability of cryptocurrencies, usually Bitcoin, to act as safe havens or hedges.

Our aim here is threefold. First, to provide an analysis of the extent and time variation in the connectedness of these assets to other financial assets; second to link, where possible, changes in the degree of interconnectedness to market and economic events; third to examine the connectedness and interrelatedness of these assets over short and long horizons.

3. Data

We collect data for cryptocurrrencies from CryproCompare.com; data on the other assets are collected from Bloomeberg. We focus on larger cryptocurrency assets , those with a market value over $1b as of end July 2017. Further, to obtain as long a period as possible, we restrict our analysis to currencies with data back to 2013. Thus we examine Bitcoin, Ripple and Litecoin. The other assets examined are the MSC GSCI Total Returns Index, the US$ Broad Exchange Rate, the SP500 Index and the COMEX closing gold price , VIX and the Markit ITTR110 index. In Figure 2 we see the evolution of these assets. Figure 1 shows a correlation matrix of the changes of these currencies and the other assets involved. Finally in Figure 3 we see that the volatility of the cryptocurrencies is significantly and manifestly higher than that of the other assets. We define returns as the daily log changes and volatility as the 5day standard deviation.

4. Empirical Approach and Results

We employ the generalized variance decomposition methodology by Diebold and Yilmaz [2012] (hereafter DY) to measure the direction and intensity of spillovers across selected markets. This provides total, directional and net spillovers indexes for both levels and volatility. The Diebold and Yilmaz [2012] methodology has been previously employed by many papers analyzed directional connectedness between financial markets (e.g., Antonakakis and Vergos [2013] ;Batten et al. [2014]; Lucey et al. [2014] ; Balli et al. [2015],Yarovaya et al. [2016], Chau and Deesomsak [2014]. FernÃąndez-RodrÃŋguez et al. [2016]). To our best knowledge, this framework has not been employed to cryptocurrencies data yet.

In contrast to Diebold and Yilmaz [2012], which employs a time domain approach, Barunik and Krehlik [2015] (hereafter BK) employ a frequency variant of Stiassny [1996] and Dew-becker and Giglio [2016] to estimate unconditional connectedness relations in time-frequency domain. This approach has been recently used by Lau et al. [2017] in an analysis of spillovers between the white precious metals and gold, oil and global equity.This framework allows to investigate connectedness at short and long frequencies.

4.1. Results

As we are concerned with the way in which the various assets interact we first obtain Z-Scores of each of the dynamic relationship series. This not only has the effect of standardizing the results but shows more clearly when a significant divergence happens. In our analysis, we focus on Bitcoin, as the largest of the three cryptocurrencies. [2]

4.1.1. Time Domain Analysis

. Table 1 displays the values of directional, pairwise and total spillover indexes (TSI). The results show that the TSI is higher for price *levels* (49.58%) than for *volatility* (38.04%), which pattern is also evident for the directional and pairwise indexes. The notable exceptions are for VIX, Lite and FX , which have higher values of direction spillovers (contribution to other markets) estimated for volatilities.

Insert Table 1 about here

The linkages indicate that Bitcoin prices affect both Ripple (28.37%) and Lite (42.3%), but Ripple and Lite have limited influence on Bitcoin, the values of pairwise spillovers indexes being 7.11% and 5.47% respectively. Within the cryptocurrency market Bitcoin is the clear leader. However, for volatility spillovers the patterns are markedly different. Bitcoin volatility can explain only 6.39% of Ripple and 26.8% of Lite, lower than was found for levels. By contrast, the value of pairwise volatility spillovers from Lite to Bitcoin is 31.69%, and from Lite to Ripple is 15.95%. These results indicate that both Bitcoin and Ripple can be susceptible to volatility shocks transmitted from Lite. In summary, the price and volatility spillover tests demonstrate that Ripple and Lite are strongly interconnected.

Our results suggest that cryptocurrencies are rather isolated from the other markets. The values for directional return and volatility from VIX, Bond, Gold, FX, SP500 and GSCI to cryptocurrency markets are very low. It would seem that over this period general financial market conditions are less important influences on cryptocurrencies than structural conditions related to the design, operation and clearing of cryptocurrencies.

Among all cases, the highest values of pairwise indexes are found for price spillovers from FX to Bitcoin (4.18%), followed by Bond to Bitcoin (2.75%). Dyhrberg [2016b] and Dyhrberg [2016a] suggests safe haven properties for Bitcoin versus gold and FX markets, which would be consistent with this lack of linkage, as would the findings

[2]Results for the other currencies are of course available on request

of Bouri et al. [2017], Bouri et al. [2017] and Bouri et al. [2017] Furthermore, the low linkages with other markets reinforce the findings in papers suggesting diversification opportunities for the investors.

We also investigated the *recipients* of spillovers from the cryptocurrency markets. For example, FX is a recipient of levels spillovers from both Bitcoin (15.25%) and Lite (9.64%) markets. Similarly, the value of pairwise spillovers from Bitcoin to GSCI (10.63%) is higher than from GSCI to Bitcoin (2.38%), which makes GSCI a net-recipient of the information transmitted from Bitcoin. Figure 4 plots the pairwise spillovers between Bitcoin and other assets for price levels during the period from 2013 to 2017.

Insert Figure 4 about here

An analysis of the dynamics of pairwise spillovers provides additional information on interconnectedness between the selected markets. The findings show that intensity of spillovers varies over time. Examining for example Bitcoin to Ripple suggests that the increased price for Ripple has been driven by the rapid growth of Bitcoin. The direction of this dependency was similar for all observation period. Alternatively, for Bitcoin-GSCI , we can see the instability of the relationships between markets. While spillover analysis reveals that GSCI is a recipient of spillovers from Bitcoin, the dynamics of spillovers indicates that the direction of spillovers changed in the Q2 of 2016 (Bitcoin's price surged leading up to the Brexit vote), and the beginning of 2017 (Ripple (XRP) entered the major exchanges such as Bitstamp). For Bitcoin VIX and SP500 , the spillover plot shows a high intensity of spillovers from Bitcoin to these markets in Q3 2015. This corresponds to the 29% collapse of Bitcoin prices on the 19th of August 2015, which caused a volatility shock transmitted to both VIX and SP500.

Figure 5 displays the dynamics of volatility spillovers from Bitcoin to other assets. The intensity of volatility spillovers is constantly changing during the estimation period. The direction of the identified relationships is inconsistent, and intensity of spillovers is highly erratic. We can suggest that the volatility spillovers are highly time dependent, relatively small in magnitude, and unstable

Insert Figure 5 about here

4.1.2.

Frequency Domain Analysis

To further explore the interconnectedness between cryptocurrency markets and other assets at short and long frequencies we employ the Barunik and Krehlik [2015] methodology. Table 2 for levels and Table 3 for volatilities presents the decomposition of time-frequency dynamics of connectedness. We found that cryptocurrencies and other assets are typically not connected at short frequencies. At long frequencies, the results reveal similar patterns to those that have been discussed in previous section of this paper.

Insert Table 2 about here

According to the frequency domain analysis, there is little evidence of volatility spillovers between cryptocurrencies and other financial markets at short frequencies. However, the cryptocurrency markets influence each other at both long and sort frequencies. Table 3 presents the results for volatilities.

Insert Table 3 about here

We plot the pairwise spillovers between the Bitcoin and other assets to analyse the differences in connectedness in short- and long-run. Figures 6-11 show the dynamics of the pairwise spillovers at various frequencies. The results support the previous findings of this paper. However, there are several cases, where we can observe an increase in spillovers from Bitcoin to other markets at short frequencies. For example, Bitcoin-SP500 and Bitcoin-VIX levels during Q3 of 2015 (Bitcoin flash crash), Bitcoin-FX, Bitcoin-Gold and Bitcoin-GSCI levels during Q2 of 2016 (Brexit referendum).

Insert Figures 6-11 about here

5. Conclusion and Suggestions for further work

Our research suggest a role for cryptocurrencies in an investor portfolio, they being highly connected to each other and disconnected from mainstream assets, but the cryptocurrency market contains its own idiosyncratic risks that are difficult to hedge against. Our results also support the position that cryptocurrency markets is a new investment asset class, since they are interconnected with each other and have similar patterns of connectedness with other asset classes. Further research is needed to observe the behaviour of cyrptocurrencies with respect to monetary policy and regulatory arbitrage.

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Table 1: Diebold Yilmaz Spillovers

Levels										
	Bitcoin	Ripple	Lite	VIX	Bond	Gold	FX	SP500	GSCI	From
Bitcoin	76.56	7.11	5.47	0.37	2.75	0.56	4.18	0.61	2.38	2.6
Ripple	28.37	60.97	5.19	1.38	1.59	0.2	0.51	1.48	0.32	4.34
Lite	42.3	19.62	31.32	0.48	0.42	4	1.17	0.51	0.18	7.63
VIX	1.17	0.77	0.12	44.71	6.36	5.77	2.21	30	8.87	6.14
Bond	0.61	2.58	4.02	3.58	57.21	5.85	5.64	4.18	16.32	4.75
Gold	4.48	0.7	1.58	2.61	24.9	48.64	7.36	8.98	0.75	5.71
FX	15.25	0.85	9.64	2.43	4.87	3.87	38.23	19.8	5.07	6.86
SP500	2.1	1.09	3.3	20.9	11.9	4.11	1.68	41.25	13.67	6.53
GSCI	10.63	0.71	4.63	2.02	1.09	15.55	0.14	10.33	54.89	5.01
To	11.66	3.71	3.77	3.75	5.99	4.44	2.54	8.43	5.28	49.58
Volatility										
	Bitcoin	Ripple	Lite	VIX	Bond	Gold	FX	SP500	GSCI	From
Bitcoin	61.64	3.52	31.69	0.72	0.16	0.43	0.35	0.28	1.22	4.26
Ripple	6.39	75.25	15.95	0.14	0.15	0.16	0.76	0.12	1.08	2.75
Lite	26.8	5.99	65.35	0.47	0.34	0.1	0.26	0.28	0.41	3.85
VIX	0.35	0.75	0.39	54.02	4.73	1.39	5.65	28.73	3.99	5.11
Bond	0.42	0.12	0.51	7.31	58.15	6.2	12.95	7.64	6.7	4.65
Gold	1.55	0.27	0.39	3.18	7.85	70.68	6.23	4.44	5.41	3.26
FX	0.35	1.11	0.52	6.48	10.52	3.48	61.35	7.06	9.13	4.29
SP500	0.77	1.19	0.25	30.87	5.97	2.49	5.1	46.87	6.48	5.9
GSCI	0.47	2.05	1.45	7.26	4.39	3.79	5.53	10.71	64.34	3.96
To	4.12	1.67	5.68	6.27	3.79	2	4.09	6.59	3.82	38.04

Table shows the estimated spillovers from (along columns) and to (along rows) of various combinations of financial assets , estimated using the Diebold and Yilmaz [2012] methodology.

Table 2: Frequency Domain Spillover Table for Levels

Short	Bitcoin	Ripple	Lite	VIX	Bond	Gold	FX	SP500	GSCI	From A	From W
Bitcoin	0.28	0.22	0.27	0	0.02	0	0.02	0	0.02	0.06	3.1
Ripple	0.01	0.74	0.03	0	0	0	0	0	0.01	0.01	0.34
Lite	0.11	0.1	0.96	0	0	0	0.01	0	0.01	0.02	1.27
VIX	0.02	0.01	0	4.15	0.55	0.18	0.09	3.03	0.16	0.45	22.84
Bond	0.01	0.01	0.02	0.06	0.47	0.19	0.03	0.11	0	0.05	2.54
Gold	0.02	0	0	0	0.04	0.66	0.05	0	0.04	0.02	0.87
FX	0.08	0	0.05	0.01	0.1	0.08	1	0.07	0	0.04	2.21
SP500	0.02	0.02	0.02	0.95	0.49	0.13	0.01	1.09	0.03	0.18	9.42
GSCI	0.07	0.01	0.02	0.09	0.04	0.02	0.01	0.27	0.23	0.06	3.03
To Abs	0.04	0.04	0.04	0.12	0.14	0.07	0.02	0.39	0.03	0.89	
To Wth	1.88	2.09	2.28	6.33	7.14	3.42	1.22	19.79	1.47		45.62
Long	**Bitcoin**	**Ripple**	**Lite**	**VIX**	**Bond**	**Gold**	**FX**	**SP500**	**GSCI**	**From A**	**From W**
Bitcoin	76.27	6.89	5.2	0.37	2.73	0.56	4.17	0.61	2.37	2.54	2.59
Ripple	28.36	60.23	5.16	1.37	1.58	0.19	0.51	1.48	0.31	4.33	4.42
Lite	42.19	19.52	30.37	0.48	0.42	4	1.16	0.51	0.17	7.61	7.76
VIX	1.16	0.77	0.12	40.56	5.81	5.59	2.12	26.97	8.71	5.7	5.81
Bond	0.6	2.56	4	3.51	56.75	5.66	5.61	4.07	16.31	4.7	4.8
Gold	4.46	0.7	1.58	2.61	24.85	47.97	7.31	8.98	0.71	5.69	5.8
FX	15.17	0.84	9.59	2.42	4.77	3.79	37.22	19.73	5.07	6.82	6.96
SP500	2.07	1.08	3.28	19.95	11.41	3.98	1.67	40.16	13.64	6.34	6.47
GSCI	10.57	0.7	4.61	1.92	1.05	15.54	0.13	10.05	54.66	4.95	5.05
To Abs	11.62	3.67	3.73	3.63	5.85	4.37	2.52	8.05	5.26	48.69	
To Wth	11.85	3.75	3.8	3.7	5.96	4.46	2.57	8.21	5.36		49.66

Table shows the estimated spillovers from (along columns) and to (along rows) of various combinations of financial assets , estimated using the Barunik and Krehlik [2015] methodology. To Abs and To Wth refer to absolute and within the estimated system. Long refers to horizons of greater than 4 days, while short refers to horizons of up to 4 days.

Table 3: Frequency Domain Spillover Table for Volatilities

Short	Bitcoin	Ripple	Lite	VIX	Bond	Gold	FX	SP500	GSCI	From A	From W
Bitcoin	7.87	0.29	3.09	0.1	0.05	0.06	0.05	0.06	0.05	0.42	2.11
Ripple	0.36	10.19	0.53	0.02	0.02	0.03	0.01	0	0.02	0.11	0.56
Lite	3.48	0.53	9.83	0.1	0.13	0.06	0.07	0.07	0	0.49	2.5
VIX	0.09	0.01	0.07	10.85	1.23	0.5	1.1	6.4	0.81	1.13	5.75
Bond	0.07	0.02	0.19	1.79	18.7	2.59	3.59	2.4	1.09	1.3	6.61
Gold	0.07	0.01	0.04	1.08	2.98	20.82	2.43	1.69	1.43	1.08	5.47
FX	0.07	0.01	0.09	1.54	3.25	1.54	15.1	1.68	0.98	1.02	5.15
SP500	0.04	0.01	0.03	4.62	1.14	0.59	0.93	8.35	0.8	0.91	4.6
GSCI	0.05	0.03	0.02	0.9	0.9	1	0.85	1.15	12.81	0.54	2.76
To Abs	0.47	0.1	0.45	1.13	1.08	0.71	1	1.49	0.58	7.01	
To Wth	2.39	0.51	2.29	5.71	5.47	3.58	5.09	7.57	2.92		35.51
Long	**Bitcoin**	**Ripple**	**Lite**	**VIX**	**Bond**	**Gold**	**FX**	**SP500**	**GSCI**	**From A**	**From W**
Bitcoin	53.77	3.23	28.6	0.62	0.1	0.37	0.3	0.22	1.16	3.85	4.79
Ripple	6.02	65.06	15.42	0.12	0.13	0.13	0.75	0.12	1.06	2.64	3.29
Lite	23.32	5.46	55.52	0.37	0.21	0.04	0.19	0.21	0.41	3.36	4.18
VIX	0.26	0.74	0.32	43.17	3.5	0.89	4.55	22.33	3.19	3.97	4.95
Bond	0.35	0.1	0.32	5.53	39.45	3.61	9.35	5.24	5.61	3.35	4.17
Gold	1.49	0.26	0.35	2.1	4.88	49.86	3.8	2.76	3.98	2.18	2.71
FX	0.29	1.11	0.43	4.94	7.27	1.94	46.25	5.38	8.15	3.28	4.08
SP500	0.73	1.18	0.22	26.25	4.83	1.9	4.17	38.51	5.68	5	6.22
GSCI	0.42	2.03	1.43	6.36	3.49	2.79	4.68	9.56	51.53	3.42	4.26
To Abs	3.65	1.57	5.23	5.14	2.71	1.3	3.09	5.09	3.25	31.03	
To Wth	4.55	1.95	6.52	6.41	3.38	1.62	3.85	6.34	4.05		38.66

Table shows the estimated spillovers from (along columns) and to (along rows) of various combinations of financial assets , estimated using the Barunik and Krehlik [2015] methodology. To Abs and To Wth refer to absolute and within the estimated system. Long refers to horizons of greater than 4 days, while short refers to horizons of up to 4 days.

Table 4: Sample Statistics for return series

Investment Product	Sample Period	Mean	Std. dev.	Skewness	Kurtosis	JB-stat.	Ljung-Box (12)
Cryptocurrencies	1. 4/13 to 2/14	0.0045	0.0761	0.6826	7.7196	54.86	0.4277
	2. 2/14 to 4/17	0.0021	0.0405	0.0881	10.0477	78.36	0.0003
Bonds	1. 4/13 to 2/14	0.0000	0.0014	-0.6180	4.7942	41.59	0.7786
	2. 2/14 to 4/17	0.0000	0.0012	-0.0922	2.4278	59.04	0.1752
Commodities	1. 4/13 to 2/14	0.0004	0.0060	-0.4750	2.7267	26.28	0.9439
	2. 2/14 to 4/17	0.0002	0.0067	-0.3710	5.1969	42.73	0.3551
Foreign Exch.	1. 4/13 to 2/14	0.0002	0.0035	0.2972	2.2724	18.97	0.4246
	2. 2/14 to 4/17	-0.0002	0.0048	0.1760	4.7241	46.25	0.2309
Equities	1. 4/13 to 2/14	-0.0005	0.0107	-0.4422	3.2690	28.53	0.9153
	2. 2/14 to 4/17	0.0000	0.0075	0.3226	4.5419	46.32	0.2278

Note: The table reports sample statistics for daily return distributions of portfolios of cryptocurrencies, bonds, equities, foreign exchange and commodities calculated for the two sample periods, i.e. means, standard deviations, measures of skewness and kurtosis, and Jarque Bera (JB) and Ljung Box Q statistics. Sample (1) cover the full sample between 29 April 2013 and 7 February 2014. Sample (2) cover the full sample between 10 February 2014 and 30 April 2017. This sample division investigates the collapse of Mt. Gox which is observed by many cryptocurrency analysts as a defining moment in the life of Bitcoin and broad cryptocurrencies. The JB statistic is defined as JB=n/6(S^2+0.25K^2), where N,S denote sample size, skewness and kurtosis. As is typical, all of the sample return series exhibit abnormal skewness ($S \neq 0$) and excess kurtosis (K$>$ 3). The null hypothesis that the data are from a normal distribution is a joint hypothesis of the S=0 and K$<$3, and rejected accordingly. Under the null hypothesis that the series is white noise, the Q-statistic is distributed chi-square with k degrees of freedom, reflecting the number of autocorrelations. ***, **, and * indicate level of significance at 1%, 5%, and 10% respectively.

Figure 1: Correlation Analysis

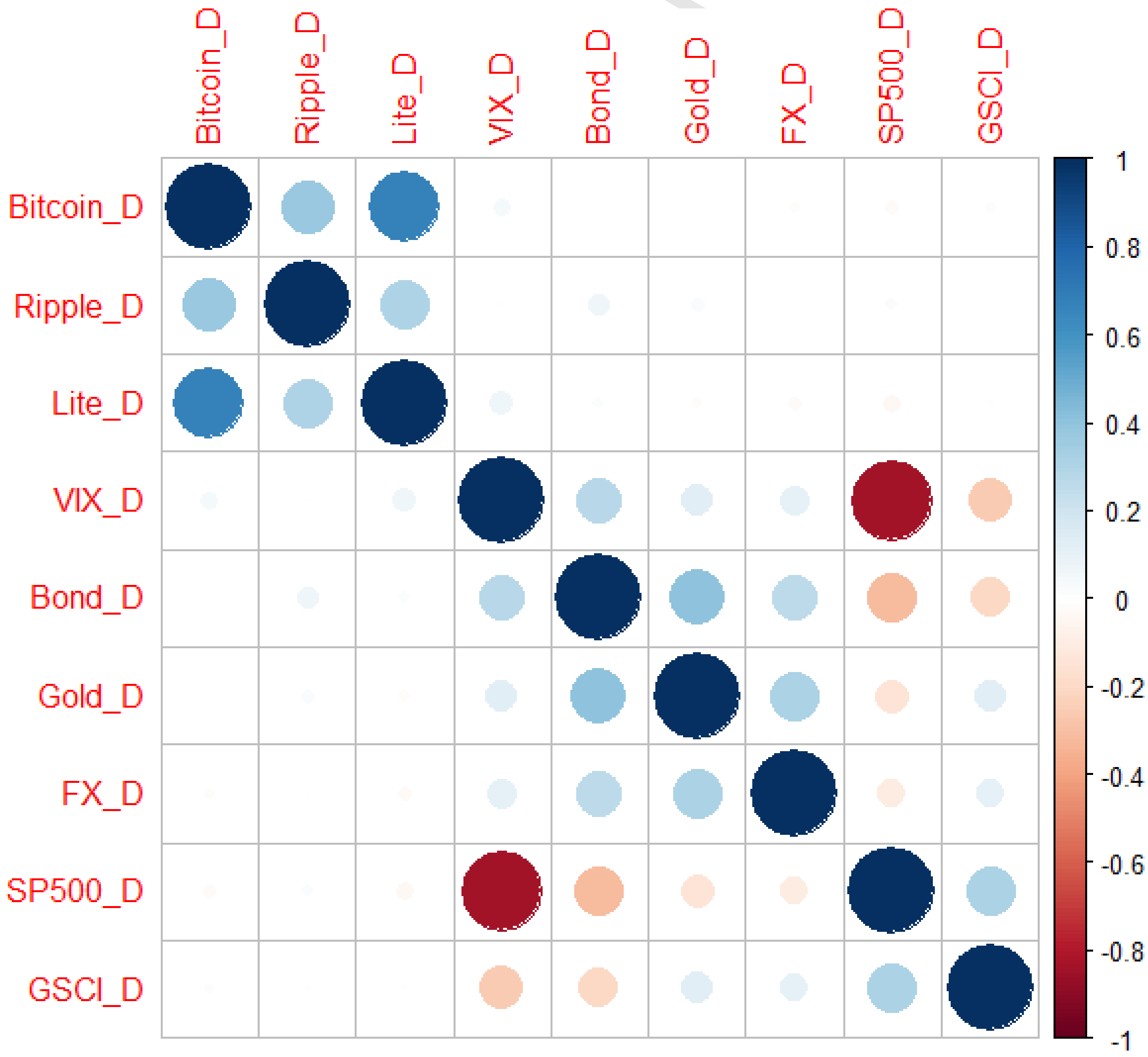

Figure 2: Evolution of selected Cryptocurrencies

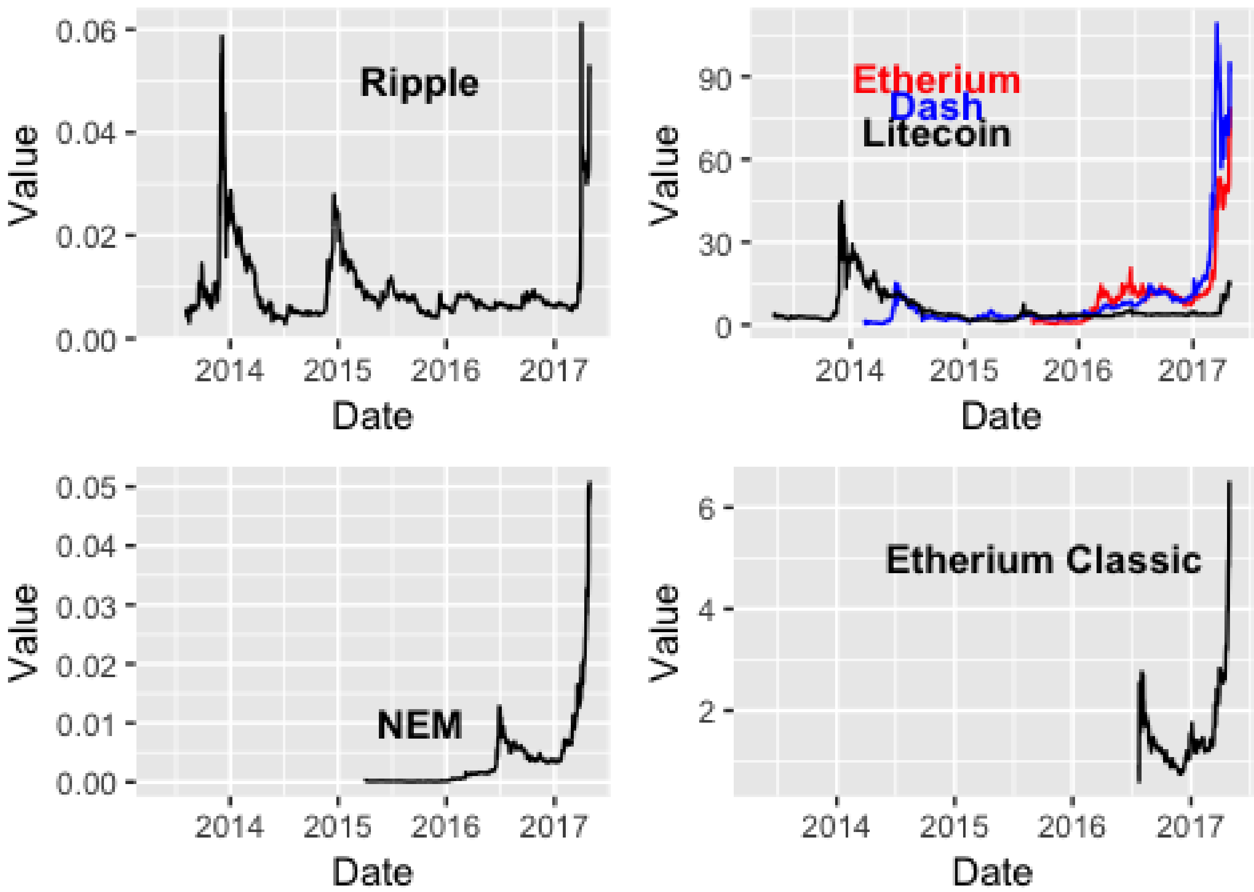

Figure 3: Box and whisker Analysis of volatilities

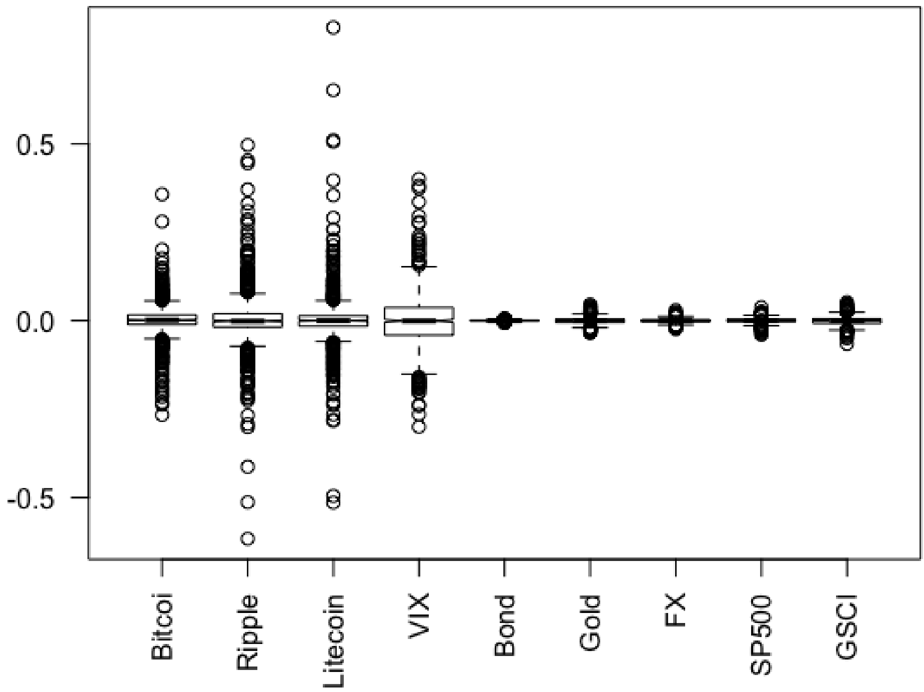

Figure 4: Diebold Yilmaz Pairwise Spillovers - Levels

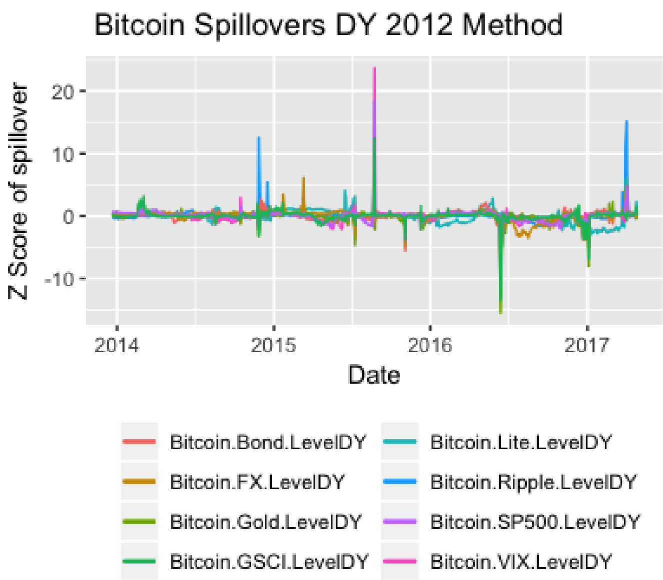

Figure 5: Diebold Yilmaz Pairwise Spillovers - Volatility

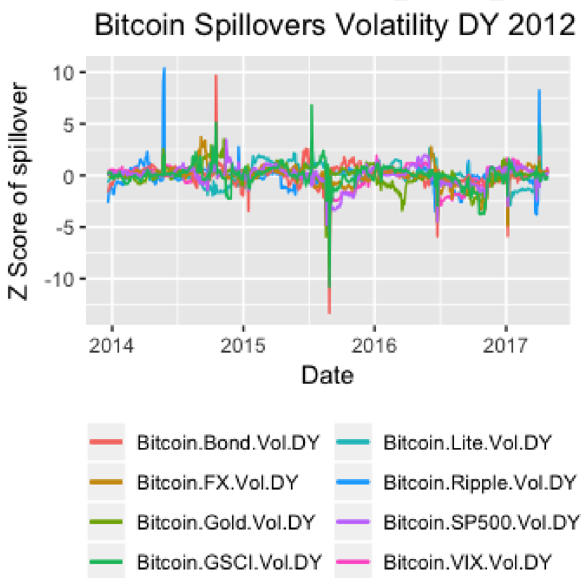

Figure 6: Bitcoin to Bonds

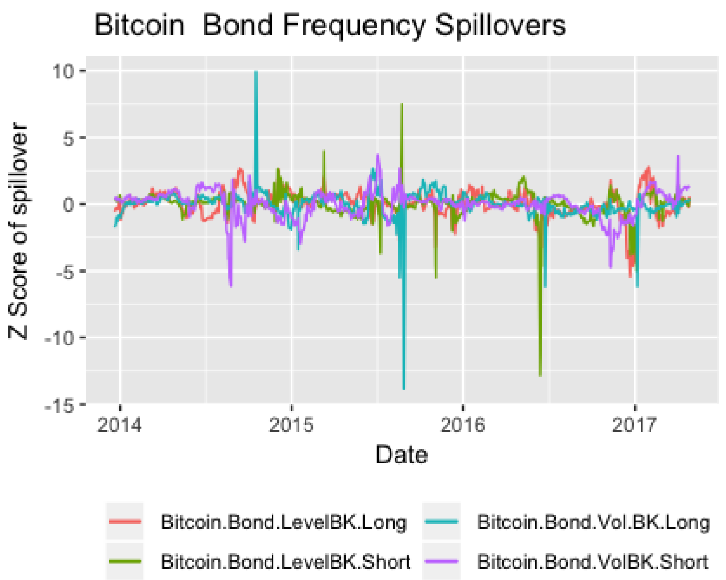

Figure 7: Bitcoin to Stocks

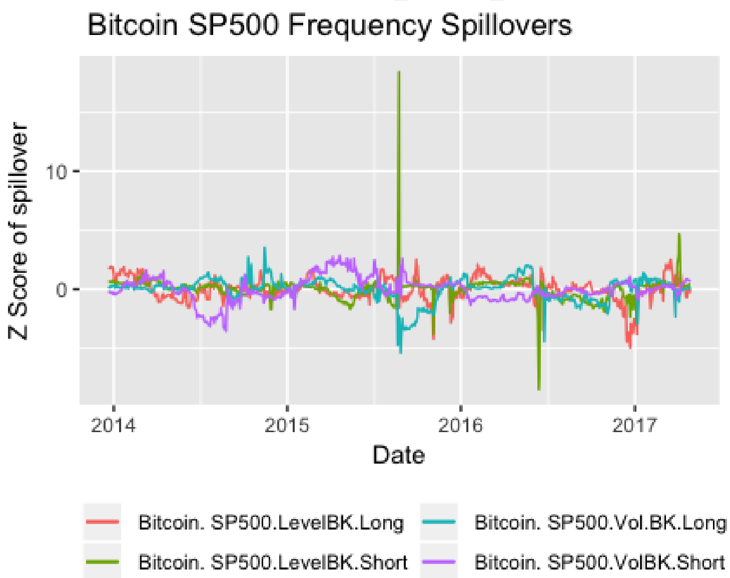

Figure 8: Bitcoin to Vix

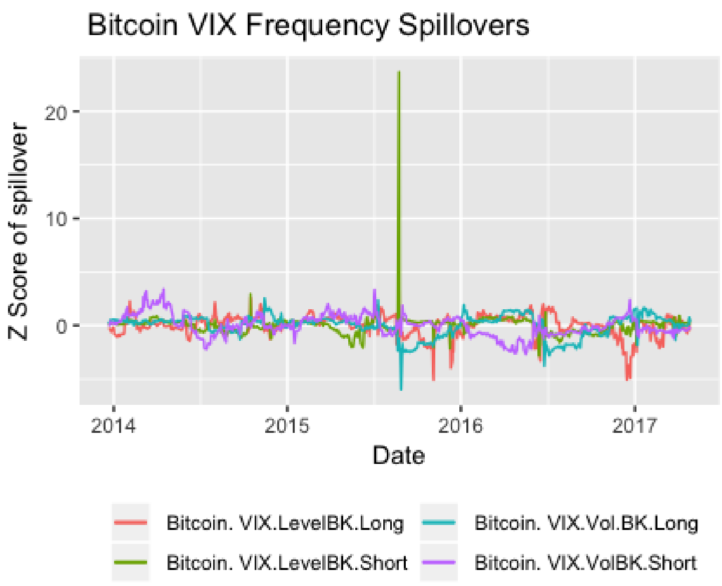

Figure 9: Bitcoin to FX

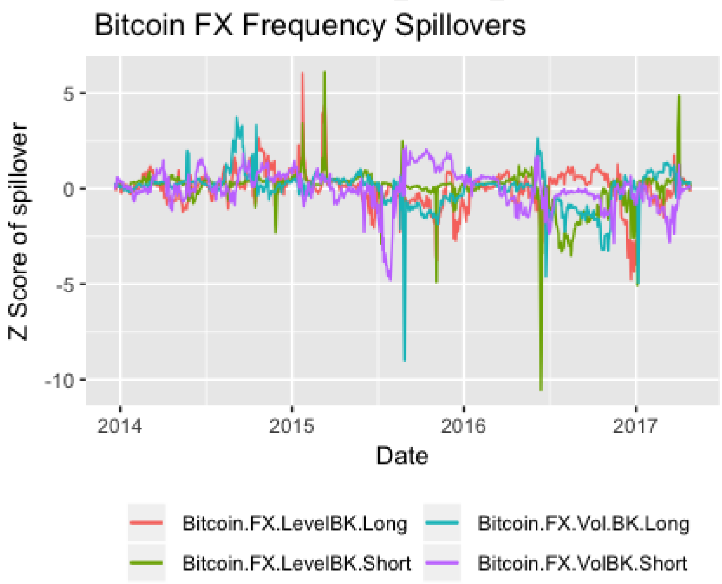

Figure 10: Bitcoin to Gold

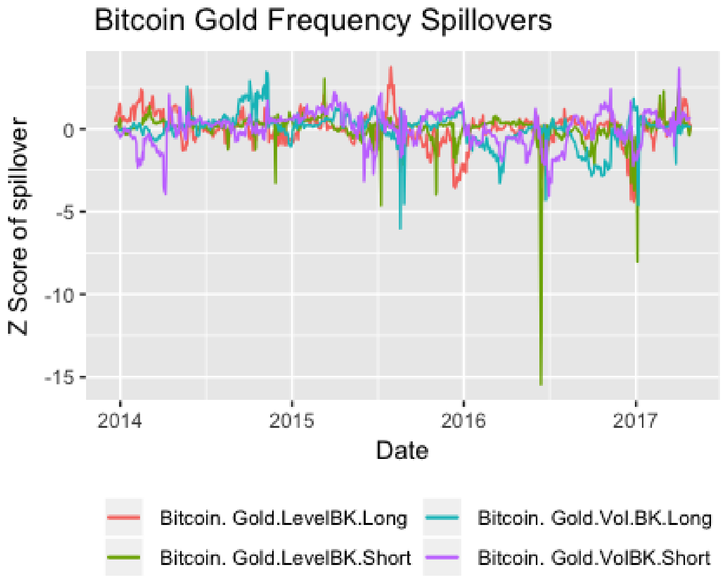

Figure 11: Bitcoin to GSCI