Contagion of Uncertainty: Transmission of Risk from the Cryptocurrency Market to the Foreign Exchange Market

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Abstract:

Earlier research documented that cryptocurrencies, including Bitcoin, have experienced dramatic fluctuations in both market capitalization and market share in recent years. Unsurprisingly, Bitcoin returns exhibit higher volatility than traditional G-10 currencies. Our paper extends earlier research and investigates the potential impact of news originating from the Bitcoin market. Confirming earlier studies, we find that Bitcoin exhibits dramatically higher volatility than the dollar factor. Surprisingly, our findings indicate that only hacking incidents that occur in the Bitcoin market result in high levels of co-movement in the risk of both markets the cryptocurrency and the G-10 currency market, whereas good news do not have such effects. Our findings may serve as an important tool for guiding policy makers who target financial stability across markets.

JEL Classification: G12, G14

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1. Introduction

Satoshi Nakamoto, an anonymous programmer introduced Bitcoin on 31st October 2008.[1] Bitcoin is the first decentralized cryptocurrency that is based on cryptographic proof rather than the trust system as in traditional currencies. Bitcoin transactions are peer-to-peer without any intermediation and control. All bitcoin transactions are recorded in a public distributed ledger system called the 'Blockchain' (Osterrieder and Lorenz, 2017). From barter to blockchain, we came across the different medium of exchanges: gold, gold coins, metal coins, paper money, credit cards, digital money to cryptocurrency. Gold came both as a store and measure of value. As gold is a scarce resource, governments realized the need for alternative currencies. Selgin (2015) identifies three types of currencies: commodity currency, Fiat currency, and synthetic commodity currency.[2] Commodity currency is similar to gold where the price is determined by supply and demand. Traditional currencies, on the other hand, are controlled by the monetary authorities. The author describes cryptocurrency as synthetic commodity money. He finds the possibility of stable monetary regimes if cryptocurrencies like Bitcoin are used properly. Nevertheless, there is not a single currency in the world that is on the gold standard. Likewise, cryptocurrency is also not backed by gold or any other precious metals. Since both of these currencies are not backed by any precious metals, these two currencies have value as long as people have beliefs that support this perception.

Traditional currency has a long history and thus the trust and belief system is stronger than of the newly discovered cryptocurrencies. Therefore, the cryptocurrency ecosystem will have to strengthen its security standards to gain the trust of traditional investors. The recurring cyber-attacks have a strong impact on investors' psychology (Klein, Thus and Walther, 2018). Recently, cryptocurrencies have attracted significant amounts of popular attention (Frisby, 2014; Vigna and Casey, 2015). Interestingly, Fry and Cheah (2016, p.350) highlight that "from an economic perspective the sums of money involved are substantial.

On both levels blockchain and exchange, cryptocurrencies are vulnerable to cyber-attacks. Rauchs and Hileman (2017) document that small cryptocurrency exchanges have a chance of getting hacked corresponding to 79%, whereas the corresponding figure for large exchanges is 74%. To avoid the hacking incidents 92% of the exchanges use some type of cold storage system where they keep their keys offline. Number of Bitcoin wallet has increased more than 4 times from 8.2 million in 2013 to 35 million in 2016. Leading cryptocurrency exchange Coinbase has over 13 million users in 32 different countries. It offers Bitcoin, Ethereum and Litecoin against 32 established national currencies.[3] The authors estimate around 20 million cryptocurrency users globally. Bit4X is the first forex exchange launched in 2012 where they offered 30 national currency pairs to trade against Bitcoin. It has now grown to become a leading platform for trading everything from high liquidity forex to other

[1] See Nakamoto (2008).
[2] In this context, Fiat means 'without any intrinsic value'.
[3] So far, there are no statistics available about the users in emerging markets.

crypto markets with Bitcoin. One can now trade 41 currency pairs using Bitcoin. There are millions of active traders under one single forex broker and there are hundreds of those offering forex against Bitcoin (e.g., Plus500, AVATRADE, eToro, MARKETS.COM, FXCM).[4]

According to FBS (Online Forex Broker), there are multiple benefits of trading forex using cryptocurrencies. Standard international transfers involving different traditional foreign currencies may take multiple days. There are different unpredictable costs associated with the transfer that the traders have to face, for example exchange rate, taxes, banks and other financial intermediaries' fees. Forex traders look for a cost efficient way to enter and exit the market. One simple solution that is available nowadays is to employ cryptocurrencies. Traders usually prefer privacy coins like Monero, Dash, etcetera, if they want certain degree of privacy. Bitcoin has eliminated some of the global boundaries; one can trade any available currency pairs using Bitcoin from any part of the globe. As a consequence, the forex traders are more and more getting into the cryptocurrency market. At the same time, millions of cryptocurrency holders are active also in foreign exchange market. Global cryptocurrency benchmark report of Rachus and Hileman (2017) shows that 67% of total transaction volumes (in USD) of cryptocurrency payment companies are national currency to cryptocurrency and vice-versa. National to National currency payments are 27%, whereas cryptocurrency to cryptocurrency payments are just 6% (see, Table A.2 in Appendix).

Several cryptocurrencies, including Bitcoin, have experienced dramatic fluctuations in both market capitalization and market share in recent years. As an example, on August 2, 2016, in an attack 119,756 Bitcoins were hacked corresponding to a monetary equivalent of 77 million US dollar. Interestingly, the annualized weekly volatility increased already before the event became public knowledge from 0.82% per annum in the second week of July to 82.55% in the third week of July. However, even minor events result in dramatic increases in cryptocurrency's market risk.[5] While there are a few recent papers that explore the volatility clustering in cryptocurrencies (Katistampa, 2017; Balcilar, Bouri, Gupta, and Roubaud, 2017), there is no paper available that analyzes potential volatility spillover effects between the new cryptocurrency market and the traditional foreign exchange market.

Hence, the purpose of this paper is to uncover potentially time-dependent interdependencies between the uncertainty in the cryptocurrency market and the uncertainty in the foreign exchange market. Consequently, the research question that we address in our paper is whether the uncertainty of those markets would share a common source of risk. To explore this issue in detail, we first employ daily data of the log-returns of the dollar factor of the G-10 currencies as foreign exchange rate market factor as well as the log-returns of Bitcoin that serve as proxy for the cryptocurrency market.

[4] See bitcoinist.com. Moreover, in Table A.1 in the appendix, we report the percentage of cryptocurrency exchanges supporting also national currencies (e.g., G-10 currencies).

[5] As an example, in November 2013 two Bitcoin exchanges were hacked in the same month (Picostocks and Inputs.io) lost collectively around three and a half million dollar. In the wake of the cyberattack, the monthly average of the annual volatility increased from 55.34% in October 2013 to 104.10% in November.

We use those data to estimate the corresponding weekly realized variance time series' for both the G-10 dollar factor and the Bitcoin time series. Using our weekly data from July 18, 2010 to September 16, 2018, we estimate volatility spillover indices that reveal whether or not the uncertainty in those two distinct markets − in terms of their second moments − spills over to the other asset market. In robustness checks, we explore whether changing the order of the variables in the underlying Vector-Autoregressive models used to estimate our spillover indices has any impact on our results.

Our paper contributes to the existing literature in many important ways. There is a wide-strand of literature investigating volatility spillovers in currency market settings. Baruník, Kočenda, Vácha (2017) explore asymmetries in volatility spillovers in the forex market. Their findings indicate that the dominating asymmetries in spillovers are due to bad, rather than good, volatility. Grobys (2015) investigates volatility spillover effects between the foreign exchange market and the equity market. Employing a sample from 1986–2014 his findings indicate that volatility spillovers are time-varying: volatility spillovers are high in times of economic stress, but if the economy is quiet, volatility spillover effects are virtually non-existent. In another recent paper, Grobys and Heinonen (2017) extend Diebold and Yilmaz's (2009) volatility spillover methodology using option-implied data for estimating the option-implied volatilities for the G-10 dollar risk factor and the carry risk factor. Their study finds that those risk factors, which are statistically orthogonal in their first moments, share a common source of risk in their volatilities whenever the economy faces periods of stress. This current research closes an important gap in this stream of literature by exploring potential spillover effects between uncertainties in the cryptocurrency and the traditional currency market. In doing so, our paper also extends Osterrieder and Lorenz (2017) who find that Bitcoin returns exhibit higher volatility than traditional G-10 currencies. Unlike Osterrieder and Lorenz (2017) and Katisiampa (2017), however, we do not only study the volatilities themselves but rather focus on exploring potential interdependencies between the volatility in the cryptocurrency market and the traditional currency market. Our paper is also contributing to the very recent stream of literature that considers cryptocurrencies from a finance perspective (Urquhart, 2016; Cheah and Fry, 2015; Dyhrbeg, 2016).[6] Finally, Cheah and Fry (2015) and Osterrieder and Lorenz (2017) discuss the need of academic research on cryptocurrency and argue that many academic research studies are focusing on the legality of cryptocurrencies rather than the comprehensive analysis related to statistical and financial aspects of it. In this regard, our research closes an important gap in the financial literature; as pointed out in Grobys (2015, p.72): "A policy maker would like to know how spillover effects will behave during economic downturns and whether they can be employed to predict the future evolution of specific market indicators. A tool capable of describing the behavior of spillover effects in different economic states could guide policy actions intended to monitor, control, or forecast contagion effects across markets that could lead to financial instability." Knowing about the potential contagion from

[6] There are several academic journals with the most downloaded and most cited articles related to Bitcoin, discussing about the nature and volatility of it; see Table A.3 in the appendix.

risk changes in the cryptocurrency market to the real currency market might serve as a valuable fundament for monetary policy decision makers.

Our results provide strong evidence for that the uncertainty in the cryptocurrency market and the traditional currency market share a common risk driver in times of troubles. The phenomenon of time-varying interdependencies is in line with earlier literature documenting bursts of volatility spillovers associated with crisis events when volatility spillover indices were implemented using local-currency stock market volatilities (Diebold and Yilmaz, 2009), US financial institutions' stock return volatilities (Diebold and Yilmaz, 2014), realized exchange rate volatility and realized US equity market volatility (Grobys, 2015), option-implied currency market risk factor volatilities (Grobys and Heinonen, 2017), and realized value and momentum factor volatilities (Grobys and Vähämaa, 2018). Specifically, in our analysis, we distinguish between good events and bad events that occurred in the cryptocurrency market involving hackings, thefts, and losses. We find that the volatility of the foreign exchange market co-moves with the volatility of the cryptocurrency market in the wake of hacking incidents happening in the cryptocurrency market only. This finding supports Baruník et al. (2017) who found that the dominating asymmetries in spillovers are due to bad volatility. Interestingly, our findings also indicate that the time lengths of these co-movements are especially associated with hacking, and moreover, depend on the total market value of Bitcoin hacked. Moreover, our findings may be surprising to the naïve investor who might have expected that the cryptocurrency market and the traditional currency market do not share the same risks due to their very distinctive nature. Notably, Grobys (2015) finds that the volatility of the foreign exchange market and the equity market also share a common factor in times of economic stress. Likewise the foreign exchange market and equity market are also very distinctive markets. Our study is also in line with Grobys and Heinonen's (2017) recent study, who find that volatilities of two statistically orthogonal currency market risk factors exhibit time-varying interdependencies. In the same manner, we find that our dollar factor and Bitcoin are statistically uncorrelated in their first moments but show strong time-dependent patterns of co-movement in their second moments. Another novel finding, implied by our results from the robustness checks, is that it appears to be the change in volatility originating from the cryptocurrency market that is the core driver of the spillovers and not the corresponding measure associated with the dollar factor even though the traditional currency market is considerably larger. Finally, our realized volatility approach confirms Osterrieder and Lorenz (2017) in finding that Bitcoin log-returns exhibit dramatically higher volatility than the log-returns of the dollar factor of the G-10 currencies.

The remainder of our paper is organized as follows. The next section provides an overview about the recent academic literature that explores that cryptocurrency market. The third section presents the econometric model employed and in the fourth sections we present and discuss our results. The last section concludes.

2. Literature Review

There are already over two thousand cryptocurrencies in the market.[7] Many new cryptocurrencies are also lined up for their ICOs (Initial Coin Offerings).[8] Leading cryptocurrencies like Bitcoin, Ethereum, and Ripple are affected by the events on one another. One stream of literature studies the volatility in the cryptocurrency market. Fry and Cheah (2016) investigated price spillovers between two of the largest cryptocurrencies after the negative bubble of 2014 when the Bitcoin price dropped sharply. Their findings indicate that there is a spillover from Ripple to Bitcoin. In another recent paper, Katisiampa (2017) investigates the optimal conditional heteroskedasticity model with regards to goodness-of-fit to Bitcoin price data. Employing a whole battery of different GARCH-type model, that study finds that the AR-CGARCH model is the best model to estimate the Bitcoin price volatility. In search of a reliable model to forecast the risk of Bitcoin, Ardia, Bluteau, and Rüede (2018) test the presence of regime changes in the GARCH volatility dynamics of Bitcoin log–returns employing Markov–switching GARCH (MSGARCH) models. Employing a sample period from August 19, 2011 to March 2, 2018, their findings indicate that daily log–returns of Bitcoin exhibit regime changes in their volatility dynamics. Specifically, a two-regime MSGARCH model exhibits the best in-sample performance with an inverted leverage effect in both low–and high–volatility regimes.[9] Furthermore, demand and supply of the dollar as well as other major currencies play an important role in the foreign exchange market. Surprisingly, Balcilar, Bouri, Gupta, and Roubaud (2017) empirical findings indicate that volume is not able to predict the return volatility of Bitcoin in any point of the conditional distribution.

Another strand of literature takes the perspective of cryptocurrencies being an asset class. Urquhart (2016) concludes that the Bitcoin is still emerging as a new investment asset; thus the returns from it do not satisfy the efficient market hypothesis. In an extension of that study, Nadarajah and Chu (2017) show just the opposite by simple power transformation of the Bitcoin returns. Cheah and Fry (2015) also argue that the fundamental value of Bitcoin is zero. Moreover, Hayes (2017) identifies three main drivers of the Bitcoin price: the level of competition in the network of crypto miners, unit production rate and mining difficulty. Pieters and Vivanco (2017) document significant differences in Bitcoin prices of 11 crypto exchanges representing 26% of global Bitcoin trade volume. They also find Bitcoin price difference around exchanges based on the customer identification disclosure rule. Exchanges needing customer identification are less likely to deviate from the representative market price. Urquhart (2017) finds significant evidence of Bitcoin price clustering

[7] As of 29 October 2018, there are 2076 cryptocurrencies in the market that are traded at 15,429 exchanges having a market capitalization of USD 202,873,975,753 with Bitcoin (BTC) dominance of 54.20%; see https://coinmarketcap.com/all/views/all/ (accessed on 29 October 2018, 15:00 EST.

8 To find the active and upcoming ICOs in the market visit, https://www.icoalert.com/en/?q=&is_v=1

[9] Other papers that investigate the response of the conditional variance to past positive and negative shocks and find an inverted leverage effect are Baur, Dimpfl, and Kuck (2018) and Stavroyiannis (2018).

around whole numbers where more than 10% of the price has double zeros at the end. They could not find any predictable patterns in the return even after rounding price to the whole numbers.

Dyhrberg (2016) takes also the perspective of cryptocurrencies being an asset market and categorizes Bitcoin in between gold and dollar; gold as a store of value and dollar as a medium of exchange. Risk-averse investors can use Bitcoin as a safe haven against the turmoil on commodity and forex market. Unlike Dyhrbeg (2016) who considers Bitcoin as a virtual gold, Baur et al., (2018) argue that Bitcoin does not share commonalities in risk and return with any other traditional assets such as stocks, bonds, and commodities. Bouri, Molnár, Azzi, Roubaud, and Hagfors (2017) find Bitcoin as a hedge against global uncertainty but only for the short term. They decompose Bitcoin returns into its various investment horizons. In their quantile-on-quantile (QQ) regressions[10], they could identify hedging at both lower and upper ends of Bitcoin returns and global uncertainty, but only at shorter investment horizons. However, Cheah and Fry (2015) find that the cryptocurrency market is vulnerable to speculative bubbles. Klein, Thu, and Walther (2018) find correlations between Bitcoin and dollar behave differently from correlations between Bitcoin and gold, particularly in market distress. They also find that Bitcoin does not resemble any other conventional asset from an economic perspective. The main difference between cryptocurrency and traditional currency is the finality of cryptocurrency (e.g., Bitcoin) is not guaranteed by any banking institutions. This might be an advantage for some but for many, the system requiring blind faith in anonymous persons' expertise and its complexities are the disadvantages (Dwayer, 2015).

In the literature, different views regarding the risk return and other characteristics of cryptocurrency are discussed. For instance, one group believes cryptocurrency is different from Traditional currency and commodity (eg., Baur, Dimpfl and Kuck, 2018; Baur, Hong and Lee, 2018; Klein et al., 2018), whereas the other group takes the viewpoint that crypto shares some commonalities with those (e.g., Dixon et al., 2018; Bouri et al., 2017; Dyhrbeg, 2016). For instance, Dixon et al. (2018) support the risk sharing views arguing that a key challenge for cryptocurrency holders is managing foreign exchange risk. In this regard, however, there is not paper available yet that uncovers the dynamic interplay between foreign exchange rate risk and the risk in the cryptocurrency market. The current research employs a novel approach to fill this gap.

Currency crises, stock market crashes, or large bank failures are some major events that lead to large losses for investors. Cryptocurrencies exhibit even larger volatility swings and more extreme tail events than Traditional currencies (Osterrieder and Lorenz, 2017). In our current research, we seek to uncover the dynamics in risk spillovers between the cryptocurrency market and the traditional foreign exchange rate market which are – at least theoretically – two distinct markets. Dwayer (2015, p.81-91) argues that "the average monthly volatility of returns on Bitcoin is higher than for gold or a

[10] They argue that they are the first researchers to formally analyze the ability of Bitcoin to hedge global uncertainty using standard OLS and two different quantile-based approaches: standard quantile and quantile-on-quantile (QQ) regressions (see Bouri et al., 2017).

set of foreign currencies in dollars, but the lowest monthly volatilities for Bitcoin are less than the highest monthly volatilities for gold and the foreign currencies". There is still no consensus achieved yet on the risk and return nature of Bitcoin. Our studies focus on the dynamics in the co-movement of risk in cryptocurrency and foreign exchange market. It further strengthens the commonality aspect of Bitcoin sharing risk with Traditional currency. Osterrieder and Lorenz (2017) also find that the Bitcoin return shows higher volatility than traditional G-10 currencies. Our study is unique from their study in the sense that it studies not only the volatilities but also the potentially reciprocal volatility spillover from crypto to Traditional currencies.

3. Methodology

Following Grobys (2015), we model spillover effects in the second moment between the currency market and the cryptocurrency market by employing realized variances. Specifically, we employ the dollar factor of the G-10 currencies and Bitcoin due to the following reasons: First, according to Bank of International Settlements (BIS), the G-10 currencies comprise about 70% of the total USD 5.3 trillion turnovers in the global currency market.[11] Hence, these currencies exhibit the highest liquidity in the FX market. Furthermore, the dollar factor is an equally weighted portfolio of all nine currencies against the US-dollar and corresponds to Lustig, Roussanov, and Verdelhan (2011) in essence to the first principal component spanning the universe of currency returns and is therefore the key factor in FX markets.

Second, considering the top-ten cryptocurrencies that exhibit the highest market capitalization, we found that Bitcoin comprises about 60% of the overall market share. Moreover, Bitcoin exhibit the longest available time series. Therefore, we use Bitcoin as a proxy for the cryptocurrency market (see table A.4. in the appendix).[12] We downloaded daily data for Bitcoin from finance.yahoo.com covering the time period July 16, 2010 until September 28, 2018. For the same time span, we retrieved daily spot data for the G-10 currencies from datastream. We matched both price series, leaving us with 2141 daily observations and compounded the log returns. Next, we followed Grobys and Heinonen (2017) in operating with weekly time series. In their paper, the authors investigate volatility spillover effects between the dollar risk factor and carry trade risk factor. They find that those risk factors exhibit strong stochastic interrelations in the second expected moment even though they are orthogonal in the first moments.

Unlike Grobys and Heinonen (2017), who employ option data, we follow Grobys (2015) in compounding weekly realized variances as follows:

[11] See BIS Quarterly Review, December 2013. The G-10 currencies are the US-dollar, the Euro, the Pound sterling, the Japanese yen, the Australian dollar, the New Zealand dollar, the Canadian dollar, the Swiss Franc, the Norwegian Krone, and the Swedish Krone.

[12] This approach is also in line with earlier research (see Ardia, Bluteau and Rüede, 2018; Baur et al., 2018; Osterrieder and Lorenz, 2017; Bouri et al., 2017; Cheah and Fry, 2015). Moreover, it is also important to note that Bitcoin exhibits the longest available data series in the cryptocurrency universe.

$$VAR_t^{Dollar} = \sum_{t,i}^{K} r_{Dollar,t,i}^2, \text{ and} \tag{1}$$

$$VAR_t^{Crypto} = \sum_{t,i}^{K} r_{Crypto,t,i}^2, \tag{2}$$

where $r_{Dollar,t,i}^2$ denotes the squared daily return of day i in week t of the dollar factor and $r_{Crypto,t,i}^2$ denotes the squared daily return of day i in week t of the Bitcoin time series. Since cryptocurrencies are traded 24/7, we match the trading days from our basket of currencies in terms of US-dollar with Bitcoin and assume that each trading week comprises $K = 5$ daily returns leaving us with 428 (non-overlapping) weekly observations[13]. The descriptive statistics are reported in Table 1. From Table 1 we observe that the realized weekly variance of Bitcoin is notably higher than the realized variance of the dollar factor which confirms Osterrieder and Lorenz (2017). The maximum of the weekly Bitcoin variance is 4591.65, whereas the corresponding figure for the dollar factor is 1.50, only. In Figure 1 and 2 we plot the evolutions of the corresponding annualized volatility series over time. The realized volatility series of the dollar factor shown in Figure 1 overlaps to a great deal the option-implied volatility series in Grobys and Heinonen (2017, p.85) and shows very similar time series evolutions. Moreover, visual inspection shows that the realized volatility of Bitcoin is considerably more erratic. For instance, in the first two years of our sample (e.g., from 2010 to 2012), both volatilities exhibit similar evolutions, whereas the volatility peak in the Bitcoin series that occurred in February 2014 is obviously not reflected in the dollar factor's volatility. In Table 2 we report the correlation matrix. We observe that the dollar factor is statistically uncorrelated with Bitcoin over the sample period. We also observe that the realized variances are unconditionally orthogonal.

Another interesting finding from Table 2 is that both the dollar factor and Bitcoin are contemporaneously positively correlated with their respective (realized) variances. Moreover, the orthogonality in the unconditional first and second moment is a remarkable issue and similar evidence has been documented in Lustig et al. (2011) and Grobys and Heinonen (2017) concerning the currency market. Namely, the authors' findings indicate that the dollar risk and carry risk factors are orthogonal in their first moments at both frequencies, monthly and weekly. To investigate potential dynamic spillover effects in the second moments, we followed Grobys (2015) and employed the following Vector-Autoregression (VAR) model

$$\boldsymbol{Y}_t = \boldsymbol{c} + \boldsymbol{A}_1\boldsymbol{Y}_{t-1} + \cdots + \boldsymbol{A}_p\boldsymbol{Y}_{t-p} + \boldsymbol{u}_t, \tag{3}$$

where, $\boldsymbol{Y}_t = \left(VAR_t^{Dollar}, VAR_t^{Crypto}\right)'$, and $\boldsymbol{A}_1, \dots, \boldsymbol{A}_p$ are 2×2 parameter matrices and the error term $\boldsymbol{u}_t$ is assumed to be multivariate normal distributed with $\boldsymbol{u}_t \sim MVN(\boldsymbol{0}, \boldsymbol{\Sigma_u})$ where $\boldsymbol{\Sigma_u}$ denotes the

[13] Bitcoin trades around the clock (24/7). To make the date uniform across G10 and Bitcoin we matched weekly price series of our G10 currency basket with Bitcoin. Therefore, a trading week in our sample comprises of 5 days for Bitcoin too.

corresponding covariance matrix. Moreover, $\boldsymbol{c}$ is a 2×1 vector containing the constant terms. Then, in line with Grobys and Heinonen (2017), we employed a rolling time window of 36 weeks, three different lag orders of $p = (2, 4, 6)$. To construct the volatility spillover indices, we estimated the moving average representation which is methodologically detailed in Diebold and Yilmaz (2009, pp. 158–160). We use the estimated parameter matrices $\widehat{\boldsymbol{A_1}}, \ldots, \widehat{\boldsymbol{A_{t-p}}}$ from Equation (3) and model the corresponding Wold moving average (MA) representation

$$\boldsymbol{Y_t} = \boldsymbol{\Phi_0 u_t} + \boldsymbol{\Phi_1 u_{t-1}} + \boldsymbol{\Phi_2 u_{t-2}} + \cdots, \tag{4}$$

where $\boldsymbol{\Phi_0} = \boldsymbol{I_2}$ and the

$$\boldsymbol{\Phi_s} = \sum_{j=1}^{s} \boldsymbol{\Phi_{s-j}} \widehat{\boldsymbol{A_j}}, \qquad s = 1,2, \ldots \tag{5}$$

is compounded recursively. We use then the Cholesky decomposition of the covariance matrix $\boldsymbol{\Sigma_u}$ which we define as matrix $\boldsymbol{D}$. If $\boldsymbol{D}$ is a lower triangular matrix such that $\boldsymbol{\Sigma_u} = \boldsymbol{DD'}$ the orthogonalized shocks are given by $\boldsymbol{\varepsilon_t} = \boldsymbol{D^{-1} u_t}$. Consequently, we obtain

$$\boldsymbol{Y_t} = \boldsymbol{\Psi_0 \varepsilon_t} + \boldsymbol{\Psi_1 \varepsilon_{t-1}} + \boldsymbol{\Psi_2 \varepsilon_{t-2}} + \cdots, \tag{6}$$

where $\boldsymbol{\Psi_i} = \boldsymbol{\Phi_i D} (i = 0,1,2, \ldots)$. Since $\boldsymbol{\Psi_0} = \boldsymbol{D}$ is a lower triangular, a shock occurring on the first variable has in instantaneous effect on the second variable in the system. From Equation (4), we define the h −step forecast error as

$$y_{k,T+h} - y_{k,T+h|T} = \boldsymbol{\Psi_0 \varepsilon_{T+h}} + \boldsymbol{\Psi_1 \varepsilon_{T+h-1}} + \ldots + \boldsymbol{\Psi_{h-1} \varepsilon_{T+1}} \tag{7}$$

Further, if we denote the ijth element of $\boldsymbol{\Psi_n}$ by $\psi_{ij,n}$, the kth element of the forecast error vector becomes

$$y_{k,T+h} - y_{k,T+h|T} = \sum_{n=0}^{h-1} \left(\psi_{k1,n} \varepsilon_{1,T+h-n} + \cdots + \psi_{kK,n} \varepsilon_{K,T+h-n} \right), \tag{8}$$

with corresponding forecast error variance

$$\sigma_k^2(h) = \sum_{n=0}^{h-1} \left(\psi_{k1,n}^2 + \cdots + \psi_{kK,n}^2 \right) = \sum_{j=1}^{K} \left(\psi_{kj,0}^2 + \cdots + \psi_{kj,h-1}^2 \right). \tag{9}$$

Due to our chosen ordering $\boldsymbol{Y}_t = \left(VAR_t^{Dollar}, VAR_t^{Crypto} \right)'$,, the term $\left(\psi_{kj,0}^2 + \cdots + \psi_{kj,h-1}^2 \right)$ is interpreted as the contribution of the volatility from the dollar factor to the h −step forecast error variance of the volatility of Bitcoin. Compounding $h-$step forecast error variance for all variables, we stuck the elements in a 2x2 matrix defined as $\mathbf{\Theta}_k^2(h)$. Following Grobys (2015) and Diebold and Yilmaz (2009), the volatility spillover index is then constructed by summing up all elements above and below the main diagonal of $\mathbf{\Theta}_k^2(h)$, and dividing it by the total sum of all elements in $\mathbf{\Theta}_k^2(h)$, which is in our context the part of the volatilities of the dollar factor and Bitcoin that is unexplained by the factors' own volatilities. As in Grobys (2015), we employed a rolling window of 60 months and a forecast-error variance decomposition using a horizon of h=1 month. The models were updated at the beginning of each week. Figure A.2 in the appendix illustrates the time series evolutions of the second moments' spillover indices over the sample period.

The correlations between the models of lag-order p with $(p = 2, p = 4)$, $(p = 4, p = 6)$, and $(p = 2, p = 6)$ are estimated at 0.40, 0.30, and 0.29. Notably, a principal component analysis of those three indices clearly indicates that the three time series vectors exhibit one dominant eigenvalue with an economic magnitude of 1.66 explaining 55% of the covariance matrix.[14] As a consequence, we can conclude that all three indices incorporate the same information that measures, roughly speaking, the dynamic interdependencies between the uncertainty of the foreign exchange market and the cryptocurrency market. We compound the corresponding time series of the eigenvector related to the first principal component and plot it in Figure 3. From Figure 3 in association with Figure A.2, we observe that periods of high co-movement in the spillovers are alternating with periods of low co-movement in the second moments. This alternating co-co-movement phenomenon in the second moment has been reported in earlier research in different other research contexts (Diebold and Yilmaz, 2009; Grobys, 2015; Grobys and Heinonen, 2017; Grobys and Vähämaa, 2018). Considering Figure A.2, a value of one in the spillover index indicates that the second moments of the return distributions of the dollar factor and Bitcoin are driven by the same factor, whereas a value of zero indicates that the second moments of the dollar factor and Bitcoin are orthogonal.

4. Results

Those strong patterns of time-varying interdependencies may be surprising as the naïve investor might have expected that the cryptocurrency market and the traditional currency market should not share the same risks simply due to their distinctive nature. Even though Baur et al. (2018) argue that Bitcoin would not exhibit commonalities in risk and return with any other assets, our study provides some novel evidence. Over the past years, Bitcoin experienced many major and minor incidents; some good (e.g., Japan recognizing Bitcoin as a legal method of payments, CME lunching Bitcoin Futures, Goldman Sachs announcing to open Bitcoin trading operation), but many bad events including hacking, theft, loss, and seize. In Table 3 we report the major Bitcoin heists from June 2011 till September 2018. We found altogether 20 major hacking incidents, and 14 of these incidents

[14] The remaining two eigenvalues are 0.73 and 0.60, and hence, we do not consider those as dominant.

correspond to a monetary equivalent of more than a million dollar. Like traditional currency, Bitcoin runs on the belief system too. Bad news like being "hacked", "theft" or "lost" make investors uncertain about the security of the blockchain system, as pointed out in Klein et al. (2018). Though the value of Bitcoin hacked might be small in terms of its economic magnitude, the occurrence of hacking itself might have a significantly negative impact on the investors' common risk perception simply because one may argue that if it's possible to hack small amounts of Bitcoin there exists also a potential possibility to hack even larger amounts. In fact, hacking is a serious security breach for any system.

Kahneman and Tversky (1979) proposed the nowadays well-known prospect theory that describes the way people choose between probabilistic alternatives involving risk, where the probabilities of outcomes are uncertain. One important implication of Kahneman and Tversky's (1979) prospect theory is that people overreact to negative events: When losing a certain amount of monetary equivalent, the investor's utility decreases in relative terms more than it would increase when the same amount of monetary equivalent is gained. This behavioral phenomenon is often referred to as loss aversion. Moreover, Kahneman (2011) points out that biologically, people pay more attention to negative news than positive news. Another effect that might play a role in our current research is referred to as availability heuristic which is according to Kahneman (2011) a cognitive bias. As a typical and intuitive example for such availability heuristic, Kahneman (2011) refers to peoples' decision to go by train instead of taking an airplane after two airplane crashes might have occurred in the last month which implies that people over-estimate the risk of airplane crashes as their memories recall those immediate negative examples. These two effects combined might provide a potential explanation for investor behavior that we observe in our study: First, investors feel threatened by hacking that occurred in the cryptocurrency market. Even small losses are perceived as large threats for the security system. Due to availability heuristic investors form the perception that the threat could be also present in other currency markets such as the traditional currency market. In turn, the uncertainty in the foreign exchange market co-moves with the uncertainty is the cryptocurrency market.

As a first example, let's consider 'The Silk Road Article' published on 1st June, 2011 which drew large number of media attention about the misuse of Bitcoin. One could buy any imaginable drug from the dark web using Bitcoin. A 28-year-old physicist from Texas lunched the startup 'Silk Road, anonymous marketplace' in February 2011. Within just few months he became one of the greatest drug lords in history and changed the way people buy and sell illegal drugs.[15] This bad incident on Bitcoin was immediately followed by the first ever Bitcoin hacking from Mt. Gox

[15] See www.techrepublic.com published on May 10, 2017.

Exchange. On 19 June, 2011, a hacker altered the nominal value of Bitcoin to one cent and transferred 2000 BTC and later sold them at the original price.[16]

At that point in time, there was a little awareness about the possible security breach on the exchange level, but people had started believing that cryptocurrency will be the next generation money. Unfortunately, these two events decreased the trust and consequently market participators started questioning whether or not Bitcoin is a scam. Interestingly, in the wake of those two major incidents, the risk co-movement of Bitcoin with traditional currency market spiked. People overreacted to negative events and uncertainty spilled over from the cryptocurrency market to the traditional foreign exchange market. From Figures 3 and 4 we observe that the volatility spillover index spiked in the middle of April 2011 and remained high until June 2011 implying that the volatility in both markets shared a common component during that period.

Furthermore, in autumn 2011 there were no major incidents reported in the Bitcoin market. Figures 3 and 4 show that the volatility spillover index exhibits very low levels of co-movement in autumn 2011 implying that the risk in the cryptocurrency market is (conditionally) uncorrelated with the traditional foreign exchange market during that period. After everything was looking calm, however, MyBitcoin exchange suffered a theft worth a million dollar, which gradually started increasing the level of risk co-movements between Crypto and Traditional currency market. Bitcoin faced three minor hackings in between March 2012 to September 2012 (see Table 3). Even though the collective value of Bitcoin hacked was less than a million dollar, it raised an issue regarding the security of the blockchain system. After these events, we again observe a high level of co-movement between the risk in Bitcoin and foreign exchange market (caused by hacking events 3 and 4; see Table 3). It is interesting to note that the huge spike in the realized volatility of Bitcoin (see Figure 2) started even before the withdrawals halts from Mt. Gox on 7 February 2014 due to insolvency. The volatility spike also ends along with the trading suspension of Mt. Gox on 24 February 2014.

In November 2013, two Bitcoin exchanges were hacked in the same month. Picostocks and Inputs.io lost collectively around three and a half million dollar (see Table 3). Again, from Figures 3 and 4 we observe that these incidents were associated with a high level of co-movement in volatility lasting for fifteen weeks. After the collapse of Mt. Gox in February 2014, three other Bitcoin exchanges were hacked. Good events such as 'BitLicense' and 'Braintree' (see Table 4) do not result in a decrement of co-movements, but back to back hacking again leads to high levels of co-movement in volatility between Crypto and Foreign Exchange market (Figure 3 and 4). Similar patterns can be seen when Mintpal hacking was followed by three other major hackings. They collectively lost around eleven million dollar. During the same period, New York Department of Finance released 'BitLicense', which we denoted as acceptance, (7A in Figure 4) does not seem to play any significant

[16] BTC means unit of Bitcoin.

role in driving down the risk co-movement. In fact, the risk co-movement stayed for 22 weeks (Figure 3). This implies that bad events overshadow good events in regard with risk co-movement.

Next, when Bitstamp was hacked the second time in January 2016 with equivalent values of five million dollar, the later hacking incident did not get much attention despite of equal value lost. We can see the small spike in Figure 3, but with just a marginal effect. Furthermore, within just a couple of months two more hackings took place between August and October 2016: In the history of Bitcoin, Bitfinex hacking was the highest ever hacked value compared to previous hackings, thus it dramatically shook the market. Bitfiex suffered seventy seven million dollar loss whereas Bitcurex faced one and a half million dollar in loss (see incidents 16 and 17 in Table 3). These incidents scared both types of currency investors and kept the risk co-movement on a high level for more than six months (33 weeks as reported in Figure 3). When hacking started becoming a common phenomenon in the cryptocurrency market, to keep the exchange and the trust of customers alive, many exchanges started paying their customers from their own assets. For example, sixty two million dollar worth of Bitcoin from Nicehash Exchange was hacked during December 2017, but Nicehash repaid almost sixty percentage of total value lost to its customers from their repayment program.[17] As a result, the co-movement spike came down immediately after the reimbursement announcement. From Figure 3 and 4 in association with Tables 3 and 4 we can observe that virtually all spikes in the volatility spillover indices are accompanied by the Bitcoin hacking incidents. From Figures 1 and 2 we can see that the volatilities in both time series were relatively low but the evolution of our spillover indices shows high levels of co-movements indicating that the uncertainty in those distinct markets were driven by a common component.

In Figure 4, we plot the events related to acceptance or banns excluding hacking and theft incidents, along with the first principal component of our volatility spillover indices. We found that news regarding acceptance or banning of the Bitcoin has no consistent effect on the risk co-movement. We will discuss this issue in more detail in the robustness check section. Moreover, the time varying interdependence, in our case the risk co-movement with the foreign exchange market, stays for a longer period of time if the incidents are related to hacking. Specifically, Table 3 in association with Figure 3 provides evidence for that the duration of co-movement depends in particular on the total market value of Bitcoin hacked: The higher the market value of Bitcoin hacked, the longer is the duration of risk co-movement. If there are multiple hackings within a short span of time, the co-movement is longer in comparison to single hacking incidents where the lost value is higher. There are series of good events that make Bitcoin more authentic and trustworthy. But, one minor hacking incident overshadows all previously accumulated good events. One simple explanation to this phenomenon is related to general human psychology: due to market participators' overreaction

[17] See www.nicehash.com, published on May 1, 2018.

to bad news in association with availability heuristics, risk spills over from Bitcoin to G-10 currencies.

Even if there are multiple good events happening in the market, one small hacking incident outweighs them. This is line with Baumeister, Brastslavsky, Finkenauer and Vohs (2001) who briefly discuss on the reasoning for ‘why should bad be stronger than good?’ They argue that survival requires urgent reaction to possible bad incidents than good incidents. For an adaptive reasoning, we are psychologically designed to respond to bad events more strongly than to good ones. Since our respond to bad events is stronger than to good ones, bad events will have longer duration and generate more intense outcomes than our responds to good events. We can feel that the effects of good incidents disappear quicker than those of bad incidents. The authors further find that single bad events are far stronger than multiple strongest good ones, which is, in essence, what we find in our study as well. The long term impact of bad incidents like hackings can clearly be observed in our empirical analysis.

One could wonder if there were any incidents or crisis periods in the currencies that are employed to compound the dollar factor. Considering the G-10 currency market, however, we could not observe any major crisis event in any of those currencies. The only potential candidate for a currency crisis could have been the Euro due to the European debt crisis. However, the first phase of the global financial crisis began on 9 August 2007 with the seizure in the banking system precipitated by BNP Paribas announcing that it was ceasing activity in three hedge funds that specialized in US mortgage debt, whereas 9 May 2010 marked the peak of the Euro debt crisis where the focus of concern switched from the private sector to the public sector due to the severe problems in Greece.[18] However, this period is not a part of the sample that we employed in our study. Notably, Vidal-Tomás and Ibañez (2018) examine the semi-strong efficiency of Bitcoin in two biggest Bitcoin exchanges. They study how Bitcoin responds to its own events and traditional monetary policy. Their findings indicate that Bitcoin has become more efficient over time with respect to events occurring in the Bitcoin market, whereas they did not find any evidence of Bitcoin being affected by any monetary policy news. Their study covers the monetary policy events announced during 2011 and 2017 by major central banks around the world: Federal Reserve System, European Central Bank, Bank of Japan, and Bank of England. Their findings show that cryptocurrency markets are not affected by events originated from the traditional currency market, which strongly supports our findings. In the next section, we will see that the data show that the risk spillovers originate from Bitcoin.

[18] Larry Elliott is Economics editor of The Guardian and his article *Global financial crisis: five key stages 2007-2011*was published online on Sunday 7 August 2011 16.49 BST.

5. Robustness Checks

Concerning the econometric model, one could argue that the selection of an in-sample rolling time-window corresponding to 36 weeks is an arbitrary choice. We would like to mention, however, that Grobys and Heinonen (2017) also face a similar lack of data availability and operate with an in-sample rolling time-window 36 weeks in their main analysis. To clarify what is the impact of the choice concerning the length of the in-sample time-window, we again follow Grobys and Heinonen (2017) and re-estimate the model using an in-sample time-window of only 30 weeks employing otherwise the same parameter constellations for the VAR model as in the previous analysis. The results are shown in Figure A.2 in the appendix. Visual inspection of Figure A.2 shows that the spillover indices exhibit virtually the same clustering as in Figure A.1 which confirms the findings in Grobys and Heinonen (2017). Moreover, we again employed a principal component analysis and found that the covariance matrix of all three spillover indices exhibits only one dominant eigenvalue with an economic magnitude of 1.44 explaining 48% of the covariance matrix. The remaining two eigenvalues are 0.94 and 0.62. Again, we compounded the corresponding time series of the eigenvector related to the first principal component and plot it in Figure A.3 in the appendix. Visual inspection of Figure 3 and Figure A.3 reveals that both time series evolutions share very similar features.[19]

However, another valid concern that is not addressed in Grobys and Heinonen (2017) could be that the ordering of the variables in the *y*-vector could matter because the Cholesky decomposition of the covariance matrix, used to estimate the forecast-error variance decompositions, is a lower triangular. Specifically, Lütkepohl and Krätzig (2004, p.166) argue that a shock in "the first variable may have an instantaneous effect on all the variables, whereas a shock in the second variable cannot have an instantaneous impact". The authors also highlight that using a Cholesky decomposition approach is to some extent arbitrary. Applied to our current research setting, choosing the vector $\boldsymbol{Y}_t = \left(VAR_t^{Dollar}, VAR_t^{Crypto}\right)'$ means that we implicitly make the assumption that the uncertainty of the dollar factor, measured by its variance, may have an instantaneous effect on the uncertainty of the cryptocurrency, whereas the variance of the cryptocurrency is assumed not to have an instantaneous effect. While this might seem intuitively plausible as the real foreign exchange market is considerably larger in turns of turnover than the corresponding digital counterpart, there is, however, no theoretical model available to justify this approach. Therefore, to address this issue, we re-organized the vector as $\boldsymbol{Y}_t = \left(VAR_t^{Crypto}, VAR_t^{Dollar}\right)'$. Using the same parameter constellations as in the initial analysis, we first estimated the corresponding spillover indices using an in-sample time-window of 36 months and then, as an additional robustness check, we also estimated the spillover indices using an in-sample

[19] Unsurprisingly, the economic magnitude of the corresponding first principal component between those two time series is 1.50 and explains 75% of the covariance matrix.

time-window of 30 months. We plot the corresponding spillover indices in Figure A.4 and A.5 in the appendix.

While those indices appear to be somewhat smoother compared to the initial analysis, we again observe the same type of clustering. Periods of high and low levels of volatility spillovers alternate and coincide with those periods shown in the graphs of Figures 3, 4 A.1. and A.2. To clarify statistically whether the ordering matters or whether those indices where we changed the order of variables would indeed measure the same stochastic interdependencies as shown in the main analysis, we employ all those 12 estimated spillover indices and make use of principal component analysis. Strikingly, there is only one dominant eigenvalue with an economic magnitude of 5.16 explaining 43% of the overall covariance matrix. Furthermore, we compound the corresponding time series of the eigenvector related to the first principal component and plot it in Figure 5. Figure 3 and 5 exhibit virtually the same stochastic patterns. In fact, the correlation between the two indices is as high as 0.86 which implies that the ordering of the variable is in our research setting negligible. This finding has indeed another important implication namely that both markets – even though they are very distinct in their nature – respond to the same news components.

Next, we employ the time series of the first principal component of 12 volatility spillover indices and again plot the hacking incidents in Figure 5. Our findings indicate that the duration of risk co-movement is consistent with our previous findings. Interestingly, the plot shows even clearer pattern compared to the one in Figure 3. Since Figure 5 is less erratic, the duration triggered by Linode and Bitcoinca hacking incidents (incidents 3 and 4 in Table 3) as well as Nicehash and CoinSecure hacking incidents (incidents 18 and 19 in Table 3) are visually clearer to observe. Using the same time series of the first principal component, we highlight in Figure 6 Bitcoin acceptance (denoted as ‘good events’) and banns (denoted as ‘bad events’) incidents. Again, this analysis confirms our previous finding that market participators do not seem to care about any major or minor incidents unless the incident is related to hackings. Our empirical findings have an important implication namely that the common driving force that links the market risk in Bitcoin and Foreign Exchange market originates from bad incidents related to Bitcoin, specifically hacking incidents. This means, in turn, that uncertainty that originates from the smaller market infects the larger market but there is no such evidence the other way around. However, that anecdotal fact that smaller entities are capable of shaking large entities is certainly nothing new. The European debt crisis might serve as most recent example: The European debt crisis started first in Greece which is, in terms of GDP, among the smallest economies in Europe. In the wake of severe financial problems faced in Greece, other and considerably larger economies started to report problems also and then the whole vehicle of the European Monetary Union ended up in troubles.

There might be many aspects for why hacking is driving the co-movement of risk as a common factor. For instance, human psychology might give us some guidance in terms of investors’ behavior on perceiving good and bad events. Generally, people tend to overreact to bad news and underreact on good news, as pointed out in Baumeister, Brastslavsky, Finkenauer and Vohs (2001). They argue that the power of bad events is higher over goods events as people tend to process bad information more thoroughly than good information. In our current research context, one single bad event – especially hacking – is perceived stronger than multiple good events in the cryptocurrency market which in turn temporarily links the risk of the foreign exchange market and the cryptocurrency market together.

Another explanation of the risk co-movement could be the rising number of common investors between these two markets. Many investors have been using Bitcoin to trade many traditional currency pairs since 2012. Rauchs and Hileman (2017) also reported that 67% of the cryptocurrency exchanges are national currency to cryptocurrency and vice-versa. The number is rising as is the number of cryptocurrencies and exchanges. According the survey done by Global Blockchian Business Council and Survey Monkey (around 3 million American people took the survey) even though only 5% of Americans own Bitcoin, 60% of them know about it. The recent data on Bitcoin indicates that around 8% of Americans own Bitcoin. This could be similar in other developed countries. The Google search trends figure for 'Bitcoin' in Appendix A.6 shows that it is equally searched by the people of the entire national currency holder nation under G-10 currency group, except for Japan. The search trends shows that people from Switzerland and Norway are more interested in Bitcoin than other G-10 currency nations.

6. **Conclusion**

Due to the failure of cash systems with a central entity, the original purpose of cryptocurrency was to build decentralized digital cash system. A new strand of literature investigates cryptocurrencies from different angels. Following earlier research, we focus on Bitcoin as cryptocurrency, as first of all we have access to the longest time series and second, Bitcoin comprise the lion's share in terms of cryptocurrency market capitalization. By construction, Bitcoin returns lack of correlations to other assets including traditional currency. As a consequence, the finance industry utilized this feature already by launching a whole battery of mutual funds that invest in the cryptocurrency market. Earlier research has shown that Bitcoin volatility is dramatically higher than the volatility of traditional currency. Our current research confirms those findings and, moreover, extends earlier research in important ways. We proxy the traditional currency market by employing the dollar factor. As dollar factor we use an equal-weighted basket of G-10 currencies corresponding to about 70% of the market capitalization in the traditional currency market. First, we find that Bitcoin is unconditionally uncorrelated with our dollar factor even in the second moment of the distributions. To uncover potentially time-varying interdependencies between the uncertainty in the cryptocurrency market and the traditional currency market, we employ recently proposed spillover indices that show to which degree the variance of crypto, respectively, traditional currency is driven by the other market.

Strikingly, our results provide strong evidence for time-varying interdependencies in the conditional second moment. Hacking incidents in the Bitcoin market have an effect on the conditional second moment of dollar factor. Specifically, in the wake of hacking news both markets respond with a high level of co-movement in the variance processes, whereas they are orthogonal when there is no news or good news related to Bitcoin arriving the markets. Another novel aspect that would like to highlight is that the origin for the time-varying pattern in co-movement in the second moment can be traced to the considerably smaller Bitcoin market. This may be surprising news to the naïve investor as this result implies that the smaller market has an impact on the larger one but we do not find such evidence the other way around. Our findings have some important implications for policy makers that target stability in financial markets. The uncertainty in the Bitcoin market has been extraordinary high and even relatively small hacking incidents are found to have a detectable effect on the traditional currency market. Our proposed model may serve as a tool that could guide policy actions intended to monitor, control, or forecast contagion effects across markets helping to ensure financial instability. Future research is encouraged to explore the reciprocity of cryptocurrencies with other conventional assets like commodities, stocks and bonds in similar scenarios.

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Figures

Figure 1. Realized volatility of the dollar factor

This figure plots the realized weekly volatility (annualized) of the dollar factor. As dollar factor we use an equally weighted basket of the G-10 currencies in terms of US-dollar. We employ daily closing price data to calculate the daily returns series for the dollar factor used to estimate the realized weekly volatilities. The data were retrieved from datastream. The sample starts on July 16, 2010 and ends on September 28, 2018.

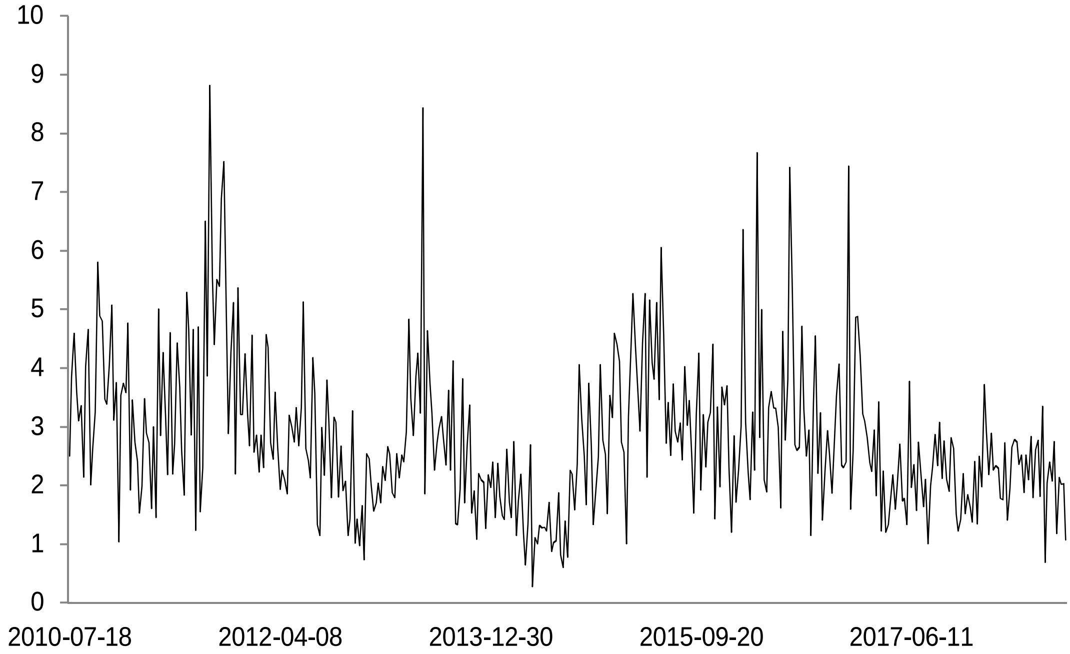


Figure 2. Realized volatility of Bitcoins

This figure plots the realized weekly volatility (annualized) of Bitcoins. We employ daily closing price data to calculate the daily returns series for Bitcoins used to estimate the realized weekly volatilities. For visualization we cap the Bitcoin volatility series for all values above 1100% (corresponding to 10% of the volatility distribution). The data were retrieved from yahoo.com. The sample starts on July 16, 2010 and ends on September 28, 2018.

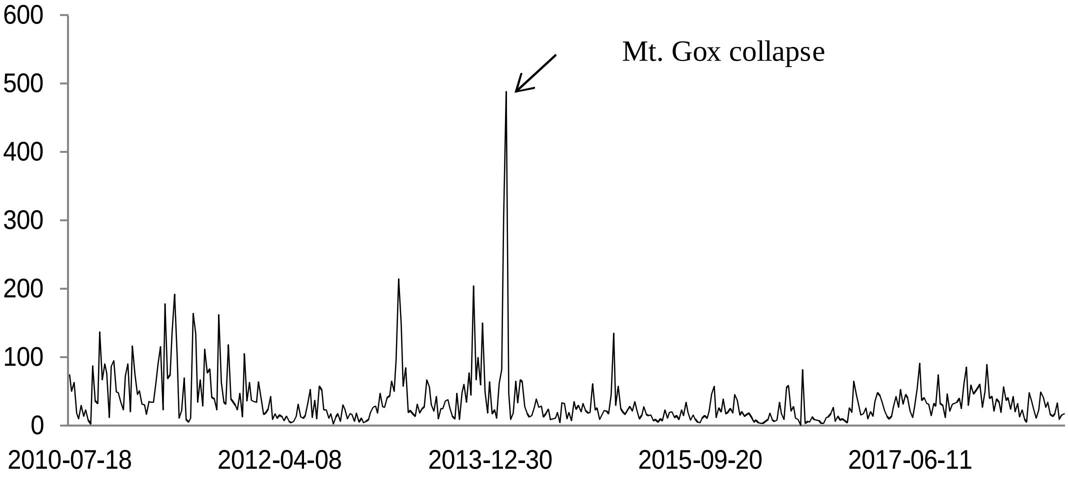


Figure 3. Volatility spillover index between the dollar factor and Bitcoins (Reporting Hacking Incidents Only)

This figure reports the volatility spillover index between the dollar factor and Bitcoins. The spillover index is the first principal component of three volatility spillover indices employing different lag-orders to estimate the underlying Vector-Autoregressive (VAR) models. The VAR models employ a rolling time-window of 36 weeks to estimate the parameter matrices. The data starts on March 21, 2011 and ends on September 28, 2018.

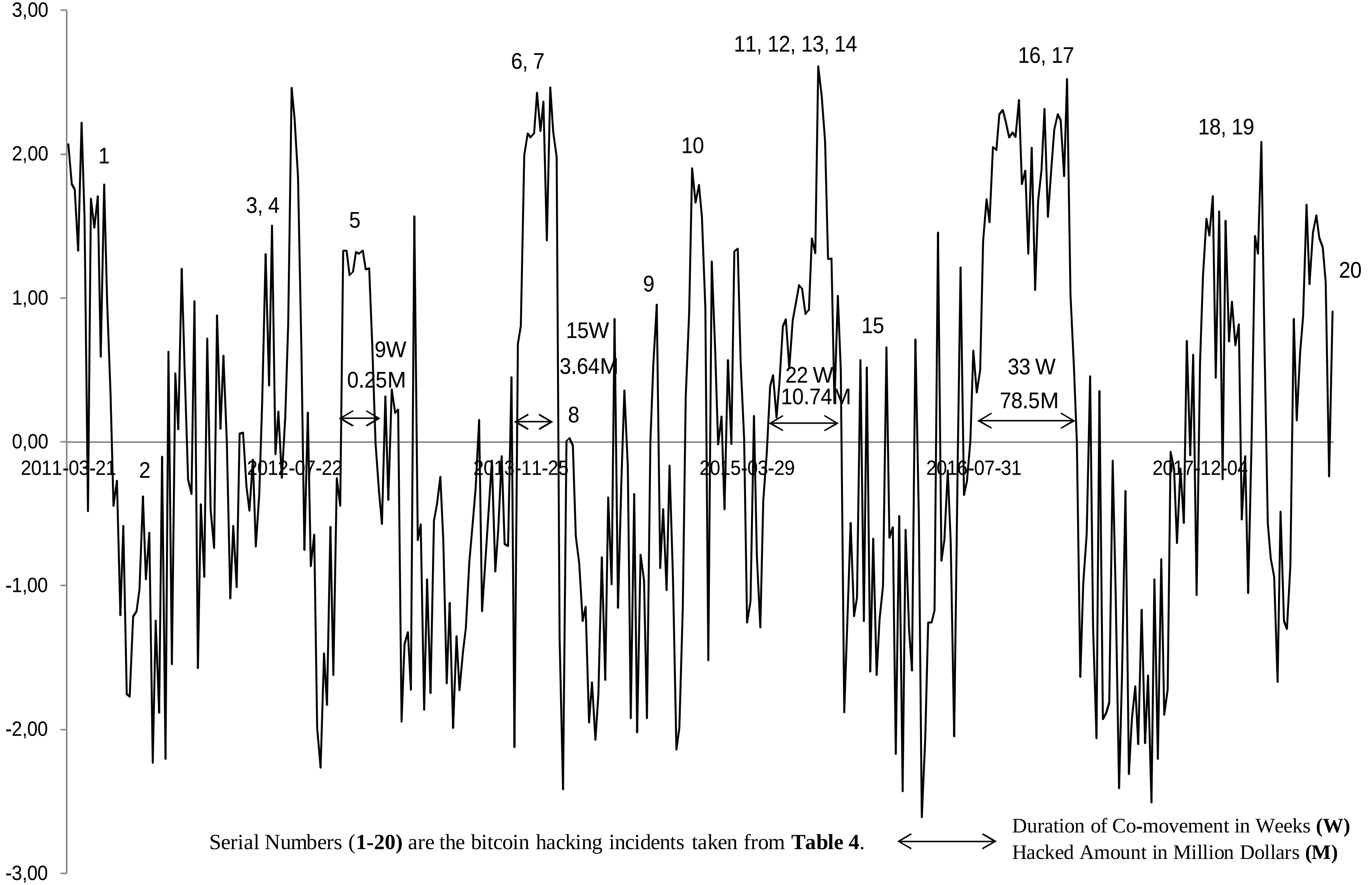
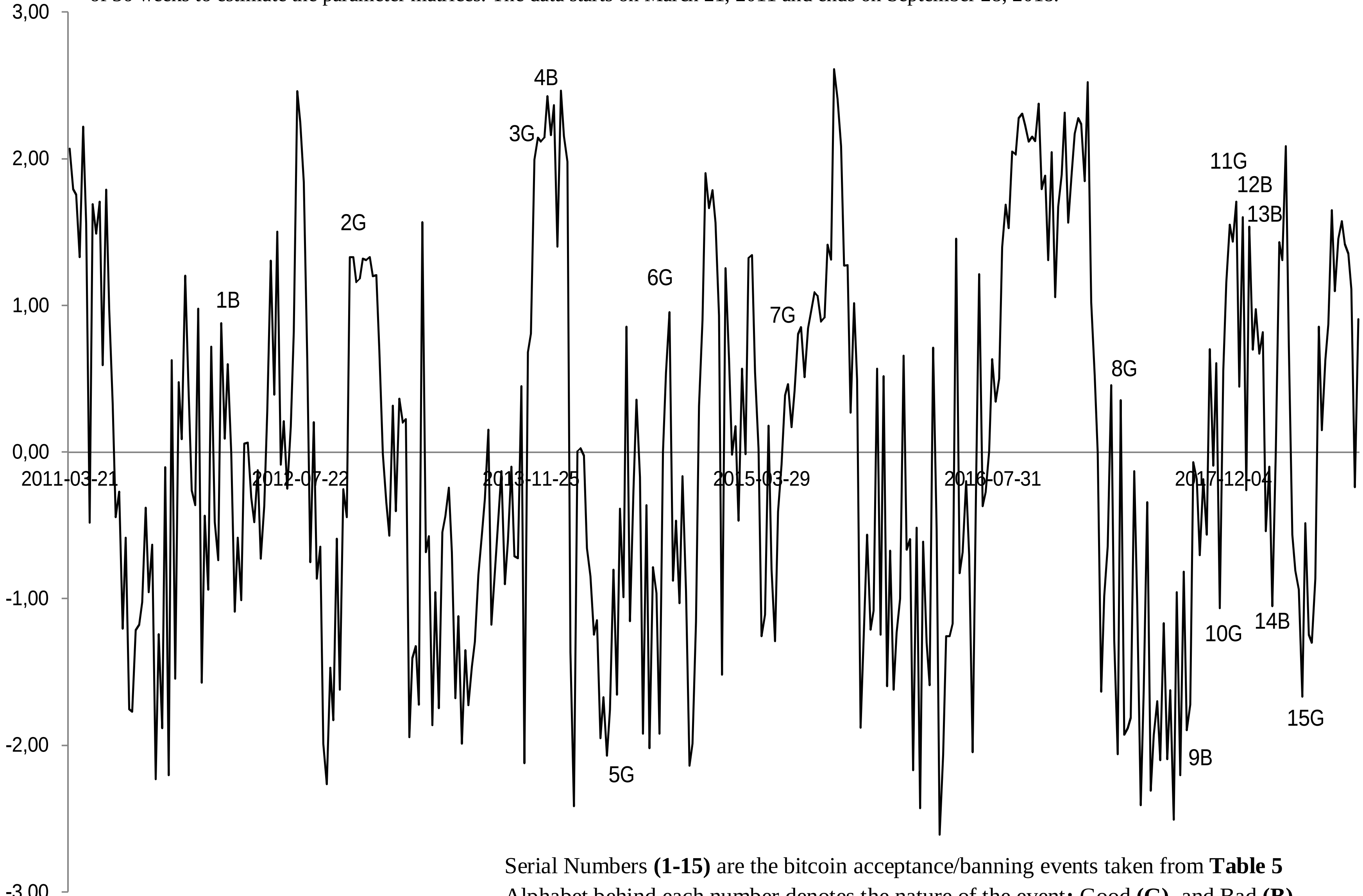


Figure 4. Volatility spillover index between the dollar factor and Bitcoins (Reporting Events Excluding Hacking Incidents)

This figure reports the volatility spillover index between the dollar factor and Bitcoins. The spillover index is the first principal component of three volatility spillover indices employing different lag-orders to estimate the underlying Vector-Autoregressive (VAR) models. The VAR models employ a rolling time-window of 36 weeks to estimate the parameter matrices. The data starts on March 21, 2011 and ends on September 28, 2018.



Serial Numbers **(1-15)** are the bitcoin acceptance/banning events taken from **Table 5**

Alphabet behind each number denotes the nature of the event**:** Good **(G),** and Bad **(B)**

Figure 5. Principal component of volatility spillover indices between the dollar factor and Bitcoins (Hacking Incidents Only)

This figure reports the time series evolution of the first principal component of 12 volatility spillover indices between the dollar factor and Bitcoins. The underlying spillover indices employ different lag-orders (two, four or six lags), different rolling time-windows (30 or 36 weeks), and different ordering of the y-vector $((dollar\ factor_i, bitcoin_t)'$ or $((bitcoin_t, dollar\ factor_i)')$ to estimate the underlying Vector-Autoregressive (VAR) models. The data starts on March 21, 2011 and ends on September 28, 2018.

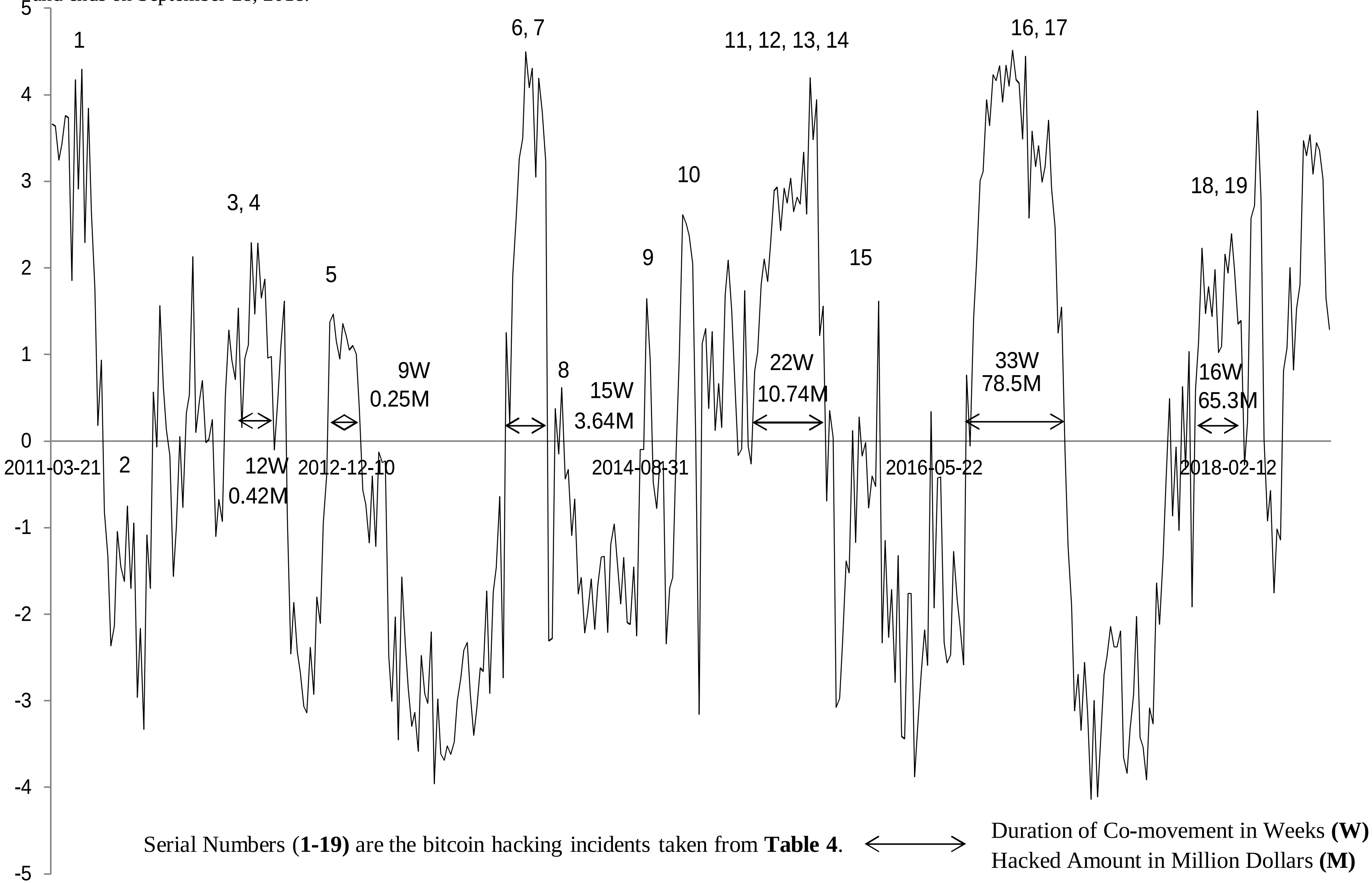
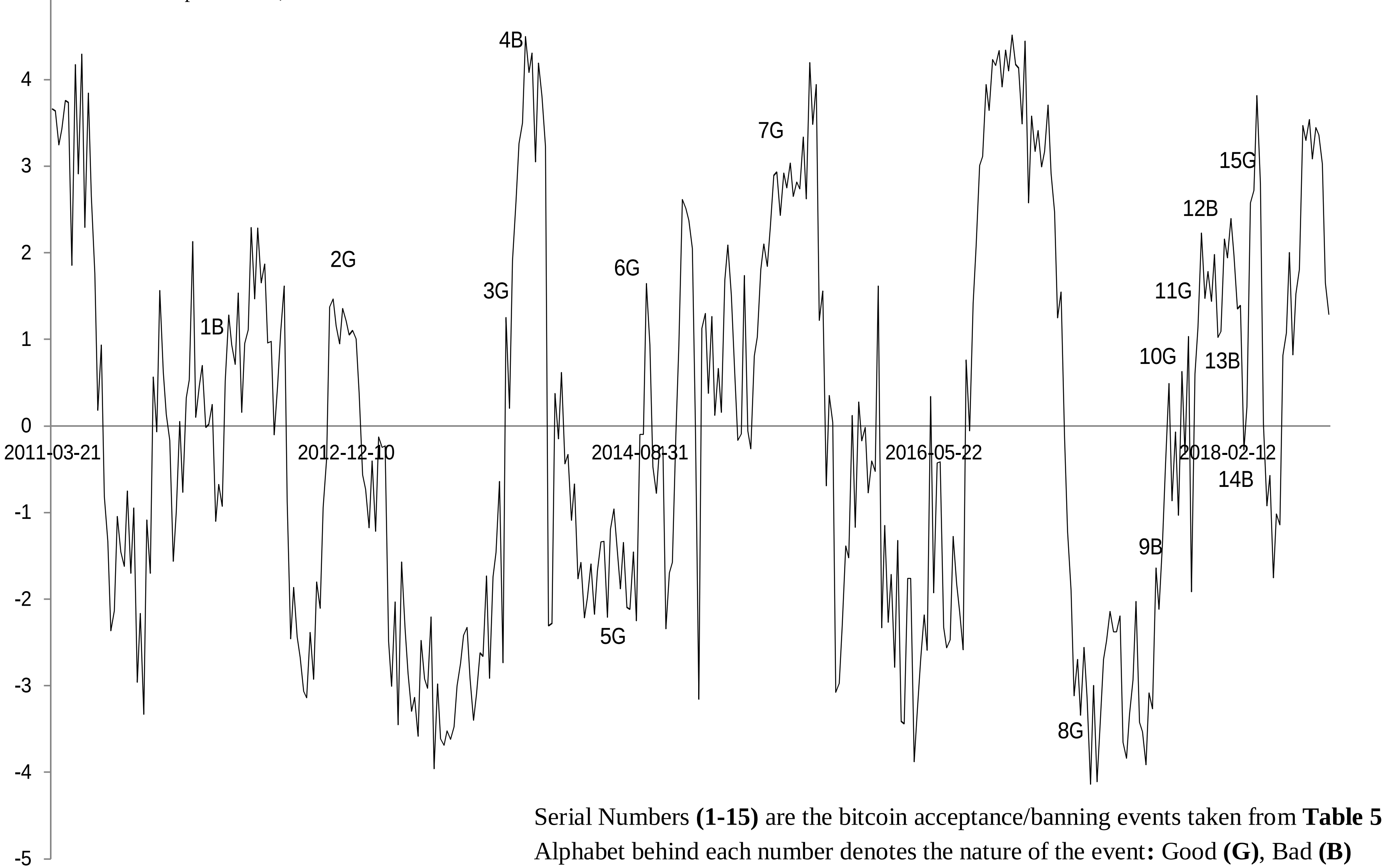


Figure 6. Principal component of volatility spillover indices between the dollar factor and Bitcoins (Excluding hacking incidents)

This figure reports the time series evolution of the first principal component of 12 volatility spillover indices between the dollar factor and Bitcoins. The underlying spillover indices employ different lag-orders (two, four or six lags), different rolling time-windows (30 or 36 weeks), and different ordering of the y-vector $((dollar\ factor_i, bitcoin_t)'$ or $((bitcoin_t, dollar\ factor_i)')$ to estimate the underlying Vector-Autoregressive (VAR) models. The data starts on March 21, 2011 and ends on September 28, 2018.



Tables

Table 1. Descriptive statistics

This table reports the descriptive statistics of the weekly returns of the dollar factor and Bitcoins and the weekly volatilities of the corresponding data series. As dollar factor we use an equally weighted basket of the G-10 currencies in terms of US-dollar. We employ daily closing price data to calculate the daily returns series for the dollar factor and the Bitcoins series to estimate the realized weekly volatilities. The data were retrieved from datastream. The sample starts on July 16, 2010 and ends on September 28, 2018.

	Dollar factor[1]	**Bitcoin[1]**	**Dollar factor volatility[a]**	**Bitcoin volatility[a]**
Mean	0.02	1.19	0.18	57.37
Median	0.01	0.88	0.13	11.81
Maximum	1.56	71.14	1.50	4591.65
Minimum	-1.08	-58.36	0.00	0.01
Std. Dev.	0.44	8.25	0.19	1839.03
Skewness	0.26	0.93	3.04	14.20
Kurtosis	3.19	22.72	16.28	240.71
Jarque-Bera	5.43	6978.97	3794.27	1019711.00
(p-value)	(0.07)	(0.00)	(0.00)	(0.00)
Observations	427	427	427	427

[1] in per cent
[a] weekly variance

Table 2. Correlation matrix

This table reports the correlation matrix of weekly returns dollar factor and Bitcoins returns and the weekly variances of the corresponding data series. The data were retrieved from DataStream. The sample starts on July 16, 2010 and ends on September 28, 2018. The corresponding *t*-statistics are reported in parentheses.

	Dollar factor	**Bitcoin**	**Dollar factor variance**	**Bitcoin variance**
Dollar factor[1]	1			
Bitcoin[1]	-0.07 (-1.52)	1		
Dollar factor variance[a]	0.10** (2.10)	-0.03 (-0.60)	1	
Bitcoin variance[a]	-0.01 (-0.29)	0.27*** (5.73)	0.00 0.02	1

** Statistically significant on a 5% level
*** Statistically significant on a 10% level
[1] in per cent
[a] weekly variance

Table 3. Major Bitcoin Heist in Chronological Order

This table reports the major Bitcoin heist since June 2011 to September 2018. The heist includes incidents like hacking and theft of Bitcoin from the exchange as well as the collapse of it. There are many other incidents of Cryptocurrency exchange heists; we take into considerations of those incidents where Bitcoin is lost. Volume includes the number of Bitcoin lost and Value includes the lost value in US Dollar based on the market price on that particular incident day.

S.No.	Date	Exchange/Event	Volume (BTC)	Value ($)
1	June 19, 2011	Mt. Gox Hacking	2000	47123
2	Aug 2011	MyBitcoin Theft	154,406	2 Million
3	March 1, 2012	Linode Hacking	46,653	223278
4	May 12, 2012	Bitcoinica Hacking	18,547	191638
5	Sept 5, 2012	BitFloor Hacking	24,000	250,000
6	Nov, 2013	Picostocks Hacking	5896	3 Million
7	Nov, 2013	Inputs.io Hacking	4,100	640615
8	Feb, 2014	Mt. Gox Collapse	850,000	450 Million*
9	July 29, 2014	Cryptsy Hacking	13,000	7,5 Million
10	Dec 11-12, 2014	BitPay Hacking	5000	1.8 Million
11	Dec, 2014	Mintpal Hacking	3,894	3,2 Million
12	Jan 4, 2015	Bitstamp Hacking	19,000	5,1 Million
13	Feb 2015	Kipcoin Hacking	3,000	690,000
14	Feb 2015	Bter Hacking	7,170	1,75 Million
15	Jan, 2016	Bitstamp Hacking	18,866	5,2 Million
16	Aug 2, 2016	Bitfinex Hacking	119,756	77 Million
17	Oct 2016	Bitcurex Hacking	2300	1,5 Million
18	Dec 2017	Nicehash Hacking	4,700	62 Million
19	April, 2018	CoinSecure Hacking	438	3,3 Million
20	Sept 2018	Zaif Hacking	5,966	60 Million

Source: Bitcointalk.org

***** This is the collective amount of Bitcoin hacked/lost from Mt. Gox over several years. The name Mt. Gox is an acronym for “Magic: The Gathering Online Exchange.” At its peak, it was the world’s largest bitcoin exchange: handling up to 80% of trading volume. It halted withdrawals on 7 February 2014 due to insolvency and also suspended trading on 24 February 2014.

Table 4. Some Major Bitcoin Events (Excluding hacking and theft)

This table reports the major Bitcoin acceptance and banning events in chronological order. In our notation, banning events that have a negative impact on Bitcoin are denoted as B (e.g, Bad), and accepting events that have a positive impact on Bitcoin are denoted as G (e.g., Good).

S.No.	Date	Events	Nature
1	11-Feb-12	Paxum and Tradehill drop Bitcoin as online payment	**B**
2	15-Nov-12	Wordpress starts accepting Bitcoin	**G**
3	20-Nov-13	Peoples' Bank of China allows Bitcoin	**G**
4	5-Dec-13	China bans financial institutions from using Bitcoin	**B**
5	18-Jul-14	Dell starts accepting Bitcoin as online payment	**G**
6	8-Sep-14	Paypal subsidiary 'Braintree' starts accepting Bitcoin	**G**
7	3-Jun-15	New York Department of Finance releases "BitLicense"	**G**
8	1-Apr-17	Japan recognizes Bitcoin as a legal method of payment	**G**
9	15-Sep-17	China shuts down all Bitcoin and Crypto exchanges in China	**B**
10	31-Oct-17	CME announces Bitcoin Futures	**G**
11	11-Dec-17	CBOE lunches Bitcoin futures	**G**
12	28-Dec-17	South Korea threatens to shut down Cryptocurrency	**B**
13	30-Jan-18	Facebook bans Crypto ads	**B**
14	14-Mar-18	Google bans Crypto ads	**B**
15	2-May-18	Goldman Sachs announces to open Bitcoin trading operation	**G**

Source: 99Bitcoins.com

Appendix

Figure A.1. Volatility spillovers indices using a rolling time window of 36 weeks and variations of the lag order

This figure plots the time series evolutions of volatility spillover indices using the realized weekly volatilities of the dollar factor and Bitcoins. The underlying Vector-Autoregressive models account for a rolling time-window of 30 weeks and different lag-orders between two, four or six weeks. We employ forecast-error variance decompositions using horizons of $h = 1$ month. The data start on March 21, 2011 and end on September 28, 2018.

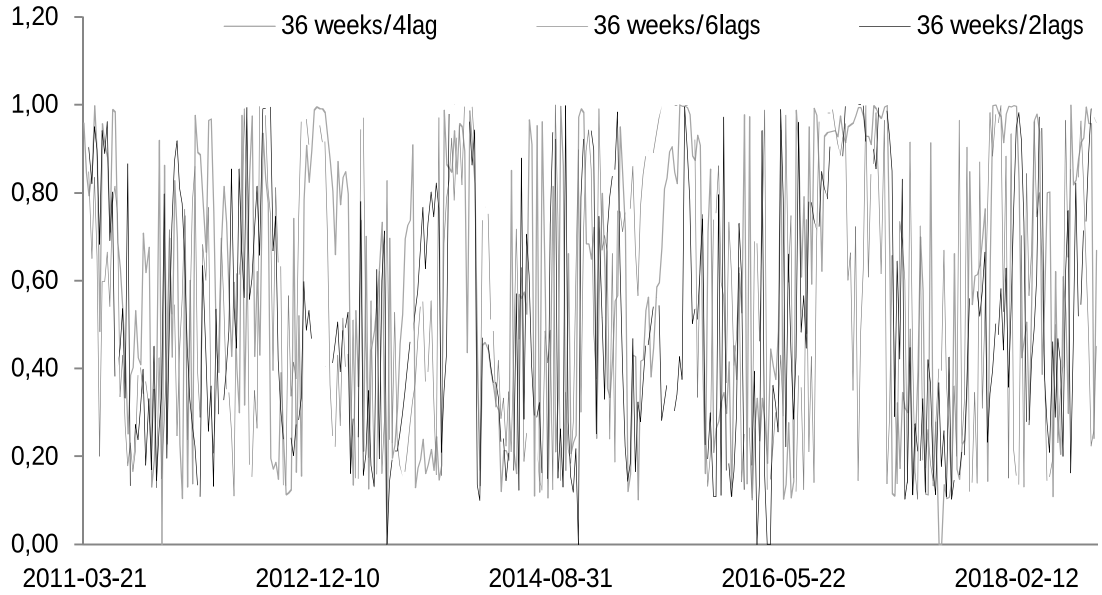


Figure A.2. Volatility spillovers indices using a rolling time window of 30 weeks and variations of the lag order

This figure plots the time series evolutions of volatility spillover indices using the realized weekly volatilities of the dollar factor and Bitcoins. The underlying Vector-Autoregressive models account for a rolling time-window of 30 weeks and different lag-orders between two, four or six weeks. We employ forecast-error variance decompositions using horizons of $h = 1$ month. The data start on March 21, 2011 and end on September 28, 2018.

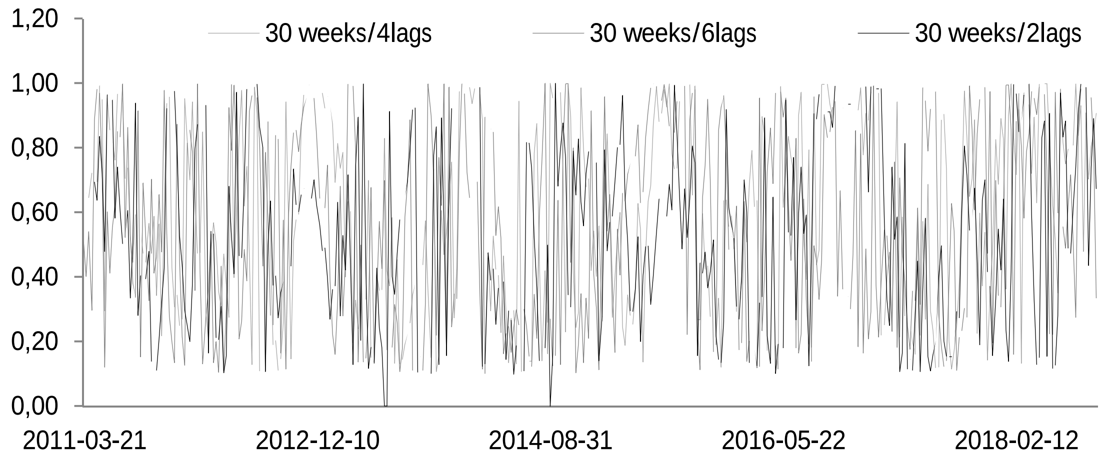


Figure A.3. Volatility spillover index between the dollar factor and Bitcoins employing a rolling time-window of 30 weeks

This figure reports the volatility spillover index between the dollar factor and Bitcoins. The spillover index is the first principal component of three volatility spillover indices employing different lag-orders to estimate the underlying Vector-Autoregressive (VAR) models. The VAR models employ a rolling time-window of 30 weeks to estimate the parameter matrices. The data starts on March 21, 2011 and end on September 28, 2018.

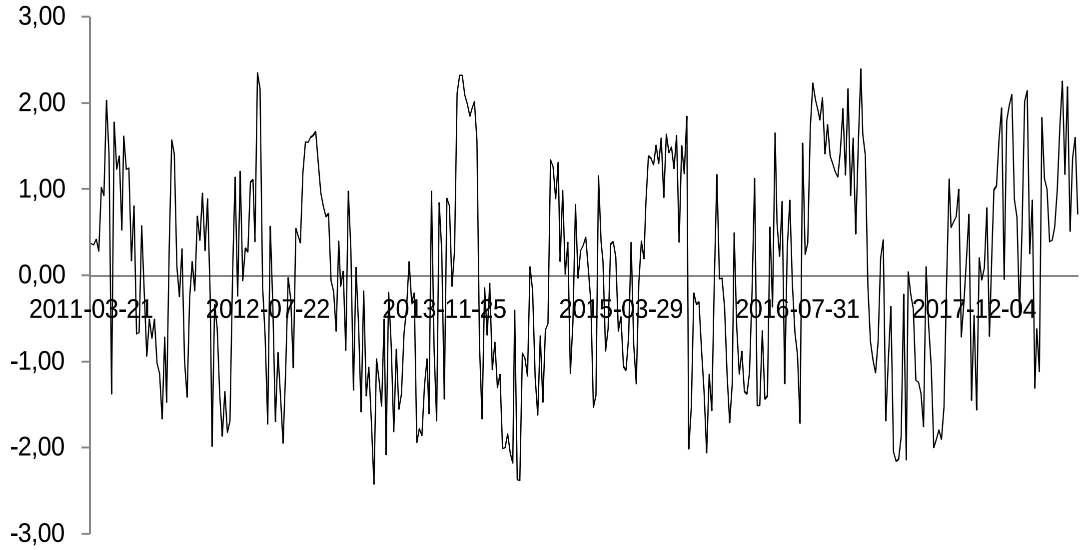


Figure A.4. Volatility spillovers indices using a rolling time window of 36 weeks, variations of the lag order and changing the cholesky ordering

This figure plots the time series evolutions of volatility spillover indices using the realized weekly volatilities of the dollar factor and Bitcoins. The underlying Vector-Autoregressive (VAR) models account for a rolling time-window of 36 weeks and different lag-orders between two, four or six weeks. For setting up the VAR models, the input vectors are ordered such that the volatility series of the Bitcoins is the first element in the y-vector and the volatility series of the dollar factor is the second element. We employ forecast-error variance decompositions using horizons of $h = 1$ month. The data start on March 21, 2011 and end on September 28, 2018.

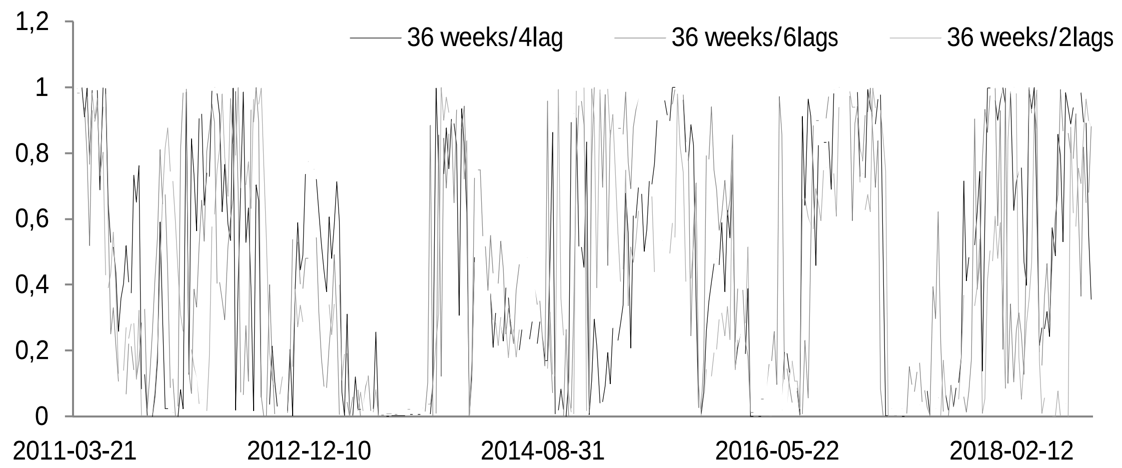


Figure A.5. Volatility spillovers indices using a rolling time window of 30 weeks, variations of the lag order and changing the cholesky ordering

This figure plots the time series evolutions of volatility spillover indices using the realized weekly volatilities of the dollar factor and Bitcoins. The underlying Vector-Autoregressive (VAR) models account for a rolling time-window of 30 weeks and different lag-orders between two, four or six weeks. For setting up the VAR models, the input vectors are ordered such that the volatility series of the Bitcoins is the first element in the y-vector and the volatility series of the dollar factor is the second element. We employ forecast-error variance decompositions using horizons of $h = 1$ month. The data start on March 21, 2011 and end on September 28, 2018.

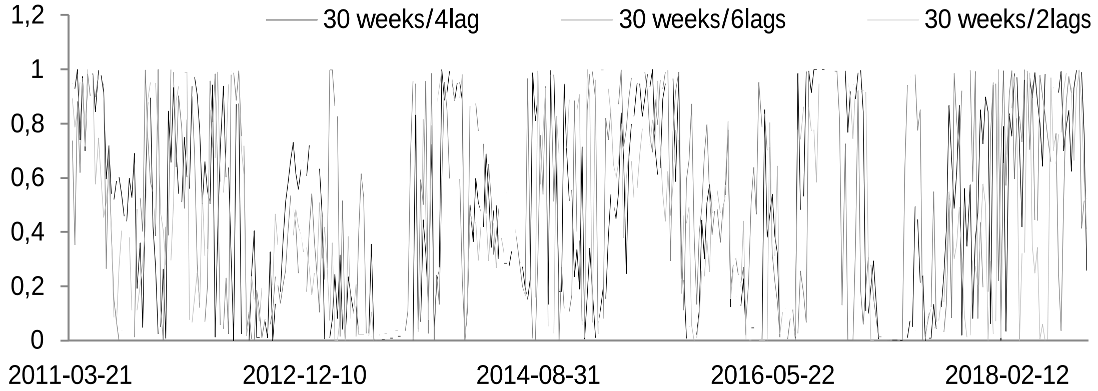


Figure A.6. Google search trends of 'Bitcoin' for last 5 years around G-10 countries

This figure reports the Google search trends of the term 'Bitcoin' in 9 different nations of G-10 currency countries during 17.11.2013 to 17.11.2018. The daily search data is downloaded from the Google Trends.

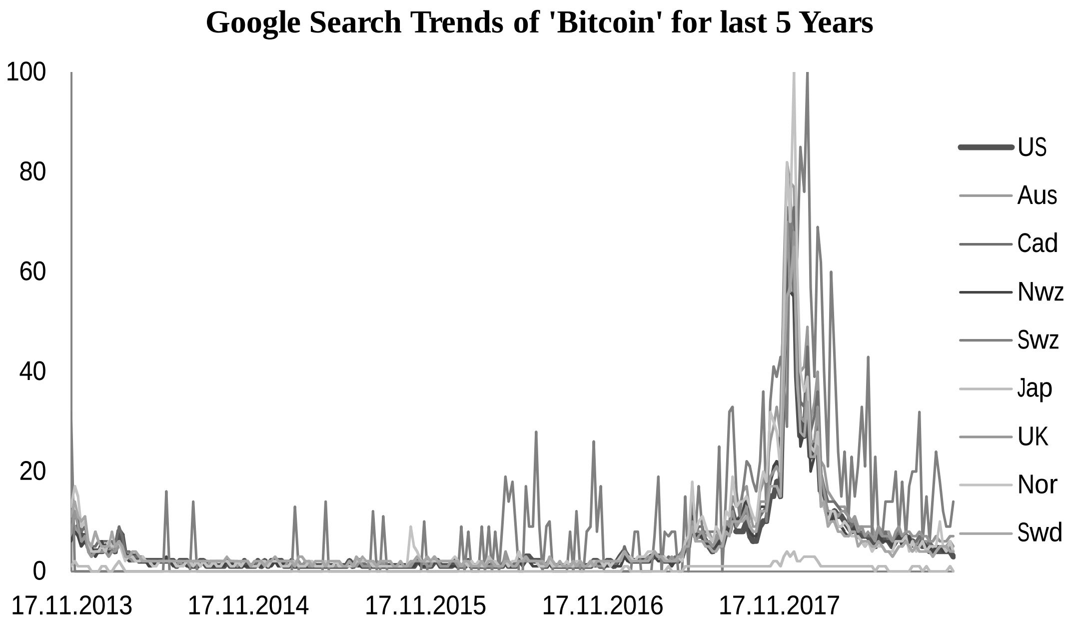


Table A.1. Percentage of Exchanges Supporting National Currencies

This table reports the percentage of cryptocurrency exchanges supporting national currencies as a medium of exchange. Besides USD, EUR, GBP and JPY, other remaining G-10 currencies fall under the 'Other' category which includes 42 other national currencies.

S.No.	Currency	% of Exchange
1	USD	65
2	EUR	49
3	GBP	39
4	JPY	18
5	CNY	14
6	Other (42 National Currencies)	53

Source**:** Rauchs and Hileman (2017)

Table A.2. Currency mix of payment service providers

This table reports the currency mix of cryptocurrency payment service providers. National to national is the old method of payment where the payment service providers allow deposits and withdrawal in traditional currencies only. In the national to cryptocurrency mix (and vice-versa), they accept deposits and withdrawal in either of the currencies. Cryptocurrency to cryptocurrency payment mix is limited to cryptocurrencies only.

S.No.	Currency Mix	Number of Transactions in %	Transaction Volume($) in %
1	National to National	26	27
2	National to Crypto (and vice-versa)	68	67
3	Cryptocurrency to Cryptocurrency	6	6

Source**:** Rauchs and Hileman (2017)

Table A.3. Most Downloaded and Most Cited Articles that are related to Bitcoin in some high class Journals[a]

Journal	Articles	Most Downloaded	Most Cited
Journal of Financial Stability	The economics of Bitcoin and similar private digital currencies- (Dwyer, 2015)	×	×
Journal of International Financial Markets, Institutions and Money	Virtual relationships: Short- and long-run evidence from BitCoin and altcoin markets- (Ciaian and Rajcaniova, 2018)	×	
	Bitcoin: Medium of exchange or speculative assets?- (Baur, Hong and Lee, 2018)	×	
	Price discovery on Bitcoin exchanges- (Brandvold et al., 2015)	×	×
Economic Letters	Speculative bubbles in Bitcoin markets? An empirical investigation into the fundamental value of Bitcoin- (Cheah and Fry, 2015)	×	×
	Volatility estimation for Bitcoin: A comparison of GARCH models- (Katsiampa, 2017)	×	
	The inefficiency of Bitcoin- (Urquhart, 2016)		×
	On the inefficiency of Bitcoin- (Nadarajah and Chu, 2017)		×
Finance Research Letter	Bitcoin, gold and the dollar - A GARCH volatility analysis- (Dyhrberg, 2016)	×	×
	Hedging capabilities of bitcoin. Is it the virtual gold? - (Dyhrberg, 2016)	×	×
	On the hedge and safe haven properties of Bitcoin: Is it really more than a diversifier? – (Bouri et al., 2017)		×
	Bitcoin, gold and the US dollar – A replication and extension- (Baur et al., 2018)	×	

[a] As of October 2018

Table A.4. Market capitalization of Cryptocurrencies

This table reports the market capitalizations of the ten Cryptocurrencies that exhibit the highest market capitalization. The data was retrieved from coinmarketcap.com.

No.	Name	Market Capitalization[a]	Share (in %)
1	Bitcoin	113 960 844 389	61
2	Ethereum	22 845 301 537	12
3	XRP	20 692 808 794	11
4	Bitcoin Cash	8 936 883 916	5
5	EOS	5 203 368 771	3
6	Stellar	4 603 595 003	2
7	Litecoin	3 407 911 963	2
8	Tether	2 795 605 608	1
9	Cardano	2 113 148 215	1
10	Monero	1 875 406 824	1

[a] As of October 5, 2018 (source: https://coinmarketcap.com)