Asymmetric effect of volatility spillover in global Virtual Financial

Assets (VFAs) markets: A case of Bitcoin

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Abstract: In this paper, we measure the asymmetric volatility spillover among six Bitcoin markets from 1 January 2014 to 30 September 2017, using the volatility spillover index based on Markov regime switching VAR model, and provide the static and dynamic analysis under different regime. The static results show that asymmetric effects of volatility spillover exist in total, own and net volatility spillover of different Bitcoin markets under different regime. The dynamic results show that there are significantly asymmetric effects in total, directional and net volatility spillover. Thus, the authorities should monitor the specific regime of VFAs and improve market mechanisms.

Keywords: Asymmetric effect, spillover, Virtual Financial Assets, Bitcoin, MSVAR

1 Introduction

Bitcoin, which is the most notable currency in VFAs markets, has captured the interested of the public. By 1 Nov 2018, the market capitalization of Bitcoin, which accounts for 54% of total VFAs market, has surpassed 203 billion US dollars (USD) according to coinmark-etcap.com. A great deal of literature has focus on the performance of VFAs (Begušić 2018; ElBahrawy 2017; Li 2018; Phillip 2018; Pichl 2017; Takaishi 2018). However, most of literature focuses on Bitcoin only and pays little attention to the relationship,

especially return-volume or price inconsistency, among global VFAs markets (Pieters 2017; Zhang 2018).

Exploring the asymmetric effect of volatility spillover among global VFAs market contributes to understanding the dynamics of volatility spillover and providing useful information for market participants (e.g., investors and policy makers). Asymmetry effect characterizes the differences of spillover in different VFAs' volatility regimes. On the one hand, due to the characteristics existing among VFAs market, such as long-range memory and randomness (Lahmiri 2018), the dynamics of VFAs market volatility may exhibit some unique performance, such as heterogeneity and nonlinear, require further documentation and analysis in order to better comprehend the inherent dynamics of VFAs market. On the other hand, Bitcoin is mainly used as a speculative investment or a tool of money laundering in global VFAs markets as country become more financial integrated (Baur 2018; Gandal 2018; Kethineni 2018). Oftentimes, if investors have useful information in the global VFAs market, they can use it to adjust asset portfolios or create investment or hedging strategies when the market is in a different level of volatility. For policy makers, it is difficult to implement global regulatory framework as there are no uniform in VFAs markets. In general, many process of money-laundering use VFAs as medium of exchange because they provide additional confidentiality by its anonymity. The seemingly invisible nature of VFAs makes it difficult to identify who is using them and what they are buying. These unique features make it beneficial for international criminals to replace old-fashioned cash transactions with digital currency (Mihm 2013). Therefore, to explore how asymmetric effect existing in global VFAs markets is important for market participants.

This paper use the spillover indexes proposed in Diebold and Yilmaz (2009) and its variant to obtain an overall picture of volatility shock among different Bitcoin markets and investigates how this evolves over time. Chow (2017) and Nishimura (2018) use Diebold-Yilmaz spillover indexes to compute the return volatility among different stock market. Of other studies that apply the same methodology, Yi (2018) and BenSaïda (2018), which examines the volatility spillover in the cryptocurrency market and spillover shifts in global financial market, respectively, is closest to our paper. Unlike these papers, we extend the work by incorporating a Markov regime framework with two regimes into the generalized vector autoregressive (VAR) model among six Bitcoin markets. Our motivation for Markov regime framework is to extend the volatility spillover analysis, by shedding light on the dynamics of volatility spillovers among global Bitcoin markets during largely documented turmoil periods.

There exists extensive literature dealing with the differences between VFAs markets. Some studies focus on the characteristics such as price, return-volume and nonlinear volatility, among different Bitcoin markets. Pieters (2017) examines the differences in Bitcoin price across 11 different markets and conclude that those which do not require customer identification for establishing an account are more likely to deviate from representative market prices than those which do. Zhang (2018) finds that the nonlinear dependencies and power-law cross-correlations in return-volume relationship among 8 Bitcoin market and the price of small fluctuations is more persistent than that of the volume, while the volume of larger fluctuations is more anti-persistent. Lahmiri (2018) provides evidence that Bitcoin cannot be considered suitable for hedging purposes as Bitcoin markets are highly disordered and risky.

Alongside the high volatility of Bitcoin markets are paid more attention, there are good reasons to believe that Bitcoin and altcoin might be interdependent. An econometric investigation by Ciaian (2018) proves that indeed Bitcoin and altcoin markets are interdependent and the Bitcoin-altcoin price relationship is significantly stronger in the short-run than in the long-run. Wei (2018) examines the liquidity of 456 different cryptocurrencies and concludes that liquidity plays a significant role in market efficiency and return predictability of new cryptocurrencies. In addition, Gandal and Halaburda (2016) examine the impact of network effects on the Bitcoin and six altcoins markets and found heterogeneous behavior of their prices over time. They find that in the early period Bitcoin and altcoins were purchased as financial assets rather than for usage as currency driven by the increased general interest in virtual currencies, as opposed to Bitcoin specifically. In latter period their results show the presence of strong network effects favored Bitcoin against altcoins causing divergent price development between them. Osterrieder et al. (2017) have investigated statistical similarities and extreme value behavior of the six virtual currencies. Their results suggest that the virtual currencies exhibit non-normal statistical properties that are similar for similar virtual currencies which share the same underlying technology.

Another strand of literature concentrates on linkages among VFAs as well as other assets. A growing research emerges on relationships between Bitcoin and other traditional assets and assessment whether Bitcoin can be used as, a safe-haven, or a hedging asset (Baur, Dimpfl, and Kuck 2018; Bouri et al. 2018; Ji et al. 2018). For example, Baur et al. (2018) analyzes the relationship between Bitcoin, gold and the US dollar and concludes that Bitcoin exhibits distinctively different return, volatility and

correlation characteristics compared to other assets including gold and the US dollar. Bouri et al. (2018) finds significant evidence that Bitcoin returns are related quite closely to those of most of the other assets studies, particularly commodities, and therefore, the Bitcoin market is not isolated completely. Ji et al. (2018) uses a data-driven methodology to uncover the contemporaneous and lagged relations between Bitcoin and other asset and finds that the Bitcoin market is quite isolated, and no specific asset plays a dominant role in influencing the Bitcoin market. Otherwise, some studies focus on the potential crowding-out effects of fiat currency or VFAs. For instance, Hong et al. (2018) finds that crowding out occurs only under extreme assumptions, i.e., extremely high costs associated with the use (medium of exchange and store of value) of one currency and extremely low costs associated with the use of the other currency. Luther (2016) uses an even simpler network effects model to consider the conditions under which a cryptocurrency like Bitcoin might crowd-out an existing money. Hendrickson et al. (2016) consider the potential for government transaction policy to prevent an alternative money like Bitcoin from circulating in an endogenous search model. However, to accurately investigate the asymmetric effect of volatility spillover, we prefer the full power of unpredictable regime shift detection offered by Markov regime switching models.

Our works focus on the asymmetric effect of volatility spillover in global VFAs market has following contributions. First, we investigate volatility spillovers based on the global VFAs markets. Much previous research has focus on the interconnectedness among different cryptocurrencies. But there is a lack of research on the spillover in global VFAs markets. Second, this article incorporates a Markov regime-switching into a vector autoregressive model to infer the multiple spillover indices. Unlike existing literature, we

explore the asymmetric effect in different regimes and provide static and dynamic analysis on the patterns of volatility spillover (including total spillover, directional spillover and net spillover) in the VFAs market. The static results show that in the same regime, different markets show different spillover in own and nets and asymmetric effects of volatility spillover exist in total, own and net volatility spillover of different Bitcoin markets under different regime. The dynamic results show that there are significantly asymmetric effects in total, directional and net volatility spillover.

The remainder of the article is organized as follows. Section 2 discusses the research methodology. Section 3 presents the data and discusses the results. Section 4 shows robustness about our analytic solutions. Finally, Section 5 summarizes the main findings and provides concluding remarks.

2 Methodology and variable

2.1 Markov regime-switching vector autoregressive (MSVAR)

The multivariate VAR model can be employed as a simple framework to measure volatility spillovers across different markets (Diebold and Yilmaz 2009, 2012). In this paper, we further explore the asymmetric effect of volatility spillover in global VFAs markets, by allowing a Markov regime-switching vector autoregressive (MSVAR). Consider a K-state MSVAR model in (1).

$$\mathbf{y}_t | s_t = \mathbf{v}_k + \sum_{i=1}^p \Phi_{k,i} \mathbf{y}_{t-i} + \mathbf{u}_{s_t,t}. \quad (1)$$

where $\mathbf{y}_t$ is a 6-dimensional volatility vector including six Bitcoin markets in global markets, such that USD, EUR, JPY, GBR, KRW, CNY¹; s_t is an unobservable variable

¹ We focus on these six markets based on the market share and data availability.

governed by a first order Markov process; $\{\Phi_{k,i}\}_{i=1}^p$ are (n×n) state-dependent matrices ($\Phi_{k,p} \neq \mathbf{0}$, where $\mathbf{0}$ denotes the n-by-n null matrix) and $\mathbf{u}_{s_t,t}$ is a vector of residuals.

To allow for different variances in each regime, we set $\mathbf{u}_{s_t,t} = \Sigma_k \varepsilon_t$, with ε_t is a stationary and ergodic sequence of zero-mean independently and identically distribution (i.i.d.) white noise process assumed to be multivariate normal, i.e. $\varepsilon_t \sim i.i.d.N(\mathbf{0}_n, \mathbf{I}_n)$, where $\mathbf{I}_n$ is (n×n) identity matrix, and $\mathbf{0}_n$ is a (n×1) vector of zeros. Σ_k represents a lower triangular (n×n) regime-dependent Cholesky factorization of the symmetric variance-covariance matrix denoted Ω_k . In other words, $\Omega_k = \Sigma_k \Sigma_k'$. Hence, we can get (2).

$$\mathbf{v}_k | s_t \sim N(\mathbf{0}, \Omega_k). \quad (2)$$

Each regime $k=1,2,\dots,K$ can be characterized by its variance-covariance matrix Ω_k . The model need not artificially set thresholds to determine different regime levels of spillover, nor does it need to estimate in advance the timing of each regime. Moreover, the spillover level is determined by smooth transition according to the state of Bitcoin market. The autoregressive parameter matrices control the intensity of spillovers among different market volatility, depending on the regime. The Markov switching heteroskedastic variance-covariance matrix is exploited to identify structural shocks in the errors (Herwartz and Lütkepohl 2014).

The state variable $\{s_t\}$ evolves according to a discrete, homogeneous, irreducible and ergodic first-order Markov chain with the transition probability matrix $\mathbf{P}$, i.e., for K

regimes $s_t = \{1, 2, \dots, K\}$. Each element of $\mathbf{P}$ stands for the probability of being in regime j at time t , knowing that at time $t-1$ the regime was i . This can be expressed as (3).

$$\mathbf{P} = \begin{pmatrix} p_{1,1} & \cdots & p_{1,K} \\ \vdots & \ddots & \vdots \\ p_{K,1} & \cdots & p_{K,K} \end{pmatrix} \quad (3)$$

$$p_{i,j} = \Pr(s_t = j \mid s_{t-1} = i).$$

where each column of $\mathbf{P}$ sums up to one, $\sum_{i=1}^K p_{i,j} = 1$. In case of two regimes, the transition matrix becomes (4).

$$\mathbf{P} = \begin{pmatrix} p & 1-q \\ 1-p & q \end{pmatrix}. \quad (4)$$

The ergodic or unconditional probability $\boldsymbol{\pi}$ is the eigenvector of $\mathbf{P}$ corresponding to the unit eigenvalue normalized by its sum. It satisfies $\mathbf{P}\boldsymbol{\pi} = \boldsymbol{\pi}$ and $\mathbf{1}_K' \boldsymbol{\pi} = 1$, where $\mathbf{1}_K$ is a $(K \times 1)$ column vector of ones (Hamilton 1994, 684). Formally,

$$\boldsymbol{\pi} = (\mathbf{A}'\mathbf{A})^{-1} \mathbf{A}' \begin{bmatrix} \mathbf{0}_K \\ 1 \end{bmatrix}. \quad (5)$$

where $\mathbf{0}_K$ is a $(K \times 1)$ column vector of zeros, and

$$\mathbf{A}_{(K+1) \times K} = \begin{bmatrix} \mathbf{I}_K - \mathbf{P} \\ \mathbf{1}_K' \end{bmatrix}. \quad (6)$$

In other words, $\boldsymbol{\pi}$ is the $(K+1)$ th column of $(\mathbf{A}'\mathbf{A})^{-1} \mathbf{A}'$. In the special case of two regimes, the unconditional probabilities are expressed as (7).

$$\begin{cases} \pi_1 = \frac{1-q}{2-p-q} \\ \pi_2 = \frac{1-p}{2-p-q} \end{cases}. \quad (7)$$

Estimating MSVAR models is rather difficult, especially for large number of variables. In this paper, we perform the estimation by maximum likelihood (ML) using the iterative expectation-maximization (EM) algorithm, as discussed in Krolzig (1997,

103) and BenSaïda (2018). Each iteration of the EM algorithm consists of two steps E (expectation) and M (maximization), repeated until convergence². In addition, we also restrict the intercept vector to be constant across regimes to isolate the asymmetric effect of volatility spillover through heteroskedastic variance-covariance matrix.

2.2 The concept of spillovers

The error variance decomposition records how much of VFAs market i influences the h -step-ahead forecast error of another market j . Based on this, Diebold and Yilmaz (2009, 2012) develop a spillover measure and extend the spillover metric to make it invariant to ordering. The proposed framework conveys a great deal of market information via a single spillover measure.

Formally, consider the covariance-stationary K -state MSVAR model propose in (1).

The vector moving average (VMA) representation of that model is (8).

$$\mathbf{y}_t | s_t = \boldsymbol{\omega}_k + \sum_{j=0}^{\infty} \mathbf{A}_{k,j} \mathbf{u}_{s_t, t-j} \cdot \boldsymbol{\omega}_k. \quad (8)$$

where $\mathbf{A}_{k,j}$ are $(n \times n)$ matrices that obey to (9).

$$\mathbf{A}_{k,j} = \sum_{i=1}^p \boldsymbol{\Phi}_{k,i} \mathbf{A}_{k,j}. \quad (9)$$

with the initial value being the identity matrix $\mathbf{A}_{k,0} = \mathbf{I}_n$ and $\mathbf{A}_{k,j} = \mathbf{0}$ for $j < 0$. The vector

$\boldsymbol{\omega}_k$ is obtained by applying the infinite order inverse autoregressive lag-operator to $\mathbf{v}_k$, i.e., $\boldsymbol{\omega}_k = (\mathbf{I}_n - \sum_{i=1}^p \boldsymbol{\Phi}_{k,i})^{-1} \mathbf{v}_k$, and it does not interfere with the variance decomposition.

Generally, the infinite-order VMA in (8) is truncated at h -step-ahead to forecast the error variance.

² The detail can be seen in BenSaïda (2018).

The generalized h -step-ahead forecast error variance decomposition shares in regime k can be defined as (10).

$$\theta_{k,ij}^g = \frac{\sigma_{k,ij}^{-1} \sum_{l=0}^{h-1} (\mathbf{e}_i' \mathbf{A}_{k,l} \Sigma_k \mathbf{e}_j)^2}{\sum_{l=0}^{h-1} (\mathbf{e}_i' \mathbf{A}_{k,l} \Sigma_k \mathbf{A}_{k,l}' \mathbf{e}_i)}. \quad (10)$$

where $\sigma_{k,ij}$ is the standard deviation of the error for the j th VFAs markets, and $\mathbf{e}_i$ is a selection column with the i th element equals one and zeros elsewhere. Since the variance decomposition is based on the generalized impulse response functions, the sum of each row in the variance decomposition table is $\sum_{j=1}^n \theta_{k,ij}^g(h) \neq 1$. Therefore, we should normalize the variance shares to ensure that row sums up to one as (11).

$$\bar{\theta}_{k,ij}^g(h) = \frac{\theta_{k,ij}^g(h)}{\sum_{j=1}^n \theta_{k,ij}^g(h)}. \quad (11)$$

We define the total spillover index in regime k to measure the contribution of spillover of volatility among global VFAs markets to the total forecast error variance in (12).

$$S_k^g(h) = \frac{1}{n} \sum_{\substack{i,j=1 \\ i \neq j}}^n \bar{\theta}_{k,ij}^g(h). \quad (12)$$

Alternatively, we can compute the directional spillover to explore the contribution of each VFAs markets in the spillovers of other markets and their directions. We respectively define that the spillover received by VFAs market i from all other market in (13) and the spillovers transmitted from VFAs market i to all other markets in (14).

$$S_{all \rightarrow i}^g(h) = \frac{1}{n} \sum_{\substack{j=1 \\ i \neq j}}^n \bar{\theta}_{k,ij}^g(h). \quad (13)$$

$$S_{i \rightarrow all}^g(h) = \frac{1}{n} \sum_{\substack{i=1 \\ i \neq j}}^n \bar{\theta}_{k,ij}^g(h). \quad (14)$$

Contribution from other markets in (13) is simply the off-diagonal row sum of normalized generalized variance decomposition shares in (11), and can never exceed the 1 because each row of the forecast error variance decomposition shares matrix sum up to one. Similarly, contribution to other VFAs market is the off-diagonal column sum of the normalized generalized variance decomposition shares in (11), and can exceed 1 when the market in concern has a major impact in transmitting shocks to others.

Furthermore, we define the net volatility spillovers from VFAs market i to all others in (15) as the difference between the gross volatility shocks transmitted from i to others, and the gross volatility shocks received by i from others.

$$S_{k,i}^g(h) = S_{k,i \rightarrow all}^g(h) - S_{k,all \rightarrow i}^g(h). \quad (15)$$

2.3 Variable measurement

Fundamental information regards VFAs' prospects. Price time-varying and the continuous nature of diffusion path are fundamental information of VFAs. The price of Bitcoin mainly dependent on two separate sources: arbitrage trades and speculative trades from investors. Since the information is asymmetry and the price is unlimited, the price changes have made the VFA market unstable, which in turn affects investors' expectations of the market. What's more, the diffusion path is another key factor for investors to make investment decision. In addition, while many varieties of public data in Bitcoin are possible, we also should consider here only those which are truly universal in their accessibility to investors, namely, data appearing in the financial pages of the newspaper. In particular, we shall consider volatility estimators which are based on the historical opening, closing, high and low prices. Therefore, follow Garman and Klass

(1980), we use daily range-based volatility to estimate daily volatility of each Bitcoin markets. From market i on day t , we can define the volatility as (16).

$$V_{i,t} = 0.511(H_{i,t} - L_{i,t})^2 - 0.019[(C_{i,t} - O_{i,t})(H_{i,t} + L_{i,t} - 2O_{i,t}) - 2(H_{i,t} - O_{i,t})(L_{i,t} - O_{i,t})] - 0.383(C_{i,t} - O_{i,t})^2. \quad (16)$$

where $H_{i,t}$, $L_{i,t}$, $C_{i,t}$ and $O_{i,t}$ high, low, closing and opening price of Bitcoin market i on day t .

3 Data and static analysis

3.1 data used in the analysis

In the analysis, we use six Bitcoin markets from 1 January 2014 to 30 September 2017. These markets including BitStamp (USD), LocalBitcoins (EUR), BTCBOX (JPY)³, LocalBitcoins (GBP), Korbit (KRW) and BtcTrade (CNY). We obtain the data including high, low, closing and opening prices for each Bitcoin market from <https://bitcoincharts.com/>. The beginning date of the sample is determined by the standard of least missing value in six markets. We choose the ending date of the sample because the People's Bank of China and other seven ministries and commissions issued the "Announcement on Preventing the Risk of Subsidy Issuance Financing", stating that the financing of token issuance is essentially an un-authorised illegal public financing, and various types of token financing activities are immediately stopped at 4 September 2017. In order to compare the fluctuations of Bitcoin's different market fluctuations and prevent the complexity of analysis due to excessive data, this paper normalizes the fluctuations obtained by eq. 16 and plots these in Figure 1.

³ We collected data from 1 January 2014 to 28 February 2014 in Mt.Box (JPY).

Figure1 Volatility indices in different Bitcoin markets

Figure 1 shows the volatility indices in six Bitcoin markets during the sample period. We can clearly notice that there are significant differences of volatility between different markets at different times. On the one hand, a difference exists in the magnitude of the fluctuations. In the initial sample period, JPY, KRW, CNY reach a peak and there is basically no volatility at other Bitcoin markets. What's more, JPY has the heaviest volatility. Since the end of 2016, however, the volatility of different Bitcoin markets has

increased significantly, and the magnitude in developing countries markets (KRW, CNY) is larger than that in developed countries. The reason of this phenomenon is that Bitcoin was proposed by Nakamoto at 2008 and began to enter the market for trading in 2011. This makes Bitcoin has more volatile in the Asian markets. Due to the borderlessness of Bitcoin, more and more international investors pay attention to the changes in the Bitcoin price. The trading difference between Bitcoin and traditional financial assets provides an opportunity for investors to earn the excess expected returns. Meanwhile, the influx of investors also poses a major challenge for markets regulation. The financial market in developed countries has a long development time and high effectiveness, so it can better control the Bitcoin market fluctuations.

On the other hand, there is significant difference in the cluster of volatility. It can be seen from Figure 1 that the cluster mainly exists in the JPY, KRW, CNY Bitcoin markets in the initial sample period. And at the end of sample period, the cluster exists in all Bitcoin markets but the duration time has significant difference. This further proves that the more effectiveness in financial market, the better volatility regulation in Bitcoin market. Otherwise, the plots clearly exhibit some similarities in the volatility patterns, which strongly suggest the presence of a spillover effect in global Bitcoin market.

3.2 estimation of MSVAR

It is a baseline for estimating MSVAR model to test unit root in order to preventing the pseudo-regression. In this paper, we carry out the ADF test for each volatility series. The results show as Table 1.

It can be seen from Table 1 that all ADF statistics are significant at the 5% level, suggesting that the Bitcoin markets volatility in USD, EUR, JPY, GBP, KRW and CNY are suitable for MSVAR model.

Table 1: The results of ADF test

	ADF-1% level	ADF-5% level	ADF-10% level	ADF-Statistics	Prob.
USD	-2.5667	-1.9411	-1.6165	-18.3260	0.000
EUR	-2.5667	-1.9411	-1.6165	-8.0944	0.000
JPY	-2.5667	-1.9411	-1.6165	-6.1480	0.000
GBP	-2.5667	-1.9411	-1.6165	-15.9179	0.000
KRW	-2.5667	-1.9411	-1.6165	-17.1305	0.000
CNY	-2.5667	-1.9411	-1.6165	-2.2088	0.026

After solving the unit root test, we need to determine the regime number before estimating the MSVAR model. Several studies suggest that financial market evolve according to two distinct regimes, a high-risk regime during crisis (bad time), and a low-risk regime during non-crises (good time) (Rigobon 2016; Leung et al. 2017). Therefore, following BenSaïda (2018), we limit our MSVAR to two regimes to study the inherent dynamics of volatility spillover, i.e., moderate and intense spillovers. The result can be seen in Table 2.

From Table 2, we characterize the different regime in variance-covariance matrix Ω_1 and Ω_2 . In regime 1, the diagonal elements of the Ω_1 is 0.016, 0.010, 0.072, 0.005, 0.077, 0.121, which are smaller than these in regime 2, that is 303.34, 322.66, 304.66, 321.31, 266.90, 260.31. It is clearly know that variance-covariance matrix can be exploited to identify structural shocks if the reduced form error covariance matrix varies across states (Lanne 2010). Therefore, we define the regime of volatility spillover in global Bitcoin markets via variance-covariance matrix. In this paper, we regard regime 1 as moderate spillover regime and regime 2 as intense spillover regime. Furthermore, we

can see the expected duration is 16.66 days in moderate regime and 5.87 in intense spillover regime, which claims that it is easier to maintain the existing state under moderate regime. The same result can be obtained from Figure 2 as well.

Table 2 Markov regime switching VAR

Volatility			USD	EUR	GBP	JPY	KRW	CNY		
R E G I M E 1	AR(1) autoregression matrix									
	USD	Coff.	0.121***	0.0301*	0.184***	0.0066	0.121***	0.1389**		
		Std	0.0210	0.0176	0.0360	0.0142	0.0201	0.0581		
	EUR	Coff.	0.0362	0.756***	0.356***	0.312***	0.401***	0.624***		
		Std	0.0229	0.0235	0.0164	0.0158	0.0941	0.1210		
	JPY	Coff.	0.106***	0.081***	0.188***	-0.005	0.146***	0.0697**		
		Std	0.0126	0.0093	0.0194	0.0066	0.0272	0.0348		
	GBP	Coff.	0.172***	0.2470	0.475***	0.859***	0.434***	0.547***		
		Std	0.0204	0.019***	0.0509	0.0088	0.0872	0.0970		
	KRW	Coff.	0.1184	0.0066	0.0010	-0.009*	0.143***	0.0017		
		Std	0.0104	0.0135	0.0027	0.0052	0.0258	0.0041		
	CNY	Coff.	0.0233	-0.042***	-0.011	-0.06***	0.059***	0.134***		
		Std	0.0347	0.011	0.024	0.0045	0.0198	0.0382		
	Expected duration			16.66	$\Omega_1 (\times 100)$					
	Unconditional probability			0.74	(0.016	0.010	0.072	0.005	0.077	0.121)
AR(1) autoregression matrix										
R E G I M E 2	USD	Coff.	0.408***	-0.006	-0.005	-0.009	-0.003	-0.004		
		Std	0.0474	0.015	0.0124	0.037	0.011	0.016		
	EUR	Coff.	-0.004	0.074***	0.0791*	0.0459	0.0771	0.2336		
		Std	0.013	0.014	0.0433	0.0427	0.022***	0.045***		
	JPY	Coff.	-0.001	-0.034	-0.043	-0.015	-0.233	-0.221		
		Std	0.004	0.0626	0.125	0.061	0.117	0.056***		
	GBP	Coff.	-0.006	0.0089	0.0422	0.1091*	0.0239	0.0461		
		Std	0.017	0.039	0.0495	0.0542	0.0763	0.1125		
	KRW	Coff.	-0.004	-0.029	0.1536**	0.0036	0.696***	0.215***		
		Std	0.015	0.096	0.0668	0.0131	0.058	0.0614		
	CNY	Coff.	-0.004	0.1276	0.295***	0.0788	-0.027	0.532***		
		Std	0.005	0.1754	0.046	0.2354	0.109	0.0607		
	Expected duration			5.87	$\Omega_2 (\times 100)$					
	Unconditional probability			0.26	(303.34	322.66	304.66	321.31	266.90	260.31)
	AIC	-2.95		BIC	-2.89		LogL	14850.19		
Transition probability matrix			p		0.94***					
			q		0.83***					

Note: This table reports the estimation results of a two-regime switching VAR (1).

- *Statistically significant at 0.1 confidence level.
- **Statistically significant at 0.05 confidence level.
- ***Statistically significant at 0.001 confidence level.

The smooth probabilities between moderate and intense spillover regime are plotted in Figure 2. Combining with Table 2, we clearly notice that switching between different regimes occur randomly with significant transition probabilities $p=0.94$ and $q=0.83$, which means that once the volatility spillover for one day in moderate regime, then on average, 0.94 of the time it will remain in this regime for the next day. Similarly, if the volatility spill over for one day in intense regime, the average probability of maintaining the same regime in the next is 0.83. This indicates that the moderate regime is more persistent than intense spillover regime.

Figure 2: Smooth probability between moderate and intense spillover regime

3.3 static analysis

Table 3 is the volatility spillover table for full sample. We estimate volatility at the forecast horizon $H=6$ and the lag order $p=1$. The estimated forecast error variance of

Bitcoin market i contributed by innovations to Bitcoin market j is shown in table's ij -th element. The off-diagonal column and row sum of the table are contributions to other Bitcoin market and contributions from others, respectively. In addition, the row sum is 1, and the volatility spillover contributions from others equal to 1 minus the self-spillover. The difference between “contribution to others” and “contribution from others” is equal to Nets. The Total is off-diagonal column sum (or row sum) divided by the column sum including diagonal elements (or row sum including diagonal elements).

In the same regime, different markets show different spillover in own and nets. In regime 1, the diagonal elements, which represent own volatility spillover, are the largest elements in the same column and all are below 0.70. Among them the largest elements is 0.673 (USD's own spillover) and the smallest is 0.062 (CNY's own spillover). USD is the largest transmitter and the smallest recipient of volatility spillover, which is 2.62 and 0.32, respectively. Conversely, CNY is the smallest transmitter and the biggest recipient of spillover with the degree of 0.008 and 0.937, respectively. To figure out how volatility shocks transmit across six Bitcoin markets, we furthermore discuss the Nets in Table 3. The largest one is net volatility spillover from USD to other markets (2.296), followed by the net volatility from EUR to others (0.706). It is noting that the net spillover in developing market, such as KRW and CNY, are all above 0.80. And the smallest is the net volatility spillover from CNY to others (-0.929). It claims that The USD Bitcoin market is highly effective and can better balance its own spillovers and other market spillovers. The Chinese market with many speculators has a short development time, so it is vulnerable to influence from other markets.

Performing a similar analysis in regime 2, we can clearly know that the own spillovers are the largest individual elements in the table and all above 0.33. Among of them the largest element is 0.9998 (USD's own volatility spillover). USD is both the smallest transmitter and recipient of volatility spillover. What's more, we focus on the net volatility spillover. It is interesting that the largest net spillover is from JPY to other Bitcoin markets. This claims that JPY, as the original of Bitcoin, would transmit their risk into the whole Bitcoin market in the intense volatility spillover. Otherwise, the smallest net volatility spillover is CNY (-0.629). This also demonstrates the importance of market effectiveness and integrity in dealing with volatility spillovers in the Bitcoin market.

Table 3 Directional detailed spillovers under MSVAR

Regime 1							
	USD	EUR	JPY	GBP	KRW	CNY	Contribution from Others
USD	0.673	0.2238	0.0412	0.0476	0.0133	0.0012	0.3271
EUR	0.5859	0.3676	0.0066	0.0377	0.0004	0.0019	0.6325
JPY	0.446	0.2564	0.2506	0.0453	0.0003	0.0013	0.7493
GBP	0.6003	0.2972	0.0023	0.0968	0.0011	0.0024	0.9033
KRW	0.4872	0.267	0.0523	0.0494	0.1426	0.0014	0.8573
CNY	0.5043	0.2945	0.0684	0.0491	0.0215	0.0622	0.9378
Contribution to Others	2.6237	1.3389	0.1708	0.2291	0.0366	0.0082	Total=
Nets	2.2966	0.7064	-0.5785	-0.6742	-0.8207	-0.9296	0.7346
Regime 2							
USD	0.99985	0.00003	0.00003	0.00005	0.00004	0.00001	0.00016
EUR	0.0001	0.99297	0.00121	0.00017	0.00062	0.00492	0.00702
JPY	0.00026	0.01547	0.90049	0.0028	0.05584	0.02514	0.09951
GBP	0.00021	0.00524	0.00185	0.98932	0.00126	0.00212	0.01068
KRW	0.00034	0.00743	0.2138	0.00066	0.77069	0.00707	0.22930
CNY	0.00058	0.08693	0.39389	0.00481	0.18262	0.33118	0.66883
Contribution to Others	0.00149	0.11510	0.61078	0.00849	0.24038	0.03926	Total=
Nets	0.00133	0.10808	0.51127	-0.00219	0.01108	-0.62957	0.1693

Moreover, asymmetric effects of volatility spillover exist in total, own and net volatility spillover of different Bitcoin markets under different regime. The total volatility spillover indicate that 0.7346 and 0.1693 of the average forecast error variance in six

Bitcoin markets come from spillovers in regime 1 and regime 2, respectively. This also indicates that the spillover between different Bitcoin markets in moderate regime is significantly higher than that in intense regime. The same results can be obtained by the diagonal elements. It can be seen from Table 3 that own volatility spillover has significantly increased under intense regime compared with moderate regime. The largest one is own volatility in GBP (from 0.096 to 0.989), and the smallest one is own volatility in CNY (from 0.062 to 0.331). This claims that there are asymmetries in the defense mechanisms of different Bitcoin markets. Under the intense spillover regime, developed countries and regions pay attention to the construction of their own market relevance, and reduce the spillover of other Bitcoin markets by increasing their own spillovers.

Asymmetric effect of net volatility spillover could better depict the risk transmit in different market. The sign of the net volatility spillover represents the size compared transmitter to recipient of volatility. It is worth noting (i) that the net volatility spillover of USD Bitcoin market is changed from the positive largest in moderate regime to the smallest in intense regime, which are 2.296 to 0.001, (ii) that the net spillover of JPY and KRW Bitcoin markets change negative to positive. It is interesting that JPY changes from third negative to largest positive, which are -0.578 to 0.511. But the KRW changes from -0.820 to 0.011. And (iii) that the net volatility spillover of CNY Bitcoin market in different regimes both are the largest one, which is -0.929 and -0.629. These indicate that market participants have asymmetric information about the Bitcoin market, and the heterogeneity existing in the different markets makes the own ability to resist risks have greater differences.

4 Dynamics analysis

The full sample and unconditional analysis provides a good characterization for volatility spillover from average and static perspective. However, there are many changes in the six Bitcoin markets during our sample from 1 January 2014 to 30 September 2018. For example, the Commodity Futures Trading Commission, CFTC, classified Bitcoin as a commodity in September 2015. VFAs exchanges or trading platforms were effectively banned by regulation in September 2017. As of 2017, the government of the United Kingdom has stated that bitcoin is unregulated and that it is treated as a 'foreign currency' for most purposes, including VAT/GST⁴.

4.1 Total volatility spillover

Policy plays an important role on Bitcoin markets. CNY Bitcoin markets became the No. 1 market with the most active trading volume and transaction volume in the global Bitcoin markets during 2016 and 2017. In addition, the People's Bank of China and other seven ministries and commissions issued the "Announcement on Preventing the Risk of Subsidy Issuance Financing" at September 2017. What's more, combining the result in section 3.3, we note that the net volatility spillover of CNY Bitcoin market is the largest one regardless of whether it is in the moderate regime or intense regime. In order to further explore the dynamics volatility spillover nearly one year, we perform the subsample from August 2016, i.e., the subsample length of 901 days. Total volatility spillovers inferred from the MSVAR are plotted in Figure 3.

From Figure 3, we notice that the total volatility spillover exerts heterogeneous under different regimes in different periods. We have marked with I, II, III... As marked, in the stage I, The amplitude of the intense regime is larger than the moderate regime, and

⁴ Source: https://en.wikipedia.org/wiki/Legality_of_bitcoin_by_country_or_territory.

the fluctuation direction is inconsistent. This explains that the effect of total volatility spillover in the six markets is more significant under intense regime at this time. Furthermore, since the volatility spillover mainly depicts the exchange between different Bitcoin markets, the relationship between the markets will be more unstable under intense regime.

Figure 3: Total volatility spillover

In the stage II, the total volatility spillover of the moderate regime is greater than that of the intense regime. The fluctuation frequency is enhanced compared with I stage, and the fluctuation direction in moderate intense regime are synchronous. This indicates that the Bitcoin market has effectively adjusted the allocation of resources in the market, and the market has entered a stable development regime after a period of development. Bitcoin investors are watching the market and paying attention to the direction of policies and markets, so most traders are constantly spilling across different markets. Speculators

follow the market trend, so there is a wave of synchronization in fluctuation direction in moderate and intense regime.

In the period III, the total volatility spillover of moderate regime has dropped sharply, while the intense regime has declined very little at the initial of this stage. After that, the total volatility spillover of the moderate regime has been fluctuating under the total volatility of the intense regime, and the total volatility spillover in intense regime remains high. These mainly result from the speculators. Speculators have a rich access to information, making Bitcoin investors heterogeneous in information processing. Speculators go through the follow-up operation of the stage II, gradually become familiar with the operating rules of the market, and then use their advantages in information acquisition and market awareness to obtain their own excess expected returns by trading between different markets. Because speculators have a large amount of capital, their transactions increase the capital flow between different Bitcoin markets, and the total volatility spillover between markets is more intense.

In the stage IV, the total spillover of the intense regime is greater than the spillover of the moderate regime, and the total volatility spillover of the intense regime has large fluctuations. In addition, the fluctuation frequency of the total volatility spillover is smaller than the fluctuation frequency of the stage II. This indicates that speculators' manipulation of the Bitcoin market has attracted policy makers to supplement the Bitcoin market due to the lack of market regulation. Otherwise, after the market has adjusted itself in the stage II, the Bitcoin market efficiency has increased. Therefore, the adjustment of the market at this time makes the total volatility spillover smaller and the frequency slows down.

4.2 Directional volatility spillover

To get better understanding the dynamic direction spillover in different Bitcoin markets, we further estimate dynamic directional volatility spillover for six Bitcoin markets in the same period as 4.1. The dynamic directional volatility spillover from each of six Bitcoin markets to others plotted in Figure 4 and the dynamic directional volatility spillover from others to each six Bitcoin markets show as Figure 5.

Figure 4: Dynamic directional volatility spillover from each of six Bitcoin markets to others

It can be seen from Figure 4 that asymmetric effect in dynamic direction volatility spillover from each of six Bitcoin markets to others under different regimes exists

heterogeneity in different markets. On the one hand, from the single country market, the dynamic direction volatility spillover from USD to other markets in regime 1 is greater than this in regime 2. On the contrary, the dynamic direction volatility spillover from EUR to other markets in regime 2 is greater than this in regime 1. Moreover, the dynamic direction volatility spillover from JPY to other markets in regime 1 plays a key role in JPY market, while the dynamic direction volatility spillover from GBP to other markets in regime 2 plays a key role in JPY market. The dynamic direction volatility spillover from KRW or CNY to other markets has the same trend. It is noting that different Bitcoin development willingness. Exactly, USD and GBP Bitcoin markets are focus on the intense development in Bitcoin, while EUR and JPY emphasize the moderate. It is easy for the KRW and CNY Bitcoin markets, however, to be influenced by other Bitcoin markets. On the other hand, from the perspective of the country's economic development level, the dynamic direction volatility spillovers from developed countries or region markets, such as USD, EUR, JPY and GBP, to other markets are greater than these from developing countries, like KRW and CNY, to other markets. Specially, the largest one is in the direction volatility spillovers from USD to other Bitcoin markets.

The dynamic directional volatility spillover from others to each six Bitcoin markets can be depicted the one aspect of Bitcoin market efficiency. From Figure 5, we can notice that, on the one hand, the dynamic directional volatility spillover from others to USD or EUR in regime 2 is greater than regime 1. On the contrast, the dynamic directional volatility spillover from others to JPY, GBP, KRW or CNY in regime 1 is greater than regime 2. On the other hand, from the perspective in different market, the smallest one is the directional volatility spillover from others to USD. The bigger, while, are the

directional volatility spillovers from others to GBP, KRW and CNY. In addition, the directional volatility spillover from others to each six Bitcoin markets is much smaller than the directional volatility spillover from each of six Bitcoin markets to others. It is worth note that market effectiveness is the basis of market operation. The United States, as a developed country, has higher financial market effectiveness than the other five countries or regions. Therefore, the USD Bitcoin market can better regulate the impact of different bitcoin markets on itself. However, it is more susceptible for developing countries Bitcoin markets to interference from other markets according to the insufficient effectiveness of the Bitcoin markets, coupled with imperfect financial institutions.

Figure 5: Dynamic directional volatility spillover from others to each six Bitcoin markets

4.3 Net volatility spillover

One of the things one notices between Figure 4 and Figure 5 is their substantial differences, which can be called “net volatility spillover”. In order to better understand the dynamic behavior for each Bitcoin markets, we rank the six Bitcoin markets based on net volatility spillover in moderate and intense regime in Figure 6-7, respectively, where the colors from red to yellow represent the ranking from 1-6.

From Figure 6 and 7, we observe that there are significant differences in different markets net volatility spillover under same regime. In the regime 1, the net volatility spillovers in the USD, EUR and JPY markets fluctuated between one and three, and ones in GBP, KRW and CNY alternated between the four and six. Moreover, the net volatility in KRW, CNY, and GBP is more volatile. The USD and the EUR, as countries and regions with earlier development of financial markets, have evolved from the development of markets and the evolution of institutions in other markets. As a birthplace of Bitcoin, Japan pay attention to the stability of Bitcoin while study the institutional construction of the USD and EUR markets. In addition, GBP, KRW and CNY are easy to create opportunities for speculators in the process of learning about institution conducting. Therefore, under the moderate regime, USD, EUR and JPY are the main spillover countries and regions. In the regime 2, the net spillovers in the USD and GBP market fluctuated between one and two, and KRW and CNY fluctuated between five and six. The ranking of the net fluctuations in JPY, EUR and KRW are more volatile. Under the intense regime, the perfection of the Bitcoin market is the key to the stable operation of the market. The GBP in financial markets makes it easier to cope with fluctuations in the Bitcoin market, while the USD is responding to the volatility of the Bitcoin market by continuing to expand its influence in global VFAs markets. In addition, because of the

borderlessness of Bitcoin investors, emerging markets are more difficult to stabilize against net spillovers. As a result, the net spillovers in emerging markets are more unstable.

Figure 6: the ranking of net volatility in moderate regime

Figure 7: the ranking of net volatility in intense regime

Asymmetric effect exists in net volatility spillover under different regimes. Overall, the net spillover of the regime 1 is more stable than the net spillover of the regime 2 in different markets. The larger change is the net volatility in the EUR, JPY, GBP and KRW markets. This mainly results from the increased possibility of external influences on the market as the spillover expands, and the diversification of investors makes the Bitcoin market structure relatively complicated. In addition, due to the lack of perfection of the bitcoin market, the “herd effect” of regime 2 is more obvious, and the follow-up of investors makes the difference of spillovers increase. Furthermore, comparing regime 1 to regime 2, the net volatility spillover of GBP is significantly enhanced; the net volatility spillover of EUR is weakened; the net volatility spillover of CNY is enhanced; the net volatility spillover of USD is still the first and the stability of JPY net overflow is weakened. This mainly results from the market access differences. The spillover between different Bitcoin markets is mainly reflected in the behavior of investors, and the borderlessness of investors has a strong correlation with market access. Due to the greater control of the CNY market, the threshold for entry is higher, and the difficulty for investors to enter the market increases. Therefore, the spillover of the relevant information in CNY markets will not expand with the change of the regime. Similarly, the spread of information in USD market makes that the market still have the most important net volatility spillover. Because of the increase in spillover between markets, investors pay attention to the degree of perfection of financial markets. Compared with EUR, the GBP has higher financial market perfection, so the net volatility spillover and its fluctuation in GBP Bitcoin market increases. In addition, due to the influence of other

markets such as GBP, the fluctuations in net volatility spillover in JPY markets have increased.

5 Conclusions

Exploring the asymmetric effect of volatility spillover among global VFAs market has become crucial to investors and policy makers, whose main objective is the design of optimal investment environment. In this paper, we measure the asymmetric volatility spillover among six Bitcoin markets from 1 January 2014 to 30 September 2017, using the volatility spillover index based on MSVAR model. Furthermore, we have provided static and dynamic analysis under different regimes. Specific conclusions are as follows.

Static results show that asymmetric effects of volatility spillover exist in different regimes. On the one hand, in the same regime, different VFAs markets show different spillover in own and nets. Specifically, in regime 1, the largest own volatility spillover is 0.673 (USD's own spillover) and the smallest is 0.062 (CNY's own spillover). And the largest one is net volatility spillover from USD to other markets (2.296), followed by the net volatility from EUR to others (0.706). It is noting that the net spillover in developing market, such as KRW and CNY, are all above 0.80. In regime 2, the largest net spillover is from JPY to other Bitcoin markets and the smallest net volatility spillover is CNY (-0.629). On the other hand, asymmetric effects of volatility spillover exist in total, own and net volatility spillover of different VFAs markets under different regime. Exactly, the total spillover between different Bitcoin markets in moderate regime is significantly higher than that in intense regime. And the largest own volatility difference is GBP (from 0.096 to 0.989), and the smallest one is CNY (from 0.062 to 0.331). Otherwise, the net volatility spillover of USD Bitcoin market is changed from the positive largest in

moderate regime to the smallest in intense regime and the net volatility spillover of CNY Bitcoin market in different regimes both are the largest one.

Dynamic results depict that there are significantly asymmetric effects in total, directional and net volatility spillover. Concretely, the total volatility spillover has a phased nature, and different stages have different characteristics. The directional volatility spillover can be divided into the directional volatility spillover from each of six VFAs markets to others and the directional volatility spillover from others to each six VFAs markets. Respectively, asymmetric effect on direction volatility spillover from each of six VFAs markets to others under different regimes exist heterogeneity in different markets, and the directional volatility spillover from others to USD or EUR in regime 2 is greater than regime 1 and the directional volatility spillover from others to JPY, GBP, KRW or CNY in regime 1 is greater than regime 2. Moreover, the directional volatility spillover from others to each six VFAs markets is much smaller than the directional volatility spillover from each of six VFAs markets to others. About the net volatility spillover, we observe that there are significant differences in different markets net volatility spillover under same regime and Asymmetric effect exists in net volatility spillover under different regimes, i.e., the net spillover of the regime 1 is more stable than the net spillover of the regime 2 in different markets. Therefore, the authorities should monitor the specific regime of VFAs and improve market mechanisms. Furthermore, in order to effectively protect the legitimate rights and interests of investors, they also should learn the system construction of financial markets in developed countries and set up trading supervision intervals. For investors, they should improve their judgment

ability and clarify the market trend. What's more, they should obtain relevant investment information from formal channels and work together to maintain market order.

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