Causality and Dynamic Spillovers among Cryptocurrencies and Currency Markets

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Abstract

This paper utilises two methods to uncover the causality dynamic between the three leading cryptocurrencies: Bitcoin, Litecoin, Ripple, and nine major foreign currency markets. Firstly, we implement the technique of Diebold-Yilmaz to compute the spillover index between cryptocurrencies and currency markets. We find a significant return spillover effect between Bitcoin and Litecoin in the first three quarters of 2017. Still, the return spillover is merely meaningful in the first three quarters of 2015 for Ripple. However, the total volatility spillover index in the system decreases in the fourth quarter of 2017. Secondly, we apply the Bayesian Graphical Structural Vector Autoregressive estimations and find that the current level of Bitcoin depends only on the previous level of the Chinese Yuan. The current level of Ripple strongly depends on the prior levels of Bitcoin, followed by Litecoin. The current level of Litecoin strongly depends on the previous level of Ripple, followed by the Chinese Yuan. These results indicate that there is a significant causal relationship among cryptocurrencies. However, except for the Chinese Yuan, major traditional currencies do not significantly affect cryptocurrencies.

Keywords: cryptocurrencies; currency markets; return spillover; volatility spillover; Bayesian estimation techniques; structural vector autoregressive models

JEL Codes: G12; F31; C58; C11

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Highlights

- We examine the volatility transmission and causality dynamic between Bitcoin, Litecoin, Ripple, and top traded traditional currencies worldwide.
- We implement the technique of Diebold-Yilmaz to compute the spillover index between cryptocurrencies and currency markets
- We find the significant return spillover effect in different periods
- We also apply the BSGVAR method
- We observe that there is a significant causal relationship among cryptocurrencies
- Except for the Chinese Yuan, major currencies do not significantly affect cryptocurrencies

1. Introduction

Cryptocurrencies have received significant attention from academicians, investors, media, and policymakers since the quick rise of prices in 2017, followed by the substantial decline of prices in 2018. It should be noted that not only the opportunities of higher returns but also the possible benefits of Blockchain technology and transparency are among the primary reasons for the rising interest in cryptocurrencies.[1] Due to these reasons, the empirical literature has focused on the different features of cryptocurrencies to understand whether their characteristics are different from traditional assets (e.g., commodities, precious metals, and stock markets) and exchange rates. Individually, previous empirical papers have examined the various aspects of cryptocurrencies, including the bubble behaviour (Cheah and Fry, 2015; Corbet et al., 2018b; Fry and Cheah, 2016), the drivers of attention (Dastgir et al., 2019; Shen et al., 2019), the market efficiency (Bariviera, 2017; Cheah et al., 2018; Jiang et al., 2018; Kristoufek, 2018; Nadarajah and Chu, 2017; Sensoy, 2019; Tiwari et al., 2018; Urquhart, 2016; Vidal-Tomás and Ibañez, 2018), the portfolio diversification (Corbet et al., 2019; Guesmi et al., 2019), the price clustering (Urquhart, 2017), and the price volatility (Katsiampa, 2017).

In this paper, we focus on the hedging capabilities of cryptocurrencies against the exchange rates. Specifically, we investigate the return, the price volatility dynamics (connectedness) and the causal relationship between three cryptocurrencies (Bitcoin-BTC), (Litecoin- LTC), (Ripple-XRP), and nine major exchange rates namely: the Australian Dollar (AUD), the Great Britain Pound (GBP), the Canadian Dollar (CAD), the Chinese Yuan (CNY), the Euro (EUR), the Japanese Yen (JPY), the New Zealand Dollar (NZD), the Swedish Krona (SEK), and the Swiss Franc (CHF).[2] Several papers in the literature have illustrated that

[1] According to the data from http://www.coindesk.com, Bitcoin is the most traded cryptocurrency, and the trading volumes of Ethereum, Ripple, and Litecoin have also increased since 2017.
[2] According to the Bank for International Settlements (BIS) (2016), these are the most actively traded currencies in the foreign exchange rate market.

cryptocurrencies (especially Bitcoin) have some hedging capabilities against traditional assets, such as gold, stocks, and the USD as well as some indicators of uncertainty.

However, it is necessary to enhance our knowledge of the hedging capability of cryptocurrencies by including other major cryptocurrencies and exchange rates; thus, the present study aimed to achieve that. Our research task can be necessary if the demand for cryptocurrencies will be associated with the dynamics of specific exchange rate markets. Therefore, the evidence of this paper will evaluate the hedging property of cryptocurrencies against major cryptocurrencies. Besides, the findings will provide evidences on how potential devaluations or revaluations in exchange markets might affect cryptocurrencies.

To the best of our knowledge, this is the first paper in the literature that examines the causal relationship between various major cryptocurrencies and exchange rates. Specifically, we analyse whether cryptocurrencies have a hedging property against the exchange rates, using data for the period from e. To this end, we apply the volatility spillover technique of Diebold and Yilmaz (2009, 2012, 2014, and 2015) to estimate the spillover index between the cryptocurrency and exchange rate markets. These approaches also considered the Generalized Forecast Error Variance Decomposition (GFEVD) analysis in the linear and the nonlinear models, provided by Koop et al. (1996) and Pesaran and Shin (1998), respectively. Besides, in the present study, we utilise the Bayesian Graphical Structural Vector Autoregressive (BGSVAR) estimations of Ahelegbey et al. (2016).

At this stage, we have two main contributions to the existing literature. First, we examine the causality between three cryptocurrencies and nine exchange rates, most of which are neglected by previous studies. We also calculate the variance decompositions and the volatility connectedness among the large basket of cryptocurrencies and exchange rates. Second, we consider the BGSVAR estimations; and therefore, we obtain not only the direction of the causal relationship but also the magnitude of the causal relationship at different quantiles.

In this paper, we observe a significant return spillover effect between Bitcoin and Litecoin in the first three quarters of 2017, but the return spillover was only significant at the first three quarters of 2015 for Ripple. However, the volatility spillover index in the system decreased in the fourth quarter of 2017. Furthermore, we find that the current level of BTC depends on the previous level of CNY, while the current level of XRP strongly depends on the prior level of BTC followed by LTC. The current level of LTC strongly depends on the previous level of XRP, followed by CNY. Thus, we find that there is a significant causal relationship among cryptocurrencies; however, except for the Chinese Yuan, major currencies do not significantly affect cryptocurrencies. In short, there is a limited hedging capability of cryptocurrencies against the exchange rates.

The remainder of this paper is organised as follows. Section 2 discusses the previous articles on the empirical literature of cryptocurrencies. Section 3 presents the data and econometric methodology. Section 4 provides the empirical results. Section 5 offers the concluding remarks.

2. Literature Review

This paper contributes to empirical literature that investigates the potential hedging features of cryptocurrencies against other financial assets and uncertainty indicators. For instance, Baur et al. (2018) concluded that Bitcoin is a suitable asset for speculation, does not have the function of a medium of exchange and the potential for being an alternative currency. However, Dyhrberg (2016) indicated that Bitcoin has a hedging capability against the United States Dollar (USD) and the U.S. stock markets; therefore, Bitcoin can be used for purposes of portfolio diversification. Similar evidence was obtained by Bouri et al. (2017b) since the authors concluded that Bitcoin has significant hedging properties against several assets.

On the other hand, Bouri et al. (2017a) and Demir et al. (2018) concluded that Bitcoin could be used for hedging purposes against uncertainty indicators, such as the indices of the

Volatility (VIX) and the Economic Policy Uncertainty (EPU). Aysan et al. (2019) also showed that the index of geopolitical risks (GPR) could predict Bitcoin returns and its price volatility. However, Bitcoin does not have a hedging feature against the events leading to the geopolitical risks. Similarly, Gozgor et al. (2019a) concluded that Bitcoin does not have a hedging capability against trade policy uncertainty.

Previous studies have also investigated the possible causal relationship between the cryptocurrencies and exchange rates. For instance, Baruník et al. (2017) found significant asymmetric volatility connectedness in the foreign exchange rate (FOREX) markets for the period from 2007 to 2015, using the Diebold-Yilmaz test techniques. Looking at the sign of the spillovers, the authors observed more negative than positive spillovers. Negative spillovers were found during the period of the European Sovereign Debt Crisis, while positive spillovers were obtained during the period of the Global Financial Crisis of 2008-9. Li and Wang (2017) also concluded that the Bitcoin/USD exchange rate is determined by economic fundamentals and market conditions rather than technological progress in the short-run. This evidence is stronger in the long-run. Gandal et al. (2018) found that the Bitcoin price against the USD is linked to increases in the exchange rate, mainly due to the unregulated cryptocurrency markets and manipulation.

Furthermore, employing the quantile cross-spectral approach, Baumohl (2019) also investigated the volatility connectedness between six cryptocurrencies and six exchange rates throughout September 2015–December 2017. According to the results, they are significant and negative, but there is a weak linkage between cryptocurrencies and exchange rates. Ji et al. (2019) also used the method of Diebold-Yilmaz to investigate the connectedness of return- and the price volatility spillovers among six major cryptocurrencies for the period from August 2015 to February 2018. The results of the return spillovers and the price volatility spillovers showed that Litecoin and Bitcoin have the most effects on other cryptocurrencies. The Dash has a very weak connectedness, and this is evidence of hedging feature. Besides, a higher price of Gold and the U.S. EPU spur the net directional negative-return spillovers. However, a higher price of Gold increases the negative-volatility spillovers, while the U.S. EPU positively affects it.

Despite that fact that research in this area has burgeoned, no previous attempt has been made to examine volatility connectedness and causality dynamic between cryptocurrencies and major traditional currencies based on a more comprehensive approach. Furthermore, empirical results from previous literature could be biased and misleading due to the omission of relevant variables from empirical models. To this end, our paper extends the evidence of Ji et al. (2019) by including the exchange rates and utilising a more recent method; i.e., the Bayesian Graphical Structural Vector Autoregressive (BGSVAR) approach. Moreover, Urquhart and Zhang (2019) observe that Bitcoin could be used for hedging and safe haven properties against the CHF and GBP; however, it acts as a diversifier for the AUD, CAD, and JPY. Our paper also extends the evidence of Urquhart and Zhang (2019) by including other major cryptocurrencies.

3. Data and Methodology

3.1 Data Sources and Descriptive Statistics

The empirical analysis was estimated using daily returns for major cryptocurrencies and the top 10 most traded traditional currencies in the world over the period from August 5, 2013, to December 31, 2018, with all prices quoted against the U.S. Dollar (BIS, 2016, Baruník et al., 2017). Our dataset includes the largest cryptocurrencies in terms of market capitalisation value, as well as the availability of historical data as at the end of December 2018.[3] Therefore, we restricted our sample to cryptocurrencies with available data back to 2013. Subsequently, the dataset consists of three cryptocurrencies: Bitcoin (BTC), Ripple (XRP) and Litecoin (LTC)

[3] Ethereum was excluded due to data availability as it started from August 7, 2015.

as well as nine traditional currencies namely: The Australian Dollar (AUD), the Great Britain Pound (GBP), the Canadian Dollar (CAD), the Euro (EUR), the Japanese Yen (JPY), the New Zealand Dollar (NZD), the Swedish Krona (SEK), the Swiss Franc (CHF), and the Chinese Renminbi (Yuan) (CNY). The daily prices of cryptocurrencies were collected from coinmarketcap.com, whereas the spot exchange rates of the top traded currencies worldwide were sourced from WM/Reuters via DataStream.[4]

According to Figure 1, the three cryptocurrencies have similar trends, but they do not follow the same price pattern over the sample period. Therefore, it seems there is no dominant cryptocurrency. In particular, cryptocurrencies witnessed a notable price appreciation over 2017, where Bitcoin and Litecoin reached their maximum prices during December 2017, whereas Ripple recorded its highest value in early January 2018. In contrast, during 2018, the prices of Bitcoin, Ripple, and Litecoin continued to decline to reach 3742, 0.35, and 30.47, respectively, by December 31, 2018.

[Insert Figure 1 here]

The remaining graphs show the dynamics of the exchange rates of all nine currencies against the U.S. Dollar. On the one hand, AUD, CAD, and NZD share a similar overall trend. On the other hand, EUR and SEK exhibited co-movement over the sample period. Different exchange rates, GBP, JPY, CHF and CNY, have remarkably different patterns. Generally speaking, all exchange rates involve several ups and downs corresponding to major events such as the Quantitative Easing measures by the Federal Reserve during 2013/2014, Brexit voting in June 2016, abundant of exchange rate ceiling by the Swiss National Bank in January 2015 and the forward reserve requirement by the People's Bank of China on October 2015.

[Insert Table 1 around here]

[4] The data that support the findings of this study are available from the corresponding author upon reasonable request.

Table 1 presents the descriptive statistics of returns and volatilities for both cryptocurrencies and top traded currencies. The three cryptocurrencies have higher standard deviations compared with the traditional currencies and as a result, enjoy mean returns, which are slightly more elevated than zero. As expected, the value of the kurtosis coefficient is significantly positive and more significant than zero, indicating that both returns and volatilities are not normally distributed. These results have been confirmed by Jarque-Bera test statistics, rejecting the null hypothesis of normality for all series at the 1% level of significance.

Furthermore, Ljung-Box Q and Q^2 statistics are presented in Table 1, which test the null hypothesis of no serial correlation in raw and squared series, respectively, against the alternative that they are serially correlated. Whereas Q statistics show that only AUD, GBP, EUR, NZD and SEK return series follow a random walk process, Q^2 statistics confirmed that all returns and volatilities series are serially correlated and exhibit strong non-linear dependencies. These findings were confirmed by the Engle's LM test, where the null hypothesis of no Autoregressive Conditional Heteroskedasticity (ARCH) effects was rejected, indicating significant ARCH effects in all the variables at the 1% level of significance. Subsequently, the presence of higher-order serial correlation and non-linear dependency of all series suggest the use of the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) process in modelling the conditional volatilities of the variables under consideration. Finally, the Dickey-Fuller GLS (ERS) unit root test indicated that all series are level stationary at 10%, which supports the use of a Vector Autoregressive model (VAR) model in our analysis. Therefore, the preliminary investigations show that we need to use a method to model strong non-linear dependencies among the assets. That's why we use the volatility spillover method of Diebold and Yilmaz in the first phase and then utilise the BGSVAR estimations.

Regarding the correlation analysis, Figure 2 presents the correlation matrix for both returns and volatilities in the pattern (a) and (b), respectively. Both graphs show the fragile association between cryptocurrencies and foreign exchange markets. Over and above, it should be noted that the Chinese Yuan (CNY) is disconnected from cryptocurrencies as well as other foreign exchange markets.

[Insert Figure 2 here]

3.2 Empirical Methodology

3.2.1 Connectedness Approach Based on VAR Decomposition

The methodology framework of this paper follows the spillover approach newly developed by Diebold and Yilmaz (2009, 2012, 2014, and 2015) in constructing static and dynamic interconnectedness among major cryptocurrencies and top worldwide foreign exchange markets. In particular, this approach is mainly based on forecast error variance decomposition associated with the VAR model. The use of variance decomposition function allows decomposition of forecast error variation in a variable (i) and assessing whether it is due to internal or external shocks. By assuming stationary covariance, the $N - variable\ VAR\ (p)$ model could be written as follows:

$$y_t = \sum_{i=1}^{p} \Phi_i y_{t-i} + \varepsilon_t \qquad (1)$$

Where y_t is a vector of N endogenous variables, Φ_i are $N \times N$ autoregressive coefficient matrices and ε_t is a vector of disturbances assumed to be serially uncorrelated over time. Since the VAR model above is covariance stationary, the corresponding moving-average representation is given by $y_t = \sum_{j=0}^{\infty} A_j \varepsilon_{t-j}$, with A_j are $N \times N$ coefficient matrices which obey a recursion of the form $A_j = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + \cdots + \Phi_p A_{j-p}$ where A_0 is $N \times N$ identify identity matrix and $A_j = 0$ for all $j< 0$. Estimating the variance decompositions matrix based on the above moving-average approach is quite important and convenient, as it allows us to calculate and understand the dynamics of volatility transmissions among variables. Further, Diebold and Yilmaz (2012) showed that constructing connectedness indices from forecast error variance decomposition, based on a generalized VAR developed by Koop et al. (1996), and Pesaran and Shin (1998), hereafter KPPS, is more accurate, robust and insensitive to the ordering of the variables compared with Cholesky decomposition. Following the KPPS-VAR framework, the H-step-ahead generalised forecast-error variance decomposition is given by:

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (\acute{e}_i A_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (\acute{e}_i A_h \Sigma \acute{A}_h e_i)} \tag{2}$$

Where σ_{jj} denotes the standard deviation of the error term for the j^{th} equation, Σ is the variance matrix of the disturbance ε, and e_i represents a selection vector with a value of 1 for i^{th} elements and 0 otherwise. Finally, θ_{ij}^{g} is the $N \times N$ variance decomposition matrix where the variances of each variable could be divided into two parts; own-variance and cross-variance. The main diagonal elements of the matrix display the own-variance, the shares of the *H*-step-ahead error variance in variable *j* is attributed to its shocks. Whereas off-diagonal entries represent the variance contribution of variable *j* to the *H*-step-ahead forecast error variance of variable *i*, in other words, cross-variance shares (hereafter spillovers). The own and cross-variance shares of each variable does not equal to one and hence, should be normalised by the row sum as follows:

$$\breve{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)} \tag{3}$$

By construction, $\sum_{j=1}^{N} \breve{\theta}_{ij}^{g}(H) = 1$ and $\sum_{i,j=1}^{N} \theta_{ij}^{g}(H) = N$. On that basis, the total spillover index is calculated as the ratio of the sum of all off-diagonal elements to the total variance, that is the addition of all entries in the matrix. It, therefore, represents the average contribution of volatility spillovers across all variables to the total forecast error variance. In other words, total spillover measures the degree of integration among all variables.

$$C_{Total} = \frac{\sum_{i,j=1,i\neq j}^{N} \breve{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \breve{\theta}_{ij}^{g}(H)} \times 100 = \frac{\sum_{i,j=1,i\neq j}^{N} \breve{\theta}_{ij}^{g}(H)}{N} \times 100 \quad (4)$$

The above representation of the generalised variance decomposition matrix is beneficial as it allows rapid estimation of directional spillovers indices between variables. The total directional spillovers "From" is defined as the information received by variable *j from* all other variables, which is measured as:

$$C_{j\leftarrow\cdot} = \frac{\sum_{j=1,j\neq i}^{N} \breve{\theta}_{ji}^{g}(H)}{\sum_{i,j=1}^{N} \breve{\theta}_{ji}^{g}(H)} \times 100 = \frac{\sum_{j=1,j\neq i}^{N} \breve{\theta}_{ji}^{g}(H)}{N} \times 100 \quad (5)$$

Likewise, the total directional spillovers "To" denotes the informational outflow transmitted from variable *j to* all other variables, which is given by:

$$C_{j\rightarrow\cdot} = \frac{\sum_{j=1,j\neq i}^{N} \breve{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \breve{\theta}_{ij}^{g}(H)} \times 100 = \frac{\sum_{j=1,j\neq i}^{N} \breve{\theta}_{ij}^{g}(H)}{N} \times 100 \quad (6)$$

Subsequently, the net directional spillovers are the net informational flow transmitted/received by variable j, measured as the difference between total directional spillovers "To" and "From" variable j:

$$C_j = C_{j\rightarrow\cdot} - C_{j\leftarrow\cdot} \quad (7)$$

The calculation of net spillover indices is very valuable as it allows us to determine whether a given variable is a net transmitter or receiver of shocks. Finally, a directional connectedness network could be constructed based on the generalised variance decomposition matrix and all associated measures of connectedness in which nodes represent components of generalised variance decomposition matrix, variables, whereas edges demonstrate the direction and strength of the pairwise connectedness. In other words, the linkages between nodes are directed given the fact that $\breve{\theta}_{ij}^{g} \neq \breve{\theta}_{ji}^{g}$; the strength of the *ij* connectedness, that is volatility spillover transmitted from variable j to variable i is not necessarily equivalent to those transmitted from i to j.

As an extension to the connectedness approach based on VAR decomposition, we did not only examine the spillover effect of traditional currencies on digital currencies; we also investigated the directional causality of traditional currencies on digital currency. The approach of Ahelegbey et al. (2016) can be used to examine the predictive power of conventional currencies on digital currencies. The Diebold-Yilmaz approach is useful for analysing the dynamics of currencies by solely relying on the impulse response function (i.e., to measure the magnitude of responses of endogenous variables to isolated unexpected shocks). However, the Ahelegbey et al. (2016) approach also revealed the effects of contemporaneous and lagged causality across currencies variables by relying on a graph representation of conditional independence among the traditional and digital currencies.

3.2.2 BGSVAR Model

To compare the DY methodology, this section aimed to explore the contemporaneous and delayed causality between the three major cryptocurrencies: Bitcoin (BTC), Litecoin (LTC), Ripple (XRP) as response variables, and the nine major currency markets: the Australian Dollar (AUD), the Great Britain Pound (GBP), the Canadian Dollar (CAD), the Chinese Yuan (CNY), the Euro (EUR), the Japanese Yen (JPY), the New Zealand Dollar (NZD), the Swedish Krona (SEK), and the Swiss Franc (CHF), as predictor variables, overfull and rolling sub-samples. Therefore, to commence, the dependence/causality relationship was represented by a Structural Vector Autoregressive (SVAR) model, as shown below:

$$Y_t = B_0 Y_t + \sum_{i=1}^{p} B_i Y_{t-i} + \sum_{i=1}^{p} C_i Z_{t-i} + \varepsilon_t \tag{8}$$

Where $t = 1, \dots, T$ and p are the maximum lag order. Both Y_t and Z_t are n_y and n_z vectors of response (the three major cryptocurrencies: BTC, LTC, XRP) and predictor variables (nine major currency markets), respectively. ε_t is the $n_y$vector of structural residuals, it is characterised independently, identically and normally distributed with mean zero and covariance matrix Σ_ε ; B_0 is a $(n_y \times n_y)$ zero diagonal matrix of contemporaneous structural coefficients, with zero diagonals; B_i and C_i with $one \leq i \leq p$ are $(n_y \times n_y)$ and $(n_y \times n_z)$ matrices of the parameters. Therefore, the BGSVAR estimations can provide the direction of the causal relationship but also the magnitude of the causal relationship at the different quantiles. Compared to other VAR-type models, it is a more flexible method to capture the potential issues of asymmetries, non-linearity, and outliers in the samples. The BGSVAR method can also consider the momentum effect; that is newly-introduced cryptocurrencies are gradually cutting into Bitcoin's historically dominant value-based market share, suggesting that investors have started thinking alternative investments in cryptocurrencies other than Bitcoin over the period under concern (Gozgor et al., 2019b).

4. Empirical Results and Discussion

Return and volatility connectedness were examined to identify the informational flows and risk transmission mechanisms between cryptocurrencies and major foreign exchange markets.

4.1 Results of the Return Spillovers Analysis

Static and dynamic returns spillovers networks were investigated over the full sample. Table 2 presents the directional spillovers matrix and static interconnectedness network among cryptocurrencies and traditional currencies. In particular, it reports informational outflows transmitted from each currency to all other currencies “Connection to others” as well as informational inflows directed from all other currencies to a particular currency “From others”. Consequently, “Net Spillovers” raw shows the net directional spillover for each currency, where a positive (negative) value implies a net transmitter (receiver) of spillover effects to (from) other currencies. The results showed that Bitcoin (BTC), Litecoin (LTC), the Australian Dollar (AUD), the Euro (EUR), the New Zealand Dollar (NZD), and the Swedish Krona (SEK) are the net transmitters of return spillover. On the contrary, Ripple (XRP), the Great Britain Pound (GBP), the Canadian Dollar (CAD), the Chinese Yuan (CNY), the Japanese Yen (JPY), and the Swiss Franc (CHF) are the net receivers. Notably, the Euro is the giant net transmitter of spillover among all currencies followed by the Swedish Krona, yet both the Chinese Yuan and the Japanese Yen are the largest net receivers. Furthermore, the total spillover index reaches 48.5% indicating, on average, that half of the total forecast error variance can be attributed to returning spillovers effects. This evidence confirms a sizable interconnectedness among all currencies over the sample period.

[Insert Table 2 around here]

To get a better picture of return connectedness among cryptocurrencies and traditional currencies, we took a closer look at the pairwise network connectedness as well as directional and strength of spillover effects among the variables under investigation. In particular, it portrays the average pairwise directional spillovers among all possible pairs in the network where the node's colour implies whether a variable is a net transmitter/receiver of return spillovers. The thickness and the colour of the arrows represent the magnitude and strength of the average return spillover between each pair.

Figure 3 reveals weak pairwise spillovers between cryptocurrencies and traditional currencies on the one hand but strong interconnectedness among currencies within each of the two groups on the other hand. All pairwise measures among cryptocurrencies and traditional currencies are deficient and range between 0% and 0.22% at maximum. Furthermore, Bitcoin, Litecoin and Ripple are highly interlinked and connected, whereas conventional currencies are more related and attached.

[Insert Figure 3 here]

The above analysis does not reveal the time-varying nature of returns spillover and hence, overlooks significant changes in total and directional spillover patterns over the sample period. To this end, a dynamic return spillover index was estimated based on a Vector Autoregressive model of order (1) with 10 H-steps forecast horizon and 200-days rolling window. Figure 4 shows the time-varying trajectory of the Total Spillover Index (TSI). TSI is very responsive to both national and international events and hence, varies considerably over the sample period. During 2016 and early 2017, the value of the TSI continued to escalate possibly due to the hack of Bitfinex (largest cryptocurrency exchange by volume), Brexit referendum, Ripple entered major exchanges and being used as a bridge between currencies, rejection of the first Bitcoin Exchange-Traded Fund (Corbet et al., 2018a). Another hike in the TSI started in December 2017 and was sustained during 2018 because of the Cryptocurrency Bubble, the hack of Coincheck Exchange, and the fork of Bitcoin Cash.

[Insert Figure 4 here]

The dynamic net directional return spillover from each currency to all other currencies is illustrated in Figure 5; where the positive (negative) value of the index indicates that a currency is a net transmitter (receiver) of return spillover to (from) all other currencies. Interestingly, the results from net directional spillovers coincide with our previous findings from the static network analysis. On the one hand, the Australian Dollar, Bitcoin, the Euro, the New Zealand Dollar, and the Swedish Krona were the major sources of return spillovers in our sample. On the other hand, the Canadian Dollar, the Chinese Yuan, the Japanese Yen, Ripple, and the Great Britain Pound were the leading net receivers of shocks from other currencies.

[Insert Figure 5 here]

4.2 Results of Volatility Spillovers Analysis

This section reports the volatility connectedness network across major cryptocurrencies and traditional currencies using a VAR of conditional volatilities estimated from a GARCH model. Starting with the static analysis, Table 3 presents the forecast-error variance decomposition matrix of the volatility analysis. The magnitude of total volatility spillover index recorded at 36.6% is lower than that of the return spillover index. This evidence indicates higher connectedness in returns network among the currencies under consideration compared with volatility.

Similar to the results of return spillovers, Bitcoin, the Australian Dollar, the Euro, and the Swedish Krona were the net transmitters of risk to all other currencies in the sample with Bitcoin being the most significant net transmitter of volatility spillover followed by the Euro. Contrary to its position in the case of return network analysis, Litecoin is a net receiver of spillovers.

[Insert Table 3 around here]

To examine the direction of risk transmission, Figure 6 presents the network diagram of pairwise net volatility spillovers. As expected, it was found that a secure connection and risk transmission exists between Bitcoin and Litecoin relative to their association with the Ripple. Furthermore, there are strong to moderate risk spillovers among traditional currencies. However, there is very little evidence of volatility transmission between cryptocurrencies on the one side and conventional currencies on the other side.

[Insert Figure 6 here]

Moving on to the time-varying volatility network analysis based on 200-day rolling windows and a forecast horizon of 10 days over the sample period; Figure 7 depicts the dynamic volatility spillover index that exhibited, to some extent, a somewhat similar pattern to that of the dynamic return spillover index. It can be seen that the volatility spillover index surged to around 90% in December 2014, probably due to the CHF/EUR crisis and depreciation of most currencies against the U.S. Dollar. Afterwards, it accelerated during 2016 and 2017 before dropping to its lowest value (38%) by the end of 2017. Through 2018, it remained relatively small and smooth in values around 40%.

[Insert Figure 7 here]

Lastly, Figure 8 displays the time-varying net directional volatility spillovers for all currencies included in the model. As noted, net volatility spillover indices switch between positive and negative territories, suggesting that each currency could be a net transmitter or a net receiver of volatility at different points in time. Once again, these results are in line with the findings obtained from static volatility spillover presented in Table 3 and Figure 6. Throughout the sample period, Bitcoin and Euro were the significant sources of volatility spillovers to other currencies.

[Insert Figure 8 here]

The results obtained from the spillover approach confirmed that returns and volatility spillover indices are very responsive and sensitive to international shocks as well as economic and financial turbulence. It varied considerably over the sample period. However, the magnitude of the total volatility spillover index is lower than that of the return spillover index, suggesting higher spillovers in returns network compared with volatility connectedness. Furthermore, Bitcoin, the Australian Dollar, the Euro, and the Swedish Krona were significant sources of volatility spillovers to all other currencies in the sample with Bitcoin being the most significant net transmitter of volatility spillover followed by the Euro. Besides, both diagrams of pairwise net returns and volatility spillovers show that cryptocurrencies are highly interlinked and connected among each other, whereas traditional currencies are more related and attached. However, there is very little evidence of volatility transmission across cryptocurrencies on one side and conventional currencies on the other side. Also, this study revealed the existence of a secure connection and risk transmission between Bitcoin and Litecoin relative to their relationship with the Ripple.

4.3 Results from the BGSVAR Model

The analysis is conducted for the returns causality. The aim of using Ahelegbey et al.'s (2016) method was to uncover the contemptuous and lagged causality between conventional and digital currencies. Depending on the predictive power of variables, the approach can examine the effects of contemporaneous and lagged causality across currencies variables by relying on a graphical representation of the conditional independence among traditional and digital currencies.

According to the results of the BGSVAR model, Table 4 shows the case of the Multivariate Instantaneous (MIN) structures. The highest posterior probabilities for BTC was provided by XRP (with a value of 0.5176), and the highest posterior probabilities for XRP was provided by LTC (with a value of 0.493), the highest posterior probabilities for LTC was provided by XRP (with a value of 0.507).

[Insert Table 4 around here]

We also focus on the Multivariate Autoregressive (MAR) structures of the three cryptocurrencies mentioned above and the nine major currency markets in Table 5. Under the MAR structures with evidence of at least posterior probabilities of 30%, the current level of BTC depends on the previous level of CNY, while the current level of XRP strongly depends on the prior level of BTC followed by LTC. The current level of LTC strongly depends on the previous level of XRP, followed by CNY.

[Insert Table 5 around here]

Our results show a strong dependence between Bitcoin in particular and the Chinese Yuan which is confirmed by the graphical illustration of regional distribution and the trading composition of Bitcoin by currency in fig. 9. It is worth noting that China and the Chinese yuan dominate the trading market of Bitcoin currency. Approximately 85% of the trading volume took place via the China's mainland currency (yuan) against 10% only for the US dollar over the sample period.

[Insert Figure 9 here]

These findings are in line with previous literate, which indicates that Chinese citizens have increased their Bitcoin holdings in order to hedge against the inflationary pressures and potential devaluation of the Chinese Yuan due to high uncertainty caused by the trade war with the USA (Bovaird, 2018; Davis, 2018). Furthermore, Gozgor et al., (2019) argued that Bitcoin would a good hedge in the times of uncertainty, inflationary pressures and volatile exchange rates due to the fixed supply of Bitcoin currency.

5. Conclusion

This paper examined the time-varying volatility spillovers and the causality dynamic between the three leading cryptocurrencies: Bitcoin, Litecoin, and Ripple, as well as the nine major currency markets: The Australian Dollar, the Great Britain Pound, the Canadian Dollar, the Chinese Yuan, the Euro, the Japanese Yen, the New Zealand Dollar, the Swedish Krona, and the Swiss Franc. In doing so, we utilised two innovative methods. Firstly, the technique of Diebold-Yilmaz was applied to estimate and compute the spillover index between cryptocurrency and currency markets. Secondly, we used the BGSVAR model of Ahelegbey et al. (2016).

According to the results for the return spillover analyses, we found a significant spillover effect between cryptocurrency and currency markets in the first three quarters of 2017 for both BTC and LTC. However, the spillover was only significant in the first three quarters of 2015 for XRP. While BTC affected mostly CHF, LTC affected mainly CAD and GBP, XRP affected CNY. LTC was affected primarily by AUD, GBP, CAD, and CNY. XRP was mostly influenced by EUR, JPY, NZD, SEK, and CHK. Finally, while the total spillover index for return in the system increased from its lowest point in the fourth quarter of 2017, the volatility spillover index in the system decreased at the same period.

According to the results of the BGSVAR model, the prices of Bitcoin and Litecoin strongly depend on the Chinese Yuan, and other major currencies do not significantly affect the cryptocurrencies. The significant causality from the Chinese Yuan to Bitcoin and Litecoin could be associated with the demand of Chinese citizens for cryptocurrencies. We can suggest that Bitcoin and Litecoin have a hedging property against the inflationary pressures in the Chinese economy and the potential devaluations of the Chinese Yuan. Therefore, exchange rates hedging and create a market timing trading strategy is only valid for the Chinese Yuan. For other exchange rates, our evidence shows that they do not help to predict magnitudes and movements of cryptocurrencies or different exchange rates.

Of course, our main evidence is open to be enhanced by future studies. The data used in this study is the daily data, and one can benefit from looking at intra-day (high-frequency) data and try to see whether the intra-day prices behave similarly under our methods. Another exciting research task would be to examine whether our results could be satisfied by other minor cryptocurrencies. Major cryptocurrencies may have a better hedging role as they may lead the minor ones. On the other hand, small cryptocurrencies may have less informed traders, and so any general signal leads to hedging due to herd behaviour. One can also control for hedging on leading news events or events more broadly affecting the cryptocurrency markets. Alternatively, one can use news, and direct or indirect effects about exchange rates (e.g. Brexit and the jumps in the GBP, Federal Reserve announcements, etc.) since the base currencies have a significant impact to smaller ones, which would be an interesting exercise.

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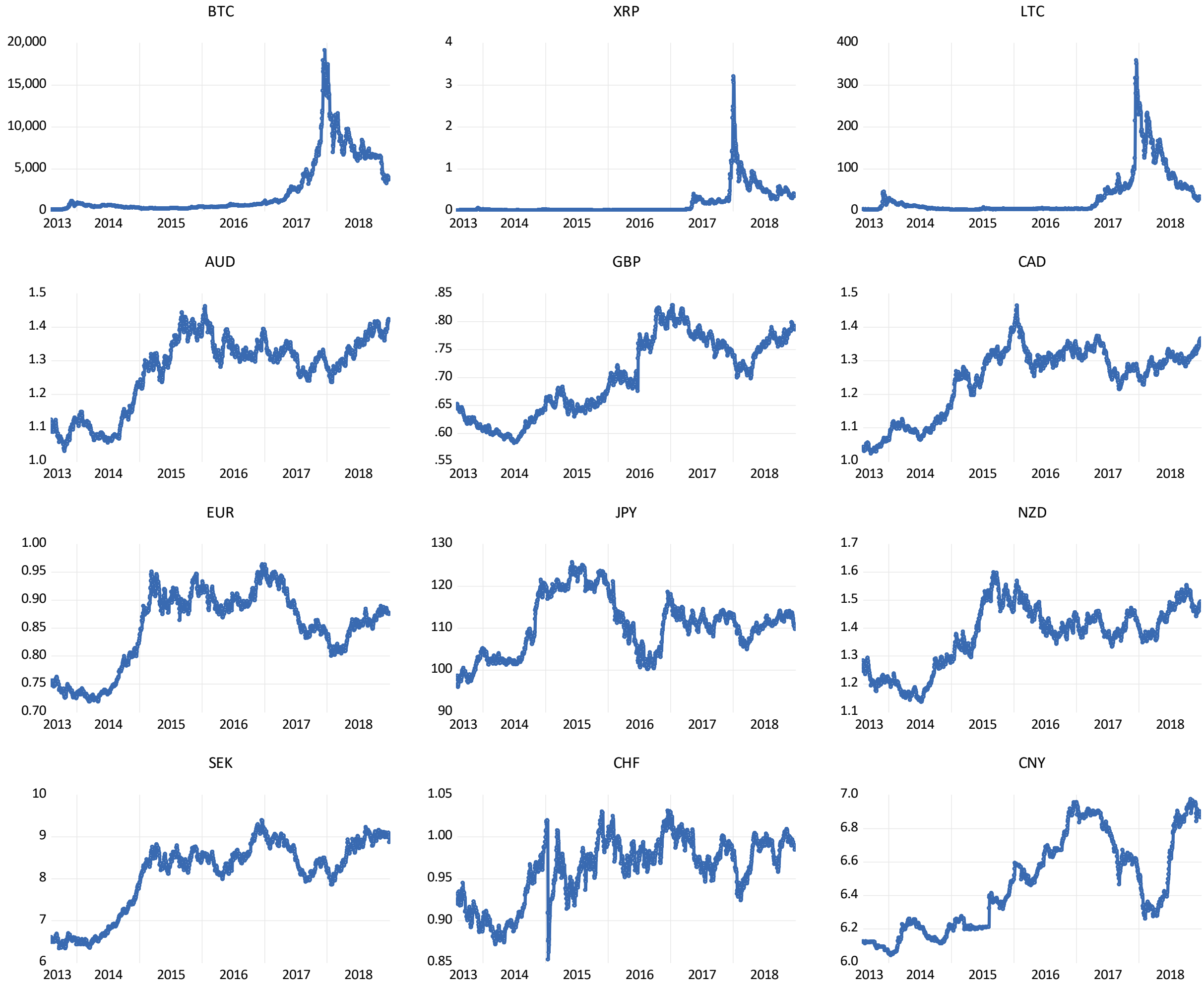
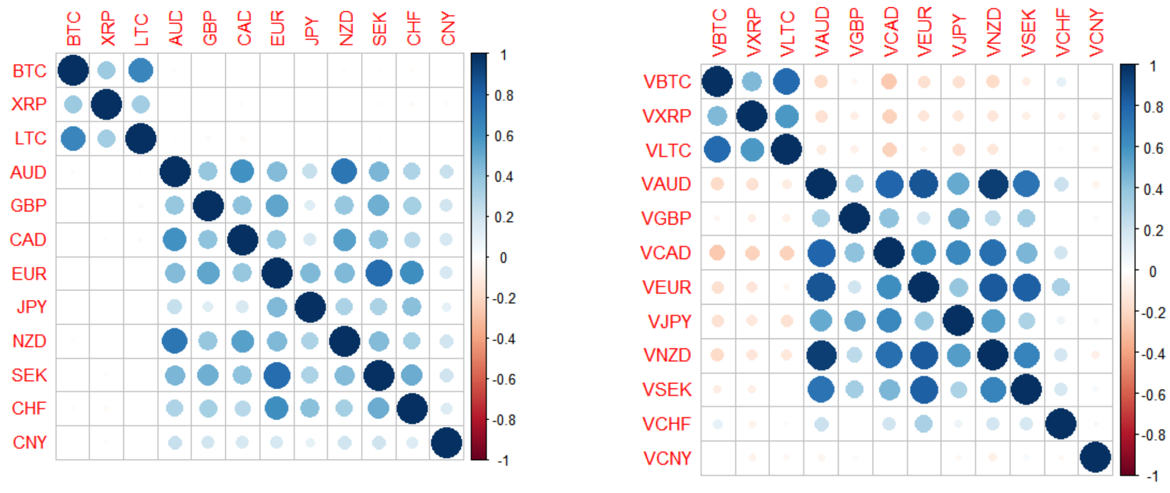


Fig.1. Historical trend of cryptocurrency prices and spot exchange rates of the top 10 traded currencies worldwide.



(a) Return Correlation Matrix (b) Volatility Correlation Matrix

Fig. 2. Correlation Analysis

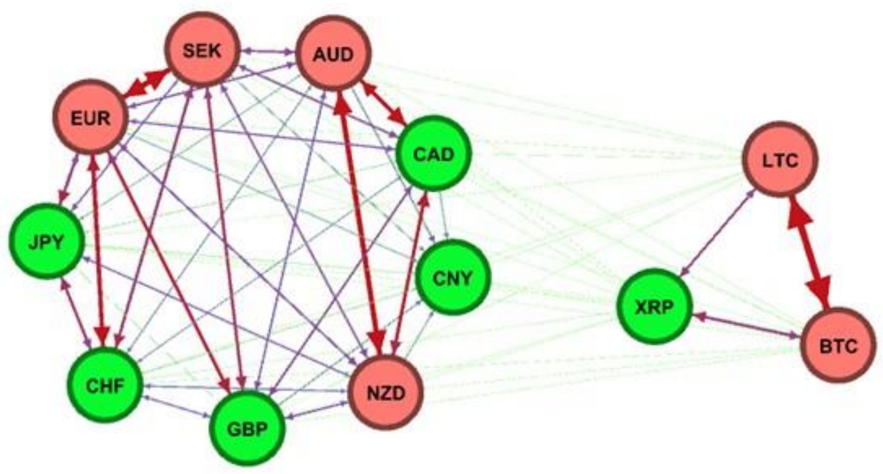


Fig. 3. Directional connectedness network of pairwise return spillovers. Note: this diagram shows the average pairwise directional return spillovers among all possible pairs of our variables where a node's colour implies whether a variable is a net transmitter/receiver of return spillovers. The pink colour indicates net transmitters while the green colour shows net receivers. Furthermore, the thickness and the colour of the arrows represent the magnitude and strength of the average return spillover between each pair where red indicates strong, purple shows moderate, and green refers to weak return spillovers.

Fig. 4. Total return spillover index. Note: This graph displays the time-varying behaviour of the total return spillover index between cryptocurrencies and the top nine most-traded currencies worldwide. This index has been estimated based on a VAR(1) with 10 H-steps forecast horizon and 200-days rolling window.

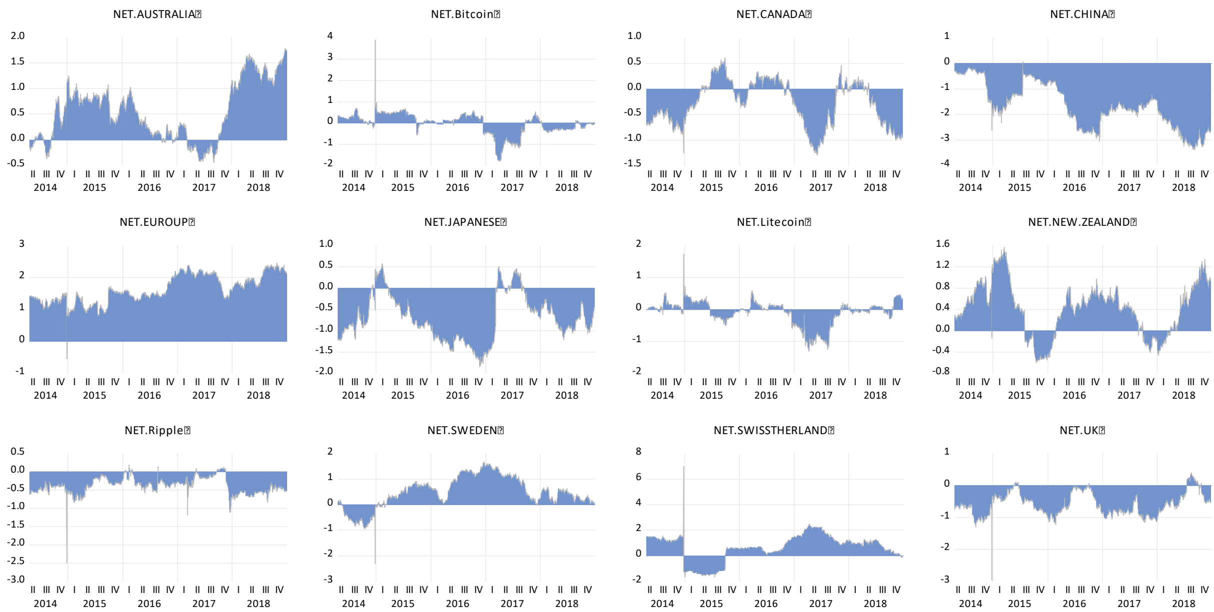


Fig. 5. Net directional return spillover indices. Note: This graph represents the time-varying behaviour of the net directional return spillover index for each of the cryptocurrencies and top nine most-traded currencies worldwide. Positive (negative) values of the index indicate that the variable is a net transmitter (receiver) of return spillover to (from) all other variables. These indices have been estimated based on a VAR(1) with 10 H-steps forecast horizon and 200-days rolling window.

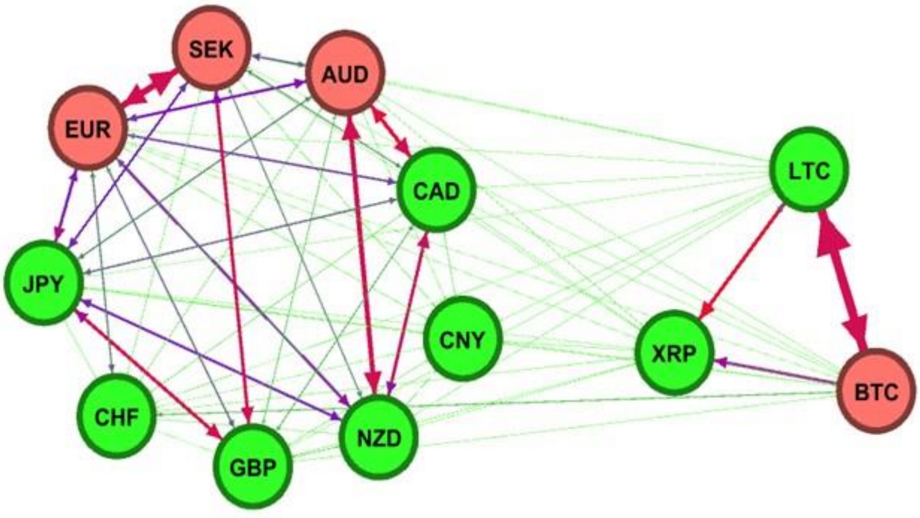


Fig. 6. Directional connectedness network of pairwise volatility spillovers. Note: This diagram shows the average pairwise directional volatility spillovers among all possible pairs of our variables where a node's colour implies whether a variable is a net transmitter/receiver of volatility spillovers with pink colour indicating a net transmitter while green colour shows net receivers. Furthermore, the thickness and the colour of the arrows represent the magnitude and strength of the average volatility spillover between each pair where red indicates strong, purple shows moderate, whereas green refers to weak volatility spillovers.

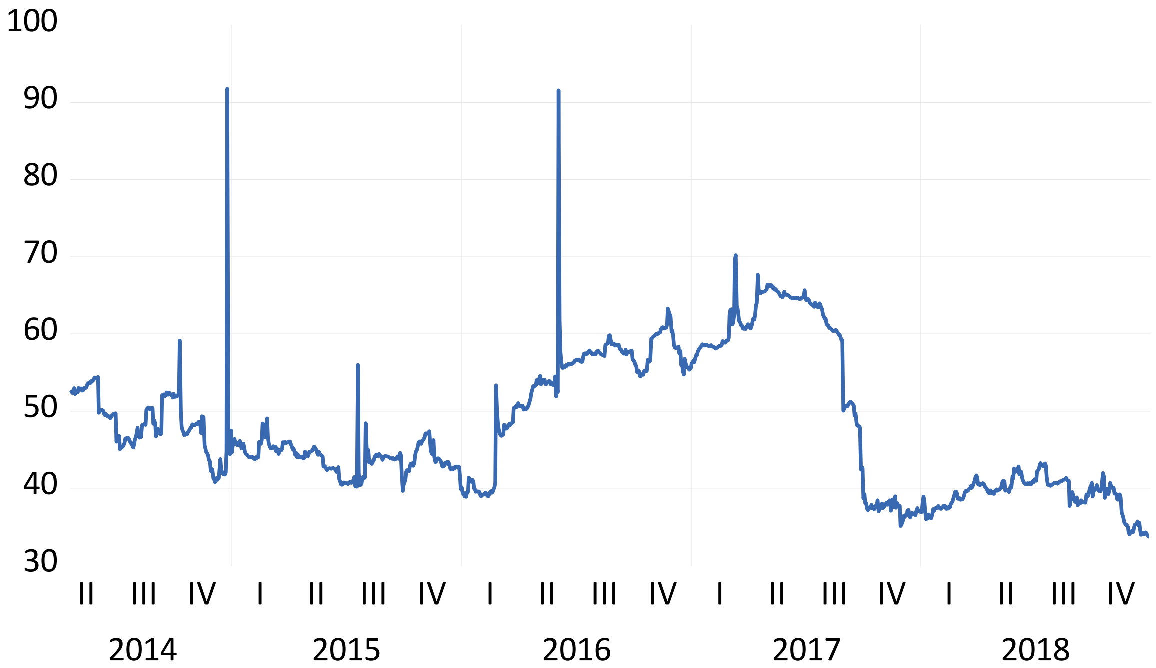


Fig. 7. Total volatility spillover index. Note: This graph displays the time-varying behaviour of the total volatility spillover index between cryptocurrencies and the top nine most-traded currencies worldwide. This index has been estimated based on a VAR(1) with 10 H-steps forecast horizon and 200-days rolling window.

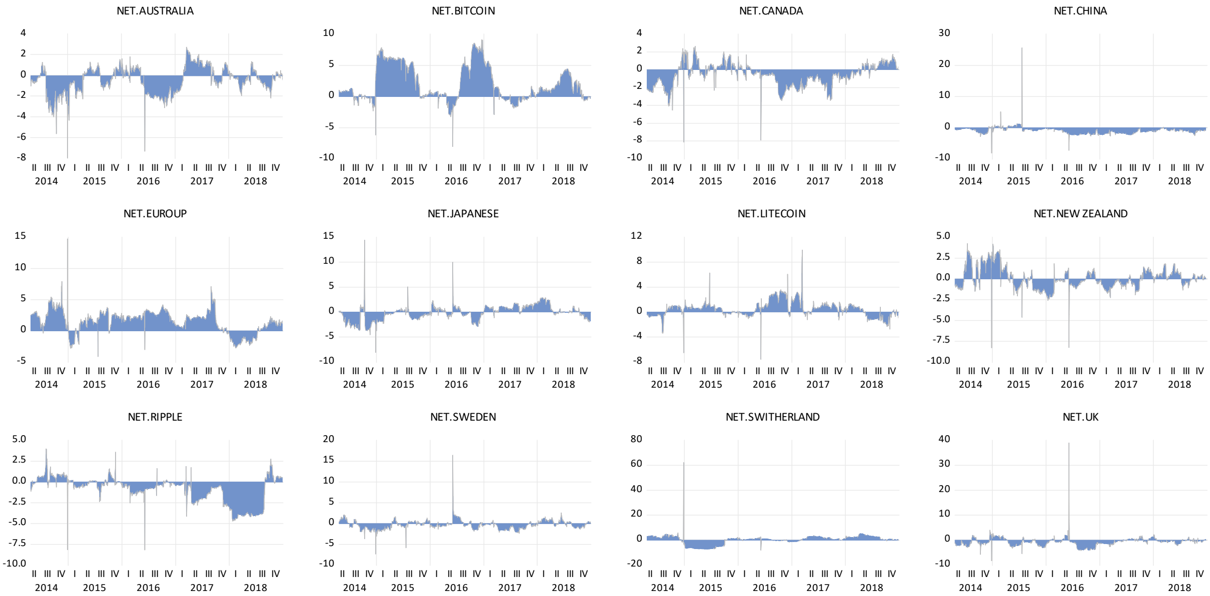


Fig. 8. Net directional volatility spillover indices. Note: This graph denotes the time-varying behaviour of the net directional volatility spillover index for each of the cryptocurrencies and top nine most-traded currencies worldwide. Positive (negative) values of the index indicate that the variable is a net transmitter (receiver) of volatility spillover to (from) all other variables. These indices have been estimated based on a VAR(1) with 10 H-steps forecast horizon and 200-days rolling window.

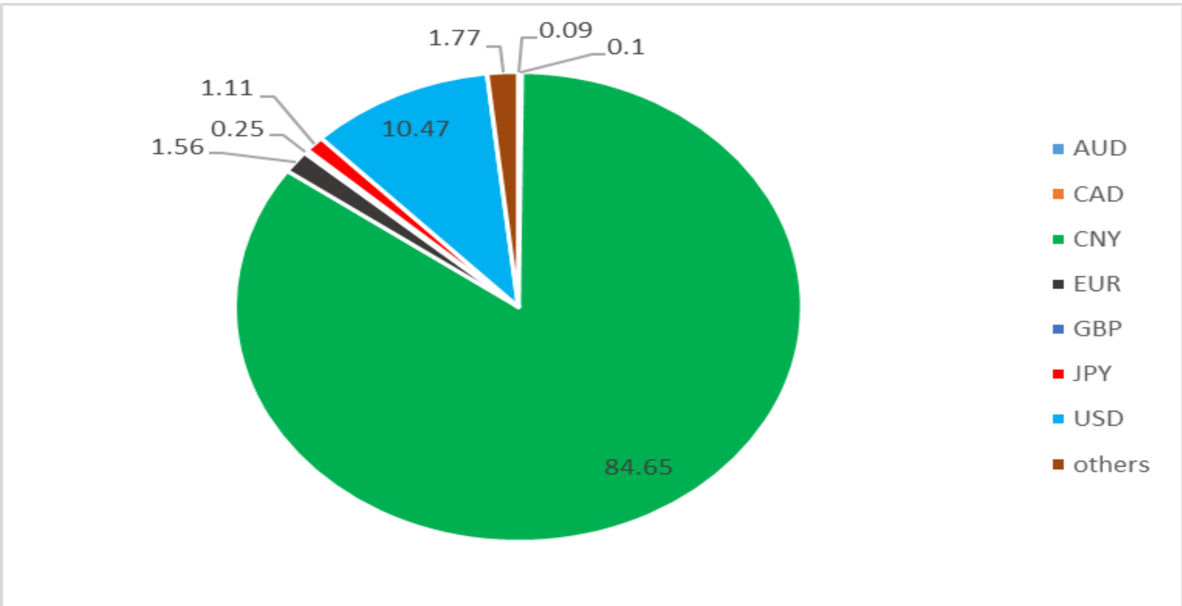


Fig. 9. Currency composition of the global Bitcoin trading volume (%). Note: this figure shows the relative composition (in percentages) of major currencies used to trade Bitcoin over the period January 2013–December 2018. Source: http://data.BitCoinity.org/

Table 1. Descriptive statistics for returns and volatilities of cryptocurrencies and exchange rates of the top 10 traded currencies worldwide.

	BTC	XRP	LTC	AUD	GBP	CAD	EUR	JPY	NZD	SEK	CHF	CNY
Panel A: Returns												
Mean	0.002	0.003	0.002	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Std. Dev.	0.051	0.088	0.079	0.006	0.006	0.005	0.005	0.006	0.007	0.006	0.006	0.002
Maximum	0.521	0.751	0.800	0.023	0.083	0.023	0.023	0.030	0.030	0.031	0.025	0.018
Minimum	-0.266	-0.513	-0.514	-0.026	-0.028	-0.029	-0.026	-0.034	-0.034	-0.025	-0.114	-0.011
Skewness	0.485	1.624	1.724	0.020	2.085	-0.187	-0.058	-0.238	-0.007	-0.017	-5.415	0.415
Kurtosis	14.882	16.639	22.260	4.239	34.657	4.816	5.261	6.856	4.830	4.701	97.356	13.876
JB	8557***	11947***	22767***	94***	59993***	203***	311***	905***	199***	173***	543625***	6564***
Q(20)	52.995***	75.012***	48.566***	11.83	28.18	36.939**	26.817	33.459**	20.527	20.696	64.279***	54.173***
Q2(20)	246.79***	342.16***	335.43***	152.33***	77.55***	138.47***	185.26***	134.46***	123.11***	63.851***	120.15***	127.54***
ARCH(20)	8.192***	10.052***	11.995***	4.276***	3.301***	4.292***	5.153***	4.077***	3.832***	2.212***	6.368***	4.748***
ERS	-38.30***	-4.59***	-35.47***	-5.73***	-32.68***	-10.69***	-7.10***	-3.07**	-3.09**	-4.70***	-7.55***	-34.52***
Panel B: Volatilities												
Mean	0.003	0.009	0.007	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Std. Dev.	0.004	0.018	0.010	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Maximum	0.038	0.217	0.117	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.001	0.000
Minimum	0.000	0.001	0.002	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Skewness	4.745	5.763	5.154	0.736	8.613	1.367	1.073	1.221	0.707	0.941	6.526	8.333
Kurtosis	34.430	46.448	38.011	2.359	90.729	4.938	3.312	3.861	2.383	3.498	50.819	114.840
JB	63325***	118711***	78258***	151***	469595***	659***	276***	393***	139***	222***	144351***	751173***
Q(20)	10896***	3848.1***	9647***	25916***	9202.5***	24574***	25358***	20949***	26039***	22873***	13726***	1479.6***
Q2(20)	4035.7***	911.44***	4304.2***	19058***	4110.2***	20326***	19732***	11313***	18685***	15826***	8102.1***	478.85***
ARCH(20)	233.44***	41.51***	254.8273***	1181.988***	332.797***	1293.441***	1739.874***	569.859***	1265.696***	1029.838***	1317.952***	36.302***
ERS	-5.98***	-8.78***	-5.92***	-1.86*	-6.67***	-2.41**	-1.87*	-3.32***	-1.74*	-2.70***	-5.40***	-16.05***

Note: JB is the Jarque-Bera test for Normality, Q(20) and Q2(20) is the Ljung-Box statistic for serial correlation in raw series and squared residuals, respectively. ARCH (20) testing Engle's ARCH effects up to 20 lags. ERS is the Dickey-Fuller GLS unit root test. ***, **, * indicate significance at 1, 5 and 10% levels.

Table 2. Total return spillovers across the cryptocurrency and foreign exchange markets.

	BTC	XRP	LTC	AUD	GBP	CAD	EUR	JPY	NZD	SEK	CHF	CNY	From Others*
BTC	63.51	8.69	27.28	0.1	0.01	0.06	0.02	0.02	0.04	0.05	0.02	0.2	36.5
XRP	10.93	79.42	8.74	0.02	0.07	0.03	0.15	0.09	0.13	0.17	0.22	0.03	20.6
LTC	27.45	7.76	64.13	0.12	0.09	0.1	0.07	0.07	0	0.03	0.01	0.18	35.9
AUD	0.03	0	0.01	37.84	5.67	13.97	7	2.08	19.98	7.99	3.48	1.95	62.2
GBP	0.1	0.01	0.06	6.91	46.78	7.55	12.75	0.88	6.69	11.12	5.46	1.68	53.2
CAD	0.03	0.01	0.06	16.2	7.01	43.89	6.4	1.28	12.88	7.37	3.4	1.47	56.1
EUR	0	0.02	0.03	6.17	9.13	4.87	33.32	6.76	6.59	19.36	12.76	0.99	66.7
JPY	0.02	0	0.01	3.2	1.07	1.72	11.87	8.96	5.87	5.89	10.63	0.76	41
NZD	0.02	0	0	20.29	5.53	11.26	7.62	3.82	38.4	7.25	4.32	1.5	61.6
SEK	0.01	0.01	0.01	7.61	8.63	6.02	20.85	3.59	6.83	35.9	9.06	1.48	64.1
CHF	0.12	0.02	0.05	4.13	5.26	3.59	16.91	7.98	5.01	11.15	44.8	0.97	55.2
CNY	0.02	0.03	0	5.59	4.37	4.29	3.93	1.35	4.11	3.93	1.89	70.49	29.63
Cont.to others**	38.7	16.6	36.3	70.3	46.8	53.5	87.6	27.9	68.1	74.3	51.2	11.2	
Cont. including own***	102.2	96	100.4	108.2	93.6	97.4	120.9	86.9	106.5	110.2	96.1	81.7	
Net Spillovers	2.27	-4.04	0.39	8.36	-6.46	-2.7	20.95	-13.2	6.71	10.2	-3.93	-18.53	48.50%

Notes: *From Others indicates directional spillover from all currencies j to currency i. **Contribution to others measure spillovers from market i to all markets j. ***Contribution including own shows directional spillover from market i to all markets j including a contribution from own innovations; Other columns contain pairwise (i,j)-th spillovers measures. Total Return Spillover Index demonstrates that 48.5% of the forecast error variance comes from spillovers.

Table 3. Total volatility spillovers across the cryptocurrency and foreign exchange markets.

	BTC	XRP	LTC	AUD	GBP	CAD	EUR	JPY	NZD	SEK	CHF	CNY	From Others*
BTC	72.51	0.61	26.33	0.23	0.07	0.13	0.04	0.02	0.00	0.00	0.06	0.00	27.49
XRP	9.79	75.81	13.10	0.37	0.15	0.11	0.13	0.06	0.04	0.09	0.24	0.13	24.19
LTC	35.15	5.48	58.76	0.17	0.06	0.06	0.01	0.01	0.08	0.03	0.06	0.14	41.24
AUD	0.06	0.37	0.02	48.53	1.84	12.86	8.54	3.78	18.20	4.86	0.76	0.18	51.47
GBP	0.20	0.08	0.00	2.12	64.29	2.65	5.16	12.24	0.87	12.07	0.01	0.32	35.72
CAD	0.01	0.43	0.09	14.26	2.98	53.64	6.48	5.08	11.75	3.61	0.82	0.85	46.36
EUR	0.00	0.18	0.10	6.68	3.33	4.31	48.58	7.85	5.49	19.50	3.86	0.13	51.42
JPY	0.18	0.04	0.02	4.39	9.87	5.10	10.52	54.67	7.58	7.49	0.03	0.13	45.33
NZD	0.00	0.07	0.20	17.15	1.44	9.39	9.34	8.33	49.37	4.00	0.32	0.40	50.63
SEK	0.01	0.14	0.19	6.13	8.55	3.73	22.89	6.65	2.55	48.48	0.42	0.26	51.52
CHF	3.11	0.11	0.01	0.17	0.01	0.04	5.30	0.48	0.14	0.60	90.05	0.01	9.95
CNY	0.01	0.29	0.16	0.48	0.40	0.48	0.64	0.40	0.24	0.89	0.07	95.95	4.06
Cont.to others**	48.52	7.80	40.21	52.13	28.70	38.84	69.03	44.92	46.93	53.13	6.63	2.54	
Cont. including own***	121.03	83.61	98.97	100.66	92.99	92.48	117.61	99.59	96.30	101.61	96.68	98.48	
Net Spillovers	21.03	-16.39	-1.03	0.66	-7.01	-7.52	17.61	-0.41	-3.70	1.61	-3.32	-1.52	36.61%

Notes: *From Others indicates directional spillover from all currencies j to currency i. **Contribution to others measure spillovers from market i to all markets j. ***Contribution including own shows directional spillover from market i to all markets j including a contribution from own innovations; Other columns contain pairwise (i,j)-th spillovers measures. Total Volatility Spillover Index demonstrates that 36.6% of the forecast error variance comes from spillovers.

Table 4. MIN Structure.

	BTCL,t	XRP,t	LTC,t
BTC,t	0	**0.4824**	**0.4882**
XRP,t	**0.5176**	0	**0.507**
LTC,t	0.5118	**0.493**	0

Note: Bold red entries represent the selected edges for the MIN structures based on posterior probabilities higher than or equal to 0.50; Bold green (blue) [brown] indicate posterior probabilities greater than or equal to 0.40 (0.30) [0.20].

Table 5. MAR Structure.

	BTC,t	XRP,t	LTC,t	AUD,t-1	GBP,t-1	CAD,t-1	EUR,t-1	JPY,t-1	NZD,t-1	SEK,t-1	CHF,t-1	CNY,t-1
BTC,t	0.1228	0.0822	0.121	0.143	0.113	0.12	0.0726	0.0776	0.1542	0.1206	0.074	0.4266
XRP,t	0.9952	1	0.3386	0.0944	0.118	0.082	0.1672	0.1276	0.1254	0.1596	0.1986	0.0948
LTC,t	0.2278	0.987	0.1584	0.1956	0.0884	0.1276	0.11	0.1414	0.1338	0.0836	0.114	0.3506

Note: Bold red entries represent the selected edges for the MAR structures based on posterior probabilities higher than or equal to 0.50; Bold green (blue) [brown] indicate posterior probabilities greater than or equal to 0.40 (0.30) [0.20].