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PII: S1059-0560(20)30249-5

DOI: https://doi.org/10.1016/j.iref.2020.10.021

Reference: REVECO 2081

To appear in: *International Review of Economics and Finance*

Received Date: 29 May 2019

Revised Date: 18 August 2020

Accepted Date: 25 October 2020

Please cite this article as: Umar Z., Trabelsi N. & Alqahtani F., Connectedness between cryptocurrency and technology sectors: International evidence, *International Review of Economics and Finance* (2020), doi: https://doi.org/10.1016/j.iref.2020.10.021.

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Connectedness Between Cryptocurrency and Technology Sectors: International Evidence

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Abstract

This paper investigates the connectedness between the technology sector and cryptocurrency markets using Diebold and Yilmaz's (2012, 2014) network connectedness measures. The data cover the period from 1 August 2014 to 31 October 2018. Despite the existence of significant interconnectedness between technology sectors worldwide, the results show that contributions from and to the cryptocurrency market are negligible. The cryptocurrency market appears to be less integrated with the technological system and structurally less exposed to systemic risk. To check robustness, application of Fernández-Macho's (2018) wavelet local multiple correlations found an almost exact linear relationship between global technology sectors for periods of quarterly and longer. Additionally, the Granger causality test confirmed the independence results except for in Japan, Turkey and the USA, where possible changes in cryptocurrency prices may be effective in predicting returns. These findings provide insights for cryptocurrency regulators and potential investors around the world.

JEL Classification: G15–G17

Keywords: Cryptos; Technology sector; Connectedness; Spillover effects; Systemic risk.

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1. Introduction

Financial integration has brought financial markets in advanced economies closer, enabling the mobilisation of capital and the opening of new investment opportunities for international investors. However, increased integration results in a decline in diversification opportunities available to investors and may lead to an increase in contagion (Umar et al., 2019 a,b; Zaremba et al, 2020; Kenourgios et. al., 2020). For instance, financial disaster such as the Asian financial crisis of 1997–1998, the global financial crisis of 2008 and the sovereign debt of the eurozone in 2010 affected most global financial markets. The increased risk of contagion and spillover underscores the importance of understanding the way shocks spread across different economies, markets and sectors, which is of utmost importance for policymakers, regulators and other stakeholders. (Guimarães-Filho & Hong, 2016; Umar et al., 2020 a,b ; Zaremba et al., 2019; Riaz et al, 2019,2020; Naeem et al., 2020). In addition, from an investor's perspective, it is equally important to seek new markets and asset classes that can provide diversification opportunities. During recent years, cryptocurrencies have emerged as one such investment alternative that is attracting a lot of attention from investors, academics and regulators.

Early empirical studies have focused on the nature and characteristics of cryptocurrency and on whether it can be classified with traditional asset classes such as equities, bonds or commodities or even considered a currency (Baur, Hong, & Lee, 2016; Dyhrberg, 2016; Wu & Pandey, 2014; Yermack, 2015). Other studies have analysed the risk–return and hedging attributes of cryptocurrencies from investors' portfolios (Bouoiyour & Selmi, 2017; Bouri et al., 2017; Briere, Oosterlinck, & Szafarz, 2015; Selmi, Mensi, Hammoudeh, & Bouoiyour, 2018; Umar and Gubareva, 2020). There is another strand of literature that is focused on spillovers among

cryptocurrency and other financial markets (Katsiampa et al., 2019 a,b; Bouri et al., 2018; Trabelsi, 2018; Koutmos, 2018; Nikolaos , 2019 and the references therein).

The objective of this paper is to contribute to the growing body of literature on cryptocurrencies by investigating the connectedness between cryptocurrencies and the technology sector. Specifically, we investigate spillover and dependence across major information technology sector markets in advanced[1] and emerging[2] economies, according to FTSE classification as on September 2019[3]. Given that one of the main driving forces of both cryptocurrencies and the technology sector is technological innovation, which subjects them to similar market dynamics, an empirical investigation of the connectedness of these important constituents of technology sector is relevant. In particular, it will enable us to gain insight into the risk transmission and spillover channels, which are important in making optimal financial decisions. To the best of our knowledge, this is the first study to investigate the connectedness between cryptocurrency and technology sectors. Sound understanding of the connectedness of these markets may assist investors in designing better investment and risk management strategies.

To accomplish this task, we use a three-stage empirical methodology. First, we used the network connectedness measures of Diebold and Yilmaz (2014)[4]. The advantage of the network connectedness approach lies in its ability to overcome the shortcomings of traditional correlation-related measures such as pairwise correlation. Diebold and Yilmaz (2014) argue that their measure overcomes the major limitations of measures such as conditional value-at-risk (Adrian and Brunnermeier, 2016) and marginal expected shortfall (Acharya et al., 2012), which detect

[1] United Kingdom, United States, Canada, Japan, Netherlands, Sweden and South Korea.

[2] China, India, Turkey, Thailand and Taiwan.

[3] https://research.ftserussell.com/products/downloads/FTSE-Country-Classification-Update_latest.pdf

[4] Our choice stems from the wide popularity of this approach in recent literature due to its theoretical and practical significance. (Malik and Umar, 2019)

correlations between individual–firm and overall market movements both unidirectionally and bidirectionally. Diebold and Yilmaz (2014) methodology gives us the connectedness estimates in time domain only. To analyse connectedness in the time–frequency domain, we also employed the wavelet local multiple correlation (WLMC) framework proposed by Fernández-Macho (2018). Lastly, in order to analyse the portfolio implications we perform a portfolio hedging effectiveness analysis in the spirit of Kroner and Ng(1998).

This study is focused on the technology sector because it is one of the most significant segments of the world economy. Technology companies have witnessed a continuous increase in their proportionate share in the overall global economy. According to the International Data Corporation (IDC) forecasts in 2019, the global technology market may reach a new height of $5 trillion of market value, with the US technology market being the largest market worldwide by far with approximately 31% of the total international technology market. Moreover, this sector may reach a growth rate of 6.4%, making it one of the main drivers of economic growth in the world economy. Additionally, the final product of these technological companies may have a significant impact on other business domains such as Transportation, Finance, Healthcare, Education and Energy etc. Thus, we may argue that there is a higher level of integration and spillover among technology sector and other business that they attempt to serve. During COVID-19 pandemic, technology sector has attracted even more significance due to its role in reducing the effects of social distancing, self-isolation and travel restriction on economic activities. There is large strand of literature analysing the integration, spillover and portfolio choice issues at aggregate and sectorial level of emerging and advanced markets (Umar 2017, a, b, c; Shahzad et al. 2017; Stereńczak et al., 2020; Kenourgios et al., 2020; Umar et al., 2020). We extend this

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literature by analysing the interdependence and portfolio implications for the technology sector across various advanced and emerging markets.

The cryptocurrency market is based on blockchain technology, which, in turn, is the result of advances and visionary developments in the technology industry. As mentioned above, the existing research on the cryptocurrency market has focused either on the risk and return characteristics of cryptocurrencies as an asset class or on their portfolio attributes as a safe haven and hedge. Thus, we extend this literature by examining the connectedness between the cryptocurrency market and the technology sector. Most of the existing literature has focused primarily on investigating the desirability of Bitcoin as an asset class or in a portfolio context (Baur et al., 2016; Dyhrberg, 2016; Wu & Pandey, 2014; Yermack, 2015). This is not surprising given that Bitcoin, which was launched in 2009, was the first cryptocurrency and dominated the market for years. By April 2018, the total market value of Bitcoin had exceeded $116 billion[5]. However, at the same time, the total market value of cryptocurrencies, numbering around 1,600, exceeded $295 billion (Yi et al., 2018). Our current work considers Bitcoin as well as the cryptocurrency index (CRIX) developed by Trimborn and Härdle (2018). The CRIX index encompass a number of cryptocurrencies and, thus, can be used as a broader proxy for the cryptocurrency market.

Our results indicate the existence of a significant interconnectedness between technology sectors worldwide. However, the contribution from and to the cryptocurrency market remains trivial. This market appears to be less integrated with the combined technological system framework and is structurally less exposed to systemic risk, suggesting that Bitcoin may offer diversification benefits for investors against technology sector risk. To test robustness, we repeated our analysis

[5] According to coinmarketcap.com.

using the WLMC method of Fernández-Macho (2018), and our results were qualitatively similar. Lastly, the portfolio analysis provides that CRIX could be used for diversification by technology investors but cannot be used as effective hedge or safe haven.

The remainder of this paper is structured as follows: Section 2 presents the data and methods; Section 3 provides the empirical results, and Sections 4 and 5 present the robustness check and conclusion, respectively.

2. Data and Methodology

2.1. Data and descriptive statistics

To analyse the connectedness of the technology sector and cryptocurrencies, we used daily total returns of 12 technology sector equity indices in both developed and emerging economies. Developed markets included the UK, the USA, Canada, Japan, the Netherlands and Sweden, while emerging markets included South Korea, China, India, Turkey, Thailand and Taiwan. We used US dollar-denominated total return indices covering the technology sector of each country, provided by Thompson Reuters Datastream. Data for Bitcoin/USD was also obtained from Thompson Reuters Datastream. We used the CRIX index proposed by Trimborn and Härdle (2018)[6]. Data were collected from the period 1 August 2014 to 31 October 2018. Following date matching and removal of holidays, we were left with 1,109 observations. Table 1 presents the summary statistics for each series under consideration.

(Insert Table 1)

[8] https://thecrix.de

Table 1 shows that average returns were positive for all indices except for those in Thailand, Sweden and South Korea. The highest historical average was achieved by CRIX. In the technology sector, the highest average level was recorded by the Turkish technology index, followed by technology sectors in China and the US. It was also observed that the unconditional volatility of CRIX was higher compared with other indices. With respect to skewness and kurtosis measures, the findings show that distributions of all daily returns differed from the normal distribution. The Jarque–Bera test also confirmed this non-normality. Finally, the statistics (bottom of Table 1) show no correlation between technology sectors and CRIX. This measure indicates only the strength and direction of a linear relationship between two variables. However, this study considers the strength of the dependence between two variables in tails of their support.

2.2. Methodology

Following Diebold and Yilmaz (2009, 2012, 2014), the forecast error variance decomposition (FEVD) networks associated with an *n*-variable vector autoregressive (VAR) model was used to define weighted and directed networks from market data. The n-variate stationary process $Y_t = (y_{t,1}, \dots, y_{t,n})$ by structural VAR(p) at t = 1,…, T was formally described as:

$$\Phi(L)Y_t = \varepsilon_t \tag{1}$$

We defined the daily return as $y_{t,n} = (\ln P_t / \ln P_{t-1,n})$, where $P_{t,n}$ is the daily closing value of the nth index on day t and n = 13, reflecting the set of 12 technology sectors and CRIX.

We assume that the roots of $|\Phi(z)|$ lie outside of the unit circle. Under this assumption, the VAR process has the following MA(∞) representation:

$$Y_t = \Psi(L)\varepsilon_t \tag{2}$$

where $\Psi(L)$ is an $n \times n$ infinite lag polynomial matrix of coefficients.

We defined owned variance shares as fractions of the *H*-ahead error variances in forecasting y_j that were attributable to return shocks to y_j, for $j = 1, 2\ldots,n$ and across variance shares, or spillovers, as fractions of the *H*-ahead error variances in forecasting y_j that were attributable to return shocks to y_k, for $k = 1,2,\ldots,n$, such that $j \neq k$. This can be written as:

$$(\theta_H)_{j,k} = ((\Sigma)_{k,k})^{-1} \sum_{h=0}^{H-1} \left((\Psi_h \Sigma)_{j,k}\right)^2 / \sum_{h=0}^{H-1} (\Psi_h \Sigma \Psi_h')_{j,j} \tag{3}$$

where Ψ_h is an $n \times n$ matrix of coefficients corresponding to lag *h*, and $\sigma_{kk} = (\Sigma)_{k,k}$.

$(\theta_H)_{j,k}$ captures the Pesaran–Shin generalised forecast error variance decomposition (GFEVD) partial contribution from k index to j index.

Given that the effect did not add up to 1 ($\sum_{h=0}^{H} \theta_{j,k} \neq 1$) in the columns in the generalised VAR process of FEVDs, Diebold and Yilmaz (2012, 2014) propose the use of Pesaran and Shin's (1998) GFEVD, which is invariant to variable ordering, to identify uncorrelated structural shocks from correlated reduced form shocks. This extension enables the evaluation of the pairwise connectedness, noted as $C_{j \leftarrow k}(H)$, in each market. This made it possible to determine total directional connectedness, the whole connectedness index and the net pairwise directional connectedness as follows:

1) The total directional connectedness from variable *k* to other variables:

$$C_{j \leftarrow \blacksquare}(H) = 100 \times \sum_{j \neq k, j=1}^{n} C_{j,k}(H) / \sum_{j,k=1}^{n} C_{j,k}(H) \tag{4}$$

Similarly, the total directional connectedness of other variables to *j* is given by:

$$\mathrm{C}_{\blacksquare\leftarrow k}(H) = 100 \times \sum_{j\neq k,k=1}^{n} \mathrm{C}_{j,k}(H) / \sum_{j,k=1}^{n} \mathrm{C}_{j,k}(H) \tag{5}$$

2) The total connectedness of the whole system:

$$\mathrm{C}_H = 100 \times \frac{\sum_{j\neq k}(\tilde{\theta}_H)_{j,k}}{\sum(\tilde{\theta}_H)_{j,k}} = 100 \times \left(1 - \frac{\mathrm{Tr}\{\tilde{\theta}_h\}}{\sum \tilde{\theta}_h}\right) \tag{6}$$

where Tr{.} is the trace operator. The standardised effects $(\tilde{\theta}_H)_{j,k}$ is:

$$(\tilde{\theta}_H)_{j,k} = (\theta_H)_{j,k} / \sum_k (\theta_H)_{j,k} \tag{7}$$

3) The net pairwise directional connectedness between indices *j* and *k* is the difference between gross spillover effects transmitted from index *j* to index *k* and those transmitted from *k* to *j*:

$$C_{jk}^{g}(H) = \left(\frac{\bar{\theta}_{kj}^{g}(H) - \bar{\theta}_{jk}^{g}(H)}{N}\right) \times 100 \tag{8}$$

Net pairwise connectedness indicates whether index *j* is a net receiver or a net transmitter of information from or to index *k*. Positive values from the net pairwise spillovers index imply that market *j* is a net transmitter of spillover effects to market *k*, whereas negative values imply that market *j* is a net receiver of spillover effects from index *k*.

3. Empirical Results

To provide a global view of spillovers across the technology indices between real and virtual systems, we explored three systems: the first (S1), which included only technology stock indices, we used as the benchmark; the second (S2) was an asset class mix that included, besides CRIX,

the set of technology sectors; the third (S3) was also an asset class mix but, instead of CRIX, we considered Bitcoin returns from S2.

Table 2 presents the results from S1. We used VAR with order p selected using the Akaike information criterion for each estimation approach and a 100-day forecasting horizon. This table provides detailed insights into the decomposition of global forecast error variance in the set of 12 technology sector indices. For example, the *ij*th entry is the estimated contribution to the forecast error variance of index *i* coming from innovations to index *j*. The off-diagonal column sums (labelled 'To') and row sums (labelled 'From') express directional connectedness (see Eqs. 4 and 5).

(Insert Table 2 here)

In the final row of this table, the total connectedness ratio (see Eq. 6) appears to be relatively larger, indicating that, on average, roughly 38% of the forecast error variance across technology stock indices comes from spillovers.

The net pairwise directional index (NDC) was measured using Eq. 8. This provided useful information on the major net recipients and contributors of shocks. As shown in Table 2, we found that Canada, the Netherlands and USA were the highest net transmitters of return shocks, whereas the remaining markets (Japan, South Korea, China, India, Turkey, Thailand and Taiwan) were net receivers of return shocks from other markets. Among the net transmitter markets, we found that the US market was the highest transmitter of the shock channel, followed by the Canadian technology sector. The Japanese technology sector was the highest receiver of shocks from other technology sectors, followed by the Taiwanese and South Korean technology sectors. The Turkish market was less susceptible to global shocks, indicating that, in the last decade, its

overall integration with other technological markets was low. Given that the Turkish technology sector can be used to hedge against negative shocks from other technology stock markets, these findings are crucial for international investors and portfolio managers.

Table 3 depicts the results of S2, including CRIX and the set of technology sectors from S1.

(Insert Table 3 here)

The cryptocurrency market showed negligible spillover transmitters and recipients of shock channels. More precisely, the results show that directional spillover from and to CRIX varied between 0% and 3% over the sample period. As Trabelsi (2018) asserts, this low connectedness is attributable to different drivers of returns in crypto markets (e.g. investor adoption and legal and regulatory developments) versus, for example, the stock and bond markets, which are driven more by economic growth, interest rates and corporate profits. Additionally, these results support the general hypothesis that, because the blockchain technology of cryptocurrencies is relatively new and insignificant in the world of trade and finance, past global shocks, such as the Chinese Government banning of Bitcoin transactions in December 2013, the US taxation of Bitcoin as property in March 2014, the hacking of Bitstamp in July 2015 and Bitfinex in August 2016 and the resignation of Mike Hearn from Bitcoin in January 2016, were unable to influence the stability of the whole technological system.

Table 4 shows the results of S3, which included BTC instead of CRIX. The results were similar to those from S2, and from these we concluded that the virtual market is not an integrated part of the global technology system as designed in S1.

(Insert Table 4 here)

In summary, there is a moderate connection between the global technology indices. More precisely, innovations (i.e. shocks) to technology sectors around the world are responsible for more than 50% of the error variance in the 100-day forecasting of stock returns in the US, China, Taiwan and the Netherlands against only 2% in the 100-day forecasting of CRIX or BTC returns. That is, return spillovers among technology stock markets were much larger than those from the virtual technology market for the rest of the sample. Moreover, total return spillovers from the US technology sector was higher than those of any other sector, while the total return spillovers from other markets was highest in Japan (see Figure 2). Hence, the US and Japanese technology sectors are more vulnerable and higher contributors to the technology crisis than any other regional market.

(Insert Figure 2 here)

We estimated dynamic connectedness using 275-day rolling window samples. The resulting time series of the system's contributions to each variable and each variable's contribution to the system are presented in Figure 1 Panels A and B, respectively. Panel C is related to total connectedness evolution in S1 and S2.

(Insert Figure 1 here)

Our first observation revealed that the spillover shape clearly shows a slight time-varying connectedness (i.e. without sudden spikes and dips) during our short sample period, but this does not mean that all considered variables moved in tandem or responded to events in the same manner. Specifically, we can see that variable contributions to system variance error were, in general, higher than the contribution of the system to each variable. A weak estimated value of around 1% for both cases was attributed to CRIX. With respect to the technology sectors, it

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appears that most cases, except for Thailand and Turkey, were similar in magnitude. For instance, Panel A shows that the system contribution to the USA and Canada was between 40% and 50% from our sample data, indicating that these markets are more closely linked with the global technology system. In addition, Panel B shows that the USA influenced a higher number of technology sectors around the world. However, it also appears to be the most affected by shocks from other sectors, except for CRIX and BTC. These results are in line with our previous results related to static spillover measures (see Table 2).

4. Robustness Check

4.1. Granger causality test

For check for robustness, we first used the linear Granger causality test to confirm our initial basic findings on the independence of CRIX from other technology sectors. We formally tested two times series, the daily returns from the technology sector and CRIX, denoted by $\{X_t\}$ and $\{Y_t\}$, $t \in \mathbb{Z}$, respectively. We also designated the information sets $\{X_t\}$ and $\{Y_t\}$ to time t-1, $\Psi_{X,t-1}$ and $\Psi_{Y,t-1}$, respectively. In respect to lags l_x, l_y and k, $\{X_t\}$ is said to Granger-cause $\{Y_t\}$ if:[7]

$$(Y_t, \dots, Y_{t+k}) \mid (\Psi_{Y,t-ly}, \Psi_{X,t-lx}) \nsim (Y_t, \dots, Y_{t+k}) \mid \Psi_{Y,t-ly} \tag{9}$$

This means that $\{X_t\}$ is a Granger-cause of $\{Y_t\}$ if the distribution of $\{Y_t\}$, conditional on its own history, is not the same as it can be predicted by the histories of both $\{X_t\}$ and $\{Y_t\}$.

(Insert Table 5 here)

[7] We use '$\sim$' to show equivalence in distribution.

Table 5 shows the *p*-values of the linear Granger causality test between different pairs. From this test, three major findings emerged: (1) There is strong evidence of causality from CRIX to the Japanese and Turkish technology sectors at a 5% significance level; therefore, CRIX can help predict returns in both sectors. (2) There is no significant causality from all considered technology sectors to CRIX, which reflects the difficulty detected by many researchers (e.g. Trabelsi, 2018) regarding the predictability of CRIX prices. (3) There is sufficient evidence of causality from the US technology sector to CRIX at a 10% significance level (which may not constitute strong evidence). Figure 3 shows causal features in one-to-one pairs, clearly indicating that there are a higher number of significant arrows from global markets to Japan. This means that prediction of Japan's technology returns is mostly influenced by other technological markets around the world. In addition, there are significant arrows from Japan to other markets. Specifically, Japan's technology sector can significantly contribute to predicting returns of three major technology markets, namely USA, Canada and China. This reflects the presence of high technological interactions between these nations.

(Insert Figure 3 here)

4.2. Wavelet local multiple correlations

To confirm our second basic finding on the integration of technology stock markets, we used a new statistical tool, WLMC, which is useful for the analysis of co-movements within a set of time series. Compared with existent analysis techniques (e.g. cross-correlation, neural networks, long memory and causality), the emphasis is to use a moving weighted regression on wavelet coefficients to detect co-movement dynamics in the multiscale analysis of multivariate time

series. Specifically, WLMC was used to produce a single set of multiscale correlations over time (see Appendix).

Figure 4 Panel A shows the WLMCs obtained as a measure of co-movement dynamics in the set of 12 technology indices. As shown, the correlation structure between these indices during the past four years was not homogeneous because it varied over time and across frequencies. Specifically, the correlation structure appears to be quite stable over time, with multiple high correlations starting at around 0.90 and reaching values near 1.0 at the longest timescales (monthly and above). This may be interpreted as near integration of technology stock markets at monthly horizons and above in the sense that the returns obtained from any of them may be determined by the overall performance of other markets. Below the fortnightly scale, we observed that short-term multiple correlations increased from 0.6 to 0.9 in early 2016. The technology sectors were significantly affected by the turmoil in this period as contagion.

The interpretation of Panels B and C of Figure 4 is similar to that of Panel A. This supports the absence of significant correlation between CRIX or BTC with other technology sectors, which is in line with our findings based on Diebold and Yilmaz's (2012, 2014) model.

4.3. Portfolio implications

To show how CRIX can help investors in reducing their portfolio risk, we propose to assess the diversifier, the hedge and the safe-haven properties of CRIX for the overall sample then during the recent COVID-19 pandemic crisis period. Typically, we analyse three portfolios: The first one is the market benchmark portfolio proxy by the technology sector index, where the second is the optimal portfolio using mean–variance optimization framework which selects optimal weights by minimizing risk under budget balance restrictions, and the third is the hedged

portfolio with an investor has long position on technology index and short one on CRIX (for more details see Kroner and Sultan, 1993; Kroner and Ng, 1998; among others). The results are documented in Table 6.

(Insert Table 6 here)

The measures of standard deviations show that most regional investors will reduce their risk by diversifying their wealth between technology stocks and CRIX. According to hedged portfolio results, CRIX could not be considered as a strong hedge asset against the risk of Technology stocks in different regions around the world. In fact, one can see closed-zero hedging effectiveness (HE) for different cases which means that the variance of unhedged portfolio and the variance of hedged portfolio are similar. These results are in line with our previous results that support the less integration of the virtual currency market into the technology sectors and thus they can be a good diversifier but not a hedge instrument for the last five years, but what about the recent crisis onset by the discovery of the COVID-19 coronavirus?

Table 6 shows that the benchmark portfolios exhibit a similar pattern defined by a high risk during the recent COVID-19 crisis. By constructing the mean-variance portfolios consisting of CRIX and tech sector stocks, we find that adding a small quantity of CRIX reduces the risk for all cases (except JP). This implies that including CRIX in a tech stock portfolio will provide a suitable level of risk to technology investors around the word. Concerning the hedging strategy, one can see a rise of hedge ratio for the most cases (except CAN, US and SW) due to the increase of the unconditional correlation between examined assets. In these sectors, investors would sell more futures contracts on the virtual market to cover their risk during the ongoing COVID-19 crisis. The HE is already closed to zeros which means that CRIX cannot be characterized as a

safe-haven asset for these regional investors during the ongoing COVID-19 crisis but it remains a good diversifier asset. This result is consistent with the conclusion of a recent study by Corbet, Larkin, and Lucey (2020) that Bitcoin does not offer hedging nor safe haven properties during the COVID-19 pandemic.

5. Conclusion

The recent boom and bust of the cryptocurrency market has attracted much attention from investors, regulators and other stakeholders in financial markets. This paper adds to the growing body of literature by investigating the interlinkages between the cryptocurrency market and the technology sector. In this paper, we performed refined measures of connectedness (i.e. static and rolling window analysis) between several advanced and emerging technological sectors and the cryptocurrency market. The results show that, in general, cryptocurrencies are less integrated with the global system. The lack of connectedness of cryptocurrencies has a number of implications for investors, regulators and other stakeholders. For investors interested in seeking exposure in the technology sector, the results imply that cryptocurrencies may be used as a diversifier for technology sector investments. In particular, based on the findings from our sample, for a technology sector investor looking to diversify internationally, cryptocurrencies have a lower integration than any other technology sector. These findings provide insights for cryptocurrency regulators and potential investors globally. Given that government regulation has been shown to cause significant fluctuations in certain cryptocurrency prices (e.g. the 2013 Chinese Government ban of Bitcoin in financial institutions and the 2014 US Government taxing of Bitcoin as property), our results, primarily the lower exposure of Bitcoin to systemic risk, may help reduce the issuing of warnings by regulators and stabilise the digital market. In contrast, cryptocurrencies may offer better diversification opportunities, improving its acceptance by large

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banks, technology companies and financial service firms, which have vested interests in the development of blockchain technology.

For financial modelling problems, non-linear and non-parametric techniques have become increasingly used in research. In line with our research question, both Baruník and Krehlik (2017) and Diks and Wolski (2018) have developed new methods to test instantaneous and lagged connectedness between markets or quintiles of joint distribution in the frequency domain. These methods are an excellent platform for further research in financial technology and a natural extension of our paper.

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Appendix

Let us consider $W_{jt} = \{\omega_{1jt},\ \omega_{2jt}, \dots ,\ \omega_{njt}\}$ to be the scaler λ_j wavelet coefficients obtained by applying the maximal overlap discrete wavelet transform (MODWT) to each time series.[8] Following Fernández-Macho (2012), at each λ_j we calculate a series of local multiple correlation coefficients as the square roots of the regression coefficients of determination for that linear combination of variables ω_{ijt}, i = 1…n. In practice, the coefficient of determination can be obtained as $R_i^2 = 1 - 1/\rho^{ii}$, where $\rho^{ii}$is the *i*th diagonal element of the complete correlation matrix P. Therefore, $\varphi_X(\lambda_j)$ is obtained as:

$$\varphi_X(\lambda_j) = \sqrt{1 - \frac{1}{\max diag\, P_{j,s}^{-1}}}, s = 1 \dots T. \tag{10}$$

where $P_{j,s}^{-1}$ is the $(n \times n)$ weighted correlation matrix of ω_{jt} with weights $\theta(t-s)$, the $\max diag\ (.)$ operator selects the largest element in the diagonal of the argument and *n* is the number of indices in each system (i.e. for S1, *n* = 12; for S2 and S3, *n* = 13).

Since a regression coefficient of determination can also be obtained as the square of the correlation between observed values and fitted values, $\varphi_X(\lambda_j)$ can also be expressed as:

$$\varphi_X(\lambda_j) = Corr(\theta(t-s)^{\frac{1}{2}}\omega_{ijt}, \theta(t-s)^{\frac{1}{2}}\widehat{\omega}_{ijt}$$

$$= \frac{Cov(\theta(t-s)^{\frac{1}{2}}\omega_{ijt}, \theta(t-s)^{\frac{1}{2}}\widehat{\omega}_{ijt})}{\sqrt{Var\left(\theta(t-s)^{\frac{1}{2}}\omega_{ijt}\right)Var\left(\theta(t-s)^{\frac{1}{2}}\widehat{\omega}_{ijt}\right)}}\ s = 1 \dots T. \tag{11}$$

8 The discrete wavelet transform is a wave designated to work with time series defined essentially over a range of integers.

where ω_{ij} is chosen to maximise $\varphi_X(\lambda_j)$ and $\widehat{\omega}_{ij}$ are fitted values in the local regression of ω_{ij} on the rest of wavelet coefficients at scale λ_j.

Applying a MODWT of order J to each of the univariate time series, we would obtain J length-T vectors of MODWT coefficients $\widehat{W}_{jt} = \{\widehat{\omega}_{1jt},\ \widehat{\omega}_{2jt}, \dots ,\ \widehat{\omega}_{njt}\}$, for j = 1…J. From Eq. 11, the WLMC of scale λ_j is a non-linear function of all the $n(n$-1)/2 of W_{jt}. Therefore, a consistent estimator of the WLMC based on the MODWT is given by:

$$\hat{\varphi}_X(\lambda_j) = \sqrt{1 - \frac{1}{\max diag \hat{P}_{j,s}^{-1}}} \tag{12}$$

To calculate the scales λj, we chose J = 6 so that seven vectors (six wavelet coefficients and one scaling coefficient) were produced for each daily returns series.[9] We also followed Whitcher, Guttorp and Percival (2000) to define each scale by $[2^{-j}\pi, 2^{1-j}\pi)$. After inverting that frequency range, the corresponding periods were within $(2^j, 2^{j+1}]$ time units intervals. Therefore, with five daily data per week, the scales of the wavelet coefficients were associated with periods of 2–4 days (which includes most intraweek scales), 4–8 days (including the weekly scale), 8–16 days (fortnightly scale), 16–32 days (monthly scale), 32–64 days (quarterly scale) and 64–128 days (quarterly to biannual scale), respectively.

[9] The maximum decomposition level J is given by $[\log_2(T)]$, which, in the present case, means a maximum level of 10. Since the number of feasible wavelet coefficients becomes critically small at high levels, we chose to carry out the wavelet analysis with J = 6 (Percival & Walden, 2006).

Tables and Figures

Table 1. Descriptive statistics

	CAN	JP	UK	USA	NL	SW	CHN	IND	KOR	TUR	TH	TW	CRIX
Mean (%)	.065	0.018	0.002	0.060	0.048	−0.022	0.062	0.023	−0.002	0.075	−0.000	0.029	0.253
Max. (%)	7.000	4.000	23.044	5.00	9.000	8.471	8.000	5.208	5.106	13.363	9.710	6.737	19.854
Min. (%)	−5.000	−6.000	−28.377	−4.901	−6.000	−14.453	−7.000	−6.050	−6.000	−21.13	−22.112	−7.700	−25.334
Stdev (%)	1.246	1.105	1.867	1.078	1.524	1.669	1.652	1.173	1.533	2.537	1.477	1.288	4.490
Skw.	0.191	−0.284	−1.824	−0.459	−0.097	−1.303	0.052	−0.233	−0.253	−0.945	−2.855	−0.213	−0.538
Kurt.	4.960444	5.093	75.31	5.607	5.400	14.54	4.667	5.390	3.899	12.61	55.38	6.162	8.085
JB	175.9223	207.4	231,104.8	337.0	255.6	6,170.7	123.1	261.3	47.0	4,236.1	122,396.8	448.9	1,191.2
Prob.	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Correlation	0.020	0.004	0.012	0.018	0.044	0.045	0.009	(0.002)	0.013	0.042	0.012	(0.005)	1.000
Obs.	1,058	1,058	1,058	1,058	1,058	1,058	1,058	1,058	1,058	1,058	1,058	1,058	1,058

Note. This table presents the descriptive statistics of the series used in this study. CAN: Canada, JP: Japan; UK: United Kingdom; USA: United States; NL: Netherlands; SW: Sweden; CHN: China; IND: India; KOR: South Korea; TH: Thailand; TW: Taiwan, TUR: Turkey; CRIX: cryptocurrency index.

Table 2. Connectedness between technology sectors (S1)

	CAN	JP	KOR	NL	SW	UK	USA	CHN	IND	TUR	TH	TW	From	NDC
CAN	-	0.01	0.01	0.07	0.04	0.05	0.18	0.03	0.02	0.01	0.01	0.02	0.44	0.22
JP	0.07	-	0.04	0.05	0.03	0.04	0.11	0.04	0.02	0.01	0.01	0.04	0.44	(0.31)
KOR	0.03	0.04	-	0.04	0.03	0.02	0.07	0.07	0.01	0.01	0.01	0.09	0.43	(0.14)
NL	0.07	0.00	0.02	-	0.09	0.10	0.10	0.04	0.01	0.01	0.01	0.03	0.49	0.17
SW	0.06	0.00	0.01	0.11	-	0.06	0.06	0.03	0.02	0.01	0.01	0.01	0.38	0.02
UK	0.06	0.00	0.01	0.12	0.06	-	0.07	0.03	0.01	0.00	0.01	0.02	0.39	0.00
USA	0.17	0.00	0.01	0.09	0.04	0.04	-	0.04	0.01	0.01	0.01	0.02	0.46	0.44
CHN	0.05	0.02	0.07	0.05	0.03	0.03	0.09	-	0.02	0.01	0.02	0.08	0.47	(0.06)
IN	0.05	0.01	0.01	0.02	0.03	0.02	0.05	0.02	-	0.01	0.01	0.03	0.26	(0.11)
TUR	0.02	0.01	0.01	0.01	0.01	0.00	0.02	0.02	0.01	-	0.01	0.01	0.12	(0.03)
TH	0.02	0.00	0.01	0.02	0.01	0.01	0.03	0.02	0.01	0.00	-	0.02	0.17	(0.05)
TW	0.06	0.03	0.08	0.07	0.02	0.03	0.12	0.08	0.02	0.01	0.02	-	0.52	(0.14)
To	0.66	0.13	0.29	0.66	0.40	0.40	0.89	0.41	0.15	0.09	0.12	0.38		
													Total connectedness ratio	**0.3802**

Note. This table presents the connectedness results for the technology sectors of various countries. Values are in absolute numbers. To report percentages, multiply by 100. NDC: net directional connectedness. CAN: Canada, JP: Japan; UK: United Kingdom; USA: United States; NL: Netherlands; SW: Sweden; CHN: China; IND: India; KOR: South Korea; TH: Thailand; TW: Taiwan, TUR: Turkey.

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Table 3. Connectedness between technology sectors and CRIX (S2)

	CAN	JP	KOR	NL	SW	UK	USA	CHN	IND	TUR	TH	TW	CRIX	From	NDC
CAN	-	0.01	0.01	0.07	0.04	0.05	0.18	0.03	0.02	0.01	0.01	0.02	0.00	0.44	0.22
JP	0.07	-	0.04	0.05	0.03	0.04	0.11	0.04	0.02	0.01	0.01	0.04	0.00	0.44	(0.31)
KOR	0.03	0.04	-	0.04	0.03	0.02	0.07	0.07	0.01	0.01	0.01	0.09	0.00	0.43	(0.14)
NL	0.07	0.00	0.02	-	0.09	0.10	0.10	0.04	0.01	0.01	0.01	0.03	0.00	0.49	0.17
SW	0.06	0.00	0.01	0.11	-	0.06	0.06	0.03	0.02	0.01	0.01	0.01	0.00	0.38	0.02
UK	0.06	0.00	0.01	0.12	0.06	-	0.07	0.03	0.01	0.00	0.01	0.02	0.00	0.39	0.00
USA	0.17	0.00	0.01	0.09	0.04	0.04	-	0.04	0.01	0.01	0.01	0.02	0.00	0.46	0.44
CHN	0.05	0.02	0.07	0.05	0.03	0.03	0.09	-	0.02	0.01	0.02	0.08	0.00	0.47	(0.06)
IND	0.05	0.01	0.01	0.02	0.03	0.02	0.05	0.02	-	0.01	0.01	0.03	0.00	0.26	(0.12)
TUR	0.02	0.01	0.01	0.01	0.01	0.00	0.02	0.02	0.01	-	0.01	0.01	0.00	0.13	(0.02)
TH	0.02	0.00	0.01	0.02	0.01	0.01	0.03	0.02	0.01	0.00	-	0.02	0.00	0.17	(0.05)
TW	0.06	0.03	0.08	0.07	0.02	0.03	0.12	0.08	0.02	0.01	0.02	-	0.00	0.52	(0.14)
CRIX	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	-	0.03	(0.01)
To	0.66	0.13	0.29	0.66	0.40	0.40	0.90	0.41	0.15	0.10	0.12	0.38	0.02		
							Total connectedness ratio							**0.3544**	

Note. This table presents the connectedness results for the technology sectors and CRIX. Values are in absolute numbers. To report percentages, multiply by 100. NDC: net directional connectedness. CAN: Canada, JP: Japan; UK: United Kingdom; USA: United States; NL: Netherlands; SW: Sweden; CHN: China; IND: India; KOR: South Korea; TH: Thailand; TW: Taiwan, TUR: Turkey; CRIX: cryptocurrency index.

Table 4. Connectedness between technology sectors and BTC (S3)

	CAN	JP	KOR	NL	SW	UK	USA	CHN	IND	TUR	TH	TW	BTC	From	NDC
CAN		0.01	0.01	0.07	0.04	0.05	0.18	0.01	0.03	0.02	0.01	0.01	0.00	0.44	0.20
JP	0.07	-	0.04	0.05	0.03	0.04	0.11	0.01	0.04	0.02	0.01	0.01	0.00	0.43	(0.31)
KOR	0.04	0.05	-	0.04	0.03	0.02	0.07	0.01	0.08	0.01	0.01	0.01	0.00	0.37	(0.15)
NL	0.07	0.00	0.02	-	0.09	0.11	0.11	0.00	0.04	0.01	0.01	0.01	0.00	0.48	0.16
SW	0.06	0.00	0.01	0.11	-	0.06	0.06	0.01	0.03	0.02	0.01	0.01	0.00	0.38	0.03
UK	0.06	0.00	0.01	0.13	0.06	-	0.07	0.01	0.03	0.01	0.00	0.01	0.00	0.38	0.01
USA	0.17	0.00	0.01	0.09	0.04	0.05	-	0.01	0.04	0.01	0.01	0.01	0.00	0.45	0.43
CHN	0.02	0.01	0.01	0.03	0.01	0.01	0.08	-	0.03	0.01	0.00	0.00	0.00	0.22	(0.13)
IND	0.06	0.02	0.07	0.06	0.04	0.03	0.10	0.01	-	0.02	0.01	0.02	0.00	0.43	(0.06)
TUR	0.05	0.01	0.01	0.02	0.03	0.02	0.05	0.01	0.02	-	0.01	0.01	0.00	0.25	(0.11)
TH	0.02	0.01	0.01	0.01	0.01	0.00	0.02	0.00	0.02	0.01	-	0.00	0.00	0.11	(0.02)
TW	0.02	0.00	0.01	0.02	0.01	0.01	0.03	0.00	0.02	0.01	0.00	-	0.00	0.15	(0.04)
BTC	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-	0.02	(0.00)
To	0.64	0.12	0.22	0.64	0.41	0.39	0.88	0.09	0.37	0.14	0.09	0.11	0.01		
											Total connectedness ratio			**0.3160**	

Note. This table presents the connectedness results for the technology sectors and BTC. Values are in absolute numbers. To report percentages, multiply by 100. NDC: net directional connectedness. CAN: Canada, JP: Japan; UK: United Kingdom; USA: United States; NL: Netherlands; SW: Sweden; CHN: China; IND: India; KOR: South Korea; TH: Thailand; TW: Taiwan, TUR: Turkey; BTC: Bitcoin.

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Table 5. *p*-values of the Granger causality between different pairs

	CAN	JP	KOR	NL	SW	UK	USA	CHN	IND	TUR	TH	TW

	CAN	JP	KOR	NL	SW	UK	USA	CHN	IND	TUR	TH	TW	CRIX
CAN	-	0.01	0.46	0.00	0.06	0.01	0.05	0.03	0.50	0.35	0.63	0.01	0.41
JP	-	-	0.00	-	0.00	0.00	-	0.00	0.00	0.01	0.00	0.00	0.10
KOR	0.00	0.48	-	0.00	0.00	0.00	-	0.03	0.35	0.04	0.23	0.11	0.53
NL	0.00	0.26	0.13	-	0.49	0.07	0.00	0.27	0.38	0.52	0.10	0.02	0.56
SW	0.00	0.14	0.06	0.33	-	0.97	0.00	0.35	0.68	0.31	0.31	0.00	0.28
UK	0.01	0.23	0.03	0.21	0.27	-	0.00	0.23	0.04	0.33	0.94	0.08	0.19
USA	0.06	0.00	0.17	0.01	0.03	0.04	-	0.29	0.30	0.66	0.78	0.00	0.13
CHN	0.00	0.01	0.16	0.00	0.00	0.00	-	-	0.28	0.04	0.79	0.03	0.20
IND	0.00	0.49	0.20	0.00	0.00	0.02	0.00	0.02	-	0.41	0.48	0.01	0.62
TUR	0.62	0.71	0.34	0.22	0.69	0.80	0.15	0.85	0.64	-	0.54	0.99	0.05
TH	0.04	0.51	0.48	0.37	0.66	0.55	0.02	0.83	0.64	0.71	-	0.50	0.57
TW	-	0.38	0.55	-	0.00	0.00	-	0.01	0.37	0.00	0.04	-	0.16
CRIX	0.22	0.10	0.30	0.43	0.26	0.31	0.14	0.30	0.71	0.12	0.61	0.32	-

Note. This table presents the P-values of the granger causality between technology sector and CRIX. Values are in absolute numbers. To report percentages, multiply by 100. NDC: net directional connectedness. CAN: Canada, JP: Japan; UK: United Kingdom; USA: United States; NL: Netherlands; SW: Sweden; CHN: China; IND: India; KOR: South Korea; TH: Thailand; TW: Taiwan, TUR: Turkey; CRIX: cryptocurrency index.

Table 6. Portfolio analysis

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	Period from 1 August 2014 to 31 October 2018											
Benchmark Portfolio												
Stdev (%)	1.22	1.13	1.51	1.51	1.64	1.85	1.06	1.61	1.17	2.50	1.46	1.27
Mean-Variance optimal portfolio												
Tech weights	0.93	0.94	0.90	0.91	0.89	0.85	0.95	0.88	0.93	0.76	0.90	0.92
Stdev (%)	1.18	1.18	1.18	1.19	1.19	1.19	1.19	1.18	1.18	1.19	1.18	1.18
Hedged portfolio												
hedge ratio (%)	0.56	0.15	0.64	1.87	2.05	1.11	0.65	0.76	-0.13	2.28	0.73	-0.08
Stdev (%)	1.22	1.13	1.52	1.51	1.64	1.85	1.06	1.62	1.18	2.51	1.46	1.28
HE	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	COVID-19 pandemic period from 15 November 2019 to 10 July 2020											
Benchmark Portfolio												
Stdev (%)	2.79	1.66	2.59	2.64	2.62	2.67	2.74	1.85	2.50	2.91	1.88	1.83
Mean-Variance optimal portfolio												
Tech weight	0.76	1	0.87	0.82	0.79	0.83	0.74	0.90	0.87	0.78	0.93	0.97
Stdev (%)	2.38	1.66	2.50	2.45	2.30	2.50	2.13	1.76	2.41	2.62	1.85	1.82
Hedged portfolio												
Hedge ratio (%)	-0.15	1.15	0.48	0.20	-0.09	0.27	-0.51	0.07	0.43	0.14	0.47	0.73
Stdev (%)	2.78	1.55	2.52	2.63	2.62	2.64	2.64	1.85	2.45	2.90	1.85	2.00
HE	0.01	0.13	0.05	0.01	0.00	0.02	0.07	0.00	0.04	0.01	0.03	-0.19

Note. This table presents the results of three portfolios: The first one is the market benchmark portfolio proxy by the technology sector index, where the second is the optimal portfolio using mean–variance optimization framework, and the third is the hedged portfolio with an investor has long position on technology index and short one on CRIX. CAN: Canada, JP: Japan; UK: United Kingdom; USA: United States; NL: Netherlands; SW: Sweden; CHN: China; IND: India; KOR: South Korea; TH: Thailand; TW: Taiwan, TUR: Turkey. HE hedging effectiveness. Stdev standard-deviation.

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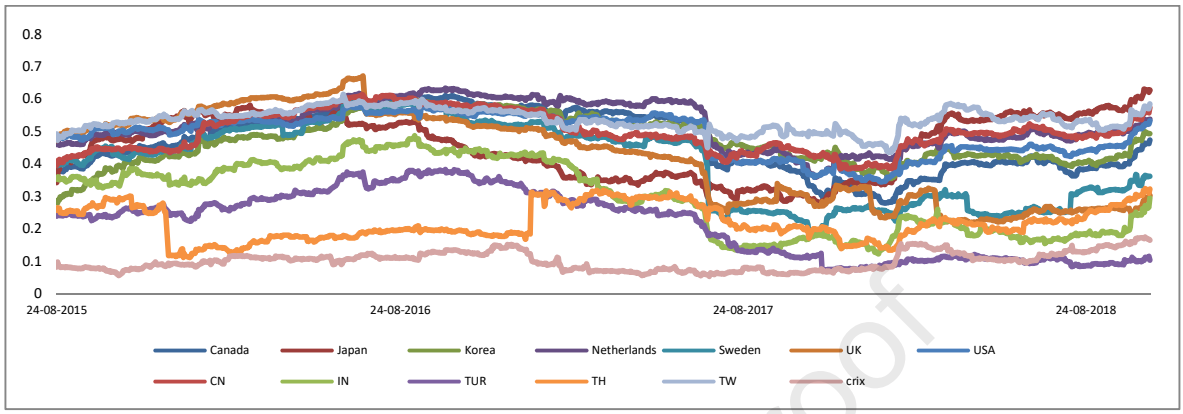
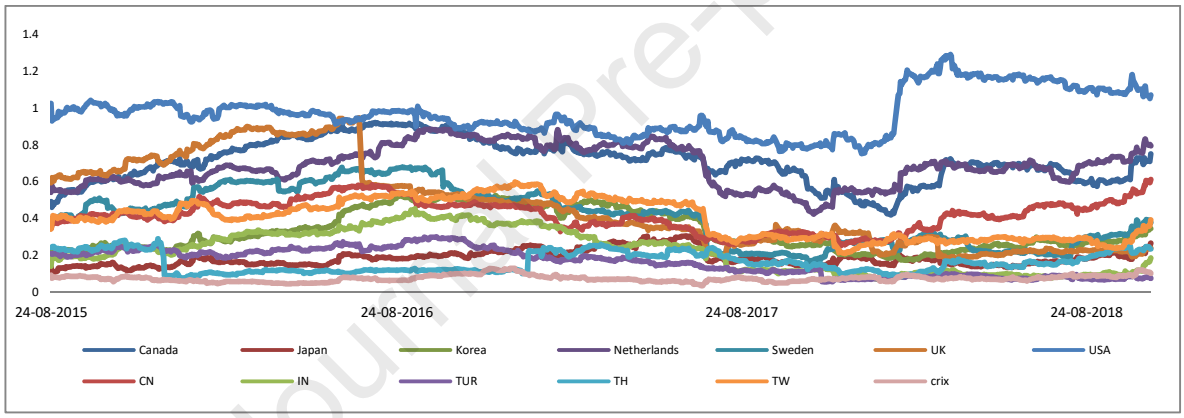
Figure 1. Rolling window dynamic of net directional connectedness

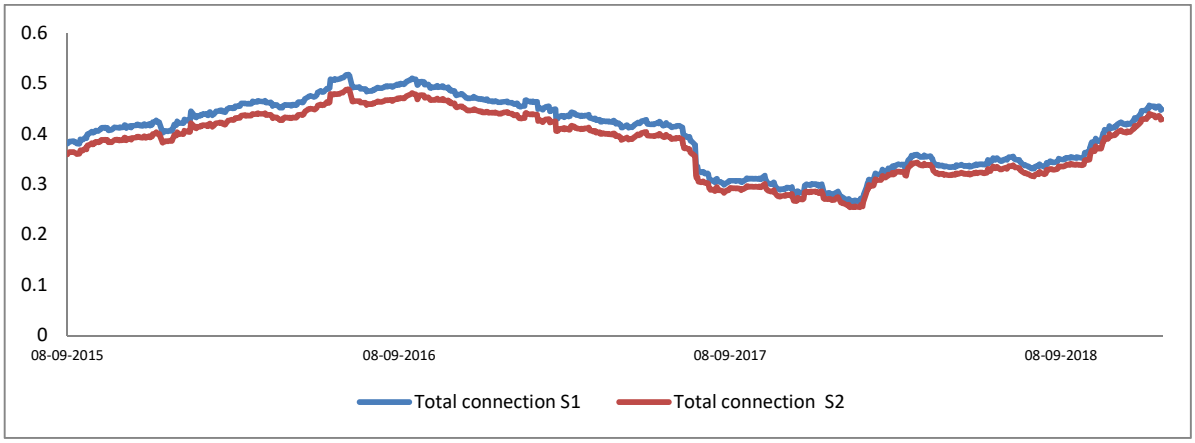
Panel A. Rolling window of system contributions to each variable



Panel B. Rolling window of each variable contribution to system

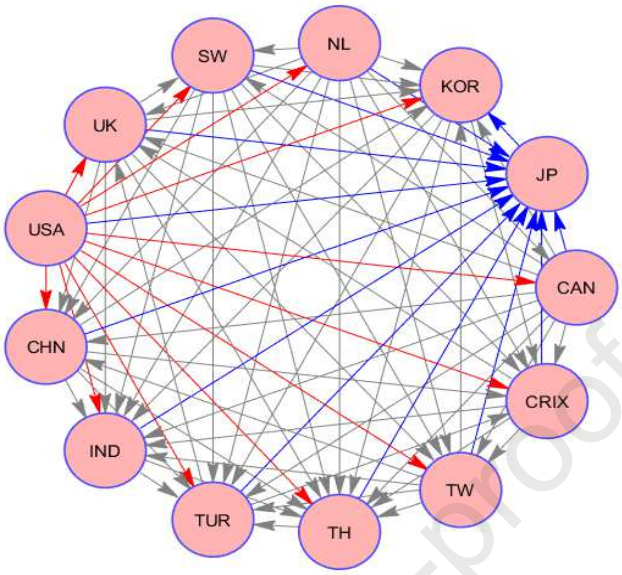


Panel C. Rolling window of total connectedness ratio of S1 and S2



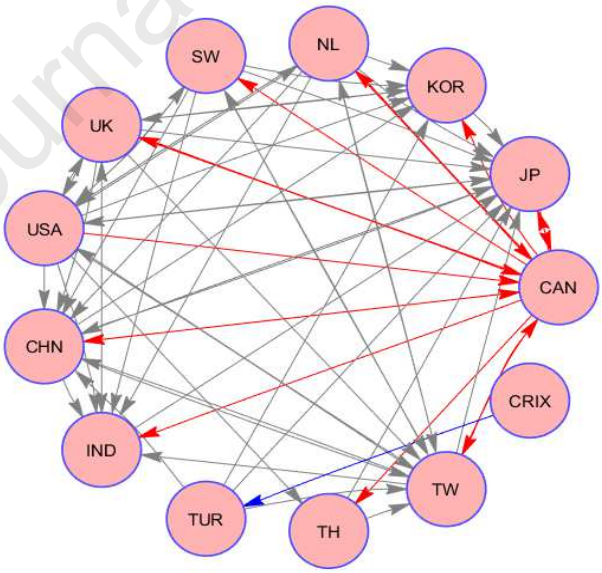
Note. S1: system involving 12 main technology sectors of UK, US, JP, CAN, CHN, KOR, IN, TH, TW, TUR, NL and SW. S2 system involving S1 and the cryptocurrency index (CRIX).

Figure 2. Arrows indicating connectedness between variables



Note. Arrows indicate positive net directional connectedness from the source toward the edge of the arrow. A greater number of arrows indicates greater connectedness. UK: United Kingdom; USA: United States; CHN: China; IND: India; TH: Thailand; TW: Taiwan, TUR: Turkey; CRIX: cryptocurrency index.

Figure 3. Arrows indicating statistically significant Granger causality at 5%.



Note. UK: United Kingdom; USA: United States; CHN: China; IND: India; TH: Thailand; TW: Taiwan, TUR: Turkey; CRIX: Cryptocurrency index.

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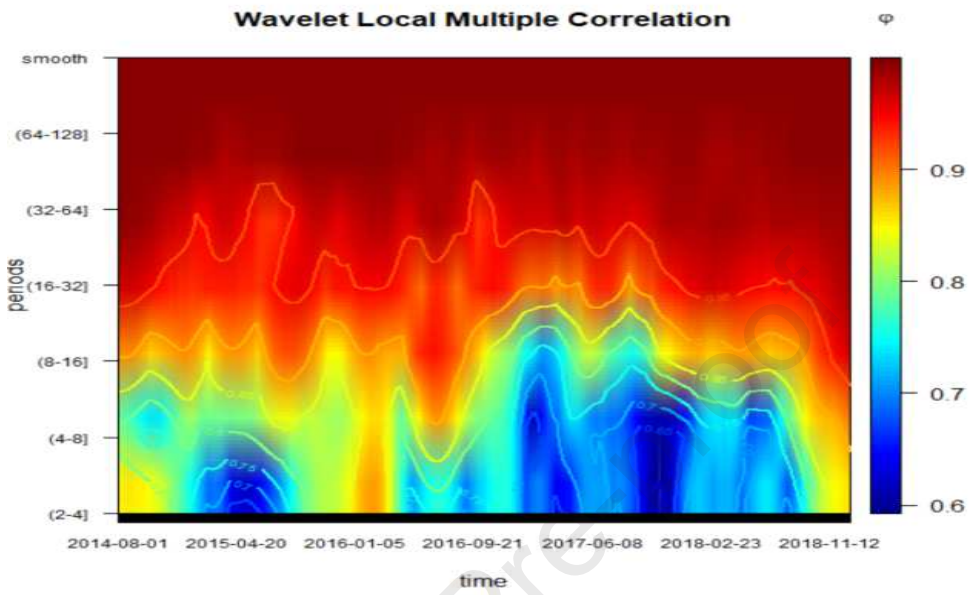
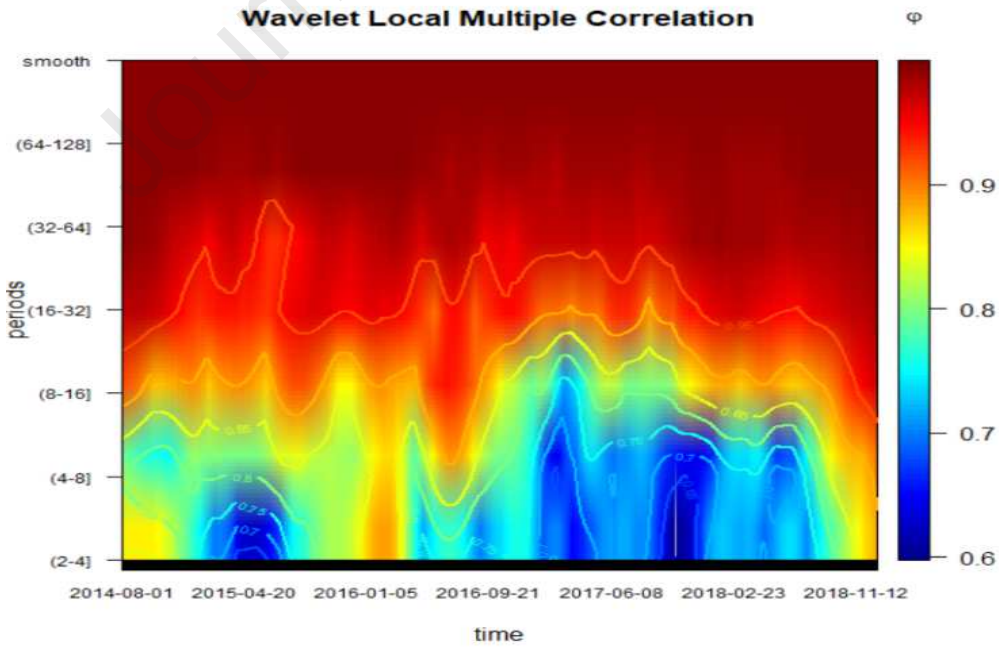
Figure 4. Wavelet local multiple correlations (WLMC)

Panel A. WLMC of S1



Panel B. WLMC of S2



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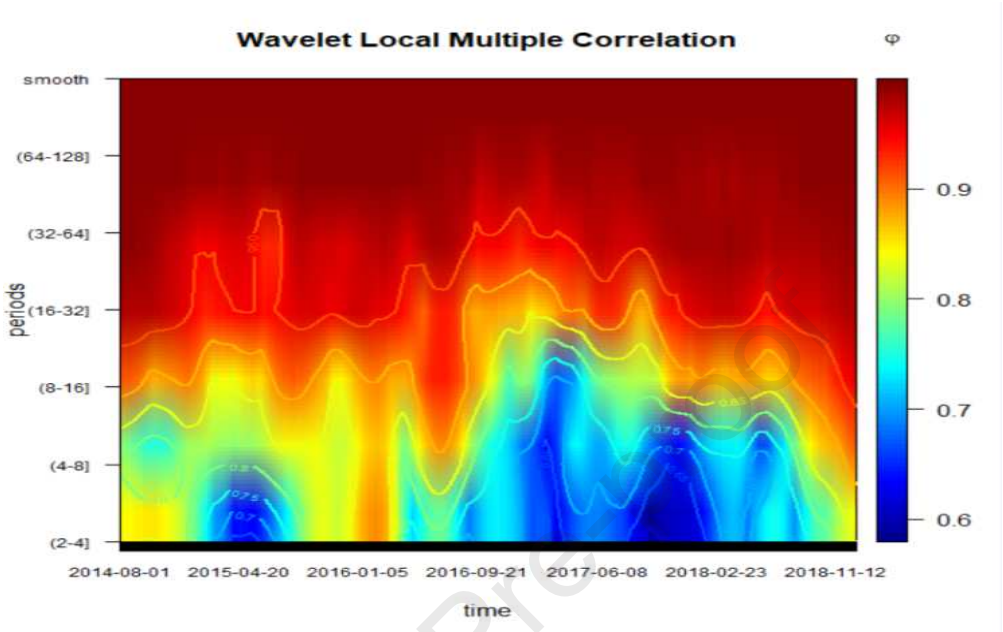
Panel C. WLMC of S3



Note. S1: system involving 12 main technology sectors of UK, US, JP, CAN, CHN, KOR, IN, TH, TW, TUR, NL and SW. S2 system involving S1 and the cryptocurrency index (CRIX). S3 system involving S1 and BTC.

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Dear Professor Hamid Beladi

We are pleased to submit the re-revised manuscript entitled “Connectedness Between Cryptocurrency and Technology Sectors: International Evidence”.

We thank the editors and the reviewers for offering us the opportunity to revise our paper and improve its quality. We would especially like to thank the reviewers for their constructive comments, which have significantly improved the manuscript.

We do hope that we have been able to meet your expectations in regard to the revision of this paper.

This manuscript has not been published or presented elsewhere in part or in entirety and is not under consideration by another journal. We have read and understood your journal’s policies, and we believe that neither the manuscript nor the study violates any of these. There are no conflicts of interest to declare.

Thank you for your consideration. I look forward to hearing from you.

Yours sincerely,

Faisal Alqahtani

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