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When bitcoin lost its position: Cryptocurrency uncertainty and the dynamic spillover among cryptocurrencies before and during the COVID-19 pandemic

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A B S T R A C T

This paper examines the dynamic spillovers among the major cryptocurrencies under different market conditions and accounts for the ongoing COVID-19 health crisis. We also investigate whether cryptocurrency policy (CCPO) uncertainty and cryptocurrency price (CCPR) uncertainty affect the dynamic connectedness. We adopt the Quantile-VAR approach to capture the left and right tails of the distributions corresponding to return spillovers under different market conditions. Generally, cryptocurrencies show heterogeneous responses to the occurrence of the COVID-19 pandemic. We find that the total spillover index (TCI) varies across quantiles and rises widely during extreme market conditions, with a noticeable impact of the COVID-19 pandemic. Bitcoin lost its position as a dominant "hedger" during the health crisis, while Litecoin became the most dominant "hedger" and/or "safe-haven" asset before and during the pandemic period. Moreover, our analysis shows a significant impact of market uncertainties on total and net connectedness among the five cryptocurrencies. We argue that the COVID-19 pandemic crisis plays a vital role on the relationship between CCPO as well as CCPR and the dynamic connectedness across all market conditions.

1. Introduction

After the global financial crisis, with the failure of the world financial system, cryptocurrencies or digital currencies have been created as a new class of assets. Due to their attractiveness, cryptocurrencies have received great attention from policymakers and investors. These assets are isolated from the conventional financial system through the "blockchain" technology (Antonakakis, Chatziantoniou, & Gabauer, 2019; Yermack, 2017). Bitcoin was the first invented digital currency remaining the most popular cryptocurreny. After that, other crypto-currencies, such as Ethereum, Litecoin, and Ripple, have been created and started gaining pace, especially after the so-called "Bitcoin crash" in early 2018. Consequently, a great interest in these assets has been renewed making a significant jump in their market capitalization from 295 billion USD in 2018 to 2.12 Trillion USD in April 2021. These assets marked a significant contribution by their speculative nature and their substitutive character of conventional currencies (Mokni & Ajmi, 2021). In another vein, cryptocurrencies are alluring investment tools as they are often considered "safe haven" assets against other asset classes (e.g., Bouri, Gupta, Tiwari and Roubaud, 2017b; Mokni, Bouri, Ajmi and Vo, 2021b;Urquhart & Zhang, 2019, among others) or uncertainty (Mokni, 2021; Mokni, Al-Shboul, & Assaf, 2021a; Mokni, Youssef, & Ajmi, 2022; Wu, Tong, Yang, & Derbali, 2019).

Given the interest in the cryptocurrency market and its pertinence for businesses and individuals from different cultures, backgrounds, and geographical regions, there has been considerable research attention directed toward examining the system of connectedness and/or spillover effects in the cryptocurrency market (Antonakakis et al., 2019; Bouri, Saeed, Vo and Roubaud, 2021c; Ciaian, Kancs, & Rajcaniova, 2018; Corbet, Lucey, & Yarovaya, 2018; Elsayed, Gozgor, & Lau, 2022a; Gandal & Halaburda, 2016; Ji, Bouri, Lau, & Roubaud, 2019; Shahzad, Bouri, Kang, & Saeed, 2021; Zięba, Kokoszczyński, & Śledziewska, 2019,

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among others). However, these studies have reported mixed results and conflicting evidence of cryptocurrencies' connectedness as well as they have failed to provide clear-cut evidence of spillover effects. In addition, existing studies have not looked at the role of uncertainty in driving the spillover effects between cryptocurrencies, making this issue to remain appealing.

To overcome these limitations, this paper has two objectives. Firstly, we explore the dynamic spillovers between the five major cryptocurrencies. Secondly, we investigate the effect of cryptocurrencies uncertainties, in the spirit of Lucey, Vigne, Yarovaya, and Wang (2021), on the dynamic connectedness between these assets before and over the COVID-19 pandemic period. In this regard, Lucey et al. (2021) developed two cryptocurrency market uncertainty indices, namely: the cryptocurrency policy uncertainty (CCPO) and the cryptocurrency price uncertainty (CCPR). Unlike other uncertainty measures, which depend on major newspapers (e.g., Baker, Bloom, & Davis, 2016; Carriero, Clark, & Marcellino, 2018; Rice, Vehbi, & Wong, 2018), cryptocurrency uncertainty indices are developed based on a very wide range of newspapers and news-wire suppliers of media information. The reason for using a wider range of media sources (e.g., news wire feeds and media news transcripts, among others) is to identify the "social" aspect of cryptocurrencies. Thus, it is of great interest to examine the impact of the CCPO and CCPR on cryptocurrencies' connectedness.

In contrast to prior studies, using the global or country-specific economic policy uncertainty (EPU) invented by Baker et al. (2016), focusing on the CCPO and CCPR can provide a wide-ranging image about the cryptocurrency market uncertainty as a driver of dynamic connectedness between different assets. Such an analysis could be useful for investors in the design of their portfolios as well as for risk management analysis. Moreover, although the vast majority of prior studies have largely focused on using the EPU indices (e.g., geopolitical risk (GPR), Global Economic Policy Uncertainty index (GEPU), News-based Implied Volatility index (NVIX), CBOE-stock volatility index (VIX), Trade Policy Uncertainty (TPU)), and others (see, Aysan, Demir, Gozgor, & Lau, 2019; Conlon, Corbet, & McGee, 2020; Davis, 2016; Fang, Su, & Yin, 2020; Gozgor, Tiwari, Demir, & Akron, 2019; Manela & Moreira, 2017), none of these studies has investigated the effect of the cryptocurrency uncertainties on the dynamic spillover. Thus, our study is considered the first to examine the impact of uncertainty (policy and price) related to cryptocurrencies on the dynamic connectedness of cryptocurrencies.

This paper contributes to the literature in some ways. First, unlike previous studies realized over a limited time period of COVID-19, it considers a more updated time period including the vaccination effect. This allows us to highlight the relative importance of connectedness over different stages of the pandemic. Such an analysis makes our study the first to deliver evidence on the dynamic volatility spillover of the five leading cryptocurrencies within the COVID-19 period including the vaccination effect. Second, contrary to prior studies, which examined the connectedness among cryptocurrencies using the conventional mean-based estimators to measure the system of average shocks, our paper implements the Quantile-VAR approach (quantile-based approach) in the spirit of Diebold and Yilmaz (2009, 2012, 2014) framework to capture the left and right tails of the distributions of the cryptocurrencies return spillovers: the bear, normal, and bull market states. Third, our analysis is the first to examine whether the dynamic connectedness is affected by the cryptocurrency policy and price uncertainty (CCPO and CCPR) proposed by Lucey et al. (2021). These indices may accurately evaluate how policy and regulatory debates influence cryptocurrency returns and volatility, and how such influence differs from reaction to Bitcoin attention in general. The use of these indices is also useful because they allow for a better understanding of the behavior of different sets of investors in cryptocurrency markets. For example, better-informed investors might be vulnerable to changes in policy uncertainty, yet, the less-informed ones might react differently to general media attention, and then to cryptocurrency uncertainties. Furthermore, the increase in the institutional interest in digital assets could also make cryptocurrency markets more inclined to policy uncertainty over time.

The main findings of this paper are addressed as follows. We find that the total spillover index (TCI) varies across quantiles and rises widely during extreme market conditions. Although Bitcoin is always a risk diversifier cryptocurrency, it lost its position as a dominant hedge during the crisis, while Litecoin acts as a stronger hedger before the crisis and a value saver during the crisis period. Other cryptocurrencies show heterogeneous responses to the occurrence of the COVID-19 pandemic. This confirms that the quantile-based approach outperforms the mean-based approach in capturing the dynamic connectedness among cryptocurrencies. Our analysis also reports evidence of the impact of CCPO and CCPR on the total connectedness among the five cryptocurrencies as well as on the net spillover of each cryptocurrency. We argue that the COVID-19 pandemic has a significant impact on the relationship between CCPO and CCPR and the dynamic connectedness.

This paper has several policy implications. First, it can provide useful information concerning investment and hedging decisions. It allows investors to have a better insight into active diversification strategies in portfolios predominantly constituted by cryptocurrencies. Second, the paper can help central banks and regulators to follow certain prudential regulatory policies in order to stabilize the financial market. Third, one can use the highly or weakly interconnected cryptocurrencies to overcome the risk associated with the COVID-19 crisis. Fourth, this study can also allow investors and market participants to distinguish whether the transmission of shocks among cryptocurrencies has a short and long-run effect, leading to a better evaluation of systematic risk. Fifth, given that different kind of uncertainty, may have different impacts and predictive power on the cryptocurrency market, investors can learn from the results of our study on how to adjust their portfolios based on evidence on market volatilities. Finally, it allows investors to explore the relative importance of negative and positive shocks to each or from each cryptocurrency.

The remainder of the paper is structured as follows: Section 2 comprehensively addresses the literature review. Section 3 discusses the data and methodology. The empirical results are discussed in Sections 4 and 5 presents the concluding remarks.

2. Literature review

A growing body of literature has been recently observed in examining the connectedness (and/or spillover effect) among cryptocurrencies' returns. Although the evidence of connectedness is well established, the empirical literature has not reached clear-cur evidence of the direction and the nature of the connectedness among cryptocurrencies' returns. By focusing on the connectedness among cryptocurrencies, the existing literature can be categorized into two strands of studies, namely: *i*) research studies that examined the connectedness among cryptocurrencies and/or with other assets (mostly financial assets) and *ii*) the recent studies that examined the impact of policy uncertainty on the connectedness among cryptocurrencies.

Starting with the first strand of the literature, research studies have found different results of connectedness among cryptocurrencies and/or between cryptocurrencies with other conventional assets. Although several studies have examined the connectedness between cryptocurrencies and other financial assets, they have reported mixed results and inconclusive evidence. For instance, Corbet, Meegan, Larkin, Lucey, and Yarovaya (2018), using the generalized variance decomposition methodology, found that cryptocurrencies (Bitcoin, Ripple, and Litecoin) have relatively no connectedness with the global financial market indices (the MSC-GSCI Total Returns Index, the US dollar Broad Exchange Rate, the S&P500 Index, the COMEX closing gold price, VIX and the Markit ITTR110 index). In another study by Fry and Cheah (2016), a low level of connectedness among Bitcoin, fiat currencies, and gold was found, suggesting that Bitcoin cannot play the role of traditional currencies or cannot be used as a hedging instrument. By extending the GARCH volatility analysis, as proposed by Dyhrberg (2016a, 2016b), to examine the return and volatility connectedness among Bitcoin, gold, and the US dollar, Baur, Dimpfl, and Kuck (2018) showed that Bitcoin rather resembles a highly speculative asset compared to gold and the US dollar. Baur, Hong, and Lee (2018) reported that Bitcoin is uncorrelated with traditional asset classes, such as stocks, bonds, and commodities, both in normal and distressing periods. Based on the generalized forecast error variance decomposition analysis, Trabelsi (2018) showed no significant spillover effects between cryptocurrencies and other financial markets, suggesting that cryptocurrencies are real independent financial assets that cause no effect on financial system stability. They also claimed that the connectedness cryptocurrencies are mostly used for speculation purposes.

More recently, research studies have examined the volatility spillover with other asset classes. Kurka (2019) argued that the volatility spillover between cryptocurrencies, stocks and foreign exchange is irrelevant. However, during the periods of substantial shocks, they showed that Bitcoin became a weak hedging instrument to traditional assets. Andrada-Félix, Fernandez-Perez, and Sosvilla-Rivero (2020) argued that connectedness between cryptocurrencies and traditional currencies varies over time, with a surge during periods of increasing economic and financial instability. Using a sample period covering the age of the 4th industrial revolution, Le, Abakah, and Tiwari (2021) argued that the total connectedness among cryptocurrencies is very high in normal and turbulent economies. In particular, Bouri, Gabauer, Gupta and Tiwari (2021b), using the DCC-GARCH model, suggested that cryptocurrencies are used for hedging when investor sentiment is weak. When investors are optimistic, cryptocurrencies were strong diversifiers when investors are happy rather than when sentiment is weak due to low total connectedness among cryptocurrencies associated with high common volatility.

Another group of studies has purely examined the connectedness among cryptocurrencies. Notably, these studies have also failed to report conclusive evidence of such connectedness. For instance, Zięba et al. (2019) reported that changes in Bitcoin prices are not affected by changes in the prices of other cryptocurrencies. Utilizing the network effects analysis, Gandal and Halaburda (2016) found that Bitcoin and other cryptocurrencies were well connected, confirming the network effects and winner-take-all dynamics. Over several events (e.g., the Silk Road website closure and the Chinese banks using Bitcoin), Fry and Cheah (2016) reported evidence of a negative bubble between Bitcoin and Ripple after 2014, but the spillover effect among cryptocurrencies was mixed due to speculative bubbles in Bitcoin. By examining relations among three popular cryptocurrencies (Bitcoin, Ripple, and Litecoin), Corbet, Lucey, and Yarovaya (2018) argued that the three popular cryptocurrencies are highly connected, confirming their benefit to risk diversification. Moreover, Ciaian et al. (2018) indicated that Bitcoin and the 16 altcoins are interdependent in the short run because their interdependencies could not be detected in the long run since Bitcoin could not raise the prices of altcoins in the long run. Ji et al. (2019) argued that Litecoin and Bitcoin were the most connected cryptocurrencies in which any shock arising from these two cryptocurrencies has the most effect on other cryptocurrencies. However, they also reported that Ripple and Ethereum were the top absorbers of return and volatility shocks. Thus, cryptocurrencies are important tools for hedging and diversification opportunities.

Accounting for the recent cryptocurrency crisis, several studies have examined the connectedness among cryptocurrencies. For instance, Yi, Xu, and Wang (2018) concluded that the connectedness among the eight major cryptocurrencies varied cyclically and had shown a noticeable increase since the end of 2016 when the crisis of the cryptocurrency market had started. By employing the TVP-FAVAR connectedness approach, Antonakakis et al. (2019) argued that most of the top 9 cryptocurrencies exhibited large dynamic spillover effects, particularly during the period of the failure of the cryptocurrency market in 2017. Although Bitcoin remains an influential cryptocurrency, Ethereum has become the most net transmitter during the crisis. In a similar vein, Elsayed, Gozgor, & Lau (2022a) argued that the three major cryptocurrencies (Bitcoin, Litecoin, Ripple) exhibited an increase in the return spillover effect during the cryptocurrencies crisis in 2017. Balli, de Bruin, Chowdhury, and Naeem (2020) found that the magnitude of short-term connectedness of the six major cryptocurrencies (Bitcoin, Ripple, Stellar, Litecoin, Monero, and Dash) is much higher than medium and long-term, highlighting the popularity of such cryptocurrencies in recent years.

As of the COVID-19 pandemic crisis, few research studies have examined the connectedness among cryptocurrencies. Based on a quantile-based connectedness analysis, Bouri, Cepni, Gabauer and Gupta (2021a) argued that the connectedness in the upper and lower quantiles are much greater than those in the mean and median of the conditional distribution, but the degree of connectedness was instable over the COVID-19 outbreak. Bouri, Roubaud, and Shahzad (2020) found a significant connectedness in the 12 cryptocurrencies, especially Ripple, Bitcoin, and Litecoin and the degree of connectedness increased during the COVID-19 pandemic crisis. Using the Markov regime-switching vector autoregressive with exogenous variables model, Shahzad et al. (2021) found various patterns of spillover among 18 cryptocurrencies in high and low volatility regimes, especially during the COVID-19 crisis. The total spillover index varies over time and increases following the COVID-19 crisis, especially in the high volatility regime, confirming the perception of contagion during stress periods. Aslanidis, Bariviera, and Perez-Laborda (2021) argued that there is a substantial increase in the connectedness among cryptocurrencies, especially during the COVID-19 crisis, arguing that financial and regulatory implications strongly affect the degree of connectedness among cryptocurrencies. In summary, mixed results and conclusive evidence are noticed in the above-referenced studies.

In the second strand of literature, a large number of studies have examined the impact of the economic policy uncertainty and the cryptocurrency market. However, these studies reported mixed results and conflicting evidence of such impact and they have generally relied on the general economic uncertainty indices, monetary policies, and geopolitical risk indices, whereas very limited use of the cryptocurrencies uncertainty indices. For instance, Demir, Gozgor, Lau, and Vigne (2018) concluded that Bitcoin is considered a hedging tool against economic policy uncertainty using the quantile-on-quantile regression. However, other studies pointed out that cryptocurrencies can be used for speculation, and changes in the prices of cryptocurrencies lead to uncertainty by reducing the price stability. By examining the effect of macroeconomics news announcements on the returns of Bitcoin, Corbet, Larkin, Lucey, Meegan, & Yarovaya (2020) reported that news about GDP and CPI seems to exhibit no statistically significant association with Bitcoin. When testing for the connectedness among several cryptocurrencies during two specific events (the adjustments of the US Federal Fund interest rate and the quantitative easing (QE) announcement), Corbet, Lucey, Urquhart, and Yarovaya (2019) found that cryptocurrencies are strongly interlinked and they are more vulnerable to monetary policy shocks.

Utilizing the Continuous Wavelet Transform to rationalize the connectedness of cryptocurrencies with common economic and financial market uncertainty, Balli et al. (2020) showed a negative relationship between economic uncertainty and the connectedness among cryptocurrencies, highlighting the potential for cryptocurrencies to be an alternative instrument for hedging against underlying uncertainty. Mokni, Ajmi, Bouri, and Vo (2020), while accounting for the structural changes in Bitcoin prices, they argued that the economic policy uncertainty adversely influenced the dynamic conditional correlations between the US stock markets and Bitcoin only after the Bitcoin crash of December 2017. In the context of China, Yen and Cheng (2021) argued that Bitcoin and Litecoin act as hedging tools against the risk associated with the economic policy uncertainty of China. However, after the Chinese government's regulation of crypto-trading, the economic policy uncertainty did not affect cryptocurrency volatility. It follows that Cheng and Yen (2020) reported that the economic policy uncertainty of China had a predictive power only on the Bitcoin returns, with no predictive power for the other main cryptocurrencies, while the economic policy uncertainty of the U.S. or other Asian countries had no effect of cryptocurrency returns.

Ji et al. (2019) argued that higher US economic uncertainty led to greater net directional negative-return spillovers of cryptocurrencies, whereas they did the opposite for net directional positive-return spillovers. The connectedness of the global economic policy with equity, bonds, and Bitcoin was examined by the study of Fang, Bouri, Gupta, and Roubaud (2019). They argued that the global EPU adversely affected the connectedness among Bitcoin and bonds, whereas positively affected the connectedness of Bitcoin with equities and with commodities, indicating that Bitcoin can act as a hedge under economic uncertainty conditions. Conlon et al. (2020) found that Bitcoin and Ethereum do not play the role of a safe haven for most international equity markets, but Chinese equity investors exhibit benefits from the modest downside risk of these two cryptos. However, Tether acted as a safe haven investment for all of the international indices due to its peg to the US dollar during the COVID-19 crisis. Elsayed, Gozgor and Lau (2022b) argued that during the COVID-19 period the EPU is the only global index that generates higher volatility in Bitcoin.

Altogether, although much effort has been devoted to examining whether the characteristics of cryptocurrencies are different from those of other financial assets, diminutive attention is paid to the connectedness, e.g., volatility and/or return connectedness, or spillover effects, among different cryptocurrencies. Thus, there is still room for examining such topics for the sake of risk management and portfolio diversification. Given the general lack in the literature implementing the Quantile-VAR framework, using such a framework for measuring the spillover effect might overcome the limitation with the mean-based approach. The Quantile-VAR method leads to measuring shocks in the spirit of the upper and lower tails (quantiles) of the distribution. Previous studies also have overlooked examining the spillovers among cryptocurrencies during the COVID-19 crisis and especially the most recent period covering the COVID-19 vaccine effect. Finally, since previous studies have mostly focused on examining the effect of economic policy uncertainty on the spillover among cryptocurrencies, none of the existing studies have taken into account the effect of the cryptocurrency policy uncertainty index (CCPO) and the cryptocurrency price uncertainty index (CCPR), developed by Lucey et al. (2021) when examining for the effect of uncertainty on the spillover effect of cryptocurrencies.

3. Data and methodology

3.1. Data

We use the weekly prices of the five leading cryptocurrencies considered by Lucey et al. (2021), such as Bitcoin (BTC), Litecoin (LIT), Ethereum (ETH), Tether (TETH), and Ripple (XRP), over the period spanning from the 09/08/2015 to 02/21/2021. These cryptocurrencies are considered based on their highest market capitalization in the past few years.[1] The study period is suggested by the availability of data for the five cryptocurrencies. This period allows capturing the dynamics of such cryptocurrencies during periods of boom and busts. Moreover, this period accounts for the cryptocurrency crisis that occurred at the end of 2017 and the global economy and financial markets turbulence around the globe, suggested by the ongoing COVID-19 pandemic crisis. All the data are collected from the websitehttp://http://coinmarketcap.com and confirmed by the series at the DataStream database.

Fig. 1 depicts the price (first column) and returns (second column) series of the different cryptocurrencies. It can be seen from this figure that prices are showing a large drop after the beginning of 2018, reaching the lowest level of prices by the end of 2018, except for Tether. This level of prices continues at the same level until the end of 2019 when some upside movements and large price corrections had to occur for all cryptocurrencies under study. Afterward, the price trend shows a sharp increase in the price level after the end of 2020 (except for Ripple and Tether). This period coincides with the beginning of the outbreak of COVID-19. Therefore, it is noticeable that there are persistent falling and rising patterns in the return series, indicating the possibility of extreme return spillovers and calling into question the appropriateness of considering systems of average shocks. The continuously compounding return series are computed by using the natural logarithm returns r_{it} at time t for each cryptocurrency i for the closing price p as: $r_{it} = 100 \times \ ln(p_{it}/p_{it-1})$. We comprise 290 weekly return observations for each cryptocurrency.

Fig. 1 also shows the behavior of the returns series of the five cryptocurrencies during the full considered period. The graphical evolution during the COVID-19 period shows a large uptrend with an increase in volatility, and volatility cluster, indicating price instability and high levels of risk displayed in all considered cryptocurrencies.

To examine the effect of the uncertainty on the cryptocurrencies' connectedness, we also consider weekly observations for policy (CCPO) and price (CCPR) uncertainty indices, developed by Lucey et al. (2021). The two indices are obtained from the webpage of the authors: https://sites.google.com/view/cryptocurrency-indices/home?authuser=0. These new cryptocurrency uncertainty indies are implemented to value how policy and regulatory disputes impact cryptocurrency returns and volatility and how this impact varies in response to Bitcoin in general. Distinguishing between these two types of cryptocurrency uncertainty is helpful to understand better the behavior of different groups of investors in the cryptocurrency market. Better-informed investors may be highly sensitive to policy uncertainty changes, while less-informed investors may respond more strongly to general media attention associated with changes in cryptocurrencies prices. Furthermore, given the increasing interest of institutional investors - in cryptocurrencies, the cryptocurrency market would be more sensitive to policy uncertainty over time. To design the two indices, Lucey et al. (2021) collected a massive number of news stories (around 726.9 million stories) from the LexisNexis database covering the period from January 2014 to January

[1] While the number of cryptocurrencies is important, the considered top-5 cryptocurrencies represent more than 90% of the market capitalization. Furthermore, the choice of these five cryptos is by following previous studies considering only a limited number of cryptocurrencies to represent this market given that they represent the majority of the market in terms of market capitalisation (Bouri, Cepni, Gabauer and Gupta, 2021a; Fousekis & Tzaferi, 2021; Ji et al., 2019; Li, Wang, & Huang, 2020, among others). Moreover, these five cryptocurrencies are considered by Lucey et al. (2021) to construct the two measures of cryptocurrencies uncertainty that were adopted in the second part of our analysis. Therefore, the focus of our study was based only on those five cryptos.

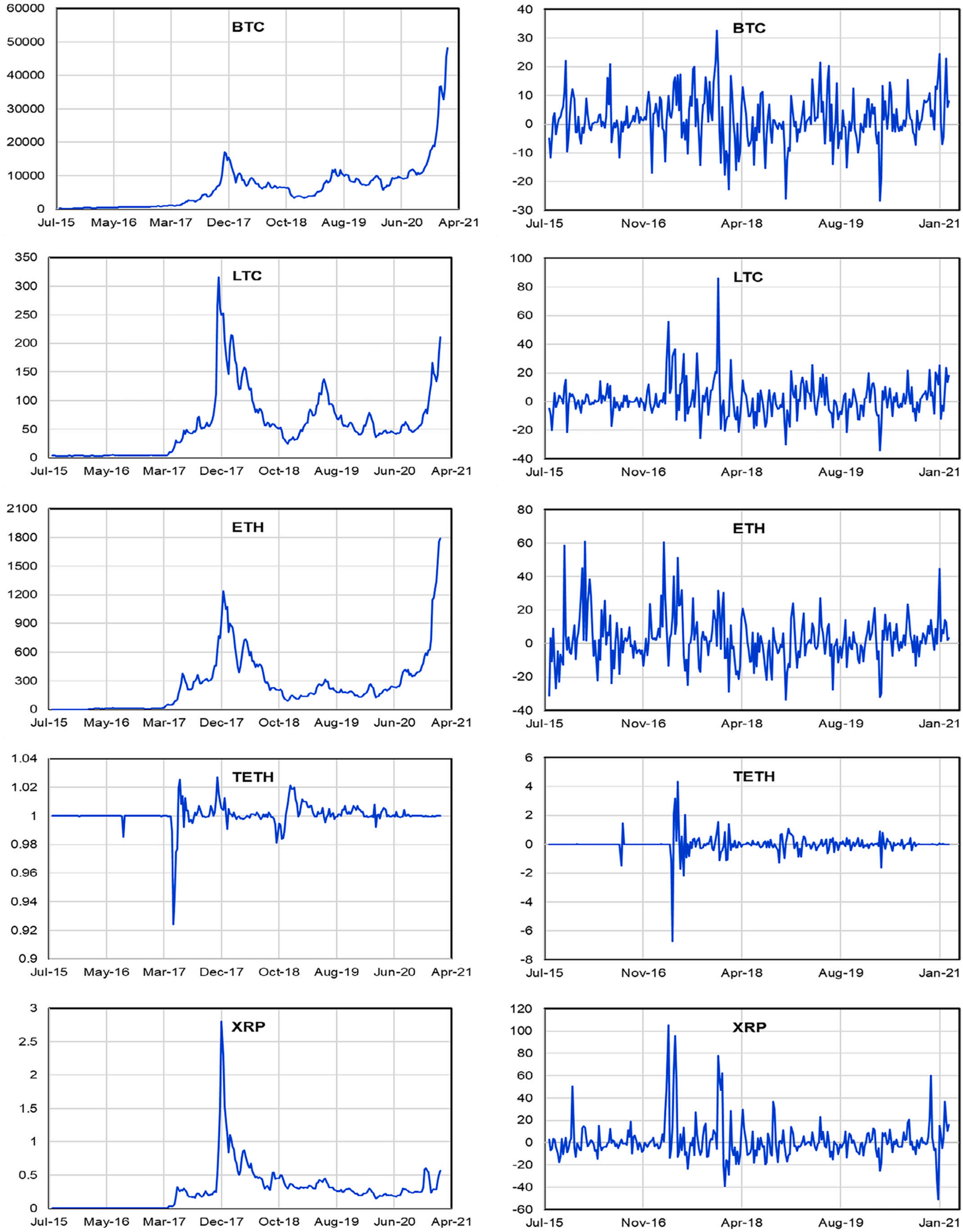

Fig. 1. Prices and returns series of the major cryptocurrencies.

2021. Unlike other measures that exist in the literature; these indices were constructed by relying on major newspapers with a wider spread of sources, including news wire feeds and media news transcripts, to recognize the "social" aspect of cryptocurrencies. Lucey et al. (2021) pointed out that cryptocurrencies as a new phenomenon may be subject to extensive discussions not only in traditional media but also in social media. They tested the contributions of these indices to the historical decomposition of the index around major events in cryptocurrency markets and then compared them with other popular uncertainty measures as well as gold and Bitcoin price uncertainties.[2]

Table 1 shows the summary statistics and preliminary tests for the log-return series. Mean returns show positive values (except the Tether), indicating that the cryptocurrency market has beneficial investment opportunities. Ethereum has the highest positive mean returns. According to the variances, which inform about the risk level, it appears that Ripple and Ethereum are the highest volatile cryptocurrencies.

Furthermore, Table 1 shows that the return series are asymmetric and fat-tailed based on normality, kurtosis excess, and skewness values. Moreover, based on the Jarque-Berra statistic and its *p*-values, the null hypothesis of normality for both sub-periods cannot be rejected (at 1% significance level for all return series), indicating that a quantile-based analysis is applicable in our data.[3] In addition, the results of the unit root tests are reported in Table 1. We apply the ADF of Dickey and Fuller (1979), the PP of Phillips and Perron (1988) unit root, and the ERS of Elliot, Rothenberg, and Stock (1996) tests. These tests show that the null hypothesis of unit root is rejected for all returns series, meaning that returns series are stationary. Besides, the Ljung-Box Q(10) and Q2(10) tests shows a strong serial correlation of returns and squared returns series (present *p*-values lower than 5%), indicating that the null hypothesis of no autocorrelation cannot be rejected for almost of cryptocurrencies.

We also report the correlation matrix among cryptocurrencies returns as well as with the cryptocurrency uncertainty indices (CCPR and CCPO). The results show positive correlations among cryptocurrencies but with different levels. This confirms the findings of previous studies (i.e., Antonakakis et al., 2019; Bouri, Gabauer, Gupta and Tiwari, 2021b). The strongest correlation is between Bitcoin and Litecoin by a value of 0.692. We notice that both indices are highly correlated, with a value of 0.974. The other issue in Table 1 is that Litecoin and Ripple show the highest correlated cryptocurrencies with both uncertainty indices.

Fig. 2 plots the two uncertainty indices developed by Lucey et al. (2021). The graphical evolution of these two indices indicates that the cryptocurrency market uncertainty level varies remarkably across time, reaching maximum levels at the end of the study period with the COVID-19 crisis. During this pandemic, the increased uncertainty can be explained by the great interest in the cryptocurrency market for diversification and hedging purposes, as well as the usefulness of these digital currencies as a payment method in-line with the health measures taken by most countries of the world.

3.2. Methodology

We discuss here the econometric methodology of the empirical analysis of the total and directional connectedness between cryptocurrencies by means of the quantile-VAR modeling. First, we describe the quantile regression methodology invented by Koenker and Bassett Jr (1978) and then address the methodology proposed by Diebold and Yilmaz (2009, 2012) and Diebold and Yılmaz (2014) to briefly outline the dynamic connectedness process based on the quantile-VAR procedure.

3.2.1. The quantile VAR model

To study the dynamic connectedness among cryptocurrencies, we first apply the quantile regression approach. This permits us to estimate the dependence of y_t on z_{t-1}at the quantile τ of the conditional distribution of $(y_t|z_t)$ (Koenker & Bassett Jr, 1978; Koenker, 2005; Bouri, Cepni, Gabauer and Gupta, 2021a). It can be represented by,

$$Q_\tau(y_t|z_t) = z_t\delta(\tau) \tag{1}$$

where Q_τ refers to the τ^{th} conditional quantile function of $y_t(\tau \in (0,1))$; z_t is a vector of explanatory variables; and $\delta(\tau)$ determines the dependence relationship between z_t and the τ^{th}conditional quantile function of y_t. To be specific, $\delta(\tau)$ is the parameter vector estimated at the τ^{th} conditional quantile τ via the following expression:

$$\widehat{\delta}(\tau) = argmin_{\beta(\tau)} \sum_{t=1}^{T} \left(\left(\tau - 1_{[y_t < z_t\delta(\tau)]} \right) |y_t - z_t\delta(\tau) \right) \tag{2}$$

Consequently, the n-variable quantile VAR-process of s^{th} order is:

$$y_t = c(\tau) + \sum_{i=1}^{S} \theta_i(\tau) y_{t-i} + \varepsilon_t(\tau), t = 1, \ldots, T \tag{3}$$

where y_t is an *n-vector* of dependent variables. $c(\tau)$ and $\varepsilon_t(\tau)$ are, respectively, n-vector of constant and residuals at quantile τ, and $\theta_i(\tau)$ is the matrix of the lagged coefficients of the dependent variable at quantile τ, with $i = 1, \ldots, S$. $\widehat{\theta}_i(\tau)$ and $\widehat{c}(\tau)$ are estimated by assuming that the residuals conform to the population quantile restriction, $Q_\tau(\varepsilon_t(\tau)| y_{t-1}, \ldots, y_{t-s}) = 0$. The population τ^{th} conditional quantile of response y is given in Eq. (4). The latter can be estimated on an equation-by-equation at every quantile τ.

$$Q_\tau(y_t|y_{t-1}, \ldots, y_{t-s}) = c(\tau) + \sum_{i=1}^{S} \widehat{\theta}_i(\tau) y_{t-i} \tag{4}$$

3.2.2. The connectedness measures at various quantiles

To compute the various measures of return connectedness at each quantile, we follow the novel work of Ando, Greenwood-Nimmo, and Shin (2018), which extends the mean-based approach proposed by Diebold and Yilmaz (2012).

Then, we re-write Eq. (3) as an infinite order vector moving average (VMA) process based on the Wold representation theorem:

$$y_t = \mu(\tau) + \sum_{k=1}^{\infty} \gamma_k(\tau) \varepsilon_{t-k}(\tau), t = 1, \ldots, T \tag{5}$$

with:

$$\mu(\tau) = (I_n - \beta_1(\tau) - \ldots - \beta_s(\tau))^{-1} c(\tau), \gamma_k(\tau)$$

$$= \begin{cases} 0, k < 0; I_n; s = 0 \\ \delta_1(\tau)\gamma_{k-1}(\tau) + \ldots + \beta_s(\tau)\gamma_{k-s}(\tau), S > 0 \end{cases}$$

where y_t is given by the sum of the residuals $\varepsilon_t(\tau)$.

In addition, we follow the frameworks of Koop, Pesaran, and Potter (1996) and Pesaran and Shin (1998), which are invariant to variable ordering. We attempt to generate the spillover effect or the connectedness of the generalized forecast error variance decomposition (GFEVD) of a variable attributable to shocks of various variables for a forecast horizon F by the following specification:

$$\varphi_{ij}^{g}(F) = \frac{\sigma_{ji}^{-1} \sum_{f=0}^{F-1} \left(\varepsilon_i' \gamma_k \sum \varepsilon_j \right)^2}{\sum_{f=0}^{F-1} \left(\varepsilon_i' \gamma_k \sum \varepsilon_j \right)} \tag{6}$$

where $\varphi_{ij}^{g}(F)$ is the contribution of j^{th} variable to the variance of forecast error of the variable ith at horizon F. $\sum$ denotes the variance matrix of the vector of errors, σ_{jj} is the jth diagonal element of the $\sum$ matrix and ε_i is a vector with a value of 1 for ith element and 0 otherwise.

Then, each entry of the variance decomposition matrix is normalized

[2] See Lucey et al. (2021) for more details about the methodology of the indices.

[3] Koenker and Bassett (1978) indicated that the quantile-based analysis is appropriate for non-normal series.

Table 1
Descriptive statistics and preliminary tests.

	Cryptocurrencies					Uncertainty measures	
	BTC	LTC	ETH	TETH	XRP	PolicyUn	PriceUn
Descriptive statistics							
Mean	1.828	1.437	2.515	0.000	1.514	100.157	100.163
Variance	72.492	151.11	203.837	0.445	291.664	1.046	1.038
Skewness	0.072	1.596***	0.923***	−2.270***	2.445***	2.534***	3.127***
	(0.609)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ex Kurtosis	1.148***	8.621***	2.748***	43.383***	10.443***	8.336***	14.177***
	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Preliminary tests							
JB	16.123***	1017.593***	131.940***	22,912.241***	1601.235***	1146.108***	2891.404***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ERS	−2.372**	−4.026***	−7.100***	−10.948***	−5.366***	1.508	2.908
	(0.018)	(0.000)	(0.000)	(0.000)	(0.000)	(0.133)	(0.004)
ADF	−11.457***	−11.994***	−12.169***	−18.345***	−10.726***	−4.329***	−4.008***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
PP	−11.352***	−12.004***	−12.168***	−92.978***	−10.452***	−4.452***	−4.114***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Q.10.	45.994***	36.981***	56.204***	25.742***	57.790***	567.116***	595.043***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Q2.10.	29.629***	5.958	13.516**	50.766***	78.543***	564.884***	586.714***
	(0.000)	(0.371)	(0.012)	(0.000)	(0.000)	(0.000)	(0.000)
Correlations Metrics							
BTC	1						
LTC	0.692	1					
ETH	0.503	0.472	1				
TETH	0.061	−0.014	0.057	1			
XRP	0.379	0.574	0.368	0.053	1		
PolicyUn	0.033	0.063	0.028	0.003	0.060	1	
PriceUn	0.014	0.044	0.000	0.004	0.049	0.974	1

Notes: This table reports the descriptive statistics of cryptocurrencies before and during the COVID-19 pandemic period. JB is the Jarque-Bera normality test statistics. ADF, PP, and ERS are the statistics of Dickey-Fuller, Phillips-Perron, and Elliot-Rothenberg-Stock unit root tests, respectively. Q(10) and Q2(10) are the Ljung-Box tests for 10th order serial correlations for returns and squared returns, respectively. (***), (**) and (*) indicate the statistical significance, respectively, at the 1%, 5%, and 10% levels.

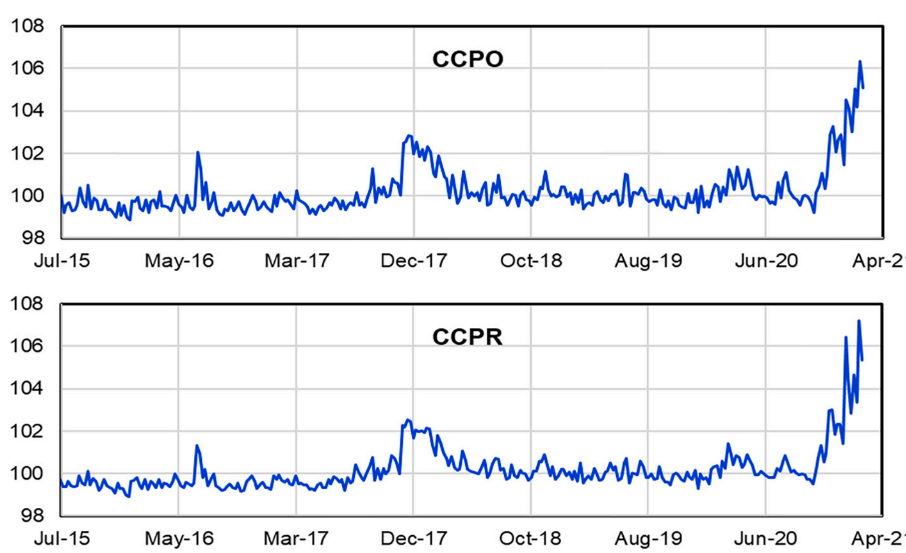

Fig. 2. Cryptocurrencies' policy (CCPO) and prices (CCPR) uncertainty indices of Lucey et al. (2021).

by the following specification:

$$\tilde{\varphi}_{ij}^{g}(F) = \frac{\varphi_{ij}^{g}(F)}{\sum_{j=1}^{N} \varphi_{ij}^{g}(F)} \tag{7}$$

After that, four measures of connectedness at each quantile are generated by applying the GFEVD.

The first measure is the total connectedness (spillover) index (TCI) at quantile τ is

$$\mathrm{TCI}(\tau) = \frac{\sum_{i=1}^{N}\sum_{j=1, i\neq j}^{N} \tilde{\varphi}_{ij}^{g}(\tau)}{\sum_{i=1}^{N}\sum_{j=1}^{N} \tilde{\varphi}_{ij}^{g}(\tau)} \times 100 \tag{8}$$

The second measure is the total directional connectedness index ($\mathrm{TDI}_{i\rightarrow j}$) from index i to indices j (known as "TO") at quantile τ is

$$\mathrm{TDI}_{i\to j}(\tau) = \frac{\sum_{j=1,i\neq j}^{N} \varphi_{ji}^{\sim g}(\tau)}{\sum_{j=1}^{N} \varphi_{ji}^{\sim g}(\tau)} \times 100 = TO \tag{9}$$

Likewise, the third measure is the total directional connectedness index ($\mathrm{TDI}_{i\leftarrow j}$) from indices j to index I (known as "From") at quantile τ is

$$\mathrm{TDI}_{i\leftarrow j}(\tau) = \frac{\sum_{j=1,i\neq j}^{N} \varphi_{ij}^{\sim g}(\tau)}{\sum_{j=1}^{N} \varphi_{ij}^{\sim g}(\tau)} \times 100 = From \tag{10}$$

The fourth measure is the net pairwise directional connectedness index (NDI) at quantile τ is

$$\mathrm{NDI}_i(\tau) = \mathrm{TDI}_{i\to j}(\tau) - \mathrm{TDI}_{i\leftarrow j}(\tau) = NDI \tag{11}$$

The empirical analyses are performed based on a lag order of 1, selected according to the Akaike information criteria (AIC) and a forecast horizon of 20 for the full sample and both sub-periods. To show the time-varying component in various spillover measures, we use a rolling-window approach using 40 weeks.

4. Empirical analysis

The empirical analysis of this paper is twofold. Firstly, we investigate the dynamic connectedness (or spillover effect) among cryptocurrencies under different market conditions using the Diebold and Yılmaz (2014)-based Quantile VAR (Q-VAR) methodology. Secondly, we investigate whether the cryptocurrencies' policy and prices uncertainty could drive this spillover effect.

4.1. Dynamic connectedness results

Our results of the dynamic connectedness among cryptocurrencies are obtained using the quantile-based vector autoregression (Q-VAR) estimation approach. This approach can capture the connectedness between the considered cryptocurrencies under different market conditions (normal, bearish, and bullish markets). In other words, it allows us to capture the quantile connectedness at the lower and upper tails of the conditional distributions, leading us to finally differentiate between extreme negative and positive shocks transmission. The Q-VAR in Eq. (3) is estimated based on the lag order of 1 (based on the AIC) for each quantile. Furthermore, the other connectedness indices are computed, such as the TCI (Eq. (8)),[4] the directional "TO" (Eq. (9)), the directional "FROM" (Eq. (10)), and the "NDI" (Eq. (11)). We used nine quantiles equally spaced from 0.1 to 0.9. The quantiles (0.10, 0.20, and 0.30) represent the bearish market, the quantiles (0.40, 0.50, 0.60) represent the normal market, and the quantiles (0.70, 0.80, and 0.90) represent the bullish market.

4.1.1. Average of total and net connectedness

The results of the average total and directional spillover indices are reported in Table 2. The results show that the total spillover index (TCI) varies across quantiles' orders, suggesting that the connectedness among cryptocurrencies prices changes is reliant on market conditions. In general, the values of the total connectedness measures are larger at the extreme right and extreme left tails than those in the mean of the distribution. The total average spillover index is about 60% for the extreme quantiles 0.1 and 0.9 and less than 37% for the median. Thus, extreme positive/negative shocks from some events such as the crush of end-2017 and the COVID-19, among others, have a higher impact on the system of returns spillover, making the total connectedness in the left and right tails higher than those for the mean or median. Importantly, the contributions to others and from others in both the left and right tails are much stronger than those for the median. These results are also confirmed in Fig. 3. This figure represents the total connectedness index across quantiles. It shows that the spillover effects among the cryptocurrencies increase widely during extreme market conditions, and the TCI reached its maximum values at 0.10 and 0.90 quantile orders. Furthermore, the shape of the total spillover index indicates that the quantile-based approach is more relevant than the mean based-approach in which the connectedness is found to be similar to whatever the markets state in the later approach.[5]

Table 2 also shows the estimated results of the directional connectedness among cryptocurrencies represented by different transmissions from each cryptocurrency to others ("TO") as well as the amount of shocks received by each cryptocurrency from the system ("From").

Table 2
Average dynamic connectedness measure across quantiles' orders.

	BTC	LTC	ETH	TETH	XRP
$\tau = 0.1$					
Total	59.93				
Contribution to others	75.45	73.13	66.61	22.88	61.60
From	66.42	66.92	66.05	37.28	63.00
Net Spillovers	9.03	6.21	0.56	−14.4	−1.40
$\tau = 0.2$					
Total	46.98				
Contribution to others	64.56	62.70	53.33	4.06	50.24
From	57.46	60.16	56.58	7.06	53.62
Net Spillovers	7.1	2.53	−3.26	−3.00	−3.37
$\tau = 0.3$					
Total	42.08				
Contribution to others	58.25	61.08	45.74	1.12	44.2
From	52.34	57.18	50.38	2.12	48.38
Net Spillovers	5.91	3.90	−4.63	−1.00	−4.18
$\tau = 0.4$					
Total	39.13				
Contribution to others	52.89	60.31	39.76	0.82	41.86
From	49.05	54.61	45.87	1.26	44.86
Net Spillovers	3.84	5.70	−6.11	−0.44	−3.00
$\tau = 0.5$					
Total	36.45				
Contribution to others	48.21	58.6	35.53	0.73	39.19
From	44.81	52.61	42.65	0.76	41.43
Net Spillovers	3.40	5.99	−7.12	−0.03	−2.25
$\tau = 0.6$					
Total	37.13				
Contribution to others	47.8	58.74	37.00	2.41	39.69
From	46.81	53.00	44.41	0.99	40.42
Net Spillovers	0.99	5.73	−7.41	1.42	−0.74
$\tau = 0.7$					
Total	40.28				
Contribution to others	49.76	59.68	43.75	2.91	45.3
From	52.03	55.17	49.72	1.71	42.76
Net Spillovers	−2.27	4.50	−5.98	1.20	2.55
$\tau = 0.8$					
Total	46.76				
Contribution to others	56.59	66.16	55.14	3.74	52.17
From	57.82	58.33	55.68	13.41	48.57
Net Spillovers	−1.23	7.83	−0.53	−9.68	3.60
$\tau = 0.9$					
Total	59.21				
Contribution to others	70.03	75.9	69.88	18.31	61.92
From	65.22	63.48	65.71	47.24	54.38
Net Spillovers	4.8	12.42	4.17	−28.93	7.54

Notes: This table shows the average of connectedness estimated using the Q-VAR model. Based om the quantile's order, the table provides the average total spillover index ("Total" hereafter as shorter), the directional volatility spillover received ("From" hereafter as shorter), and transmitted ("Contribution to others" hereafter as shorter) by each variable. The net directional spillover ("Net Spillovers" hereafter as shorter) is the difference between directional 'To' spillovers and directional 'From' spillovers.

[4] The TCI values vary between 0 and 100.

[5] Yi et al. (2018) indicates that cryptocurrencies such as MAID, FCT and GAME with small market value may also be important risk emitters in this market. We estimated the system including those cryptos but the results remain the same. We thank a referee for pointing at this issue.

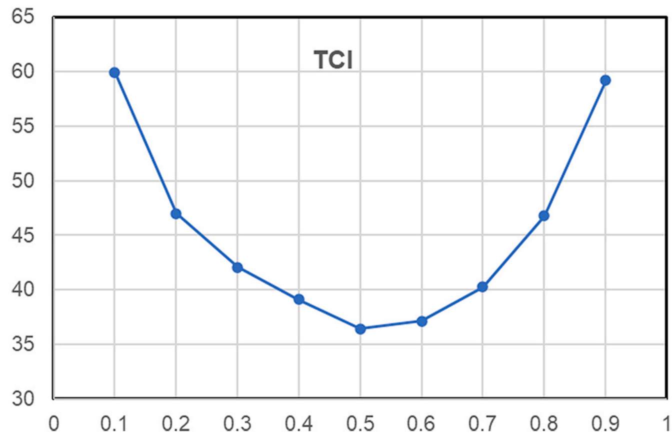

Fig. 3. Total average connectedness under markets conditions.

Generally, the contributions from others and contributions to others in both lower and upper tails are mostly stronger than those for the mean and median. Moreover, the results emphasize that Litecoin and Bitcoin exhibit the highest amounts of shocks transmitted and received from the system across all quantiles. More specifically, Litecoin has overcome Bitcoin in this case showing the highest amounts of shocks transmitted to and received from the system across all quantiles. Bitcoin appears as the most transmitter of shocks only when the cryptocurrency market is bearish, while Litecoin takes its position under other market conditions. These results confirm that i) Bitcoin has lost its position as a dominant cryptocurrency as a transmitter, whereas Litecoin becomes the dominant transmitter, and ii) the dominance of cryptocurrencies in the shock transmission changes from one cryptocurrency to another across market conditions.

Looking at the information receipt from the system, we see interesting results. We notice that Litecoin is the most receiver of shocks from the system across all quantiles, except in some cases related to the bull condition, where Bitcoin and Ethereum are the most receivers of shocks only in the bull market. This result indicates that Bitcoin and Litecoin seem to behave as strong hedgers. Although Ethereum and Ripple act as receivers, they have not reached the same level of information receipt as Bitcoin and Litecion. In terms of Tether, we see that it acts as the lowest receiver of information from the system.

In comparison to Ripple, Ethereum shows a higher transmission level of shocks to others under bullish and bearish market conditions. In the case of shocks reception, Ethereum shows a higher level of shocks reception in all market conditions than Ripple. Regarding Tether, the results show a particular pattern compared to other cryptocurrencies. This digital asset is the least transmitter and receiver of shocks under all market conditions. Moreover, we find that Tether has the lowest contributions to others and contributions from others at extreme markets conditions (0.10 and 0.90 quantiles' orders). Finally, our cryptocurrencies exhibit evidence of transmission and receiving of shocks but with different levels across different market conditions. Bitcoin acts as a strongest hedger only in bearish market conditions, whereas Litecoin is the strongest hedger in all market conditions. Litecoin also acts as the

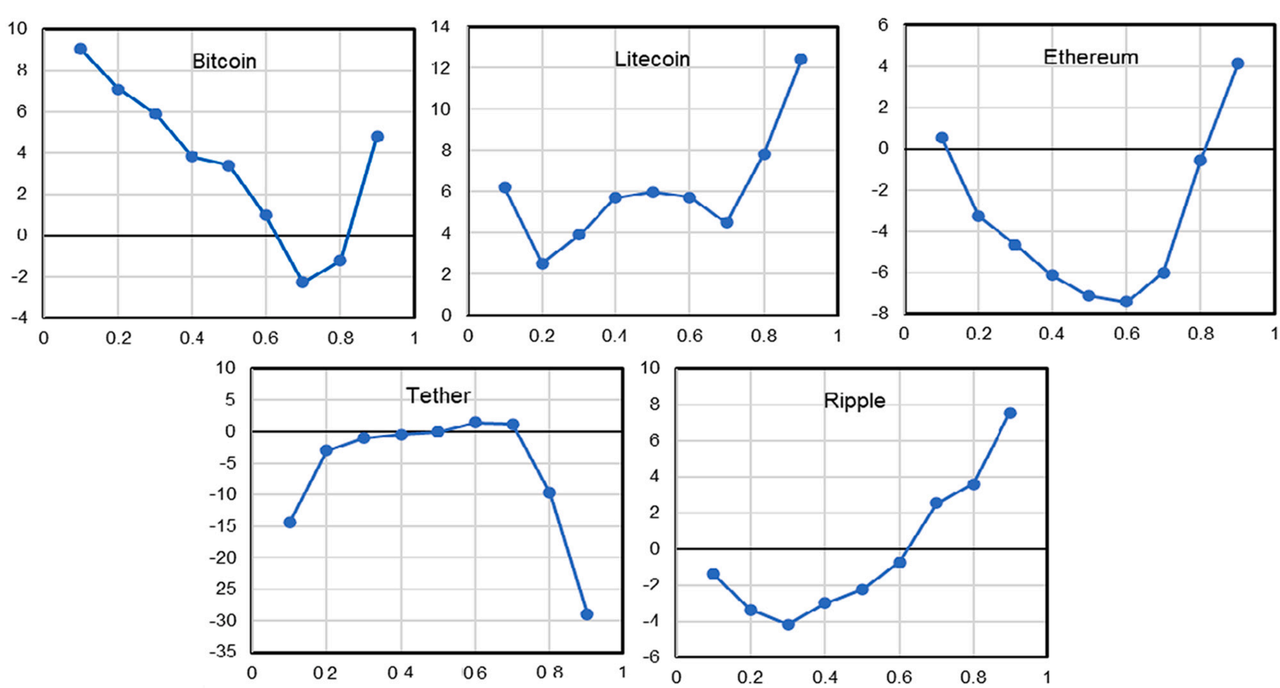

Fig. 4. Average net connectedness under markets conditions.

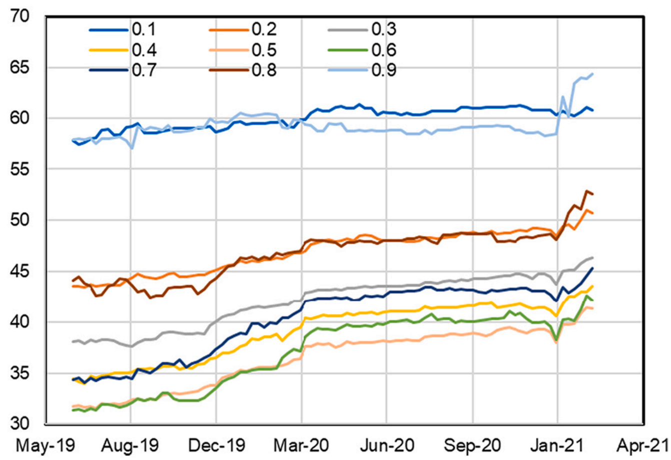

Fig. 5. Total spillover under markets conditions.

strongest and the most dominant safe-haven asset in all market conditions. Ethereum and the Ripple are also the strongest safe-haven asset only in the extreme right and extreme left tails.

By looking at the net spillover effects as the difference between the transmitted and received shocks, our results in Table 2 provide evidence of net transmitting and net receiving of shocks across cryptocurrencies. The net transmitter (net receiver) of shocks can be counted if this index is positive (negative). To better visualize the connectedness structure, we plot the total and net spillover indices for the different cryptocurrencies across quantiles in Figs. 3 and 4, respectively. We observe that each cryptocurrency acts as a net transmitter or a net receiver depending on the market condition, justifying the usefulness of the quantile-based analysis again. As shown in Fig. 4, Bitcoin and Litecoin are net transmitters of shocks across all quantiles, except 0.7 and 0.8 for Bitcoin, indicating that these two assets lose their positions as hedge and/or safe-haven assets, but only can act as effective diversifiers to risk resulted from the system and other cryptocurrencies. This result is in-line with the findings of Bouri, Molnár, Azzi, Roubaud and Hagfors (2017b) and Ciaian et al. (2018), who indicated that the information conveyed by the movement of the prices of both cryptocurrencies, in the long run, might not be related to global macroeconomic and financial developments and but only highly sensitive to cryptocurrency market forces and digital specific factors, such as the attractiveness of cryptocurrencies for investors.

Our results also show that Ethereum and Tether are net receivers of shocks at almost all of the quantiles' orders. Ethereum cannot act as a hedge and safe-haven when the cryptocurrency market is bearish or bullish. Regarding Ripple, the results show that this asset is a net receiver (transmitter) of shocks under bear and normal (bull) market conditions. This finding means that Ripple can act as a hedge and safe-haven only under bullish marker conditions. Given that the net spillover of Ripple is negative in almost all market conditions including in extreme market conditions, we can consider Ripple as a hedge and/or a safe-haven factor. A safe haven issue is essential to investment since it offers a means for protecting or expanding the capital when it has to move from the existing markets that are experiencing turbulence (Baur & Lucey, 2010; Ratner & Chiu, 2013).

4.1.2. Time-varying total and net spillover effects

To investigate whether shock transmission or reception among cryptocurrencies prices is time-varying at different quantiles, we consider the dynamic connectedness indices presented in Fig. 5, which plots the dynamic total connectedness index (TCI) among cryptocurrencies at the different quantiles' orders. We observe a remarkable difference regarding the total spillovers across quantiles orders. Compared to other quantile orders, the TCI is relatively high at the lower (0.10) and upper quantiles (0.90) of the distribution. Furthermore, we also notice that for each quantile order, the TCI is time-varying, having the highest values over the outbreak of COVID-19 period for all considered quantiles. The results in Fig. 5 support those reported in Fig. 3 and Table 2.

As far as the net connectedness of each cryptocurrency is concerned, we display the behavior of the net spillover indices at different quantiles in Fig. 6. To make it clear, we use the behavior of such indices for only three quantiles (0.1, 0.5, and 0.9). As can be seen from this figure, the net spillovers of our subject cryptocurrencies have a time-varying pattern, and the quantile-based method is extremely appropriate for our analysis. Furthermore, the evolution of the net spillovers index for the different cryptocurrencies is mixed between net transmitter and net receiver across quantiles' orders, supporting the results found in Fig. 4. Particularly, Bitcoin and Litecoin are found to be mostly net transmitters of shocks under different market conditions. Moreover, the position of the net spillover for Ethereum varies over time and according to market conditions.[6] When the cryptocurrency market is bullish, this asset acts as a net transmitter. However, under bear market conditions, Ethereum is a net receiver of shocks from the system and becomes a net transmitter from the propagation of the COVID-19 outbreak, losing its position as a hedge and safe-haven asset during this crisis. When the market is in normal condition, Ethereum is a net receiver over the whole period. Ripple is a net transmitter only when the cryptocurrency market is bullish (0.90) and acts as a net receiver of shocks under normal and bearish market conditions. Finally, Tether is a net receiver of shocks over all the period of study and whatever the market condition.

Moreover, by looking at Figs. 5 and 6, we see that the COVID-19 pandemic has a strong role in the total and net spillover index of cryptocurrencies. Indeed, our results suggest a more intricate pattern for all the considered cryptocurrencies, especially under extreme conditions.

[6] In order to infer more insight about the role played by Bitcoin relative to other cryptos, and as suggested by one referee, we provide two empirical applications accounting for the lead-lag relationships between Bitcoin and the rest of the cryptocurrencies. We apply the cross-correlation to investigate how Bitcoin is cross-correlated with the other cryptos, and then provide scatter plots of the Bitcoin/Litecoin relationship using different lags. Both are provided in Appendix B. It is observed that Bitcoin leads most of the changes in the other cryptos, yet, when looking at the scatter plot between Bitcoin and Litecoin, we find that Bitcoin leads changes in Litecoin up to 3-weeks period, yet the magnitude of impact is small.

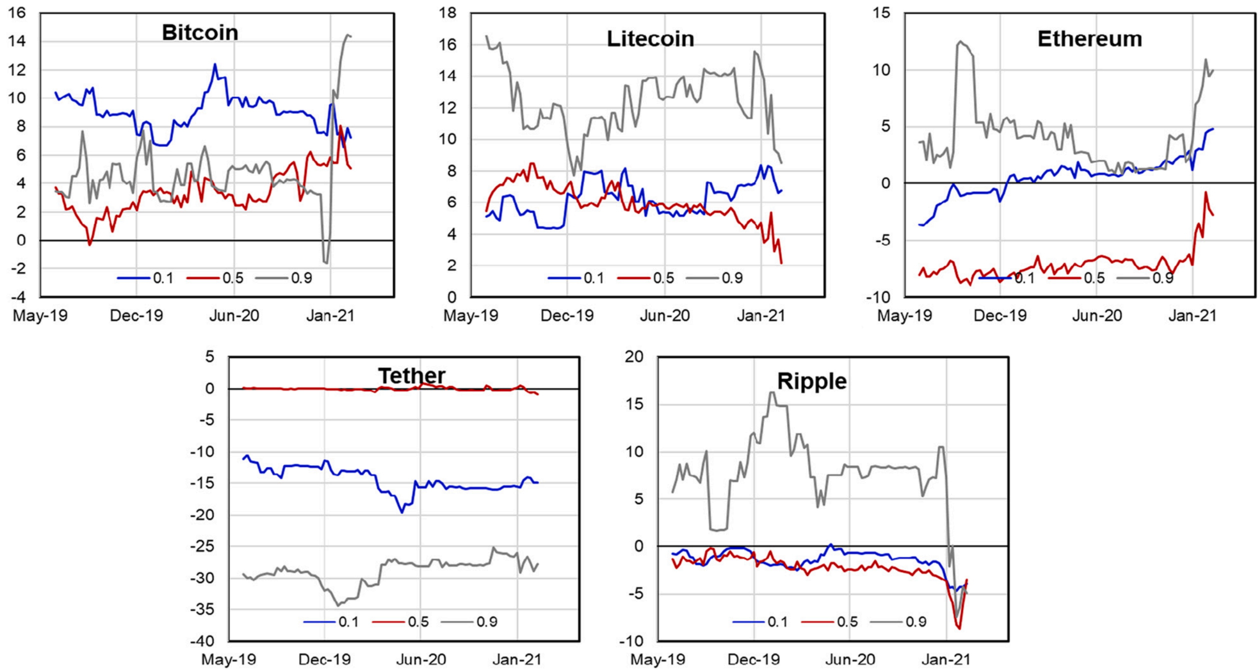

Fig. 6. Net spillover under markets conditions.

Particularly, a specific pattern is shown by high variability of the net connectedness and a remarkable increase of the total connectedness index throughout the COVID-19 pandemic. These intricate patterns may be due to the increased uncertainty created by the COVID-19 crisis. This case can be interpreted as those investors are not sure about their portfolio investment decisions as well as the level of risk associated with their portfolio investment. This is due to the unknown future situation of this pandemic. Furthermore, the fluctuation in the net spillover index across quantiles might be due to discovering several vaccines against this deadly disease. In this regard, it is important to investigate the effect of the policy uncertainty on the dynamic connectedness under different market conditions before and during the ongoing health crisis.[7]

4.2. Cryptocurrency uncertainty and dynamic spillover

The second step of our empirical analysis is investigating the effect of the cryptocurrency policy and price uncertainty indices (CCPO and CCPR, respectively), as developed by Lucey et al. (2021), on the connectedness among the cryptocurrencies. We utilize these indices to gauge how policy and regulatory debates affect cryptocurrency returns and volatility and how this effect differs per cryptocurrency. Furthermore, the use of such indices may assist in understanding better the behavior of different types of investors in cryptocurrency markets. For example, skilled and informed investors might be affected by changes in policy uncertainty, and other investors, such as amateur ones, might respond more strongly to the media attention associated with cryptocurrencies prices. A rise in the institutional investments in digital assets would also make cryptocurrency markets more sensitive to policy uncertainty over time, which helps to substantiate the importance of such indices.

Motivated by the above reasoning, we intend to examine the effect of cryptocurrency price and policy uncertainty indices on the dynamic total or net spillover among cryptocurrencies. The model is specified by the following regression model:

$$Conn_t^{\tau} = \alpha_0^{\tau} + \alpha_1^{\tau} CCUI_t + e_t^{\tau} \quad (9)$$

where t and τ are the week date and the quantile, respectively. $Conn_t^{\tau}$ denotes the total connectedness or the net connectedness index among cryptocurrencies at quantile τ and week t. $CCUI_t$ represents the natural logarithm of uncertainty indices (i.e., CCPO and CCPR) and e_t is the error term. If α_1^{τ} is statistically significant, the *CCUI* exerts a significant effect on the dynamic spillover index and then pushes the spillover between the considered cryptocurrencies.

To provide a more comprehensive analysis of such a relationship, we estimate the regression analysis for the different quantiles' orders. This analysis is motivated by the fact that the different connectedness measures vary across different quantiles' orders. The results of this regression (the estimated parameter α_1^{τ} and its estimated standard error) are reported in Table 3. Figs. 7 and 8 also show the estimated parameter for the full sample period, before and during COVID-19 periods at different quantile orders.

To investigate the impact of the COVID-19 pandemic on the impact of uncertainty on the connectedness among cryptocurrencies, we divide the spillovers and uncertainty indices into two sub-sample periods before and after 03/11/2020, when the World Health Organization

[7] Investors in the cryptocurrency markets are generally active traders who are prone to investment biases and usually hold risky portfolios characterizing these assets. Crypto investors are greatly affected by the media sentiment and likely to employ heuristics from technical analysis, as evidenced by the recent findings of Hackethal, Hanspal, Lammer, and Rink (2021). The authors analyze the average cryptocurrency traders and found them to increase their account logins and trading activity after their first purchase. They also found that investors in these markets tend to shift their portfolios toward more risky securities after cryptocurrency adoption. Generally, investors in these markets are likely to trade the new products, which may have a significant impact on its future success, and will be the ones who invest in new innovative products with high risk characteristics, such as the NFT, DeFi, or Tokens. We thank a referee for this point.

Table 3
Total Connectedness and Uncertainty Indices using Levels.

	CCPO			CCPR		
	Whole period	Before COVID	During COVID	Whole period	Before COVID	During COVID
Quantile						
0.1	0.244 (0.001)***	−0.425 (0.047)**	−0.004 (0.914)	0.238 (0.001)***	−0.487 (0.081)*	−0.006 (0.853)
0.2	0.802 (0.000)***	−0.315 (0.408)	0.344 (0.000)***	0.770 (0.000)***	−0.326 (0.509)	0.316 (0.000)***
0.3	0.956 (0.000)***	−0.095 (0.864)	0.359 (0.000)***	0.920 (0.000)***	−0.116 (0.873)	0.336 (0.000)***
0.4	0.958 (0.000)***	−0.314 (0.585)	0.280 (0.000)***	0.928 (0.000)***	−0.215 (0.773)	0.263 (0.000)***
0.5	1.075 (0.000)***	−0.317 (0.582)	0.419 (0.000)***	1.037 (0.000)***	−0.286 (0.702)	0.390 (0.000)***
0.6	1.154 (0.000)***	−0.0975 (0.882)	0.228 (0.004)***	1.108 (0.000)***	0.021 (0.980)	0.204 (0.006)***
0.7	1.070 (0.000)***	−0.30 (0.716)	0.207 (0.000)***	1.038 (0.000)***	−0.195 (0.857)	0.198 (0.000)***
0.8	1.054 (0.000)***	0.491 (0.375)	0.537 (0.000)***	0.993 (0.000)***	0.434 (0.546)	0.491 (0.000)***
0.9	0.547 (0.000)***	−0.428 (0.230)	0.645 (0.000)***	0.550 (0.000)***	−0.483 (0.297)	0.625 (0.000)***

Notes: This table presents the regression results of total connectedness on uncertainty indices for the whole period, and before and during COVID-19 periods. Numbers in parentheses indicate the probabilities of estimated coefficients. (*), (**), and (***) indicate significance at 10%, 5%, and 1% respectively.

declared that COVID-19 is a pandemic.[8] Table 3 reports the estimated parameter α_1^τ of Eq. (9), indicating the impact of the cryptocurrencies' uncertainty indices on the total connectedness in the full sample and the two sub-samples at the different quantiles' orders. In Appendix A, we also report the estimated parameters of the relationships between the net dynamic connectedness of each cryptocurrency and uncertainty indices. Fig. 7 also confirms the results of Table 3. Our results emphasize that CCPO and CCPR have a significant impact on the total and net spillovers of cryptocurrencies, and the results relating to those indices are found to be quite similar and consistent. In the full sample, our analysis shows a significant positive effect of cryptocurrencies uncertainty (both indices) and the total spillover in all market conditions.[9] This finding indicates that an augmented uncertainty provides a sign of good news, pushing crypto-traders and investors to trade more in the cryptocurrency market, seeking benefits of portfolio diversification. This suggests that an increase in cryptocurrency policy and price uncertainties had led to a greater total dynamic connectedness among cryptocurrencies at all quantile orders.

In the subsamples, we find contradictory results. Before the health crisis, cryptocurrency uncertainties (CCPO and CCPR) are negatively associated with the total connectedness at all quantiles, while they are positively associated with the total connectedness during the health crisis. This indicates that before the crisis, cryptocurrency market uncertainties had led to a lower connectedness among cryptocurrencies. This means that before the crisis, investors were using our subject cryptocurrencies mostly for value savings. However, during the crisis, uncertainty in the cryptocurrency market had led to an increase in the connectedness among currencies, suggesting that investors rush to trade more cryptocurrencies to diversify the risk of their portfolios. Thus, our results are different across both subsamples for both cryptocurrency uncertainty indices.

Turning into the results of the effect of CCPR and CCPO on the net spillover, our analysis in Fig. 7 shows evidence of the heterogeneous impact of cryptocurrency uncertainties on the net spillover in the full sample period. The five cryptocurrencies are distinguished by different time responses to shocks under different market conditions. We notice that there are different effects of cryptocurrency market uncertainties on the net spillover of Bitcoin. The net spillover of this cryptocurrency increases when market uncertainties increase only in the normal and bullish markets, indicating that investors trade more Bitcoin in the normal and bullish market conditions. This means that Bitcoin has lost its position as a net diversifier when the cryptocurrency market is bearish and at some moments in the normal markets.

However, the net spillover of Ethereum increases with the increase in market uncertainties under all market conditions. This digital currency is the most attractive cryptocurrency used for risk diversification. The net spillovers for Litecoin and Ripple are negatively associated with cryptocurrency uncertainties at almost all quantiles, except Litecoin in the left tails. This means that Litecoin and Ripple are the most value-saving cryptocurrencies. Ripple is the greatest value saver in the bullish market, whereas Litecoin is the greatest value saver under normal market conditions. Although Tether mostly appears to be a value-saver, it is the weaker value-saving asset, except at quantile orders of 0.60 and 0.90. Finally, Bitcoin has lost its position as a risk diversifier, leaving the position of risk diversification to Ethereum. This also confirms the validity of the quantile-based approach in comparison to the mean-based approach.

Fig. 8 shows the impact of the uncertainty policy index (CCPO) on the net spillover of each cryptocurrency before and during the COVID-19 health crisis. Our results are quite interesting. The net spillover for the five cryptocurrencies is distinguished by different time responses to shocks in the policy index under different market conditions. Bitcoin was used as a risk diversifier against the market policy uncertainty at almost all quantities in both subperiods, but with some exceptions. Bitcoin turns out to be a saver of value in the extreme upper quantile (0.90) before the crisis and in the extreme lower quantile (0.10 and 0.20) during the heath crisis. Although Ethereum acts mostly as a risk diversifier in all market conditions during the crisis, it acted as a value saver against the market policy uncertainty at all quantiles before the crisis.

We find that the uncertainty in the policy index is negatively associated with the net spillover of Ripple at all market conditions before and during the crisis. This indicates that investors use Ripple as a value saver asset under all market conditions before and during the crisis. We notice mixed behavior of the effect of the market policy uncertainty on the net spillover of Litecoin and Tether in the sub-periods. Litecoin acts as a value saver at almost all quantiles during the pandemic (except at the extreme lower quantile), while before the pandemic, it acts as a risk diversifier mostly during the bearish and bullish market conditions. Tether shows evidence of risk diversification in the bearish and bullish markets before the crisis, but during the pandemic, it shows evidence of value saver at the bearish and bullish market conditions, except in the normal market and extreme right tail of the distribution. The bottom line is that Bitcoin is the dominant risk diversifier before and during the

[8] We use the date 03/10/2020 as the beginning of the pandemic period based on the WHO announcement that COVID-19 is a pandemic in 03/10/2020. Moreover, several previous studies divided the sample period based on the date of January 1, 2020, since that was the date when the first cases of COVID-19 appeared in Wuhan, China. Bouni et al. (2021a) used also January 13, 2020 as the cutoff period, since that was the date of first cross border transmission of infection reported by the Thai authorities. Assaf, Charif, and Mokni (2021) and Mokni et al. (2021a) use March 11, 2020 to be the cutoff period since that was the date when the WHO announced that COVID-19 is a pandemic. We followed Assaf et al. (2021) and Mokni et al. (2021a) on the cutoff date.

[9] In estimating the quantile regression, we include other lags of policy uncertainty measures, and the results were insignificant. To save space we do not report the estimation results, yet, they are available upon request.

Fig. 7. The effect of CCPO and CCPR on the total and net spillover in the full sample.

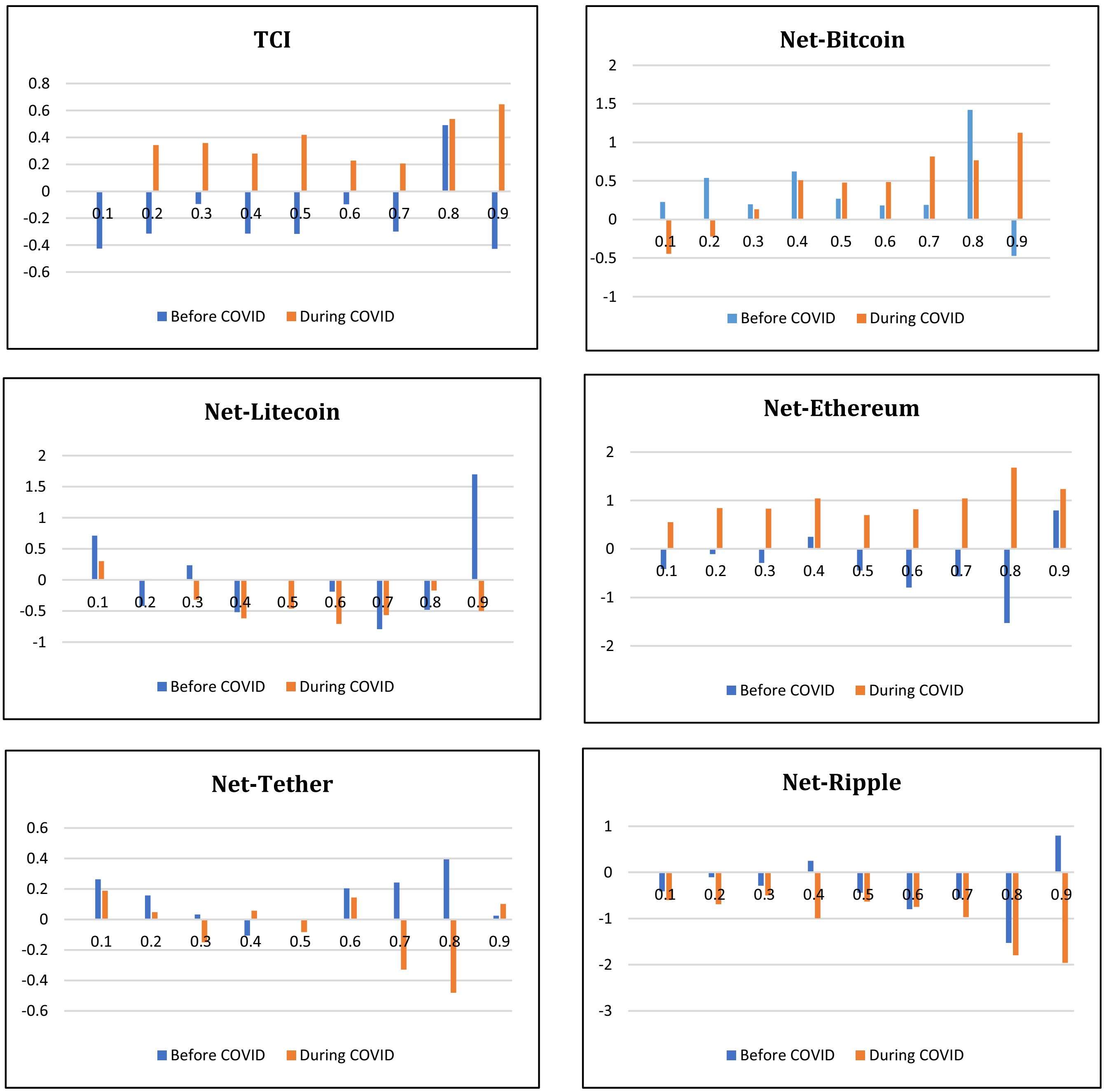

Fig. 8. The effect of CCPO on the total and net spillover before and during the COVID-19 period.

crisis, while Ripple is the dominant value saver in both subsamples. We also argue that there were heterogeneous responses to the market policy uncertainty before the crisis.

The plots in Fig. 9 show the effect of cryptocurrency price uncertainty (CCPR) on the total and net spillovers in the sub-periods (before and during COVID-19). Our results are similar to those reported in Fig. 8 for both the total and the net spillovers. Overall, our analysis provides a detailed picture of the impact of cryptocurrency policy and price uncertainties on the total and the net connectedness among cryptocurrencies. It shows that, generally, the impact of such uncertainties on the dynamic connectedness varies across different market conditions, and cryptocurrencies offer beneficial diversification opportunities. Our findings also indicate that more attention should be directed toward examining such a relationship during a high level of total connectedness, especially in a period where the effect of the uncertainties is more pronounced. To some extent, these assets are 'safe-havens', but their connectedness and volatility during financial or pandemic crises may change according to market conditions.

In summary, there is evidence of the heterogeneous impact of cryptocurrency policy uncertainty on net spillover, suggesting that our cryptocurrencies are distinguished by different time responses to shocks under different market conditions (e.g., bear, normal, and bull). The net spillovers of cryptocurrencies in the study show evidence of the varied impact of cryptocurrency policy uncertainty in both subperiods and across quantiles.

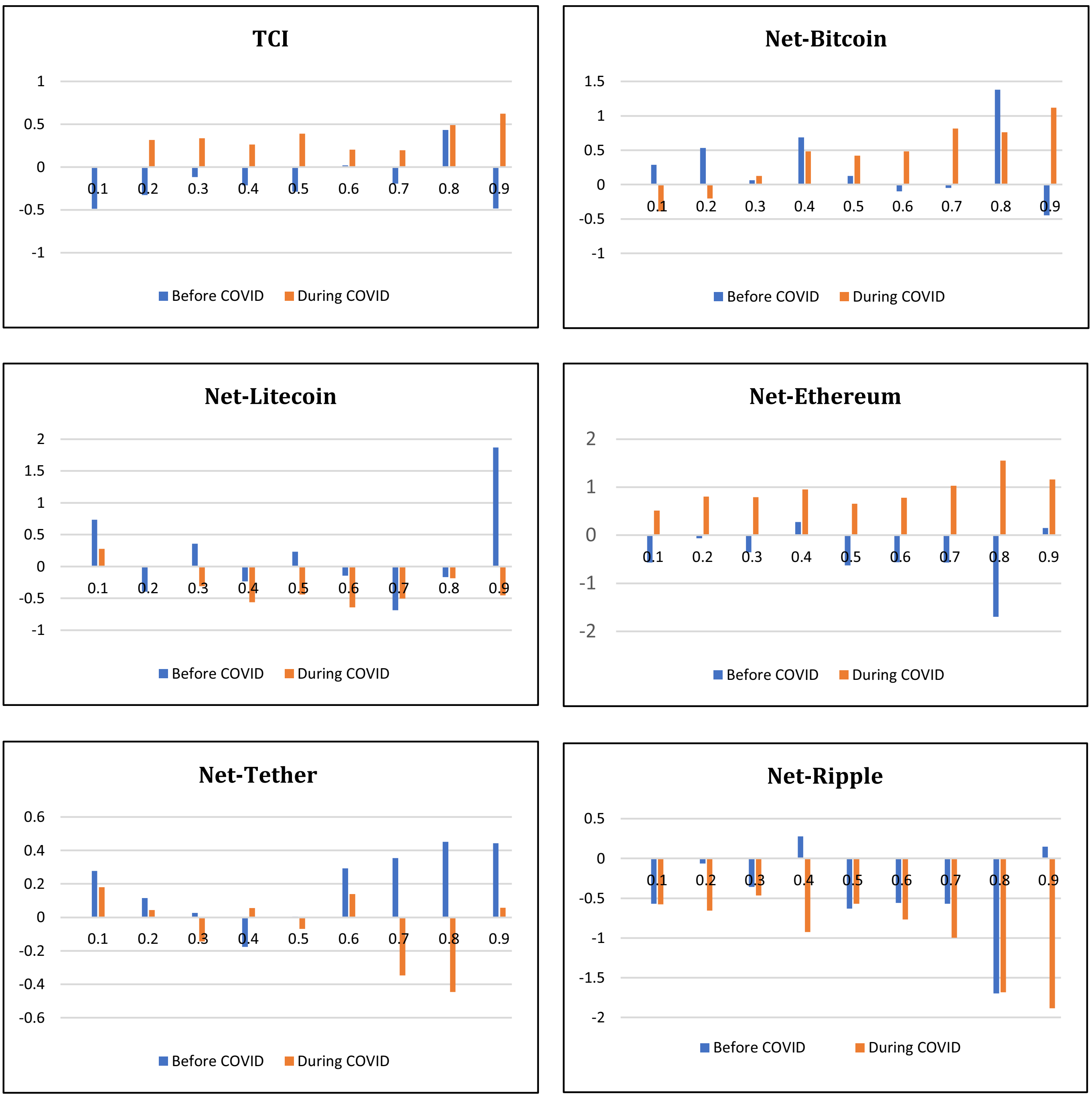

Fig. 9. The effect of CCPR on the total and net spillover before and during the COVID-19 period.

5. Concluding remarks

This paper provides a comprehensive analysis of the dynamic connectedness among five major cryptocurrencies using the Quantile-VAR approach proposed by Diebold and Yilmaz (2009, 2012, 2014), allowing to differentiate between the return spillovers in upper, middle, and lower quantiles. The paper also contributes to the impact of COVID-19 on the return spillovers by considering two periods, namely the before and during the COVID-19 pandemic periods. Then, we examine whether the dynamic connectedness is affected by the cryptocurrency policy and price uncertainty (CCPO and CCPR) proposed by Lucey et al. (2021). We use the weekly price data of the five leading cryptocurrencies considered by Lucey et al. (2021), such as Bitcoin (BTC), Litecoin (LIT), Ethereum (ETH), Tether (TETH), and Ripple (XRP).

The main findings can be summarized as follows. First, Bitcoin and Ethereum are the highly influential cryptocurrencies in the network of return connectedness in the market, with the total spillover index (TCI) varying across quantiles and increasing widely during the recent extreme market conditions due to the COVID-19 pandemic. Litecoin acted as a dominant hedger and/or a value saver during and before the pandemic while Bitcoin lost its position as a dominant hedger during the crisis. Second, our findings report further support for the impact of both the CCPO and CCPR on the total connectedness among the five cryptocurrencies, as well as on the net spillover of each one. Third, Bitcoin is still the dominant risk diversifier cryptocurrency before and during the crisis, while Ethereum acts as a risk diversifier before the crisis and a value saver during the crisis period. Interestingly, Bitcoin acts as a risk diversifier against the market policy and price uncertainty at almost all quantities in both sub-periods, but with some exceptions. However, Bitcoin turns out to be a saver of value in the extreme upper quantile before the crisis and in the extreme lower quantile during the health crisis. Yet, Ethereum acts as a risk diversifier in all market conditions during the crisis and plays the role of a value saver against the cryptocurrency market policy and price uncertainty at all quantiles before the crisis.

Our results also reveal that policy uncertainties are negatively associated with the net spillover of Ripple at all market conditions before and during the crisis, indicating that Ripple is used by investors as a value saver asset under all market conditions. Results for Litecoin and Tether are mixed, where Litecoin acts as a value saver at almost all quantiles during the pandemic period, while Tether shows evidence of value saver during the bearish and bullish market conditions. Overall, Bitcoin maintains its role as a dominant risk diversifier before and during the crisis, while Ripple is the dominant value saver in both subsamples, with some noticeable heterogeneous responses of the net connectedness of each cryptocurrency to market uncertainties.

This paper has several policy implications. First, by understanding the effects and size of the spillovers on the connectedness of cryptocurrencies, regulators can use policy measures and tools to more effectively manage the impact of potential adverse effects arising from extreme risk spillovers in the cryptocurrency markets. The findings on extreme connectedness measures in the different quantiles provide an important view of the importance of tail risk propagation within the group of cryptocurrencies and their relation to market uncertainties. Efforts by regulators, in this case, should be devoted toward the extreme events since the focus on average shocks with the system of connectedness may lead to non-optimal policies during periods of market stress. Second, our findings can provide useful information concerning investment and hedging decisions related to cryptocurrency markets (see, for example, Matkovskyy, Jalan, Dowling, & Bouraoui, 2021). Investors, in this case, should focus more on the tail behavior of connectedness as opposed to the average shocks since that will entitle better risk management during stress periods (Baur, Hong, & Lee, 2018; Bouri, Lucey, & Roubaud, 2020). That will allow investors and market participants to distinguish whether the transmission of shocks among cryptocurrencies has a short and long effect, leading to a better evaluation of systematic risk. Third, given that market uncertainties may have different impacts on cryptocurrency markets and each cryptocurrency, investors can use that in building their portfolios, exploring the relative importance of negative and positive shocks to each or from each cryptocurrency.

Future studies can explore the application of quantile-VAR to the behavior of cryptocurrencies by using data at different frequencies as suggested by Vidal-Tomás (2020) and Zhang, Chan, and Chu (2019), or by using other forms of quantile connectedness approaches in the spirit of those proposed by Baruník and Kley (2019). Other studies might involve applying regime change within the spirit of Diebold and Yilmaz (2012). Moreover, connectivity analysis among cryptocurrencies and traditional financial assets can be explored. In this regard, future research can compare the impact of the December 2017 cryptocurrency price crash and the COVID-19 pandemic on the connectivity among cryptocurrency market and financial markets.

Data availability

Data will be made available on request.

Appendix A. Net connectedness and uncertainty indices

Notes: The tables present the estimation results of net connectedeness of each cryptocurrency in relation to uncertainty indices. The esimtation is run for the whole period, and before and during CCOVID-19 periods. Numbers in parentheses are the probabilities of estimated coefficients at each quantile.

	Bitcoin					
	CCPO			CCPR		
	Whole period	Before COVID	During COVID	Whole period	Before COVID	During COVID
Quantile						
0.1	−0.277 (0.003)	0.228 (0.618)	−0.444 (0.000)	−0.247 (0.006)	0.289 (0.626)	−0.389 (0.000)
0.2	−0.340 (0.000)	0.540 (0.025)	−0.220 (0.000)	−0.333 (0.000)	0.534 (0.094)	−0.202 (0.000)
0.3	0.255 (0.000)	0.195 (0.601)	0.133 (0.000)	0.240 (0.000)	0.064 (0.894)	0.127 (0.000)
0.4	0.610 (0.000)	0.624 (0.169)	0.509 (0.000)	0.582 (0.000)	0.687 (0.245)	0.483 (0.000)
0.5	0.667 (0.000)	0.270 (0.484)	0.480 (0.000)	0.611 (0.000)	0.128 (0.798)	0.421 (0.000)
0.6	0.069 (0.623)	0.181 (0.630)	0.485 (0.000)	0.083 (0.538)	−0.097 (0.842)	0.485 (0.000)
0.7	0.264 (0.108)	0.189 (0.466)	0.818 (0.000)	0.288 (0.071)	−0.047 (0.887)	0.817 (0.000)
0.8	0.516 (0.001)	1.422 (0.028)	0.769 (0.000)	0.506 (0.001)	1.379 (0.107)	0.761 (0.000)
0.9	0.977 (0.000)	−0.473 (0.363)	1.124 (0.000)	1.007 (0.000)	−0.445 (0.511)	1.121 (0.000)

(continued on next page)

(*continued*)

	Bitcoin					
		CCPO			CCPR	
	Whole period	Before COVID	During COVID	Whole period	Before COVID	During COVID

	Litecoin					
		CCPO			CCPR	
	Whole period	Before COVID	During COVID	Whole period	Before COVID	During COVID
Quantile						
0.1	0.360 (0.000)	0.715 (0.113)	0.302 (0.000)	0.328 (0.000)	0.736 (0.211)	0.275 (0.000)
0.2	0.039 (0.451)	−0.418 (0.142)	0.015 (0.744)	0.042 (0.404)	−0.394 (0.289)	0.010 (0.824)
0.3	−0.416 (0.000)	0.236 (0.407)	−0.319 (0.000)	−0.413 (0.000)	0.359 (0.330)	−0.312 (0.000)
0.4	−0.582 (0.000)	−0.518 (0.085)	−0.615 (0.000)	−0.534 (0.000)	−0.233 (0.557)	−0.562 (0.000)
0.5	−0.593 (0.000)	0.001 (0.996)	−0.460 (0.000)	−0.574 (0.000)	0.234 (0.543)	−0.439 (0.000)
0.6	−0.887 (0.000)	−0.188 (0.353)	−0.704 (0.000)	−0.834 (0.000)	−0.146 (0.580)	−0.640 (0.000)
0.7	−0.688 (0.000)	−0.790 (0.036)	−0.562 (0.000)	−0.628 (0.000)	−0.685 (0.168)	−0.504 (0.000)
0.8	−0.040 (0.779)	−0.479 (0.251)	−0.166 (0.387)	−0.044 (0.748)	−0.168 (0.758)	−0.184 (0.318)
0.9	−0.185 (0.223)	1.700 (0.041)	−0.498 (0.000)	−0.192 (0.192)	1.869 (0.086)	−0.452 (0.000)

	Ethereum					
		CCPO			CCPR	
	Whole period	Before COVID	During COVID	Whole period	Before COVID	During COVID
Quantile						
0.1	0.761 (0.000)	−0.413 (0.141)	0.554 (0.000)	0.740 (0.000)	−0.570 (0.117)	0.510 (0.000)
0.2	1.150 (0.000)	−0.105 (0.638)	0.844 (0.000)	1.121 (0.000)	−0.065 (0.821)	0.805 (0.000)
0.3	1.128 (0.000)	−0.290 (0.261)	0.835 (0.000)	1.099 (0.000)	−0.357 (0.287)	0.793 (0.000)
0.4	1.127 (0.000)	0.249 (0.188)	1.042 (0.000)	1.062 (0.000)	0.278 (0.259)	0.950 (0.000)
0.5	0.746 (0.000)	−0.446 (0.036)	0.700 (0.000)	0.719 (0.000)	−0.630 (0.021)	0.657 (0.000)
0.6	0.760 (0.000)	−0.798 (0.060)	0.820 (0.000)	0.733 (0.000)	−0.560 (0.318)	0.783 (0.000)
0.7	1.054 (0.000)	−0.563 (0.130)	1.041 (0.000)	1.046 (0.000)	−0.569 (0.241)	1.032 (0.000)
0.8	1.953 (0.000)	−1.528 (0.015)	1.679 (0.000)	1.857 (0.000)	−1.699 (0.040)	1.552 (0.000)
0.9	0.575 (0.011)	0.797 (0.626)	1.236 (0.000)	0.593 (0.007)	0.148 (0.944)	1.158 (0.000)

	Tether					
		CCPO			CCPR	
	Whole period	Before COVID	During COVID	Whole period	Before COVID	During COVID
Quantile						
0.1	−0.302 (0.040)	0.264 (0.371)	0.189 (0.081)	−0.291 (0.041)	0.278 (0.468)	0.181 (0.082)
0.2	−0.100 (0.053)	0.158 (0.265)	0.048 (0.284)	−0.101 (0.044)	0.116 (0.530)	0.044 (0.306)
0.3	−0.167 (0.000)	0.032 (0.635)	−0.151 (0.000)	−0.164 (0.000)	0.027 (0.755)	−0.143 (0.000)
0.4	−0.160 (0.006)	−0.107 (0.525)	0.057 (0.009)	−0.150 (0.008)	−0.177 (0.420)	0.055 (0.008)
0.5	−0.067 (0.002)	−0.003 (0.925)	−0.084 (0.009)	−0.056 (0.010)	0.005 (0.994)	−0.068 (0.028)
0.6	0.386 (0.000)	0.203 (0.131)	0.144 (0.022)	0.374 (0.000)	0.293 (0.092)	0.140 (0.020)
0.7	−0.226 (0.000)	0.243 (0.161)	−0.329 (0.000)	−0.252 (0.000)	0.354 (0.115)	−0.347 (0.000)
0.8	−0.557 (0.000)	0.395 (0.475)	−0.482 (0.000)	−0.537 (0.000)	0.452 (0.529)	−0.446 (0.000)
0.9	0.488 (0.001)	0.025 (0.971)	0.101 (0.367)	0.448 (0.003)	0.443 (0.626)	0.057 (0.598)

	Ripple					
		CCPO			CCPR	
	Whole period	Before COVID	During COVID	Whole period	Before COVID	During COVID
Quantile						
0.1	−0.542 (0.000)	−0.413 (0.141)	−0.602 (0.000)	−0.530 (0.000)	−0.570 (0.117)	−0.578 (0.000)
0.2	−0.748 (0.000)	−0.106 (0.638)	−0.688 (0.000)	−0.728 (0.000)	−0.065 (0.821)	−0.657 (0.000)
0.3	−0.799 (0.000)	−0.290 (0.261)	−0.498 (0.000)	−0.763 (0.000)	−0.357 (0.287)	−0.464 (0.000)
0.4	−0.995 (0.000)	0.249 (0.188)	−0.993 (0.000)	−0.959 (0.000)	0.278 (0.259)	−0.926 (0.000)
0.5	−0.750 (0.000)	−0.446 (0.036)	−0.636 (0.000)	−0.699 (0.000)	−0.630 (0.021)	−0.570 (0.000)
0.6	−0.329 (0.101)	−0.798 (0.060)	−0.745 (0.003)	−0.357 (0.066)	−0.560 (0.318)	−0.769 (0.000)
0.7	−0.403 (0.052)	−0.563 (0.130)	−0.968 (0.000)	−0.453 (0.024)	−0.569 (0.241)	−0.997 (0.000)
0.8	−1.872 (0.000)	−1.528 (0.015)	−1.799 (0.000)	−1.780 (0.000)	−1.699 (0.040)	−1.683 (0.000)
0.9	−1.855 (0.000)	0.797 (0.626)	−1.964 (0.000)	−1.857 (0.000)	0.148 (0.944)	−1.884 (0.000)

Appendix B

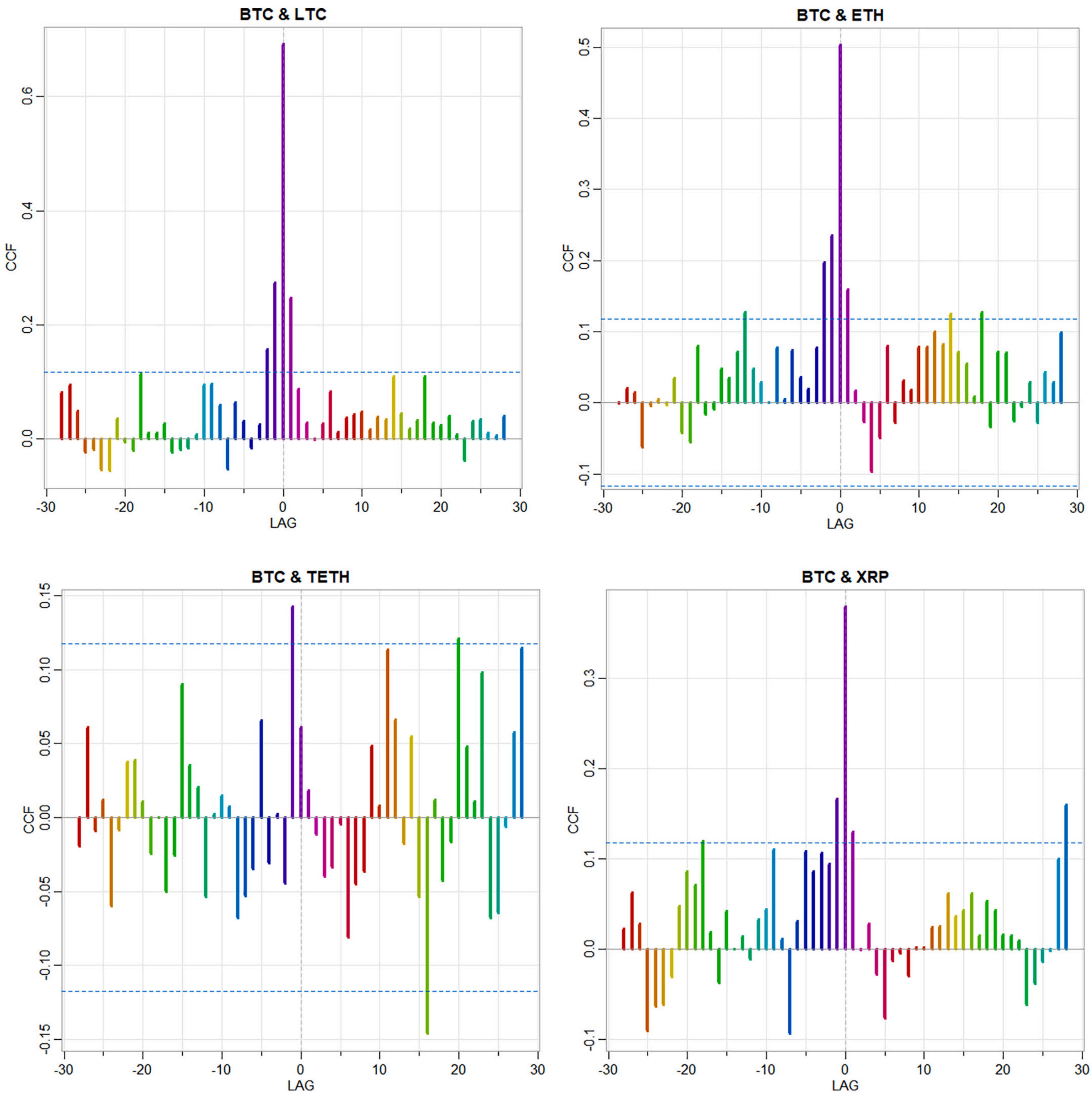

Fig. B1. Cross Correlation between Bitcoin and the rest of cryptocurrencies.
Notes: the figure presents the cross correlation between Bitcoin and the rest of cryptocurrencies indicating the lead-lag relationship over the sample period.

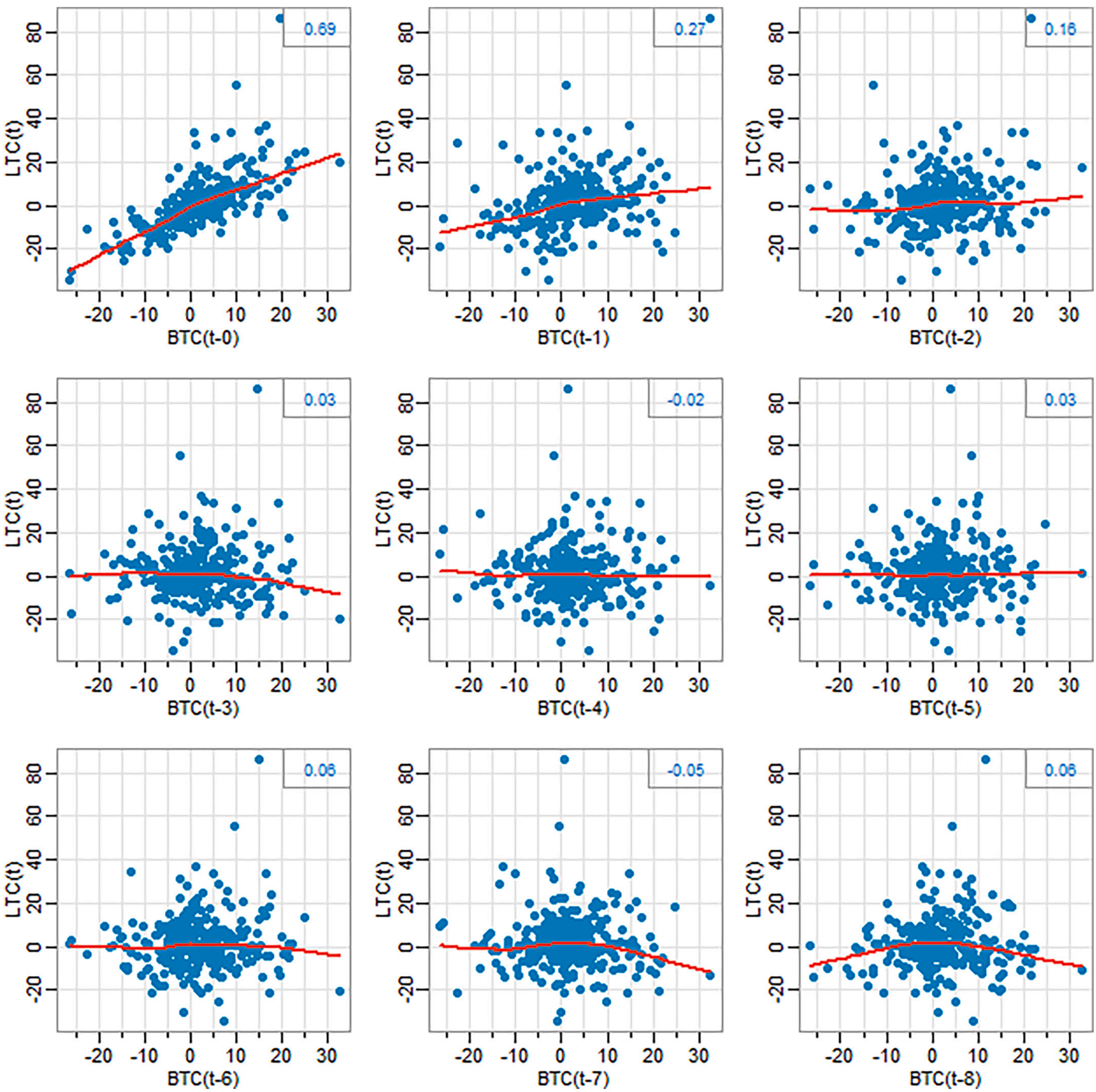

Fig. B2. Litecoin and Bitcoin Scatterplot relating Litcoin to the lags of Bitcoin.

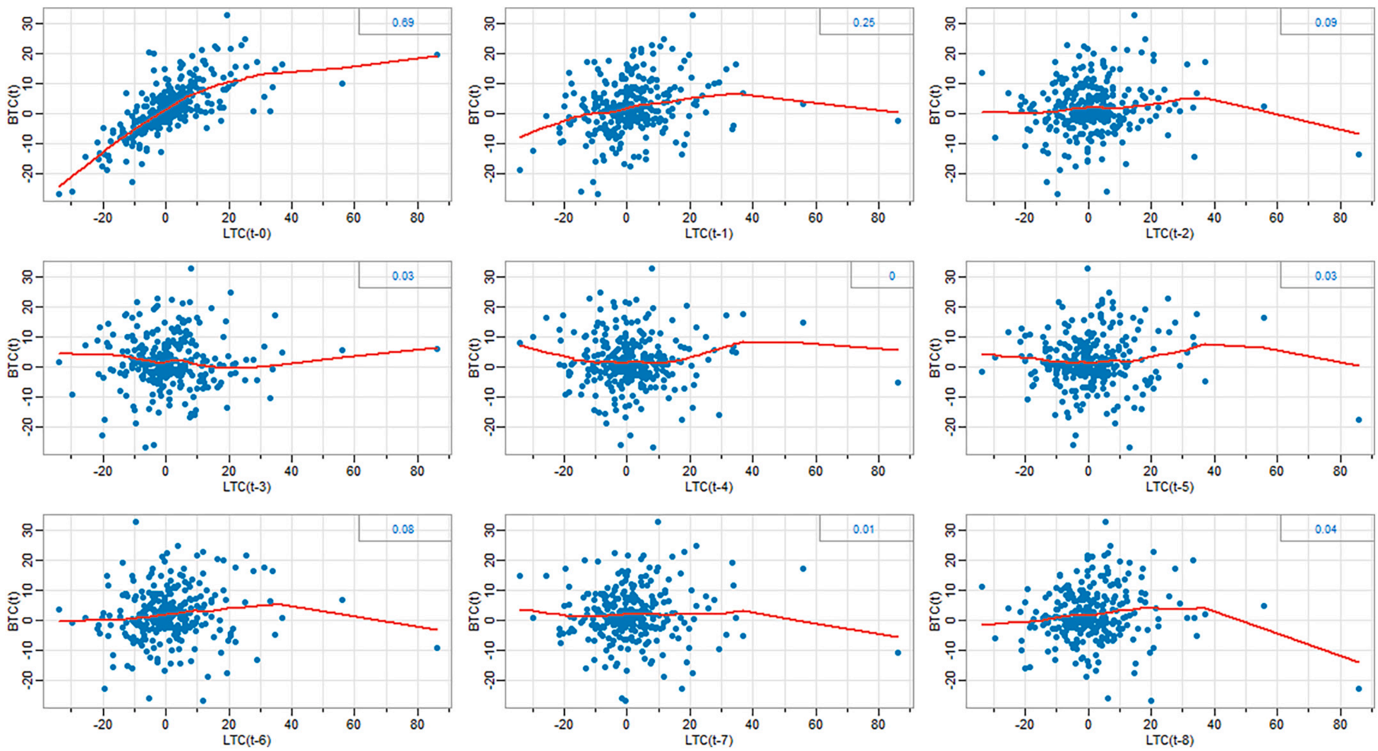

Fig. B3. Bitcoin and Litecoin Scatterplot relating Bitcoin to the lags of Litecoin.

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