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Cryptocurrency market connectedness in Covid-19 days and the role of Twitter: Evidence from a smooth transition regression model

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ABSTRACT

This paper presents new evidence on connectedness across cryptocurrencies in the era of the Covid-19 pandemic. The results from the TVP-VAR dynamic connectedness approach show that the degree of connectedness is time-varying, indicating a decline during the Covid-19 period. Next, this paper highlights the nonlinear characteristics of the relationship between connectedness and its explanatory variables. The results from the LSTR model indicate that the regression coefficients change smoothly between the low and the upper regimes as anxiety across Twitter users increases. As the latter changes smoothly from low to high values, the impact of higher Disease-based volatility or Twitter-based uncertainty on connectedness turns gradually from positive to negative. The upper regime is dominant during the Covid-19 pandemic. Important implications for investors and policy makers are derived.

1. Introduction

The cryptocurrency market is already in its second decade of life. It was 2008 when Satoshi Nakamoto\(^1\) introduced the first digital currency, named Bitcoin, which was intended to be neither issued nor controlled by a central monetary authority. Since then, a huge number of new virtual currencies with the same characteristics has been launched in the market. The so-called cryptocurrency market has grown rapidly as an ever-increasing number of investors has chosen to trade with cryptocurrencies.\(^2\) The rapid growth of cryptocurrency trading has attracted the interest of academics and policy makers. An important issue under investigation in the literature is the interdependence among cryptocurrencies. Connectedness in the cryptocurrency market is crucial from investors perspective because it is directly related with contagion (i.e. return and volatility spillovers) and hedging (i.e. risk management and portfolio diversification strategies) during turmoil periods, such as the current Covid-19 pandemic crisis.

Although an adequate number of studies has examined this important issue, the existing literature contains a limited number of studies dealing with interdependence in the cryptocurrency market during the Covid-19 pandemic crisis period. Most of the existing studies focus on the pre-Covid-19 period (see, Koutmos, 2018; Yi et al., 2018; Ji et al., 2019; Katsiampa et al., 2019a,b; Apergis et al.,

\(^1\) It is still unclear whether Satoshi Nakamoto is a real person or instead corresponds to a pseudonym of a person or a group of people.

\(^2\) On the other hand, many national and multinational companies have announced that accept cryptocurrencies as a formal payment method, while some Central Banks (i.e. People’s Bank of China, Swiss National Bank, South African Reserve Bank, European Central Bank) are considering the possibility of introducing their own digital currency (Central Bank Digital Currencies). In addition to this development, El Salvador has adopted Bitcoin as a legal tender.

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The literature on cryptocurrencies is growing fast along with the cryptocurrency market. Main issues of empirical investigation in the literature are the volatility dynamics of cryptocurrency returns, the degree of connectedness across cryptocurrencies and the interdependence among the cryptocurrency market and asset markets. Dealing with volatility, Ben Cheikh et al. (2020) report the sharp ups and downs observed in the cryptocurrency market during the Covid-19 pandemic crisis. This new market is characterized by high volatility and sensitivity to news, events and forecasts about the future. Although these characteristics are common in almost all financial assets, it is remarkable that volatility in cryptocurrencies is much higher than this of fiat currencies and traditional financial assets (Baur and Dimpfl, 2021). In addition, this paper aims to fill the aforementioned gaps in the literature and to shed more light on the connectedness across cryptocurrencies based on an extended period of time, which covers the early as well as the mature stages of the Covid-19 pandemic crisis.  

Employing the time-varying properties of the dynamic connectedness approach of Diebold and Yilmaz (2014), as extended by Antonakakis et al. (2020), we estimate return-spillover dynamics among 5 cryptocurrencies (Bitcoin, Ethereum, Litecoin, Dash and Monero) from August 8, 2015 to May 11, 2021. An interesting finding is that the Covid-19 period is associated with a decline in the degree of connectedness across the cryptocurrencies of the network. But what is of special interest is to identify the driving forces of connectedness. So, at the second stage of the estimation procedure, a nonlinear Logistic Smooth Transition Regression (LSTR) model is estimated to detect the factors that determine the interrelationship among cryptocurrencies. Focusing on the nonlinear characteristics of the relationship between connectedness and its regressors, the LSTR model is preferred instead of alternative nonlinear models because the smooth transition across different regimes is more suitable to the cryptocurrency market. In this framework, we test the research hypothesis that connectedness across cryptocurrency markets is driven by global factors that influence the investors’ behavior, such as financial markets volatility, economic uncertainty, the current pandemic crisis and investment opportunities. These factors include volatility and uncertainty measures (CBOE Volatility Index, Infectious Disease Equity Market Volatility, Twitter-based Uncertainty Index) and an alternative investment asset (gold).  

This paper contributes to the literature by a number of ways. First and foremost, this paper employs variables related to the pandemic crisis as determinants of connectedness in the cryptocurrency market. To the best of the author knowledge of the literature, this is the first paper that examines Disease-based and Twitter-based uncertainty as determinants of cryptocurrencies connectedness. The motivation behind the selection of the Disease-based uncertainty variable is the Covid-19 pandemic crisis. On the other hand, Twitter-based uncertainty is chosen because of the increased role of Twitter in spreading economic and other news. Second, this paper emphasizes on the nonlinear characteristics of the relationship between connectedness and its explanatory variables. The nonlinear Logistic Smooth Transition Regression model sheds light on the role of each of the determinant variable across different regimes. As far as the author knows, this is the first time that the LSTR model is employed in determining the driving forces of connectedness across cryptocurrencies. This allows us to present new evidence. As uncertainty across Twitter users changes smoothly from low to high values, the impact of higher Disease-based volatility or Twitter-based uncertainty on connectedness turns gradually from positive to negative. Third, a longer and up-to-date time span is employed to cover the mature stages of the Covid-19 pandemic. In most of the existing studies in the literature, the period of estimation stops in March or April 2020, a time period which coincides with the emergence of the pandemic. The longer estimated period of this study allows us to capture the consequences of the lockdowns and the accompanied uncertainty. Fourth, important implications are derived for investors in terms of contagion and hedging behavior against risk during crisis periods.

The rest of the paper is organized as follows. The next section reviews the related literature and Section 3 presents the econometric methodology. Section 4 illustrates the data, while the results are presented in Section 5. A final section concludes.

2. Literature review

The literature on cryptocurrencies is growing fast along with the cryptocurrency market. Main issues of empirical investigation in the literature are the volatility dynamics of cryptocurrency returns, the degree of connectedness across cryptocurrencies and the interdependence among the cryptocurrency market and asset markets. Dealing with volatility, Ben Cheikh et al. (2020) report the

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3 On the other hand, very few studies have examined connectedness across cryptocurrencies covering a large enough time span of the pandemic (see, Raza et al., 2022; Naem et al., 2022).
4 To find more about the findings and the limitations in the existing literature, see Section 2.
5 We define the early stages of the pandemic as the period that starts with the emergence of the coronavirus in China and lasts until its worldwide spreading in March 2020. Accordingly, the mature stages of the pandemic correspond to the periods that follow, i.e. the first Covid-19 wave in April 2020, the second wave that started in September of the same year and the third wave of the pandemic, which started in March 2021.
6 This paper focuses on the impact of exogenous factors on connectedness. Hence, to avoid endogeneity issues, the trading volume of cryptocurrencies is not considered here as a determinant.
7 We focus on gold as an alternative to cryptocurrencies financial asset because a significant relationship between gold and cryptocurrency returns has been reported in the literature (see, inter alia, Bouri et al., 2018; Henriquees and Sadorskys, 2018).
8 On the other hand, economic policy uncertainty has already been tested in the literature as a determinant of cryptocurrency returns (Nguyen Quang et al., 2020) and connectedness among cryptocurrency markets (Bouri et al., 2021). This paper differs from these studies by focusing on (1) the uncertainty across Twitter users and (2) the volatility related to the Covid-19 pandemic crisis.
existence of inverse leverage effect in volatility dynamics of four major cryptocurrencies (Bitcoin, Ethereum, Ripple, Litecoin),\(^9\) implying supporting evidence of the safe-haven hypothesis. Next, investigating the relationship between economic policy uncertainty and volatility of three cryptocurrencies (Bitcoin, Litecoin, Ripple), \(\text{Yen and Cheng (2021)}\) find that higher economic policy uncertainty is linked with lower cryptocurrencies’ volatility. This result implies that cryptocurrencies may act as a hedging tool against economic uncertainty. Similar results have been reported, among others, by \(\text{Demir et al. (2018)}\). In addition, \(\text{Yin et al. (2021)}\), find that oil market shocks affect the volatility dynamics of three cryptocurrencies (Bitcoin, Ethereum, XRP) through the macroeconomic channel and conclude that cryptocurrencies could act as a hedge under specific economic uncertainty conditions.

Another strand of the literature examines the degree of connectedness among cryptocurrencies. Based on the connectedness approach of Diebold and Yilmaz (D-Y), \(\text{Koutmos (2018)}\) finds high interdependence among 18 cryptocurrencies, implying evidence of high degree of contagion. Similar results, but for a shorter sample, have been reported by \(\text{Yi et al. (2018)}; \text{Katsiampa et al. (2019a)}\) and \(\text{Moratis (2021)}\). Specifically, \(\text{Yi et al. (2018)}\), employing the D-Y connectedness approach along with the LASSO VAR for the period 2013–2018, report evidence of volatility connectedness across cryptocurrencies that increased after 2016. \(\text{Moratis (2021)}\) combines the D-Y approach with a rolling-window Bayesian model and finds evidence of spillover effects among 30 cryptocurrencies for the period 2016–2020. Using a different methodology (i.e. pairwise bivariate BEKK-GARCH models), \(\text{Katsiampa et al. (2019a)}\) find evidence of bidirectional transmission of shocks among Bitcoin, Ether and Litecoin. Slightly different are the results presented by \(\text{Apergis et al. (2021)}\). Based on the \(\text{Phillips-Sul (2007)}\) methodology, the authors report absence of overall convergence among the 8 cryptocurrencies of the sample, but they find evidence of convergence when distinct cryptocurrency clubs are considered.

An interesting aspect of the above research question is to test the response of connectedness across cryptocurrencies during periods of distress, such as this of the Covid-19 pandemic crisis. However, the literature contains a limited number of studies dealing with interdependence in the cryptocurrency market during the Covid-19 period. The vast majority of the existing studies dealing with Covid-19 covers only the very early stage of the pandemic crisis, which coincides with the emergence of the pandemic crisis (see, \(\text{Conlon et. al. (2020)}; \text{Demir et al., (2020)}; \text{Yousaf and Ali, (2020)}; \text{Corbet et al., (2020)}; \text{Khelifa et al., (2021)}\)). Very few studies have examined connectedness across cryptocurrencies covering a large enough time span of the pandemic period. \(\text{Raza et al. (2022)}\) focus on the period from January 2020 to April 2021 and find evidence of spillovers among the 8 cryptocurrencies under consideration. \(\text{Naeem et al. (2022)}\) estimate a larger period of time (August 2015 – October 2020), which is divided into pre and post Covid-19 period. The results verify a network of integration across cryptocurrencies before the Covid-19 outbreak but imply complex clusters of connectedness during the post-Covid-19 period.\(^{10}\)

This strand of the literature also includes studies that investigate the determinants of interdependence among cryptocurrencies. Scholars employ a two-stage procedure: at the first stage, an index of connectedness or correlation across the cryptocurrencies of the sample is estimated, while at the second stage, this index is regressed by a number of relevant explanatory variables. \(\text{Ji et al. (2019)}\) employ the D-Y approach to construct the connectedness index for six cryptocurrencies over the period 2015–2018 and OLS regressions to find out which factors can affect connectedness in the cryptocurrency market. The authors report that global financial stress has a positive impact on cryptocurrencies connectedness, while US economic policy uncertainty is negatively linked with connectedness. On the other hand, gold prices and energy prices have a negative impact on connectedness when returns are positive, but US VIX has a positive impact when returns are negative. Similarly, \(\text{Bouri et al. (2021)}\), estimating a Dynamic Equicorrelation model and OLS regressions from August 2015 to February 2019 find that the main driving forces of correlation among the 12 cryptocurrencies of the sample are trading volume, economic policy uncertainty and stock market volatility. However, they conclude with the statement that integration in the cryptocurrency market is weakly connected with the global financial system. On a similar manner, but investigating an alternative methodology (Logit model) and a different set of determinants, \(\text{Apergis et al. (2021)}\) find that market capitalization, range volatility and mining fees are positively related to convergence among cryptocurrencies.

Summing up this brief review of the literature, scholars have reported evidence of interdependence across cryptocurrencies and signs that the cryptocurrency market interacts with financial markets and economic activity. In line with this finding, crisis periods and subsequent macroeconomic facts, such as these related to the Covid-19 pandemic, are expected to affect the connectedness in the cryptocurrency market. Although the literature on cryptocurrencies is not poor, there are a few limitations and gaps that need to be addressed. First, the vast majority of the empirical studies in the existing literature focuses on the early stages of the pandemic crisis and thus, the consequences of the mature stages of the crisis have not been highlighted. Second, the strand of the literature that seeks to find the determinants of connectedness in the cryptocurrency market relies more on endogenous factors (trading volumes, mining fees) but less on factors related to the pandemic crisis. Hence, this gap needs to be filled in order to identify the impact of the pandemic crisis and the resulting uncertainty on connectedness across cryptocurrencies. Finally, the existing empirical studies on this strand of the literature employ linear regression models without testing the hypothesis that the impact of the determinants on connectedness may be nonlinear. If linearity is not the case, nonlinear models may shed light on interesting aspects of the relationship between cryptocurrency connectedness and its regressors.

\(^9\) Specifically, higher (lower) volatility is observed during good (bad) news.

\(^{10}\) This section of the literature also includes studies dealing with connectedness of cryptocurrencies with other assets during the Covid-19 crisis period, such as gold (\(\text{González et al., (2021)}\)), equity markets (\(\text{Goodell and Goutte, (2021)}\)) and renewable energy stock markets (\(\text{Li and Meng, (2022)}\)).
3. Econometric methodology

3.1. TVP-VAR dynamic connectedness

To produce spillovers among the cryptocurrencies under consideration, this study focuses on the connectedness approach, originally presented by Diebold and Yilmaz (2009, 2012, 2014) and its TVP-VAR extension, proposed by Antonakakis et al. (2020). More precisely, the Time-Varying Parameter Vector Autoregression (TVP-VAR) dynamic connectedness approach combines the dynamic connectedness methodology (Diebold and Yilmaz, 2014) with the assumption that the variance-covariance matrix is allowed to vary (Koop and Korobilis, 2014). This methodology is superior to the standard connectedness approach (Diebold and Yilmaz, 2009, 2012) because (i) the results are not sensitive to the choice of the rolling-window size, (ii) there is no loss of observations, and (iii) the results are not affected by outliers.

The TVP-VAR(p) model is written as follows:

\[ x_t = A_y y_{t-1} + \epsilon_t, \quad \epsilon_t | \Omega_{t-1} \sim N(0, \Sigma_t) \]  

\[ \text{vec}(A_t) = \text{vec}(A_{t-1}) + \xi_t, \quad \xi_t | \Omega_{t-1} \sim N(0, \Xi_t) \]  

With \( y_{t-1} = \begin{pmatrix} x_{t-1} \\ x_{t-2} \\ \vdots \\ x_{t-p} \end{pmatrix} \) and \( A_t' = \begin{pmatrix} A_{11} \\ A_{21} \\ \vdots \\ A_{mp} \end{pmatrix} \).

where \( x_t \) and \( y_{t-1} \) are m×1 and mp×1 vectors, respectively. \( A_t \) and \( A_y \) are m×mp and m×m dimensional vectors, respectively. Moreover, \( \text{vec}(A_t) \) is an m^2p×1 dimensional vector, \( \epsilon_t \) and \( \xi_t \) are m×1 vector and m^2p×1 dimensional vector, respectively. \( \Sigma_t \) and \( \Xi_t \) are the time-varying variance-covariance matrices and represent m×m and m^2p×m^2p dimensional matrices, respectively. \( \Omega_{t-1} \) represents the information set available until t-1.

Extending the generalized connectedness approach of Diebold and Yilmaz (2014), the time-varying coefficients and variance-covariance matrices are utilized to estimate the Generalized Impulse Response Functions (GIRF) and the \( H \)-step ahead (scaled) Generalized Forecast Error Variance Decompositions (GFEVD) in line with Koop et al. (1996) and Pesaran and Shin (1998). To do so, the TVP-VAR model is transformed via the Wold representation theorem into a time-varying parameter vector moving average (TVP-VMA) as it is shown in the following equation:

\[ x_t = \sum_{j=1}^{p} A_{nj} y_{t-j} + \epsilon_t = \sum_{j=0}^{m} B_{pj} \epsilon_{t-j} \]  

Next, we calculate the scaled GFEVD, \( \widetilde{\phi}^j_{ij}(H) \), which represents the pairwise directional connectedness from \( j \) to \( i \). In other words, this indicator shows the h-step error variance in forecasting the return of cryptocurrency \( i \) that is due to innovations to the return of cryptocurrency \( j \).\(^{11}\) This is calculated as follows:

\[ \widetilde{\phi}^j_{ij}(H) = \sum_{i=1}^{H-1} \psi^j_{ij}(H) \]  

with \( \psi^j_{ij}(H) = \sum_{j=1}^{H} B_{ij} \epsilon_{t-j} \), \( \sum_{j=1}^{m} \widetilde{\phi}^j_{ij}(H) = 1 \) and \( \sum_{i=1}^{H} \widetilde{\phi}^m_{ij}(H) = m \), where \( H \) is the forecast horizon.

Once the pairwise directional connectedness from \( j \) to \( i \) is computed, the next step is to calculate:

(i) the total directional connectedness to others (TO), which shows how much of a shock (i.e. innovations to returns) in cryptocurrency \( i \) is transmitted to all other cryptocurrencies:

\[ TO = \sum_{j=1}^{m} \widetilde{\phi}^j_{ij}(H) \]

(ii) the total directional connectedness from others (FROM), which measures how much of a shock in all other cryptocurrencies is transmitted to cryptocurrency \( i \):
FROM = C^G_{m,n}(H) = \frac{\sum_{i=1}^{m} \phi_i(H)}{\sum_{i=1}^{m} \phi_i(H)} \quad (6)

(iii) the net total directional connectedness (NET), which shows the net impact of cryptocurrency $i$ on the network of cryptocurrencies:

\[ NET = C^G_{i} = C^G_{n,i}(H) - C^G_{m,i}(H) \quad (7) \]

Positive (negative) values indicate that cryptocurrency $i$ is net transmitter (receiver) of shocks.

(iv) the net pairwise directional connectedness (NPDC), which gives the bilateral spillovers between cryptocurrencies $i$ and $j$:

\[ NPDC_{ij} = \phi^G_{ij}(H) - \phi^G_{ji}(H) \quad (8) \]

Positive (negative) values indicate that cryptocurrency $i$ transmits more (less) shocks to cryptocurrency $j$ than receives from it.

(v) the total connectedness index (TCI), which is an average value implying the degree of interconnectedness among cryptocurrencies:

\[ TCI = C^G_{i}(H) = \frac{\sum_{i,j=1}^{m} \phi^G_{ij}(H)}{m} \quad (9) \]

Following Chatziantoniou and Gabauer (2021), the above index is slightly adjusted to ensure that values do not exceed unity:

\[ Adjusted \ TCI = C^G_{i}(H) = \frac{\sum_{i,j=1}^{m} \phi^G_{ij}(H)}{m - 1} \quad (10) \]

3.2. Smooth transition regression model

The computed series of expression (10) is regressed to a selection of regressors based on a battery of nonlinear models, in which the transition is smooth. A two-regime Logistic Smooth Transition Regression (LSTR) model is written under the following form:

\[ TCI_t = k\bar{Z}_t + \lambda_i \bar{Z}_t G(s_t, c, \gamma) + u_t, \quad (11) \]

with $G(s_t, c, \gamma) = [1 + \exp\{-\gamma(s_t - c)\}]^{-1}, \quad (12)$

where $TCI_t$ is the computed total connectedness index, $\bar{Z}_t$ includes the explanatory variables (VIX, IDEMV, TUI and Gold), $k$ and $\lambda_i$ represent the parameters of the linear and nonlinear part of the model, respectively and $u_t$ is the error term. $G$ stands for the transition function which encloses the specification parameters of the model, such as the threshold variable ($s$), the location parameter ($c$) and the slope parameter ($\gamma$). Keeping Eq. (11), but changing (12) with (13), we get an alternative form of the STR model, the Exponential Smooth Transition Regression (ESTR) model:

\[ G(s_t, c, \gamma) = 1 - \exp\{-\gamma(s_t - c)^2\} \quad (13) \]

The difference between the LSTR and ESTR models is that the former is monotonically increasing in the threshold variable, while the latter is increasing in the absolute deviations of the threshold variable from the estimated location parameter. Finally, a third specification model is the second-order LSTR, in which two threshold points are estimated, thereby implying the estimation of a $3$-regime threshold model when $\gamma \to \infty$. The transition function of the second-order LSTR model is as follows:

\[ G(s_t, c, \gamma) = [1 + \exp\{-\gamma(s_t - c_1)(s_t - c_2)\}]^{-1} \quad (14) \]

To choose among the alternative forms of the STR model, we need to select the threshold variable and test the linearity hypothesis. First, we consider all explanatory variables as possible thresholds and estimate the STR model of expression (11) for each candidate threshold. Then, we choose this one with the minimum sum of squares. Next, given the threshold variable, we test the linearity hypothesis and if rejected we choose the form of the STR model. The null hypothesis of linearity stands for $\gamma = 0$. The problem is that the parameters $c$ and $\lambda$ cannot be identified under the null hypothesis. To overcome this inconvenience, we approximate the transition function with a fourth-order Taylor series expansion, as proposed by Escribano and Jordá (1999). Then we get the following auxiliary regression:

\[ TCI_t = \delta_0 + \delta_1 \bar{Z}_t + \beta_1 \bar{Z}_t S_t + \beta_2 \bar{Z}_t s^2_t + \beta_3 \bar{Z}_t s^3_t + \beta_4 \bar{Z}_t s^4_t + v_t \quad (15) \]
Based on expression (15), Escribano and Jordá (1999) propose a joint procedure to test both the linearity hypothesis and the appropriate form of the STR model. Firstly, the linearity hypothesis is tested against the alternative hypothesis of smooth threshold regression. The null hypothesis states $H_0: \beta_1 = \beta_2 = \beta_3 = \beta_4 = 0$. Secondly, the null hypothesis $H_0: \beta_1 = \beta_2 = 0$ tests the linearity hypothesis against the LSTR model, while the hypothesis $H_0: \beta_1 = \beta_3 = 0$ tests linearity against the ESTR model.\footnote{An alternative procedure has been suggested by Terasvirta (1994), which may lead to erroneous implications on the selection of the model, especially when the sample is not large enough. So, in this study, we employ the Escribano-Jordá procedure to avoid this inconvenience. To find more about the procedure, see Escribano and Jordá (1999).}

4. Data

The main data set consists of daily closing prices in US dollars for five cryptocurrencies, i.e. Bitcoin, Ethereum, Litecoin, Dash and Monero, from August 8, 2015 to May 11, 2021. These data are retrieved from https://coinmarketcap.com, which provides daily accurate information about the global cryptocurrency market to investors and researchers.\footnote{Closing prices for each cryptocurrency are calculated as a volume-weighted average of closing prices in all exchange markets, such as Binance, FTX, etc.}

The selected cryptocurrencies were chosen following two main criteria: (a) market capitalization and (b) data availability. This explains why cryptocurrencies with high market capitalization have been excluded from this analysis. For example, Cardano is shown to have the third higher capitalization in the global cryptocurrency market, but data are available only after June 2017. Thus, this analysis focuses on cryptocurrencies with high market capitalization under the condition that an adequate data span is achieved.

Returns of cryptocurrency $i$ are calculated as daily log differences of closing prices, i.e., $\ln\left(\frac{P_i}{P_{i-1}}\right) \times 100$, where $P_{i,t}$ is the closing price of cryptocurrency $i$ at time $t$. Descriptive statistics of cryptocurrency returns are presented in Table 1. As shown there, the mean does not differ significantly across the computed returns. In contrast, min and max values differ considerably across series, with Bitcoin to be the one with the lowest divergence between min and max values. Consequently, Bitcoin is shown to exhibit the lowest standard deviation, while Monero exhibits the highest. Not surprisingly, the Jargue-Bera statistics reveal that normality is rejected for all returns under consideration. Specifically, the skewness statistic implies that all series, apart from this of Monero, are negatively skewed, thereby implying that small positive returns are more often than large negative returns. Skewness statistic for Monero is positive but very close to zero, implying that returns are almost symmetrically distributed. On the other hand, it is more than clear that all series follow a leptokurtic distribution with the highest values of excess kurtosis to be observed in the returns of Etherum, Litecoin and Dash. This implies that investment in these cryptocurrencies is considered as highly risky because of the high probability of extreme (large and small) returns. Finally, unit root tests reveal that all return series are integrated of order zero, i.e. I(0).

Turning now to the supplementary dataset, the following variables have been employed as potential determinants of connectedness among the cryptocurrencies under consideration: (i) CBOE Volatility Index (VIX), (ii) Infectious Disease Equity Market Volatility (IDEMV), (iii) Twitter-based Uncertainty Index (TUI) and (iv) gold price (returns).\footnote{These variables have been chosen based on what we have learned from the literature (i.e. previous evidence, gaps in the existing literature) as well as on the hypothesis that connectedness across cryptocurrencies is driven by global factors that influence the investors’ behavior. The existing literature reports evidence that connectedness is affected by global factors, such as economic uncertainty, financial volatility and alternative investment opportunities. However, variables that are related to the Covid-19 crisis are missing from the literature. In light of these facts, we have employed volatility and uncertainty measures (CBOE Volatility Index, Infectious Disease Equity Market Volatility, Twitter-based Uncertainty Index) and an alternative asset (gold).}

VIX data have been retrieved from the FRED Economic Data of the Federal Reserve Bank of St. Louis, while IDEMV and TUI data have been collected from https://www.policyuncertainty.com. IDEMV is a newspaper-based uncertainty index, which focuses on posts that include various related terms, such as economy, stock market, risk, disease, pandemic, coronavirus, etc. On the other hand, TUI is a Twitter-based uncertainty index, which focuses on tweets that include various uncertainty-related keywords, such as uncertain, uncertainty, economy, economic, etc. Finally, gold price data have been retrieved from the Federal Reserve Bank of St. Louis. Gold price refers to gold fixing price 3:00 P.M. (London time) in London Bullion Market and is expressed in US dollars per troy ounce. All the above data have been collected in a daily frequency, from August 8, 2015 to May 11, 2021, and are expressed in natural logarithms.\footnote{The above series are found to be I(0). Unit root test results are not reported here to save space. However, they are available upon request.}

5. Empirical findings

5.1. Interconnection across cryptocurrencies

To preview the relationship among the cryptocurrencies of the sample, we take a first look on Table 2, which shows that all return series are correlated each other. It is also evident that the highest correlation is observed in the pair between Bitcoin and Ethereum. This result is in line with previous evidence reported in the literature (see, inter alia, Katsiampa et al., 2019a).

Next, we perform the Time-Varying Parameter Vector Autoregression (TVP-VAR) dynamic connectedness approach, to produce accurate estimates of the interrelationship among the cryptocurrencies of the network. We first estimate a TVP-VAR model with four lags based on the Bayesian Information Criterion (BIC). Then, we compute the generalized variance decompositions of the 10-days-ahead forecast errors and estimate the spillovers among the cryptocurrencies of the sample. Table 3 presents the averaged
connectedness-spillovers measures. The diagonal elements of Table 3 shows own-cryptocurrency spillovers, which reflect the percentage of the forecast error variance of a cryptocurrency return that is caused by a shock in the same cryptocurrency market. It is shown that all cryptocurrency returns are mainly affected by shocks in their own markets. For instance, a shock in the Bitcoin market can explain the 52.35% of the error variance in forecasting Bitcoin returns. Nonetheless, Bitcoin returns exhibit the lowest dependence from own shocks, while the highest dependence from own-market shocks is observed in the market of Monero (i.e., 67.15%). The evidence of dominant own-market shocks is common in the related literature (see, inter alia, Koutmos, 2018; Ji et al., 2019).

Cross-market spillovers are shown in the off-diagonal elements of Table 3. Each column of the table, apart from the last one, presents how much of a shock in a given cryptocurrency market is transmitted to the rest of the markets. Taking Bitcoin as an example, the second column of Table 3 shows that the 47.73% of a shock in Bitcoin returns is transmitted to the rest of the cryptocurrency markets. More specifically, 9.81% is transferred to Ethereum, 18.03% to Litecoin, 9.90% to Dash, and 9.38% to Monero market. This means that shocks in Bitcoin market are mostly transmitted to the Ethereum market. On the other hand, the third column shows that an Ethereum-market shock is mainly transmitted to the Bitcoin market (i.e., 13.41% of a shock). Similarly, Litecoin-market shocks are more easily transferred to the Bitcoin market as well (i.e., 17.64% of a shock). Dash and Monero market shocks are more symmetrically transferred across cryptocurrency markets. The overall impact of each market to the rest of the markets is shown in the row labeled “To others”, which implies that Bitcoin and Litecoin markets are main transmitters, with 47.73% and 43.50% of an own-market shock, respectively, to be transmitted to the rest of the markets. Ethereum follows with 40.94%, while Dash and Monero exhibit the lowest spillover transmission with 30.96% and 30.83%, respectively.

Spillovers in the opposite direction are shown in rows of Table 3. In line with the above results, Bitcoin receives spillovers mainly from Litecoin market. The 17.64% of the forecast error variance of Bitcoin returns is due to disturbances in Litecoin market. Ethereum market receives spillovers mainly from Bitcoin and Litecoin, while the main transmitter to Litecoin returns is the Bitcoin market. As also noted previously, there is no main transmitter to Dash and Monero returns because spillovers are symmetrically received by the rest of the cryptocurrency markets.

The column labeled “From others” illustrates the part of the forecast error variance of each cryptocurrency return-series that is due to innovations in other cryptocurrency markets. Bitcoin and Litecoin markets are shown to be the ones that receive the highest

### Table 1
Descriptive Statistics: Cryptocurrency Returns.

|          | Bitcoin | Ethereum | Litecoin | Dash | Monero |
|----------|---------|----------|---------|------|--------|
| Mean     | 0.252   | 0.348    | 0.214   | 0.232| 0.305  |
| Max.     | 31.264  | 155.059  | 121.269 | 121.557| 88.242 |
| Min.     | -46.473 | -147.961 | -131.541| -128.949| -93.467|
| St. Dev. | 4.157   | 9.472    | 6.984   | 8.682| 11.491 |
| Skewness | -0.772***(0.00) | -0.844***(0.00) | -0.752***(0.00) | -0.212***(0.00) | 0.039***(0.00) |
| Kurtosis | 12.219***(0.00) | 138.358***(0.00) | 112.507***(0.00) | 95.344***(0.00) | 28.004***(0.00) |
| Jargue-Bera | 17,935.72***(0.00) | 1,606,453***(0.00) | 1,051,477***(0.00) | 747,588.7***(0.00) | 54,809.9***(0.00) |
| ADF      | -46.816***(0.00) | -22.952***(0.00) | -54.812***(0.00) | -13.535***(0.00) | -28.292***(0.00) |
| KPSS     | 0.118   | 0.164    | 0.122   | 0.232| 0.175  |

Notes: Numbers in parentheses are p-values. * ** denotes rejection of the null hypothesis at the 1% level of significance.

### Table 2
Correlation coefficients: cryptocurrency returns.

|          | Bitcoin | Ethereum | Litecoin | Dash | Monero |
|----------|---------|----------|---------|------|--------|
| Bitcoin  | 1       | 0.261    | 0.476   | 0.252| 0.236  |
| Ethereum | 0.261   | 1        | 0.246   | 0.212| 0.128  |
| Litecoin | 0.476   | 0.246    | 1       | 0.249| 0.173  |
| Dash     | 0.252   | 0.212    | 0.249   | 1    | 0.189  |
| Monero   | 0.236   | 0.128    | 0.173   | 0.189| 1      |

### Table 3
Connectedness matrix of returns: TVP-VAR model.

|          | Bitcoin | Ethereum | Litecoin | Dash | Monero | From others |
|----------|---------|----------|---------|------|--------|-------------|
| Bitcoin  | 52.35   | 13.41    | 17.64   | 7.65 | 8.95   | 47.65       |
| Ethereum | 9.81    | 66.73    | 9.30    | 7.47 | 6.68   | 33.27       |
| Litecoin | 18.03   | 11.14    | 56.50   | 7.44 | 6.88   | 43.50       |
| Dash     | 9.90    | 9.31     | 8.75    | 63.73| 8.32   | 36.27       |
| Monero   | 9.98    | 7.09     | 7.38    | 8.40 | 67.15  | 32.85       |
| To others| 47.73   | 40.94    | 43.07   | 30.96| 30.83  | 47.65       |
| Net      | 0.09    | 7.67     | -0.43   | -5.32| -2.02  | TSI = 38.71 |

Notes: Generalized variance decompositions of a TVP-VAR(4) model based on BIC. The (i,j)th value is the estimated contribution to the error variance in the 10-month-ahead forecasts of cryptocurrency i stemming from innovations of cryptocurrency j.
spillovers in the cryptocurrency network. The last row, labeled “Net”, subtracts the values in column “From others” from the values in row “To others”. In other words, for each cryptocurrency, we subtract the spillovers received from other markets from the spillovers transmitted to other markets and find the net position of each cryptocurrency. According to this outcome, Ethereum is shown to be the main net transmitter, while Dash is the main net receiver of the cryptocurrency network. Monero is considered as net receiver as well, but Bitcoin and Litecoin exhibit a balance between both directions of transmission. Specifically, Bitcoin is only marginally net transmitter, while Litecoin is slightly net receiver. Finally, the TSI index, which measures the average spillovers for all the cryptocurrencies of the sample, implies that on average the 38.71% of the forecast error variance of the return-series is due to spillovers.

Next, utilizing the time-varying properties of the dynamic connectedness approach, Fig. 1 presents the plot of the estimated total connectedness index over time.\(^{16}\) It is shown that connectedness among cryptocurrencies follows a cyclical pathway with evident ups and downs. TCI was following a downward trend from the start of the estimated period to the end of 2016, while during 2017 that series was in general increasing. In the very next period, connectedness was following a decreasing trend until November 2018. Since then and until March 2020, the interdependence among the cryptocurrencies under consideration has been gradually increased.\(^{17}\) The stop at the increasing trend in connectedness coincides chronically with the emergence of the pandemic Covid-19 and the first negative consequences on the global economy.

During the first period of Covid-19, connectedness remained stable, but after September 2020, when the second period of the pandemic was started, the interdependence among the cryptocurrencies followed a declining trend that lasted until the end of the estimated period. It is shown form the figure that the Covid-19 pandemic is related with a decrease in connectedness.\(^ {18}\) Fig. 2 shows the dynamic directional spillovers from all the other cryptocurrencies to each given cryptocurrency. What can be easily observed from the five individual graphs is that the influence each cryptocurrency receives fluctuates over time. It can be also easily seen that each cryptocurrency receives a stable grade of spillovers during the first period of Covid-19 pandemic, while shocks received from other cryptocurrencies are reduced at the later stages of the pandemic. The same view is shown in Fig. 3, which plots the spillovers transmitted from each given cryptocurrency to all the other cryptocurrencies of the network. The transmission of shocks fluctuates over time with a general decrease to be observed during the Covid-19 pandemic. Nonetheless, this decreasing trend is not observed in the cases of Litecoin and Dash. Spillovers from the Litecoin and Dash markets are stable even in the mature stages of the pandemic.

The plots of cryptocurrencies’ net position over time are shown in Fig. 4. Positive values indicative that the cryptocurrency is net transmitter, while negative values imply that the cryptocurrency is net receiver. It is obvious that the influence of Ethereum to the other cryptocurrencies increased sharply in late 2018. At that time, Ethereum changed its status from net receiver to net transmitter. In contrast, during the same period, net receiving was at the highest level for Bitcoin, Litecoin and Dash. This observation implies the increased impact of Ethereum returns on the other cryptocurrency markets. To shed more light on this, it is useful to take a look on Fig. 5, which presents the net pairwise directional spillovers over time. Positive (negative) values show that the first cryptocurrency of the pair transmits (receives) spillovers to (from) the other. Indeed, these plots support the above observation, i.e., Ethereum was net transmitter for Bitcoin, Litecoin and Dash from late 2018 until the appearance of the Covid-19 pandemic. For the rest of the pairs, we generally observe stable and moderate connectedness during the whole period of estimation. An exception is the pair Dash-Bitcoin, in which we observe an increase of spillovers from Bitcoin to Dash from late 2018 to late 2019. Overall, the results imply that, since late 2018, Ethereum has the main transmitting role in the cryptocurrency network. This finding is in line with a previous evidence in the literature that Bitcoin does not any more lead the connectedness in the cryptocurrency market (see, Yi et al., 2018; Katsiampa et al., 2019b).

5.2. Determinants of connectedness

At the first stage of the empirical analysis, we found evidence of time-varying connectedness across cryptocurrency returns. It is shown there that the degree of connectedness changes over time reflecting its sensitivity to external factors. At the present stage of analysis, we aim to identify those factors that drive connectedness across cryptocurrencies. We test the conjecture that connectedness across cryptocurrency returns is driven by factors that influence the investors’ behavior, such as financial markets volatility, economic uncertainty, the current pandemic crisis and alternative investment opportunities. Hence, we consider the CBOE Volatility Index (VIX), the Infectious Disease Equity Market Volatility (IDEMV), the Twitter-based Uncertainty Index (TUI) and gold returns as determinant factors.

To regress the computed TSI on the above explanatory variables, we consider the Smooth Transition Regression (STR) model, in which the regression coefficients change smoothly between regimes. This model allows us to capture any nonlinear behavior of connectedness and for this reason it has been chosen instead of alternative linear regression models used in the literature. A key property of the STR model is that the transmission across different regimes is smooth rather than sharp as in alternative nonlinear models, such as the Markov-switching regression (M-SR) model. A sharp switch across regimes implies that all market participants react to a certain shock at the same time. On the contrary, a smooth transition indicates a gradual response of market participants to shocks, thereby implying that each participant reacts at a different time. Due to the characteristics of the cryptocurrency market (i.e. large market, heterogeneous investors), we believe that the smooth transition is more suitable to this case. Thus, the STR model is

\(^{16}\) The adjusted TCI along with the standard TCI is plotted following Chatziantoniou and Gabauer (2021).

\(^{17}\) However, this increasing path was interrupted for a short period, during May-July 2019.

\(^{18}\) The impact of Covid-19 pandemic will be more formally tested in the next section.
5.2.1. Linearity test and specification of the STR model

Before estimating the nonlinear STR model, we need to test the linearity hypothesis, choose the appropriate form of the STR model and identify the properties of the model, such as the threshold variable, etc. As explained in the econometric methodology section, we consider all regressors as possible thresholds, estimate the STR model of expression (11) and choose the one with the minimum sum of squares. The results, shown in Table 4 imply that the Twitter Uncertainty Index (TUI) should be chosen as the threshold variable of the model.

As the threshold variable has been chosen, the next step is to test the linearity hypothesis. Following the Escribano and Jordá (1999) methodology and the proposed fourth-order Taylor series approximation of the transition function, we find strong evidence against linearity.

The results in Table 5 show that all null hypotheses are strongly rejected, thereby implying the evidence of nonlinearity. Finally, based on these results and following the selection procedure of Escribano and Jordá (1999), we choose the LSTR model as the one that describes the nonlinear relationship between the TCI and the four regressors shown above.

5.2.2. Estimation of the LSTR model

To estimate the LSTR model we modify Eqs. (11) and (12) in the following way:

\[ \text{TCI} = \sum_{i=1}^{4} \beta_i \times \text{Reg}_i + \alpha \times \text{TUI} + \epsilon \]

This equation allows for the estimation of the total connectedness index (TCI) considering the uncertainty index (TUI) and the four regressors.

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Fig. 1. Total Connectedness Index. Notes: TCI stands for the estimated total connectedness index. TCI_adj is the adjusted total connectedness index as proposed by Chatziantoniou and Gabauer (2021).

Fig. 2. Spillovers FROM others. Note: The plots show how much of a shock in all other markets is transmitted to an individual cryptocurrency.
Fig. 3. Spillovers TO others. Note: The plots show how much of a shock in a given cryptocurrency is transmitted to all other cryptocurrency markets.

Fig. 4. Net Position. Note: Positive (negative) values indicative that the cryptocurrency is net transmitter (receiver).
where $k_i$ and $\lambda_i$ represent the parameters of the linear and nonlinear part of the model, respectively. The transition function is a continuous and bounded function of the Twitter Uncertainty Index (threshold variable), while the smoothness of the transition process is given by $\gamma$. When $\gamma \to \infty$, the model becomes a discrete two-regime model. In contrast, when $\gamma = 0$, the transition function is constant and the model is linear. The regression coefficients vary depending on the value of the transition function. When $G = 0$, the regression coefficients are given by $k_i$, but when $G = 1$ they are equal to $k_i + \lambda_i$. Within the extreme values of the transition function, the regression coefficients range between $k_i$ and $k_i + \lambda_i$. In this case, the slope parameters are given as the weighted average of the estimated parameters $k_i$ and $\lambda_i$. The estimated threshold weights are shown in Fig. 6. It is obvious that since 2019 the threshold variable belongs to the upper regime, indicating high values of Twitter-based uncertainty. What is of special interest on it, is that the extreme value of one

Table 4
Threshold variable selection.

| Candidate Threshold | RSS    |
|---------------------|--------|
| VIX                 | 191.47 |
| IDEMV               | 219.9  |
| TUI                 | 190.77 |
| Gold                | 198.18 |

Note: RSS stand for Residual Sum of Squares of the STR model for each of the candidate variables. The selected threshold variable is this one with the minimum RSS.

Table 5
Linearity Test and Model Selection.

| Null Hypothesis            | F-statistic | p-value |
|----------------------------|-------------|---------|
| $H_0: \lambda_1 = \lambda_2 = \lambda_3 = \lambda_4 = 0$ | 25.585 *** | (0.00) |
| $H_0: \lambda_2 = \lambda_4 = 0$ | 16.853 *** | (0.00) |
| $H_0: \lambda_1 = \lambda_3 = 0$ | 17.509 *** | (0.00) |

Notes: $H_0$ tests the linearity hypothesis. $H_0L$ tests the linearity hypothesis against the LSTR. $H_0E$ tests the linearity hypothesis against the ESTR. Numbers in parentheses are p-values. * * * denotes rejection of the null hypothesis at the 1% level of significance.
is observed from March 2020 until the next March of 2021, a period which coincides with the Covid-19 pandemic crisis. Since then and until the end of the estimation period, the transition function remains very close to unity, indicating the dominance of the upper regime for this time period.

The results of the estimated LSTR model are shown in Table 6. The bottom part of the table presents the specification of the model, i.e. the threshold variable (TUI), the smoothness parameter ($\gamma = 13.816$) and the critical value of TUI ($c=4.458$) at which the series is divided into low and high values. The estimated transition function is illustrated in Fig. 7.

More interestingly, the upper part of the table presents the estimated slope parameters of the regressors. Starting with VIX, the parameter $k_1$, is shown to be negative and statistically significant ($k_1 = -0.386$). This implies that an increase in the volatility index causes a decline in connectedness among the cryptocurrencies under consideration. However, when the transition from the low to upper regime is considered, the impact of VIX on connectedness is shown to be positive and statistically significant at the 10% level of significance ($\lambda_1 = 0.173$). This means that when TUI changes form low to high values, indicating higher uncertainty, an increase in the volatility index tends to increase connectedness. In other words, when the concern about economic uncertainty across Twitter users is high enough, a rise in VIX causes an increase in connectedness across cryptocurrencies returns.19 This evidence is in line with Ji et al. (2019) who report a positive effect of US VIX on return spillovers. The intuition behind this finding is that cryptocurrencies may act as a hedging tool against volatility, the cryptocurrency market becomes more liquid and then the cryptocurrencies tend to be more interconnected each other. According to Yen and Cheng (2021), when financial markets are turbulent, investors invest more to

\begin{table}[ht]
\centering
\caption{LSTR model estimation.}
\begin{tabular}{|l|l|}
\hline
\textbf{Slope parameters of the Linear part}  & \\
\hline
Constant ($k_0$) & 18.978***(0.00) \\
VIX ($k_1$) & -0.386***(0.00) \\
IDEMV ($k_2$) & 0.038*** (0.00) \\
TUI ($k_3$) & 0.197** (0.02) \\
Gold ($k_4$) & -1.894*** (0.00) \\
\hline
\textbf{Slope parameters of the Nonlinear part}  & \\
\hline
Constant ($\lambda_0$) & -31.409*** (0.00) \\
VIX ($\lambda_1$) & 0.173* (0.08) \\
IDEMV ($\lambda_2$) & -0.025* (0.05) \\
TUI ($\lambda_3$) & -0.342*** (0.00) \\
Gold ($\lambda_4$) & 4.093*** (0.00) \\
\hline
\textbf{Specification of the model}  & \\
\hline
Threshold variable & TUI \\
Location parameter ($c$) & 4.458*** (0.00) \\
Slope Parameter ($\gamma$) & 13.816*** (0.00) \\
\hline
\end{tabular}
\end{table}

Notes: Numbers in parentheses are $p$-values. *** denotes rejection of the null hypothesis at the 1% level of significance. ** denotes rejection of the null hypothesis at the 5% level of significance. * denotes rejection of the null hypothesis at the 10% level of significance.

19 Nonetheless, this outcome should be handled with caution because the estimated parameter of the nonlinear part is statistically different from zero only when the 10 % level of significance is chosen. Thus, we avoid to characterize this as evidence of contagion in the cryptocurrency market.
cryptocurrencies and the cryptocurrency market becomes more liquid and less volatile. Hence, as reported in the existing literature (see, inter alia, Apergis et al., 2021; Bouri et al., 2021), higher liquidity is linked with higher connectedness in the cryptocurrency market.

The inverse is observed when the Disease-based volatility (IDEMV) is considered. As shown in Table 6, an increase in this type of volatility increases connectedness in the low regime (i.e., small values of TUI), but decreases it in the upper regime (i.e., high values of TUI). Namely, as Twitter-based uncertainty exceeds its threshold value, the positive impact of IDEMV on TCI becomes weaker and turns to be negative when the transition function takes the extreme value of one. As shown in Fig. 6, the latter happens after the emergence of the Covid-19 pandemic period, in consistency with the negative trend of the estimated TCI shown in Fig. 1. This evidence is new in the literature as IDEMV is for the first time used as a determinant of connectedness in the cryptocurrency market. So, what could imply this new evidence? Presumably, this outcome reveals that investors changed their behavior during the Covid-19 pandemic crisis. It is implied that during the mature stages of the pandemic – where both Disease-based volatility and Twitter Uncertainty indices were high – cryptocurrencies could not be used as a hedge. A possible explanation of this case is that the cryptocurrency market was highly volatile during that period with many ups and downs, which caused worries to investors about the stability of the market.

Similarly, an increase in Twitter-based uncertainty has a positive impact on TCI in the lower regime and negative in the upper regime. This means that when anxiety across Twitter users increases and overshoots its threshold value, connectedness across cryptocurrencies declines. Given the estimated slope parameters shown in Table 6 and the threshold weights presented in Fig. 6, the positive impact of TUI on TCI becomes smoothly weaker around the estimated threshold value and negative as the transition function approaches the value of unity. This evidence is consistent with the behavior of TUI as threshold variable of the model. As TUI changes smoothly from low to high values, the impact of higher uncertainty across Twitter users on connectedness tends to be gradually negative, thereby implying lack of evidence of contagion. As Twitter-based uncertainty is for the first time considered as a determinant, this evidence is new in the literature. However, it is in line with the impact of the Disease-based volatility and the pandemic crisis on connectedness as reported above. Investors’ worries reduce investment and liquidity in the cryptocurrency market and as consequence the interconnectedness across cryptocurrencies is also reduced.

On the contrary, gold price returns have a negative impact on connectedness when Twitter-based uncertainty is low, which turns to be positive when Twitter users’ anxiety exceeds the threshold value. This is evident in Table 6, which shows that the slope parameter of the linear part is negative ($k_4 = -1.894$), this of the nonlinear part ($\lambda_4 = 4.093$) is positive, while both are statistically different from zero at any level of significance. Taken this into account, the weighted average will be mainly positive apart from the very low levels of TUI. This allows us to conclude that gold returns are mainly positively related with connectedness, while this impact tends to be stronger as uncertainty across Twitter users rise. This evidence is partly in line with Ji et al. (2019) who find a positive impact of gold on connectedness when cryptocurrency returns are negative, but a negative impact when returns are positive. On the other hand, Panagiotidis et al. (2018) report a positive relationship between gold and cryptocurrency returns. In connection with our evidence, a rise in gold prices signals higher investment and liquidity in the cryptocurrency market as gold and cryptocurrencies share similar hedging properties (Dyhrberg, 2016). Consequently, a more liquid market supports higher interdependence among cryptocurrencies.

6. Concluding remarks

Focusing on the impact of the Covid-19 pandemic crisis, this paper examines the interconnectedness in the cryptocurrency market following a two-stage estimation procedure. At the first stage, the degree of connectedness among selected cryptocurrencies is measured, while the second stage analyzes the driving factors of interdependence among these cryptocurrencies. The results of the Time-Varying Parameter Vector Autoregression (TVP-VAR) dynamic connectedness approach show that the degree of interdependence among the cryptocurrencies of the sample varies over time. It is evident that the degree of connectedness declines after September 2020, a time period which coincides with the second wave of the Covid-19 pandemic. This declining trend lasts until the end of the estimated period. It is implied that the degree of connectedness changes over time reflecting its sensitivity to external
factors, including the Covid-19 pandemic. So, at the second stage of estimation, we consider a number of determinant factors, such as the CBOE Volatility Index (VIX), the Infectious Disease Equity Market Volatility (IDEMV), the Twitter-based Uncertainty Index (TUI) and gold returns, to explain the fluctuation of connectedness in the cryptocurrency market.

Since the linearity hypothesis cannot be accepted, a nonlinear Logistic Smooth Transition Regression (LSTR) model is estimated at this stage of estimation. A first interesting finding is that the smooth transition process is driven by the Twitter Uncertainty Index, reflecting the impact of Twitter users’ anxiety on the cryptocurrency market. In other words, the results reveal that the impact of each of the regressors on connectedness changes as the Twitter-based uncertainty moves below or over the estimated threshold value. Specifically, the estimated sign of the Disease-based volatility (which encloses the Covid-19 pandemic), is positive for low values of Twitter-based uncertainty, but tends to be negative as Twitter-based uncertainty takes extreme (high) values. Accordingly, as Twitter-based uncertainty changes smoothly from low to high values, the impact of higher uncertainty across Twitter users on connectedness tends to be gradually negative. However, this outcome does not hold when gold is considered as regressor. Gold returns are mainly positively related with connectedness, while this impact tends to be stronger as uncertainty across Twitter users rise.

The results highlight important implications for investors and policy makers. From investors perspective, the evidence of lower connectedness during the mature stages of the Covid-19 (i.e., when Disease-based volatility and Twitter-based uncertainty increase) indicates weaker evidence of contagion. This implies the presence of diversification opportunities in the cryptocurrency market during the Covid-19 pandemic crisis. But it is also implied that investors changed their behavior during the pandemic crisis, leading to lower connectedness in the cryptocurrency market. On the other hand, the key role of the Twitter-based uncertainty, measured by Tweets across Twitter users, should not be ignored by market participants. This new finding is an indication that the cryptocurrency market is sensitive to news or rumors circulating on the internet, thereby implying its vulnerability to manipulation. This is a characteristic of an immature market that should be taken into account by both investors and policy makers.

Data availability

Data will be made available on request.

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