7-1-2021

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Technological Forecasting & Social Change 172 (2021) 121025

Contents lists available at ScienceDirect

Technological Forecasting & Social Change

journal homepage: www.elsevier.com/locate/techfore

The impact of COVID-19-related media coverage on the return and volatility connectedness of cryptocurrencies and fiat currencies

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ARTICLE INFO

JEL classification:
C22
C51
D53
H12

Keywords:
Cryptocurrencies
Fiat currencies
Coronavirus media coverage index (MCI)
Connectedness
COVID-19 pandemic crisis

ABSTRACT

This research explores the impact of COVID-19-related media coverage on the dynamic return and volatility connectedness of the three dominant cryptocurrencies (Bitcoin (BTC), Ethereum (ETH) and Ripple (XRP)) and the fiat currencies of the euro, GBP and Chinese yuan. The sample period covers the first and second devasting waves of the COVID-19 pandemic crisis and ranges from January 1, 2020, to December 31, 2020. The dynamic return and volatility connectedness measures are estimated using the time varying parameter-VAR approach. Our return connectedness analysis shows that the media coverage index (only before the first wave) and the cryptocurrencies are the net transmitters of shocks while the fiat currencies are the net receivers of shocks. Similar results are obtained in terms of volatility, except for the euro, which shows a clear net receiver profile in January and February. This fiat currency (the euro) became a net transmitter in March and during the first wave of the COVID-19 crisis, which possibly shows the virulence of the pandemic on the European continent. Moreover, the most relevant differences between the net dynamic (return and volatility) connectedness of these two groups of currencies are focused on the beginning of the sample period, just before the first wave of the SARS-CoV-2 pandemic crisis, although some differences are observed during the first and second waves of the coronavirus outbreak.

1. Introduction

The world is currently experiencing the most critical period of economic and social turbulence since the 2007–08 global financial crisis, namely, the SARS-CoV-2 coronavirus pandemic. The disease was defined as COVID-19 by the World Health Organization (WHO) on February 11, 2020.

In particular, the cryptocurrency market has been greatly affected by the COVID-19 crisis. This market suffered a collapse on March 8, 2020, which was caused by the massive sale of cryptocurrencies; this resulted in a loss of $21 billion in the total capitalization value of the cryptocurrency market in 24 h and led to Black Monday in the stock market on March 9.[1] One of the main reasons for the collapse of this market is that much of Europe was already in quarantine, and the rest of Europe was considering similar measures. This situation in the cryptocurrency market worsened further just two days later when, on March 11, the World Health Organization (WHO) categorized the COVID-19 outbreak as a worldwide pandemic. As a consequence, on March 13, the cryptocurrency market lost almost half of its total market capitalization value, thus leading to a sharp fall in the capitalization value and prices of the major cryptocurrencies. However, this situation reversed. The cryptocurrency market fully recovered at the end of May, and the total market capitalization value remained above the values before the massive sales on March 8 at all times. Moreover, since the end of May 2020, the total cryptocurrency market capitalization value has experienced an incredible rise, surpassing the $300 billion barrier at the end of July, the $400 billion barrier in early November, the $500 billion barrier in late November, the $600 billion barrier in mid-December, the $700 billion barrier in late December and finally reaching a peak of over $760 billion on 31 December 2020. Furthermore, this peak on the last day of December 2020 virtually coincides with the historical maximum of the total market capitalization value reached at the beginning of January 2018. In terms of the percentage of total market capitalization, Bitcoin maintains a clearly dominant position with respect to the remaining

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[1] The total cryptocurrency market capitalization on March 7, 2020, was $251.5 billion.

https://doi.org/10.1016/j.techfore.2021.121025
Received 22 September 2020; Received in revised form 6 July 2021; Accepted 10 July 2021
Available online 14 July 2021

cryptocurrencies, with an average market share of approximately 64% throughout the period. It should be noted that the market share of Bitcoin was close to 68% at the beginning of January while that of Ethereum was only 7.3% and XRP was 4.3% before Black Monday; at the beginning of March, these percentages were 63.2%, 10.2% and 4.1%, respectively. Bitcoin reached a new peak in its market share on May 20, exceeding 68%. Specifically, the market shares were 68.4% for BTC, 9.1% for ETH and 3.5% for XRP. However, since then, Bitcoin's market share has progressively fallen to a low of 56.7% on September 14 (when Ethereum's market share rose to 12.21% and XRP's decreased to 3.23%), although it recovered again, reaching a maximum for the entire sample period at the end of this period on December 28, 2020, when the peak market share was 69.2% for Bitcoin, while Ethereum reached 11.1% and XRP fell to 1.8%.

Furthermore, recent studies, such as Umar and Gubareva (2020) and Majdoub et al. (2021), analyse the potential interdependences between foreign exchange and cryptocurrency markets from the perspective of contagion and their possible role as safe havens during periods of economic turbulence, such as the SARS-CoV-2 outbreak. Thus, this phenomenon impacts portfolio risk management, strategic asset allocation, and financial instrument pricing, as highlighted by Umar and Gubareva (2020).

Considering the relevance of the impact of COVID-19 on the cryptocurrency market, this research explores the dynamic return and volatility connectedness of the three most relevant cryptocurrencies (Bitcoin (BTC), Ethereum (ETH) and Ripple (XRP)) and coronavirus news proxied by the Coronavirus Media Coverage Index (MCI), as applied in Cepoi (2020), among other recent studies. For comparison purposes, this study also analyses the dynamic return and volatility connectedness of the fiat currencies of the euro, GBP and Chinese yuan and the MCI. These dynamic connectedness measures are estimated in the context of the COVID-19 pandemic crisis by using the TVP-VAR methodology (Antonakakis and Gabauer, 2017; Gabauer and Gupta, 2018; Antonakakis et al., 2020), which is suitable for short time series data, in comparison with alternative approaches such as that proposed by Diebold and Yilmaz (2012 and 2014). Thus, the main advantage of this methodology is that it allows us to compute the dynamic spillovers without using the rolling window technique (as a modification of the original Diebold-Yilmaz approach). Given the short time series of the COVID-19 pandemic, the use of this methodology is appropriate. In addition, the approach is robust and has been used in many other studies to determine connectedness.

Thus, this paper extends the analysis developed in other related previous studies in the following aspects. First, this research explores the dynamic return and volatility connectedness of the dominant cryptocurrencies and three relevant fiat currencies, the euro, GBP and yuan, for comparison purposes and focuses the analysis on the SARS-CoV-2 coronavirus crisis. In addition, this paper applies the TVP-VAR approach (Antonakakis and Gabauer, 2017) as an alternative methodology to that proposed by Diebold and Yilmaz (2012 and 2014) and includes the coronavirus MCI to deepen the impact of the COVID-19 pandemic crisis on the currency market. Moreover, our sample period is extremely recent because it runs from January 1, 2020, to December 31, 2020, thereby marking a central period identified as the heart of the pandemic crisis (between March 10, 2020, and June 30, 2020) during which to conduct an in-depth study of the cryptocurrency and fiat currency markets analysed in this paper. This focuses not only on the first wave but also on the second wave of the coronavirus crisis. Third, the methodology applied in this paper allows us to distinguish between currencies that are net transmitters and net receivers. Last, we contribute to the growing strand of literature on the impact of media-driven sentiment on financial markets (Yang et al., 2015; Sul et al., 2017; Gubareva and Umar, 2020; Duz and Tas, 2021; Umar et al., 2021). Thus, we contribute to extending this strand of literature by documenting the impact of COVID-induced media-driven sentiment on cryptocurrencies and fiat currencies.

Some relevant findings are the following. As expected, the dynamic total return and volatility connectedness fluctuate over time with two peaks, one at the beginning of the sample period (January 2020) and one at the start of the COVID-19 pandemic crisis (March 2020, that is, the first wave), for both returns and volatility. In addition, the cryptocurrencies analysed in this paper are clearly net transmitters to the system, but the fiat currencies emerge as net receivers from the system, mainly in the study of the net dynamic return connectedness. Regarding the net dynamic volatility connectedness, we find similar results except for the euro, which shows a clear net receiver profile in January and February and becomes a net transmitter during the first wave of the COVID-19 crisis. Finally, the differences between the two groups of currencies become more acute at the beginning of the sample period just before the WHO declared the COVID-19 crisis to be a pandemic. Subsequent small differences are shown during the first and second waves of the pandemic.

The remainder of the paper is structured as follows. Section 2 includes a recent literature review on connectedness measures of the cryptocurrency market in the context of the SARS-CoV-2 coronavirus pandemic. Section 3 describes the dataset used in this paper and explains the recent TVP-VAR methodology. Section 4 presents a detailed interpretation of our empirical results. Finally, Section 5 offers the most relevant conclusions of our research.

2. Literature review

The cryptocurrency market has aroused great interest in recent years, and this has led to a great deal of empirical research on this topic. From our point of view, interest in studying the cryptocurrency market is even more justified in the current context of the COVID-19 pandemic crisis as the market is suffering from severe fluctuations depending on the evolution of SARS-CoV-2 and its waves. As we will explain in the data section, the cryptocurrency market experienced a massive amount of sales on March 8, 2020, i.e., the day before Black Monday of the stock markets (March 9). On that date, a large part of Europe was already quarantined, and the rest of Europe was considering similar measures. Furthermore, on March 11, 2020, the Director General of the World Health Organization (WHO) defined the COVID-19 outbreak as a worldwide pandemic; this further alarmed the markets, including the cryptocurrency market, which, as a consequence, lost approximately half its total capitalization value on March 13. However, the cryptocurrency market has recovered from its ashes. The market has managed to far exceed the total market capitalization value prior to this fall ($251.5 billion on March 7, 2020) and even tripled this amount at the end of the sample period ($760.7 billion on December 31, 2020), almost reaching the historical maximum value achieved in early 2018 ($786 billion on January 6, 2018). Due to the great interest in the cryptocurrency market and in order to analyse the impact of the COVID-19 pandemic crisis on it, as this pandemic crisis represents the largest episode of global turmoil since the 2008 global financial crisis, much research work is being conducted, both on the cryptocurrency market and other markets, using different datasets and applying all types of methodologies.

There is a branch of recent literature that studies the cryptocurrency market in depth. Corbet et al. (2019) conduct a complete review of the financial literature on the cryptocurrency market and state that cryptocurrencies face accusations of possible illicit use and even of being a system of inexperienced exchange, among others. Jareño et al. (2020) study the potential interdependent relationship between Bitcoin and gold price returns and find positive and statistically significant connectedness. González et al. (2020 and 2021) analyse the interdependence between Bitcoin and ten other altcoin returns and find positive interdependences among them. Demir et al. (2021) find long- and short-run asymmetry in the impact of Bitcoin on altcoin. Song et al. (2019) study the structure of the cryptocurrency market and highlight the leadership of Bitcoin and Ethereum. Shi et al. (2020) find correlations between six cryptocurrencies and state that it is necessary to possess knowledge on them in order to implement trading strategies. Canh et al. (2019) analyse the diversification capability of major cryptocurrencies against shocks in oil and gold prices, interest rates, the strength of the USD and the stock market. Selmi et al. (2018) find evidence in favour of cryptocurrencies being a safe haven during crisis periods; in the same line, Klein et al. (2018) and Beneki et al. (2019) call Bitcoin the new gold. Kyriazis (2019) finds relationships between several virtual currencies and summarizes previous literature about return and volatility spillovers in the cryptocurrency market. Katsiampa (2019) investigates volatility movements of the major cryptocurrencies and finds interdependencies in the cryptocurrency market and the influence of relevant events on volatility.

Undoubtedly, the most recent branch of literature focuses on the current crisis caused by the COVID-19 pandemic (Umar et al., 2021a). Ali et al. (2020) analyse the responses, in terms of volatility, of financial markets as COVID-19 spread from China to Europe and the US and find that global markets went into a freefall in March 2020 and that even safer commodities suffered due to the arrival of the pandemic in the US. Corbet et al. (2020) examine the potential contagion effects of the COVID-19 pandemic on gold and cryptocurrencies and consider that cryptocurrencies may play a role similar to that of precious metals during economic crises. Gharib et al. (2021) study how the economic impact of COVID-19 has influenced the relationship between oil and gold spot prices and find a bilateral contagion effect in oil and gold markets during the pandemic crisis. Bakas and Triantafyllou (2020) analyse the influence of the COVID-19 pandemic crisis on commodity price volatility. Rizwan et al. (2020) examine how COVID-19 influenced the banking sector of the eight countries most affected by SARS-CoV-2. Sharif et al. (2020) study the connectedness between the spread of COVID-19, the stock market, oil price volatility shocks, geopolitical risk and economic policy uncertainty in the US and find a relevant effect of COVID-19 on geopolitical risk.

There is also a branch of recent literature that studies the interdependences among cryptocurrencies following different methodologies such as the quantile regression approach (Jareño et al., 2020), ARDL models (Ciaian et al., 2018 and Nguyen et al., 2019), NARDL models (González et al., 2020 and 2021; Jareño et al., 2020), wavelet-based models (Kumar and Ajaz, 2019; Omane-Adjepong and Alagidede, 2019; Mensi et al., 2019; Sharif et al., 2020), VAR models (Bação et al., 2018), GARCH models (Corbet et al., 2020), VAR-GARCH models (Symitsi and Chalvatzis, 2019), the bivariate diagonal BEKK model (Katsiampa, 2019; Katsiampa et al., 2019), BEKK-GARCH models (Beneki et al., 2019), BEKK-MGARCH models (Tu and Xue, 2019), the GARCH-MIDAS model (Walther et al., 2019), DCC models (Charfeddine et al., 2020; Kumar and Anandarao, 2019), the Diebold and Yilmaz (2009) approach (Koutmos, 2018) and Diebold and Yilmaz (2012) indices (Ji et al., 2019; Umar et al., 2021b), among others. In this paper, we use an extension and improvement of the two previous models, Diebold and Yilmaz's (2009 and 2012) approach, which is a time-varying parameter vector autoregression (TVP-VAR) model developed by Antonakakis and Gabauer (2017). In particular, we apply this methodology to study the connectedness between the three major cryptocurrencies (Bitcoin, Ethereum and Ripple); the fiat currencies of the euro, GBP and Chinese yuan and the RavenPack media coverage index during the COVID-19 pandemic crisis. Other authors, such as Bouri et al. (2021), apply the TPV-VAR model to analyse the return connectedness across asset classes such as gold, crude oil, world equities, currencies and bonds around the COVID-19 outbreak. They find that the dynamic total connectedness across the five assets was moderate and quite stable until early 2020, at which point the total connectedness spiked and the structure of the network of connectedness was altered by the outbreak of COVID-19. In addition, Gabauer and Gupta (2018) also use the TVP-VAR approach to study the economic policy uncertainty spillovers between the US and Japan. Antonakakis et al. (2020) use the TVP-VAR approach to analyse the dynamic connectedness measures of the four most traded foreign currencies (EUR, GBP, CHF and JPY) against the US dollar. Finally, Elsayed et al. (2020) use an extension of the Diebold and Yilmaz (2009, 2012 and 2014) approach to analyse the static and dynamic interconnectedness among major cryptocurrencies and top worldwide foreign exchange markets (for a sample period from August 5, 2013 to December 31, 2018). They find that there is a significant causal relationship among cryptocurrencies. However, except for the Chinese yuan, major traditional currencies do not significantly affect cryptocurrencies.

Furthermore, in the current situation where the COVID-19 pandemic is threatening the entire world, there are many papers that study the socioeconomic impacts of COVID-19. Kurita and Managi (2020) affirm that social stigma is crucial in the fight against COVID-19 because it reduces the spread of infection through individual self-restraint behaviour. Katafuchi et al. (2021) report that the behaviour of going out was suppressed under the state of emergency and after it was lifted, even when going out did not result in penalties. Mandel and Veetil (2020) estimate the costs of the lockdown for some sectors of the world economy in the wake of COVID-19 and study the process of economic recovery following the end of the lockdowns. These authors affirm that the world economy takes approximately one quarter to move towards the new equilibrium in the optimistic and unlikely scenario of the end of all lockdowns. Gharehgozli et al. (2020) and Martin et al. (2020) evaluate the socioeconomic impacts of COVID-19 on individuals at the regional level. Considering the massive economic shocks that the COVID-19 pandemic has caused worldwide, Nakamura and Managi (2020) calculate the overall relative risk of the importation and exportation of COVID-19 and assert that it is indispensable for countries to undertake countermeasures for this disease. Furthermore, the number of studies on the influence of media information on infectious diseases on investors' decisions is increasing significantly (Umar and Gubareva, 2021a, 2021b; Zaremba et al, 2021). Cepoi (2020) and Haroon and Rizvi (2020) use the Coronavirus Media Coverage Index (MCI) to study the connectedness between the sentiment generated by news related to COVID-19 and volatility levels in different sectors of the US equity markets. This index, namely, the Coronavirus Media Coverage Index (MCI), measures the amount of coronavirus-related news compared to other types of news and is also an effective indicator of the percentage of sources covering coronavirus news among all news sources.

Finally, to the best of our knowledge, this paper contributes to the previous literature by providing the first research on the impact of SARS-CoV-2-related news on several dynamic return and volatility connectedness measures of the three dominant cryptocurrencies and the fiat currencies of the euro, GBP and Chinese yuan around the global crisis caused by the COVID-19 pandemic.

3. Data and methodology

3.1. Data

The dataset used in this paper consists of three different groups of data. First, the daily log returns of the three largest cryptocurrencies, Bitcoin (BTC), Ethereum (ETH) and Ripple (XRP), as ranked by market capitalization during the sample period (from January 1, 2020, to December 31, 2020), are included. These top three cryptocurrencies represent 82.1% of the cryptocurrency market, and Bitcoin alone has a 69.2% share in this market at the end of December 2020. Second, the exchange rates of the three major fiat currencies, the euro, GBP and Chinese yuan, against the US dollar are included. Third, the RavenPack Coronavirus Media Coverage Index (MCI) was used to measure the level of media coverage with this issue.[2] This coronavirus index (MCI) is the

[2] See the https://www.ravenpack.com/ website, which provides insights generated automatically from real-time news from over 22,000 news and social media sources.

percentage of news sources that cover the coronavirus.

The sample period runs from January 1, 2020, to December 31, 2020, and focuses on the COVID-19 pandemic crisis. Thus, our period includes the first months of 2020 when we already knew about the existence of the coronavirus but it had not yet been declared a global pandemic, the first wave of COVID-19 with its devastating effects in Europe in March and its boom in the United States in mid-April, and the second wave that hit the entire world from August until December 2020.

Table 1 collects the descriptive statistics and unit root tests of the top three cryptocurrency (Bitcoin, Ethereum and Ripple) returns and the returns of the fiat currencies of the euro, GBP and Chinese yuan for daily data for the entire sample period. The three cryptocurrencies and two of the three fiat currencies (the euro and GBP) show positive mean and median log returns with the exception being the Chinese yuan, which shows low but negative mean and median values. The standard deviations are rather low for all variables; they range from 4.22 to 7.43% for cryptocurrencies and from 0.29 to 0.69% for fiat currencies. All variables except for Ripple and the Chinese yuan show negative skewness, and all of them exhibit excess kurtosis. The standard Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) stationarity test confirm that all variables are stationary.

Table 2 collects the descriptive statistics and unit root tests of the volatilities of the Bitcoin, Ethereum and Ripple cryptocurrencies and the euro, GBP and Chinese yuan fiat currencies for the same frequency and period. The three cryptocurrencies and fiat currencies show positive mean values, and only two cryptocurrencies (Ethereum and Ripple) and two fiat currencies (the euro and GBP) show positive median values. The standard deviations of all variables are much higher in terms of volatility than in terms of returns since they range from 13.68 to 22.48% (regardless of the type of variable). Four out of six variables show positive skewness (except for the euro and GBP), but all variables show excessive kurtosis. The standard Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) stationarity test confirm that all variables are stationary.

3.2. Methodology

To study the returns and volatility connectedness of the top three cryptocurrencies (Bitcoin, Ethereum and Ripple), the fiat currencies of the euro, GBP and Chinese yuan and the RavenPack Coronavirus Media Coverage Index (MCI), the time-varying parameter vector autoregression (TVP-VAR) methodology developed by Antonakakis and Gabauer (2017) is applied. Some of the main advantages of this methodology are (1) that it adjusts immediately to events, (2) that there is no loss of observations, (3) that there is no need to arbitrarily choose the size of the rolling window because it adjusts automatically and (4) that it can also be used for low-frequency datasets. All these advantages of the time-varying parameter vector autoregression (TPV-VAR) methodology are very necessary when studying the effects of the COVID-19 crisis as the data series are somewhat short. Specifically, we apply this methodology to estimate the connectedness between these variables and the coronavirus media coverage index to analyse the degree to which the returns and volatilities of these variables have been affected by the COVID-19 pandemic crisis.

The time-varying parameter vector autoregression (TVP-VAR) model is an extension of the Diebold and Yilmaz (2009, 2012) connectedness approach proposed by Antonakakis and Gabauer (2017) and is as follows:

$$\boldsymbol{Y}_t = \boldsymbol{\beta}_t \boldsymbol{Y}_{t-1} + \epsilon_t \quad \epsilon_t | \boldsymbol{F}_{t-1} \sim N(0, \boldsymbol{S}_t) \tag{1}$$

$$\boldsymbol{\beta}_t = \boldsymbol{\beta}_{t-1} + \boldsymbol{v}_t \quad \boldsymbol{v}_t | \boldsymbol{F}_{t-1} \sim N(0, \boldsymbol{R}_t) \tag{2}$$

where $\boldsymbol{Y}_t$ is an $N \times 1$ dimensional vector, $\boldsymbol{Y}_{t-1}$ represents an $Np \times 1$ dimensional vector, $\boldsymbol{\beta}_t$ is an $N \times Np$ dimensional time-varying coefficient matrix, ϵ_t is an $N \times 1$ dimensional error disturbance vector with an $N \times N$ time-varying variance-covariance matrix $\boldsymbol{S}_t$, and, finally, $\boldsymbol{v}_t$ is an $N \times Np$ dimensional error matrix with an $Np \times Np$ variance-covariance matrix, $\boldsymbol{R}_t$.

Additionally, the vector moving average (VMA) is used as a transformation of the well-known VAR to calculate the generalized impulse response functions (GIRFs) and the generalized forecast error variance decompositions (GFEVDs) introduced by Koop et al. (1996) and Pesaran and Shin (1998) since the Diebold and Yilmaz (2014) connectedness procedure is based on them:

$$\boldsymbol{Y}_t = \boldsymbol{\beta}_t \boldsymbol{Y}_{t-1} + \epsilon_t \tag{3}$$

$$\boldsymbol{Y}_t = \boldsymbol{A}_t \epsilon_t \tag{4}$$

$$\boldsymbol{A}_{0,t} = \boldsymbol{I} \tag{5}$$

$$\boldsymbol{A}_{i,t} = \boldsymbol{\beta}_{1,t} \boldsymbol{A}_{i-1,t} + \ldots + \boldsymbol{\beta}_{p,t} \boldsymbol{A}_{i-p,t} \tag{6}$$

where $\boldsymbol{\beta}_t = [\boldsymbol{\beta}_{1,t}, \ \boldsymbol{\beta}_{2,t}, \ldots, \boldsymbol{\beta}_{p,t}]'$, $\boldsymbol{A}_t = [\boldsymbol{A}_{1,t}, \ \boldsymbol{A}_{2,t}, \ldots, \boldsymbol{A}_{p,t}]'$, and $\boldsymbol{\beta}_{i,t}$ and $\boldsymbol{A}_{i,t}$ are $N \times N$ dimensional parameter matrices.

The reactions of all variables to a change in variable i are represented in the GIRFs. The differences between a J-step-ahead forecast once variable i is impacted and once variable i is not impacted are computed:

$$GIRF_t(J, \boldsymbol{\delta}_{j,t}, \boldsymbol{F}_{t-1}) = E(\boldsymbol{Y}_{t+J} | \epsilon_{j,t} = \boldsymbol{\delta}_{j,t}, \boldsymbol{F}_{t-1}) - E(\boldsymbol{Y}_{t+J} | \boldsymbol{F}_{t-1}) \tag{7}$$

Table 1
Descriptive statistics of the cryptocurrency and fiat currency returns.

	Bitcoin	Ethereum	Ripple	Euro	GBP	Chinese.RMB
Mean	0.0053	0.0067	0.0006	0.0003	0.0001	-0.0003
Median	0.0038	0.0040	0.0023	0.0002	0.0005	-0.0005
Maximum	0.1584	0.1744	0.5658	0.0146	0.0270	0.0112
Minimum	-0.3173	-0.4048	-0.4919	-0.0206	-0.0378	-0.0089
Std. Dev.	0.0422	0.0569	0.0743	0.0047	0.0069	0.0029
Skewness	-1.5518	-1.3185	0.1319	-0.3070	-0.6334	0.4487
Kurtosis	17.3383	13.8250	23.3043	4.8456	7.3496	4.3050
JB	2349.4720***	1355.1460***	4501.3300***	41.3004***	224.0510***	27.3831***
ADF	-16.2650***	-9.7786***	-13.7511***	-14.1755***	-13.2766***	-17.8041***
PP	-16.2978***	-16.6093***	-13.6193***	-14.2340***	-13.4094***	-17.7389***
KPSS	0.2958	0.0732	0.0647	0.1694	0.1647	0.4747**
Obs.	262	262	262	262	262	262

Notes: This table collects the descriptive statistics of daily cryptocurrency and fiat currency returns. The sample period ranges from January 1, 2020 to December 31, 2020, during the first and second waves of the COVID-19 pandemic crisis. They include mean, median, minimum (Min.) and maximum (Max.) values, standard deviation (Std. Dev.) and Skewness and Kurtosis measures. JB denotes the statistic of the Jarque-Bera test for normality. The results of the augmented Dickey-Fuller (ADF, 1979) and Phillips-Perron (PP, 1988) unit root tests, and the Kwiatkowski et al. (KPSS, 1992) stationarity test are also reported in the last three lines. As usual, *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 2
Descriptive statistics of the cryptocurrency and fiat currency volatilities.

	Bitcoin	Ethereum	Ripple	Euro	GBP	Chinese.RMB
Mean	0.0029	0.0001	0.0093	0.0012	0.0010	0.0022
Median	-0.0050	0.0015	0.0041	0.0000	0.0015	-0.0021
Maximum	1.0352	0.8182	1.0053	0.5518	0.5589	0.9404
Minimum	-0.7583	-0.7326	-1.1099	-0.7348	-0.7376	-0.8199
Std. Dev.	0.2187	0.2037	0.2248	0.1368	0.1466	0.1676
Skewness	0.9289	0.2141	0.1809	-0.3025	-0.5380	0.4489
Kurtosis	7.9476	7.4010	9.5893	8.5963	7.6325	11.2033
JB	304.9059***	213.4454***	475.4196***	345.8896***	246.9096***	743.4159***
ADF	-17.9775***	-18.7153***	-16.3195***	-16.1116***	-14.7779***	-7.1878***
PP	-17.9739***	-18.8311***	-16.3195***	-16.1127***	-14.7346***	-19.2478***
KPSS	0.0337	0.0321	0.0782	0.0392	0.0289	0.07194
Obs.	262	262	262	262	262	262

Notes: This table collects the descriptive statistics of daily cryptocurrency and fiat currency returns. The sample period ranges from January 1, 2020 to December 31, 2020, during the first and second waves of the COVID-19 pandemic crisis. They include mean, median, minimum (Min.) and maximum (Max.) values, standard deviation (Std. Dev.) and Skewness and Kurtosis measures. JB denotes the statistic of the Jarque-Bera test for normality. The results of the augmented Dickey-Fuller (ADF, 1979) and Phillips-Perron (PP, 1988) unit root tests, and the Kwiatkowski et al. (KPSS, 1992) stationarity test are also reported in the last three lines. As usual, *, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

$$\boldsymbol{\psi}^{g}_{j,t}(J) = \frac{\boldsymbol{A}_{J,t}\boldsymbol{S}_t\epsilon_{j,t}}{\sqrt{S_{jj,t}}}\frac{\boldsymbol{\delta}_{j,t}}{\sqrt{S_{jj,t}}} \quad \boldsymbol{\delta}_{j,t} = \sqrt{S_{jj,t}} \tag{8}$$

$$\boldsymbol{\psi}^{g}_{j,t}(J) = S_{jj,t}^{-1/2}\boldsymbol{A}_{J,t}\boldsymbol{S}_t\epsilon_{j,t} \tag{9}$$

where $\boldsymbol{\psi}^{g}_{j,t}(J)$ represents the GIRFs of variable j, J is the forecast horizon, $\boldsymbol{\delta}_{j,t}$ is the selection vector equal to one on the jth position and zero otherwise, and $\boldsymbol{F}_{t-1}$ is the information set until $t-1$.

Furthermore, the generalised forecast error variance decomposition (GFEVD), understood as the part of the variance that one variable i has over the other variables j, is as follows:

$$\widetilde{\varphi}^{g}_{ij,t}(J) = \frac{\sum_{t=1}^{J-1}\boldsymbol{\psi}^{2,g}_{ij,t}(J)}{\sum_{j=1}^{N}\sum_{t=1}^{J-1}\boldsymbol{\psi}^{2,g}_{ij,t}(J)} \tag{10}$$

where $\sum_{j=1}^{N}\widetilde{\varphi}^{N}_{ij,t}(J) = 1$ and $\sum_{i,j=1}^{N}\widetilde{\varphi}^{N}_{ij,t}(J) = N$.

The total connectedness index computes the degree to which a shock in one variable i extends to the other variables j. This total connectedness index is constructed from the generalized forecast error variance decompositions (GFEVDs) as follows:

$$C^{g}_{t}(J) = \frac{\sum_{i,t=1,i\neq j}^{N}\widetilde{\varphi}^{g}_{ij,t}(J)}{\sum_{i,t=1}^{N}\widetilde{\varphi}^{g}_{ij,t}(J)} * 100 \tag{10}$$

$$= \frac{\sum_{i,t=1,i\neq j}^{N}\widetilde{\varphi}^{g}_{ij,t}(J)}{N} * 100 \tag{12}$$

Furthermore, this total connectedness index can estimate different directions of the relationships between the variables. First, the "*total directional connectedness to others*" (TO) measures the degree to which a shock in variable i extends to all other variables j as follows:

$$C^{g}_{i\rightarrow j,t}(J) = \frac{\sum_{j=1,i\neq j}^{N}\widetilde{\varphi}^{g}_{ji,t}(J)}{\sum_{j=1}^{N}\widetilde{\varphi}^{g}_{ji,t}(J)} * 100 \tag{13}$$

Second, the "*total directional connectedness from others*" (FROM) measures the aggregated influence all other variables j has on variable i as follows:

$$C^{g}_{i\leftarrow j,t}(J) = \frac{\sum_{j=1,i\neq j}^{N}\widetilde{\varphi}^{g}_{ij,t}(J)}{\sum_{i=1}^{N}\widetilde{\varphi}^{g}_{ij,t}(J)} * 100 \tag{14}$$

Moreover, the "*net total directional connectedness*" (NET) is calculated by subtracting the influence of all other variables j on variable i from the impact of variable i on all other variables j, that is, by subtracting Eq. (14) from Eq. (13):

$$C^{g}_{i,t} = C^{g}_{i\rightarrow j,t}(J) - C^{g}_{i\leftarrow j,t}(J) \tag{15}$$

Thus, a positive value of the "net total directional connectedness" indicates that variable i influences all other variables j (or the system) more than the remainder of the variables j influences this variable i. For example, a shock in the Coronavirus Media Coverage Index (MCI) would influence the returns or the volatilities of the top three cryptocurrencies and the three fiat currencies more than these variables influence the coronavirus index. Conversely, a negative value of the "net total directional connectedness" indicates that variable i is influenced by the remainder of the variables j (or the system) more than the other variables j are influenced by variable i. For example, a shock in the coronavirus index (MCI) would be influenced by the returns or the volatilities of the top three cryptocurrencies and the three fiat currencies. Finally, a "net total directional connectedness" equal to zero indicates that variable i neither influences nor is influenced by the remainder of the variables j (or the system). To take the same example, a shock to the coronavirus index (MCI) would neither influence nor be influenced by the returns or volatilities of the three major cryptocurrencies and the three fiat currencies analysed in this paper.

4. Empirical results

This paper studies the connectedness between the three largest cryptocurrencies (Bitcoin, Ethereum and Ripple), the fiat currencies of the euro, GBP and Chinese yuan, and the RavenPack media coverage index (MCI), as recently applied by Cepoi (2020) and Haroon and Rizvi (2020), during the COVID-19 pandemic crisis. Following Gabauer and Gupta (2018) and Antonakakis et al. (2020), we show the dynamic connectedness measures using the TVP-VAR methodology proposed by Antonakakis and Gabauer (2017) between January 1, 2020, and December 31, 2020, that is, in the context of the SARS-CoV-2 global crisis.

4.1. Dynamic rolling return connectedness

This section includes different return connectedness measures between some relevant cryptocurrencies and fiat currencies during the recent coronavirus global crisis. First, the mean contributions to the system of each variable (in return) during the first and second waves of the COVID-19 pandemic crisis are shown in Fig. 1.

According to these preliminary results, the highest mean contributor to the system is Ethereum, then Bitcoin and, finally, Ripple. Therefore, the selected cryptocurrencies show a stronger mean contribution to the system than the fiat currencies studied in this research (the GBP, euro

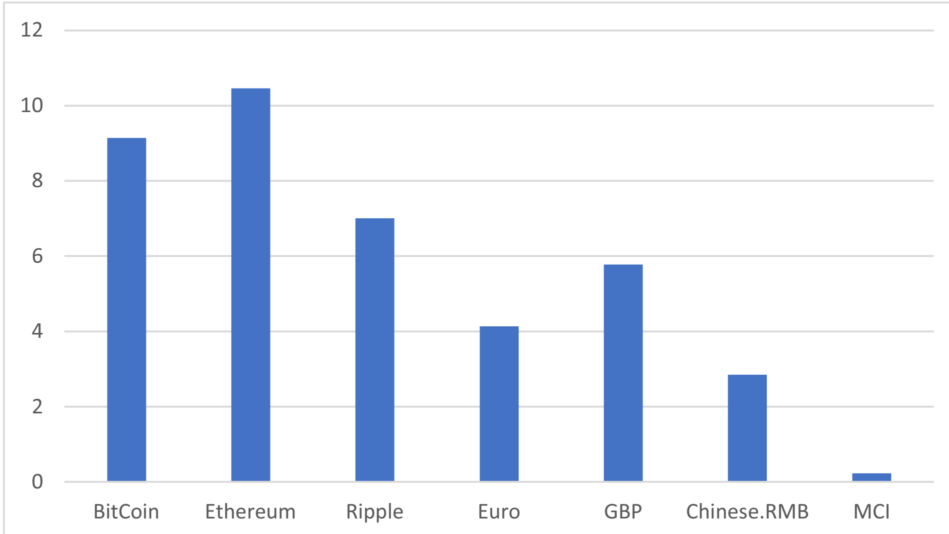

Fig. 1. Mean contribution TO the system of each variable (in return) *Notes*: We study the return connectedness between the three biggest cryptocurrencies (Bitcoin, Ripple and Ethereum), the fiat currencies for GBP, Euro and Chinese Yuan, and the RavenPack media coverage index (MCI), within the TVP-VAR framework (Antonakakis and Gabauer, 2017).

and Yuan). However, there are important differences among the fiat currencies. The GBP makes the highest contribution to the system, followed by the euro and, last and unexpectedly, the yuan. Overall, the lowest contribution to the system is from the Coronavirus Media Coverage Index (MCI). Alternatively, Fig. 2 shows the mean contribution from the system to each variable in terms of returns. We now observe few differences between cryptocurrencies and fiat currencies. Nevertheless, the mean contribution from the system to cryptocurrencies is still slightly higher than that to fiat currencies. Ethereum and the GBP show the highest values for each type of currency. The coronavirus MCI still exhibits the lowest average contribution from the system.

To finish this preliminary analysis, Fig. 3 collects the dynamic total return connectedness of the cryptocurrencies and fiat currencies included in our study using the coronavirus MCI. As expected, the dynamic total return connectedness fluctuates over time, which is in line with Gabauer and Gupta (2018), Umar et al. (2020 and 2021c) and Bouri et al. (2021), among others. Concretely, the dynamic total return connectedness begins the sample period with an increase and a subsequent decrease between January and March 2020, just before the epicentre of the first wave of the COVID-19 pandemic crisis (Jareño and González, 2020; Jareño et al., 2020), as identified with a shaded area. However, a peak is reached during March 2020, which coincides with the start of the intensification of the pandemic caused by the SARS-CoV-2 coronavirus (first wave of the pandemic). This result agrees with Antonakakis et al. (2020) and Elsayed et al. (2020), among others, that confirm very sensitive returns and volatility spillovers during periods of economic and financial turbulence. Since that time, the dynamic total return connectedness measure remains more or less constant throughout the sample period (first and second wave of the pandemic), perhaps observing a slight (very subtle) decline as we approached the end of the sampling period.

Once the preliminary analysis was completed, the dynamic total return connectedness was split into the connectedness to and the connectedness from, as shown in Fig. 4 and Fig. 5, respectively.

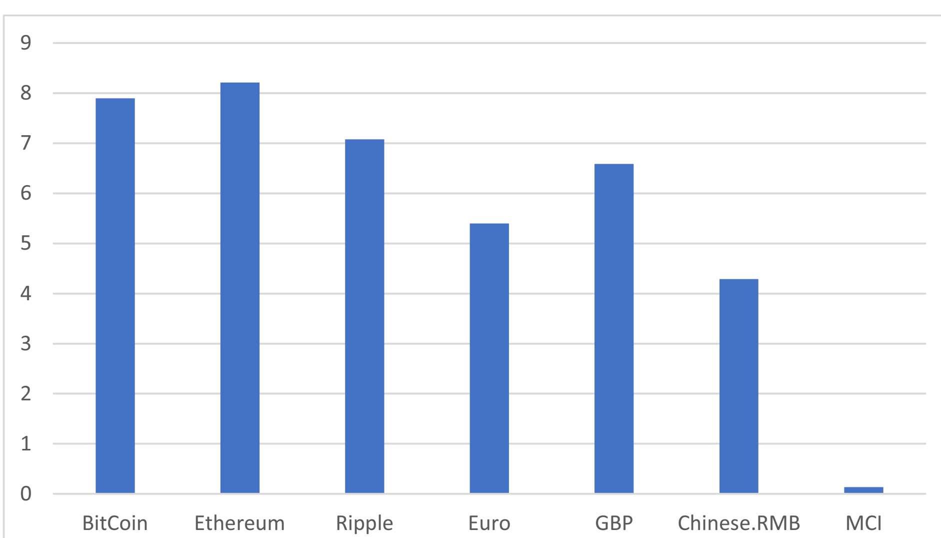

Fig. 2. Mean contribution FROM the system to each variable (in return) *Notes*: We study the return connectedness between the three biggest cryptocurrencies (Bitcoin, Ripple and Ethereum), the fiat currencies for GBP, Euro and Chinese Yuan, and the RavenPack media coverage index (MCI), within the TVP-VAR framework (Antonakakis and Gabauer, 2017).

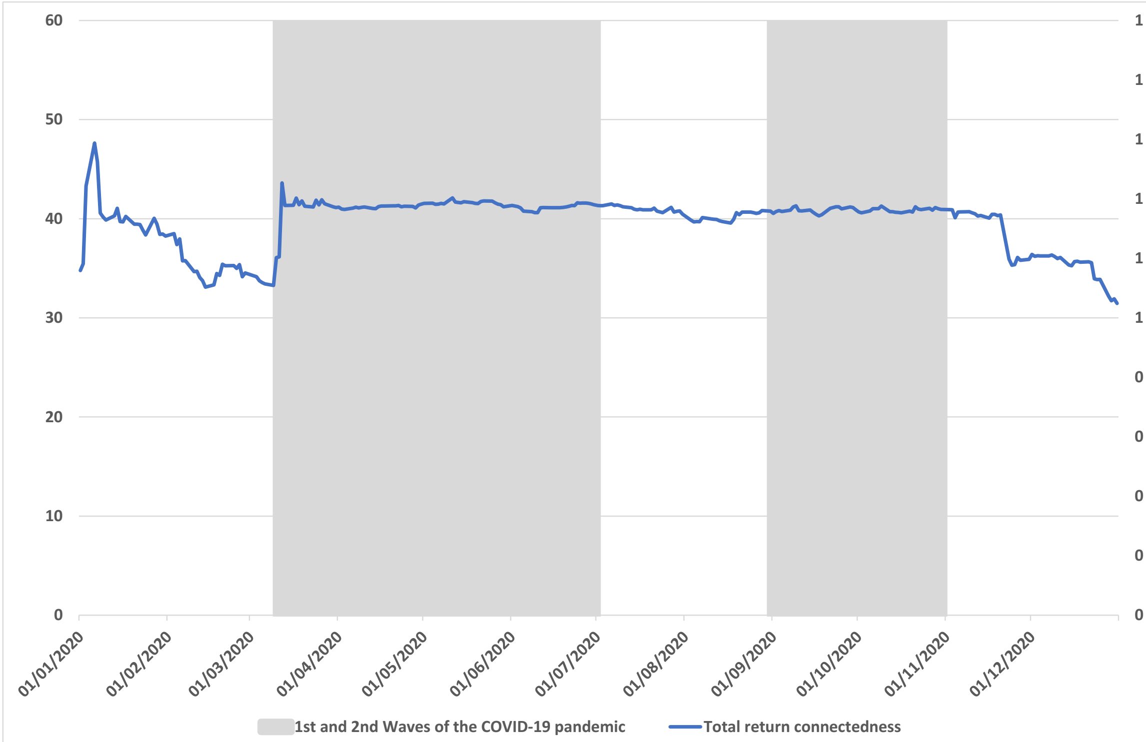

Fig. 3. Dynamic total return connectedness over time *Notes*: We study the return connectedness between the three biggest cryptocurrencies (Bitcoin, Ripple and Ethereum), the fiat currencies for GBP, Euro and Chinese Yuan, and the RavenPack media coverage index (MCI), within the TVP-VAR framework (Antonakakis and Gabauer, 2017).

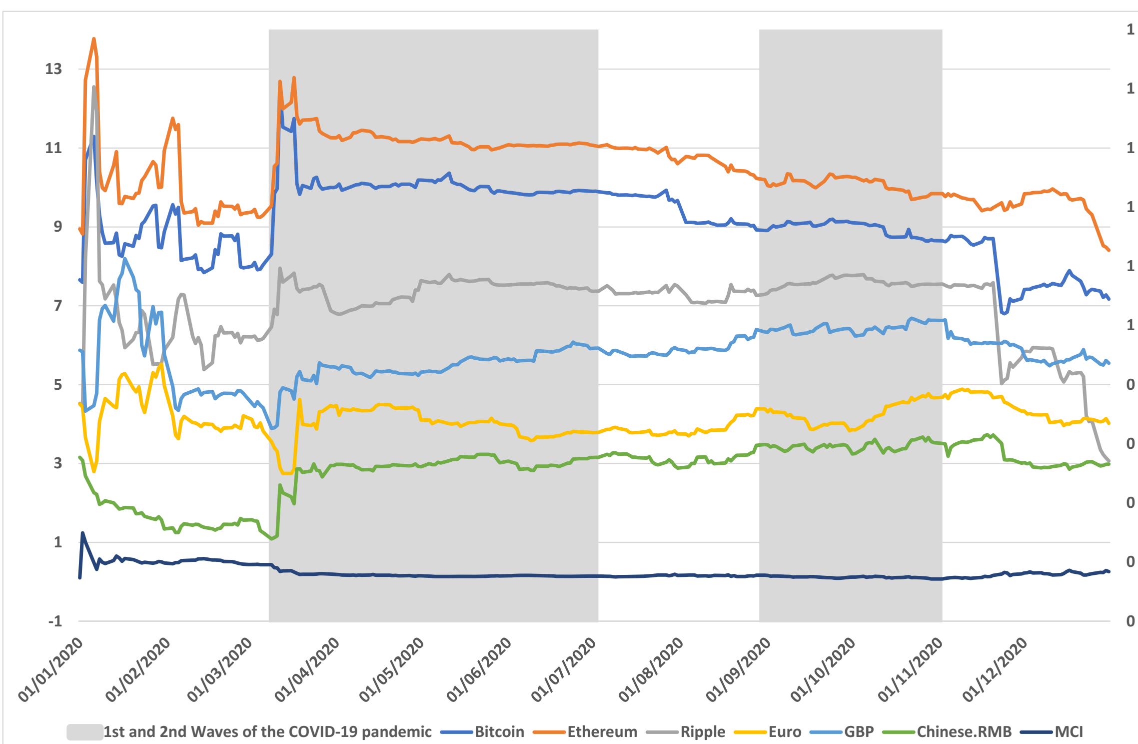

Fig. 4. Dynamic contribution of the selected cryptocurrencies and fiat currencies TO the system (in return) *Notes*: We study the return connectedness between the three biggest cryptocurrencies (Bitcoin, Ripple and Ethereum), the fiat currencies for GBP, Euro and Chinese Yuan, and the RavenPack media coverage index (MCI), within the TVP-VAR framework (Antonakakis and Gabauer, 2017).

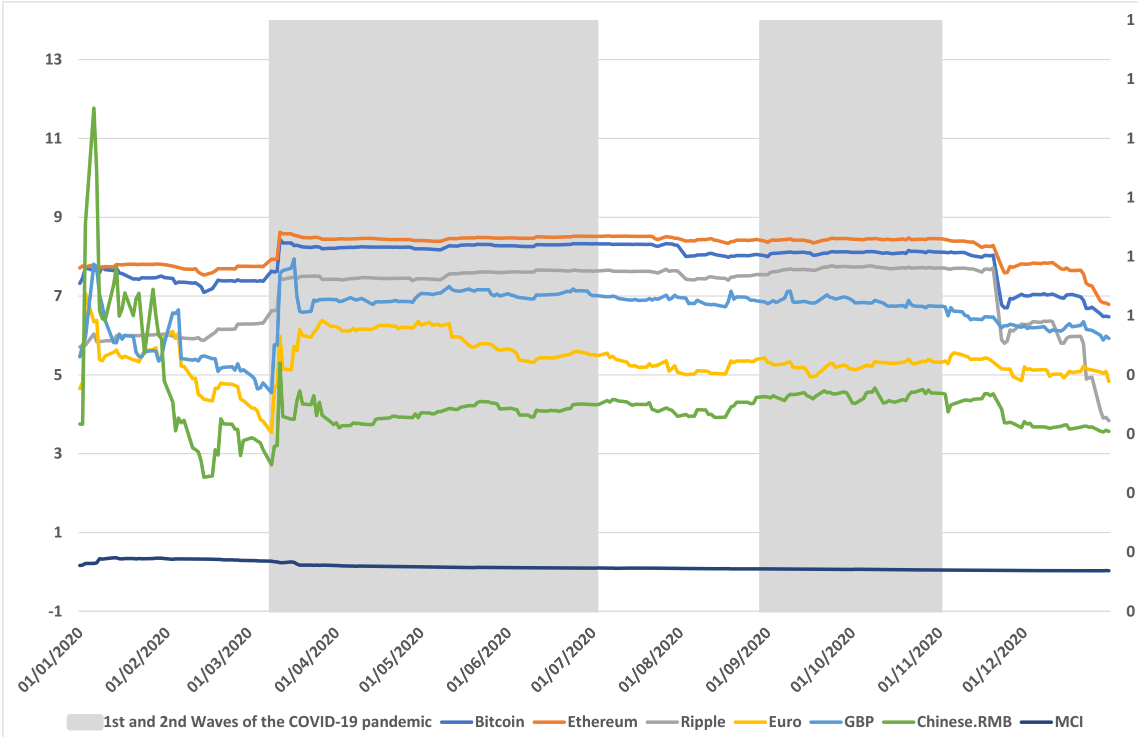

Fig. 5. Dynamic contribution FROM the system to the selected cryptocurrencies and fiat currencies (in return) *Notes*: We study the return connectedness between the three biggest cryptocurrencies (Bitcoin, Ripple and Ethereum), the fiat currencies for GBP, Euro and Chinese Yuan, and the RavenPack media coverage index (MCI), within the TVP-VAR framework (Antonakakis and Gabauer, 2017).

Regarding the dominant transmitters to the system, there are clearly three different profiles. First, cryptocurrencies are the most relevant transmitters to the system in the following order: Ethereum, Bitcoin and Ripple. This is as expected due to the results observed in the preliminary analysis. Second, the fiat currencies analysed in this paper exhibit a lower level of transmission to the system than the cryptocurrencies. Nevertheless, the order between currencies is maintained with the GBP, followed by the euro and, finally, the yuan, exhibiting the highest connectedness to the system. Finally, coronavirus MCI is the less relevant transmitter to the system. Third, regarding the evolution of the return connectedness to the system over time, it is similar for all currencies, although at different levels depending on the type of currency (virtual or fiat). Thus, we observe high variability and high levels of connectedness to the system at the beginning of the sample period, mainly in January 2020, with a decline in the level of this connectedness in February. Only at the start of the peak of the first wave of the global pandemic (March 2020) due to the spread of the SARS-CoV-2 coronavirus, there is an increase in the return connectedness to the system for all the currencies analysed, although the increase is greater and slightly anticipated in the case of cryptocurrencies. These currencies show a slight decrease in the connectedness to the system at the end of the first wave of the pandemic, thus maintaining the levels reached, with a slight decrease after the second wave of the pandemic. Developments in the connectedness to the system for fiat coins are similar, although there is a very slight increase at the end of the sample period. Finally, the coronavirus MCI shows a connectedness to the system that remains flat throughout virtually the entire sample period.

Regarding the dynamic total return connectedness from the system, there are almost unnoticeable differences between the connectedness for the three cryptocurrencies analysed. However, we continue to observe different levels in the connectedness from the system for by the cryptocurrencies and the fiat currencies with that of the former being higher than that of the latter. The only exception is the yuan, which shows the highest values of all the coins analysed at the beginning of the sample period (January 2020), drastically reducing the connectedness from the system shown in February 2020. The yuan becomes the currency with the lowest level of this return connectedness measure from that moment until the end of the sample. This reflects that the Chinese currency could have maintained a higher level of return connectedness from the system before the spread of COVID-19 worldwide, as China is the country in which the SARS-CoV-2 coronavirus was generated; therefore the incidence of the disease occurred much earlier in China than in the rest of the world. Moreover, the evolution of this return connectedness measure is quite similar to that of the return connectedness to the system. That is, there are high volatility and levels at the beginning of the sample, then a drop in February (mainly for the yuan), and a significant increase in the connectedness from the system at the beginning of the first wave of the global pandemic. The main difference from the connectedness to the system measure is that this increase occurs mainly in fiat currencies, unlike the larger increase in cryptocurrencies in the case of the connectedness to the system. After the aforementioned increase, this return connectedness measure maintains the same levels until the end of the second wave of the pandemic. Once again, the return connectedness from the system for the coronavirus MCI is well below those of the rest of the variables and remains constant throughout the period studied in this research, which focuses on the environment of the crisis generated by the COVID-19. Thus, both connectedness measures (to and from) rebound in mid-March 2020, coinciding with an increase in SARS-CoV-2 coronavirus infections (first wave), a period of confinement and a slowdown in economic activity worldwide.

To complete the study of the connectedness in terms of returns, Fig. 6 collects the net dynamic total return connectedness (the difference between the connectedness to and from) of the virtual and fiat currencies selected in this research. First, we note that the differences between the net dynamic connectedness of the different currencies analysed are much greater at the beginning of the sample period and during the first wave of the pandemic than at the end (after the second wave). Moreover, this connectedness measure exhibits high volatility. In fact, these

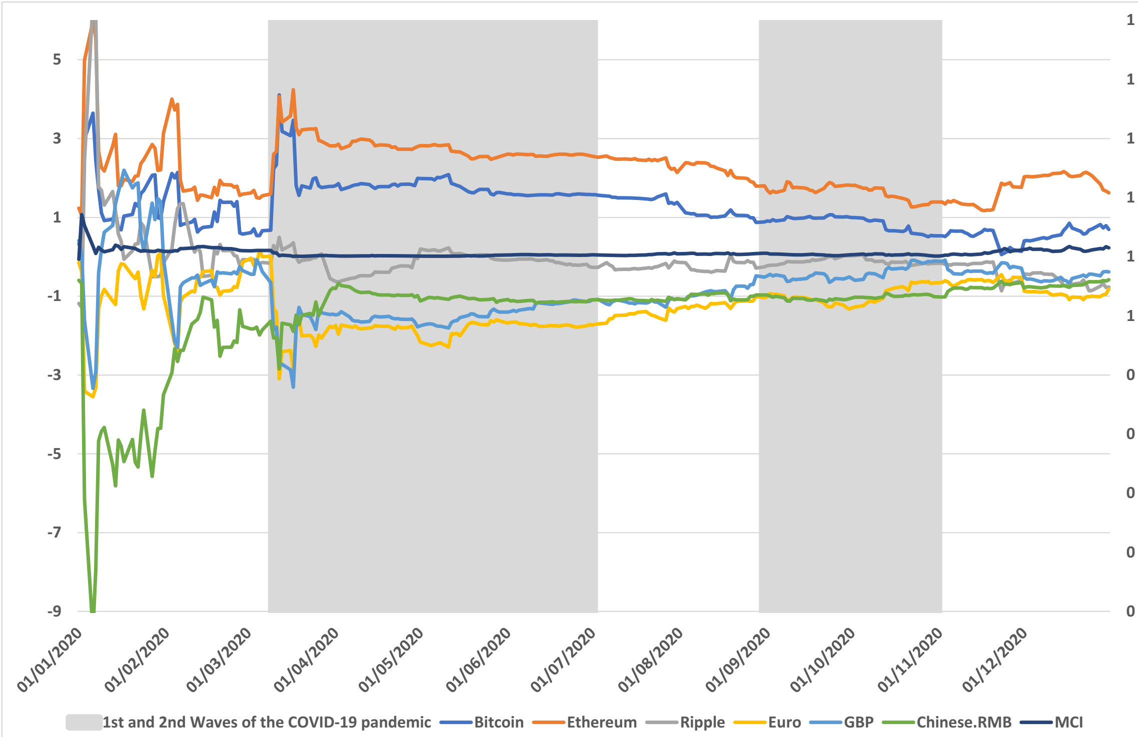

Fig. 6. Net dynamic total connectedness (in return) *Notes*: We study the return connectedness between the three biggest cryptocurrencies (Bitcoin, Ripple and Ethereum), the fiat currencies for GBP, Euro and Chinese Yuan, and the RavenPack media coverage index (MCI), within the TVP-VAR framework (Antonakakis and Gabauer, 2017).

differences are substantial during the months of January and February 2020, and, again, they increase at the beginning of the first wave of the SARS-CoV-2 pandemic epicentre. At the end of the sample period, the net dynamic return connectedness slightly converges between these two groups of currencies (virtual *vs.* fiat). Clearly, cryptocurrencies (mainly Bitcoin and Ethereum) are net transmitters. They possess positive net connectedness measures with some peaks in the first days of January, February and March, the starting point of the first wave of the COVID-19 pandemic crisis. In addition, the net dynamic total return connectedness is higher for Ethereum than for Bitcoin and, in turn, than for Ripple (where it is virtually zero). This result agrees with Antonakakis et al. (2020), Elsayed et al. (2020) and Adekoya and Oliyide (2021), among other recent papers, by showing that leading cryptocurrencies would be net transmitters. However, fiat currencies show evolution opposite to that observed for cryptocurrencies; furthermore, the fiat currencies exhibit a net receiving position with negative values for the net connectedness measure in terms of returns. The result that must be highlighted in the case of fiat currencies is the evolution that we observe in the case of the yuan, which shows very negative values at the beginning of the sample period, especially between the months of January and February 2020. This is an expected result. Since China is the country of origin of the SARS-CoV-2 coronavirus, its currency experienced greater effects from the COVID-19 crisis and anticipated its effects of the crisis on the rest of the world. However, starting from the first wave of the global pandemic, the three fiat currencies show similar evolution with a small negative peak at the beginning of the first wave of the mentioned crisis (in March 2020), and they maintain a stable level of the (negative) net connectedness measure until the end of the sample period. Again, these results coincide with Bouri et al. (2021) because they also find that the USD has been a net receiver throughout the COVID-19 pandemic crisis. Last, the MCI shows a neutral position during the entire period with a slight increase at the beginning of the sample. Interestingly, the MCI appears to be the measure that allows separating the evolution of the cryptocurrencies (with net transmitter positions) and fiat currencies (with net receiver profiles).

4.2. Dynamic rolling volatility connectedness

Similar to the study of the return connectedness, this research then focuses on analysing the connectedness measures of the currencies included in the study in terms of volatility around the first and second waves of the global COVID-19 pandemic crisis.

First, Figs. 7 and 8 illustrate the mean connectedness to and from the system studied in this paper in terms of volatility and conduct an in-depth analysis of the period affected by the SARS-CoV-2 coronavirus pandemic.

As we have observed in the analysis of alternative connectedness measures in terms of returns, the most relevant transmitters to the system (in mean volatility) are the three cryptocurrencies included in this analysis, which are Ethereum, Bitcoin and Ripple. Fiat currencies (the euro, GBP and yuan) exhibit lower contributions to the system in terms of volatility, as previously seen with returns. Finally, the coronavirus MCI shows a mean volatility connectedness to the system that is virtually zero. Furthermore, the mean contribution from the system (in terms of volatility) continues to exhibit differences between cryptocurrencies and fiat currencies, which are greater than those observed in the analysis of returns. Again, in terms of mean volatility, the lowest average contribution from the system clearly corresponds to the coronavirus MCI.

Regarding the dynamic total volatility connectedness of the cryptocurrencies and fiat currencies during the COVID-19 pandemic crisis, Fig. 9 shows again that this volatility connectedness measure oscillates over time. Specifically, this connectedness measure presents a peak at the beginning of the sample period (January 2020), decreases during February and increases at the beginning of the first wave of the COVID-19 pandemic. This level is slightly higher during this first wave of the global crisis, decreases after the first wave, and is again higher during the second wave of the pandemic until the end of the sample. In contrast

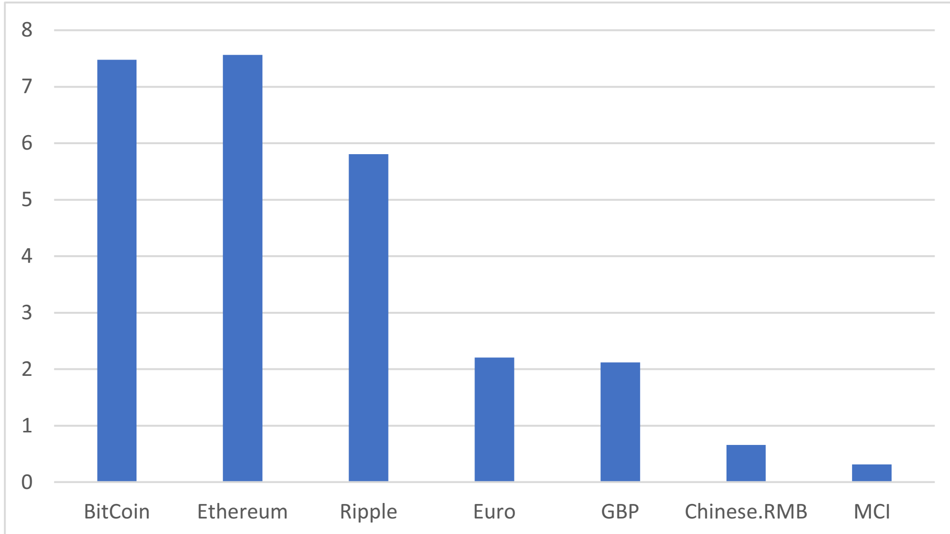

Fig. 7. Mean contribution TO the system of each variable (in volatility) *Notes*: We study the return connectedness between the three biggest cryptocurrencies (Bitcoin, Ripple and Ethereum), the fiat currencies for GBP, Euro and Chinese Yuan, and the RavenPack media coverage index (MCI), within the TVP-VAR framework (Antonakakis and Gabauer, 2017).

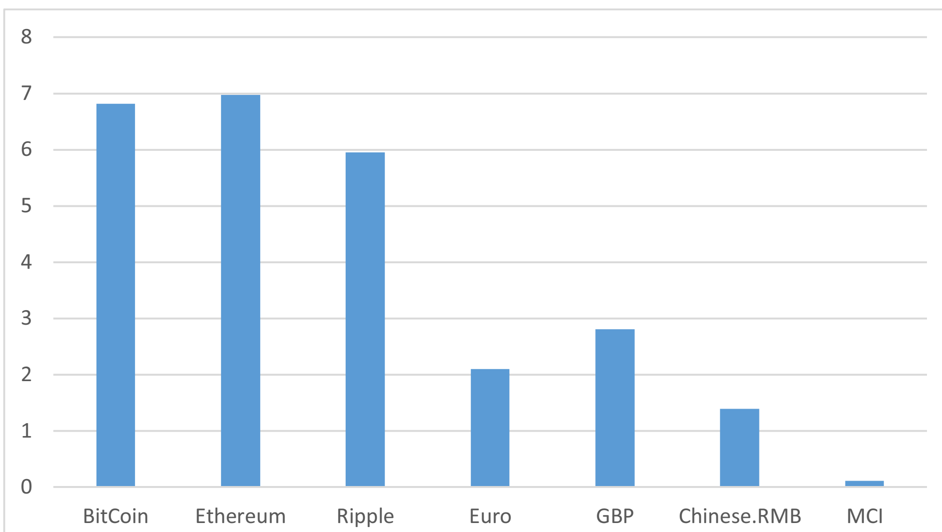

Fig. 8. Mean contribution FROM the system to each variable (in volatility) *Notes*: We study the return connectedness between the three biggest cryptocurrencies (Bitcoin, Ripple and Ethereum), the fiat currencies for GBP, Euro and Chinese Yuan, and the RavenPack media coverage index (MCI), within the TVP-VAR framework (Antonakakis and Gabauer, 2017).

with some previous studies (Umar et al., 2020), the course of the total connectedness measure in terms of volatility is less smooth than that in terms of returns. According to Bouri et al. (2021), financial spillover is especially high during turbulent periods such as the global COVID-19 pandemic crisis.

To better distinguish between transmitter and receiver profiles for the currencies included in this study during the first and second waves of the COVID-19 pandemic crisis, the dynamic total volatility connectedness is separated into two different measures: the dynamic volatility connectedness to (Fig. 10) and from (Fig. 11) the system. First, the most relevant transmitters to the system in terms of volatility among the currencies included in this study are the cryptocurrencies (Ethereum, Bitcoin—virtually the same—and Ripple, respectively). In addition, there is a huge distance between the evolution of these currencies and the fiat currencies analysed in this research (the euro, GBP and yuan). Therefore, these results are quite similar to those obtained in terms of returns. Furthermore, all cryptocurrencies show a pronounced peak in January 2020, dropping later in February 2020. This measure of volatility of the connectedness to the system increases just at the beginning of the first wave of the COVID-19 pandemic crisis. After this, the level of this connectedness measure is maintained during this first wave of the COVID-19 crisis, decreases slightly at the beginning of the second wave, increases during this wave, and is maintained at the level reached up to the end of the period analysed in this paper. Furthermore, the evolution of fiat currencies is more stable over time. We only observed an increase before the first wave of the pandemic crisis, first in the GBP and then in the euro. Finally, for the coronavirus MCI, the volatility connectedness to the system is greater at the beginning of the COVID-19 pandemic crisis period, decreases in February 2020 and remains practically zero until the end of the sample, as expected.

Regarding the dynamic total volatility connectedness from the system, again, there are relevant differences between cryptocurrencies and

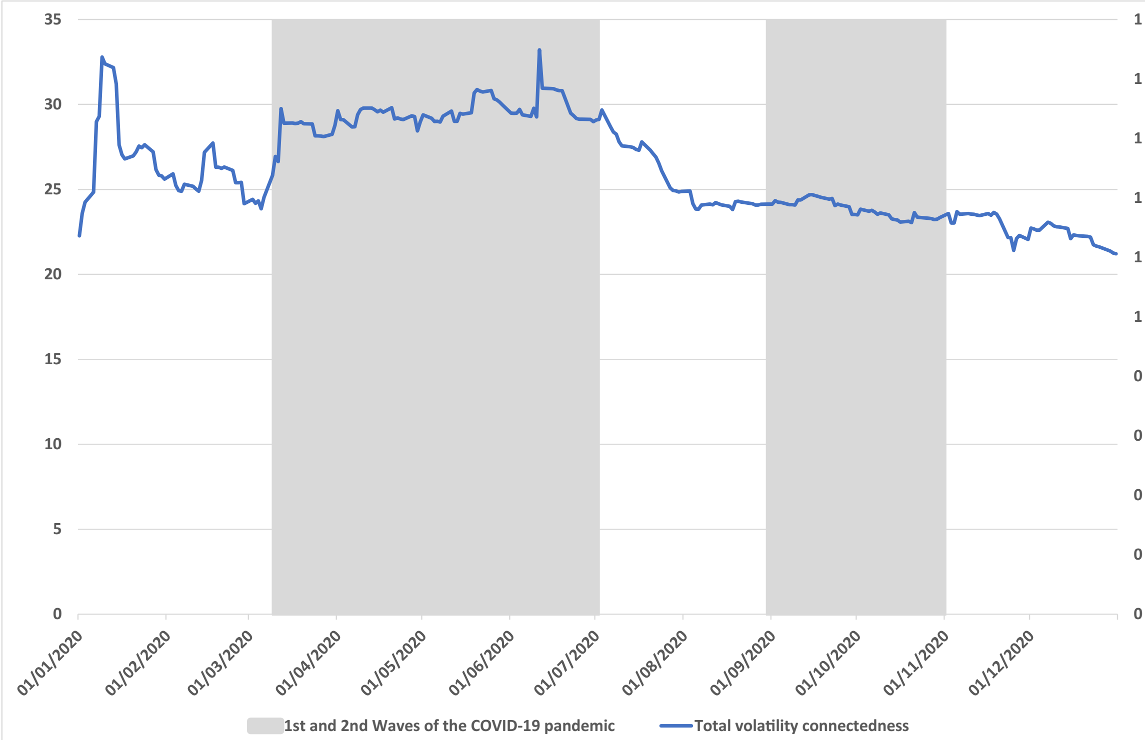

Fig. 9. Dynamic total volatility connectedness over time *Notes*: We study the return connectedness between the three biggest cryptocurrencies (Bitcoin, Ripple and Ethereum), the fiat currencies for GBP, Euro and Chinese Yuan, and the RavenPack media coverage index (MCI), within the TVP-VAR framework (Antonakakis and Gabauer, 2017).

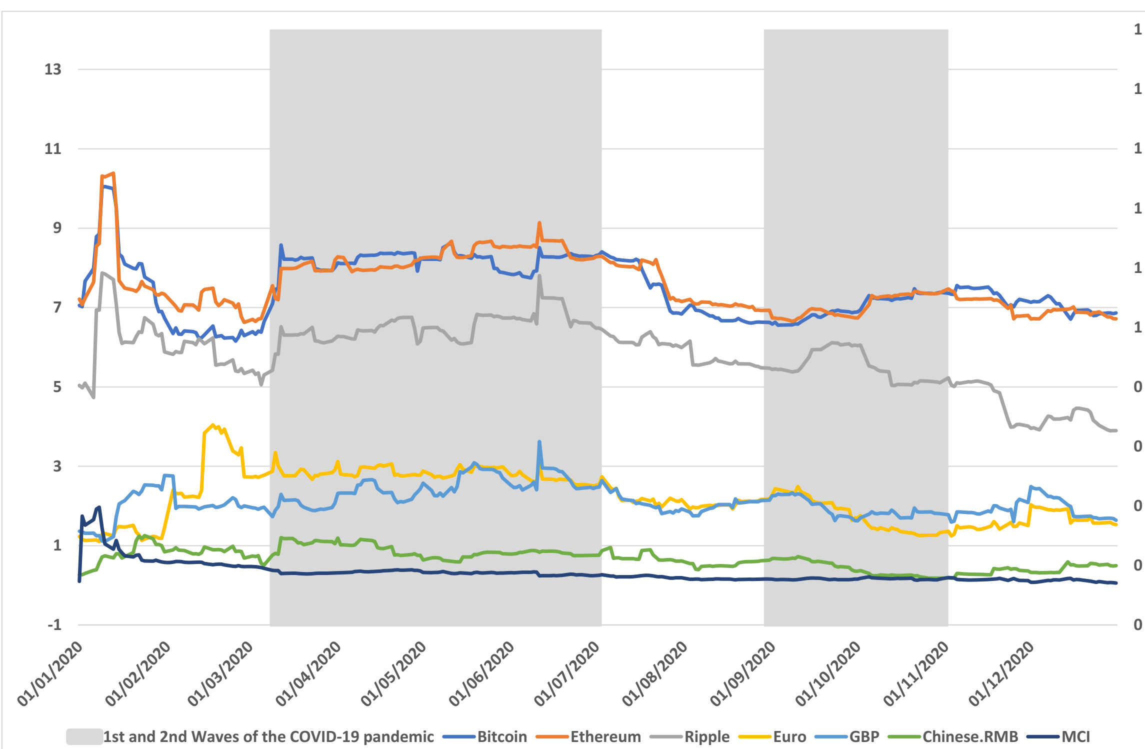

Fig. 10. Dynamic contribution of the selected cryptocurrencies and fiat currencies TO the system (in volatility) *Notes*: We study the return connectedness between the three biggest cryptocurrencies (Bitcoin, Ripple and Ethereum), the fiat currencies for GBP, Euro and Chinese Yuan, and the RavenPack media coverage index (MCI), within the TVP-VAR framework (Antonakakis and Gabauer, 2017).

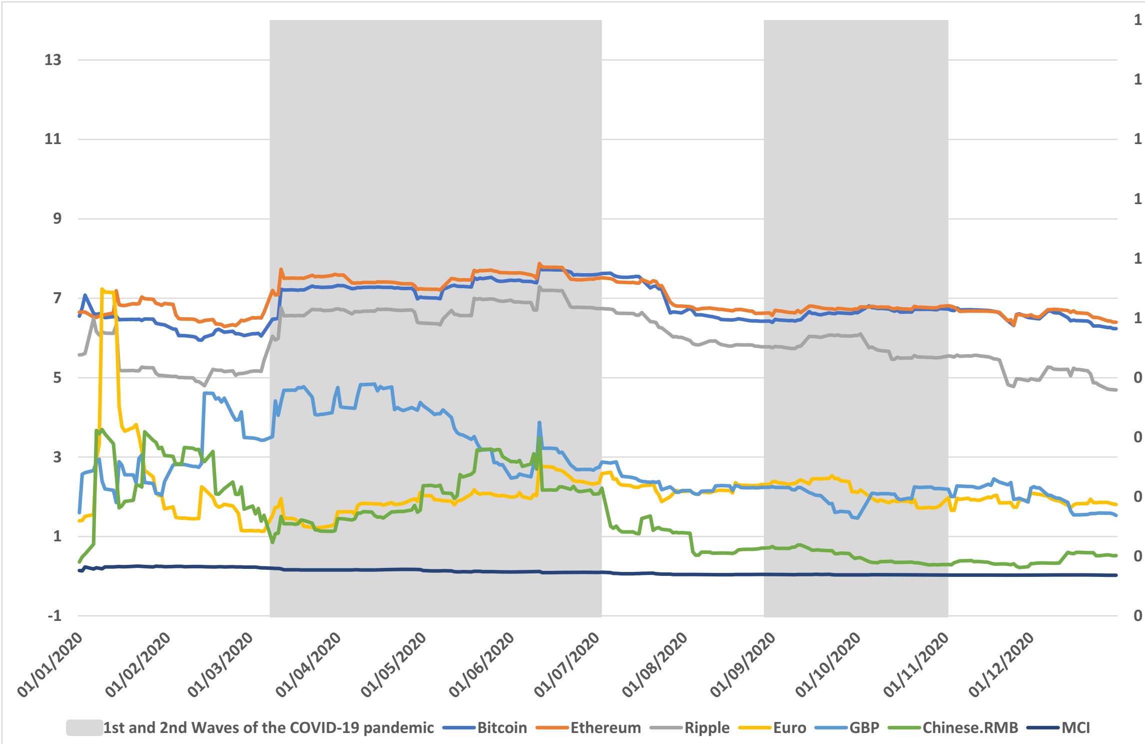

Fig. 11. Dynamic contribution FROM the system to the selected cryptocurrencies and fiat currencies (in volatility) *Notes*: We study the return connectedness between the three biggest cryptocurrencies (Bitcoin, Ripple and Ethereum), the fiat currencies for GBP, Euro and Chinese Yuan, and the RavenPack media coverage index (MCI), within the TVP-VAR framework (Antonakakis and Gabauer, 2017).

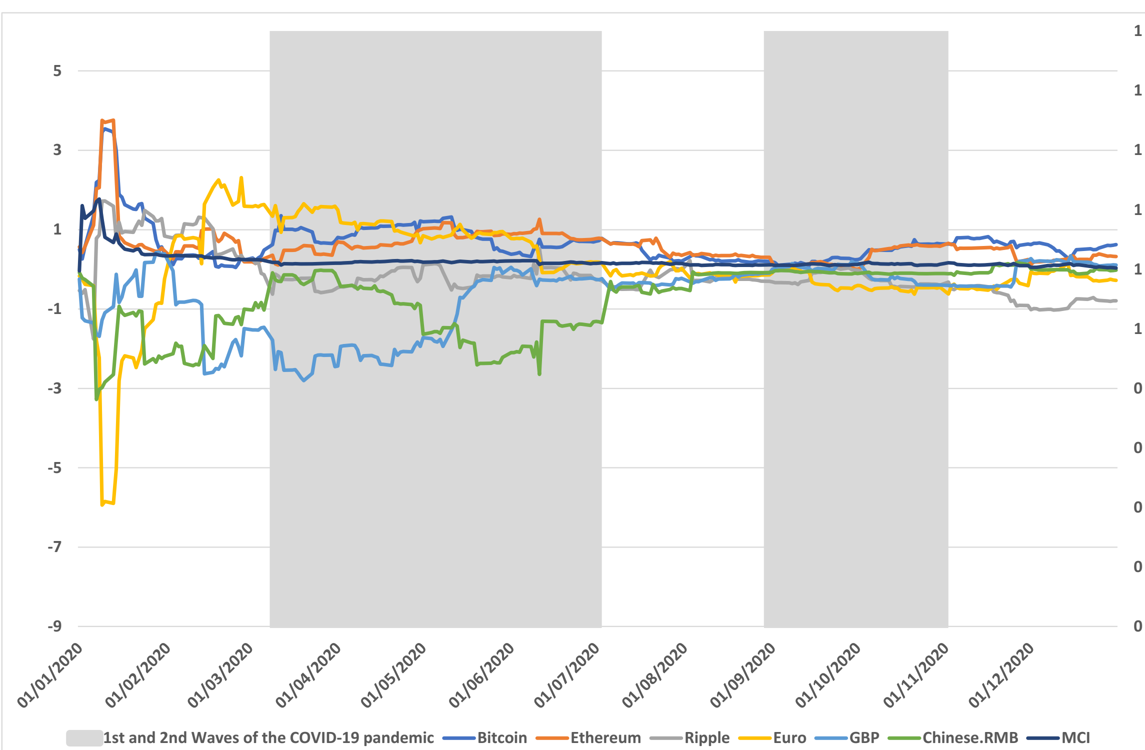

Fig. 12. Net dynamic total connectedness (in volatility) *Notes*: We study the return connectedness between the three biggest cryptocurrencies (Bitcoin, Ripple and Ethereum), the fiat currencies for GBP, Euro and Chinese Yuan, and the RavenPack media coverage index (MCI), within the TVP-VAR framework (Antonakakis and Gabauer, 2017).

fiat currencies. However, these differences are less than those observed for the previous connectedness measure. Even the euro shows a surprising peak in the month of January, i.e., becoming the currency with the highest connectedness from the system, then decreases drastically at the beginning of February, and is even below those of the other fiat currencies at that time and in several subsequent stretches of the sample period. Furthermore, it should be noted that the cryptocurrencies show a similar evolution with decreased connectedness at the beginning of the sample, increased values at the beginning of the peak of the coronavirus pandemic (during the first wave) and values that maintained their level until they started to decrease slightly at the end of the sample period. In contrast, the fiat currencies show differences between them, again with the opposite evolution between the GBP and yuan. Especially, between the months of February and July 2020, the connectedness measures of both currencies decrease, and this also occurs midway through the second wave of the pandemic and up to the end of the sample period. It is interesting to note the high level observed in the connectedness from the system for the GBP during the months of March to May 2020 (first wave of the pandemic). Finally, the coronavirus MCI has a practical nil connectedness measure.

Conclusively, Fig. 12 exhibits the net dynamic total volatility connectedness, which is the difference between the connectedness to and from the system, for the cryptocurrencies and fiat currencies in the SARS-CoV-2 pandemic crisis. Thus, this measure reveals which currencies are net transmitters or net receivers. First, we note that the differences between the net dynamic connectedness of the different currencies analysed are much greater at the beginning of the sample period (before and during the first wave of the pandemic) than at the end because this connectedness measure has high vast volatility. In fact, these differences are substantial during the months of January and February 2020, although they slightly decrease at the epicentre of the first wave of the SARS-CoV-2 pandemic. After the end of the first wave of the pandemic and during the second part of the second wave of the coronavirus crisis, the net dynamic volatility connectedness is similar for all the currencies analysed, all of which are approximately zero. Last, these differences become somewhat larger again at the end of the second wave and beyond. Examining the results more closely, there still seems to be a difference between the net connectedness of the cryptocurrencies and the net connectedness of the fiat currencies. In particular, Bitcoin, Ethereum and Ripple appear to be net transmitters (Antonakakis et al., 2019a, 2020; Adekoya and Oliyide, 2021), although at specific moments, their net dynamic volatility connectedness could be negative. Regarding the fiat currencies, their role changes throughout the sample period, starting with a net receiver profile between January and February 2020, with the negative peak observed for the euro being particularly large (in line with Elsayed et al. 2020, for the Chinese yuan and GBP). However, the euro shows a dramatic increase in the net connectedness measure analysed in terms of volatility in the months of February and March, exhibiting the highest net transmitter profile to the system just prior to the start of the first wave of the pandemic (same result found in Antonakakis et al. 2019b and 2020). At the epicentre of the COVID-19 crisis, the net connectedness of the euro begins to decline, although it remains positive, reaching negative values after the first wave and during the second wave of the pandemic until the end of the sample period. The GBP and yuan are net receivers throughout the sample period, converging to a neutral position at the end of the period analysed. Moreover, it is interesting to note that the evolution of the net dynamic volatility connectedness of these two measures is opposite: while one increases its value, the other decreases, and vice versa. Thus, the observed differences between net transmitters and receivers are more pronounced in the first part of the sample period (first wave of the pandemic) and were virtually eliminated during the second half of the sample period, although they re-emerged at the end of the second wave and until the end of the sample. Finally, the MCI is a net transmitter during the month of January 2020. Its net connectedness measure decreases until reaching values close to zero during the month of February, which are maintained until the end of the period analysed in this research. In line with Baig et al. (2021) and Bouri et al. (2021), the MCI is a net transmitter of shocks after the onset of the first wave of the SARS-CoV-2 pandemic crisis. These results show that coronavirus-related news reports generally have negative sentiment. Combined with the reduced mobility implemented by governments, the impact of this negative sentiment on business might have a strong association with the volatility of financial markets. Moreover, these results confirm that investors tried to sell more liquid securities to obtain cash since other financial assets such as investment-grade corporate and municipal bond ETFs are traded at large discounts relative to their net asset values during crisis periods (Bouri et al., 2021).

4.3. Pairwise spillovers between the virtual and fiat currencies selected in this study and the coronavirus MCI

Finally, Fig. 13 and Fig. 14 show the pairwise connectedness between the three most important virtual (Bitcoin, Ethereum and Ripple) and fiat (the euro, GBP and Chinese yuan) currencies and the coronavirus MCI in terms of returns and volatility, respectively.

Thus, in terms of returns, the pairwise connectedness analysed in this study moves significantly over time. It is highly volatile at the beginning of the sample period due to the uncertainty generated by the cases of people affected by SARS-CoV-2 before the declaration of a global pandemic on March 11, 2020, by the World Health Organization (WHO). In addition, relevant increases of these pairwise spillovers are observed during the first wave of the COVID-19 pandemic, in the second wave and in what could be the beginning of a third wave of the pandemic, not included in this study. Furthermore, some pairwise spillovers are positive (Bitcoin-Chinese yuan and Bitcoin-Ethereum, among others) and others are negative (Ethereum-GBP and Bitcoin-GBP, among others), showing opposing evolutions over time.

Furthermore, in terms of volatility, the pairwise connectedness clearly shows higher volatility in the first part of the sample (before and during the first wave of the pandemic) and lower volatility in the second part (from the end of the first wave and until the end of the sample period). In addition, we find extraordinarily negative pairwise connectedness before the first wave of the pandemic for Ethereum-euro and Ripple-Chinese yuan and before and during the first wave of the pandemic for Euro-GBP, among others. Additionally, it is interesting to note an increase in the pairwise spillover for Ethereum-euro just before and during the first part of the second wave of the COVID-19 pandemic. Finally, some peaks in the pairwise spillovers related to the coronavirus MCI are observed at the beginning of the sample, just prior to the declaration of a global pandemic (GBP-MCI, Ripple-MCI, and Bitcoin-MCI, among others), reinforcing the importance of this index just prior to the first wave of the pandemic.

5. Concluding remarks

This study researches the dynamic return and volatility connectedness of the two groups of currencies: the three most relevant cryptocurrencies (Bitcoin (BTC), Ethereum (ETH) and Ripple (XRP)) and the fiat currencies of the euro, GBP and Chinese yuan. In addition, the main aim of this paper is to explore the potential impacts of the first and second waves of the COVID-19 pandemic crisis on this system; therefore, this study proposes the inclusion of the Coronavirus Media Coverage Index (MCI) and analyses the sample period from January 1, 2020, to December 31, 2020. To estimate the dynamic return and volatility connectedness measures, this paper applies the TVP-VAR approach, which is an alternative methodology to the spillover index approach of Diebold and Yilmaz (2014).

Our paper adds to the previous literature by providing fresh research on the impact of COVID-19-related news on some dynamic return and volatility connectedness measures of the three leading cryptocurrencies and the fiat currencies of the euro, GBP and Chinese yuan around the

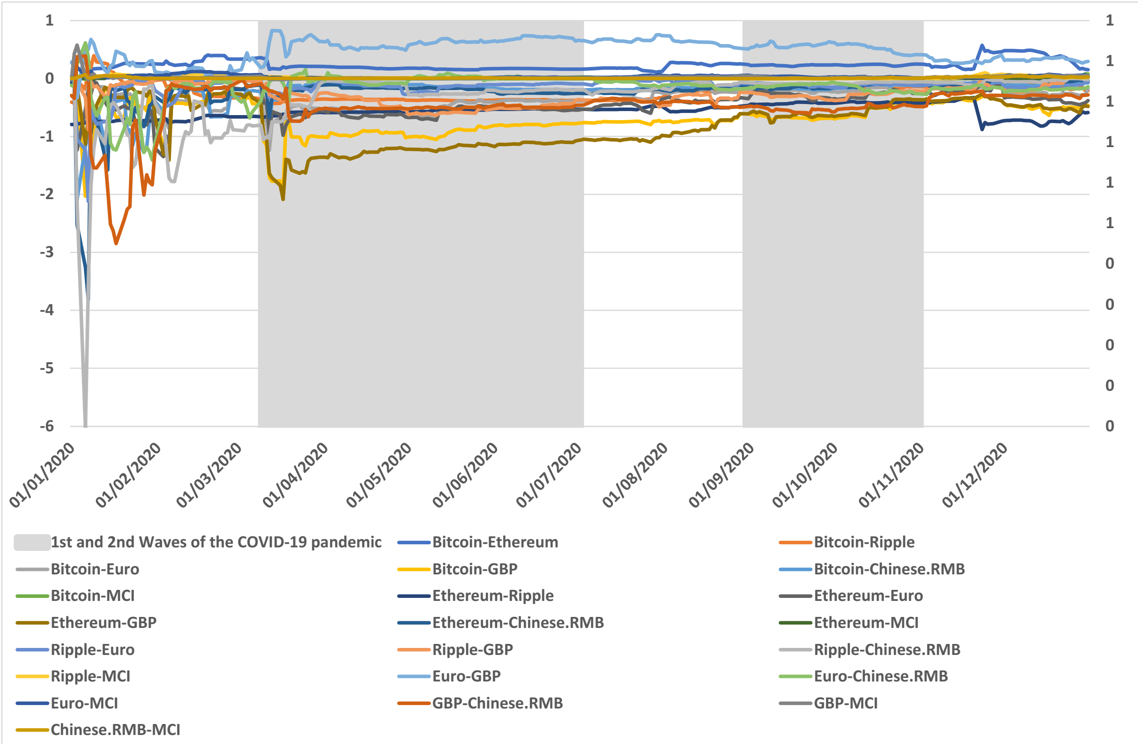

Fig. 13. Pairwise spillovers (in terms of return).

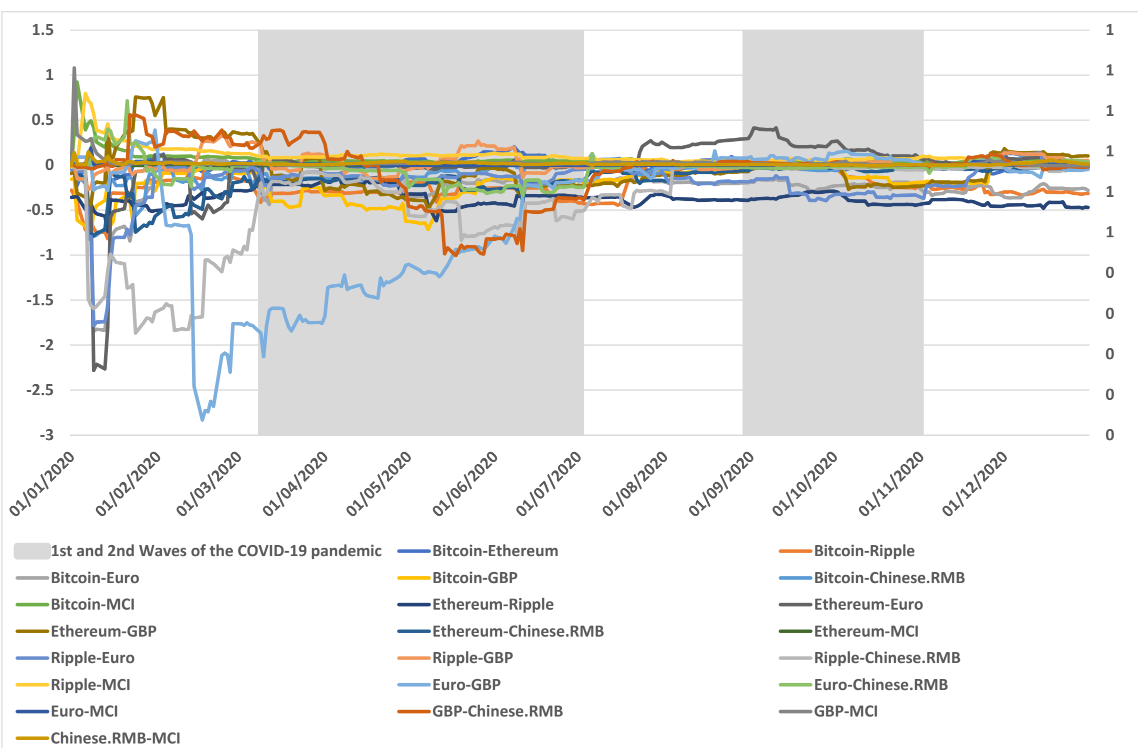

Fig. 14. Pairwise spillovers (in terms of volatility).

first and second waves of the recent global pandemic crisis by applying an extension of the Diebold and Yilmaz (2012 and 2014) methodology, the TVP-VAR approach, suitable for small samples.

We find some interesting results. First, the dynamic total return and volatility connectedness vary over time, and these estimates show two peaks: one at the beginning of the sample and one at the start of the first wave of the global pandemic spike. Second, it is possible to distinguish two clearly different behaviours between the dominant cryptocurrencies and the fiat currencies analysed in this research. Thus, the cryptocurrencies (BTC, ETH, and XRP) are net transmitters, and the fiat currencies (the euro, GBP and yuan) are net receivers not only in terms of returns but also volatility. The only exception is the euro that, in the analysis of the net dynamic volatility connectedness, shows a clear net receiver profile at the beginning of the sample and a net transmitter profile throughout the first wave of the COVID-19 pandemic crisis. This result demonstrates the special virulence of this wave of the SARS-CoV-2 coronavirus pandemic crisis in Europe. Finally, it is particularly noteworthy that the most relevant differences between the net dynamic (returns and volatility) connectedness of the two types of currencies (crypto and fiat) are located at the beginning of the sample period, just before the SARS-CoV-2 pandemic crisis spike, although some small differences occur during the first and second waves of the pandemic, but to a lesser extent. A potential explanation of these results could be that the COVID-19 outbreak may lead to investors liquidating their positions, resulting in massive demand for cash. Moreover, firms without ample cash at hand may have sought cash to continue their operations during the SARS-CoV-2 pandemic crisis. In this context, policymakers proposed a series of stimulus measures, such as fiscal packages, adjustments to labour laws, and public sector backstops, to private businesses to reduce the potential contagion effects between financial markets.

These interesting results would have policy implications because different behaviours between the dominant cryptocurrencies and the fiat currencies may require implementing alternative economic policy measures to control them in periods of economic turbulence, such as the COVID-19 pandemic crisis. Furthermore, a natural extension of this research could consist of applying this fresh TVP-VAR connectedness methodology to other relevant cryptocurrencies and fiat currencies from Europe and other economic areas of international relevance, such as the United States, South America, and Asia-Pacific areas, also hit by the global pandemic. After the crisis caused by the COVID-19 pandemic, government intervention seems necessary to reduce uncertainty.

Furthermore, additional relevant implications of our results can be applied during periods of economic turbulence because market participants such as investors and policymakers can make good use of information on the net connectedness measures to achieve some interesting goals: improve portfolio decisions and safeguard financial stability. Finally, our results could be interesting for currency traders and investors to design cross-currency hedging strategies in periods such as the coronavirus outbreak.

CRediT authorship contribution statement

Zaghum Umar: Conceptualization, Data curation, Methodology, Software, Supervision, Writing – review & editing. **Francisco Jareño:** Visualization, Investigation, Writing – original draft, Validation, Writing – review & editing, Funding acquisition, Formal analysis, Formal analysis. **María de la O González:** Investigation, Validation, Writing – review & editing, Funding acquisition, Formal analysis.

Acknowledgments

This work was supported by the Spanish Ministerio de Economía, Industria y Competitividad (ECO2017-89715-P)

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