Connectedness between cryptocurrencies, gold and stock markets in the presence of the COVID-19 pandemic

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Received 17 October 2021
Revised 21 January 2022
Accepted 8 April 2022

Abstract

Purpose – This paper analyzes the connectedness with network among the major cryptocurrencies, the G7 stock indexes and the gold price over the coronavirus disease 2019 (COVID-19) pandemic period, in 2020.

Design/methodology/approach – This study used a multivariate approach proposed by Diebold and Yilmaz (2009, 2012 and 2014).

Findings – For a stock index portfolio, the results of static connectedness showed a higher independence between the stock markets during the COVID-19 crisis. It is worth noting that in general, cryptocurrencies are diversifiers for a stock index portfolio, which enable to reduce volatility especially in the crisis period. Dynamic connectedness results do not significantly differ from those of the static connectedness, the authors just mention that the Bitcoin Gold becomes a net receiver. The scope of connectedness was maintained after the shock for most of the cryptocurrencies, except for the Dash and the Bitcoin Gold, which joined a previous level. In fact, the Bitcoin has always been the biggest net transmitter of volatility connectedness or spillovers during the crisis period. Maker is the biggest net-receiver of volatility from the global system. As for gold, the authors notice that it has remained a net receiver with a significant increase in the network reception during the crisis period, which confirms its safe haven.

Originality/value – Overall, the authors conclude that connectedness is shown to be conditional on the extent of economic and financial uncertainties marked by the propagation of the coronavirus while the Bitcoin Gold and Litecoin are the least receivers, leading to the conclusion that they can be diversifiers.

Keywords Connectedness, Cryptocurrencies, COVID-19 crisis, Gold, Spillover

Paper type Research paper

1. Introduction

Almost all markets have witnessed strong upheavals with the spread of the coronavirus disease 2019 (COVID-19) pandemic shifting to the major digital currencies, the stock indices, the oil price and commodities. The shifts in the mentioned asset volatility have proved costly for many markets. In fact, the increase of volatility has put business operations at the risk of affecting the financial system. Therefore, the global economy is in turmoil as a result of concerns over the coronavirus epidemic. No company is immune to the challenges caused by the health crisis; besides, there are understandable concerns about the damage caused to the worldwide economy. During the propagation of the COVID-19 worldwide, an insurmountable fear was behind a global stock market crash. The 2020 stock market crash, also referred to as the Coronavirus Crash, was a major and sudden global stock market crash that began on 20 February 2020.

European Journal of Management and Business Economics
Emerald Publishing Limited
e-ISSN: 2444-8494
p-ISSN: 2444-8451
DOI 10.1108/EJMBE-10-2021-0281

The impact of the COVID-19 on the volatility of markets exceeded the one caused by the 2008 global financial crisis and continues to have an effect (Zhang and Hamori, 2021a). The pandemic created an unprecedented level of risk, such as oil triggering stock markets, which was accompanied by heavy losses for investors. As a result, the Paris Stock Exchange fell from 8.39% to 4,707.91 points at the close, its worst session since 2008 [1]. Then, the Wall Street had its worst downturn since 2008 as the coronavirus fears have wiped off almost 32%, or roughly $9 trillion, from the value of the benchmark S&P index since its record closing high on February 19, 2020 [2]. Moreover, the Dow Jones entered "bear market" territory [3] as it fell by 1,465 points or 5.9%. This was enough to put it more than 20% lower than the index recent high point on 12 February 2020. On the other hand, the Nikkei reached its lowest point in 30 years amid worsening virus fears [4]. Recent research studies evaluated and quantified the unexpected outbreak effects of the global pandemic on the stock markets' performance and proved its reducing effect in the USA (Yousfi *et al.*, 2021), in the African countries (Owusu Takyi and Bentum-Ennin, 2020), and in the USA, Japan and Germany, where the impact of the COVID-19 exceeded that of the 2008 financial crisis (Zhang and Hamori, 2021a), etc.

On the other hand, although they are new digital currencies, which established a new distributed payment system on the basis of crypto-graphical protocols which can ensure anonymity, low cost and fast speed of peer-to-peer transactions, cryptocurrencies are not immune to this financial crash caused by the new pandemic. Therefore, the major cryptocurrencies has plummeted to its lowest level since March as a stronger dollar and investor nerves strip off nearly $140bn in cryptocurrency market cap. For example, over two days in January, it plunged to 21%, which is its biggest decline since March 2019. On the other hand, Ethereum fell to 12%. The smaller coins, XRP and Litecoin shed about 18% each [5]. The BTG, which was created in 2017 to counter the centralization of Bitcoin, was notably volatile during 2020 with record in March 2020 [6]. In fact, several researchers, such as Mnif *et al.* (2020), Demir *et al.* (2020), Umar and Gubareva (2020), Bergeron *et al.* (2020), Salisu and Ogbonna (2021) and Yarovaya *et al.* (2021), studied the impact of the COVID-19 on the cryptocurrency market efficiency.

While correlations among most types of assets significantly increased, gold was the only asset to increase in value in 2020. At the time of the market turmoil, investors are more interested in gold as a safe-haven asset (Baur and Lucey, 2010; Shahzad *et al.*, 2019). This precious metal is unconnected with other assets (Baur and Lucey, 2010) and is still considered to be a zero-beta asset (McCown and Zimmerman, 2006). Among all the commodities, gold has the longest duration in the high volatility regime (Choix and Hammoudeh, 2010). In fact, the rising feeling of fear and the investors' pessimism observed during crises caused an increase of demand for gold, which results in an increase of volatility (Ghorbel, 2018). Moreover, several studies, such as those of Baur and McDermott (2010) and Creti *et al.* (2013), proved the safe-haven role of gold, particularly during the stock market crises (Anand and Madhogaria, 2012; Arouri *et al.*, 2015; Chkili, 2016; Chen and Wang, 2017; Junttila *et al.*, 2018).

Given this volatile time, we intend to study the time-varying volatility and the volatility transmission mechanisms across the most widely traded cryptocurrencies, stock indices and gold. This would be essential for both international investors and policymakers. In fact, so far, the common consensus has proven the weak correlations between cryptocurrencies and other assets. However, several observations allow revisiting this consensus (Kristoufek, 2015; Yermack, 2013a, b; Blau, 2017; Bouri *et al.*, 2018a; Jiang *et al.*, 2021). Therefore, we study the pairwise and total connectedness among the stock indices, the major cryptocurrencies and gold. Thus, our empirical study sheds lights on the literature regarding the linkages between financial and commodity markets. We particularly use data relevant for eight popular cryptocurrencies, namely Bitcoin, Dash, Ethereum, Monero, Maker, Bitcoin Gold, Litecoin and Ripple, stock indices for seven developed countries (American index S&P500,

British index FTSE, Japanese index Nikkei, German index Dax 30, Canadian index SP/TSX, French index CAC40 and Italian index FTSE MIB) and gold price.

In retrospect, this study goes one step further and contributes to the existing literature in a number of ways. First, while several research studies on the relationship between the Bitcoin and other traditional assets emerged to assess whether the Bitcoin can be used as a safe-heaven, a diversifier or a hedging asset (see, e.g. Brière *et al.*, 2015; Dyhrberg, 2016; Bouri *et al.*, 2018a, b, c; Baur *et al.*, 2018a, b; Corbet *et al.*, 2018; Feng *et al.*, 2018; Giudici *et al.*, 2018; Ji *et al.*, 2018; Symitsi and Chalvatzis, 2019), our study focuses on the eight major cryptocurrencies. Second, our analysis during the COVID-19 pandemic enabled us to revisit the common consensus regarding the weak correlation between the cryptocurrencies and the stock markets and also detect the risk of contagion. Third, our study shows to what extent the relationship between gold, the stock indexes and the cryptocurrencies can be understood in a systemic way. Fourth, our hedging effectiveness analysis is set to assess the roles of the cryptocurrencies, the stock indexes and gold in a crisis period. Doing so, we extend the correlation analysis and help portfolio hedgers to make optimal portfolio allocations, engage in risk management and forecast future volatility in financial assets and commodity markets.

We proceed as follows. The second section will present the literature review. In section 3, we discuss the construction of our sample and introduce the connectedness method proposed by Diebold and Yılmaz (2014) to investigate the investors' strategies in relation to cryptocurrencies, stock indices and gold, where we propose the data description and the summary statistics. In section 4, we provide results for the static and dynamic information spillover effect, and finally, in section 5, we conclude the paper.

2. Literature review

A large strand of literature has focused on the mutual dependencies between cryptocurrencies, stock indexes, oil and other commodities (Kurka, 2017; Corbet *et al.*, 2018; Tiwari *et al.*, 2019, 2020; Ji HoKwon, 2020; Yitong Hu *et al.*, 2020; Ahsan Bhuiyan *et al.*, 2021; Yonghong Jiang *et al.*, 2021; Lahiani *et al.*, 2021; Caferra and Vidal-Tomás, 2021). This line of thoughts is interesting and considered as a new topic because it especially considers the increased integration between financial markets in crisis period. Therefore, studying connectedness among different assets is important for two major reasons. First, the portfolio performance depends on the investor's portfolio selection and on the structure of its components (Baumöhl *et al.*, 2018). Second, policymakers could benefit from the information transmitted across assets to broadcast their policies (Ciner *et al.*, 2013). This explains the existence of a large empirical literature trying to better understand the mutual dependencies among various asset classes.

Moreover, recent studies have concentrated on the safe haven and the various roles of cryptocurrencies with respect to traditional assets (Bouri *et al.*, 2018a, b, c; Selmi *et al.*, 2018; Urquhart and Zhang, 2019), especially with the stock indices because of their universality (Dyhrberg, 2016; Bouri *et al.*, 2018a, b, c, 2020; Jiang *et al.*, 2021). Using numerous methods and techniques, it was proved that the major cryptocurrencies are in general isolated from conventional assets (Dyhrberg, 2016; Aslanidis *et al.*, 2019; Charfeddine *et al.*, 2020; Bouri *et al.*, 2020; Ghorbel and Jeribi, 2021a). However, the novel approach is to challenge this common consensus regarding the weak correlation between cryptocurrencies and the stock markets. This is explained by the fact that the cryptocurrency prices are determined by the same standard fundamental factors as in traditional assets (Kristoufek, 2015), besides their speculative nature (Yermack, 2013a, b; Blau, 2017; Bouri *et al.*, 2018a, b, c) may increase information transmission, risk contagion and the downturn between cryptocurrencies and the stock markets during the COVID-19 pandemic. For their part, Jiang *et al.* (2021) proved their dependence. In fact, it becomes interesting to challenge this traditional consensus in crisis period marked by the spread of a new global pandemic COVID-19, which destabilized the economic and financial system in the first quarter of 2020.

Furthermore, several studies presented some empirical findings on connectedness between cryptocurrencies, stocks and other assets. In this sense, Kurka (2017) documented a very low connectedness between Bitcoin and gold, oil, S&P500 and treasury notes. Moreover, Corbet *et al.* (2018) confirmed that Bitcoin, Ripple and Litecoin are isolated from other financial and economic assets, such as VIX, Bond, Gold, FX, S&P500 and GSCI. More recently, Tiwari *et al.* (2019) have used a copula-ADCC-EGARCH model to examine the time-varying asymmetric correlation between cryptocurrencies and stock returns in the USA markets. They found that Litecoin is the most efficient hedge asset against the risk in the USA stock market. While for the BRICS and developed countries, Lahiani *et al.* (2021) investigated the dependence between cryptocurrencies and the stock market returns and found evidence for the predicting role of BSE 30 for cryptocurrencies while the Bitcoin future reshaped the tail dependence between cryptocurrencies and the stock returns. As for Mokni *et al.* (2020), they took into account the economic policy uncertainty and proved its negative effect on the dynamic conditional correlation between Bitcoin and the USA stock markets only after the Bitcoin crash of December 2017. However, before the crash, they documented the existence of a positive association between the economic policy uncertainty and the weight of Bitcoin in the portfolio. Furthermore, in order to classify cryptocurrencies, Ji HoKwon (2020) proved that they are an alternative for a medium of exchange and a means of investment being far from a commodity. For their part, Ahsan Bhuiyan *et al.* (2021) also tried to identify the interrelationship between Bitcoin and the different asset classes. In fact, they found evidence of a strong bidirectional causality between gold and Bitcoin and a neutral relationship with the aggregate commodity index, crude oil, and the US dollar index. This relative isolation of Bitcoin proves its quality as a diversifier. As for Yonghong Jiang *et al.* (2021), they emphasized this finding through a novel quantile coherency approach. They proved that cryptocurrencies failed to be a strong hedge or safe haven against the stock markets while they could be diversifiers especially during the March 2020 market recession. To draw generalized conclusions, Yitong Hu *et al.* (2020) investigated the impact of the investor's attention allocation on the worldwide stock returns during extreme the Bitcoin movements. They found that these shock events decrease worldwide the stock returns especially in the emerging countries. Considering the COVID-19 pandemic, Caferra and Vidal-Tomás (2021) studied the behavior of cryptocurrencies and stock markets. They found that the price dynamics during the pandemic depends on the type of the market. In other words, despite the fall of both cryptocurrencies and stock indexes, cryptocurrencies promptly rebounded, while stock markets were trapped in the bear phase. In the same line of thoughts, Ghorbel and Jeribi (2021a) investigated the relationships between the volatilities of five cryptocurrencies, American indices (S&P500, Nasdaq, and VIX), oil, and gold and found that cryptocurrencies are diversifiers during the stability period but not a safe haven for US investors during the coronavirus crisis.

The previous empirical works have examined the volatility connectedness or spillover effects across different financial assets, which motivated us to use a newly developed systemic framework to investigate the volatility connectedness in the cryptocurrency market, stock market and gold during the crisis period. Therefore, this study is intended to fill the gap and explicitly incorporate these issues to revisit the crypto–stock–gold time-varying relationship from a global perspective. This paper also aims at answering the following questions: If the global financial markets, the crypto-currency market and gold are directly connected with financial markets, which assets can be diversifiers for investors?

3. Methodology

In this section, we will present the multivariate time-series approach proposed by Diebold and Yilmaz (2009, 2012, 2014) to investigate the crypto–gold–stock index relationship from a global perspective. In fact, the authors proposed an analytical framework that makes it possible to produce different types of connectivity from the same method: exposure, influence or global connectivity. Moreover, they made the data of different entities interact in a VAR/ VECM model and used generalized variance decomposition as the network adjacency matrix. This matrix gives an almost complete description of a network at a given time. The authors applied this method recursively to obtain the evolution of connectivity over time, which enabled them to paint a picture of the network of the major US financial institutions from a series of financial volatilities then analyze the changes in this network as the crisis unfolds. In fact, this approach fits our topic since our objective is to study the connectedness with network among the major cryptocurrencies (Bitcoin, Dash, Ethereum, Monero, Maker, Ripple, Litecoin and Bitcoin gold), the G7 stock indexes and the gold price over the COVID-19 pandemic period. We therefore used data for eight major cryptocurrencies, seven stock indexes and gold during 2020. Like Zhang and Hamori (2021b), we used the returns measured by the changes in the daily prices.

To account for interdependence in financial markets, Diebold and Yilmaz (2009) introduce a simple measure of connectedness called the multivariate time-series approach. This approach based on a vector autoregressive model (VAR) and the generalized forecasting variance decomposition method which is used to look at spillover effects in the global financial market. Due to its simplicity and flexibility, this connectedness measure has been widely applied in information spillover (Diebold and Yilmaz, 2012; Zhang and Hamori, 2021b; Ji *et al.*, 2018). The detailed procedure is as follows.

First, consider aK variable VAR model with p lagged number:

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

where y_t is a $(K \times 1)$ vector of variables at date t, Φ_i is autoregressive coefficient matrix and ε_t is a $(K \times 1)$ vector of error terms that are assumed to be serially uncorrelated. Given a stationary covariance of the VAR system, a moving average representation is written as $y_t = \sum_{j=0}^{\infty} A_j \varepsilon_{t-j}$, where the $n \times n$, coefficient matrices $A_j = \Phi_1 A_{j-1} + \Phi_2 A_{j-2} + \ldots + \Phi_p A_{j-p}$ with A_0 is the $n \times n$ identity matrix and $A_j = 0$ for $j < 0$.

To calculate the variance contribution of variable j to variable i, $\theta_{ij}(H)$, Koop *et al.* (1996) and Pesaran and Shin (1998) proposed the following H-step-ahead generalized forecast error variance decomposition:

$$\theta_{ij}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' A_h \sum e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' A_h \sum A_h' e_i\right)} \tag{2}$$

Σ is the variance matrix of the vector of errors ε,σ_{jj} is the standard deviation of ε_j and e_i is a selection vector with a value of one for the i^{th} element, and zero elsewhere. Because the row sums of the variance decomposition matrix are not necessarily equal to one, each entry in the matrix $\theta(H)$ is normalized by the row sum and hence the row sum will be equal to one. Each entry in the $k \times k$ matrix $\theta(H) = [\theta_{ij}(H)]$ measures the contribution of variable j to the forecast error variance of variable i at horizon H, $C_{i \leftarrow j}^{H}$. Note that in general $C_{i \leftarrow j}^{H} \neq C_{j \leftarrow i}^{H}$, hence, the main diagonal elements of the $\theta(H)$ matrix represent the own-variable contributions, while the off-diagonal elements represent the cross-variable contributions. Table 1 illustrates the various connectedness measures and their relationships.

Finally, net pairwise connectedness, directional connectedness and total connectedness can be calculated using the generalized forecast error variance decomposition approach (FEVD).

3.1 Net pairwise connectedness

Due to the asymmetric effect between two variables and because $C^H_{i\leftarrow j} \neq C^H_{j\leftarrow i}$, we measure the net pairwise connectedness as the difference between $C^H_{i\leftarrow j}$ *and* $C^H_{j\leftarrow i}$. Such difference, $C^H_{i\leftarrow j} - C^H_{j\leftarrow i}$, measures the net spillover effect from variable j to variable i. Based on net pairwise connectedness, a directional connectedness network can be built. In such network, each node represent an index, and a directional edge from j to i exists in the network if $C^H_{i\leftarrow j} - C^H_{j\leftarrow i}$ is positive.

3.2 "From" and "To", the total directional connectedness

In Table 1, "From" column and "To" row measure the total directional connectedness from and to each market. Total directional connectedness "From" is defined as the information spillover from other markets to one market and this number is between 0 and 1. Whereas, total directional connectedness "To" represents the information spillover from one market to other markets, and this number is not bounded by 1.

3.3 Net total directional connectedness

The difference between total directional connectedness "To" and "From" of one market measures the net information spillover contribution.

3.4 Total connectedness for the system

The average of total directional connectedness "From" or "To" for all the variables measures the total connectedness of the system, which is a representative indicator of the market integration and convergence.

The full-sample connectedness approach does not help us understand the connectedness dynamics, for this reason, Diebold and Yilmaz (2009) extend this measure by allowing for time-varying spillover effects. In the dynamic version of the measure, the used method

Table 1. Connectedness table based on the FEVD approach

	y_1	y_2	..	y_K	*From*
y_1	$C^H_{1\leftarrow 1}$	$C^H_{1\leftarrow 2}$	..	$C^H_{1\leftarrow K}$	$F_{1\leftarrow j} = \sum_{j=1}^{K} C^H_{1\leftarrow j}, j \neq 1$
y_2	$C^H_{2\leftarrow 1}$	$C^H_{2\leftarrow 2}$	..	$C^H_{2\leftarrow K}$	$F_{2\leftarrow j} = \sum_{j=1}^{K} C^H_{2\leftarrow j}, j \neq 2$
:	:	:		:	:
y_K	$C^H_{K\leftarrow 1}$	$C^H_{K\leftarrow 2}$	..	$C^H_{K\leftarrow K}$	$F_{K\leftarrow j} = \sum_{j=1}^{K} C^H_{K\leftarrow j}, j \neq K$
To	$T_{i\leftarrow 1} = \sum_{i=1}^{K} C^H_{i\leftarrow 1}$ $i \neq 1$	$T_{i\leftarrow 2} = \sum_{i=1}^{K} C^H_{i\leftarrow 2}$ $i \neq 2$	..	$T_{i\leftarrow K} = \sum_{i=1}^{K} C^H_{i\leftarrow K}$ $i \neq K$	$\frac{1}{K}\sum_{i,j=1}^{K} C^H_{i\leftarrow j}$ $i \neq j$
Net	$T_{i\leftarrow 1} - F_{1\leftarrow j}$	$T_{i\leftarrow 2} - F_{2\leftarrow j}$	..	$T_{i\leftarrow K} - F_{K\leftarrow j}$	

Note(s): Following Diebold and Yilmaz (2009, 2014) and Zhang (2017), H is set to be 10 days remains the same, but it is applied in the overlapping sub-samples. In such case, the dynamic measure of connectedness is different from a simple average of the rolling-window measures, due to the fact that the latter is obtained from different VARs models. In the dynamic version, we will be able to analyze how individual components contribute to the system over time and how much information it gains from it. Also, the dynamic model allows us to show the time-varying connectedness in the system. In this paper, the choose of the size of the rolling window is selected based on guidelines indicating that it should not be too large or too small; otherwise, it leads to estimations bias. Therefore, we choose a rolling-window size of approximately 30% of daily observations (which equal to 135) [7].

We would note that several studies on time-varying parameter vector autoregressions (TVP-VAR) dynamic connectedness have progressively begun to appear (see, Gabauer and Gupta, 2018; Antonakakis *et al.*, 2018, 2019a, b, c; Chatziantoniou *et al.*, 2022). Specifically, Antonakakis and Gabauer (2017) and Korobilis and Yilmaz (2018) both proved evidence of the superiority of TVP-VAR connectedness estimation.

4. Data and empirical results

This section mainly presented the data and analyzes the static and dynamic spillover effect across global financial system for Gold, eight major cryptocurrencies (Bitcoin, Dash, Ethereum, Monero, Litecoin, Bitcoin Gold, Maker and Ripple) and major stocks of France, USA, Britain, Italy, Canada, Germany and Japan. We will focus on connectedness at a variety of levels, from pairwise connectedness for cryptocurrencies, stock indices and Gold to the total connectedness and from the static connectedness that measures the unconditional average of connectedness over the full sample to the dynamic that represents the conditional connectedness and its movements during a crisis period.

The descriptive statistics of these return series are reported in Table 2 while the summary statistics of cryptocurrencies show that evidently, the unconditional variance of the Bitcoin is the lowest volatility, followed by that of Ripple. This means that the Bitcoin exhibits the lowest volatility and thus remains the safest currency vis-à-vis the other studied cryptocurrencies; besides, it offers the highest average returns. Meanwhile, Bitcoin Gold has experienced the lowest return and the highest volatility. This indicates that it is the most volatile and thus, the riskiest. Amid indices, Dax 30 and S&P500 offer the highest average returns and FTSE the

Variables	Mean	Standard deviation	Min	Max	Skewness	Kurtosis	Jarque–Bera
BITCOIN:BTC	0.226	4.833	−49.728	20.078	−2.508	29.161	19345
Dash	−0.039	6.520	−50.029	56.488	0.600	22.655	5028.9
ETHEREUM:ETH	0.169	5.823	−57.987	21.063	−2.414	25.229	2143.5
MONERO:XMR	0.090	5.591	−51.954	17.630	−2.192	18.888	2781
LITECOIN:LTC	−0.234	5.144	−14.723	29.062	0.586	4.290	4872.7
BITCOIN GOLD:BTG	−0.268	6.570	−54.495	71.658	1.938	46.286	1982.4
MAKER: MKR	−0.101	6.552	−81.821	31.419	−4.233	60.814	37815.8
RIPPLE: XRP	−0.106	4.995	−18.813	32.182	1.123	7.492	10542.3
Gold	0.092	1.027	−4.737	5.600	0.318	6.746	428.9
FTSE	−0.018	1.456	−11.512	8.667	−1.470	14.893	18543
CAC40	0.018	1.624	−13.098	8.056	−1.766	14.642	14287.1
FTSEMIB	0.026	1.805	−18.541	8.549	−3.341	33.005	13982.7
DAX30	0.049	1.649	−13.055	10.414	−1.156	15.404	17251.6
NIKKEI	0.047	1.150	−5.128	5.972	−0.085	4.085	20465
SP/TSX	0.028	1.652	−13.176	11.294	−1.801	26.481	21587.1
S&P500	0.049	1.773	−12.765	8.968	−0.996	13.576	31578.2

Table 2.
Descriptive statistics

lowest return (even negative). Besides, the FTSEMIB has the highest volatility and NIKKEI the lowest one. This means that the NIKKEI exhibits the lowest volatility and thus remains the safest index while FTSEMIB is the riskiest. Moreover, compared to all cryptocurrencies and indices, gold presents the lowest volatility. It is a safe investment especially during crisis periods. Thus, we join Ghorbel and Jeribi (2021a, b) and Fakhfekh *et al.* (2021), who showed that gold is a safe haven during the COVID-19 pandemic period.

The skewness statistics demonstrate that marginal distributions are asymmetrical to the left for Bitcoin, Ethereum, Maker, Monero and all stock indices for which the values are negative, except for the Dash, Litecoin, Bitcoin Gold, Ripple and gold. These positive values suppose that the marginal distributions are asymmetrical to the right. Then, the kurtosis statistics is used in order to test for the existence of heavy-tailed or light-tailed relative to a normal distribution. The obtained high values confirm the existence of fat tails in return distributions except for Litecoin, Ripple, gold and Nikkei with low values. Therefore, the assumption of Gaussian returns is rejected by the Jarque–Bera test for all digital and financial assets. All the cryptocurrencies and financial assets (gold and stock indices), as evidenced by the kurtosis and Jarque–Bera's tests are far from the normal distribution.

4.1 Static analysis of connectedness network for stocks, gold and cryptocurrencies

Table 3 summarizes the estimation results of the static connectedness measures for each stock, cryptocurrency and gold, issued from the TVP-VAR model to study the fear connectedness and the risk transfer. The total connectedness in this VAR system is 59.3%, which is mainly due to the close link among the major stocks and cryptocurrencies and the global financial system. This indicates how much spillover effects exist within this system and that cryptocurrencies and stocks are not independent from the global financial system. The average influence of the stock indices is approximately 82.01%, while the average influence of cryptocurrencies is approximately 45.66%. In fact, the large value of the stock indices shows that the international stock market spillovers are more important than those of the cryptocurrency market as a source of market fluctuations.

For cryptocurrencies, when we consider pairwise connectedness, we notice that only the contributions of Bitcoin, Dash, Ethereum and Monero are around 36% to the global system volatility, and consequently are overtaken by the information system. On the other hand, the contributions of Litcoin, Bitcoin Gold, Marker and Ripple are more important as they exceed 75%, except for Maker (52.8%). Moreover, we found that Litecoin is the least receiver from other cryptocurrencies. On the other hand, among the stock indices, we found that their own contributions are near 20%, except for SP 500 (0.077), which is overtaken by the system with an average volatility transmission of 78.4%. However, the pairwise connectedness values show that the contributions of CAC40, FTSE, FTSE MIB, DAX30 AND SP/TSX to the studied stocks range from 13% to 24%, while the contributions of NIKKEI and S&P500 to other stocks are less than 8%. According to the pairwise connectedness analysis, Litecoin is a diversifier in a cryptos' portfolio. Then, regarding gold, it becomes visible that it is a diversifier for cryptos. Besides, for a crypto and stocks portfolio, we found that the least transmitters of volatility are Dash**,** as a cryptocurrency and DAX 30, as a stock index. Table 3 indicated that the French index (CAC 40) is a diversifier in a portfolio of stocks and gold. Finally, for a stock index portfolio, FTSEMIB is the least receiver and so is a diversifier in this case. It is worth noting that in general, cryptos are diversifiers for a stock index which helps reduce volatility, especially in COVID-19 crisis. These findings will be proved checked through the following volatility connectedness analysis. The net connectedness study shows that Bitcoin contributes *81.3*% to the total variation in this system. However, this system contributes *63.1*% of the variation in Bitcoin returns, which results in the highest positive net

names	BTC	Dash	ETH	XMR	LTC	BTG	MKR	XRP	Gold	FTSE	CAC40	FTSE MIB	DAX30	Nikkei	SP/ TSX	S&P500	From
BTC	0.369	0.122	0.279	0.168	0.004	0.005	0.011	0.003	0.002	0.006	0.003	0.003	0.003	0.006	0.008	0.008	*0.631*
Dash	0.140	0.385	0.144	0.218	0.002	0.014	0.014	0.006	0.006	0.009	0.007	0.010	0.009	0.016	0.013	0.008	*0.615*
ETH	0.281	0.116	0.369	0.148	0.006	0.003	0.012	0.004	0.005	0.010	0.005	0.005	0.006	0.013	0.009	0.009	*0.631*
XMR	0.171	0.201	0.155	0.362	0.004	0.009	0.009	0.009	0.005	0.010	0.007	0.009	0.008	0.022	0.010	0.009	*0.638*
LTC	0.004	0.005	0.006	0.011	0.756	0.014	0.008	0.015	0.002	0.031	0.036	0.032	0.028	0.020	0.023	0.009	*0.244*
BTG	0.015	0.045	0.018	0.005	0.011	0.788	0.048	0.016	0.006	0.005	0.007	0.004	0.005	0.010	0.013	0.005	*0.212*
MKR	0.020	0.079	0.024	0.012	0.009	0.234	0.528	0.007	0.009	0.011	0.015	0.011	0.011	0.012	0.017	0.002	*0.472*
XRP	0.032	0.020	0.027	0.029	0.022	0.025	0.023	0.767	0.012	0.004	0.007	0.011	0.006	0.005	0.006	0.005	*0.233*
Gold	0.014	0.008	0.016	0.009	0.004	0.005	0.013	0.008	0.679	0.036	0.042	0.034	0.043	0.032	0.044	0.013	*0.321*
FTSE	0.015	0.008	0.018	0.009	0.004	0.002	0.002	0.004	0.007	0.223	0.174	0.160	0.159	0.047	0.154	0.013	*0.777*
CAC40	0.016	0.007	0.020	0.008	0.005	0.002	0.002	0.003	0.004	0.161	0.204	0.182	0.185	0.049	0.133	0.018	*0.796*
FTSEMIB	0.022	0.010	0.029	0.012	0.006	0.003	0.003	0.005	0.006	0.146	0.180	0.226	0.169	0.041	0.134	0.009	*0.774*
DAX30	0.015	0.006	0.019	0.007	0.006	0.001	0.002	0.003	0.008	0.155	0.195	0.179	0.211	0.050	0.130	0.013	*0.789*
NIKKEI	0.013	0.009	0.012	0.010	0.006	0.002	0.003	0.004	0.007	0.118	0.136	0.113	0.138	0.331	0.082	0.017	*0.669*
SP/TSX	0.030	0.015	0.033	0.018	0.004	0.005	0.003	0.004	0.007	0.146	0.146	0.166	0.134	0.035	0.240	0.016	*0.760*
S&P500	0.028	0.010	0.032	0.013	0.006	0.003	0.002	0.003	0.005	0.136	0.145	0.167	0.137	0.050	0.186	0.077	*0.923*
To	*0.813*	*0.661*	*0.831*	*0.676*	*0.097*	*0.327*	*0.155*	*0.093*	*0.092*	*0.984*	*1.105*	*1.088*	*1.041*	*0.407*	*0.962*	*0.154*	0.593
Net	*0.182*	*0.046*	*0.200*	*0.038*	*−0.147*	*0.115*	*−0.317*	*−0.140*	*−0.230*	*0.207*	*0.308*	*0.314*	*0.252*	*−0.262*	*0.201*	*−0.769*	

Table 3.
Static connectedness table

connectedness of Bitcoin relative to the system, 18.2%. This implies that Bitcoin is a significant net transmitter of volatility connectedness and even has larger a greater contribution of volatility spillovers to others. Moreover, Bitcoin price changes contribute more information to the system than they gain from. We also noted that XRP is the lowest contributor to the total variation in this system, with 9.3% while it receives up to 23.3%, which results in a negative net connectedness of XRP relative to the system. The global crypto-currency market is dominated by two major cryptocurrencies, namely, Bitcoin and Ethereum, which contribute on average over *80*% to the system and are all net contributors.

In fact, among the stock indices, CAC 40 is the most significant contributor to the total variation in this system; meanwhile, it receives 79.6% from the system, which results in a positive net connectedness relative to the system, with 30.8%. On the other hand, S&P500 is the lowest contributor to the volatility of the system, with 15.4%; meanwhile, it receives the highest contribution from system 92.3%. Consequently, S&P500 is a significant net receiver of volatility connectedness and even have larger gain of volatility spillovers among others. The global stock market is dominated by four major cryptocurrencies, including CAC40, FTSEMIB, DAX30 and SPTSX, which contribute on average over 90% to the system and they are all net contributors. Finally, for gold, we observe that it is the lowest contributor, with only 9.2% to the total variation in this system compared to cryptocurrencies and stock market indices but the system contributes up to 32.1% of the variation in gold returns, which results in a negative net connectedness of gold relative to the system −23%. This implies that gold is a significant net receiver of volatility connectedness.

To conclude the static connectedness of system, we can say that Bitcoin gold is the least receiver of volatility from the global financial system and Monero is the greatest receiver. This finding indicates that Bitcoin Gold is less vulnerable to the volatility shocks transmitted from the other seven cryptocurrencies, while Monero is the most vulnerable. Bitcoin Gold aimed at offsetting the limits of Bitcoin. It is a safe haven for the Bitcoin, which means that it was created by separating from some existing blocks of the Bitcoin blockchain. Bitcoin Gold has kept some of its promises by offering faster processing times than Bitcoin and introducing total anonymity. On the other hand, unlike most new cryptocurrencies, the Monero is not a clone of the Bitcoin, but it is based on a different cryptographic process which works entirely in peer-to-peer and uses an original system called “ring signatures”.

Among the stocks, we find that S&P500 is the most vulnerable to the shocks and that CAC 40 is the most significant transmitter of volatility to the system. Despite its low volatility, equity market sensitivity remains strong. In fact, during the third quarter of 2020, equity markets remained fairly stable but very sensitive despite the continued recovery of the global economy since the second quarter slowdown. This translates into significant short-term market fluctuations in recent times in response to unforeseen market events. Moreover, the events causing these market turbulences are likely to occur regularly in the future, but with varying degrees of severity.

4.2 Dynamic analysis of connectedness spillover for stocks, gold and cryptocurrencies

The basic full sample connectedness measure is extended to allow for time-varying spillover effects. In this vein, Diebold and Yilmaz (2009) used a rolling-window approach in order to study the dynamic connectedness on top of the static full sample. In fact, the full-sample and unconditional analysis provided a good characterization for volatility connectedness from an average and static despite the changes that occurred in the financial market during crisis period marked by the propagation of the coronavirus, which requires a specific analysis. For example, different reactions of countries through governmental responses influenced the performance of cryptocurrencies, stock indices and gold. By using a single fixed-parameter model, these movements would be ignored. To get a better understanding, we plot total connectedness over 2020 to measure its long-term trends and periodic fluctuations. We began in Table 4 with the analysis of the dynamic connectedness measures for a full sample. The total connectedness in this VAR system is 72.9%, which is higher than the static connectedness. In fact, this high value represents high spillover effects that exist within this system and that cryptocurrencies and stocks are significantly dependent on the global financial system. For their part, Aydoğan *et al.* (2022) explained this by the existence of a strong interaction between the returns and the volatility of the G7 stock markets and cryptocurrency market.

A deep study of net connectedness gave results which show that among cryptocurrencies, the Bitcoin, Dash, Monero and Ethereum are net transmitters of volatility to the system, while Bitcoin Gold, Litecoin, Ripple and Maker are net receivers. This finding does not significantly differ from that of the static connectedness spillover where Bitcoin Gold becomes a net receiver. Regarding the stock market, we found that Nikkei and SP 500 are net receivers of volatility from the global system while the rest of the studied stocks, such as CAC40, DAX 30, FTSE, FTSE MIB and SP/TSX, are net transmitters, which contradicts the findings of Lahiani *et al.* (2021), who proved the leading role of S&P500 in predicting stock returns. Finally, gold is found to be a net receiver although its own contribution to volatility is overtaken by the market (41.4% < 58.6%) and in the dynamic analysis its own contribution (67.9%) is higher than the markets influence (32.1%) in the static analysis.

Besides, we plot total connectedness over 2020 to measure its trend and periodic fluctuation. The rolling total volatility connectedness plot is shown in Figure 1, which presents some patterns showing that the connectedness in this system is changing over time, as it ranges from a high volatility of 94% to a low volatility of 67%. We can remarkably identify in the total spillover plot three shocks during crisis periods marked by the propagation of COVID-19. Even though the shock has lost scope, the volatility connectedness was maintained after the third quarter at the average level of 76%.

Thus, we confirm the previous findings of Jeribi and Kammoun Masmoudi (2021) whose empirical results proved that the stock markets as well as the crypto market responded to COVID-19 through a disturbing volatility. Therefore, we can conclude that, both the stock market and cryptocurrency returns are changing in the short and long run during the COVID-19 crisis period, Jeribi *et al.* (2021).

In Figure 2, we present the dynamic directional volatility connectedness from each of the eight cryptocurrencies, seven stocks and gold to others (corresponding to the "directional to others"). It can be seen that the to-connectedness or spillovers from each cryptocurrency fluctuate between 9% and 80% most of the time. However, the directional spillover fluctuates widely during violent times and sometimes exceeds 100%. Moreover, the scope of connectedness is maintained after the shock for most of cryptocurrencies except for Dash and Bitcoin Gold, which join the previous level. As for the stocks, the to-connectedness ranges from 15% to more than 100%. Furthermore, we noted that a high spillover is detected for all the studied stocks but a loose scope after the crisis period, which almost returns to the normal values except for Nikkei and SP 500. In fact, the great fluctuations mainly occurred in July 2020. Therefore, we can conclude that cryptocurrencies are more sensitive to shocks than to stock indices being longer affected.

Figure 3 presents the dynamic directional volatility connectedness from the system to each eight cryptocurrencies, seven stocks and gold (corresponding to the "directional from others"). They vary visibly over time and also fluctuate violently especially during crisis period. Interestingly, we note that global system transmission of volatility hold even after the shock that occurred in 2020 for cryptocurrencies, stock indices and gold. This finding does not hold for Bitcoin Gold where we observe a clear decline of volatility reception. This can be explained by the fact that Bitcoin Gold allows countless new people to take part in the mining process, being a more democratic mining infrastructure. Besides, a SIGHASH_FORK_ID

Table 4. Dynamic connectedness table for full sample

names	BTC	Dash	ETH	XMR	LTC	BTG	MKR	XRP	Gold	FTSE	CAC40	FTSEMIB	DAX30	Nikkei	SP/ TSX	S&P500	From
BTC	0.289	0.104	0.216	0.124	0.016	0.021	0.018	0.022	0.020	0.023	0.022	0.019	0.022	0.029	0.028	0.027	*0.711*
Dash	0.132	0.258	0.144	0.153	0.017	0.028	0.025	0.027	0.027	0.022	0.023	0.021	0.032	0.038	0.028	0.026	*0.742*
ETH	0.224	0.106	0.293	0.105	0.019	0.014	0.022	0.023	0.022	0.025	0.021	0.019	0.023	0.028	0.029	0.025	*0.707*
XMR	0.132	0.151	0.117	0.266	0.022	0.023	0.024	0.030	0.027	0.029	0.028	0.028	0.030	0.035	0.029	0.029	*0.734*
LTC	0.032	0.027	0.036	0.030	0.433	0.024	0.027	0.042	0.032	0.047	0.056	0.055	0.056	0.036	0.045	0.023	*0.567*
BTG	0.045	0.070	0.047	0.035	0.036	0.418	0.043	0.030	0.024	0.037	0.039	0.045	0.040	0.036	0.035	0.019	*0.582*
MKR	0.046	0.085	0.056	0.036	0.026	0.154	0.254	0.028	0.029	0.035	0.043	0.054	0.043	0.051	0.042	0.021	*0.746*
XRP	0.058	0.037	0.062	0.046	0.044	0.048	0.045	0.388	0.035	0.033	0.034	0.039	0.031	0.029	0.040	0.032	*0.612*
Gold	0.050	0.039	0.052	0.049	0.028	0.023	0.026	0.026	0.414	0.040	0.042	0.042	0.043	0.042	0.046	0.038	*0.586*
FTSE	0.037	0.023	0.038	0.030	0.016	0.017	0.016	0.015	0.016	0.220	0.151	0.113	0.131	0.047	0.113	0.019	*0.780*
CAC40	0.038	0.024	0.037	0.027	0.016	0.013	0.013	0.017	0.013	0.133	0.183	0.149	0.160	0.041	0.119	0.018	*0.817*
FTSEMIB	0.042	0.026	0.040	0.032	0.018	0.019	0.013	0.016	0.019	0.104	0.156	0.204	0.148	0.031	0.111	0.020	*0.796*
DAX30	0.037	0.025	0.035	0.026	0.018	0.013	0.013	0.014	0.015	0.123	0.169	0.147	0.193	0.041	0.112	0.019	*0.807*
NIKKEI	0.053	0.028	0.042	0.041	0.022	0.020	0.021	0.028	0.016	0.094	0.112	0.097	0.114	0.207	0.086	0.019	*0.793*
SP/TSX	0.044	0.027	0.044	0.030	0.014	0.015	0.019	0.020	0.016	0.109	0.130	0.119	0.118	0.039	0.231	0.024	*0.769*
S&P500	0.045	0.027	0.043	0.034	0.017	0.017	0.020	0.018	0.022	0.113	0.129	0.119	0.117	0.043	0.144	0.092	*0.908*
To	*1.014*	*0.799*	*1.009*	*0.797*	*0.328*	*0.450*	*0.345*	*0.356*	*0.332*	*0.967*	*1.157*	*1.064*	*1.108*	*0.567*	*1.008*	*0.359*	0.729
Net	*0.303*	*0.057*	*0.302*	*0.063*	*−0.239*	*−0.132*	*−0.401*	*−0.256*	*−0.253*	*0.186*	*0.340*	*0.268*	*0.300*	*−0.226*	*0.239*	*−0.550*	

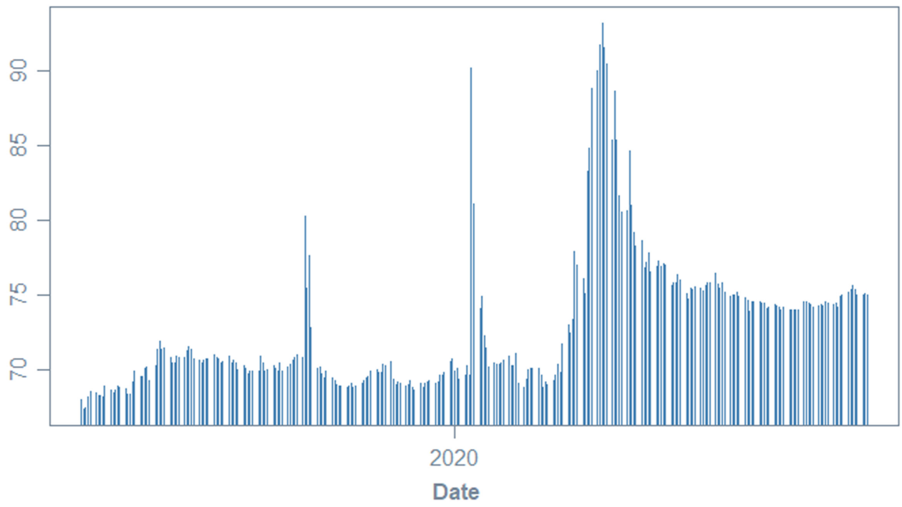

Figure 1.
Total dynamic connectedness

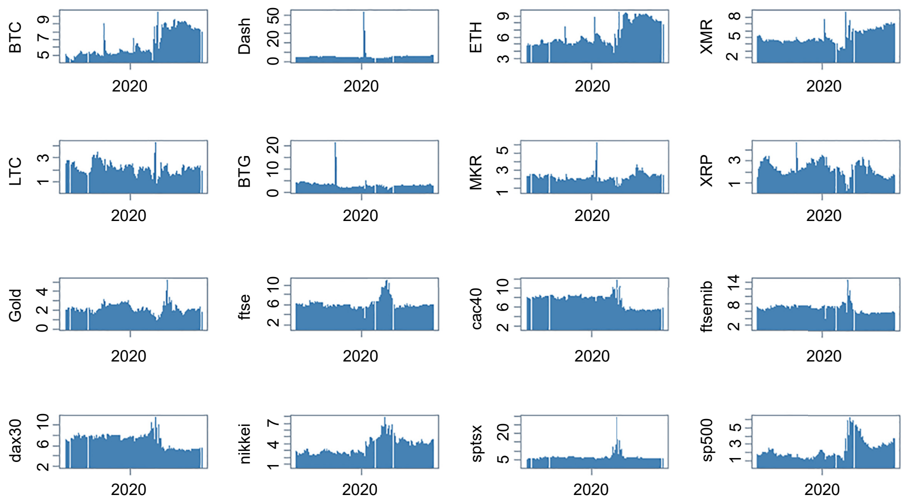

Figure 2.
The total directional connectedness -TO-

replay protection mechanism is implemented. So, every Bitcoin transaction is invalid in BTG blockchain. This explains that the Bitcoin Gold is a safe haven for other cryptocurrencies, in the COVID-19 crisis.

The from-connectedness even becomes lesser than before crisis period. We also notice substantial differences between Figures 2 and 3 which can be explained by the "net-connectedness". Note that the difference between to-connectedness and from-connectedness is equal to net-connectedness. The volatile fluctuation shows that cryptocurrencies influence each other and the effect is unstable, except for the Bitcoin Gold.

We now focus on the net total directional volatility connectedness, where a clear disparity of the net-connectedness is shown in Figure 4. Moreover, it should be noticed that among the cryptocurrencies, Bitcoin has always been the most important net transmitter of

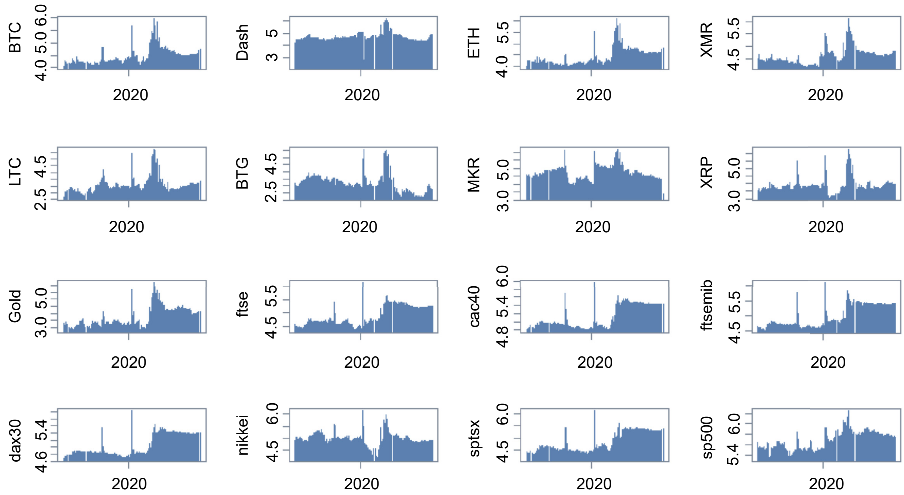

Figure 3.
Total directional connectedness – from

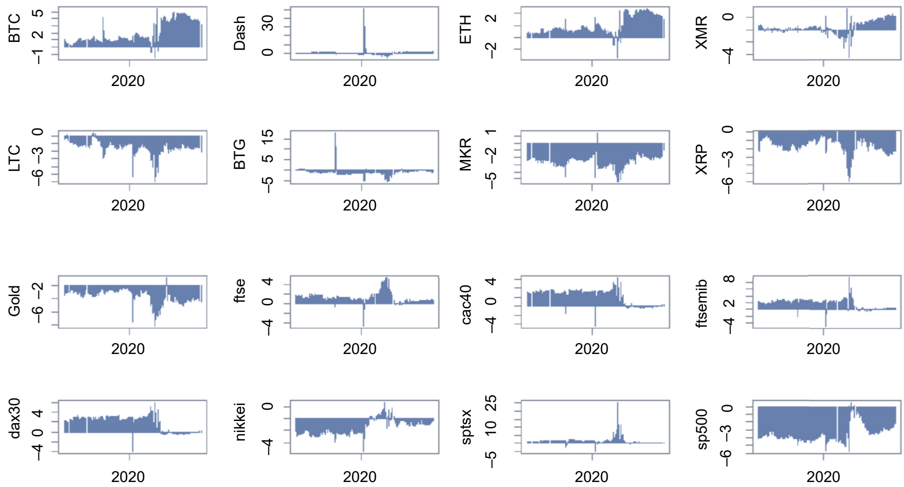

Figure 4.
Total directional net-connectedness

volatility connectedness or spillovers during crisis periods followed by Ethereum and Monero. Our result was confirmed by Jeribi and Ghorbel (2021), which indicates that the fluctuation of Bitcoin transfers significant risk to the others cryptocurrencies but the extent of this transfer is greater after the shock due to the COVID-19 crisis. We also noticed that Maker is the biggest net receiver of volatility from the global system followed by Ripple and Litecoin and that the net connectedness reception is extended during the crisis period. Economically, we can conclude that Maker, Ripple and Litecoin are significantly affected by shocks and thus are more sensitive to implied volatility fluctuations while Bitcoin, Ethereum and Monero are more powerful currencies. Furthermore, we clearly observed that the net dynamic volatility connectedness for Bitcoin Gold and Dash is barely significant, meaning that there is a sort of compensation between the net-connectedness and the from-connectedness. Bitcoin Gold is almost stable with respect to the implied volatility fluctuation in the global system. Therefore, it is a safe haven for other cryptocurrencies and especially stock indices.

Turning to the stock indices, we noticed that the net transmission of FTSE, CAC40, FTSEMIB and DAX30 significantly drops after the crisis period besides, the net reception of the volatility connectedness or the spillover of Nikkei and SP 500 is marked by a significant decline. This indicates a significant change in their characteristics due to instability. As for Sp/TSX, while the net connectedness is not significant during almost the sample period, it is marked by a great shock during the crisis period as it became a net transmitter.

Finally, regarding gold, we noticed that it remains a net receiver with a significant increase in net reception during the crisis period. Overall, we can conclude that connectedness is shown to be conditional on the extent of economic and financial uncertainties marked by the propagation of the corona virus. This confirms the results of the Jeribi and Fakhfekh (2020) and Jeribi *et al.* (2020). Such comparative studies would improve our understanding of the portfolio strategies for international investors among different assets, especially during crisis period.

Next, we construct the directional connectedness network based on the net pairwise connectedness. Figure 5 displays the network plot of the full-sample static implied volatility connectedness of each cryptocurrency, stock index and gold. Each of them is set as a node and a directional edge from *i* to *j* exists only if the net pairwise connectedness from *i* to *j* is positive. Then, the nodes represent the stock index, gold and currency series included in our analysis. The dark color of each node indicates the degree of the total "Net" connectedness of

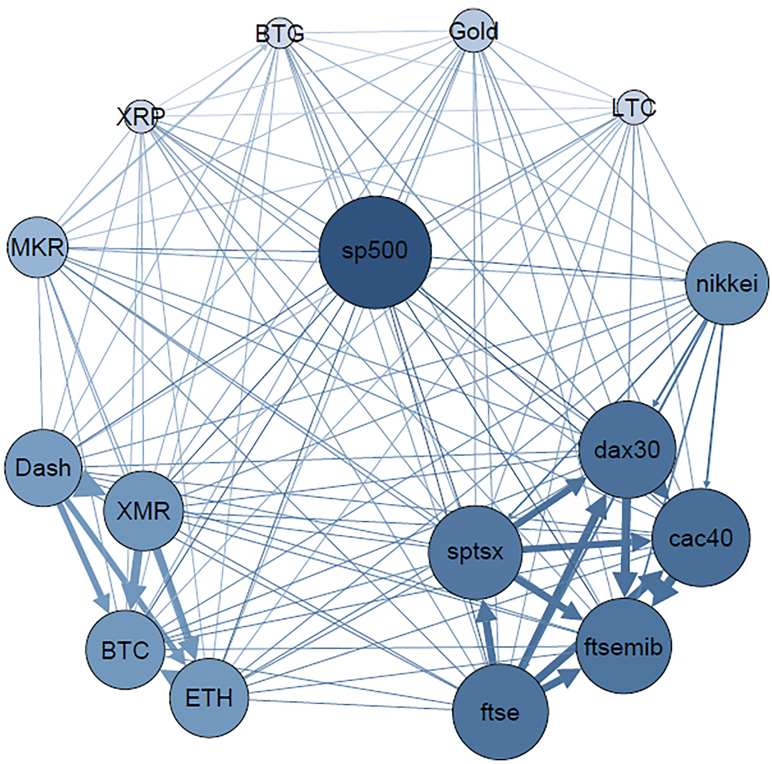

Figure 5.
Directional connectedness network (in)

the volatility indices, i.e. the net difference of "To all others" minus "From all others." These would help us identify the quantum and directions of shocks. Using the node dark color and area, we attempted to convey full-scale information of the system-wise connectedness dynamics of the stock indices, gold and cryptocurrencies covered in this paper.

To simplify visualization and interpretation, Figure 5 is based on only the maximum net pairwise connectedness from all the other nodes to each node *i*. Subsequently, in Figure 5, each node-is of degree 1, which reflects only the maximum information inflow from the other nodes. Similarly, in Figure 6, each node is of out-degree 1, which reflects only the maximum information outflow from each node to the other nodes.

In Figure 5, NIKKEI and S&P500 are the largest receivers among stocks from the system followed by the rest of stocks. We also noticed that the distances between CAC40, DAX 30, FTSE, FTSEMIB and SP/TSX are very short. This reflects the high pairwise correlation among this set of stock indices. Furthermore, the disposition of NIKKEI and S&P500 in the figure reflects their low correlation with others. The same conclusions could be drawn from the thickness of the arrows.

Besides, amid Cryptocurrencies, we figure out that DASH, MONERO, ETHEREUM and BITCOIN are not only the greatest receivers but also closely related to others in terms of volatility connectedness. They are followed by MAKER, which is not closely related to other studied cryptocurrencies, reflecting the low pairwise connectedness with others. More interestingly, we noticed that Ripple, Bitcoin Gold and Litecoin are the least receivers and disposed away from the other cryptocurrencies. Therefore, we can detect their potential status as hedge cryptocurrencies against systemic risk.

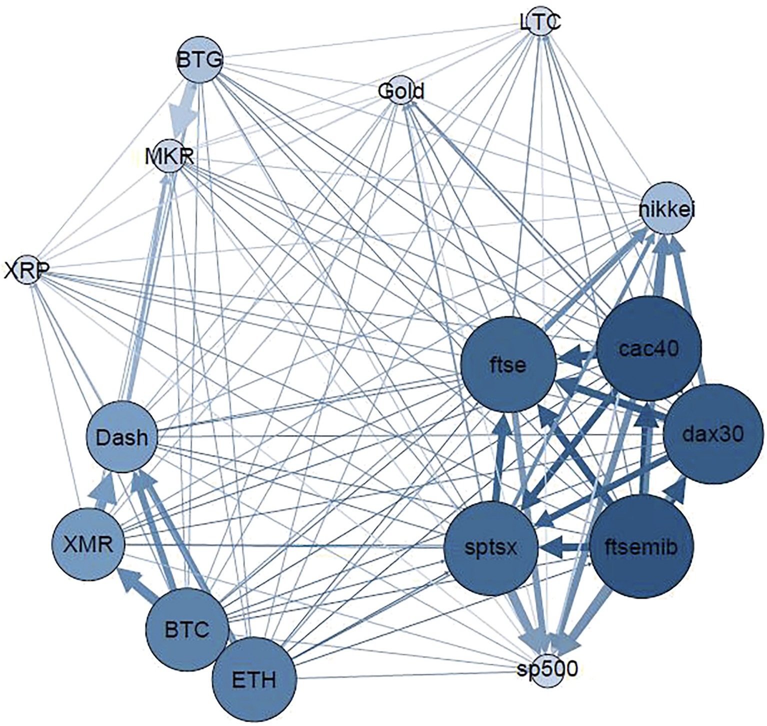

Figure 6.
Directional connectedness network (out)

In fact, Figure 6 displays the maximum information outflow from each node to the other nodes. Moreover, through the disposition of each node, its darkness and the thickness of arrows, we noticed that concerning the stock indices; CAC40, DAX30, FTSE, FTSEMIB and SP/TSX are the greatest transmitters as they are the greatest receivers. They are also highly correlated since they are closely disposed and the linking arrows are thick. We remarkably noticed that NIKKEI and S&P500 are the lowest transmitters among others; besides, they are graphically disposed far from the mentioned group of correlated indices. We can conclude that they are not significantly connected to the other indices. Turning to cryptocurrencies, we figure out that Ethereum and Bitcoin are the greatest transmitters followed by Monero and Dash as they significantly transmit volatility to Monero and Dash. On the other hand, Bitcoin Gold, Ripple, Maker and Lietcoin are the lowest transmitters since the nodes are clearer and smaller, indicating their low influence of volatility. Besides, they are graphically dispersed and the arrows are not thick, reflecting the low pairwise connectedness between them. Finally, we can easily notice that gold is a low transmitter as it is a low receiver. Besides, the gold node is graphically disposed away from others with thin arrows meaning that it is not significantly connected with other cryptocurrencies and stock indices which indicating it is a safe haven during the pandemic COVID-19.

5. Conclusion

This study investigates the connectedness between cryptocurrencies, gold and G7 stock indices and taking into account the effect of the COVID-19 crisis.

According to the pairwise connectedness analysis, Litecoin is a diversifier in a cryptos' portfolio. When we consider gold in portfolio assets, it becomes visible that gold is a diversifier for cryptos. Besides, for a crypto and stocks portfolio, we find that the least transmitters of volatility are Dash, as crypto-currency and DAX 30, as a stock index. At last and not least, CAC 40 is a diversifier in a portfolio of stocks and gold. Finally, for a stock index portfolio, FTSEMIB is the least receiver and so, it is a diversifier in this case. It is worth noting that in general, cryptocurrencies are diversifiers for a stock index portfolio and allow volatility reduction especially in crisis period.

On the other hand, dynamic connectedness results do not significantly differ from static connectedness, we just mention that Bitcoin Gold becomes a net receiver. The scope of connectedness is maintained after the shock for most of cryptocurrencies, except for Dash and Bitcoin Gold, which join previous level. For the stocks, the high spillover is detected for all the studied stocks but loses scope after the crisis period and almost returns to normal values, except for Nikkei and SP&500. However, Bitcoin has always been the greatest net transmitter of volatility connectedness or spillovers for cryptocurrencies Gold and G7 stock indices, during the COVID-19 crisis. On the other hand, Maker is the greatest net-receiver of volatility from the global system. As for gold, we noticed that it remains a net receiver with a significant increase in the net reception during the crisis period.

Overall, we can conclude that connectedness is shown to be conditional on the extent of economic and financial uncertainties marked by the propagation of the corona virus.

NIKKEI and S&P500 are the greatest receivers among stocks from the system followed by the rest of stocks, including CAC40, DAX30, FTSE, FTSEMIB and SP/TSX, which are the greatest transmitters as they are the greatest receivers. Therefore, this confirms the contagion of the COVID-19 crisis between G7 stock markets. In contrary, NIKKEI and S&P500 are the lowest transmitters. As a consequence, the American and Japanese stock markets are more attractive to investors since they are less exposed to the shocks of other markets. However, Bitcoin Gold and Litecoin are the least receivers from the other cryptocurrencies, leading to the conclusion that they can be diversifiers during crisis. As for

Ethereum and Bitcoin, they are the greatest transmitters from other cryptocurrencies, which confirm their weight and influence on the crypto-currency market.

On the other hand, gold is a low transmitter and receiver, which confirms that it is a safe haven. Therefore, the investors can diversify their portfolios in order to reduce theirs risks, by adding Bitcoin Gold and Litecoin, when investing in Gold and G7 stock markets.

Notes

1. https://www.tellerreport.com
2. https://www.reuters.com
3. https://www.barrons.com
4. https://kyodonews.net
5. https://www.businessinsider.fr
6. https://cryptonaute.fr0
7. Our results are quite robust to 100 and 150 rolling-window size as well. The results are available from the corresponding author upon request.

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