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Covid-19 pandemic and tail-dependency networks of financial assets

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ABSTRACT

This study provides evidence on the frequency-based dependency networks of various financial assets in the tails of return distributions given the extreme price movements under the exceptional circumstance of the Covid-19 pandemic, qualified by the IMF as the Great Lockdown. Our results from the quantile cross-spectral analysis and tail-dependency networks show increases in the network density in both lower and upper joint distributions of asset returns. Particularly, we observe an asymmetric impact of the Covid-19 because the left-tail dependencies become stronger and more prevalent than the right-tail dependencies. The cross-asset tail-dependency of equity, currency and commodity also increases considerably, especially in the left-tail, implying a higher degree of tail contagion effects. Meanwhile, Bitcoin and US Treasury bonds are disconnected from both tail-dependency networks, which suggests their safe-haven characteristics.

1. Introduction

Since its first case was officially reported in China in late December 2019, the Covid-19 disease has spread rapidly worldwide and was declared as a global pandemic in March 2020. Its severity has resulted in an unprecedented impact on financial markets, where investors have panic-sold out of fears. Panic trading has caused several significant drops in various markets (Zhang et al., 2020; Shehzad et al., 2020). For example, the U.S. stock markets had to activate the market-wide circuit-breakers four times since the outbreak of the Covid-19 pandemic, with respect to the S&P 500 Index drops, in an effort to calm the panic-trading. Baker et al. (2020a) assess that over the last century, no other pandemic has had such an effect on international financial markets like the Covid-19. Not only stock markets, but also other asset markets such as currencies and commodities have been affected significantly. Global travel restrictions have caused significant drops in oil prices due to lower demand for oil (leading to negative crude oil futures prices for the first time in the history) and put pressure on the commodity-based currencies, such as the Canadian dollar. Also, limited trade routes and tourism badly affected several countries, such as Australia and New Zealand, causing their currencies to weaken. On the other hand, gold prices hit all-time high levels due to concerns that an economic recovery from the coronavirus pandemic might be weakening in the United States and elsewhere. As the majority of financial markets continue to experience extreme movements and are likely interconnected, investors are left with questions about portfolio diversification and potential shifts in asset allocation. Our

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current study thus aims to shed a light on these issues before and during the Covid-19 outbreak, while considering a large and comprehensive set of assets and asset classes that are of common interest for portfolio management due to their different risk-return characteristics.\(^1\)

More precisely, we investigate the Covid-19 effects on the dependency network of equity, currency, commodity, bond, and Bitcoin markets. Our focus is on the tail-dependency network for each pair of the assets using quantile cross-spectral analysis proposed by Barunik and Kley (2019). We analyse two quantiles that represent the left tail (0.05) and the right tail (0.95) of the joint distribution. Previous studies have shown evidence of the asymmetry in tail-dependence structure in various asset markets (i.e., the effect in the left tail is stronger and more prevalent than in the right tail). For example, Okimoto (2008) and Jondeau (2016) find an asymmetric behaviour of the tail-dependence in equity portfolios, especially in the bear markets. Wang et al. (2013) document this asymmetry in the tail-dependence structure between stock and currency markets. Hammoudeh et al. (2014) confirm asymmetric tail dependence between stock and commodity futures markets. Mensi et al. (2017) provide evidence on time-varying asymmetric tail dependence in commodity markets. Following the literature, we analyse both tails of the distribution with a conjecture that there exists asymmetric behaviour in the tail-dependency network, and our empirical results confirm this hypothesis. In particular, among different types of assets, the connectivity of the tail-dependency networks among equities and commodities has increased the most due to Covid-19. We, however, find a notable result that Bitcoin and US Treasury (UST) bonds are disconnected from other assets, making them a safe haven for the investors during the Covid-19 crisis.

Our study contributes to the literature in many aspects. Firstly, we provide fresh evidence regarding the impact of Covid-19 on the tail-dependency network of financial assets. Although earlier studies have investigated the dynamics of cross-asset relations during Covid-19 period (Rizwan et al., 2020; Gharib et al., 2020; Sharif et al., 2020; Akhtaruzzaman et al., 2020), no study has been done on these relations in a network framework. This approach provides us a powerful tool to analyse an extended set of assets at once and make inference via visual analysis. Secondly, we demonstrate how the Covid-19 pandemic can amplify the asymmetry of the tail-dependency network, which is the difference between the left and the right tail of the asset return distribution. This is especially important in a period where financial markets experience extreme downturns with increased volatility due to the pandemic (Mazur et al., 2020; Baig et al., 2020; Albulescu, 2020; Bai et al., 2020; Baker et al., 2020a). Lastly, since the Covid-19 pandemic started, fear and uncertainty have taken control in the financial markets (Lyosca and Molinar, 2020) where investors started panic trading (Ortmann et al., 2020) and changed their economic behaviour (Baker et al., 2020b). Naturally, academics are still looking for strategies for risk management (Ji et al., 2020; Conlon and McGee, 2020; Corbet et al., 2020b) or assets that perform relatively better than others during the crisis period (Broadstock et al., 2020). While these studies argue that Bitcoin do not act as hedge or safe haven during the pandemic period, and support the safe-haven role of gold during the same time, our findings provide an important implication for financial risk management by showing the diversification benefit of Bitcoin and UST bond during the alike Covid-19 crisis.

2. Data and methodology

2.1. Data

We utilise daily prices of 51 international assets from Dukascopy Bank SA, a Swiss forex bank and an ECN broker with its headquarters in Geneva. In particular, our dataset consists of 23 spot exchange rates against the US dollar and the Dollar index, contracts for the difference on 11 commodities (2 precious metals, 5 agriculture and 4 energy), contracts for the difference on 14 international equity indices, contract for difference on UST bonds (30 years to maturity), and contract for difference on Bitcoin.\(^2\) As we look at the impact of the Covid-19 pandemic on the tail dependency between financial assets, our dataset spans the period from January 1, 2019 to April 30, 2020. To capture the impacts of the Covid-19 to the tail dependency between international assets, we break our sample into

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1. The mechanisms that connect our sample assets, especially during turbulent periods, have been explained and studied in detail in earlier works. Popular studies include Baksy (1989); Fleming et al. (1998) for stock-bond, Hamilton (1983); Jones and Kaul (1996) for stock-oil, Baur and Lucey (2010) for stock-gold, Roll (1992); Chow et al. (1997) for stock-fx, Gelb (1983); Krugman (1983) for oil-fx, Nicolau (2011); Ciner et al. (2013) for oil-bond, Pindyck and Rotemberg (1990); Hammoudeh et al. (2008) for oil-gold, Lothian and Wu (2011); Sensoy and Sobaci (2014) for bond-fx, and Sakemoto (2018); Bedoui et al. (2019) for fx-gold. A few studies analyzed the dependency between major asset classes simultaneously (Hartmann et al., 2004; Chan et al., 2011), whereas some others examined the dependency of several assets within the same asset class (e.g., Bekuet et al. (2005) for equities, Sensoy et al. (2015) for commodities, Lee and Wang (2020) for currencies). Finally, some recent studies focused on the relationship between a new asset, namely Bitcoin, and other major asset classes. These include Kwon (2020); Zeng et al. (2020) and Urom et al. (2020). For further information on the mechanisms that drive the relationship between our sample assets, we refer the reader to these studies and the references therein.

2. A Contract for Difference (CFD) refers to a contract that enables two parties to enter into an agreement to trade on financial instruments based on the price difference between the entry prices and closing prices. If the closing price of the position is higher than the opening price, then the seller will pay the buyer the difference, and that will be the buyer’s profit. Similarly, if the current asset price is lower at the exit position than the value at the contract’s opening, then the seller will benefit from the difference. Just like foreign exchange market, CFDs are traded continuously on every weekday for 24 hours. In case of CFDs on equity indices, trading hours still are not affected by the opening and closing hours of the stock exchange or whether the weekday is a public holiday or not. In our study, all data come from one source so there is no problem of synchronicity, and when we state that we use ‘daily’ data, we refer to the CFD prices at 00:00 GMT on every day.
two sub-samples. The without Covid-19 sample consists of observations before January, 1 2020, whereas we employ the whole sample to account for the impacts Covid-19 as the first case was officially reported in China in late December 2019.\footnote{For recent studies that use the same period as the Covid-19 phase in financial markets, see Corbet et al. (2020a,b); Zaremba et al. (2020); Akhtaruzzaman et al. (2020); Goodell and Goutte (2020); Okorie and Lin (2020); Mnif et al. (2020); Shehzad et al. (2020).} Table 1 provides the list of sample assets with their summary statistics. Panel B of Table 1, which corresponds to the sample with the Covid-19 pandemic, reveals that the volatility and kurtosis of all asset returns increase substantially, indicating a high level of uncertainty associated with the nature of the pandemic.

2.2. Methodology

We employ the quantile cross-spectral analysis proposed by Barunik and Kley (2019) to investigate the dependencies in the tails of the joint distribution for each pair of assets. This method allows direct estimates of extreme co-movements between asset returns that are independent of the joint moments across the frequency domain.\footnote{In this paper, we focus on the instantaneous impacts of the Covid-19 to the tail-dependency network of asset returns. The obtained results for the 5-day frequency, not reported here for concision purpose, are similar to those of the 1-day frequency, however the impact of the Covid-19 pandemic on the tail-dependency networks is significantly weaker. Results can be made entirely available upon request.} This is of particular interest for economic agents as the dependencies between assets tend to increase significantly during the time of distress (Akhtaruzzaman et al., 2020).

Let \( X_{i,j} \) and \( X_{j,k} \) be two stationary processes. The marginal distribution of \( X_{i,j} \) is denoted by \( F \) and the corresponding quantile function is \( q_i(\tau) := F^{-1}(\tau) := \inf\{ R : \tau \leq F(R) \} \). The matrix of quantile cross-covariance kernels, \( \Gamma(\tau_1; \tau_2) := (\gamma_{i,j}^{k,l}(\tau_1, \tau_2)) \), which measures the serial and cross-dependency structure between \( X_{i,j} \) and \( X_{j,k} \), is defined as:

\[
\gamma_{i,j}^{k,l}(\tau_1, \tau_2) := \text{Cov}\{\mathbf{1}\{X_{i,k,l} \leq q_i(\tau_1)\}, \mathbf{1}\{X_{i,k,l} \leq q_j(\tau_2)\}\}
\]

(1)

where \( k \in Z, \tau_1, \tau_2 \in [0,1]\) and \( I[A] \) is indicator function. In the frequency domain, this yields the matrix of quantile cross-spectral density kernels, \( f_\tau(\omega; \tau_1, \tau_2) := \{\hat{\gamma}_{i,j}^{k,l}(\omega; \tau_1, \tau_2)\}_{k,l,j} \), where:

\[
f_\tau(\omega; \tau_1, \tau_2) := (2\pi)^{-1} \sum_{k=-\infty}^{\infty} \hat{\gamma}_{i,j}^{k,l}(\omega; \tau_1, \tau_2) e^{-i\omega} \]

(2)

Finally, the quantile coherency kernel that measures the dynamic dependency between two processes \( (X_{i,j}) \) and \( (X_{j,k}) \) across frequency (by choosing appropriate \( \omega \)) and the quantiles (by choosing appropriate \( \tau_1 \) and \( \tau_2 \)), can be defined as follows:

\[
\mathcal{R}(\omega; \tau_1, \tau_2) := \left( \frac{\hat{f}_{\tau}(\omega; \tau_1, \tau_2)}{(\hat{f}_{\tau}(\omega; \tau_1, \tau_1)^{1/2} \hat{f}_{\tau}(\omega; \tau_2, \tau_2))^{1/2}} \right)
\]

(3)

where \( \mathcal{R}(\omega) \) captures the real part of the complex conjugate \( \bar{\omega} \). The quantile coherency kernel is estimated via the smoothed rank-based copula cross-periodograms (see Barunik and Kley, 2019, for more details).

In this study, we address the tail dependency structure for both the extreme left tail (5\%) and right tail (95\%) of the joint distribution for each pair of assets’ returns. We compute daily returns for each assets, \( r_t \), as the natural logarithm difference between closing prices of two consecutive trading days, i.e. \( r_t = \ln(P_{t+1}) - \ln(P_{t-1}) \) where \( P_j \) is the closing price of asset \( j \) on day \( t \). We follow Barunik and Kley (2019) and use returns standardized by its conditional volatility estimated by a GARCH(1,1) model of Bollerslev (1987). By doing so, we are able to focus on the tail-dependence structure between the joint distribution of asset returns without strong common factors in volatility (see, e.g., Barigozzi et al., 2014; Zikeš and Barunik, 2016, for evidence of common volatility factors and its impacts on the conditional return quantiles).\footnote{Given the rapid spread of the Covid-19’s dramatic shock to almost all financial markets, we are particularly interested in its instantaneous impact on the tail-dependency network of financial assets by considering 1-day frequency in the time domain. The estimated quantile coherency is then used as inputs to the adjacency matrix in order to build a tail-dependency network using the force-directed layout algorithm proposed by Fruchterman and Reingold (1991).}

3. Results

Table 2 reports the average return coherency between assets grouped by asset classes. We focus on two quantiles that present the extreme left tail (5\%) and right tail (95\%) of the return joint distribution. The Covid-19 pandemic significantly increases the dependence between asset classes in both lower and upper tails of the joint distribution, except for average return coherency of currency (commodity) at the lower (upper) tail. The joint dependence between commodities increase the most, particularly in the extreme negative returns.
Fig. 1 displays the two networks of extreme negative return coherency. The period without the Covid-19 pandemic is presented in the left plot, whereas the period with the Covid-19 pandemic is in the right plot. In each network, we only present the significant tail dependencies that are stronger than 0.6, in which the blue (red) lines show the positive (negative) quantile coherency. We observe considerable increase in the dependency between assets at the extreme negative return coherency. Almost all 0.05 quantile coherency between assets are positive, which is in line with the literature that assets returns tend to co-move in distress periods (Okorie and Lin, 2021).
The Covid-19 pandemic also increases the left-tail dependency between equity indices significantly, whereas the within-asset left-tail correlations between currencies are weaker. The cross-asset return coherency also increases notably by the inclusion of the Covid-19 period.

In a similar structure, Fig. 2 presents the networks of extreme positive return coherency. Before the Covid-19 pandemic, the right-tail connectedness between assets is much less significant, while there are several negative tail-correlations for some pairs of assets. The inclusion of Covid-19 pandemic changes, however, the network structure dramatically, with a substantial increase in the right-tail dependence, especially between currencies.

One notable finding is the role of Bitcoin and UST bond in the two networks. While these two assets are almost disconnected

This table reports the average return coherency in two quantiles, namely 0.05 and 0.95, between individual assets grouped under the same asset class, except for ‘Bond’ and ‘Bitcoin’ where the average correlations to other assets in the sample are reported.

|                | Without Covid-19 period | With Covid-19 period |
|----------------|-------------------------|----------------------|
|                | 0.05        | 0.95       | 0.05        | 0.95       |
| Equity         | 0.629       | 0.153      | 0.699       | 0.217      |
| Currency       | 0.247       | 0.098      | 0.159       | 0.231      |
| Commodity      | 0.045       | 0.099      | 0.218       | 0.083      |
| Bond           | -0.103      | 0.083      | -0.070      | 0.159      |
| Bitcoin        | -0.054      | 0.041      | 0.091       | 0.027      |
| Average        | 0.079       | 0.054      | 0.177       | 0.102      |

Fig. 1. Left-tail Dependency Network This network is built using the force-directed layout proposed by Fruchterman and Reingold (1991) with the adjacency matrix being built from the 0.05-quantile coherency measures. Red nodes present equity indices (14 indices), light-blue being exchange rates (24 exchange rates), orange being commodity (11 commodities), yellow being Bitcoin and blue being the UST bond. Green lines indicate positive coherency, whereas red lines present negative coherency. The left-plot is the network without the Covid-19 sample and the right-plot is the network with the Covid-19 pandemic. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

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vertices in the extreme negative return coherency, they are positively correlated with other assets in the extreme positive return coherency. Thus, they can act as safe-haven assets for international investors with well diversified portfolios.

In Table 3, we provide information on the density and centrality of the networks. Panel A reports the two centrality measures for each node, namely the strength and closeness centrality, with the average and standard deviation of centrality scores of all nodes being reported at the bottom of Panel A. On the other hand, Panel B reports the network’s density and the average clustering coefficients. As expected, the strength and closeness centrality increase considerably in the extreme negative return coherency, especially in the equity and commodity indices. The average strength increases from 12.637 to 13.441 with the inclusion of the Covid-19 pandemic. The most significant changes at the individual asset level are for the Spanish and Japanese equity indices, and for Brent and gas oil in the commodities. The strength of centrality also increases in the extreme positive return coherency, from 9.874 before the Covid-19 to 10.490 after the inclusion of the pandemic. Looking at the individual assets, however, the picture is quite different to that of the left-tail dependence. The most significant changes in strength and closeness are recorded in the foreign exchange rates and UST bond, where the strength of the Dollar index increases significantly from 8.745 to 14.051 and that of the UST bond from 9.377 to 14.127.

As expected, the network density increases considerably in both the extreme negative (from 0.165 to 0.182) and positive return coherency (from 0.081 to 0.101) in the Covid-19 sample. Interestingly, the clustering coefficients decrease from 0.479 to 0.374 in the left-tail dependency network, but it increases from 0.186 to 0.244 in the right-tail dependency network. This finding indicates that the Covid-19 induces a wider-spread network in the left-tail dependence, whereas the pandemic leads to a more compact network in the

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**Fig. 2. Right-tail Dependency Network** This network is built using the force-directed layout proposed by Fruchterman and Reingold (1991) with the adjacency matrix being built from the 0.95-quantile coherency measures. Red nodes present equity indices (14 indices), light-blue being exchange rates (24 exchange rates), orange being commodity (11 commodities), yellow being Bitcoin and blue being the UST bond. Green lines indicate positive coherency, whereas red lines present negative coherency. The left-plot is the network without the Covid-19 sample and the right-plot is the network with the Covid-19 pandemic. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

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6 Node strength is calculated as its absolute coherency with other nodes in the network. Node closeness is the average shortest path between a given node and the remaining nodes in the network.

7 Network density is the ratio of the number significant coherency over the number of all possible edge in a network. Undirected clustering coefficient (‘UCC’) measures the degree to which nodes in a graph tend to cluster together in an undirected network.
Table 3
Network Centrality and Density.

| Currency       | Without Covid-19 | With Covid-19 | Without Covid-19 | With Covid-19 |
|----------------|-----------------|---------------|-----------------|---------------|
| **Equity**     |                 |               |                 |               |
| AUSTRALIA200   | 12.815          | 0.548         | 21.266          | 0.741         |
| CHINA          | 13.268          | 0.516         | 18.284          | 0.681         |
| EUROSTOXX50    | 16.564          | 0.622         | 18.374          | 0.627         |
| FRANCE40       | 16.947          | 0.626         | 18.286          | 0.617         |
| GERMANY30      | 16.910          | 0.638         | 17.548          | 0.615         |
| HONGKONG40     | 14.965          | 0.591         | 18.914          | 0.693         |
| INDIA50        | 13.928          | 0.609         | 17.961          | 0.726         |
| JAPAN225       | 15.778          | 0.615         | 20.387          | 0.712         |
| NETHERLANDS25  | 15.753          | 0.601         | 14.722          | 0.663         |
| SINGAPORE      | 17.663          | 0.654         | 19.407          | 0.663         |
| SPAIN35        | 17.407          | 0.605         | 20.617          | 0.719         |
| SWITZERLAND20  | 14.554          | 0.592         | 17.977          | 0.618         |
| UK100          | 12.961          | 0.558         | 19.049          | 0.657         |
| USA500         | 13.585          | 0.567         | 19.946          | 0.659         |
| **Currency**   |                 |               |                 |               |
| AUDUSD         | 12.013          | 0.540         | 16.523          | 0.626         |
| DOLLAR INDEX   | 13.345          | 0.553         | 14.300          | 0.563         |
| EURUSD         | 8.843           | 0.458         | 6.875           | 0.387         |
| GBPUSD         | 7.066           | 0.425         | 11.203          | 0.500         |
| NZDUSD         | 7.719           | 0.441         | 16.751          | 0.617         |
| USDCAD         | 14.761          | 0.588         | 8.968           | 0.462         |
| USDCNH         | 9.495           | 0.485         | 8.574           | 0.514         |
| USDCHF         | 15.155          | 0.595         | 9.450           | 0.468         |
| USDHKD         | 15.106          | 0.574         | 15.978          | 0.612         |
| USDJpy         | 10.868          | 0.507         | 6.937           | 0.458         |
| USDDKK         | 10.719          | 0.516         | 9.181           | 0.483         |
| USDJPY         | 12.122          | 0.561         | 6.416           | 0.386         |
| USDKRW         | 15.467          | 0.641         | 15.070          | 0.603         |
| USDNOK         | 11.789          | 0.510         | 8.303           | 0.391         |
| USDNOK         | 12.361          | 0.533         | 8.221           | 0.422         |
| USDNOK         | 11.787          | 0.510         | 8.303           | 0.391         |
| USDPLN         | 13.604          | 0.578         | 10.636          | 0.502         |
| USDRON         | 15.143          | 0.572         | 15.046          | 0.603         |
| USDRUB         | 13.639          | 0.563         | 12.745          | 0.538         |
| USDSEK         | 13.935          | 0.598         | 7.911           | 0.452         |
| USDDGC         | 16.857          | 0.623         | 8.810           | 0.411         |
| USDTHB         | 15.614          | 0.615         | 9.348           | 0.474         |
| USDTRY         | 9.991           | 0.490         | 7.747           | 0.426         |
| USDZAR         | 15.523          | 0.611         | 9.133           | 0.464         |
| **Commodity**  |                 |               |                 |               |
| BRENT          | 8.512           | 0.421         | 15.195          | 0.593         |
| COCOA          | 8.807           | 0.457         | 9.614           | 0.497         |
| COFFEE         | 10.644          | 0.521         | 7.951           | 0.463         |
| COTTON         | 12.436          | 0.528         | 14.116          | 0.595         |
| GASOIL         | 11.711          | 0.514         | 15.818          | 0.604         |
| NATURALGAS     | 8.117           | 0.446         | 9.964           | 0.459         |
| SOYBEAN        | 9.995           | 0.472         | 14.356          | 0.566         |
| SUGAR          | 8.865           | 0.469         | 13.384          | 0.549         |
| WTI            | 9.410           | 0.465         | 14.712          | 0.576         |
| SILVER         | 8.797           | 0.486         | 14.430          | 0.577         |
| GOLD           | 11.195          | 0.521         | 6.392           | 0.374         |
| **Bond**       |                 |               |                 |               |
| USTBOND        | 11.401          | 0.518         | 9.514           | 0.473         |
| **Bitcoin**    |                 |               |                 |               |
| BTCUSD         | 6.428           | 0.418         | 7.851           | 0.423         |
| Average        | 2.948           | 0.106         | 4.521           | 0.102         |
| Std. dev.      | 0.165           | 0.479         | 0.182           | 0.374         |

This table presents the network centrality and density for the extreme return coherency. The first four columns report results for the left-tail dependency, whereas the last four columns report results for the right-tail dependency network. In Panel A, we report the strength and closeness of the
node centrality. Higher values indicate greater centrality in the network. At the bottom of Panel A, we present the average centrality scores and their standard deviations. Panel B provides information on the network density and its connectivity under the columns 'Density' and 'UCC' respectively where 'UCC' is the average undirected clustering coefficient of the nodes in the network.

right-tail dependence.

4. Conclusion

Using tail-dependency networks constructed by quantile cross-spectral analysis (Barunik and Kley, 2019), we explore the asymmetric effects of the Covid-19 outbreak on the tail dependencies of a wide range of assets, which is crucial for asset and risk management during the pandemic. As it is found out earlier for the US equities (Azimli, 2020), we show that there exists an asymmetric response in the tail dependencies to the Covid-19 crisis for various asset classes, where the effect in the left tail is stronger and more prevalent than in the right tail. Moreover, the connectivity of tail-dependency networks among equities and commodities have increased the most during the pandemic period compared to other asset groups, showing a higher tail contagion effect for these specific assets. Conlon and McGee (2020) and Corbet et al. (2020b) argue that cryptocurrencies, Bitcoin in particular, do not act as hedges, or safe havens during the pandemic, but perhaps rather as amplifiers of contagion. While this might be true for these studies due to their shorter sample periods or their focus on the whole series (not the tail behaviour), we contrarily reveal that Bitcoin, in addition to US Treasury bond, is disconnected from other assets in tail-dependency networks, making it a safe-haven asset for international investors during the extreme periods of the Covid-19 crisis, which is in line with the findings of Goodell and Goutte (2020).

CRediT authorship contribution statement

Trung Hai Le: Conceptualization, Software, Methodology, Visualization, Writing - original draft, Data curation. Hung Xuan Do: Conceptualization, Investigation, Methodology, Writing - original draft. Duc Khuong Nguyen: Conceptualization, Investigation, Methodology, Writing - review & editing, Supervision. Ahmet Sensoy: Conceptualization, Investigation, Methodology, Visualization, Writing - review & editing, Data curation.

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