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An application of a TVP-VAR extended joint connected approach to explore connectedness between WTI crude oil, gold, stock and cryptocurrencies during the COVID-19 health crisis

Le Thanh Ha [a,*], Nguyen Thi Hong Nham [b]

[a] National Economics University, Viet Nam
[b] University of Economics Ho Chi Minh City, Viet Nam

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ABSTRACT

We employ a time-varying parameter vector autoregression (TVP-VAR) in combination with an extended joint connectedness approach to study interlinkages between four markets, namely the crude oil, gold, stock, and cryptocurrency markets, by characterizing the connectedness of these four markets, from January 1, 2018, to August 1, 2021. Our results demonstrate that health shocks appear to influence the system-wide dynamic connectedness, which reaches a peak during the COVID-19 pandemic. Net total directional connectedness suggests that the gold and stock markets consistently appear to be net receivers of spillover shocks. Crude oil appears to be a critical net transmitter of shocks for almost the whole pre-COVID-19 pandemic period, but it turns into an important net receiver during the COVID-19 pandemic. The cryptocurrency market acts as the time-varying net receiver and net transmitter of our network, and it has the most inconsiderable role within our studied network. Pairwise connectedness reveals that crude oil and stock are mostly receiving spillover effects from all the other markets, while gold could be either a net transmitter or a net receiver, depending on the types of market considered. Cryptocurrency is a volatile market, and its role varies constantly over time.

1. Introduction

As the multiple waves of the COVID-19 pandemic in 2020 caused visible harm across businesses, the pandemic's negative effects are undeniable. The price of Bitcoin (BTC) fell by 36 % in March 2020, while the price of WIT crude oil fell to a negative value in the following month, for the first time in history. The energy businesses, more than any other, were severely harmed by the pandemic as a result of blockage and oversupply. This could explain both the rapid decline in oil consumption and the sharp decline in prices. The relationship between the pandemic and oil demand was discussed by Kalyuzhnova and Lee (2020). According to their conclusions, whenever oil demand is restored, the built-up oil supply will have a negative impact on pricing. Furthermore, the lack of investment in the oil industry is being emphasized as corporations cut their budgets, potentially affecting oil production capacity in the coming decade. Consequences beyond health issues are projected as a result of the energy market imbalance, which is expected to reduce demand for oil in comparison to projections made before the epidemic began (Kalyuzhnova and Lee, 2020). However, while OPEC negotiations may help to improve the oil market position, geopolitical dangers remain a major concern (Sharif et al., 2020a, 2020b). In contrast to oil prices, whose fluctuation and high volatility negatively influence the market yet provide valuable information for predicting financial asset prices, volatility in gold prices has shown good signs that gold can be utilized as a safe haven when facing financial turmoil (Baur and Lucey, 2010). Therefore, knowing that oil and gold are believed to have a strong connection with stock markets only emphasized the importance of discovering the connection between oil, gold, and stock markets and their impact on investors' portfolios.

The cryptocurrency market, like the aforementioned areas of the economy, is heavily influenced by the current health crisis. As previously stated, this market has changed dramatically throughout the time of the COVID-19 pandemic. Many academics agree that this is the worst financial catastrophe since the global financial crisis of 2008. The progression and waves of the COVID-19 pandemic are then claimed to have had significant effects on the cryptocurrency market, making it volatile and unpredictable. A few papers, however, have looked at the influences of the COVID-19 pandemic on the Bitcoin market. Cryptocurrencies

* Corresponding author.
E-mail addresses: halethanh.kt@gmail.com (L.T. Ha), nhamnth@ueh.edu.vn (N.T.H. Nham).

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(such as Bitcoin) are a volatile financial asset with superior hedging compared to other financial assets and commodities (Bouoiyour et al., 2014; Hu et al., 2019; Kostika and Laopodis, 2019; Miglietti et al., 2019; Sahoo, 2021) such as stocks and the US dollar (Dyhrberg, 2016). Consequently, during the global spread of the virus, investors diversified their portfolios in order to find a safer and more profitable investment in the short term. On March 8, 2020, there was a sudden dip in cryptocurrency trading, resulting in a loss of US$21 billion in the crypto market's overall capitalization in under 24 h. The crypto market experienced a significant collapse on Black Monday (March 9), as the situation continued to deteriorate. COVID-19 was formally declared a global threat two days after the event, compounding the damage and forcing the cryptocurrency market to lose half of its capitalization through controlled devaluation.

What had been considered to be an exponential drop, however, quickly made an astonishing recovery. As the COVID-19 pandemic quickly spread around the globe, cryptocurrency was the investment of choice. Through the potential link between cryptocurrency and foreign exchange markets, Majdoub et al. (2021) and Umar et al. (2021a, 2021b) claim that cryptocurrencies are one of the most secure investing techniques during times of economic instability, such as the COVID-19 health crisis. As a result, strategy development toward a better management of portfolio investment risk and a well-developed financial instrument pricing will all be strongly impacted by this idea (Umar and Gubareva, 2020). The cryptocurrency market accomplished even more major achievements by the end of May 2020, following a quick comeback. During this thriving period, the total value of the crypto market topped US$300 billion in less than two months, then US$400 billion in early November, US$500 billion in early December, surpassing US$760 billion on the last day of 2020. These figures surpass the goals set in January 2018. Bitcoin has the king's share of the market among major currencies, with a market share of 64 % on average for the time period under consideration. Before Black Monday, Bitcoin held about 68 % of the market capitalization, while Ethereum held 7.3 % and XRP held 4.3 %. Bitcoin's position had weakened significantly by early March, with 63 %, 10.2 %, and 4.1 %, respectively. Bitcoin, on the other hand, reached a new high (68.4 %) just two months later, retaining its market leadership, with ETH accounting for 9.1 % and XRP for 3.5 %. Unfortunately, BTC lost its dominance and rapidly lost its market share to other cryptocurrencies, holding 56.7 % of the market on September 14th, 2020 (Ethereum 12.21 % and XRP 3.23 %). By the end of 2020, however, BTC had regained market dominance, accounting for 69.2 % of the global market value, with Ethereum accounting for 11.1 % and XRP accounting for 1.8 %.

COVID-19 has been one of the major detrimental influences on the financial markets. Upon the emergence of the health crisis, radical and deep changes, which had not been seen since 2008, were made to global financial markets. Scholars and policymakers have been focusing on scrutinizing the connection between the pandemic and financial markets, as these results are important for understanding how the market would perform under different circumstances. These studies also help to build suitable coping plans to minimize the severe and detrimental effects of the pandemic, giving investors the chance of making better-informed decisions about global portfolio diversification.

In explaining the motive behind the selection of stock, prior empirical literature on financial markets has pointed out that COVID-19 has affected how different markets interact with one another. By using a variety of financial networks based on the correlation of returns of various stocks, So et al. (2021) investigated Hong Kong's networks during the pandemic. The findings showed an increment in connectedness within financial networks. Zhang et al. (2020) also voiced concerns over the consequences of COVID-19 for the global market, as they found different patterns in different periods of the pandemic. With the same interest in mind, Bissoondoyal-Bheenick et al. (2021) scrutinized the relationship between volatility and returns in stock. They reported evidence showing their emphasized connectedness and a positive correlation between this connectedness and the severity of the pandemic. In the same vein, Costa et al. (2021) investigated the U.S. stocks connectedness from 2013 to the end of 2020 in different sections. Their findings are also aligned with others in providing evidence for the increase in connectedness during the pandemic.

The literature has also revealed the interlinkages between the gold market and the cryptocurrency market (Guesmi et al., 2019; Klein et al., 2018), the oil market (Canh et al., 2019), and other markets. Adding gold into crypto portfolios is critical since this generates more diversification gains (Huynh et al., 2020a, 2020b). Scholars argue that cryptocurrencies are increasingly considered as the New Gold, and that they play a critical role in hedging against uncertainty (Bouri et al., 2019). Instead of gold, cryptocurrencies have gradually become investors' selection as a safe haven during uncertain times (Jareño et al., 2020). During the COVID-19 crisis, the gold market seems to have played a modest role in restricting the risks arising from this crisis. Many scholars, such as Shahzad et al. (2021a, 2021b) and Yousaf and Ali (2020), provide evidence for the importance of cryptocurrency in hedging, diversifying, and reducing the portfolio risk during the COVID-19 pandemic. The role of the gold market and its interlinkages with other markets has been undermined since the appearance of the cryptocurrency market, especially during the COVID-19 pandemic.

In this paper, we examine the connectedness among different types of markets, especially when the global market experiences uncertain events like the COVID-19 health crisis. Our study focuses on the volatility of the crude oil market along with that of the cryptocurrency, gold, and stock markets. When explaining the motive behind the choice of gold, cryptocurrency, and crude oil, these three assets have been proven to serve as a hedge, surrogate currency, safe-haven asset, and a solution to reduce risks for investors. For crude oil (Hamilton, 1996; Jones and Kaul, 1996; Kilian, 2009) and the trend of financialized commodities (Chen et al., 2018; Lei et al., 2019; Tang and Xiong, 2012), the above scholars stressed the importance of the asset class, in addition to it being a benchmark and critical component in the energy industry. For the past few years, the rapid development of cryptocurrencies has given rise to a growing interest in scrutinizing and examining the topic for the benefit of investors and policymakers. Interestingly, although the topic of cryptocurrency behavior raises interest, cryptocurrencies' behavior has yet to be deeply scrutinized. According to the cryptocurrencies market capitalization in 2021, the market in terms of trade volume and capitalization reached 8626 cryptocurrencies in December 2021 while Bitcoin, Ethereum, and Ripple served as three major cryptocurrencies, accounting for 70 % of the market share.

Our paper has at least two contributions to make to the literature. *First*, to the best of our knowledge, we are the first to provide a comprehensive discussion of the connectedness between these four markets (crude oil, gold, stock and cryptocurrency), and to assess the influences of uncertain events like the COVID-19 health crisis on the dynamic connectedness among these markets. To serve this goal, we collect daily data on the gold price; the benchmark crude oil (WTI) price; the benchmark and largest cryptocurrency price (we select BTC based on the market capitalization); and the S&P 500 index – generally used to reflect the performance of the stock market in the US Our data represent the period of 1st January 2018 to 1st August 2021. *Second*, we follow Balcilar et al. (2021) to employ a time-varying parameter vector autoregression (TVP-VAR) in combination with an extended joint connectedness approach. We select this empirical approach due to its diverse advantages. Specifically, this empirical approach does not reduce our observation, thus it is possible to perform it in the case of short data spanning, although that is not the case here. Moreover, the presence of an outlier does not cause a significant change in our results, and this approach provides better adjustment to parameter changes. The most significant element of our employed approach is that it allows us to compute the net pairwise connectedness, which detects transmission mechanisms among these commodity and financial markets. The findings of this paper are expected to bring forth critical insightful knowledge and warnings for both investors and authorities.

The remainder of the paper is structured as follow. The literature review of previous studies is presented in Section 2. Section 3 presents the methodology, with the data and summary statistics. The analysis of the empirical results is presented in Section 4, and we provide the conclusions in Section 5.

2. Literature review

Studies on interlinkages between distinct markets, financial assets, or commodities within the same market are becoming more common, according to the literature. In this regard, Corbet et al. (2019) review prior studies to demonstrate and prove that cryptocurrencies are accepted as legitimate investment assets with a legitimate value, despite the possibility of illicit use and the appearance of poorly structured or inexperienced trading systems. Kyriazis (2019) also reviewed key findings from earlier research on the impacts of volatility and return spillovers on the cryptocurrency market. Interlinkages among the five largest cryptocurrencies are investigated by Hyun et al. (2019), who employ a copula directional dependence. While Piñeiro-Chousa et al. (2021) highlight the importance of investor sentiments toward financial markets, extracted from social networks, López-Cabarcos et al. (2021) study the influences of social network sentiment and stock market on the volatility of the cryptocurrency market. Also studying the interconnections between various cryptocurrencies, Kim et al. (2021) utilize GARCH models and a Bayesian stochastic volatility model and provide evidence for the interlinkages of these currencies.

Prior researchers have likewise looked into the interrelationships between different markets. Klein et al. (2018) study the time-varying conditional correlation between Bitcoin and gold using the BEKK-GARCH. Aslanidis et al. (2019) investigate links between cryptocurrencies and financial assets such as the Standard & Poor 500 Composite, Gold Bullion LBM, and S&P US Treasury bond. Guesmi et al. (2019) use the VARMA-DCC-GJR-GARCH model to show that the participation of investors in the cryptocurrency market allows them to gain more diversification and hedging opportunities. While emphasizing the importance of cryptocurrencies and blockchain technology as critical drivers of the accelerated pace of the Fourth Industrial Revolution, Su et al. (2020) focus on the interlinkage between the oil and cryptocurrency markets and show that an increasing Bitcoin price may threaten the demand for oil investment. Other empirical studies look at the role of cryptocurrencies as hedges or diversifiers, and this role is dependent on the time period and the assets linked with the cryptocurrency market. As a result, Selmi et al. (2018) compared the performance of gold and Bitcoin in terms of their efficiency in being hedges or diversifiers in particular market conditions. They determined that investing in Bitcoin is a safety belt during economic and political downturns. Klein et al. (2018) concurred, proclaiming Bitcoin to be the New Gold. Furthermore, Guesmi et al. (2019) stated that by incorporating Bitcoin into only three asset classes – gold, oil, and equities – investors might profit from lower risks. Canh et al. (2019) looked at the prospect of cryptocurrencies leading the market with the largest capitalization in order to separate oil and gold price shocks. Their studies revealed only minor correlations with economic variables, limiting the diversification possibilities available to financial investors. As revealed by Bouri et al. (2017), cryptocurrency has great power to hedge against uncertainty, despite the fact that uncertainty might be damaging to Bitcoin's profit. During economic downturns, Bouri et al. (2018) believed Bitcoin to be a useful diversification tool. With the exception of gold, Kurka (2019) found no evident link between Bitcoin and other traditional assets. Smales (2019) backed up this argument by claiming that the returns of cryptocurrency have no correlation with those of commodity or financial assets. He also expressed his belief that cryptocurrencies are only considered as a safe haven if there is stability in the Bitcoin market. Das et al. (2020) discovered that Bitcoin has no advantage over other assets such as gold, commodities, or the US dollar when it comes to hedging oil-related risks. Hedging capacity like this is very reliant on the core and fundamentals of oil risks and market conditions. Symitsi and Chalvatzis (2019) showed how Bitcoin benefits considerably in terms of portfolio diversification in both optimistic and bearish market circumstances.

In terms of financial and economic disruptions, how cryptocurrencies and different types of assets (such as crude oil) interact and respond to one another is a crucial and sensitive mechanism (Charfeddine et al., 2020). Although cryptocurrencies may fail as a hedging strategy, their ability to provide diversification should be recognized, according to the findings of this study. Jareño et al. (2020) provide proof of the gold-Bitcoin link, showing that Bitcoin might be employed in uncertain times. Bouri et al. (2018) and Hussain Shahzad et al. (2020) looked at the negative risk of US market equities as well as how cryptocurrencies might be used as a hedge and haven. Cryptocurrencies have been shown to be significant assets that aid investors in better managing their cryptocurrency holdings. Although gold's diversification is steadier, both Bitcoin and gold's performance as a hedging instrument or a safe haven fluctuates (Hussain Shahzad et al., 2020). Finally, Rehman and Vinh Vo (2020) discovered that in the short run, investors should consider copper since it offers the most diversification; however, in the long run, precious metals may be a superior diversification option for investors.

Cryptocurrencies are increasingly recognized as an asset class that may be used as a hedging tool and a diversification tool. As a result, the desire to find severe conditions, such as the one caused by a health crisis, is heightened. González et al. (2020) studied the performance of three portfolios comprising financial assets (e.g., stocks or bonds), cryptocurrency, and gold. They found that while cryptocurrencies have the capacity to manage the risk and uncertainty arising from spreading out investment portfolios, only a few have been able to do so successfully in extreme circumstances. Gold was also unable to restrict risk as the COVID-19 financial crisis evolved, despite its stability. Finally, despite their lower returns, investors should look into cryptocurrencies in order to diversify their portfolios more effectively. During the COVID-19 epidemic, Shahzad et al. (2021a, 2021b) looked at various cryptocurrencies assuming that there are both low and high volatility as well as observed significant spillovers. Yousaf and Ali (2020) stated that investors can benefit from maximal diversification by evaluating three main cryptocurrencies at the same time because cryptocurrencies did not fluctuate or experience high volatility prior to the COVID-19 timeframe. During the COVID-19 period, however, correlations between various cryptocurrency pairings have become more intense. The data point to a higher hedging efficacy during COVID-19, while also underlining the importance of cryptocurrency in hedging, diversifying, and reducing the portfolio risk. In this vein, Iqbal et al. (2020) looked into the influence of the COVID-19 pandemic crisis in terms of increasing risk and uncertainty in the cryptocurrency market. Their findings revealed an unbalanced association between COVID-19 and the returns of several cryptocurrencies. What is more, they discovered that cryptocurrencies, including BTC, can play a role as a hedging tool to deal with the negative effects of COVID-19 during times of economic instability. Yarovaya et al. (2020a, 2020b) discovered that BTC is dependent on either bearish or bullish capacity in market days. However, it does not improve during the times of the COVID-19 pandemic due to the herding effect on cryptocurrency markets. Valuable studies also highlighted future study topics by comparing some specific aspects of previous crises to the COVID-19 problem, as stated by Yarovaya et al. (2020a, 2020b). Corbet et al. (2020a, 2020b) explained how cryptocurrencies can help investors to diversify their portfolios while also serving as a strong safe haven during a pandemic crisis. Corbet et al. (2020a, 2020b) were interested in the Chinese financial markets and Bitcoin, whereas earlier research was focused on how different currencies interlinked. According to their findings, these assets are viewed as contagion amplifiers rather than as hedges or safe havens during times of substantial economic and financial instability. Conlon and McGee (2020) observed that when the price of

Bitcoin fell, the S&P 500 also fell, making the practice of investing in Bitcoin as a safer alternative during market downturns undesirable and questionable. More recently, Sarkodie et al. (2022) also examined COVID-19's influences on the market signals of cryptocurrencies. They emphasized that the cryptocurrency market is volatile, with market prices changing over time.

Because the COVID-19 issue is still ongoing, the revisions made in this study will focus on the primary findings of three articles that span not only what has been labeled COVID-19's first entrance, but also the months in which additional waves emerged. During the times of the COVID-19 pandemic, Umar et al. (2021a) looked into the relationship between the returns and fluctuation of the three largest cryptocurrencies, namely Bitcoin, Ethereum, and Ripple, and three major currencies, namely the euro, the British pound, and the Chinese yuan. Although the trend was most noticeable in the initial waves, there were minor changes between the following waves (Umar et al., 2021b). Karamti and Belhassine (2021) used wavelet coherence analysis to examine and include financial contagion in pandemic anxiety, in relation to US stock markets and worldwide markets in times of the pandemic. In terms of the cryptocurrency market, in the first wave the association between Bitcoin and the US COVID-19 fear index was positive, whereas the second wave saw the fear index have an impact on the Bitcoin market (Karamti and Belhassine, 2021). This outcome has given investors peace of mind when it comes to investing in cryptocurrency as a safe haven. Goodell and Goutte (2021) expanded these findings by employing wavelet coherence and neural network analysis. Surprisingly, Goodell and Goutte's (2021) analysis shows a link between Tether and the S&P 500, which was most prominent and frequent during the COVID-19 waves.

Various methodologies have been used in previous studies to investigate the relationship between cryptocurrencies and other asset types. While VAR models are used by Conlon and McGee (2020), VAR-GARCH models are employed in Symitsi and Chalvatzis (2019). A collection of BEKK models has also been selected. Katsiampa et al. (2019) used the bivariate Diagonal BEKK model, while others used BEKK-GARCH models, for example Klein et al. (2018), and BEKK-MGARCH models, for example Tu and Xue (2019). The GARCH-MIDAS model has been considered by a number of scholars (Walther et al., 2019). By applying this strategy, wavelet-based models likewise increased in popularity, with an excessive amount of study input (Mensi et al., 2019; Sharif et al., 2020a, 2020b). Several quantile techniques, such as the quantile cross-spectral approach (Rehman and Vinh Vo, 2020) or the quantile regression approach, as in the study of Jareño et al. (2020), have also been considered. ARDL models in the papers by Ciaian et al. (2018) and Nguyen et al. (2019), and NARDL models in the papers by Bouri et al. (2018), de la O González et al. (2020) and Demir et al. (2021), have recently been applied alongside GARCH (Corbet et al., 2020a, 2020b) and multivariate factor stochastic (Shi et al., 2020). Different scholars have used the DCC models suggested in this study, such as Charfeddine et al. (2020) and Kumar and Anandarao (2019). As further examples, the DCC-MGARCH models have been utilized by Canh et al. (2019) and the VARMA-DCC-GARCH models have been employed by Guesmi et al. (2019). Koutmos (2018) followed the method and approach published by Diebold and Yilmaz (2012). Balcilar et al. (2021) aimed to detect the mechanism through which a volatility shock in one market is transmitted to other markets by combining a time-varying parameter vector autoregression (TVP-VAR) connectedness approach and the joint spillover approach. The largest advantage of our employed approach is that it is easy to calculate the net pairwise connectedness, which detects transmission mechanisms among these commodity and financial markets.

Based on our discussion, we posit the four following hypotheses:

Hypothesis 1. Crude oil appears to be a net transmitter of shocks to other markets.

Hypothesis 2. Stock appears to be a net transmitter of shocks to other markets.

Hypothesis 3. Gold and cryptocurrency play the role of either a shock transmitter or a shock receiver, depending upon the types of market considered.

Hypothesis 4. COVID-19 shocks influence the system-wide dynamic connectedness and change the role of the market.

3. Database and methodology

3.1. Database

In this paper, we employ a daily dataset of the gold price; the benchmark crude oil (WTI) price; the benchmark and price of the largest cryptocurrency (we select BTC based on the market capitalization); and the S&P 500 index, which is generally used to reflect the performance of the stock market in the US. Our data is taken from 1st January 2018 to 1st August 2021. Since our studied variables are not stationary, based on the unit root test statistics developed by Elliott et al. (1996), we have to employ the first log-differenced series that can be interpreted as a percentage change of these variables. Fig. 1 demonstrates a pattern of these series.

As displayed in Table 1, the return of all the studied markets is positive on average. In addition, cryptocurrency and crude oil are the markets with the largest variance and therefore these two markets are regarded as the riskiest choices among the considered markets for investors during the selected sample. Notably, this paper finds that all of the series' distributions are highly leptokurtic. In other works, compared to a normal distribution, the distribution of these variables has a shape with fatter tails, suggesting that they do not follow a normal distribution, as contended by Jarque and Bera (1980). Based on the ERS unit root test of Elliott et al. (1996), at a 1 % significance level, these variables are statistically stationary. Lastly, the weighted portmanteau test of Fisher and Gallagher (2012) demonstrates that there is an autocorrelation between the returns and squared returns, thus we have strong evidence to support the use of a TVP-VAR approach with a time-varying variance-covariance structure to estimate the interlinkages of these studies markets. Since the main goal of this study is to investigate changes in the interlinkages of the series in the times before and during the COVID-19 health crisis, we also provide a similar statistical description of these series in two subsamples. Since the World Health Organization formally announced the coronavirus disease outbreak of 2019 (COVID-19) to the world for the first time on 31st December 2019, we use this point of time to separate our entire sample into two subsamples: before COVID-19 (denoted as the pre-COVID-19 period starting from 1st January 2018 to 31st December 2019) and during COVID-19 (denoted as the COVID-19 period starting from 1st January 2020 to 1st August 2021).[1] Table 1 presents the significantly different statistics for these series in the two periods. For example, there is a positive average return of all series in the COVID-19 period, while the return of BTC is negative in the pre-COVID-19 period. Furthermore, the mean returns of these three markets increase after the COVID-19 health crisis hit the global economy. All markets become more volatile during the COVID-19 period as all variances increase. The results related to the ERS unit root test and the weighted portmanteau test on these variables during these two periods are more likely to remain the same as those obtained from tests on the whole sample, which also convinced us to apply our selected approach to estimate interlinkages between the considered markets in these two subsamples.

[1] A similar approach can be found in many empirical studies (e.g., Chkili, 2022; Ha, 2022; Hong and Yoon, 2022; Huynh et al., 2020a, b; Umar et al., 2021a).

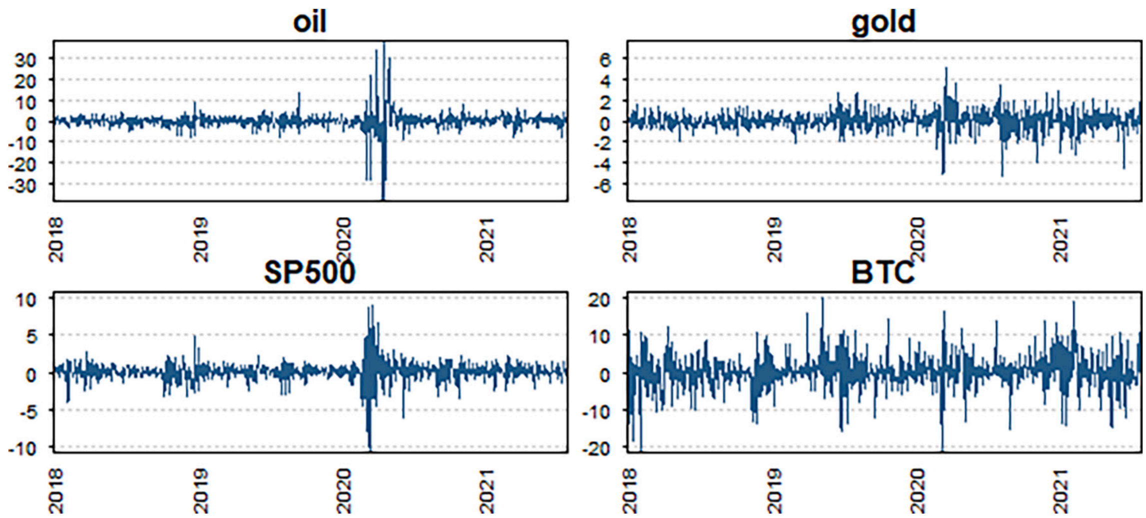

Fig. 1. Crude oil, gold, stock and cryptocurrency returns.

3.2. Empirical methodology

The most popular econometric technique used to examine connectedness is one proposed by Diebold and Yilmaz (2012). The scholars employ this methodology to monitor contagions in a predetermined network in order to resolve the adverse effects stemming from a specific economic shock. One limitation of the original approach is that it is reliant on a rolling window size chosen arbitrarily of the time variant of connectedness. Several suggestions have been provided to resolve this issue, such as the use of the mean squared prediction error of the employed rolling window VAR to select the optimal window size (Antonakakis et al., 2020); or the use of the joint spillover index (Lastrapes and Wiesen, 2021. In this paper, we follow Balcilar et al. (2021) and apply a time-varying parameter vector autoregression (TVP-VAR) in combination with an extended joint connectedness approach to study interlinkages between four markets, namely the crude oil, gold, stock, and cryptocurrency markets.

3.2.1. Vector autoregression with time-varying parameters

First, the TVP-VAR connectedness approach in combination with the original technique of Diebold and Yilmaz (2012) is outlined in this section. In this article, we estimate a TVP-VAR model that has a lag length of order one, using the Bayesian information criterion (BIC):

$$\mathrm{y}_t = \mathrm{M}_t \mathrm{y}_{t-1} + \epsilon_t, \quad \epsilon_t \sim N(0, \Sigma_t \tag{1}$$

$$vec(M_t) = vec(M_{t-1}) + u_t, \quad u_t \sim N\left(0, R_t\right. \tag{2}$$

where y_t, y_{t-1} and ϵ_t are $Z \times 1$ dimensional vectors and M_t and Σ_t are $Z \times Z$ dimensional matrices. $vec(M_t)$ and u_t are $Z^2 \times 1$ dimensional vectors whereas R_t is a $Z^2 \times Z^2$ multiple-dimensional matrix. According to this model, all parameters (M_t), as well as the relationships between successive series, may fluctuate over time. A further assumption is that the variance-covariance matrices (Σ_t and R_t) also vary over time. A number of previous studies have revealed that the variances and co-variances of financial markets are changing with time, resulting in varying market and investment risk over time.

Subsequently, the TVP-VMA model is written as follows: $y_t = \sum_{h=0}^{\infty} N_{h,t}\epsilon_{t-1}$ where $N_0 = I_Z$ and ϵ_t denotes a symmetric white noise shock that the $Z \times Z$ time-varying covariance matrix $E(\epsilon_t \epsilon_t{}') = \Sigma_t$ varies with time. Therefore, the L-step forecast error is as follows:

$$\varphi_t(L) = y_{t+L} - E\left(y_{t+L} | y_t, y_{t-1}, \dots = \sum\nolimits_{l=0}^{L-1} N_{l,t}\epsilon_{t+L-l},\right) \tag{3}$$

A matrix of forecast error covariance can be written as follows:

$$E\big((\varphi_t(L)\varphi_t'(L)\big) = N_{l,t}\Sigma_t N_{h,t}', \tag{4}$$

The proposed framework relies on Pesaran and Shin's (1998) L-step ahead generalized forecast error variance decomposition (GFEVD). The GFEVD, $gST_{ij,\,t}$, represents the impact of a shock stemming from variable j on variable i and it can be written as follows:

$$\varphi_{ij,t}^{\mathrm{gen}}(\mathrm{L}) = \frac{E\left(\varphi_{i,t}^2(L)\right) - E\left[\varphi_{i,t}(L) - E\left(\varphi_{i,t}(L)\right) | \epsilon_{j,t+1}, \dots, \epsilon_{j,t+1}\right]^2}{E(\varphi_{it}^2(L))}, \tag{5}$$

$$= \frac{\sum_{l=0}^{L-1}\left(e_i' N_{lt}\Sigma_t e_j\right)^2}{\left(e_j'\Sigma_t e_j\right).\sum_{l=0}^{L-1}\left(e_i' N_{lt}\Sigma_t N_{lt}' e_i\right)}, \tag{6}$$

$$gST_{ij,t} = \frac{\varphi_{ij,t}^{gen}(L)}{\sum_{j=1}^{L}\varphi_{ij,t}^{gen}(L)}, \tag{7}$$

where e_i denotes a $Z \times 1$ zero selection vector that has a unity on its ith position and $\varphi_{ij,\,t}^{gen}(L)$, (L), which represents a proportional reduction in the variance of the prediction error of variable i as a result of conditioning on the future shocks of variable j.

The $\sum_{j=1}^{Z}\varphi_{ij,\,t}^{gen}(L) \neq 1$ is normalized to unity, leading to the value of $gST_{ij,\,t}$. We write this metric as follows:

$$X_{i\leftarrow\bullet,t}^{gen,from} = \sum_{j=1,i\neq j}^{Z} gST_{ij,t}, \tag{8}$$

$$X_{i\rightarrow\bullet,t}^{gen,to} = \sum_{j=1,i\neq j}^{Z} gST_{ij,t}. \tag{9}$$

The net total directional connectedness is presented as: $X_{i,\,t}^{gen,\,net} = X_{i\rightarrow\bullet,\,t}^{gen,\,to} - X_{i\leftarrow\bullet,\,t}^{gen,\,from}$. If $X_{i,\,t}^{gen,\,net} < 0$ ($X_{i,\,t}^{gen,\,net} > 0$), variable i implies a net receiver (transmitter) of shocks. In other words, variable i is driven by (is driving) other variables in the network.

The total connectedness index (TCI) demonstrates the interconnectedness within the network. We define the TCI as:

$$gST_t = \frac{1}{z}\sum_{i=1}^{Z} X_{i\leftarrow\bullet,t}^{gen,from} = \frac{1}{z}\sum_{i=1}^{Z} X_{i\rightarrow\bullet,t}^{gen,to}, \tag{10}$$

where network spillovers with a higher degree have a greater value.

Lastly, the net pairwise directional spillovers can de represented as: $X_{i,\,t}^{gen,\,net} = gST_{ij,\,t}^{gen,\,to} - gST_{ij,\,t}^{gen,\,from}$. If $X_{ij,\,t}^{gen,\,net} > 0$, this suggests that series i has a more considerable influence on series j.

Table 1
Summary statistics.

	Whole sample				Pre-COVID-19 pandemic				COVID-19 pandemic			
	Crude oil	Gold	SP500	BTC	Crude oil	Gold	SP500	BTC	Crude oil	Gold	SP500	BTC
Mean	0.0223	0.0363	0.0538	0.1138	0.0022	0.0279	0.0352	−0.1425	0.048	0.0452	0.0762	0.4556
Variance	164.6301	0.823	1.9084	23.3947	4.1121	0.4111	0.8692	20.8422	374.8712	1.3628	3.2714	26.6169
Skewness	−6.379***	−0.491***	−1.061***	−1.156***	0.036***	0.407***	−0.617***	−0.303***	−4.295***	−0.636***	−1.009***	−1.973***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.007)	(0.000)	(0.000)	(0.000)	(0.005)	(0.000)	(0.000)	(0.000)
Kurtosis	400.750***	5.917***	17.737***	11.417***	5.541***	1.751***	3.804***	3.577***	177.131***	3.978***	12.741***	17.924***
JB	6,102,315.114***	1365.534***	12,112.455***	5150.219***	658.872***	80.024***	343.162***	282.414***	5175.344***	287.109***	2738.617***	5543.631***
ERS	−15.814***	−13.703***	−8.848***	−10.767***	−3.609***	−9.245***	−5.814***	−7.551***	−10.902***	−3.660***	−5.805***	−4.056***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Q(20)	156.212***	44.463***	241.554***	21.419**	24.649**	31.843**	23.995	14.178	69.715***	28.109	184.365***	36.583**
	(0.000)	(0.001)	(0.000)	(0.073)	(0.025)	(0.045)	(0.243)	(0.821)	(0.000)	(0.107)	(0.000)	(0.013)
$Q^2(20)$	189.594***	181.014***	1122.931***	18.996**	17.433**	47.301***	96.628***	37.153***	81.913***	51.599***	478.266***	7.148
	(0.000)	(0.000)	(0.000)	(0.026)	(0.050)	(0.000)	(0.000)	(0.026)	(0.000)	(0.000)	(0.000)	(0.810)

Note: *, **, and *** correspond to $p < 0.1$, $p < 0.05$ and $p < 0.01$, respectively.

3.2.2. Technique with an extended joint connectedness

The $gST_{ij,\,t}$ and $jST_{ij,\,t}$ are assumed:

$$X^{jnt,from}_{i\leftarrow\bullet,t} = \sum_{j=1,i\neq j}^{Z} jST_{ij,t}, \tag{11}$$

$$X^{jnt,to}_{\bullet\leftarrow i,t} = \sum_{j=1,i\neq j}^{Z} jST_{ji,t}, \tag{12}$$

$$\mathrm{jSI_i} = \frac{1}{z}\sum_{i=1}^{Z} X^{\mathrm{jnt,from}}_{i\leftarrow\bullet,t} = \frac{1}{z}\sum_{i=1}^{Z} X^{\mathrm{jnt,to}}_{i\rightarrow\bullet}.$$

We follow Lastrapes and Wiesen (2021) to generalize the scaling approach, in which the scaling factor η differs by each row as follows:

$$\eta_i = \frac{X^{jnt,from}_{i\leftarrow\bullet,t}}{X^{gen,from}_{i\leftarrow\bullet,t}}, \tag{13}$$

$$\eta = \frac{1}{z}\sum_{i=1}^{Z} \eta_i. \tag{14}$$

Lastly, we can obtain:

- $jST_{ij,\,t} = \eta_i gST_{ij,\,t}$,
- $jST_{ii,\,t} = 1 - X^{jnt,\,from}_{i\leftarrow\bullet,\,t}$,
- $X^{jnt,to}_{i\rightarrow\bullet,t} = \sum_{j=1,j\neq i}^{Z} jST_{ij,t}$.

Finally, allowing the scaling parameter to vary by row allows us to compute the net total and pairwise directional connectedness measures as follows:

$$X^{jnt,net}_{i,t} = X^{jnt,to}_{i\rightarrow\bullet,t} - X^{jnt,from}_{i\leftarrow\bullet,t}, \tag{15}$$

$$X^{jnt,net}_{ij,t} = gST_{ji,t} - gST_{ij,t}. \tag{16}$$

4. Results

This section starts by reporting the average TCI values for a full set of observations before displaying the pattern of the TCI over the studied period. By analyzing changes in the TCI's pattern before and after the COVID-19 health crisis, we also evaluate the effects of this uncertain event on the interlinkages between the considered markets. In the following step, we also analyze the results for net total connectedness and net pairwise connectedness, which help us to gain a more deeply insightful knowledge about the role of each market within our proposed system. It is worth noting that each market can play the role of either a net shock transmitter or net shock receiver. Finally, for comparison purposes, we then follow Lastrapes and Wiesen (2021) to quantify the joint spillover index, which can be useful to explore the reasons behind any changes in the interlinkages of these markets within the system. A similar procedure is also applied for the two subsamples to indicate the influences of the COVID-19 pandemic on the network.

4.1. Time variant of average dynamic connectedness

By using the full set of observations and the subsets of the observations based on the day the COVID-19 pandemic was first announced, the average results regarding the interlinkages of diverse markets within the network of diverse markets are reported in Table 2. In this table, the volatility of a particular market, as accounted for by its own shocks, is reported by the diagonal element, and the contribution of this market to others' volatility (FROM) and the contribution of others to this market's volatility (TO) are summarized in the off-diagonal elements. Particularly, in Table 2, we outline each individual market's contribution to a particular market's forecast error variance in the rows, while the

Table 2
Averaged joint connectedness.

	Whole sample					Pre-COVID-19 pandemic					COVID-19 pandemic				
	Oil	Gold	SP500	BTC	FROM	Oil	Gold	SP500	BTC	FROM	Oil	Gold	SP500	BTC	FROM
Crude oil	91.22	2.98	4.56	1.24	8.78	87.57	0.85	9.45	2.13	12.43	83.51	6.28	6.81	3.40	16.49
Gold	10.50	81.03	5.63	2.84	18.97	2.40	94.82	1.19	1.59	5.18	17.82	58.26	15.81	8.11	41.74
SP500	7.34	6.03	81.41	5.21	18.59	9.40	2.03	86.57	2.00	13.43	9.69	15.98	61.32	13.01	38.68
BTC	1.58	3.22	5.41	89.79	10.21	0.52	1.35	1.23	96.90	3.10	4.16	9.56	13.85	72.43	27.57
TO	19.42	12.23	15.60	9.30	TCI	12.32	4.24	11.87	5.73	TCI	31.67	31.82	36.47	24.52	TCI
NET	10.64	−6.74	−2.98	−0.91	14.02	−0.12	−0.95	−1.56	2.63	8.54	15.17	−9.92	−2.21	−3.05	30.67

columns correspond to the effect that one specific type of market has on all the other markets separately.

Considering the entire set of observations, the TCI average value is 14.02 %, implying that 14.02 % of the variance in our network of considered markets can be elucidated by fluctuations within this network. This also suggests that nearly 86 % of error variance within the system stems from idiosyncratic impacts. The last row of Table 2 indicates the role of each market, suggesting that, on net values, crude oil plays an inconsiderable role in transmitting effects and volatility of shocks to other markets within the system. By implication, gold, stock, and cryptocurrency are net receivers of the corresponding shocks, from which the most vital shock receiver is the gold market.

Considering the subsets of observations divided by the COVID-19 crisis time, we reveal that each market plays a different role in a different time. In particular, the network of all the markets can only explain a small proportion of the evolution within the network itself during the pre-COVID-19 pandemic period (TCI is 8.54 %). However, this figure increases substantially to approximately 30 % from the day when the COVID-19 pandemic hits the globe. In other words, nearly 70 % of the forecast error variance of the system can be accounted for by idiosyncratic effects during the COVID-19 pandemic period. These findings advocate the argument that these types of markets tend to comove substantially, especially during an uncertain time like that of COVID-19. During this time, crude oil acts as a net transmitter of shocks within the specific system, while gold, stocks, and cryptocurrency behave as net receivers of the corresponding shocks. This finding contrasts with the previous period, in which cryptocurrency is a net shock transmitter and other markets are net shock receivers. Our findings are consistent with previous papers and our belief. Mensi et al. (2021) also study dynamic frequency connectedness for volatility differences among cryptocurrencies, and they also reveal that each cryptocurrency may play the role of either shock transmitter or shock receiver. Matkovskyy and Jalan (2019) show that the cryptocurrency market receives shocks from financial markets. Their role is conditional on the time and frequency domains (Mensi et al., 2021; Shahzad et al., 2021a, 2021b) or their own past shocks and previous volatilities (Katsiampa, 2019). Furthermore, they also argue that only few cryptocurrencies provide diversification benefits and risk reductions. The cryptocurrency market is likely to become more volatile during uncertain times like the COVID-19 pandemic. Umar et al. (2021a) also demonstrate that the role of markets can be exchanged during the waves of the COVID-19 crisis. Even in the different waves of the COVID-19 crisis, these roles may also vary.

4.2. Time variant of total connectedness

It would be instructive to note that the aforementioned average results only present a mere summary of interlinkages among the considered markets within the system. In order to shed light on the influences of the COVID-19 health crisis on the interlinkages across a network of markets, it is vital to employ a more dynamic framework of analysis, which takes the time variance of the TCI into account and reflects the time variant of the role of the studied markets within the network. For example, it is a prerequisite to consider changes in the behavior of a particular market from a net shock transmitter to a net shock receiver, and vice versa. This paper starts with the time variant of total connectedness estimations, presenting the intertemporal changes of the TCI as illustrated in Fig. 2.

It can be seen that the TCI values vary remarkedly across our studied sample period, and it is worth noting that small TCI values suggest low contagions between the diverse types of the markets of interest. The TCI has relatively sizable values for particular points at the beginning of our sample. However, these TCI values tend to decline and then remain around a relatively small value during the 2019–2020 period. The reasons for this are threefold. First, as the cryptocurrency market is still young, the low interconnectedness values prior to the cryptocurrency's downfall of 2017 can be explained by the fact that back then, cryptocurrency price movements were rather random, highly volatile, and unaffected by price changes in other markets. As evidenced by the substantial increase in market integration that occurred afterwards, this pattern changed, reflecting the importance of the results received by investors. Second, the system benefits from relatively high network intensity and financial integration in the world, especially when there is no severe shock hitting the system, which allows the effective absorption of shocks rather than their amplification to the entire system (Affinito and Franco Pozzolo, 2017). Third, global equity and crude oil were more volatile in the 2019–2020 period due to both regional and global events like the Oil Price Crash, the War in Yemen and the Qatari Diplomatic Crisis (Yousuf and Zhai, 2021).

More importantly, the TCI increases dramatically and reaches a very high value from the day that COVID-19 first appeared at the beginning of 2020; at the highest peak it had increased by approximately 50 %.

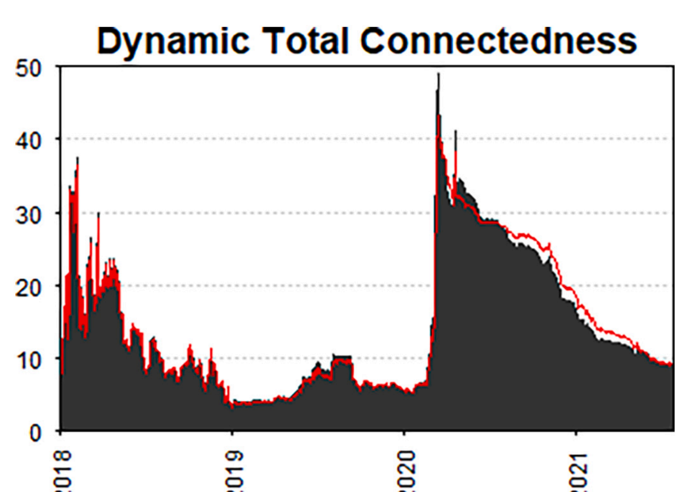

Fig. 2. Time variant of total connectedness.
Notes: We follow Balcilar et al. (2021) to set up the lead (20 leads) and lag length (1 lag) order of forecast error variance decomposition in our TVP-VAR system. The robustness checks were also conducted by changing these values. We display both the joint interlinkages (the black shaded area) and original interlinkages (the red line). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Prior studies also indicate a rise in the connectedness of some commodity markets during uncertain times such as the global financial crisis (2007–2009), for example Balcilar et al. (2021) and Zhang and Broadstock (2020). Subsequently, there is a decreasing trend in the TCI, which reaches a trough at the end of 2021. The lowest trough is approximately 10 %. The higher TCI values mean larger contagions between the diverse types of market, but these high TCI values only happen in a very short period, after the first appearance of the COVID-19 pandemic. Similar evidence is also found in the study of Balcilar et al. (2021), which also found that total connectedness values reached a new remarkable peak due to the COVID-19 crisis. These high values then last toward the end of our studied period. The study of Ji et al. (2020) also advocates the view that certain commodity markets should be regarded as safe havens for investors in uncertain times like the COVID-19 pandemic. Our findings and those of prior works hold the consensus that the time variant of the TCI is sensitive to COVID-19 shocks and that interlinkages increase if the level of uncertainty augments. Finally, by using the original method as in the series of Diebold and Yılmaz's studies, we also highlight all similar peaks and troughs.

4.3. Time variant of net total and pairwise directional connectedness

In the following analysis, we focus on net connectedness results, which can help us to classify a typical market as a net shock transmitter or a net shock receiver. The current dynamic approach differs from the classification introduced previously, as it permits us to identify the shifting in each market's role. In other words, the roles played by a specific market as a net shock receiver and a net shock transmitter in the system at different times will be conditional on the time interval and the particular types of markets within the studied network.

Our study starts with net total connectedness, which helps us detect whether there is a variation in the role of a market throughout the separated periods. In the following, we outline our estimates regarding pairwise net connectedness. The investigation of pairs of considered markets allows us to indicate how their interlinkage has changed between these two potential roles over time. We plot the estimated results in Fig. 3. It is essential to recall that the positive and negative values respectively reflect the net transmitting role and the net receiving role. Consistent with the main findings indicated previously, by using the net total connectedness results we show that both gold and the stock market consistently act as net contagion shock receivers. Crude oil and the cryptocurrency market, by contrast, shift their roles over time. Furthermore, crude oil behaves consistently as a critical net shock transmitter for the pre-COVID-19 pandemic period. In the 2019–2020 period, crude oil turns into an important net receiver. More recently, when the entire globe was hit by the COVID-19 pandemic, crude oil played a role of net shock transmitter again, until the end of our studied period. The cryptocurrency market acts as the changed net receiver and net transmitter of our network from the beginning of 2018 to the beginning of 2019. From then until 2020, the cryptocurrency market picks up as the persistent net receiver before again becoming the net transmitter throughout 2021. Finally, it is unlikely that cryptocurrency is a critical transmitter or receiver during our investigated sample period. We focus more on the COVID-19 period to highlight our findings, which are presented in Fig. 4. It is likely that crude oil is persistently a vital net shock transmitter, while the persistent net shock receivers consist of the stock and gold markets. By contrast, the cryptocurrency market varies from a net receiver at the beginning of 2020 to a net transmitter of our network until the end of our sample. Notably, it is likely that there are some initial spikes at the beginning of 2020, which we expect would disappear if the cut-off point were after the first quarter of the year.[2] Until then, it was perceived as a local phenomenon. Therefore, we exclude these three initial months and perform a similar approach as a robustness check. We demonstrate the results of this robustness check in Fig. A.1 in the Appendix. The results demonstrate that some initial spikes at the beginning of 2020 disappear, and all conclusions still remain.

It is instructive to note that the key advantage of our employed method, as compared to the original method, is that it is a theory-based normalization technique, proposed by Lastrapes and Wiesen (2021). Subsequently, our study concentrates on net pairwise connectedness estimates as displayed in Fig. 5. We firstly look into the contagion effects associated with crude oil to ascertain the critical role of crude oil within our considered network of diverse markets, as shown in Panel A. Notably, although, on net terms, the role of crude oil may exchange over time with all the other markets, there remains a relatively high magnitude of contagion activity for crude oil in 2018, but this is relatively low from 2019 toward the end of our sample, implying that in any circumstance, crude oil equally responds to shocks from other markets and influences these markets. Crude oil consistently appears as a shock transmitter in the interconnection between crude oil and gold. However, the net pairwise directional connectedness between the crude oil market and the stock market (S&P 500) follows a varying transmitting pattern during the 2018–2021 period. It is worth noting that crude oil mainly acts as a shock transmitter at the beginning of the period and during the COVID-19 period. Panel B presents the spillover effects of the gold market on other markets. Concerning the interrelation between gold and crude oil, the gold market is a persistent net shock receiver; this market appears to have changed its role over time with the stock and cryptocurrency market, but the empirical results suggest that it is more likely to be a net transmitter. Focusing primarily on the oil-SP500 interlinkage, crude oil most likely plays a role as a shock transmitter during the studied period. Concerning the stock and cryptocurrency markets, Panels C and D reveal that these two markets may play time-varying roles within the remaining markets. Specifically, the stock market mostly behaves as a shock receiver at the beginning of the period and during the COVID-19 period, when analyzing this market in relation to the crude oil market and gold market. A varying transmitting pattern is displayed clearly by the net pairwise directional connectedness between the stock market and cryptocurrency market. Panel D demonstrates that the role of the cryptocurrency market is not clear at the beginning of 2018 since this market is quite young. Regarding the interlinkage between cryptocurrency and crude oil and the stock market, BTC appears to be a shock transmitter. However, during the COVID-19 period, the net pairwise directional connectedness between BTC and SP500 reveals that BTC is a shock transmitter before turning into a shock receiver toward the end of the period. By contrast, the cryptocurrency market mostly behaves as a shock receiver during the COVID-19 period when analyzing this market in relation to the gold market, which is traditionally considered as a safe haven for investors during uncertain times. In general, we reveal that all markets are significantly interrelated, hence it is vital to perform better market management that does not focus on one market solely.

It is vital to study the time variance of the net pairwise directional interlinkages between the various markets during uncertain times like the COVID-19 health crisis. Notably, the role of these markets becomes more consistent over time. Fig. 6 presents these results. Crude oil appears to consistently be a net transmitter to all other markets within the studied network, as shown in Panel A. As displayed in Panel B, gold plays the role of a net receiver to crude oil and a net shock transmitter to stock but has two roles over time in relation to cryptocurrency; that is, it is a net transmitter at the beginning of 2020 and it becomes a net receiver for the remaining time. Panel C also suggests that the stock market is a net shock receiver from the oil and gold markets, while stock has a time-varying role in response to cryptocurrency. In any case, the responses of other markets to cryptocurrency and of cryptocurrency to other markets are all time-varying. These results suggest that cryptocurrency is a volatile market, and its role varies constantly over time.

It is worth noting that by comparing these results to those attained by

[2] We greatly appreciate a reviewer for this suggestion.

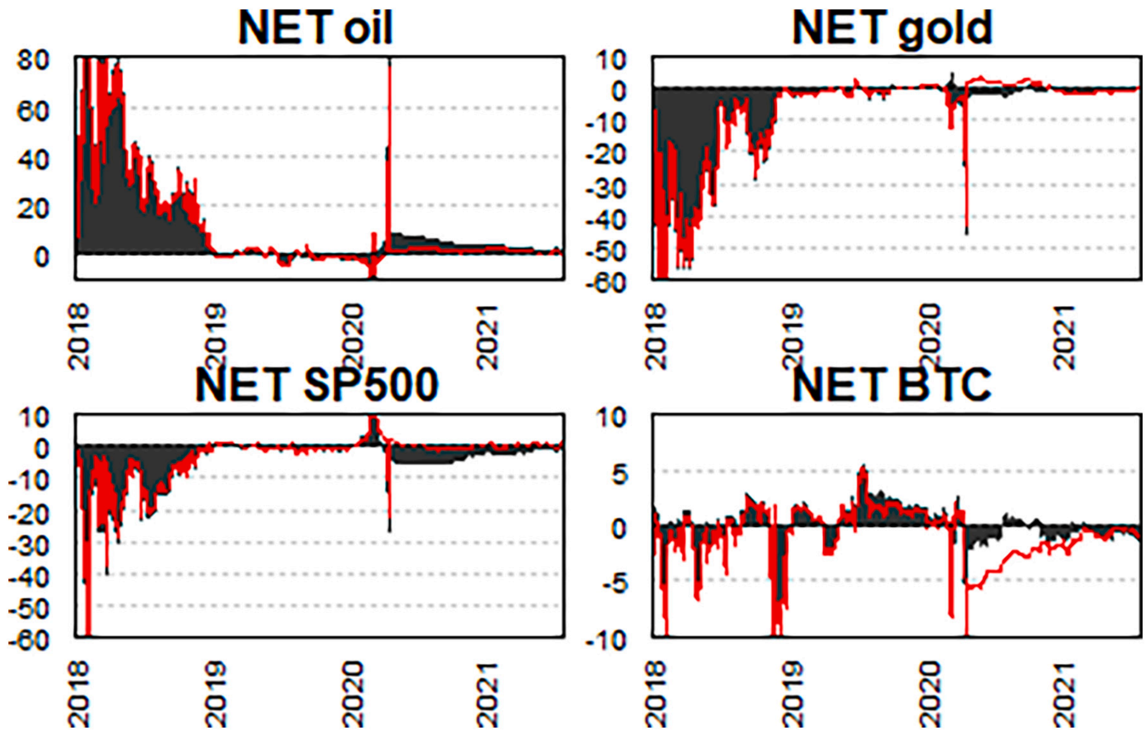

Fig. 3. Time variant of net total directional connectedness.
Notes: We follow Balcilar et al. (2021) to set up the lead (20 leads) and lag length (1 lag) order of forecast error variance decomposition in our TVP-VAR system. The robustness checks were also conducted by changing these values. We display both the joint interlinkages (the black shaded area) and original interlinkages (the red line). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

the standard approach, as in the study of Diebold and Yilmaz (2012); Diebold and Yılmaz (2014), we can see that crude oil is most likely receiving contagion effects from all the other markets investigated previously. Stock mostly behaves as a net shock receiver. Gold could be either a net shock receiver or a net shock transmitter, depending on the types of market being considered. We have a similar consensus to that of previous studies, which reveal that cryptocurrency is the most volatile market even in normal times. This volatility becomes especially high in uncertain situations.

5. Conclusions and policy implications

Our paper employs a network connectedness approach to estimate the interconnectedness of four markets, namely crude oil, gold, stock, and cryptocurrency, in a time-varying fashion using a TVP-VAR approach. We also follow Balcilar et al.'s (2021) approach, which allows for more flexibility and enables us to attain the measures for net pairwise connectedness. In this paper, we collect the daily data for the benchmark crude oil (WTI) prices, gold prices, S&P500 index and Bitcoin prices, from January 1, 2018 to August 1, 2021.

Using the full set of observations, our results show that all the studied markets are inconsiderably interconnected. However, when concentrating on the time of the COVID-19 health crisis, the interlinkages level becomes more substantial, as illustrated by the relatively small TCI value (approximately 14 % in the full sample and 30 % in the COVID-19 period). The findings suggest that our developed network is exposed to high market risk. Specifically, this paper reveals that there is a time variant of system-wide interlinkages that is motivated by the COVID-19 pandemic. What is more, we show empirical evidence that crude oil dominates the market while gold, stocks, and cryptocurrency are driven by the market. During an uncertain time, such as the period of high prevalence of COVID-19, crude oil is a net corresponding shock transmitter in the specific system, while gold, stocks, and cryptocurrency are net corresponding shock receivers. The pairwise connectedness estimates consistently indicate that crude oil responds to corresponding shocks from other markets, and at the same time it influences these other markets. Gold plays a role as a net shock receiver to crude oil and a net shock transmitter to stock but has two roles over time connected to cryptocurrency. The stock market is a net shock receiver from oil and gold, while it plays a time-varying role in response to cryptocurrency. In any case, the responses of other markets to cryptocurrency and that of cryptocurrency to other markets are all time-varying. We find evidence that cryptocurrency is a volatile market, and that its role is not persistent over our studied time period.

5.1. Theoretical implications

Our article is the first to provide a comprehensive discussion of the connectedness between these four markets, including the financial and commodity types, and to assess the influences of uncertain events like the COVID-19 health crisis on the dynamic connectedness between these markets. By adopting this novel approach, we can calculate the net pairwise connectedness, a measure of transmission mechanisms among commodity and financial markets. This study is expected to provide both investors and authorities with critical insights and warnings about the contagion influences of uncertain events that may arise in a particular market.

5.2. Practical implications

On the policy front, our findings provide vital implications for investors and authorities, along with practices from the spillover effects across the diverse markets and their interlinkages. Insightful knowledge about the key antecedents of the contagions among these markets, from crude oil, gold, and stock to cryptocurrency, also helps policymakers to design the most adequate policies to reduce these markets' vulnerabilities, and to minimize the spread of risk or uncertainty across them. Our findings show considerable interlinkages between four markets, thus

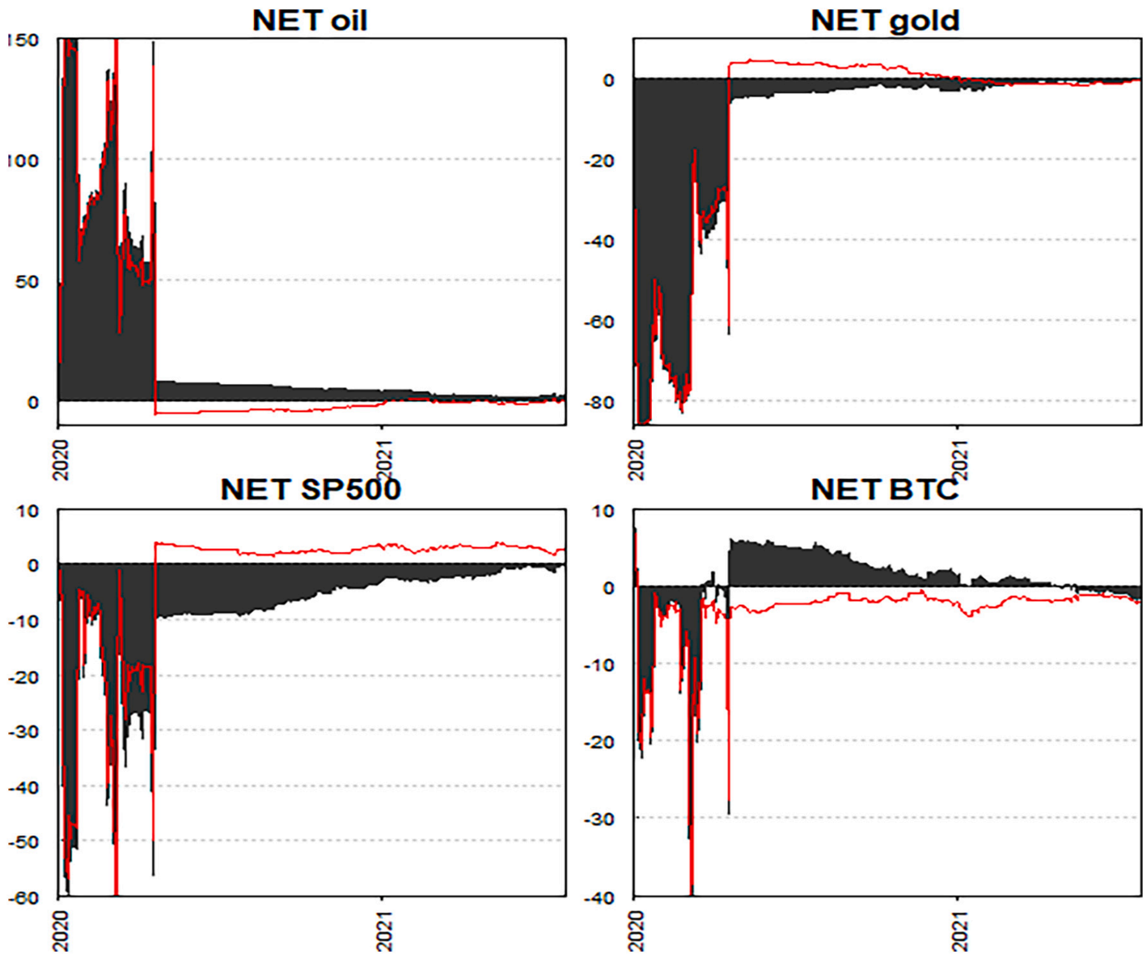

Fig. 4. Time variant of net total directional connectedness during the COVID-19 health crisis.
Notes: We follow Balcilar et al. (2021) to set up the lead (20 leads) and lag length (1 lag) order of forecast error variance decomposition in our TVP-VAR system. The robustness checks were also conducted by changing these values. We display both the joint interlinkages (the black shaded area) and original interlinkages (the red line). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

emphasizing the potential risk of either low or high diversification for investors in these markets. Our findings further underscore the increasing interlinkages within unexpected and highly uncertain events like the recent COVID-19 pandemic crisis. In our findings, we demonstrate that a shock in a typical market influences the entire network, implying that when managing an investment portfolio including gold, oil, stocks and cryptocurrency, investors and managers should be careful, and realize that the contagions of uncertainty and risk serve as an early warning signal to reconsider the investment strategy. Furthermore, the findings of this paper can also be useful for policymakers in their efforts to enhance public welfare, which stem from the direct impact of oil, financialization through the stock market, gold, and cryptocurrency. It is vital to use the key insight that there are spillover impacts of uncertainty and risk in energy markets to that on the financial market and vice versa. Hence, it is a prerequisite to take them into account when designing policies for a vulnerable group as a way to enhance the welfare of society.

5.3. Limitations and directions for the future research

The findings of this study should be interpreted in light of three limitations. Firstly, it is vital to emphasize that there was no universal law or general pattern for the influence of risk events on overall, net or pairwise spillovers. Second, the magnitude of spillover is crucial in the context of market integration. If the spillover is high, a particular market system will be heavily affected by fluctuations and shocks arising in other markets. The authorities have to take various measures to smooth the negative effect of external shocks. Authorities should pay attention to frequency-specific risk sources. The coordination of international regulatory policies related to different markets should be more oriented toward neutralizing the negative effects of short-term return spillover and long-term volatility spillover. Lastly, as many scholars consider the spillover effect across different markets, quantifying the portfolio benefits of diversification is an important extension. We will leave it for future work.

Data availability

Data will be made available on request.

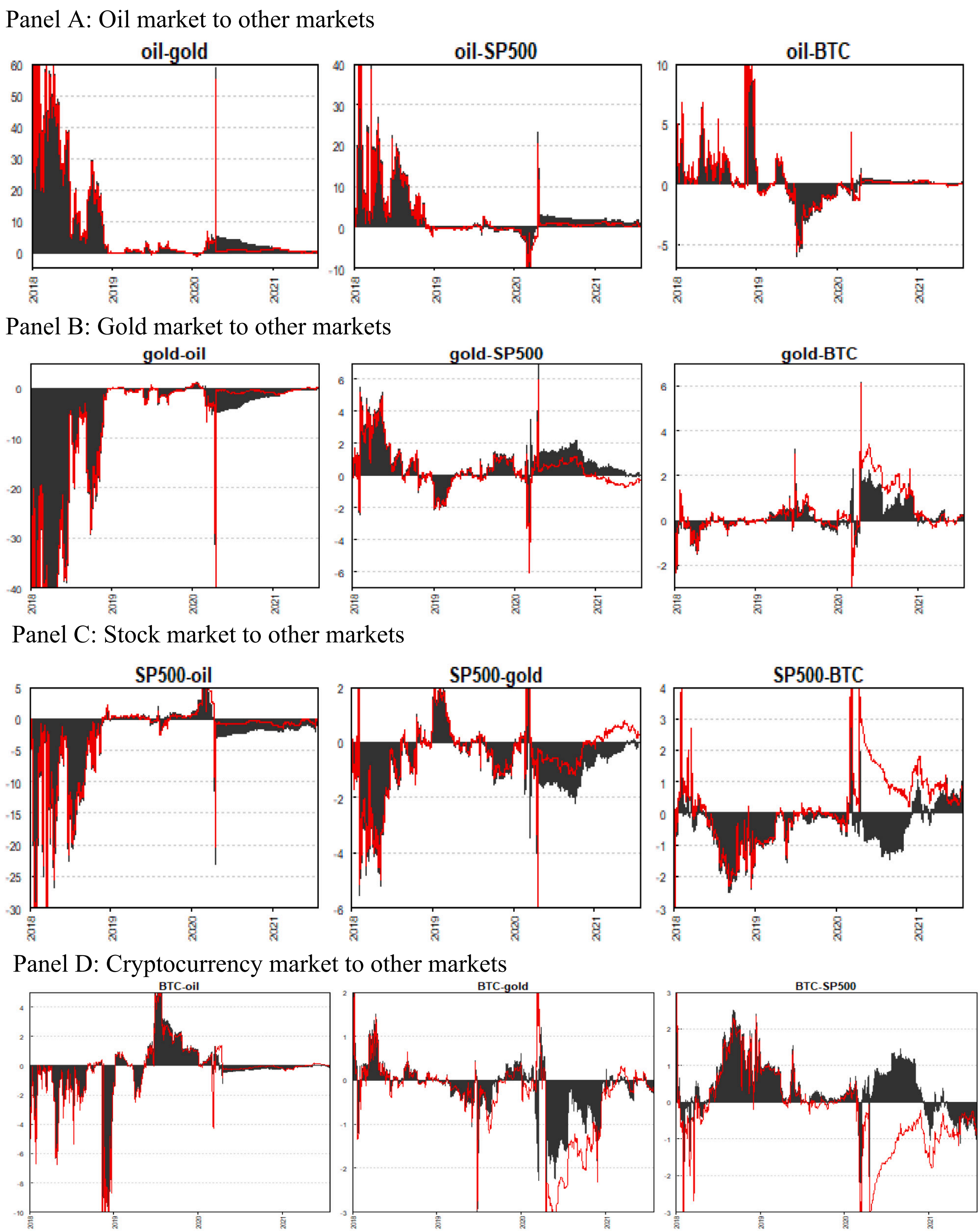

Fig. 5. Time variant of net pairwise directional connectedness.
Notes: We follow Balcilar et al. (2021) to set up the lead (20 leads) and lag length (1 lag) order of forecast error variance decomposition in our TVP-VAR system. The robustness checks were also conducted by changing these values. We display both the joint interlinkages (the black shaded area) and original interlinkages (the red line). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

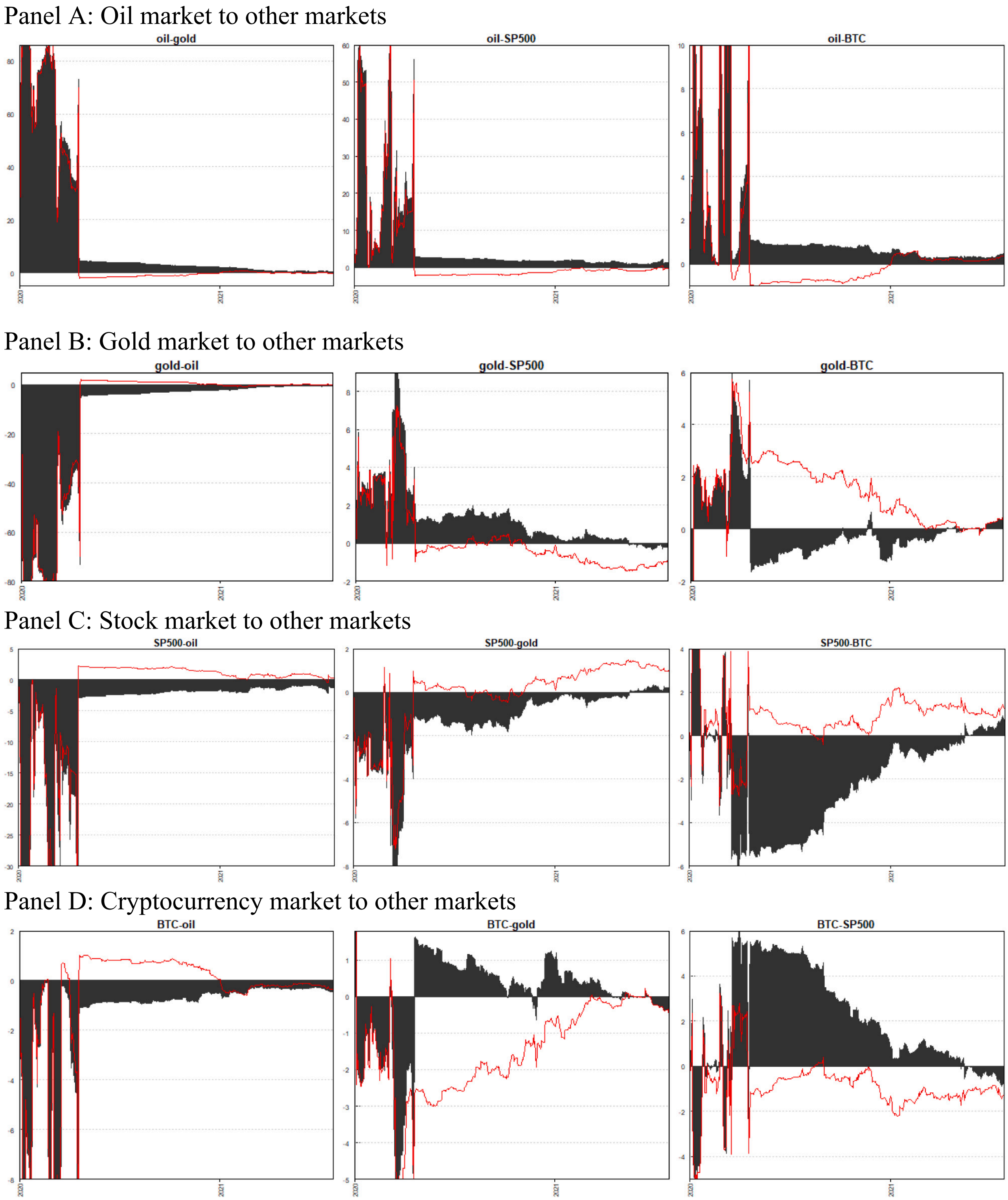

Fig. 6. Time variant of net pairwise directional connectedness during the COVID-19 health crisis.
Notes: We follow Balcilar et al. (2021) to set up the lead (20 leads) and lag length (1 lag) order of forecast error variance decomposition in our TVP-VAR system. The robustness checks were also conducted by changing these values. We display both the joint interlinkages (the black shaded area) and original interlinkages (the red line). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Appendix A

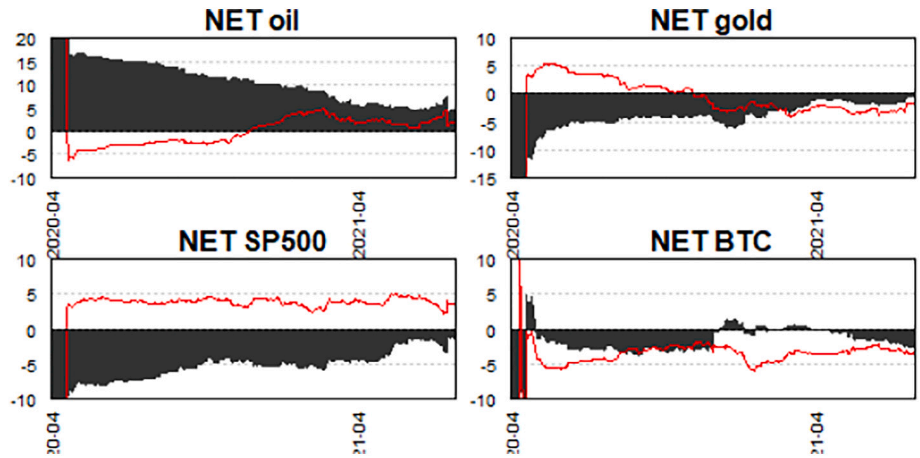

Fig. A.1. Time variance of net total directional connectedness during the COVID-19 health crisis.
Notes: We follow Balcilar et al. (2021) to set up the lead (20 leads) and lag length (1 lag) order of forecast error variance decomposition in our TVP-VAR system. The robustness checks were also conducted by changing these values. We display both the joint interlinkages (the black shaded area) and original interlinkages (the red line).

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Doctor **Le Thanh Ha** received his Ph.D in Policy Analysis from National Graduate Institute for Policy Studies. He is currently a Professor at the Faculty of Economics, National Economics University. His main research areas are digitalization, government issues, international economics, macroeconomic analysis, international economics, financial stability, and corporate performance analysis.