Return connectedness across asset classes around the COVID-19 outbreak

Elie Bouri[†], Oguzhan Cepni[‡], David Gabauer[§], and Rangan Gupta[Λ]

[†] *Holy Spirit University of Kaslik (USEK), USEK Business School, Jounieh, Lebanon.*

[‡] *Central Bank of the Republic of Turkey, Ankara, Turkey.*

[§] *Software Competence Center Hagenberg, Data Analysis Systems, Softwarepark 21, 4232 Hagenberg, Austria.*

[Λ] *Department of Economics, University of Pretoria, Pretoria, 0002, South Africa.*

[*] *Corresponding Author.*

Abstract

In this paper, we show evidence of a dramatic change in the structure and time-varying patterns of return connectedness across various assets (gold, crude oil, world equities, currencies, and bonds) around the COVID-19 outbreak. Using the TVP-VAR connectedness approach, the results show that the dynamic total connectedness across the five assets was moderate and quite stable until early 2020. After that, the total connectedness spikes and the structure of the network of connectedness alters, which concurs with the COVID-19 outbreak. The equity and USD indices are the primary transmitters of shocks before the outbreak, whereas the bond index becomes the main transmitters of shocks during the COVID-19 outbreak. However, the USD index is a net receiver of shocks to other assets during the outbreak period. Furthermore, using a recently developed newspaper-based index of uncertainty in financial markets due to infectious diseases to capture the recent impact of Covid-19, we find that connectedness is positively related to this index, and increases at higher levels (conditional quantiles) of connectedness. Overall, our results reflect the speedy disturbing effects of the COVID-19 outbreak, which matters to the formulations of policies seeking to achieve financial stability. The results also indicate a possibility to threaten investors' portfolios and fade the benefits of diversification.

Keywords: COVID-19 outbreak; financial markets contagion; return connectedness; TVP-VAR;

JEL codes: C32; C5; F3; G15.

1 Introduction

During crisis and turbulent periods, various economic agents, including investors and policymakers, can make use of the size and direction of the net spillovers for enhancing portfolio decisions and the formulations of policy to restore and safeguard financial stability. This is especially relevant in times of catastrophic events, such as the COVID-19 outbreak, during which global economic activities freeze, unemployment rate balloons, economic and financial uncertainties spike, and energy and financial markets plunge, which has led to international financial chaos that disturbed asset allocations and risk management models and importantly financial stability. In fact, the COVID-19 has triggered an economic recession coupled with an intensified uncertainty about its severity and length. It has adversely affected the global financial system, jeopardizing global financial stability. Accordingly, the risk factors of the COVID-19 have induced renewed interest in systemic risk that is often applied to shocks to various assets, which makes the empirical focus on the structural dynamics of the network of returns of various assets very important to understanding how the financial system responds to return shocks, and how the dynamics of the systemic risk materializes. Examining these issues have implications for a wide set of issues related to risk management, asset allocation, and regulatory formulation. For example, during economic and financial crisis periods, investors re-balance their portfolios by switching from risky assets to safe-haven assets in order to reduce the portfolio's risk, which results into a "flight-to-quality" or "flight-to-safety" phenomenon that tends to decrease (increase) the price of risky (safe haven) assets (Choudhry et al., 2015; Troster et al., 2019).

In this paper, we contribute to the academic literature by examining for the first time how the network of various asset returns reacts to the unprecedented catastrophic shocks of the COVID-19 that is, by capturing its time-varying structure and evolution. More specifically, we capture how the COVID-19 has made an asset to become more or less systemically important than another in the network of connectedness. Therefore, we are interested in answering the following questions: What role has the COVID-19 played in shaping the patterns of return connectedness across various assets? Does the structure of the assets returns exhibit any patterns of the main shift over time?

To answer these questions, we consider a financial system to be a network of five interconnected assets covering gold, crude oil, equities, currencies, and bonds and then apply a dynamic connectedness approach based on time-varying parameter vector auto-regressions (TVP-VAR) in line with Antonakakis et al. (2020).

Our paper is related to the literature employing connectedness measures to describe the size and direction of the return spillovers among assets and markets during crisis periods (e.g., Corbet et al., 2020a,b; Gębka and Serwa, 2006; Kang and Yoon, 2019; Tiwari et al., 2020; Antonakakis et al., 2019). Notably, our paper evaluates the response of financial systems to the catastrophic event related to the COVID-19 outbreak, which is an unprecedented research topic. This would add to recent studies that focus on the role played by the COVID-19 on economic and financial variables (Baker et al., 2020;

Haddad et al., 2020; Baig et al., 2020; Sharif et al., 2020). In addition to this academic contribution, we offer other contributions by extending previous studies that consider the transmission across markets and assets using methods such as conditional correlation, Granger-causality, conditional value-at-risk, or the approach of Diebold and Yılmaz (2012, 2014). Notably, our reliance on the TVP-VAR approach overcomes the pitfalls of the measures of connectedness based on variance decomposition from standard VAR models such as outlier sensitivity induced by the underlying Kalman filter, sensitivity of results due to the arbitrary choice of the rolling window size, and the loss of observations due to the rolling window analysis. It also allows for capturing the dynamics of the overall connectedness measure as well as the cross-asset connectedness structures.

The central finding of our analysis is that the COVID-19 has altered the network of connectedness across the five assets under study, by generating sudden increases in both the system overall connectedness and the cross-asset connectedness of various cases. These findings are intuitive and suggest that the network of the global financial system is unstable and experiences an abrupt spike in its risk build-up due to the COVID-19 outbreak, which is somewhat different from the longer-lasting build-up of the global systematic risk in the wake of the global financial crisis of 2008 (Barrell and Davis, 2008).

The remainder of this paper is organised as follows. In Section 2 we present the relevant literature review and hypotheses that emerge. In Section 3, we describe the data and set out the empirical methods employed in the study. In Section 4, we illustrate the findings of the study and discuss the relevant arguments. Finally, Section 5 summarises the key elements, provides a framework for policy implications, and concludes the study.

2 Literature Review

The consecutive financial and economic crises over the last three decades provided a suitable laboratory to capture and understand the changes in market interdependencies and returns spillovers during stress periods (Mensi et al., 2016). A large strand of academic literature examines the effect of the Global Financial Crisis (hereafter GFC) of 2008 on the relationship across various asset classes (Choudhry et al., 2015; Mensi et al., 2016; Zhang and Broadstock, 2018; Kang and Yoon, 2019, e.g.,), showing how the GFC has intensified market linkages and affected asset allocation and hedging strategies. In fact, changes in the interdependence across financial markets is a major concern for investors seeking the benefits of diversification (Brière et al., 2012).

Some studies consider the transmission across assets using various methods such as conditional correlation (Dua and Tuteja, 2016; Öztek and Öcal, 2017), Granger-causality (e.g., Billio et al., 2012; Zhang and Broadstock, 2018), copulas (Philippas and Siriopoulos, 2013; Ji et al., 2018), or conditional value-at-risk (Ji et al., 2018). However, following the influential studies of Diebold and Yılmaz (2009, 2012, 2014), a growing literature highlights the importance of uncovering spillovers of shocks in a predetermined network via the connectedness approach (e.g., Zhang, 2017; Hussain Shahzad et al., 2019). Notably, higher inter-connectedness of the network, which is an indication of higher market risk, conveys both benefits and risks. First, it can improve risk-sharing within the network through the various degree of absorption of individual asset shocks that can be asset-specific, which benefits risk diversification in a portfolio of weakly connected assets. Secondly, it can lead to financial contagion given that shocks can propagate through the network, which is an indication of instability in the financial system.

However, the existing literature on the return spillovers among a large set of asset classes such as commodities, equities, currencies, and bonds is rare. For example, Wang and Chueh (2013) focus on the linkages between oil prices, gold prices, interest rates, and currency market. They report evidence of price transmission relationship between most of the pairs of market under study and a feedback effects in the relationship between strategic commodities (gold and crude oil) and interest rates. Kang et al. (2017) also focus on the price transmission but consider precious metals, crude oil and agricultural commodities. They show evidence of stronger returns spillovers during the GFC, which can have portfolio and hedging implications.

Notably, the extended version of the Diebold and Yılmaz (2014)'s measures of connectedness has been used by Gabauer and Gupta (2018) and Antonakakis et al. (2018), which allows for refining the measurement of global uncertainty indices in a genuine time-varying setting. This is important as market networks can reveal a lot about models of panic during stress crises and the factors affecting market freezes and the structure of the financial environment and the level of systemic risk. At high levels of connectedness, the information gathering process becomes costly and less efficient. Furthermore, investors move away from risky assets like equities, towards gold and Bond markets (Choudhry et al., 2015; Brocato and Smith, 2012).

Our analysis extends the above lines of research by providing first empirical evidence on how the COVID-19 outbreak, an unprecedented and sudden global public health emergency, shaped the dynamics of return spillovers across various assets. As such, we analyze the net shocks transmitter or receiver within the system of the five various assets and extend our limited understanding of the nature and extent of the transmission of return shocks in light of the catastrophic event of the COVID-19 outbreak.

3 Data & Methodology

3.1 Summary Statistics

We employ daily data covering various assets like gold, crude oil, equities, currencies, and bonds. We consider the spot price index of S&P GSCI gold, S&P GSCI crude oil, MSCI World, USD index, and PIMCO Investment Grade Corporate bond index Exchange-Traded Fund, extracted from *Datastream*. The sample period is May 12, 2011 - May 12, 2020, yielding 2349 daily observations as dictated by data availability, and notably includes the COVID-19 outbreak period from early 2020 till the end of the sample period. The raw series are presented in Figure 1.

[Insert Figure 1 around here]

As the raw series are non-stationary according to the ERS (Elliott et al., 1996) unit-root test, we decide to take the first log-differences that can be interpreted as the daily percentage changes. The resulting series are illustrated in Figure 2. The summary statistics of the return series (Table 1) indicate that crude oil has the highest standard deviation, which is not surprising given the severe adverse impact of the COVID-19 on energy prices (Dutta et al., 2020).

[Insert Figure 2 around here]

The findings indicate that the series are significantly non-normally distributed (D'Agostino, 1970; Anscombe and Glynn, 1983; Jarque and Bera, 1980) and stationary at 1% significance level. Notably, we find pronounced autocorrelation in both, the series and the squared series (Fisher and Gallagher, 2012) implying that the mean and the variance of each series vary over time. Thus, employing a TVP-VAR model with a time-varying variance-covariance structure seems to be an appropriate econometric framework capturing all those factors.

Further results from Table 1 show the unconditional correlation matrix across the return series over the full sample period. The USD index is negatively correlated with all other assets under study, whereas the strongest positive correlation is between crude oil and equities.

[Insert Table 1 around here]

3.2 TVP-VAR-Based Dynamic Connectedness Approach

A widely used framework to trace and evaluate spillovers in a predetermined network is the connectedness approach proposed by Diebold and Yılmaz (2009, 2012, 2014). The constantly increasing attention of the framework is mainly caused by the fact that it provides researchers and practitioners both with a static and a dynamic method of time series network analysis. The static approach is employing a vector autoregressive model (VAR, see Sims, 1980) on the full dataset whereas the dynamics are estimated via a rolling-window VAR approach. The setting of this framework is discussed intensively in Antonakakis et al. (2020) who propose a dynamic connectedness approach based on time-varying parameter vector autoregressions (TVP-VAR) with the result that dynamics are not influenced by the size of the rolling window. Additional advantages of the TVP-VAR based connectedness approach are (i) the outlier insensitivity caused by the underlying Kalman filter, (ii) that there is no need to arbitrarily choose the rolling-window size, (iii) that there is no loss of observations and (iv) that it can be employed also for low frequency datasets. This study applies the same methodology as in Antonakakis et al. (2018) and Gabauer and Gupta (2018)[1]. In particular, we are estimating a TVP-VAR(1) as suggested by the

[1] Since the detailed algorithm of the TVP-VAR model with heteroscedastic variance-covariances is beyond the scope of this study interested readers are referred to Koop and Korobilis (2013) and Koop and Korobilis (2014).

Bayesian information criterion (BIC) which can be outlined as:

$$\boldsymbol{z}_t = \boldsymbol{B}_t \boldsymbol{z}_{t-1} + \boldsymbol{u}_t \qquad \boldsymbol{u}_t \sim N(\boldsymbol{0}, \boldsymbol{S}_t) \tag{1}$$

$$vec(\boldsymbol{B}_t) = vec(\boldsymbol{B}_{t-1}) + \boldsymbol{v}_t \qquad \boldsymbol{v}_t \sim N(\boldsymbol{0}, \boldsymbol{R}_t) \tag{2}$$

where $\boldsymbol{z}_t$, $\boldsymbol{z}_{t-1}$ and $\boldsymbol{u}_t$ are $k \times 1$ dimensional vector and $\boldsymbol{B}_t$ and $\boldsymbol{S}_t$ are $k \times k$ dimensional matrices. $vec(\boldsymbol{B}_t)$ and $\boldsymbol{v}_t$ are $k^2 \times 1$ dimensional vectors whereas $\boldsymbol{R}_t$ is a $k^2 \times k^2$ dimensional matrix.

Subsequently, we are calculating the H-step ahead (scaled) generalized forecast error variance decomposition (GFEVD) introduced by Koop et al. (1996) and Pesaran and Shin (1998).

Notably, the GFEVD is completely invariant of the variable ordering opposed to the orthorgonalized forecast error variance decomposition (see, Diebold and Yılmaz, 2009). Please keep in mind that the structural representations of shocks - as it is often used in applied macroeconomics - should only be used if it underlies an economic theory which is - to the best of our knowledge - not available when it comes to the series under consideration[2]. For this reason, we stick to the GFEVD spillover framework. Since this concept is built upon the Wold representation theorem we transform the estimated TVP-VAR model into a TVP-VMA process by making use of the following equality: $\boldsymbol{z}_t = \sum_{i=1}^{p} \boldsymbol{B}_{it} \boldsymbol{z}_{t-i} + \boldsymbol{u}_t = \sum_{j=0}^{\infty} \boldsymbol{A}_{jt} \boldsymbol{u}_{t-j}$.

The (scaled) GFEVD normalizes the (unscaled) GFEVD, $\phi^g_{ij,t}(H)$, in order that each row sums up to unity. Hence, $\tilde{\phi}^g_{ij,t}(H)$ represents the influence variable j has on variable i in terms of its forecast error variance share which is defined as the *pairwise directional connectedness from j to i*. This indicator is computed by,

$$\phi^g_{ij,t}(H) = \frac{S^{-1}_{ii,t} \sum_{t=1}^{H-1} (\boldsymbol{\iota}'_i \boldsymbol{A}_t \boldsymbol{S}_t \boldsymbol{\iota}_j)^2}{\sum_{j=1}^{k} \sum_{t=1}^{H-1} (\boldsymbol{\iota}_i \boldsymbol{A}_t \boldsymbol{S}_t \boldsymbol{A}'_t \boldsymbol{\iota}_i)} \qquad \tilde{\phi}^g_{ij,t}(H) = \frac{\phi^g_{ij,t}(H)}{\sum_{j=1}^{k} \phi^g_{ij,t}(H)}$$

with $\sum_{j=1}^{k} \tilde{\phi}^g_{ij,t}(H) = 1$, $\sum_{i,j=1}^{k} \tilde{\phi}^g_{ij,t}(H) = k$, and $\boldsymbol{\iota}_i$ corresponds to a selection vector with unity on the ith position and zero otherwise.

Based upon the GFEVD, Diebold and Yılmaz (2012, 2014) derived their connectedness measures as

[2]Furthermore, we want to stress out that even though we are talking about the spillovers of shocks we are well aware that those interpretation differs from the macroeconomic literature, however, with this interpretation we are just following the interpretations Diebold and Yılmaz (2009, 2012, 2014) to be in-line with the connectedness literature.

follows:

$$
\begin{aligned}
TO_{jt} &= \sum_{i=1, i\neq j}^{k} \tilde{\phi}^g_{ij,t}(H) && (3)\\
FROM_{jt} &= \sum_{i=1, i\neq j}^{k} \tilde{\phi}^g_{ji,t}(H) && (4)\\
NET_{jt} &= TO_{jt} - FROM_{jt} && (5)\\
TCI_t &= k^{-1}\sum_{j=1}^{k} TO_{jt} \equiv k^{-1}\sum_{j=1}^{k} FROM_{jt}. && (6)\\
NPDC_{ij,t} &= \tilde{\phi}_{ij,t}(H) - \tilde{\phi}_{ji,t}(H) && (7)
\end{aligned}
$$

As mentioned previously $\tilde{\phi}^g_{ij,t}(H)$ illustrates the impact a shock in variable j has on variable i. Hence, Equation (3) represents the aggregated impact a shock in variable j has on all *other* variables which is defined as the *total directional connectedness to others* whereas Equation (4) illustrates the aggregated influence all *other* variables have on variable j that is defined as the *total directional connectedness from others*.

Equation (5): Subtracting the impact variable j has on others by the influence *others* have on variable j results in the *net total directional connectedness* which provides us with information whether a variable is a net transmitter or a net receiver of shocks. Variable j is a net transmitter (*receiver*) of shocks - and hence driving (*driven by*) the network - when the impact variable j has on others is larger (*smaller*) than the influence all others have on variable j, $NET_{jt} > 0$ ($NET_{jt} < 0$). Another essential measure is given by Equation (6) the *total connectedness index (TCI_t)* which represents the average impact one variable has on all *others*. If this measure is relatively high it implies that the interconnectedness of the network and hence the market risk is high since a shock in one variable will influence others whereas a low value shows that most variables are rather independent from each other which in turn means that a shock in one variable will not cause other variables to adjust resulting in low market risk.

Since all aforementioned measures offer information on an aggregated basis, Equation (7) tells us more about the bilateral relationship between variable j and i. The so-called *net pairwise directional connectedness ($NPDC_{ij,t}$)* exhibits whether variable j is driving variable i or vice versa. Therefore, we subtract the impact variable j has on variable i by the influence variable i has on variable j. If $NPDC_{ij,t} > 0$ ($NPDC_{ij,t} < 0$), it means that variable j is dominating (dominated by) variable i.

4 Empirical Results and Discussion

4.1 Average and Dynamic Total Connectedness Measures

Table 2 presents the averaged connectedness measures. While the main diagonal of Table 2 shows own-variance shares of shocks, off-diagonal elements reflect the interaction across financial assets. In order to examine how the average connectedness of financial markets change after the onset of the COVID-19 pandemic, we divide our sample into two parts.[3] As can be seen in Table 2, several interesting observations arise when considering the periods both before and after the start of the COVID-19 pandemic. Firstly, there is evidence of increased connectedness between financial assets. The TCI value that is included in Table 2 indicates that co-movements of the financial asset are rather moderate in the post-Corona period, as they constitute 27.2% of the total forecast error variance of the network. Put differently, on average, 27.2% of the forecast error variance in one financial asset can be attributed to the innovations in all others.

In particular, MSCI World and USD index appear to be the primary transmitters of shocks before the outbreak; whereas bond index, MSCI World (with an increase in magnitude), and crude oil become the main transmitters of shocks within the network after the beginning of the global COVID-19 pandemic. This evidence implies that the elevated spillover effects from bond markets to other markets may result in recent expansionary monetary policy measures and Central Bank's liquidity injections through massive bond purchases. On the other hand, since the crude oil market has been hit by the twin shock of the COVID-19 pandemic and the unraveling of the OPEC+ production agreement, we observe that crude oil has turned a net transmitter of shocks during the Corona-outbreak periods.

[Insert Table 2 around here]

However, results presented in Table 2 are aggregate results that consider the period of study in its entirety; that is, without focusing the periods that may have lead to considerable deviations from the average TCI value which is reported above. In this regard, to identify specific episodes that affected connectedness across financial variables over time, we continue with the dynamic approach. As can be seen from Figure 3, the dynamic connectedness of our network fluctuates considerably over time, especially after the outbreak, which is suggestive of the fact that connectedness across financial markets is time-dependent. A closer look at Figure 3 reveals that pronounced connectedness is evident around the mid-March, matching with the onset of the new infectious disease all over the globe and sparking fears of the possible second wave of infections. In particular, after the onset of the outbreak, financial markets spillovers reached a higher point than the unprecedented heights during mid-2013, a period characterized by 'FED Tapering'.

[Insert Figure 3 around here]

4.2 Net Total Connectedness

In turn, we focus on the net total connectedness of the system which is presented in Figure 4. Net total connectedness practically indicates the difference between the transmitting and the receiving shocks of each financial asset considering the entire network. Note that positive values of the shaded area

[3] We choose January 13, 2020, as outbreak date of the coronavirus since the first cross-border transmission of infection was reported by Thai authorities on that date.

correspond to periods when a particular financial asset assumes a net-transmitting role, while negative values show the periods when the financial assets receive, on net terms, from others.

An inspection of Figure 4 leads to a number of clear-cut conclusions. Firstly, while the bond index is persistently receiving shocks from others with perhaps one or two short-lived exceptions, it seems to assume a persistent net-receiving role mainly after the global pandemic. The reason is that spread of U.S. investment-grade bonds has widened sharply since the onset of the coronavirus outbreak indicating the threat posed to companies' balance sheets by the coronavirus crisis. Secondly, the gold market shows a significant time-varying transmission pattern. In particular, we see that the transmission of spillovers from others to the gold market increased during the global pandemic. As suggested by Baur and Lucey (2010), Bredin et al. (2015), and Bouri et al. (2020) gold can be used as both a hedge and safe heaven by global investors during the uncertain times.

Similarly, we observe that the USD index has been a net receiver throughout the coronavirus outbreak period. The reason is that the meltdown in global markets due to the fears of the global recession has led to investors liquidate their positions resulting in huge demand for cash. Moreover, firms without ample cash at hand have tried to find cash to continue their operations during the global pandemic (Didier et al., 2020). Finally, Figure 4 also indicates that the MSCI World index is a net transmitter of shocks and hence driving the network after the onset of the coronavirus. This result in line with the findings of Baig et al. (2020) who suggest that reported number of confirmed coronavirus cases, general negative sentiment reported by media, reduced mobility, and government measures to restrict movement and business have a strong association with volatility in the stock market returns.

[Insert Figure 4 around here]

4.3 Net Pairwise Connectedness

While the net total approach can be informative, it also has its challenges, provided that total numbers invariably conceal interesting stories between specific variables of the system. Whereas net total figures explicitly display the clear picture of the network variables over time, they do not concentrate on pairs of variables to describe the associated dynamics. In this regard, in this section, we present bilateral results and investigate the specific links between the financial asset class of interest.

In Figure 5, we focus on the net pairwise directional connectedness measures of spillovers - i.e. spillovers across pairs of financial variables. We observe the following empirical regularities. First, spillovers are of greater magnitude after the onset of the global pandemic. For instance, net spillovers from the bond index to gold and USD index are particularly high during the outbreak periods and reach up to 15%. This finding reflects that the bond market became a sender of stress during the post-corona periods. The reason is that a sudden drop in the liquidity of the bond market pointed out to uncertainty in creditworthiness - particularly in the investment- grade market which in turn leads to an exacerbation in demand for liquidity.[4] Hence, it seems that the demand for cash balances and safe heaven assets is sparked. The reason may be that the COVID-19 forced shutdowns would hurt revenue flows of the corporate firms which leads to a sharp increase in the average implied default probabilities of the investment-grade bond basket (De Vito and Gómez, 2020).

Second, while the spillover from the MSCI Word index to bond index switch its behaviour between being a net transmitter or net receiver multiple times before the outbreak, the MSCI World index is driven by the bond index after the onset of the pandemic. Although bonds are generally considered safer than stocks, the unexpected movement of bond markets might trigger the stocks sell-off further (Haddad et al., 2020).

Another interesting element in our analysis that deserves further attention relates to recent periods where the spillover from MSCI World to USD index rises sharply. This evidence shows that investors tried to sell more liquid securities like stock indices to raise cash since other financial assets such as investment-grade corporate and municipal bond ETFs are traded a large discount to their net asset values during the crisis periods.

Finally, the spillovers from crude oil to USD and Bond indices seem to be low most of the sample period. Closely observing the pairwise spillovers let us realize that the oil market dominates the USD and Bond indices after the oil futures plunge to negative territory feeding the market panic. Furthermore, the reduction in mobility and the lack of industrial activity due to the outbreak significantly decreased the demand for oil, causing its price to fall with a fear of global recession.

[Insert Figure 5 around here]

4.4 Cointegration and quantile regressions between TCI and EVM

To analyze the effect of the outbreak of the COVID-19 virus on the connectedness of the asset class, we use the recently developed newspaper-based index of Baker et al. (2020), which tracks equity market volatility (EMV), in particular the movements in the Chicago Board Options Exchange (CBOE)'s Volatility Index (VIX), due to infectious diseases. This index is developed by Baker et al. (2020), with index being newspaper-based infectious disease EMV tracker, available at the daily frequency from January, 1985 till recent days.[5] To construct the EMV-ID, Baker et al. (2020) specifies four sets of terms namely, E: economic, economy, financial; M: "stock market", equity, equities, "Standard and Poors"; V: volatility, volatile, uncertain, uncertainty, risk, risky; ID: epidemic, pandemic, virus, flu, disease, coronavirus, mers, sars, ebola, H5N1, H1N1, and then obtain daily counts of newspaper articles that contain at least one term in each of E, M, V, and ID across approximately 3,000 US newspapers. After this, the raw EMV-ID counts is scaled by the count of all articles in the same day, and finally, the authors multiplicatively rescale the resulting series to match the level of the VIX, by using the overall EMV index, and then scaling the EMV-ID index to reflect the ratio of the EMV-ID articles to total EMV articles.

[4] See, for example, https://www.msci.com/www/blog-posts/credit-in-the-COVID-crisis/01795274729

[5] Data is available from: $http://policyuncertainty.com/infectious_EMV.html$.

Figure 6 shows the effect the EVM has on TCI over different quantiles (Koenker and Bassett Jr, 1978). Data has been taken after the first COVID-19 infected has appeared on the screen of the US on the January 13, 2020 as all EVM data prior to this point is only covering the economic policy uncertainty without COVID-19 affecting it. Notably, all slope coefficient estimation results are positive indicating that the higher EVM is the higher is TCI especially on the upper end. In detail, this means that the increased COVID-19 economic policy uncertainty in the US has increased the market risk across gold, crude oil, MSCI World, USD index and bond index.

[Insert Figure 6 around here]

5 Concluding Remarks

The coronavirus shock has led to large disruptions to the global financial markets. The very significant deterioration of the global growth backdrop and the sharp reduction in global risk appetite have led to growing contagion in financial markets, prompting major central banks and governments to deploy a wide range of monetary and financial easing measures.

In this study, we focus on different financial markets to highlight the effect of the global pandemic on the increased levels of stress in international financial markets. To accomplish the objectives of our study, we consider different asset classes, which include gold, crude oil, USD index, bond index, and MSCI World index covering the periods before and after the corona-outbreak. In this regard, we further employ a TVP-VAR empirical approach to measure connectedness across the different asset classes included in our study. The key advantage of the TVP-VAR model is that it practically constitutes an extension of the standard Diebold and Yılmaz (2009, 2012) approach as it does not suffer from the deficiencies of the typical rolling-windows method and thus provides refined measurements of connectedness. Moreover, using a recently developed newspaper-based index of uncertainty in financial markets due to infectious diseases to capture the recent impact of Covid-19, we find that connectedness is positively related to this index, and increases at higher levels (conditional quantiles) of connectedness.

Our findings provide clear evidence for strong spillover effects in financial markets. Financial connectedness is particularly high during elevated stress episodes after the onset of the global pandemic. In particular, we show that MSCI World and USD index appear to be the primary transmitters of shocks before the outbreak; whereas bond index becomes the main transmitters of shocks within the network after the beginning of the global COVID-19 pandemic. Hence, policymakers have announced a vast array of stimulus measures, including large fiscal packages, adjustments to labor laws, and public sector backstops to private businesses in order to mitigate the contagion effects of the bond market to other financial variables.

However, we observe that the USD index has been a net receiver of shocks throughout the coronavirus outbreak period. This result validates the recent Central Banks' actions to ensure that there is adequate liquidity to avoid financial stress or the interruption of the flow of capital including the massive rate cuts and broad re-launch of quantitative easing programs.

Furthermore, our findings can also be read from a policy-making perspective. Empirical results indicate that policymakers should pay attention to overall financial connectedness by analyzing the net shocks transmitter or receiver nature of the different asset classes. The main reason for this is that systemic financial contagion can increase swiftly to serious levels due to high spillover effects between financial asset classes. Thus, policy-making in the sense of not only monitoring total connectedness but also evaluating net directional spillovers between financial variables with a systemic perspective is vital. Therefore, if an efficient coordination mechanism is in place and spillover information across financial variables is continuously monitored, then policy-makers can design timely policy interventions to alleviate the contagion risk from inter-connectedness and financial networks.

As part of future research, it would be interesting to extend our analysis into stock, bond, and foreign currency markets of different countries. This will ensure us with the understanding of whether our results carry over to cross-country financial markets as well, which might provide insights for global investors to develop better portfolio diversification benefits.

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Table 1: Summary Statistics

	Gold	Crude oil	MSCI World	USD index	Bond index
Mean	0.003	-0.107	0.017	0.012	0.003
Variance	1.035	7.99	0.893	0.186	0.16
Skewness	-0.573***	-4.139***	-1.233***	0.047	-0.460***
	(0.000)	(0.000)	(0.000)	(0.352)	(0.000)
Kurtosis	7.926***	86.682***	19.805***	1.989***	72.451***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
JB	6274.303***	741795.582***	38967.826***	387.760***	513622.889***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ERS	-9.342***	-16.768***	-12.303***	-5.707***	-8.414***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Q(20)$	47.120***	249.873***	262.373***	30.855*	470.316***
	(0.001)	(0.000)	(0.000)	(0.057)	(0.000)
$Q^2(20)$	195.290***	468.296***	2889.681***	275.205***	2277.177***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
			Unconditional Correlations		
Gold	1.000	0.121	0.086	−0.355	0.235
Crude oil	0.121	1.000	0.353	−0.097	0.001
MSCI World	0.086	0.353	1.000	−0.203	0.080
USD index	−0.355	−0.097	−0.203	1.000	−0.139
Bond index	0.235	0.001	0.080	−0.139	1.000

Notes: ***,**,* denote significance level at 1%, 5% and 10%; Skewness: D'Agostino (1970) test; Kurtosis: Anscombe and Glynn (1983) test; JB: Jarque and Bera (1980) normality test; ERS: Elliott et al. (1996) unit-root test; $Q(20)$ and $Q^2(20)$: Fisher and Gallagher (2012) weighted portmanteau test.

Table 2: Average Connectedness Table

	Pre-Corona Outbreak (2011/08/19 - 2020/01/13)					
	Gold	Crude oil	MSCI World	USD index	Bond index	FROM
Gold	75.3	3.0	2.6	13.0	6.1	24.7
Crude oil	2.7	80.3	11.9	3.8	1.2	19.7
MSCI World	2.5	11.1	77.8	7.0	1.5	22.2
USD index	12.8	3.7	7.2	73.3	3.0	26.7
Bond index	6.7	1.6	1.9	3.5	86.4	13.6
Contribution TO others	24.7	19.5	23.6	27.3	11.9	106.9
NET directional connectedness	0.0	-0.2	1.4	0.6	-1.7	TCI
NPDC transmitter	1.0	2.0	4.0	3.0	0.0	21.4
	Post-Corona Outbreak (2020/01/13 - 2020/05/12)					
	Gold	Crude oil	MSCI World	USD index	Bond index	FROM
Gold	64.7	4.7	9.0	4.7	16.9	35.3
Crude oil	3.3	80.5	13.0	2.6	0.6	19.5
MSCI World	6.8	10.6	72.8	2.2	7.6	27.2
USD index	6.3	3.9	6.5	67.7	15.5	32.3
Bond index	9.8	2.5	4.8	4.9	78.0	22.0
Contribution TO others	26.1	21.7	33.4	14.4	40.6	136.2
NET directional connectedness	-9.2	2.2	6.2	-17.9	18.6	TCI
NPDC transmitter	1.0	3.0	3.0	0.0	3.0	27.2

Notes: Results are based on a TVP-VAR model with lag length of order one (BIC) and a 20-step-ahead generalized forecast error variance decomposition.

Figure 1: Raw Series

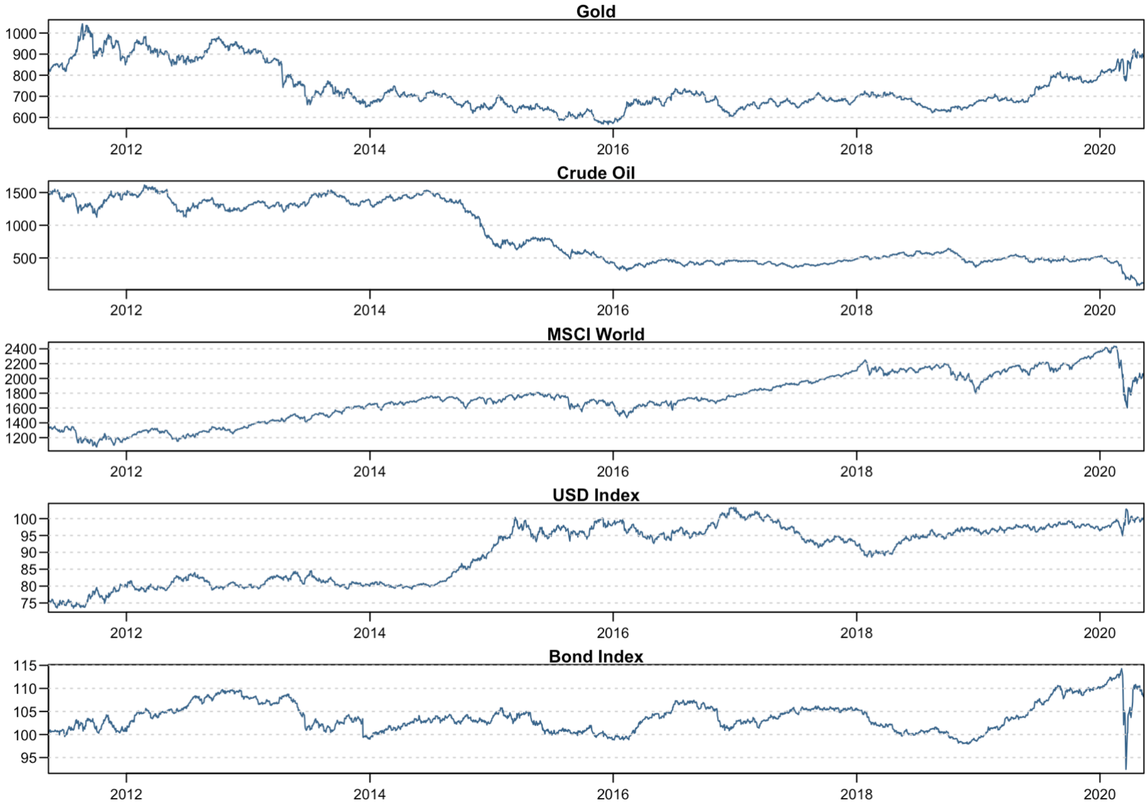


Figure 2: Daily Percentage Changes

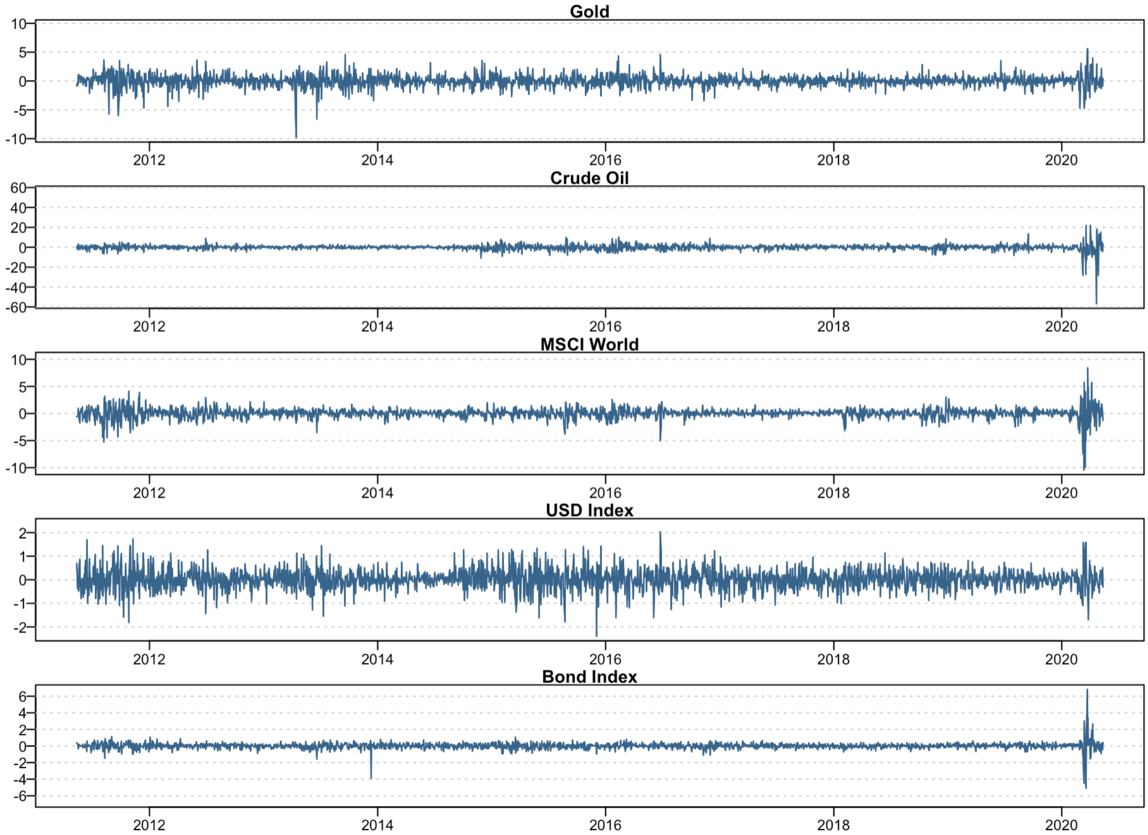
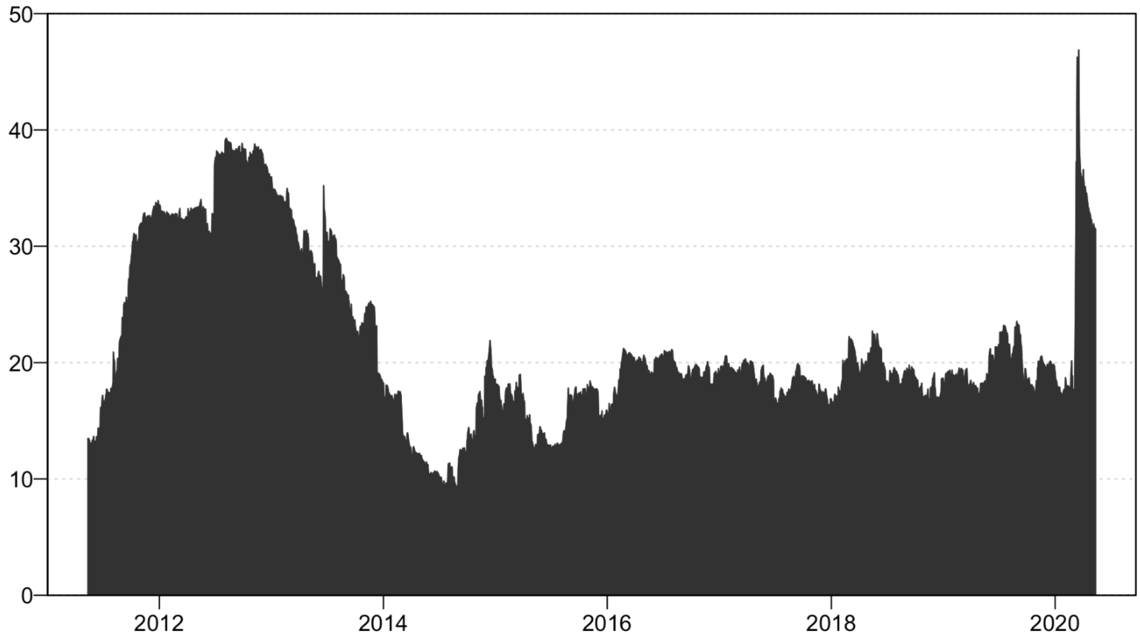
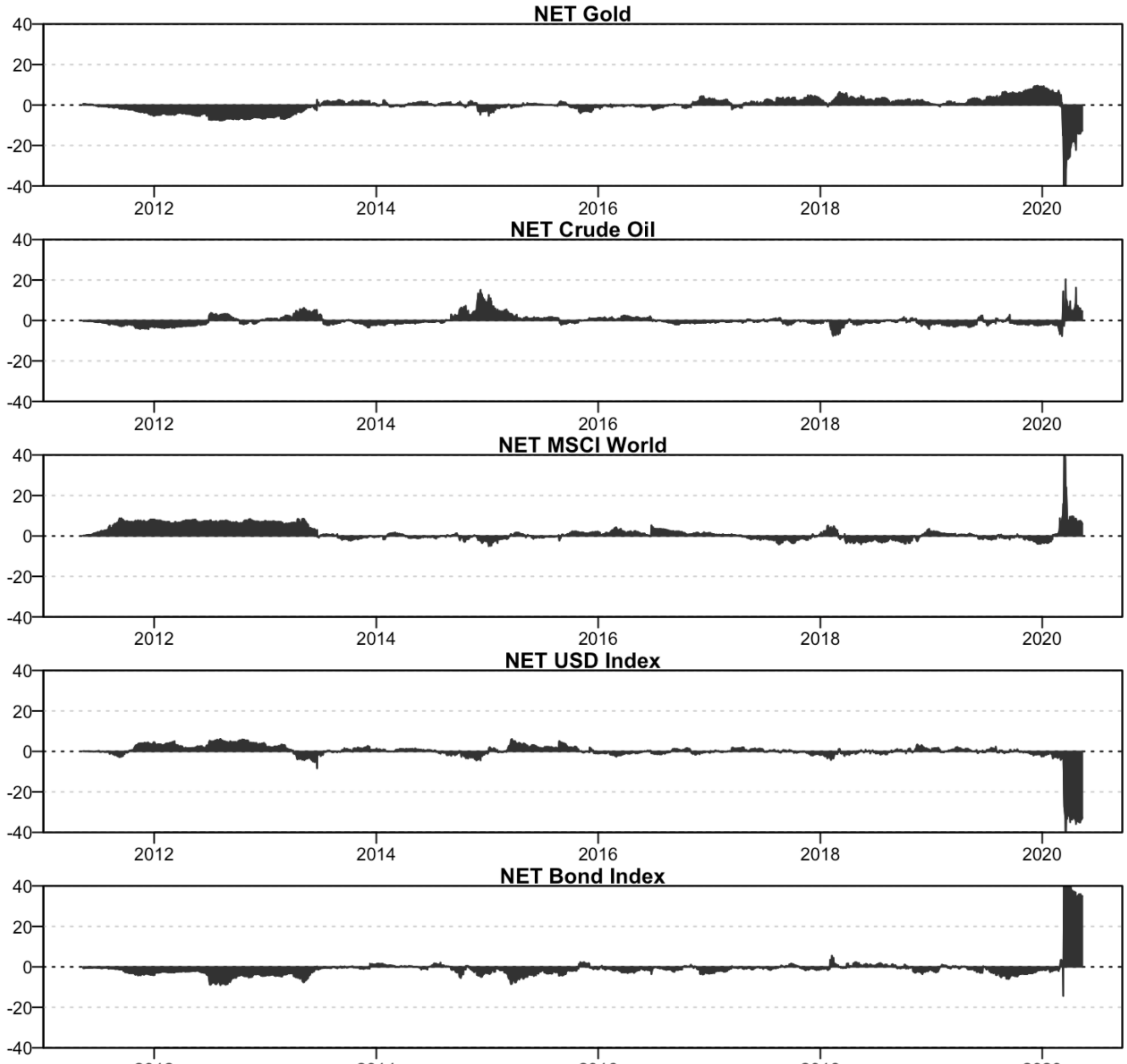


Figure 3: Dynamic Total Connectedness



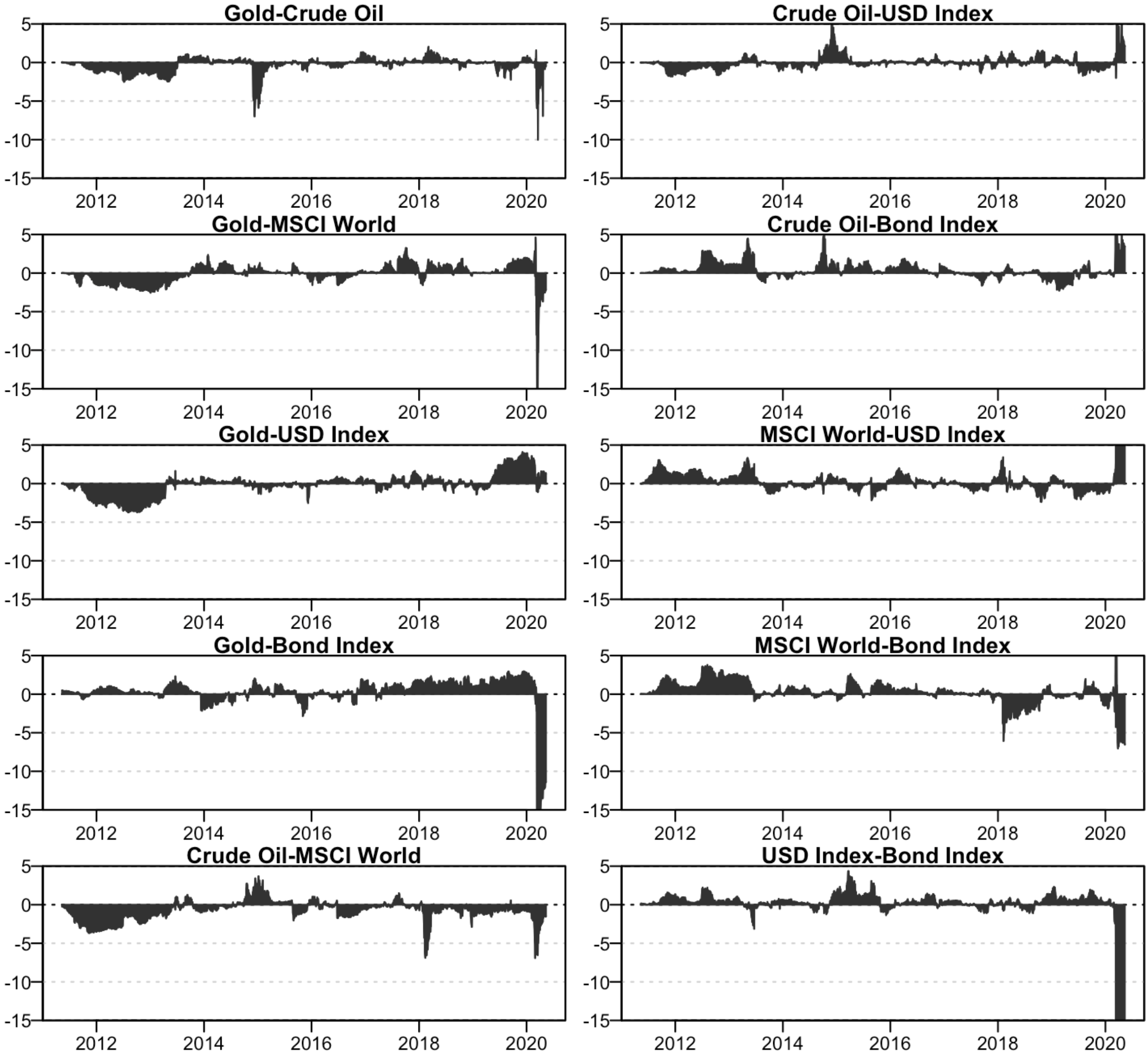
Notes: Results are based on a TVP-VAR model with lag length of order one (BIC) and a 20-step-ahead generalized forecast error variance decomposition.

Figure 4: Net Total Directional Connectedness



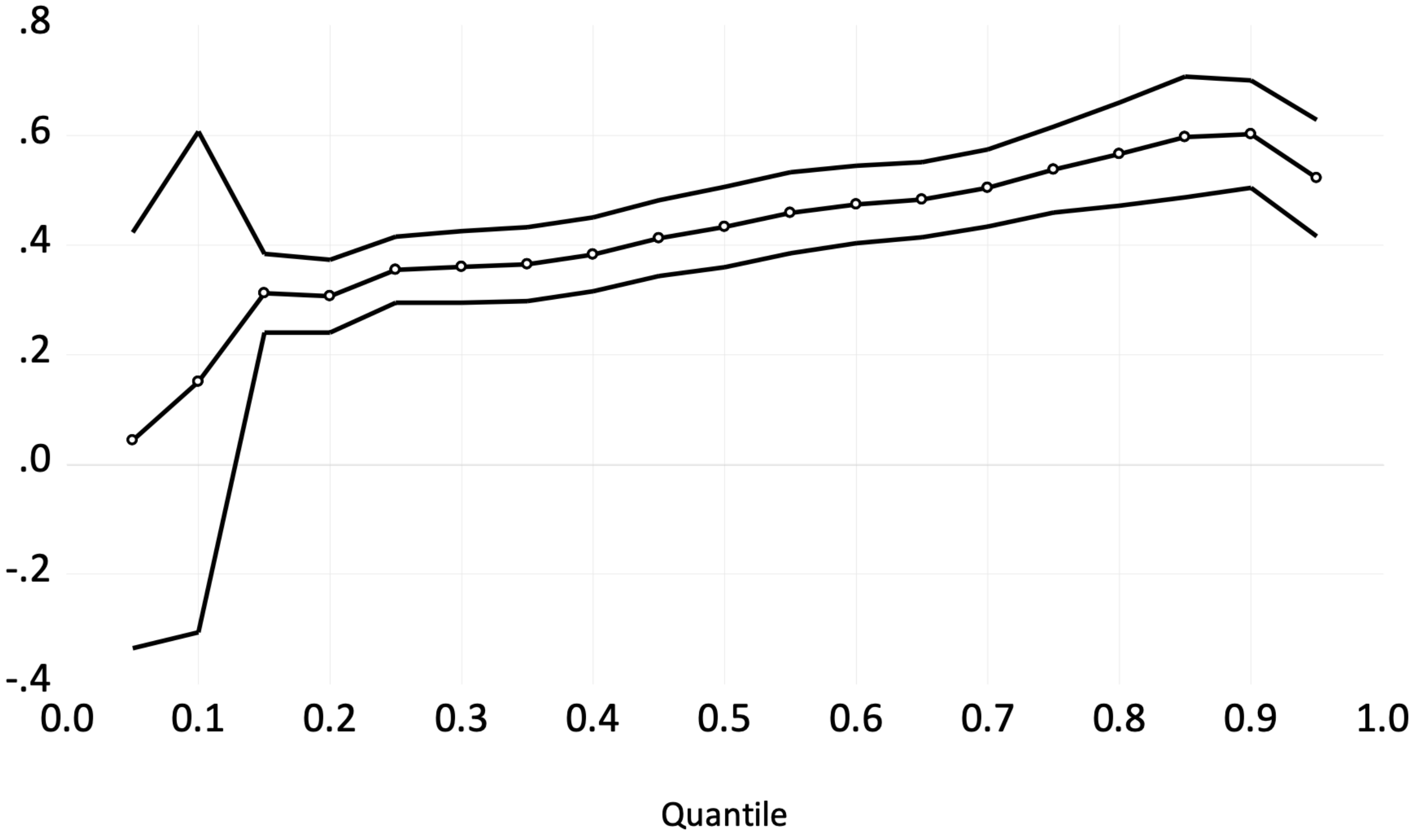
Notes: Results are based on a TVP-VAR model with lag length of order one (BIC) and a 20-step-ahead generalized forecast error variance decomposition.

Figure 5: Net Pairwise Directional Connectedness



Notes: Results are based on a TVP-VAR model with lag length of order one (BIC) and a 20-step-ahead generalized forecast error variance decomposition.

Figure 6: Quantile Regression Results



Notes: Slope estimation results with 95% confidence intervals using quantile regression approach of Koenker and Bassett Jr (1978).