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Impacts of COVID-19 on global stock sectors: Evidence from time-varying connectedness and asymmetric nexus analysis

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\textbf{ABSTRACT}

In this paper, we analyze the impact of the COVID-19 crisis on global stock sectors from two perspectives. First, to measure the effect of the COVID-19 on the volatility connectedness among global stock sectors in the time–frequency domain, we combine the time-varying connectedness and frequency connectedness method and focus on the total, directional, and net connectedness. The empirical results indicate a dramatic rise in the total connectedness among the global stock sectors following the outbreak of COVID-19. However, the high level of the total connectedness lasted only about two months, representing that the impact of COVID-19 is significant but not durable. Furthermore, we observe that the directional and net connectedness changes of different stock sectors during the COVID-19 pandemic are heterogeneous, and the diverse possible driving factors. In addition, the transmission of spillovers among sectors is driven mainly by the high-frequency component (short-term spillovers) during the full sample time. However, the effects of the COVID-19 outbreak also persisted in the long term. Second, we explore how the changing COVID-19 pandemic intensity (represented by the daily new COVID-19 confirmed cases and the daily new COVID-19 death cases worldwide) affect the daily returns of the global stock sectors by using the Quantile-on-Quantile Regression (QQR) methodology of Sim and Zhou (2015). The results indicate the different characteristics in responses of the stock sectors to the pandemic intensity. Specifically, most sectors are severely impacted by the COVID-19. In contrast, some sectors (Necessary Consume and Medical & Health) that are least affected by the COVID-19 pandemic (especially in the milder stage of the COVID-19 pandemic) are those that are related to the provision of goods and services which can be considered as necessities and substitutes. These results also hold after several robustness checks. Our findings may help understand the sectoral dynamics in the global stock market and provide significant implications for portfolio managers, investors, and government agencies in times of highly stressful events like the COVID-19 crisis.

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1. Introduction and literature review

The ongoing COVID-19 pandemic is a global public health emergency, which is significantly different from the previous extreme events related to economic and financial factors (e.g., the 1997–98 Asian financial crisis, 2007–2008 global financial crisis, and 2010–2013 European debt crisis). With extreme urgency and uncertainty, the COVID-19 crisis has caused unprecedented effects to the global economic activities and financial markets. While threatening people’s lives, health, and property, the COVID-19 crisis has also severely paralyzed the national and international real economies and the financial sphere (Hanif et al., 2021; Bakas and Triantafyllou, 2020; Goodell, 2020).

Specifically, due to the COVID-19 pandemic, financial and commodity markets worldwide have experienced various degrees of a slump (Iqbal et al., 2021). After the COVID-19 outbreak, the panic index (VIX index) rose sharply, and global stock markets continued to plummet and even triggered a circuit breaker mechanism. Among them, the strongest reaction was in the U.S. stock market; for example, the Dow Jones Index fell by 2535 points on March 12, 2020, which set the most significant one-day drop since “Black Monday” in 1987, and four “circuit breaker mechanisms” were unprecedentedly occurred in the U.S. stock market during March 2020. Moreover, stock indexes from other markets in Europe and Asia have also experienced similar declines as the U.S. In addition, due to the unprecedented low demand and unavailability of further storage capacity, we have witnessed that crude oil futures prices break new lows in succession and historically fall below zero to negative prices. It is hard to find examples of similar reactions in financial and commodity markets in modern history. (Iqbal et al., 2021; Lin and Su, 2021; Ashraf, 2020; Zhang et al., 2020).

To cope with the unprecedented epidemic, most countries responded immediately by adopting a series of emergency countermeasures such as implementing lockdown and self-isolation restrictions, suspending major cultural and social events, as well as managing economic and financial shocks by providing fiscal and monetary policy supports (Ashraf, 2020; Rizwan et al., 2020). However, due to their respective attributes in the real economy and the governments’ policy guidelines according to the severity of the epidemic, the impact of the COVID-19 outbreak on each industry is asymmetric. Specifically, some industries (Restaurants, Hotels, Entertainment and Transportation et al.) had to close during the pandemic. In contrast, others (Consumer Goods, Communication, Medical, and Pharma et al.) still operated to meet basic needs. Moreover, the COVID-19 outbreak is an extreme event that is referred to as a source of systematic risk (Hung and Xuan, 2021; Abuzayed et al., 2021). Previous evidence indicates that systemic risk means that when a financial institution (market or sector) is in danger, it will spread its risk to other financial institutions (market or sector) due to economic or financial relations, triggering the “Domino Effect” and endanger the entire financial system (Li et al., 2021; Battaglia et al., 2013). In the face of changes in investor sentiment and market conditions around the world triggered by the COVID-19 pandemic, the different characteristics of each industry (sector) will affect its returns and volatility as well as the relationship (connectedness or spillover) among the global stock sectors (Ashraf, 2020; Conlon et al., 2020; Goodell, 2020; Yi et al., 2018).

Notably, the current COVID-19 pandemic has created a dent in the global economy more than what is historically known of past crises, such as the 2008/2009 GFC. It has severely impacted market fears and economic and policy uncertainties, hence affecting the global financial cycle, output, demand, employment, earnings asset prices both in the short and long term (Adekoya and Oliyide, 2021; Bouri et al., 2021; Szczygielski et al., 2021; Li et al., 2022). Through the financial system channels, the information shocks from both the demand and supply side may transmit to various sectors, thereby causing significant changes in the connectedness among global stock sectors (Lin and Su, 2021; Mensi et al., 2021). Therefore, it is essential to examine the effects of the current COVID-19 pandemic on the strength and structure of connectedness among global stock sectors both in the short and long term. Since an accurate measure of volatility spillovers among sectors reduces future uncertainty, improves cross-sector linkages forecasts, and helps make optimal investment decisions (Kang and Lee, 2019; An et al., 2020; Mensi et al., 2021). In addition, due to various sectors’ attributes in the real economy and the governments’ policy guidelines during the pandemic, COVID-19-related volatility across global stock markets and industries has resulted in investors seeking safe-haven investments. Therefore, it is vital to analyze the heterogeneous effects of the pandemic across sectors so that investors can still seek profitable industries to invest in.

Motivated by the above realistic issues, the following specific questions have attracted our attention:

(1) Since the extent of information spillover and volatility interconnection across financial markets (assets or industries) has shown apparent changes during the previous extreme events (e.g., the 1997–98 Asian financial crisis, 2007–2008 global financial crisis, and 2010–2013 European debt crisis) (Lin and Su, 2021; Abuzayed et al., 2021; Boubaker et al., 2021; Heo et al., 2020; Baker et al. (2020a, Baker et al., 2020b; Restrepo et al., 2018; Farhi and Gabaix, 2016; Merkle and Weber, 2014). Will the volatility connectedness (spillovers) among global stock sectors exhibit a typical pattern during the COVID-19 crisis? Alternatively, is there any difference in total connectedness in the global sectoral stock market before and during the COVID-19 outbreak? Moreover, during the epidemic, what was the dynamic performance of each sector in directional and net connectedness? Are there any changes in the spillover effect (spillover direction and intensity) or spillover role (transmitter or receiver of volatility spillovers) of different stock sectors in the time–frequency domain? Are volatility spillovers more pronounced in the short term than the long term?

(2) Since many possible driving factors such as pandemic intensity, market uncertainty, and investors’ sentiment may lead to some degree of fluctuations in financial markets (Sun et al., 2021; Assaf et al., 2021; Aste, 2019; Gajardo et al., 2018; Yi et al., 2018), the economic and financial impacts of the COVID-19 are difficult to predict (Abuzayed et al., 2021). In addition, some recent studies indicate that the correlations within the traditional equity markets are not symmetric, and a nonlinear and asymmetric association between the equity markets and the COVID-19 outbreak might be observed (Lin and Su, 2021; Hanif et al., 2021; Iqbal et al., 2021; Shahbaz et al., 2018). Therefore, due to their respective attributes in the real economy and the governments’ policy guidelines, we may expect that the impacts of the COVID-19 pandemic on each stock sector are asymmetric. In other
words, what is the asymmetric relationship between each stock sector and the COVID-19 pandemic? What are the differences in the responses of various stock sectors to the pandemic?1, 2 and 3

To answer the above questions, (1) Firstly, we need to understand the dynamic spillover relationships among global stock sectors during the COVID-19 epidemic. Hence, we utilize a full-fledged time-varying parameter vector autoregressive (TVP-VAR) methodology of Koop and Korobilis (2014) and combine it with the spillover index method (DY method) of Diebold and Yilmaz (2014). Based on this framework (TVP-VAR-DY method), we could evaluate the extent of information spillover and volatility connectedness across all the stock sectors at any time point during the sampling period. Besides, compared to the popular DY method with rolling window estimation, the results obtained from this framework (TVP-VAR-DY method) are more accurate since the rolling window estimation has some apparent defects. Specifically, it is sensitive to the setting of the rolling window size and outliers, and easy to lose some observations (Lin and Su, 2021; Gabauer & Gupta, 2018; Korobilis & Yilmaz, 2018; Antonakakis & Gabauer, 2017). (2) Secondly, to investigate if the COVID-19 pandemic has an asymmetric impact on different sectors and explore how the global stock sectors respond to the pandemic, we use the Quantile-on-Quantile regression (QQR) approach, as recently proposed by Sim and Zhou (2015). The QQR approach has already been widely used in financial studies related to traditional equity markets, commodity markets, and cryptocurrency markets (Iqbal et al., 2021; Gupta et al., 2018; Shahbaz et al., 2018). The main advantage of QQR is that it enables us to investigate the relationships between financial variables at different quantiles of both variables. It combines both the techniques of non-parametric estimation and quantile regression (Iqbal et al., 2021; Han et al., 2019). Therefore, the QQR approach allows us to identify the complexities in the relationships between the COVID-19 pandemic and stock sectors that would be difficult to detect by using conventional econometric models (Shahbaz et al., 2018; Carmona et al., 2017; Mohammad and Parvaresh, 2014; Bernard et al., 2010).

Recently, several pioneer studies have examined the impact of the COVID-19 on the global financial markets, including stock markets (Rahman et al., 2021; Abuzayed et al., 2021; Ashraf, 2020; Baek et al., 2020), commodity markets (Lin and Su, 2021; Gharib et al., 2020; Ji et al., 2020) and cryptocurrency markets (Iqbal et al., 2021; Conlon et al., 2020; Dutta et al., 2020). For example, Ashraf (2020) found that stock markets responded negatively to the growth in COVID-19 confirmed cases, and the response varies over time. Rahman et al. (2021) investigated how the Australian stock market reacted to the COVID-19 pandemic and the effect of the “Job Keeper” package stimulus on Australian stock returns. Gharib et al. (2020) examined the COVID-19 on the links between crude oil prices and gold prices and found a bilateral bubble contagion effect in oil and gold markets during the COVID-19 epidemic. Lin and Su (2021) examined the impact of COVID-19 on the linkages among the global energy markets. They found that the total connectedness in global energy markets has risen dramatically following the COVID-19 outbreak, Iqbal et al. (2021) explored the impact of COVID-19 on the cryptocurrency markets. Their results revealed that these cryptocurrencies responded differently to changes in the intensity of COVID-19.

While several scholars have focused on the impacts of COVID-19 on the financial markets, only a few studies have discussed the effect of COVID-19 from a sector-level perspective (Azimli, 2020; Hanif et al., 2020; Baek et al., 2020). Additionally, there is a lack of evidence on how the COVID-19 pandemic has shaped the level of volatility connectedness across the global stock sectors from a time-varying perspective. It has important implications for market participants (e.g., investors and portfolio managers) since previous studies have revealed that different levels of volatility connectedness across financial markets can significantly affect the benefits diversification benefits for market participants. Lin and Su, 2021; Abuzayed et al., 2021; Yi et al., 2018). Furthermore, according to recent studies, most authors ignored the possibility of the nonlinear and asymmetric relations between COVID-19 and the stock sectors (Iqbal et al., 2021; Razzaq et al., 2020). However, due to their respective attributes in the real economy and the governments’ policy guidelines according to the severity of the epidemic, the impact of the COVID-19 outbreak on each industry is asymmetric. Hence, we can expect that different levels of the changes in the COVID-19 intensity (confirmed cases and death cases) may affect the stock sectors’ returns differently, at various quantiles of their returns.

In general, this study contributes to the literature on two main fronts.

(1) First, from a sector-level perspective, we focused on the unknown field of how the COVID-19 pandemic has shaped the volatility connectedness across the global stock sectors both from the time domain and frequency domain by combining the time-varying connectedness and frequency connectedness method. Furthermore, through three different connectedness analysis perspectives (total connectedness analysis, total directional connectedness analysis, net total directional connectedness analysis), we comprehensively investigate the fluctuation of the total connectedness across global stock sectors and identify changes in the spillover effects and roles of different sectors during the COVID-19 pandemic. In addition, the results of the frequency connectedness analysis help to effectively identify the dominant factors (high-frequency or low-frequency components) affecting the volatility spillovers among stock sectors in different periods of the COVID-19 pandemic, as well as the impacts of the COVID-19 pandemic on the global stock market in different frequency domains.

(2) Second, we paid attention to the ignored point about the nonlinear and asymmetric nexus between COVID-19 and global stock sectors. To the best of our knowledge, this is the first endeavor to examine how the intensity of the COVID-19 pandemic (represented by the daily new COVID-19 confirmed cases and death cases worldwide) affects the total connectedness and daily returns of the global stock sectors worldwide. Considering the possibility of the nonlinear and asymmetric relations between COVID-19 and different sectors, we use a recently developed nonlinear technique—QQR regression (Iqbal et al., 2021; Razzaq et al., 2020; Sim and Zhou, 2015) to identify the complex asymmetric nexus between the pandemic intensity and the stock sectors worldwide that would be difficult to detect using conventional econometric models (Azimli, 2020; Hanif et al., 2020; Baek, 2020). On the one hand, we first examine how the changing COVID-19 pandemic intensity asymmetrically impacts
the total connectedness among stock sectors. On the other hand, we further identify the differences in the responses of various stock sectors to the COVID-19 pandemic. Our findings have implications for the investors to respond quickly and manage corresponding investment strategies in times of highly stressful events like the COVID-19 pandemic.

The remainder of this paper is organized as follows. Section 2 outlines the data and methodological framework. Section 3 presents the empirical results. Section 4 checks for the robustness of the empirical results. Section 5 concludes the study.

2. Data and methodology

2.1. Data and summary statistics

Our sample data includes the daily prices of ten major stock sectors worldwide\(^1\) and four major international financial indices\(^2\) from Wind Information (https://www.wind.com.cn/), and the COVID-19 related data, including the daily new COVID-19 confirmed cases and the daily new COVID-19 death cases worldwide from the website designed by the Johns Hopkins University. The data for each stock sector has been converted to log returns (Li et al., 2020) that include 308 observations ranging from January 22, 2020, to April 30, 2021.\(^3\) Besides, according to the relevant literature (Gan & Xu, 2019), the COVID-19 data series are divided by 100 after converting into log values.

Table 1 provides the descriptive statistics for all the variables in this paper. The statistically significant values of the Jarque-Berra (JB) tests show an abnormality in the data distribution, validating the use of the QQR approach in this study (Iqbal et al., 2021; Razzaq et al., 2020; Shahbaz et al., 2018). Besides, to test the serial correlation and ARCH effects of the return series, the LB-test for the return series and the squared return series are performed, respectively. These two LB-test results justify the rationality of using the GARCH model to capture the volatility of the stock sectors’ returns. Moreover, considering the issue of structural breaks, the results of the Zivot-Andrew test indicate that all the variables are stationary in the presence of structural breaks.

2.2. TVP-VAR-based dynamic connectedness approach

To explore the transmission mechanism among global stock sectors in a time-varying fashion, we use the TVP-VAR methodology of Koop and Korobilis (2014) and combine it with the DY method of Diebold and Yilmaz (2014). This framework extends the original DY method by allowing the variances to vary over time via a Kalman Filter estimation with forgetting factors. Therefore, the TVP-VAR based connectedness approach overcomes the shortcomings of using rolling window estimation (the results obtained from rolling window estimation is sensitive to the setting of the rolling window size and outliers, and easy to lose some observations) in the simple VAR based connectedness method (Gabauer and Gupta, 2018; Antonakakis et al., 2019; Antonakakis et al., 2018; Korobilis & Yilmaz, 2018).

According to the Bayesian InformationCriterion (BIC), the TVP-VAR(1) model can be written as follows,

\[
\begin{align*}
Y_t &= \beta_0 Y_{t-1} + \epsilon_t \\
\epsilon_t &\sim N(0, S_t) \\
\beta_t &= \beta_{t-1} + \nu_t \\
\nu_t &\sim N(0, R_t) \\
Y_t &= \sum_{j=0}^{\infty} A_j \epsilon_{t-j}
\end{align*}
\]

(1) (2) (3)

where \(Y_t, Y_{t-1}, \) and \(\epsilon_t\) are \(N \times 1\) dimensional vectors. The parameters \(\beta_t, \nu_t,\) and \(S_t\) are \(N \times N\) dimensional matrices, whereas \(R_t\) is an \(N^2 \times N^2\) dimensional matrix.

After estimating the time-varying coefficients and variance–covariance matrices, we need to transform the TVP-VAR to a TVP-VMA (vector moving average) using the Wold representation theorem in Eq.(3). Next, using the generalized impulse response functions (GIRFs) that represent the responses of all variables under a shock in variable \(i\), we could estimate the impact of a shock in variable \(i\) to all other variables. Since we do not have a structural model, we compute the differences between an h-step ahead forecast with variable \(i\) is shocked and not shocked. The difference can be accounted to the shock in variable \(i\), which can be calculated as follows,

---

\(^1\) The ten major sectors include Energy, Materials, Industry, Unnecessary Consume, Necessary Consume, Medical & Health, Finance, Information Technology, Telecom, Utilities. The data are from MSCI Global Primary Industry Indexes obtained from Wind Information (https://www.wind.com.cn/).

\(^2\) The four major international financial indices include SP500(USA), FTSE100(UK), SSEC (China), USDX(US Dollar Index).

\(^3\) According to Ashraf (2020), our sample data starts from the day (January 22, 2020) when the COVID-19 event caught the public eye and databases started reporting the COVID-19 related information.
Table 1
Summary statistics.

| Variables          | Mean  | SD    | JB    | Q(10)    | Q^2(10) | ZA    | Break Day |
|--------------------|-------|-------|-------|----------|---------|-------|-----------|
| **Panel A: Stock sectors** |       |       |       |          |         |       |           |
| Energy             | -0.0003 | 0.0262 | 3685.89*** | 50.68*** | 161.42*** | -7.40*** | 19Mar2020 |
| Materials          | 0.0010  | 0.0160 | 2635.62*** | 56.87*** | 203.65*** | -8.34*** | 24Mar2020 |
| Industry           | 0.0007  | 0.0162 | 2068.09*** | 54.39*** | 305.22*** | -8.51*** | 24Mar2020 |
| Unnecessary Consume| 0.0012  | 0.0159 | 2045.05*** | 55.90*** | 202.76*** | -12.15*** | 24Mar2020 |
| Necessary Consume  | 0.0002  | 0.0114 | 3710.99*** | 83.96*** | 340.35*** | -9.54*** | 24Mar2020 |
| Medical & Health   | 0.0007  | 0.0133 | 1540.31*** | 115.38*** | 549.63*** | -9.04*** | 24Mar2020 |
| Finance            | 0.0005  | 0.0188 | 2059.76*** | 64.48*** | 321.97*** | -8.15*** | 24Mar2020 |
| Information Technology | 0.0015 | 0.0186 | 1673.79*** | 117.85*** | 344.85*** | -10.51*** | 24Mar2020 |
| Telecom            | 0.0010  | 0.0143 | 1607.09*** | 111.79*** | 312.77*** | -13.21*** | 24Mar2020 |
| Utilities          | 0.0002  | 0.0159 | 2939.37*** | 95.52*** | 312.77*** | -9.06*** | 24Mar2020 |
| FTSE100            | -0.0001 | 0.0159 | 1922.32*** | 56.76*** | 162.09*** | -20.84*** | 24Mar2020 |
| SP500              | 0.0009  | 0.0182 | 2666.95*** | 180.17*** | 519.13*** | -19.97*** | 24Mar2020 |
| USDX               | -0.0002 | 0.0042 | 154.59***  | 37.84*** | 444.61*** | -11.58*** | 23Mar2020 |
| SSEC               | 0.0005  | 0.0120 | 1365.65*** | 22.81*** | 87.25***  | -10.89*** | 24Mar2020 |
| **Panel B: COVID-19 related data** | 252552.3 | 214876.6 | 23.68*** | 2002.90*** | 1865.00*** | -6.33*** | 13Oct2020 |
| COVID –19c         | 5682.672 | 354.767 | 13.60*** | 1536.80*** | 1302.80 | -2.27*** | 2Nov2020 |
| COVID –19d         | 19          | 20      | 23.68*** | 2002.90*** | 1865.00*** | -6.33*** | 13Oct2020 |

Note: ***, ** and * indicate that the value is significant at the 1%, 5% and 10% levels of significance, respectively. COVID –19c and COVID –19d represent the daily new COVID-19 confirmed cases and daily new COVID-19 death cases, respectively. JB represents the Jarque-Bera test. ZA represents the Zivot-Andrew unit root test. Q(10) and Q^2(10) are the Ljung-Box(LB) test statistics for returns series and squared returns series respectively for the 10th lag.

\[
\begin{align*}
\text{GIRF}_t(h, \delta_j, F_{t-1}) &= E(Y_{t+h} | F_{t-1}) - E(Y_{t+h} | F_{t-1}) \\
\Psi_{j,t}^h(h) &= \frac{A_{j,t} S_{j,t}}{\sqrt{S_{j,t}^2}} \\
\delta_j &= \sqrt{S_{j,t}} \\
\Psi_{j,t}^h(h) &= S_{j,t}^{-1} A_{j,t} S_{j,t}
\end{align*}
\]

where \(\delta_j\) represents the selection vector with one on the \(j\)-th position and zero otherwise, \(F_{t-1}\) is the information set until \(t-1\), \(\Psi_{j,t}^h(h)\) represents the GIRFs of variable \(j\) and \(h\) represents the forecast horizon. Afterwards, we can compute the GFEVD that is interpreted as the variance share one variable has on other variables \(j\). The h-step ahead GFEVD \((\bar{\Psi}_{j,t}^h(h))\) can be calculated as follows,

\[
\bar{\Psi}_{j,t}^h(h) = \frac{\sum_{j=1}^{N} \sum_{h=1}^{H} \text{Var}_{j,t}^h(h)}{\sum_{j=1}^{N} \sum_{h=1}^{H} \text{Var}_{j,t}^h(h)}
\]

Using the GFEVD, the total connectedness index can be obtained:

\[
C_{t,j}^h(h) = \frac{\sum_{j=1}^{N} \sum_{h=1}^{H} \bar{\Psi}_{j,t}^h(h)}{\sum_{j=1}^{N} \bar{\Psi}_{j,t}^h(h)} \times 100
\]

First, we focus on the spillovers of variable \(i\) to all others \(j\), representing the total directional connectedness to others and formulated by:

\[
C_{t,ij}^h(h) = \frac{\sum_{j=1}^{N} \sum_{h=1}^{H} \bar{\Psi}_{j,t}^h(h)}{\sum_{j=1}^{N} \bar{\Psi}_{j,t}^h(h)} \times 100
\]

Second, we compute the spillovers of all variables \(j\) to variable \(i\), representing the total directional connectedness from others and defined as:
denotes an interval on the real line from the set of intervals directional connectedness:

\[ C_{ij}(h) = \frac{\sum_{i=1}^{N} \tilde{g}_{ij}(h)}{\sum_{i}^{N} \tilde{g}_{ii}(h)} \times 100 \]  

(8)

Third, we subtract the total directional connectedness to others and total directional connectedness from others to get the net total directional connectedness:

\[ C_{ij}' = C_{ij}(h) - C_{ij}(h) \]  

(9)

If\( C_{ij}' > 0 \), it means that variable \( i \) influences the network more than being influenced by it. By contrast, if\( C_{ij}' < 0 \), it means that variable \( i \) is driven by the network.

Finally, we break down the net total directional connectedness to examine the bidirectional relationships by computing the net pairwise directional connectedness (NPDC):

\[ NPDC_{ij}(h) = \tilde{q}_{ij}(h) - \tilde{q}_{ij}(h) \]  

(10)

If\( NPDC_{ij}(h) > 0 \), it means that variable \( i \) is driving variable \( j \), otherwise, variable \( i \) is driven by variable \( j \).

2.3. BK time–frequency connectedness approach

To explore connectedness in the frequency domain (long-term, medium-term, or short-term), we adopt the spectral representation of the variance decomposition method based on frequency responses to shocks following Barunik and Krekhlik (2018).

The scaled generalized FEVD on a frequency band \( d = (a, b) : a, b \in (-\pi, \pi), a < b \) can be defined as:

\[
\begin{align*}
\left( \tilde{\theta}_j \right)_{j,k} &= \left( \theta_d \right)_{j,k} / \sum_k \left( \theta_d \right)_{j,k} \\
\left( \theta_d \right)_{j,k} &= \frac{1}{2\pi} \int_{d_j} \Gamma_j(\omega) (f(\omega))_{j,k} d\omega \\
\left( \theta_w \right)_{j,k} &= \sum_d \left( \theta_d \right)_{j,k}
\end{align*}
\]  

(11)

where \( \left( \theta_d \right)_{j,k} \) denotes generalized variance decompositions on frequency band \( d \); \( \Gamma_j(\omega) \) denotes frequency share of the variance of the \( j \)-th variable; \( (f(\omega))_{j,k} \) represents the portion of the spectrum of the \( j \)-th variable at frequency \( \omega \) due to shocks to the \( k \)-th variable; \( d_j \) denotes an interval on the real line from the set of intervals \( D \).

The frequency connectedness on the frequency band \( d \) can be obtained by:

\[
C_{d} = 100 \times \left( \frac{\sum \tilde{\theta}_d - Tr\left( \tilde{\theta}_d \right)}{\sum \tilde{\theta}_w} \right)
\]  

(12)

where \( Tr(\cdot) \) is the trace operator. This frequency connectedness framework allows us to identify the short-term, medium-term and long-term connectedness when setting frequency band \( d \) to different intervals.

2.4. QQR method

Considering the asymmetric nexus between the stock sectors and the COVID-19 crisis, we introduce a non-linear method: QQR (Quantile-on-Quantile Regression) technique developed by Sim and Zhou (2015) to check their specific relations.

The QQR method is a generalization of the proposed quantile regression model. It has been used to empirically investigate how the quantiles of a variable affect the conditional quantiles of another variable. The QQR approach is the combination of the conventional quantile regression and nonparametric estimations (Iqbal et al., 2021; Han et al., 2019). First, the conventional quantile regression technique proposed by Koenker and Bassett (1978) is used to determine how the regressor affects the conditional quantiles of the regressand. Second, the quantile regression technique is a modified version of the classical linear regression approach. Similar to the ordinary least squares (OLS), the quantile regression approach can examine the effect of regressor on regressand at both the top, middle, and bottom quantiles of a given distribution. Third, the local linear regression technique proposed by Stone (1977) and Cleveland (1979) is used to examine the local effects of specific quantiles of the regressor on the fitted regressand. Moreover, the local linear regression method can effectively avoid the “curse of dimensionality” from nonparametric model estimations. Thus, the combination of the above methods allows us to investigate the effect of a regressor on the regressand at various quantiles of both distributions. In summary, it allows us to explore how the upper, lower, and middle quantiles of the COVID-19 outbreak affect the upper, lower, and middle quantiles of the stock sectors’ returns differently.

This section aims to apply the QQR method to investigate the quantiles’ impact of the daily new COVID-19 confirmed cases on the quantiles of stock sectors’ returns. In this direction, the nonparametric QQR is defined below.
where \( \text{Sector}_t \) explains the logarithm returns for a given sector in period \( t \), \( \text{COVID}_{19} \) represents the daily new COVID-19 confirmed cases worldwide in period \( t \), \( \sigma \) denotes the \( \text{th} \) quantile of the conditional distribution of \( \text{COVID}_{19} \), and \( \psi^\sigma \) denotes the quantile residual term whose conditional \( \text{th} \) quantile is equal to zero, \( \beta^\sigma(\cdot) \) is an unknown function because we lack prior information on the relationship between \( \text{COVID}_{19} \), and \( \text{Sector}_t \).

The QQR method offers detailed information on how different quantiles of the COVID-19 influence different quantiles of the sectors’ returns. To explore the linkages between the \( \text{th} \) quantile of \( \text{Sector}_t \) and the \( \text{th} \) quantile of \( \text{COVID}_{19} \), the unknown function \( \beta^\sigma(\cdot) \) should be expanded via a first-order Taylor expansion around a quantile of \( \text{COVID}_{19} \) as below.

\[
\beta^\sigma(\text{COVID}_{19}) \approx \beta^\sigma(\text{COVID}_{19}^\sigma) + \beta^\sigma(\text{COVID}_{19}^\sigma)(\text{COVID}_{19} - \text{COVID}_{19}^\sigma)
\]

where \( \beta^\sigma(\text{COVID}_{19}^\sigma) \) indicates the partial derivative of \( \beta^\sigma(\text{COVID}_{19}) \) for \( \text{COVID}_{19} \) in Eq.(14), describing it as a marginal effect. However, it reflects the same explanation to the slope coefficients in the linear regression framework. Moreover, following Sim and Zhou (2015), \( \beta^\sigma(\cdot) \) can be renamed \( \beta_0(\sigma, \tau) \). Accordingly, we can reformulate Eq. (14) as below.

\[
\beta^\sigma(\text{COVID}_{19}) \approx \beta_0(\sigma, \tau) + \beta_1(\sigma, \tau)(\text{COVID}_{19} - \text{COVID}_{19}^\sigma)
\]

Then, we substitute Eq. (15) into Eq. (13) and obtain Eq. (16).

\[
\text{Sector}_t = \beta_0(\sigma, \tau) + \beta_1(\sigma, \tau)(\text{COVID}_{19} - \text{COVID}_{19}^\sigma) + \eta_t
\]

Where the (*) shows the \( \text{th} \) conditional quantile function of \( \text{Sector}_t \). As the coefficients \( \beta_0 \) and \( \beta_1 \) depend on \( \sigma \) and \( \tau \), the given formula in Eq. (16) reflects the true association between the \( \text{th} \) quantile of \( \text{Sector}_t \) and the \( \text{th} \) quantile of \( \text{COVID}_{19} \). These parameters may vary based on \( \text{th} \) quantile of \( \text{Sector}_t \) and \( \text{th} \) quantile of \( \text{COVID}_{19} \). Moreover, there is no linear relationship anticipated at any point in time, hence, Eq. (16) measures the overall dependence relationship between (*) and \( \text{COVID}_{19} \), through the linking of their respective distributions.

Finally, we provide the estimated coefficients of the sectors, as represented by the local linear regression’s estimated parameters \( b_0 \) and \( b_1 \) in Eq. (17) by estimating the following minimization problem. Moreover, \( b_0 \) and \( b_1 \) are the estimates of \( \beta_0 \) and \( \beta_1(\sigma, \tau) \).

\[
\min_{b_0, b_1} \sum_{t=1}^{n} \rho_\sigma(\text{Sector}_t - b_0 - b_1(\text{COVID}_{19} - \text{COVID}_{19}^\sigma))K\left(F_\tau(\text{COVID}_{19}^\sigma) - \frac{\tau}{h}\right)
\]

where \( \rho_\sigma(\cdot) \) shows the quantile loss function and \( K(\cdot) \) represents the Gaussian kernel function in both the minimization problems as minimal weighting criterion to improve the estimation efficiency.

Finally, following Sim and Zhou (2015), we use the bandwidth parameter \( h = 0.05 \) for our analysis.

Fig. 1. Dynamic total connectedness index. Notes: The figure shows the dynamic total connectedness based on Eq. (8).
3. Empirical results

3.1. Dynamic connectedness analysis

Due to each industry’s own characteristics and policy restrictions, the impacts of the COVID-19 crisis on different industries are diverse. During the COVID-19 crisis, some industries (Restaurants, Hotels, Entertainment and Transportation) had to close down, while others (Consumer Goods, Communication, Medical, and Pharma et al.) still operated to meet basic needs. Consequently, we may expect that the volatility connectedness (spillovers) among global stock sectors may exhibit a differential pattern during the COVID-19 crisis, such as the fluctuation of the total (directional and net) connectedness and the changes in the risk spillover effects and roles of different sectors.

3.1.1. Dynamic total connectedness analysis

This section uses the TVP-VAR-based dynamic connectedness approach to explore the dynamic risk transmission mechanism among global stock sectors. According to Diebold and Yilmaz (2012), we set the forecasting horizon $h$ to 10 and set the lag order of the TVP-VAR model according to the Bayesian information criterion. Fig. 1 presents the results for the dynamic total connectedness among global stock sectors.

Firstly, we observe an apparent sharp fluctuation in the level of total connectedness around late February 2020. Specifically, before this time, the total connectedness index permanently stabilizes or displays a few slight jumps, ranging around 79%. In comparison, after that time, this index significantly increases and fluctuates comparatively at the highest levels from March 2020 to May 2020 and reaches a peak level of around 87% in early March 2020. The severity and extreme uncertainty of the COVID-19 epidemic greatly impacted the entity industries and investor sentiment in global financial markets, reflecting changes in the total connectedness among international stock sectors. Specifically, since March 2020, COVID-19 has broken out in European and American countries, and the number of infections and deaths of COVID-19 worldwide has increased dramatically. In addition, major U.S. and European stock indexes have experienced cliff-like declines, and U.S. stock indexes have even repeatedly triggered the circuit breaker mechanism. Moreover, international crude oil prices plummeted, and WTI crude oil futures even fell to negative values, unprecedented.

Secondly, we observe that the impact of COVID-19 is significant but not durable since the high level of the total connectedness index lasted only about two months and began to decline rapidly in early May 2020. Moreover, we found that the total connectedness index returned to the level before the COVID-19 outbreak in late August 2020. The changes mentioned above can be attributed to the following reasons: First, governments of various countries have successively adopted effective measures to control the COVID-19, such as lockdowns, self-isolation, and social distancing restrictions. Second, the global development of the COVID-19 has shown a positive trend. For example, the mortality rate of COVID-19 has decreased, and the cure rate has gradually increased. Third, successive positive news on the world economy and significant advances in COVID-19 vaccine development has boosted investor sentiment, and the global financial markets have steadily returned to stability.

Thirdly, since late November 2020, the total connectedness has increased rapidly, but the rise in the index is not considerable, and...
the duration is relatively short. The reason can be attributed to the relaxation of epidemic prevention and control and the arrival of the second wave of COVID-19 in some countries. Most countries have gradually started to ease or even cease their lockdowns. Factories, transportation, restaurants, and shopping centers are busy, and the streets are no longer empty. Social and entertainment activities have gradually returned to the past. The result is that the economy has recovered rapidly; however, the uncertainty of the development of COVID-19 has also increased significantly. In December 2020, the global development situation of COVID-19 had once again become severe and brought new challenges. On the one hand, the epidemic situation in the United States, Brazil, and European countries is getting worse, and the second and third wave of COVID-19 follow one after another; on the other hand, a new variant of COVID-19, VUI, which is more transmissible, has been discovered in England. Therefore, most countries have once again announced closed quarantine and curfew measures to varying degrees to prevent the epidemic from spreading further.

Finally, the results of time–frequency decomposition of the dynamic total spillovers in Fig. 2 indicate that total spillovers after the outbreak of the COVID-19 crisis are driven mainly by the high-frequency component (short-term spillovers), i.e., the transmission of spillovers between sectors are likely to be more short-lived during the full sample time. However, the effects of the COVID-19 outbreak also persisted in the long term since the long-term spillovers have changed significantly during the worst period of the COVID-19 epidemic (March 2020 to May 2020). A possible explanation might be that spillovers with a longer duration may be more connected to extremely unexpected shocks (sudden outbreak of the COVID-19 epidemic on a large scale) rather than anticipated events (stable and sustainable development of the COVID-19 outbreak). Our findings are consistent with those obtained by Wang et al., 2021 and Jiang & Chen, 2022.

3.1.2. Dynamic total directional connectedness analysis

From a general perspective, the dynamic total connectedness analysis shows the amount of volatility spillovers transmitted across global stock sectors and their changes over the sampling time. To better understand the dynamic performance of each sector in directional spillovers from an individual perspective, in this section, we further estimate the dynamic directional connectedness for every ten sectors over the sampling period.

Firstly, Fig. 2 presents the dynamic total directional spillovers transmitted from each of the ten sectors to others. It can be seen that the directional spillovers from each sector with different dynamic evolution characteristics behave rather heterogeneously over the sampling time. Furthermore, the directional spillovers transmitted from all the ten sectors fluctuated more wildly after the outbreak of the COVID-19 (March 2020 to May 2020), which follows a similar pattern found for the dynamic total spillovers in section 3.1.1. For example, the directional spillovers transmitted from Finance to other sectors were relatively low before March 2020. The index has risen sharply since March 2020 (especially from March 2020 to May 2020), representing a rise in their directional spillovers to other sectors. Additionally, the high level of Finance’s directional spillovers lasted only about two months, began to decline in early June 2020, and has returned to the level before the COVID-19 outbreak in October 2020. Another interesting finding is that the “To” spillovers of some sectors (Necessary Consume and Utilities) have been relatively high after the COVID-19 outbreak and have not shown a downward trend with the gradual stabilization of the epidemic.

Secondly, Fig. 3 presents the dynamic total directional spillovers transmitted from the others to each sector. The directional “From”
spillovers of each sector with different dynamic evolution characteristics behave very similarly in sampling time, which is very different from the “To” spillovers results. Specifically, each sector’s “From” spillover index rose rapidly after the outbreak of COVID-19 and then began to decline after reaching a peak gradually. Among them, the “From” spillover indexes of only two sectors (Necessary Consume and Utilities) fell relatively slowly, while others were relatively quick.

Finally, the results of time-frequency decomposition of the dynamic directional “To” and “From” spillovers in Fig. 4 and Fig. 6 indicate that directional spillovers of each sector remain driven mainly by the high-frequency component (short-term spillovers). Additionally, directional spillovers also showed long-term effects during the worst of the COVID-19 pandemic.

3.1.3. Dynamic net total directional connectedness analysis

The total directional connectedness analysis helps to understand the dynamic performance of each sector in directional spillovers from an individual perspective during the sampling period. This section aims to conduct further the dynamic net total directional connectedness analysis, which is used to determine each sector’s spillover roles (major spillover transmitters or receivers) from the time–frequency domain. Fig. 7 presents the dynamic net spillovers of each sector. We observe the following empirical regularities.

Firstly, most sectors show significant changes in their net total directional connectedness after the COVID-19 outbreak. However, most sectors did not show the changes in net spillover roles except Necessary Consume, Medical & Health, and Utilities. Specifically, before the outbreak of COVID-19, these three sectors are the major transmitters of volatility spillovers. However, after the outbreak of COVID-19, their spillover roles changed from major transmitters of volatility spillovers to major receivers of volatility spillovers.

Secondly, the significant changes in net spillovers of most sectors mainly concentrate on the extent of the spillover effect (spillover intensity) but not the role after the outbreak of COVID-19. Specifically, we observe an apparent increase in some sectors’ net total directional connectedness (Materials, Telecom, Finance) after the COVID-19 outbreak, representing that their spillover effect has increased, but their roles have not changed. Additionally, we see a decline in the net total directional connectedness of some sectors (Industry, Unnecessary Consume, Information Technology) after the COVID-19 outbreak. Similarly, they have also only changed in the spillover effect rather than the spillover role.

Thirdly, the results of time-frequency decomposition of the net spillovers in Fig. 8 indicate that net spillovers of each sector remain driven mainly by the high-frequency component (short-term spillovers), and long-term effects also persist during the worst time of the COVID-19. The visual evidence indicates that the net spillovers are not constant over time; most sectors oscillate between the roles of net transmitter and net receiver of volatility. Taking the net spillover under the short term, we find that Unnecessary Consume, Finance, Industry are net transmitters of short-term volatility spillovers before the COVID-19 crisis. At the same time, Medical & Health, Telecom, and Utilities are net receivers of short-term volatility spillovers before the COVID-19 crisis. Furthermore, Unnecessary Consume, Necessary Consume, Industry, and Telecom are net transmitters of short-term volatility spillovers during the COVID-19 crisis. Energy is a net receiver of short-term volatility spillovers during the whole period of COVID-19 crisis, while Utilities, Information technology, Medical & Health are net receivers of short-term volatility spillovers only during the localized period of the COVID-19 crisis (especially from July 2020 to September 2020). The rest of the sectors oscillate between net receivers and net transmitters of short-term volatility spillovers during the sampling period.

Above all, we can conclude that the net spillover changes in the ten stock sectors during the COVID-19 pandemic are

![Dynamic directional "To" spillovers — Frequency decomposition](image-url)
heterogeneous. For a reason, the possible driving factors are diverse, such as the public’s needs and investors’ attention. For example, during the COVID-19 pandemic, due to the consideration of avoiding infection and governments’ policy guidelines (such as lockdowns, self-isolation, and social distancing restrictions), people usually stay at home for a long time and stock up on food, clothing and other daily necessities (also include electricity, water, natural gas, etc., which all belong to Utilities), as well as masks, disinfectant and other medical products, which could significantly affect the public’s needs for these three industries (Necessary Consume, Medical & Health, Utilities). Such upward demand information spillovers from other industries (sectors) may be the main reason for changing the roles of these three sectors from major transmitters to major receivers of volatility spillovers. Moreover, the particular urgency and uncertainty of COVID-19 have brought significant challenges to the global financial system; besides, previous studies (Sun et al., 2021; Assaf et al.,
have revealed that the financial industry (such as stock market, futures market, and cryptocurrency market) is vulnerable to the investor sentiment driven by COVID-19-related information. Hence, Finance could attract more investors and dominate the market after the outbreak of COVID-19, further enhancing its role as a major transmitter of volatility spillovers.

3.2. QQR analysis

Previous studies have revealed that the correlations within the traditional equity markets are not symmetric, and a nonlinear and asymmetric association between the equity markets and the COVID-19 outbreak might be observed (Lin and Su, 2021; Hanif et al., 2021; Iqbal et al., 2021; Shahbaz et al., 2018). Therefore, using the Quantile-on-Quantile Regression (QQR) methodology, we aim to
identify the following issues: (1) How the changing COVID-19 pandemic intensity asymmetrically impacts the total connectedness among stock sectors? (2) How the changing COVID-19 pandemic intensity (represented by the daily new COVID-19 confirmed cases worldwide) asymmetrically impact the daily returns of the global stock sectors?

Fig. 9 presents the QQR results between the daily new confirmed COVID-19 cases worldwide and the TCI (total connectedness index) among global stock sectors. The vertical color bars indicate the scale, direction, and magnitude of the beta coefficients, as mentioned in section 2.4. The $x$, $y$, and $z$-axis show the quantiles of the daily new confirmed COVID-19 cases, the quantiles of the TCI, and the beta coefficients, respectively. The relationships between COVID-19 and TCI move from lower (negative) to higher (positive), respectively, as the color shifts from dark blue (downward) to light yellow (upward). Firstly, the link between lowermost quantiles (below 10th) of COVID-19 and all quantiles of TCI shows a positive association as represented by a light yellow color, implying a slight rise in COVID-19 leading to positive returns of TCI. Furthermore, the link between lowermost quantiles (below 10th) to uppermost quantiles (90th to 95th) of COVID-19 and all quantiles of TCI show a weak association as represented by green color implying that returns of TCI have few responses to moderate rise in COVID-19. In addition, the uppermost quantiles (90th to 95th) of the COVID-19 and the TCI show a stronger negative association, indicating that returns of TCI have a solid reaction to huge rise in COVID-19 (Figs. 10-13).

This section reports the results of the asymmetric nexus between the COVID-19 and the stock sectors worldwide by QQR analysis. The QQ regression offers detailed information on how different quantiles of COVID-19 influence different quantiles of the returns of a specific sector and, in turn, how this sector responds to COVID-19 across diverse quantiles. Moreover, the QQ regression has a significant advantage of elasticity as it examines the dependence between a specific sector and COVID-19 in the regions that were not formerly presumed. As COVID-19 has severely affected the global financial cycle, output, demand, employment, asset prices, etc., and various sectors (such as Energy, Necessary Consume, Medical & Health) of the real economy are subject to different government policy restrictions during the pandemic due to their respective attributes. For example, the Energy sector has been severely impacted since the stringent confinement policy and shut down several industries, including transportation, manufacturing, and industrial units, at the extreme stage of the COVID-19 pandemic, leading to lower energy consumption. However, the Necessary Consume and Medical & Health may be less impacted since some industries (Consumer Goods, Communication, Medical, and Pharma et al.) still operated to meet basic needs during the pandemic. Therefore, it is essential to analyze the heterogeneous impact of COVID-19 across industries by the QQ regression method so that investors can still find profitable sectors to invest in at the right time.

Fig. 5 displays the estimates of the slope coefficient $\beta_{1} (\sigma, \tau)$, which capture the effect of the $\tau$th quantile of the daily new COVID-19 confirmed cases on the $\sigma$th quantile of all the sectors’ returns at different values of $\sigma$ and $\tau$.

In the case of Energy, the link between COVID-19 and Energy is dominantly negative, as indicated by an overwhelming green and blue color throughout the figure, with only a few exceptions where the yellow and light-yellow color is present. The link between lower quantiles (0.05–0.35) of COVID-19 and the lower–upper quantiles (0.20–0.95) of Energy is represented by yellow, showing a moderate positive correlation. Interestingly, the link between the lowermost quantiles (0.05–0.20) of COVID-19 and the uppermost quantiles...
Fig. 10. QQR (Quantile-on-Quantile Regression) estimates of the slope coefficient $\beta_1(\sigma, \tau)$. Note: The graphs show the estimates of the slope coefficient $\beta_1(\sigma, \tau)$ in the z-axis against the quantiles of the daily new COVID-19 confirmed cases ($\tau$) in the x-axis and quantiles of the stock sectors ($\sigma$) in the y-axis. The colored bars on the right side of the 3D graphs show the strength and direction of relationship between the daily new COVID-19 confirmed cases and the stock sectors’ returns. The relationship between COVID-19 and stock sectors moves from lower and negative to the higher and positive, respectively as the color shifts from dark blue to light yellow. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)
Fig. 11. Comparison of QR (Quantile Regression) and QQR (Quantile-on-Quantile Regression) estimates. Note: The graphs display the estimates of the standard QR parameters (denoted by plain lines), and the averaged QQR parameters (denoted by dashed lines), at different quantiles of sectors (σ) all the stock sectors examined. The x-axis shows the quantiles (0.05–0.95) while the y-axis shows the coefficients of sectors (σ), estimated from QR and QQR, respectively.
Fig. 12. QQR (Quantile-on-Quantile Regression) estimates of the slope coefficient $\beta_1(\sigma, \tau)$ (Robustness check). Note: The graphs show the estimates of the slope coefficient $\beta_1(\sigma, \tau)$ in the z-axis against the quantiles of the daily new COVID-19 death cases ($\tau$) in the x-axis and quantiles of the sectors ($\sigma$) in the y-axis. The colored bars on the right side of the 3D graphs show the strength and direction of relationship between the daily new COVID-19 death cases and the stock sectors’ returns. The relationship between COVID-19 and sectors moves from lower and negative to the higher and positive, respectively as the color shifts from dark blue to light yellow. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)
Fig. 13. Comparison of QR (Quantile Regression) and QQR (Quantile-on-Quantile Regression) estimates (Robustness Check). Note: The graphs display the estimates of the standard QR parameters (denoted by plain lines), and the averaged QQR parameters (denoted by dashed lines), at different quantiles of sectors(σ) all the stock sectors examined. The x-axis shows the quantiles (0.05–0.95) while the y-axis shows the coefficients of sectors(σ), estimated from QR and QQR, respectively.
(0.85–0.95) of Energy is indicated by light yellow showing a strong positive correlation. Besides, a moderate negative effect of COVID-19 on Energy is found at the lower–upper quantiles (0.05–0.95) of Energy with the middle-upper quantiles (0.40–0.75) of COVID-19, while the effect of COVID-19 on Energy at the uppermost quantiles (0.80–0.95) of COVID-19 is strongly negative. In general, our findings suggest that the changing intensity levels of COVID-19 affect the returns of the Energy sector asymmetrically. At the initial level of the COVID-19 pandemic, it has little effect on the Energy sector, especially at the uppermost quantiles of Energy (In other words, the Energy sector has only a weak response to COVID-19 at that stage); however, with the increase in the COVID-19 pandemic intensity, the negative effect of COVID-19 on the Energy sector becomes increasingly strong.

Additionally, in the Materials and Unnecessary Consume cases, the graphs of these two sectors show significant similarities in their association with COVID-19, just like the link between COVID-19 and Energy at different quantiles mentioned above. Moreover, we find that the graph for Finance which is almost similar to the Energy, with only slight differences in two places: at the junction of the lowermost quantiles (0.05–0.10) of both the COVID-19 and Finance, as indicated by yellow, and the uppermost quantiles (0.90–0.95) of COVID-19 and the lowermost quantiles (0.05–0.20) of Finance as shown by green, respectively. This finding indicates that compared to the Energy sectors, the Finance sector exhibits a relatively weak response to the small or huge increments in the daily COVID-19 confirmed cases.

Concerning Necessary Consume and Medical & Health, the graphs of these two sectors show significant similarities in their correlation with COVID-19 at various quantiles. Compared to the other sectors, the most notable difference is that the lowermost (0.05–0.20) of COVID-19 has a stronger positive effect on the returns of these two sectors at almost all quantiles, as shown by yellow and light yellow. This result indicates that the small increments in the daily COVID-19 confirmed cases at the initial level of the pandemic have a noticeable positive impact on these two sectors.

As for Industry, Telecom, Information Technology, and Utilities, the effect of COVID-19 on these four sectors is negative at lower–upper quantiles of COVID-19(0.20–0.95) and almost all quantiles of these four sectors. The negative effect is relatively weak at lower-middle quantiles of COVID-19 and becomes strong at upper quantiles of COVID-19. Additionally, there is a positive association between COVID-19 and these four sectors at the lowest quantiles (below 0.20) of COVID-19, as shown by light green, yellow, and light yellow, respectively. However, the positive effect of COVID-19 is strong at the middle-uppermost quantiles and becomes weak at the lower quantiles of these three sectors. Furthermore, compared to the other two sectors (Information Technology and Utilities), a notable difference is that the small shocks of COVID-19 can only result in high levels of Industry and Telecom returns but have nearly no effect on the low levels of these two sectors’ returns.

Above all, we can conclude that the changing intensity levels of the COVID-19 pandemic have asymmetric impacts on different stock sectors. Additionally, it can be seen that there are different characteristics in the responses of the ten stock sectors to the changing intensity levels of the pandemic. Our results are approximately consistent with the findings by Al-Awadhi et al. (2020), Ramelli and Wagner (2020). Specifically, most sectors are severely impacted by the COVID-19. In contrast, some sectors (Necessary Consume and Medical & Health) that are least affected by the COVID-19 pandemic (especially in the milder stage of the COVID-19 pandemic) are those that are related to the provision of goods and services which can be considered as necessities and substitutes. While the COVID-19 severely impacts most sectors. Therefore, investors can still seek profitable sectors to invest in.

4. Robustness check

4.1. Robustness check for the validity of the QQR approach

In our current analysis, the QQR approach is applied to investigate the τth quantiles of COVID-19 on the σth quantiles of the sectors’ returns, i.e., it can help to capture the asymmetric effect of COVID-19 on each sector across various quantiles of σ and τ. Therefore, its parameters are indexed by both σ and τ. Thus, the QQR approach contains more disaggregated information about the COVID-19-sectors link than the standard quantile regression method whose parameters are only indexed by σ, because the link between COVID-19 and stock sectors is perceived to be potentially heterogeneous by the QQR approach, across different quantiles of sectors and COVID-19. Considering such an inherent property of decomposition in the QQR approach, we can use the QQR estimates to recover the estimates from the standard quantile regression. Specifically, the quantile regression parameters, which are only indexed by σ, can be generated by averaging the QQR parameters along τ. The slope coefficient of the quantile regression model can be obtained through the following formula: This coefficient measures the impact of COVID-19 on the quantiles of sectors’ returns, which is expressed by $\gamma_1(\sigma)$:

$$
\gamma_1(\sigma) \equiv \bar{\beta}_1(\sigma) = \frac{1}{S} \sum_{\tau} \hat{\beta}_1(\sigma, \tau)
$$

where $S = 19$ is the number of quantiles, $\tau = [0.05, 0.10, \ldots, 0.95]$, considered here. In this context, a simple way to check the validity of the QQR approach is to compare the parameters estimated through standard quantile regression with the $\tau$-averaged QQR parameters.

Fig. 6 plots the Q and the averaged QQR estimates of the slope coefficient that measures the effect of COVID-19 on the ten sectors’ returns. The ten graphs in Fig. 6 clearly show that the averaged QQR estimates of the slope coefficients are almost similar to the QR estimates for all the sectors. Therefore, the graphical evidence in Fig. 6 well validates the QQR approach and largely confirms the results of the QQR analysis reported above.
4.2. Robustness check with alternative proxy

In this section, to increase the robustness of the results reported above, following other studies on the COVID-19 pandemic (Iqbal et al., 2021; Fareed et al., 2020), we select the daily new COVID-19 death cases as the alternative proxy instead of the confirmed cases, and further use the QQR method to investigate the connection between COVID-19 and the sectors at their different quantiles. The QQR estimates based on the alternative proxy and its corresponding robustness check are reported in Fig. 7 and Fig. 8, respectively. No obvious differences are found between the graphs from Fig. 7 and Fig. 8 (for the daily new COVID-19 death cases) and those from Fig. 5 and Fig. 6 (for the daily new COVID-19 confirmed cases). Therefore, the results above once again validate the robustness of our analysis.

5. Conclusions

While threatening people’s lives, health, and property, the COVID-19 induced crisis has brought the global economy into a new crisis period, raising the risk spillovers among different assets, industries, and markets and significantly changing the investor sentiment and market conditions. In other words, the economic and financial impacts of the COVID-19 crisis concern the policymakers and all financial market participants around the world. Moreover, due to their respective attributes in the real economy and the governments’ policy guidelines according to the severity of the epidemic, the impact of the COVID-19 outbreak on each industry may be asymmetric. Hence, it is important to understand and analyze the effects of the COVID-19 pandemic on global stock sectors since it would help investors or portfolio managers make informed investment decisions and provide some implications for similar extreme events in the future.

In this context, this paper aims to examine the impacts of the COVID-19 crisis on global stock sectors from the following two perspectives. First, from a sector-level perspective, we focused on the unknown field of how the COVID-19 pandemic has shaped the time–frequency dynamics by combining the TVP-VAR (time-varying parameter vector autoregressive) based dynamic connectedness approach (Antonakakis et al., 2018; Antonakakis & Gabauer, 2017) and BK frequency connectedness method (Barunik and Krehlik, 2018). Second, we paid attention to the ignored field about the possibility of the nonlinear and asymmetric nexus between the COVID-19 outbreak and global stock sectors that would be difficult to detect using conventional econometric models. Using Quantile-on-Quantile Regression (QQR) methodology by Sim and Zhou (2015), we identified how the changing COVID-19 pandemic intensity asymmetrically impacts the total connectedness among global stock sectors and how the changing COVID-19 pandemic intensity asymmetrically impacts the stock sectors’ returns.

The empirical results from the dynamic total connectedness analysis indicate a dramatic rise in the total connectedness among the global stock sectors following the outbreak of COVID-19; however, the high level of the total connectedness index lasted only about two months, representing that the impact of COVID-19 is significant but not durable. Furthermore, the results from the dynamic directional total connectedness analysis suggest that the directional spillovers of each sector with different dynamic evolution characteristics behave rather heterogeneously over the sampling time. Moreover, the results obtained from the dynamic net directional connectedness analysis reveal that the net spillover changes in various stock sectors during the COVID-19 pandemic are heterogeneous. Specifically, the significant changes in net spillovers of most sectors mainly concentrate on the extent of the spillover effect (spillover intensity) but not the role after the outbreak of COVID-19, and the possible driving factors are diverse, such as public’s needs and investors’ attention. Finally, decomposition results at the time–frequency level for spillover indices (Total, To, and From spillovers) suggest that spillovers transmitted among stock sectors are mainly driven by the high-frequency component (short-term spillovers) during the sample time. While the spillover effects of the COVID-19 outbreak also persisted in the long term, especially evident during the worst period of the COVID-19 epidemic.

The empirical results from Quantile-on-Quantile Regression (QQR) indicate the different characteristics in responses of the ten stock sectors to the changing intensity levels of the COVID-19 pandemic. Specifically, most sectors are severely impacted by the COVID-19. In contrast, some sectors (Necessary Consume and Medical & Health) that are affected by the COVID-19 pandemic (especially in the milder stage of the COVID-19 pandemic) are those that are related to the provision of goods and services which can be considered as necessities and substitutes. Moreover, our results also hold after several robustness checks.

Our main results may have some implications for both the policymakers and investors.

First, we observe that the severity of the COVID-19 epidemic has significant impacts on the stability of the stock markets at the sectoral level, which is reflected in the changes in the total connectedness among global stock sectors. Besides, with the successful implementation of various countries’ prevention and control measures against the COVID-19 epidemic worldwide, the high level of the total volatility connectedness has gradually shown a downward trend from the peak since May 2020. However, the index has rebounded since late November 2020, which can be attributed to the relaxation of epidemic prevention and control in some countries. This phenomenon indicates that the stability of the sectoral global stock market responds clearly to how much attention is paid to the COVID-19 epidemic by governments worldwide. Accordingly, it is necessary for global governments to adopt effective measures and policies, such as lockdowns, self-isolation, and social distancing restrictions during the epidemic, since the global COVID-19 epidemic is still not over, and how to effectively improve the emergency response capabilities is the best way to control or alleviate the severe impact of COVID-19 on the stability of the global stock market, and avoid the underlying repeated waves of the occurrence of the epidemic.

Second, the global sector dynamic connectedness results may have significant implications for portfolio managers, investors, and policymakers. On the one hand, the direction and magnitude of volatility connectedness may vary over time, and frequency domains since deciphering the dynamic properties and duration of volatility spillovers allow for a deeper understanding of portfolio
management. Therefore, capturing volatility spillovers among sectors in the time–frequency domain can provide useful information to investors and portfolio managers to identify the specific stock sectors which are most vulnerable/insusceptible to external shocks and the highest contributor/receiver of spillovers (according to From, To, and Net connectedness). Investors and portfolio managers can reallocate their portfolios and adjust their short-term or long-term positions. Moreover, the assessment of the effects of dynamic net connectedness can help us to identify the main risk transmitters or risk receivers in the financial system across the time–frequency domain to stabilize the financial system for policymakers. In addition, policymakers can use this information to establish an early warning system for financial risks or implement rescue measures for some unique industries/sectors under exceptional circumstances to avoid widespread risk contagion.

Third, we observe that the directional and net spillover changes in various sectors during the COVID-19 pandemic are heterogeneous, indicating that they have been affected by the COVID-19 epidemic differently. The above changes of some sectors (Necessary Consume, Medical & Health) in responses to the COVID-19 epidemic have shown exceptional performance. For a reason, the possible driving factors are diverse, such as the public’s demand and investors’ attention to these specific industries. Moreover, we identify the different characteristics in responses of the ten sectors to the COVID-19 pandemic. Specifically, some sectors (Necessary Consume and Medical & Health) that are least affected by the COVID-19 pandemic (especially in the milder stage of the COVID-19 pandemic), which may become an essential finding for investors to adjust hedging strategies. Hence, our results may help investors and portfolio managers respond quickly and make informed decisions for their portfolios, especially during global distress such as the COVID-19 in the future.

**CRediT authorship contribution statement**

**Zibing Dong:** Writing – original draft, Software, Visualization. **Yanshuang Li:** Conceptualization, Writing – original draft, Writing – review & editing, Methodology, Software, Visualization, Data curation, Validation. **Xintian Zhuang:** Funding acquisition, Supervision. **Jian Wang:** Funding acquisition, Supervision.

**Declaration of Competing Interest**

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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**Appendix A. Supplementary data**

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