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Risk spillovers in global financial markets: Evidence from the COVID-19 crisis

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A B S TR A C T

This paper aims to comprehensively investigate the dynamics of short-, medium- and long-term risk spillovers across the major financial markets in the context of COVID-19. Our main empirical findings are as follows. First, we find that the deterioration of the COVID-19 pandemic raised the risk of stock, bond, crude oil, and foreign exchange markets sequentially in the short term. Second, from the perspective of the medium and long term, the COVID-19 pandemic triggered substantial risk spillovers across financial markets, which is also highly correlated with the degree of investor panic. Third, we show that different markets played different roles in terms of risk transmission during the pandemic. Specifically, the stock and crude oil markets acted more as risk senders, the gold and foreign exchange markets acted more as risk receivers, and the bond market served as a transfer station of risk. Finally, we find that containment and health responses can effectively mitigate risk spillovers across markets in the short term, while expansionary fiscal policy can reduce them more effectively in the medium and long term. Our findings have important implications for policymakers and investors who aim to mitigate the adverse impact of the COVID-19 pandemic on financial markets.

1. Introduction

Since the 20th century, public emergencies, including natural disasters, accidents, and public health incidents, have occurred, which have brought great challenges to the stability of the global financial system. In 2020, a pandemic of coronavirus disease 2019 (COVID-19), declared by the World Health Organization (WHO) as a "Public Health Emergency of International Concern (PHEIC)", gradually evolved into a global public health crisis, which has had a significantly negative impact on the economic and social life of most countries. Economic fundamentals have been hit on both the supply side and the demand side. Almost all financial asset and commodity prices have fallen at the same time. The U.S. stock market started to react to the spread of COVID-19 in early March and unprecedentedly triggered four "circuit breaks" on March 9, March 12, March 16, and March 18, 2020. Thus, there is increasing concern that the development of COVID-19 may have a long-term and substantial impact on global financial markets.

A large number of studies have been carried out to investigate the source of systemic risk in the financial market. In general, three important sources have been identified in the literature (for a comprehensive review, see Benoit et al., 2017). First, systemic risk may come from exogenous or systematic shock to the market. Shocks may have a significant impact on the entire financial market by

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investigate the impact of COVID-19 on the stock market from a micro perspective. They find that firms with stronger pre-2020
investors’ sentiment channel, since constantly updated COVID-19-related information, rumours, and panic may have a negative influence on
expectations (Mann, 2020). Although the economy can be brought back to normal quickly after the pandemic is over, the prerequisite for economic recovery is that the pandemic can be successfully controlled (Bofinger et al., 2020). Third, several studies investigate the impact of COVID-19 on the stock market from a micro perspective. They find that firms with stronger pre-2020 finances, less exposure to the epidemic through global supply chains and customer locations, more CSR activities, and entrenched executives experience less pandemic-induced drops in stock prices and benefit less from policy responses (Ding et al., 2021; Fahlenbrach et al., 2021).

Existing research on systemic risk and financial spillovers mainly focuses on the prevention and control of endogenous crises in the financial system (such as the 2008 global financial crisis). Some studies that investigate the impact of the COVID-19 pandemic pay more attention to the stock market (see for instance Zhang et al., 2020; Guo et al., 2021; Liu et al., 2022). However, there are relatively few studies on the impact of public health emergencies on financial spillovers across different financial markets. Due to the urgency and high uncertainty of the COVID-19 pandemic, the aim of this paper is to extend the literature by studying the impact of COVID-19 on global financial spillovers. Our study has both theoretical and practical significance because it is not only conducive to measuring and mitigating risk spillovers but also helps improve financial market stability to resist various exogenous shocks.

We contribute to an emerging literature on the impact of the COVID-19 pandemic on financial markets from three aspects. First, we construct a framework to describe the risk transmission mechanism of financial markets after receiving a shock of public emergency. In the context of global financial integration, almost all major markets have been affected by COVID-19. Therefore, it is particularly important to understand how to prevent global financial risk after being hit by an extreme exogenous shock.

Second, the global outbreak of the COVID-19 pandemic in 2020 has increased the systemic risk of global financial markets and provided a natural experiment for empirical research. Existing studies pay more attention to the impact of COVID-19 on financial markets (e.g., Corbet et al., 2020; Zhang et al., 2020), but few studies have been conducted to quantitatively analyse the impact of various pandemic response policies. Our study not only provides further insights into the evolution of risk spillover networks of global financial markets but also quantifies the dynamic roles of various policies on risk transmission across markets during the outbreak of COVID-19. Thus, our research can help policymakers better formulate targeted policies and measures to prevent and control financial risks.
spillovers caused by major public emergency events.

Third, exogenous shocks to economic activity have a negative impact on risk spillovers at different frequencies with different strengths. The existing literature mainly focuses on the short-term impact of the COVID-19 shock on financial markets (e.g., Ding et al., 2021; Guo et al., 2021; Liu et al., 2022). Our study captures the medium- and long-term trend changes brought by the impact of the COVID-19 pandemic. Compared with the short-term effect, trend changes may have a profound impact on the future economic and financial environment. Therefore, understanding the medium- and long-term effects as well as the spillover channels caused by COVID-19 can help regulators and financial institutions control and mitigate risk propagation. In addition, it is of great significance for the formulation of policies when the economy recovers in the post-pandemic period.

The rest of the paper is organized as follows. Section 2 describes the model specification. Section 3 describes the sample selection and the financial data used and presents descriptive statistics. Sections 4 and 5 investigate the risk dynamics of each financial market and risk spillovers between global financial markets in the short, medium, and long term. Section 6 concludes.

2. Model specification

In this section, we present our methodology in three parts: (1) the risk transmission mechanism that describes how a public emergency shock affects global financial markets; (2) the model to capture global financial spillovers at different time frequencies; and (3) the model to estimate risk spillovers from global financial markets to a regional financial market.

2.1. An event analysis of short-term risk at the time of COVID-19

First, we use the TGARCH of Zakoian (1994), which is commonly used to handle the leverage effect, to model the risk dynamics of a financial market. In our case, we assume that negative news is more likely to lead to an increase in volatility than positive news. Thus, this model is given by

\[ r_t = \alpha_0 + \sum_{i=1}^{m} \alpha_i r_{t-i} + \sum_{j=1}^{n} \beta_j r_{t-j} + \epsilon_t \]  

(1)

\[ \epsilon_t = \sigma_t \epsilon_t, \quad \epsilon_t \sim i.i.d N(0, 1) \]  

(2)

\[ \sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i \epsilon_{t-i}^2 + \sum_{k=1}^{r} \gamma_k \epsilon_{t-k} \epsilon_{t-k} + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \]  

(3a)

where \( I_{t-k} = \begin{cases} 1 & \epsilon_{t-k} < 0 \\ 0 & \epsilon_{t-k} \geq 0 \end{cases} \)

Eq. (1) is the model for the conditional mean and Eq. (3) is the model for conditional volatility. \( r_t \) represents the logarithmic return of assets at time \( t \), and \( \sigma_t \) represents the dynamic conditional volatility.

Second, the event analysis proposed by Gourinchas and Obstfeld (2012) and Schularick and Taylor (2012) can be used to study the impact of a certain type of event on a variable of interest (explained variable). In this paper, we use their approach to analyse the short-term risk of global financial markets in response to the COVID-19 shock. Specifically, we take the time that an event occurred as the reference point and then investigate the trend and significance of the target variable before and after the event. The regression model is shown in Eq. (3):

\[ y_t = \alpha + \sum_{i=1}^{m} \beta_i \times \delta_i + \epsilon_t \]  

(3b)

where \( y_t \) represents the risk of a single financial market, namely, the conditional volatility modelled by the TGARCH model. \( \delta_i \) denotes a dummy variable equal to 1 when the market is \( s \) periods away from a COVID-19 shock in period \( t \). \( s \) represents the time distance from the occurrence of the event measured by the number of trading days, and its value range is \( [1, m] \). \( \delta_s \) is the sum of \( N \) dummy variables, that is, \( \delta_s = \sum_{s=1}^{N} \delta_{ts} \). \( N \) represents the total number of events that occurred during the sample period, and \( \delta_{ts} \) represents the dummy variable, which is \( s \) trading days away from the occurrence date of the \( n \)th event, as shown in Eq. (4):

\[ \delta_{tn} = \begin{cases} 1 & t = t_{df,n} + s \\ 0 & \text{others} \end{cases} \]  

(4)

where \( t \) is the time variable, and \( t_{df,n} \) is the date when the \( n \)th event occurred. When the event occurrence date is a non-trading day, \( t_{df,n} \) is represented by the first trading day after the event occurs. \( \beta_s \) is the key result that we focus on, reflecting the trend of changes in market risk before and after the event, thereby showing the dynamic impact of event shocks on market volatility.

2.2. Measuring medium- and long-term risk spillovers among global financial markets

This paper uses the generalized variance decomposition spectrum proposed by Barunik and Krehlik (2018) to study the medium- and long-term impacts of COVID-19. This method is developed based on the variance decomposition model of Diebold and Yilmaz.
by considering the spectral representation of variance decompositions based on heterogeneous frequency responses to shocks. Compared with traditional methods, the generalized variance decomposition spectrum representation method takes into account the heterogeneous frequency (short-, medium- and long-term) responses of financial markets to shocks.

The logic of the heterogeneous frequency response is as follows. For different types of shocks, market participants form heterogeneous expectations at different horizons, which leads to investors’ heterogeneous asset allocation behaviours for different horizons. Thus, shocks with heterogeneous responses create linkages with various degrees of persistence and hence various sources of risk.

Specifically, risk spillovers occur at high frequencies when financial markets react more quickly to information. Shocks to the turbulent periods with high uncertainty, when investors fundamentally revise their long-term expectations after receiving exogenous shocks. Compared with short-term spillovers, the impact of long-term spillovers is more persistent and therefore more worthy of our attention.

The idea of the spectral representation of generalized variance decomposition is as follows:

1. We decompose risk spillovers in different frequency domains based on heterogeneous frequency responses to obtain the short-, medium- and long-term risk spillovers. In other words, the Diebold & Yilmaz spillover index of Diebold and Yilmaz (2014) can be decomposed into three spillover indexes in three frequency domains that satisfy additivity.

2. Economically, periods in which risk correlation is created at high frequencies (short-term cycle) are periods when financial markets seem to process information rapidly, and a shock to one asset in the system will have an impact mainly in the short term. When the risk correlation is created at lower frequencies (long-term cycle), it suggests that shocks are persistent and are being transmitted for longer periods. We construct our model through the following steps:

**Step 1.** Establish a vector autoregression (VAR) model with p lags among financial markets:

\[ X_t = \sum_{i=1}^{p} \Phi_i X_{t-i} + \epsilon_t, \quad t = 1, \ldots, T \]  

where \( \Phi_i \) is the coefficient matrix, and \( \epsilon_t \) is white noise with zero mean and covariance matrix \( \Sigma \). When the model variables are stationary, it has the following vector moving average representation:

\[ X_t = \sum_{i=0}^{\infty} \Psi_i \epsilon_{t-i} \]  

where the coefficient \( \Psi_i \) satisfies the recursive form \( \Psi_i = \sum_{i=0}^{\infty} \Phi_i \Psi_{i-i} \). When \( p > i \), \( \Psi_{i-p} = 0 \) and \( \Psi_0 = I_N \). The generalized variance decomposition of the covariance matrix can be performed on the basis of Eq. (7), so that the variance of the forecast error of each financial market variable can be attributed to the spillovers of other variables.

According to the definition of generalized variance decomposition by Barunik and Krehlík (2018), given the information of period \( t \), the proportion of the variance of the forecast error in the \( H \) th step of the financial market \( j \) that can be explained by the market \( k \) at horizon \( h \) is given by:

\[ (\theta_{hk})_{jk} = \frac{\sigma_{hk}^2 \sum_{h=0}^{H-1} (\Psi_h \Sigma_{j})^2_{kk}}{\sum_{h=0}^{H-1} (\Psi_h \Sigma_{j})^2_{jj}} \cdot H = 1, 2, 3, \ldots \]  

where \( \Psi_h \) is a matrix of moving average coefficients at lag \( h \), \( \Sigma \) is the variance matrix of the prediction error vector, and \( \sigma_{hh} \) is the standard deviation of the \( k \) th equation error term of \( \Sigma \). \( (\theta_{hk})_{jk} \) represents the contribution of the \( k \)th market to the variance of forecast error of market \( j \) at horizon \( h \). Since the row sum of the variance decomposition matrix \( \theta_{hk} \) does not necessarily equal one, each entry can be normalized by the sum of rows as:

\[ (\tilde{\theta}_{hk})_{jk} = \frac{(\theta_{hk})_{jk}}{\sum_{k=1}^{N} (\theta_{hk})_{jk}} \times 100, \quad H = 1, 2, 3, \ldots \]  

\( (\tilde{\theta}_{hk})_{jk} \) can be used to measure risk spillovers from financial market \( k \) to market \( j \) at horizon \( H \). The \( N \times N \) adjacency matrix constructed with \( (\tilde{\theta}_{hk})_{jk} \) as elements can help identify risk spillover networks of financial markets. Then, the total spillover index Total can be defined as:

\[ \text{Total} = \frac{\sum_{k,j=1}^{N} (\tilde{\theta}_{hk})_{jk}}{N} \times 100 = \frac{\sum_{k,j=1}^{N} (\tilde{\theta}_{hk})_{jk}}{N} \times 100 \]
The total spillover index Total measures the overall risk spillovers between financial markets at horizon H. The larger the value of Total is, the higher the risk connectedness between financial markets.

**Step 2.** Decompose the frequency dynamics of risk spillovers between financial markets.

First, we follow Barunik and Krehlik (2018) about \( f(\omega) \), which represents the proportion of the spectrum of market \( j \) at a given frequency \( \omega \) due to shocks in market \( k \):

\[
(f(\omega))_{jk} = \frac{\sigma_{jk}}{\sigma_j} \left| \frac{\mathcal{P}(e^{-i\omega})}{\mathcal{P}(e^{-i\omega})} \right|^2, \quad \omega \in (-\pi, \pi)
\]  

where \( \mathcal{P}(e^{-i\omega}) = \sum_{j=0}^{\infty} e^{-j\omega} \mathcal{P}_{ijk} \), which is obtained by the Fourier transformation of the impulse response.

Second, we define \( (\theta_d)_{jk} \) as the generalized variance decomposition of market \( j \) due to shocks in market \( k \) on frequency band \( d \). The variance decomposition can be obtained by the weighted average of the generalized causation spectrum \( (f(\omega))_{jk} \) on frequency band \( d \):

\[
(f(\omega))_{jk} = \frac{\sigma_{jk}}{\sigma_j} \left| \frac{\mathcal{P}(e^{-i\omega})}{\mathcal{P}(e^{-i\omega})} \right|^2, \quad \omega \in (-\pi, \pi)
\]

The weighting function \( \Gamma_j(\omega) \) represents the power of market \( j \) at frequency \( \omega \):

\[
\Gamma_j(\omega) = \frac{\langle \mathcal{P}(e^{-i\omega}) \mathcal{P}(e^{-i\omega}) \rangle_{jk}}{\int_{-\pi}^{\pi} \langle \mathcal{P}(e^{-i\omega}) \mathcal{P}(e^{-i\omega}) \rangle_{jk} d\omega}
\]

When the time series \( X_t \) is weakly stationary, the variance decomposition in the time domain and frequency domain has the following relationship:

\[
\lim_{H \to \infty} (\theta_d)_{jk} = \sum_{d \in D} (\theta_d)_{jk} = \left( \frac{\Gamma_j(\omega) \langle f(\omega) \rangle_{jk}}{2\pi} \right) d\omega
\]

where \( \bigcap_{d \in D} d = \varnothing \) and \( \cup_{d \in D} d = (-\pi, \pi) \). That is, when \( H \to \infty \), the time-domain variance decomposition \( (\theta_d)_{jk} \) can be decomposed into multiple disjoints on frequency band \( d \).

Finally, \( (\theta_d)_{jk} \) is standardized and expressed as a percentage:

\[
(\bar{\theta}_d)_{jk} = \frac{(\theta_d)_{jk}}{\sum_{k=1}^{N} \sum_{d \in D} (\theta_d)_{jk}} \times 100
\]  

Next, \( (\bar{\theta}_d)_{jk} \) is defined as the spillover indexes of different financial variables at frequency \( d \): Total Spillover Index \( Total^d \), Directional Spillover Indexes \( From^d_{ij} \) and \( To^d_{ji} \), Single Net Spillover Index \( Net^d_{id} \) and Pairwise Net Spillover Index \( Pairwise^d_{ij} \):

1. **Total Spillover Index**

   \[
   Total^d = \frac{\sum_{d \in D} \sum_{k=1}^{N} (\bar{\theta}_d)_{jk}}{\sum_{d \in D} \sum_{k=1}^{N} (\bar{\theta}_d)_{jk}} \times 100 = \frac{\sum_{d \in D} \sum_{k=1}^{N} (\bar{\theta}_d)_{jk}}{N} \times 100
   \]

   Total^d decomposes the total spillovers in the time domain into different frequency bands. The larger the value is, the higher the risk connectedness between financial markets on frequency band \( d \). The total spillover index Total^d reflects the degree of overall risk connectedness of the entire financial system, which can be used as a systemic risk indicator in the time dimension.

2. **Directional Spillover Index**

   The directional spillover index of financial market \( j \) from other markets is defined as \( From^d_{ij} \):

   \[
   From^d_{ij} = \frac{\sum_{d \in D} \sum_{k=1}^{N} (\bar{\theta}_d)_{jk}}{\sum_{d \in D} \sum_{k=1}^{N} (\bar{\theta}_d)_{jk}} \times 100 = \frac{\sum_{d \in D} \sum_{k=1}^{N} (\bar{\theta}_d)_{jk}}{N} \times 100
   \]
The directional spillover index of financial market $j$ to other markets is defined as $To_{dj}$:

$$\begin{align*}
To_{dj} &= \frac{\sum_{d=1}^{N} \sum_{j=1}^{N} (\bar{\theta}_{dj})_{j,k}}{\sum_{d=1}^{N} \sum_{j=1}^{N} (\bar{\theta}_{dj})_{j,k}} \times 100 = \frac{\sum_{d=1}^{N} (\bar{\theta}_{dj})_{j,k}}{N} \times 100
\end{align*}$$

(18)

The index $From_{dj}$ measures the magnitude of spillovers of market $j$ from other markets, which reflects the degree to which market $j$ is affected by other markets on the frequency band $d$. The greater the number of spillovers received, the more vulnerable market $j$ is. The index $To_{dj}$ represents the magnitude of spillovers from market $j$ to other markets on the frequency band $d$. The greater the number of spillovers propagated, the higher the systemic importance of market $j$ is.

Both $From_{dj}$ and $To_{dj}$ can be used as indicators of systemic risk in the spatial dimension. These two indexes represent two directions that market $j$ plays in spillovers: a risk receiver from other markets and a risk sender to other markets.

(3) Single Market Net Spillover Index

$$Net_{dj}^{i} = To_{dj}^{i} - From_{dj}^{i}$$

(19)

The single market net spillover index $Net_{dj}^{i}$ represents the difference between $To_{dj}^{i}$ and $From_{dj}^{i}$ on frequency band $d$, reflecting the role of market $j$ in the spillover network. According to Yang and Zhou (2013), a positive single market net spillover index indicates that the spillovers from market $j$ to other markets are higher than the received spillovers from other markets. In other words, market $j$ can be regarded as a ‘risk sender’ in the spillover network. In contrast, a negative single market net spillover index suggests that the spillovers received by market $j$ are higher than the spillovers to other markets, which means that market $j$ can be regarded as a ‘risk receiver’ in the spillover network. The net spillover index of a single market is close to zero when the input and output of risk spillovers are quite close. In this case, market $j$ can be regarded as a ‘transfer station’ of risk spillovers in the spillover network.

(4) Pairwise Net Spillover Index

$$Pairwise_{dj}^{ij} = \frac{(\bar{\theta}_{dj})_{ij} - (\bar{\theta}_{dj})_{ij}}{\sum_{d=1}^{N} \sum_{j=1}^{N} (\bar{\theta}_{dj})_{ij}} \times 100 = \frac{(\bar{\theta}_{dj})_{ij} - (\bar{\theta}_{dj})_{ij}}{N} \times 100$$

(20)

The pairwise net spillover index $Pairwise_{dj}^{ij}$ represents the difference between the risk spillovers from market $j$ to market $i$ and the risk spillovers from financial market $i$ to financial market $j$ on frequency band $d$, which reflects the asymmetry of risk spillovers between the two markets. If the pairwise net spillover index is positive, the spillovers between two markets are dominated by the spillovers from market $j$. In contrast, if the pairwise net spillover index is negative, the spillovers between two markets are dominated by the spillovers from market $i$. Finally, if the pairwise net spillover index is close to zero, the risk spillovers between two markets are relatively symmetric, and there is no dominant market.

In this paper, we use the rolling window to measure the dynamics of cross-market risk spillovers. The steps are as follows: First, we choose a fixed window length to calculate the risk spillover indexes (i.e., total spillover index, directional spillover index, single market net spillover index, and pairwise net spillover index) of markets. Second, we calculate rolling risk spillover indexes by moving the fixed window one day forward. Then, the dynamics of risk spillovers over the whole sample period can be obtained.

In addition, the spillover index can be used to construct short-, medium- and long-term spillover network diagrams in the spatial dimension to demonstrate the micro spillover mechanism across financial markets. We can use the rolling window method to capture the dynamics of global financial market connectedness caused by policy uncertainty and the occurrence of extreme events. This also provides us with some insights into the risk transmission channels between global financial markets and regional financial markets, which we investigate in the next section.

2.3. Measuring the effect of government policies in response to COVID-19

To investigate the effect of economic stimulus and financial stabilization policies in response to COVID-19 implemented by the U.S. government, we adopt the local projection method of Jordà (2005) in our analysis. The regression model is specified as follows:

$$Total_{t+h} = \alpha_h + \beta_s \text{shock}_t + \psi \text{Total}_t + u_{t+h} \quad h = 1, \ldots, H$$

(21)

where $Total_{t+h}$ denotes the total risk spillovers across financial markets. shock$_t$ is a variable of policy shocks. The coefficient $\beta_s$ represents the response of the total risk spillovers at time $t + h$ to the policy shock at time $t$. To test the effect of policy shocks on risk spillovers, we consider three types of policies, including expansionary monetary policy, expansionary fiscal policy, and containment and health response following Goldstein et al. (2021). Specifically, we use the daily federal funds rate from the Federal Reserve to represent expansionary monetary policy. Expansionary fiscal policy is proxied by government total expenditures. The quarterly data of government total expenditures are from the U.S. Bureau of Economic Analysis. To keep the data frequency consistent with other
variables, we use quadratic interpolation to convert it into a monthly basis. The containment and health response represent government public awareness campaigns and testing and quarantining policies, and the daily data are collected from Pericoli and Sbracia (2003). The regressions for expansionary monetary policy and containment and health response are performed using daily data, while the regression for expansionary fiscal policy is performed using monthly data.

3. Data description and preliminary results

This section contains three parts: data selection, the dummy variable of major COVID-19 events, and descriptive statistics of explanatory variables.

3.1. Data selection

In this paper, four major financial markets (i.e., the stock market, commodity market, bond market and foreign exchange market) are selected to represent global financial markets. Specifically, we use the daily closing/spot price of the MSCI World Index,\(^1\) the NYMEX WTI crude oil (rolling front-month futures contract), the LME gold, the 10-year Treasury bill rate and the U.S. Dollar Index.\(^2\) The return for each market is calculated as \(r_t^i = \ln(P_t^i/P_{t-1}^i) \times 100\), where \(P_t^i\) represents the closing price of market \(i\) at time \(t\). For the bond market, we use \(P_t^i = 100/(1 + r_t)'\) to convert the U.S. 10-year Treasury bond yield \(r_t\) into bond price \(P_t\) and then use it to calculate the logarithmic return, following Diebold and Yilmaz (2015). The volatility for each asset is estimated by the TGARCH model. All data cover the period from January 1, 2019, to April 17, 2020. The U.S. The 10-year Treasury bill data are from the Bloomberg database, and the rest are collected from the Wind database.

3.2. Dummy variable of major COVID-19 events

We construct a dummy variable that takes a value of one for the dates when a major COVID-19 event occurs and zero otherwise. We define the following events as major COVID-19 events: The World Health Organization (WHO) raising the global risk level of COVID-19, which confirms the deterioration of the COVID-19 pandemic, and the Federal Reserve employing both conventional and unconventional policy tools to mitigate the effects of the COVID-19 pandemic on the U.S. economy and financial sector. Overall, there are three WHO events and six Fed policy events. Table 1 summarizes the timeline of major events of COVID-19 from January 1, 2020, to April 17, 2020.

3.3. Summary statistics

We divide our full sample period (from January 1, 2019 to April 17, 2020) into three stages using two events: The WHO raised the global risk level for COVID-19 to “high” on January 26, 2020, and the WHO raised the COVID-19 global risk level to “very high” on February 28, 2020. First, we define the period from January 1, 2019, to January 24, 2020, as Stage I (Pre-pandemic). During this period, there is no epidemic or ‘high’ global epidemic risk declared by the WHO. Second, we define the period from January 27, 2020, to February 27, 2020, as Stage II (High Risk). During this period, the global risk level of COVID-19 declared by the WHO gradually increased from “high” to “very high”. Finally, we define the period from February 28, 2020, to April 17, 2020, as Stage III (Very High Risk), during which the global risk of the COVID-19 pandemic has increased to “very high”, as declared by the WHO.

Table 2 reports the descriptive statistics on the returns of each financial market at different stages. The second rows of Stage II and Stage III report the percentage changes in the means of each market. The negative values of change for the stock market show that the global stock markets sharply dropped after the outbreak of COVID-19. In addition, the oil price crashed to a historical low because of the dramatic decline in demand due to the COVID-19 crisis. The positive changes for gold, treasury bonds, and the U.S. dollar indicate that investors “fly to quality” when market uncertainty significantly increases after the pandemic outbreak.

Table 3 presents the descriptive statistics on the volatility of each market estimated by the TGARCH model. Similar to Table 2, the second rows of Phase II and Phase III in Table 3 report the percentage changes in the volatility of each market. Table 3 shows that all markets become more volatile after the deterioration of COVID-19.

4. Risk evolution of individual financial markets

In this section, we use an event analysis to investigate the risk evolution of each market before and during the COVID-19 pandemic. Fig. 2 shows the general trends of the volatility of the stock, crude oil, gold, bond, and foreign exchange markets during the COVID-19 pandemic.

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\(^1\) The MSCI World Index captures large and mid-cap representation across 23 developed markets including Canada, USA, Austria, Belgium, Denmark, Finland, France, Germany, Israel, Ireland, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom, Australia, Hong Kong, Japan, New Zealand, and Singapore.

\(^2\) For the commodity market, we select crude oil and gold for the following reasons. First, crude oil is an important industrial raw material, whose price can well reflect the demand of industrial activities. The price of crude oil crashed to lower than $20 per barrel after the outbreak of COVID-19 in April 2020. Second, gold can be viewed as a typical safe-haven asset, whose price can well reflect investors’ sentiment. The price of gold also fluctuated significantly along with the global spread of COVID-19.
crisis, which can roughly reflect the impact of the pandemic on financial markets. In general, market volatility sharply increased with the deterioration of COVID-19 in March 2020. After the Federal Reserve announced a series of pandemic responses to mitigate the adverse impact of COVID-19, market volatility began to gradually decrease, indicating the effectiveness of the policies. Although our graphical analysis above can provide some preliminary results to show the impact of the COVID-19 shock on financial markets, the influence of other factors has not been ruled out. Therefore, we will use an event analysis to specifically investigate the impact of COVID-19 in the next subsection.

| Date     | Impact on financial risk | Contents of the event                                                                 |
|----------|--------------------------|---------------------------------------------------------------------------------------|
| 26-Jan-20| ↑                        | WHO raised COVID-19 global risk level to 'high'.                                     |
| 28-Feb-20| ↑                        | WHO raised COVID-19 global risk level to 'very high'.                                 |
| 3-Mar-20  | ↓                        | The Federal Reserve lowered the target range for the federal funds rate by 50 basis points to a range of 1.00 percent to 1.25 percent, which is the largest magnitude of policy target rate cut since the fall of 2008. |
| 11-Mar-20 | ↑                        | WHO declared COVID-19 as a global spread pandemic                                      |
| 19-Mar-20 | ↓                        | The Federal Reserve announced the establishment of temporary U.S. dollar liquidity arrangements (swap lines) with nine additional central banks. |
| 23-Mar-20 | ↓                        | The Federal Reserve announced the start of an unlimited quantitative easing.           |
| 1-Apr-20  | ↓                        | The Federal Reserve announced a one-year temporary change to its supplementary leverage ratio rule. |
| 6-Apr-20  | ↓                        | The Federal Reserve announced three new emergency lending facilities designed to implement the Coronavirus Aid, Relief, and Economic Security (CARES) Act. |
| 9-Apr-20  | ↓                        | The Federal Reserve announced it will provide up to $2.3 trillion in loans to support the economy. |

Note: This table lists major events of the COVID-19 pandemic from January 1, 2020, to April 17, 2020, from authoritative news media.
4.1. Risk dynamics of financial markets in response to the deterioration of COVID-19

Fig. 3 shows the estimates of dummy variable $\beta_s$ in Equation (1), which represents the impact of the deterioration of the COVID-19 pandemic on financial markets. In our case, we let parameter $m$ equal six. In other words, we take the date of the deterioration event as a reference point and then investigate the trend and significance of the target variable six days before and after the event.

Overall, the deterioration of COVID-19 increased the risk of financial markets in the short term. First, for the stock market, the
declaring of COVID-19 deterioration by the WHO exacerbated the risk of the stock market immediately, and this adverse effect lasted for the next six trading days. This indicates that the panic in the stock market is persistent due to the global spread of the pandemic. Second, deterioration events have had a lagging effect on the crude oil market. Four trading days after the occurrence of the event, the risk of the crude oil market started to rise significantly. This lag can be explained by the supply and demand of oil in the world. Specifically, the intensification of the COVID-19 pandemic has caused business shutdowns and disruptions in the global industrial chain. When investors’ pessimistic expectations for the global economy are formed, the market demand declines, which eventually triggers sharp fluctuations in the crude oil market. In other words, the pandemic first had a negative impact on production and consumption activities in the real economy, and this negative impact eventually affected the crude oil market after a period of time. Third, the deterioration of COVID-19 had a small negative impact on the gold market on the day of the event, but a significantly positive impact appeared after three trading days. Fourth, for the bond market, volatility increased significantly on the day of the event and one trading day after, and this effect also lasted for at least the next five days after the event. This is because the U.S. bond market experienced severe stress and an illiquidity problem after the deterioration of COVID-19, which sharply raised the volatility of the bond market (He et al., 2022). Interestingly, the deterioration of COVID-19 had a relatively weak and lagging impact on the volatility of the foreign exchange market in the short term.

Table 4 summarizes the risk dynamics of global financial markets after the deterioration of the COVID-19 pandemic. First, from the peak of the spillovers, we find that the impact of the COVID-19 deterioration event on these markets can be arranged from high to low as follows: stock, bond, crude oil, gold, and foreign exchange markets. Second, the impact of the deterioration event has the longest duration for the stock market, followed by the bond, crude oil, and foreign exchange markets. Finally, in terms of the market response to shocks, the volatility of the stock and bond markets increased significantly immediately on the day of the event, while the crude oil and foreign exchange markets responded to the shocks 4 and 5 days later, respectively.

4.2. Risk dynamics of financial markets in response to the Federal Reserve’s policy

The Federal Reserve has taken multiple aggressive policy actions in response to the worsening of COVID-19; therefore, it would be interesting to investigate whether these actions significantly mitigate the economic impact of the COVID-19 pandemic and stabilize global financial markets. Fig. 4 shows the risk dynamics of individual financial markets in response to the Federal Reserve’s policy during the COVID-19 crisis. In general, we find that financial markets are riskier six days before the policy is announced than during “tranquil times.” After March 2020, investors’ panic caused by COVID-19 leads to considerable turbulence in financial markets. During this period, the Fed introduced a series of aggressive monetary policies, such as emergency interest rate cuts and unlimited QE in response to the panic fire-sale caused by the COVID-19 pandemic.

Fig. 4 shows that the regression coefficients of the event dummy variables on the risk of each financial market show a downward trend one to three trading days after introducing aggressive monetary policies in response to the COVID-19 crisis. However, except for the stock market, the coefficients of the dummy variables in the other markets are significantly positive within one to three trading days after the policy is introduced. This indicates that although the Federal Reserve’s monetary policy responses have had certain effects on alleviating investors’ panic in financial markets, they cannot completely mitigate the effect caused by the worsening of the COVID-19 pandemic. In addition, the effect of these policy responses is not sustainable in terms of mitigating financial risks. Starting on the fourth trading day after the policy was introduced, the risk of most financial markets began to increase again. This shows that, except for the stock market, the effect of the COVID-19 pandemic on the market still persists, and the Fed’s aggressive monetary policy can only mitigate the impact in the short term.

Table 5 shows the risk dynamics of the global financial market after the Federal Reserve responded to the COVID-19 pandemic. First, the values of maximum drawdown show that the risk mitigation policy has the largest impact on the stock market, followed by the crude oil, bond, foreign exchange, and gold markets. Second, in terms of the response speed of a market, except for the gold market, the Federal Reserve’s responses to COVID-19 have had immediate impacts on all the markets. Finally, from the perspective of the sustainability of risk mitigation, the Federal Reserve’s policy has had the longest duration in the stock market (4 days), followed by the crude oil, bond and foreign exchange markets (3 days) and the gold market (2 days). Four to five trading days after the policy took effect, the mitigation effect on the market started diminishing.

Table 4
Risk dynamics of global financial markets after the deterioration of COVID-19.

|                      | Stock market | Crude oil market | Gold market | Bond market | FX market |
|----------------------|--------------|------------------|-------------|-------------|-----------|
| Peak                 | 2.396**      | 0.846**          | 0.219       | 1.100**     | 0.207**   |
| First day            | +0           | +4               | –           | +0          | +5        |
| Duration             | 7            | 3                | –           | 4           | 1         |

Notes: This table reports the risk dynamics of global financial markets after the deterioration of the COVID-19 pandemic. The ‘Peak’ row reports the largest coefficients of the dummy variable for each market (as the volatility for each market is different in scale, we rescale the coefficients by dividing the average volatility of each market). The ‘First day’ row represents the earliest day when the coefficient of the event variable is significant after the event occurred. For instance, ‘+4’ means that the earliest day when the coefficient of the event variable is significant after the event occurred is the fourth day after the event. The ‘Duration’ row represents the longest duration in which the dummy variables are continuously significant within 6 trading days after the event. ** represents the 5% significance of dummy variables in our regression analysis.
The impact of the COVID-19 pandemic caused risk spillovers among financial markets. This section mainly explores the risk spillover path of global financial markets in the time of COVID-19. First, we use market volatility to establish a VAR model. Before establishing the VAR model, it is necessary to test the stationarity of the variables, and our results show that the volatility of the stock, gold, bond, and foreign exchange markets is stationary at the 1% significance level. The original series of the crude oil volatility is not stationary, but it is stationary at 1% after taking the first difference. We use the stationary data of each variable to establish a VAR model, and the lag order is set to three, according to the Schwarz information criterion.

Second, shocks to economic activity have a negative impact on risk spillovers at different frequencies with different strengths. Thus, we decompose risk spillovers into different frequency bands to study the short-, medium-, and long-term effects of the COVID-19 pandemic on global financial markets. Specifically, we decompose the interval into several frequency bands and set \( \pi/20, \pi \) as the high frequency band, which represents the short-term spillovers with a period of 1–20 trading days (approximately 1 month). Then, we set \( \pi/300, \pi/20 \) as the medium frequency band to obtain the medium-term spillovers (21 trading days to 300 trading days). Finally, we set \( 0, \pi/300 \) as the low frequency band to obtain the long-term spillovers (longer than 300 trading days). According to Eq. (14), the variance decomposition spectrum representation method requires the prediction step \( H \to \infty \), but we only set \( H \to 300 \), which is large enough in our practice.

Finally, we investigate the dynamic characteristics of risk spillovers between financial markets using a rolling window. Based on the principle that the window length is equal to the upper limit of the medium-term frequency, we set the window length to 300 trading days.

### Table 5

|                              | Stock market | Crude oil market | Gold market | Bond market | FX market |
|------------------------------|--------------|------------------|-------------|-------------|-----------|
| Maximum drawdown             | 1.591        | 1.558            | 0.158       | 0.72        | 0.52      |
| First day of risk mitigation | 0            | 0                | 2           | 0           | 0         |
| Duration of risk mitigation  | 4            | 3                | 2           | 3           | 3         |
| First day of risk rebound    | 5            | 4                | 4           | 4           | 4         |

Notes: This table reports the risk dynamics of global financial markets in response to the Federal Reserve’s policy. Maximum drawdown is the maximum value of drawdown of the regression coefficients of the dummy variable after the event occurs (as the volatility for each market is different in scale, we rescale the coefficients by dividing the average volatility of each market). “First day of risk mitigation” represents the trading day when the coefficient of the event variable first shows a downward trend after the event occurs. “Duration of risk mitigation” represents the longest period of the duration in when the coefficient of the event variable shows a downward trend or becomes insignificant within 6 trading days after the event. “First day of risk rebound” represents the trading day when the first significant increase in the coefficients of the event variable after the event.

### 5. Evolution of risk spillovers across financial markets in the time of COVID-19

The impact of the COVID-19 pandemic caused risk spillovers among financial markets. This section mainly explores the risk spillover path of global financial markets in the time of COVID-19. First, we use market volatility to establish a VAR model. Before establishing the VAR model, it is necessary to test the stationarity of the variables, and our results show that the volatility of the stock, gold, bond, and foreign exchange markets is stationary at the 1% significance level. The original series of the crude oil volatility is not stationary, but it is stationary at 1% after taking the first difference. We use the stationary data of each variable to establish a VAR model, and the lag order is set to three, according to the Schwarz information criterion.

Second, shocks to economic activity have a negative impact on risk spillovers at different frequencies with different strengths. Thus, we decompose risk spillovers into different frequency bands to study the short-, medium-, and long-term effects of the COVID-19 pandemic on global financial markets. Specifically, we decompose the interval into several frequency bands and set \( \pi/20, \pi \) as the high frequency band, which represents the short-term spillovers with a period of 1–20 trading days (approximately 1 month). Then, we set \( \pi/300, \pi/20 \) as the medium frequency band to obtain the medium-term spillovers (21 trading days to 300 trading days). Finally, we set \( 0, \pi/300 \) as the low frequency band to obtain the long-term spillovers (longer than 300 trading days). According to Eq. (14), the variance decomposition spectrum representation method requires the prediction step \( H \to \infty \), but we only set \( H \to 300 \), which is large enough in our practice.

Finally, we investigate the dynamic characteristics of risk spillovers between financial markets using a rolling window. Based on the principle that the window length is equal to the upper limit of the medium-term frequency, we set the window length to 300 trading days.
days, and the result is from January 1, 2019, to April 17, 2020.

5.1. Risk spillovers in global financial markets

In this part, we measure risk spillovers between financial markets from four aspects: total spillovers, directional spillovers, single market net spillovers, and pairwise net spillovers. Specifically, the total spillovers measure the overall level of cross-market spillovers of the entire financial system for all the selected markets. It also shows the degree of connectedness across markets. The directional spillovers reveal the magnitude of each market’s risk spillovers from or to other markets. The single market net spillovers reveal the relationship between the input and output risk spillovers of a single market and reflect its role in the spillover network. The pairwise net spillovers measure the pairwise risk spillovers and spillover asymmetry between two markets.

5.1.1. Total spillovers

Table 6 shows the magnitude of total risk spillovers in global financial markets at different phases from January 1, 2019 to April 17, 2020. After the WHO raised the global risk level for COVID-19 to “high”, the total risk spillovers across financial markets in each frequency domain were clearly higher than those of the pre-pandemic period. In addition, after the global risk level was adjusted to “very high” by the WHO, the medium- and long-term total spillovers increased to more than three times that of Phase I. This suggests that with the further global spread of COVID-19, the connectedness of markets within the entire financial system significantly increased, especially the medium- and long-term connectedness. This is probably caused by the significant uncertainty about the pandemic’s trajectory for the next twelve months or longer.

Compared with Phase III (Very High Risk), the short-term total spillovers in Phase II (High Risk) are slightly reduced (from 11.83 to 11.66), but the long-term total spillovers in Phase III are twice that of Phase II. This shows that financial markets have become more volatile after the deterioration of COVID-19, and short-term spillovers have shifted to the longer term. In addition, the fluctuation of risk spillovers also significantly increased at all frequencies during the same period. This confirms the powerful and long-lasting impact of the COVID-19 pandemic as a driver of financial market volatility. Such a significant influence might be caused by the increasing severity of the COVID-19 pandemic, the apparent ease with which the virus spreads, and the non-negligible mortality rate of infected people.

The upper part of Fig. 5 presents the dynamics of the total spillover index and the VIX index. The VIX index is from the Chicago Board Options Exchange (CBOE), which can be viewed as a measure of market risk and investors’ sentiments. A higher VIX index indicates that market participants expect higher market risk and stress in the future. We can examine whether the COVID-19 pandemic could influence market risk spillovers through the investor sentiment channel by studying the contemporaneous relationship between the VIX and risk spillovers. First, Fig. 5 shows that the trends of the total spillover index and the VIX index are highly consistent. Specifically, the correlation coefficient between the two indexes is 0.90 from January 1, 2019, to April 17, 2020, showing that investors’ panic has triggered considerable volatility spillovers across global financial markets. Second, both the total spillover indexes and the VIX index peaked during the period that contains four circuit breakers of the U.S. stock market. As investors’ panic intensifies, investors may adjust their asset allocation, transferring from high-risk assets to low-risk assets (flight-to-quality). Thus, the risk is transmitted from one market to another through the channel of investor sentiment. After that, the VIX index gradually declined, but the total spillover index remained high. This shows that the global volatility spillovers caused by COVID-19 are more persistent than investors’ panic in the market. Third, we decompose total spillovers into different frequencies to study the risk dynamics and spillovers at different horizons (see lower panel of Fig. 5). During January 1, 2019 and April 17, 2020, the correlations between the short-, medium-, and long-term total spillover indexes and the VIX index are 0.26, 0.83 and 0.60, respectively, indicating strong contemporaneous relationships between risk spillovers (the medium- and long-term) and investors’ panic during the period of COVID-19. Finally, we find that medium-term risk spillovers have the strongest persistence among all frequencies. Overall, our results confirm that the COVID-19 shock can trigger medium- and long-term risk spillovers through the investor sentiment channel.

The mean values of the short-, medium-, and long-term total spillovers in Phase I (Pre-pandemic) are 9.09, 10.64 and 2.75, respectively. After the global risk level of the pandemic was adjusted to ‘High Risk’, the risk spillovers between financial markets at all frequencies increased. During Phase III (Very High Risk), the average short-term risk spillovers fell to 11.67, and the medium- and long-

Table 6
Descriptive statistics of the total risk spillovers in global financial markets.

| Stage                     | Statistics | Short-term cycle | Medium-term cycle | Long-term cycle | The time domain |
|---------------------------|------------|------------------|-------------------|----------------|-----------------|
| Phase I (Pre-pandemic)    | Mean       | 9.089            | 10.64             | 2.754          | 22.488          |
| 2019.1.1–2020.1.24        | SD         | 1.548            | 1.571             | 2.165          | 4.197           |
| Phase II (High Risk)      | Mean       | 11.83            | 13.463            | 3.503          | 28.800          |
| 2020.1.27–2020.2.27       | SD         | 0.511            | 0.557             | 0.118          | 0.763           |
| Phase III (Very High Risk)| Mean       | 11.662           | 39.808            | 15.094         | 66.564          |
| 2020.2.28–2020.4.17       | SD         | 8.116            | 14.026            | 15.381         | 12.388          |
| Full sample               | Mean       | 9.557            | 13.941            | 4.118          | 27.615          |
| 2019.1.1–2020.4.17        | SD         | 3.135            | 10.133            | 6.538          | 14.622          |

Note: This table shows the mean and standard deviation of the total risk spillovers across global financial markets in the short, medium and long term. The total risk spillover index is estimated by the dynamic spillover method of the generalized variance decomposition spectrum proposed by Barunik and Kreihlik (2018).
term risk correlations increased to higher levels (39.81 and 15.09, respectively). During the first two triggering circuit breakers of the U.S. stock market, the short- and medium-term risk spillovers peaked at 49.36 and 72.67, respectively. After the fourth triggering circuit breaker, the short-term risk spillovers decreased to the pre-pandemic level, while the medium-term spillovers remained high. This suggests that investors’ expectations of uncertainty about the pandemic’s trajectory sharply increased with the global spread of COVID-19. This is because the pandemic has caused industrial chain disruption, business shutdown and increased unemployment,

![Graph](image-url)

**Fig. 5.** Total Spillover Index and VIX index (upper panel) and Total Spillover Index at different frequencies (lower panel). Notes: a. The horizontal axis represents the date, and the vertical axis represents the total spillover index or the VIX index; b. Phases I, II and III represent periods of Pre-pandemic, High Risk and Very High Risk, respectively; c. The shaded area indicates the period from March 9, 2020 to March 18, 2020, during which four circuit breakers were triggered on March 9, 12, 16 and 18 in the U.S. stock market.

![Graph](image-url)

**Fig. 6.** Risk spillovers received from other markets to one market at different frequencies. Notes: a. The horizontal axis represents the date, and the vertical axis represents the directional risk spillover index From at different frequencies; b. Phases I, II and III represent the periods of Pre-pandemic, High Risk and Very High Risk, respectively; c. The shaded area indicates the period from March 9, 2020 to March 18, 2020, during which four circuit breakers were triggered on March 9, 12, 16 and 18 in the U.S. stock market.
which have adversely affected both the supply and demand sides of most countries. Thus, economic activities were substantially disrupted, and global financial markets were severely and profoundly affected.

5.1.2. Directional risk spillovers

Next, we analyse the characteristics of each financial market’s risk spillovers accepted from other financial markets. The spillover degree received by one market largely depends on its ability to withstand exogenous shock. Specifically, markets that are easily affected by panic tend to passively accept more risk spillovers and become more vulnerable in a crisis.

Fig. 6 presents the dynamics of the directional risk spillover index \( d_{ij} \) for five markets at different phases of COVID-19 spread. First, there is no significant difference between Phase I (Pre-pandemic) and Phase II (High Risk) in terms of the gross risk spillovers from other markets to one market. After entering Phase III (Very High Risk), the tendency of gross risk spillovers to be received by each market changed significantly compared with Phase I and Phase II. In Phase III, although the capacity to resist the spillovers of each market is different, the magnitude of spillovers received by each market changes simultaneously. This indicates that all the markets are systematically affected by the global spread of the COVID-19 pandemic.

Most of the time, the difference between directional spillovers across markets at the same frequency is nonsignificant or small in magnitude. It is worth noting that the foreign exchange market receives the largest medium- and long-term spillovers among all the markets, indicating that the foreign exchange market is more vulnerable than other markets during the crisis. The vulnerability of the foreign exchange market stems from two aspects. On the one hand, investors tend to hold U.S. dollars while selling other risk assets after the outbreak of COVID-19. On the other hand, loose monetary policies in response to the negative effect of the pandemic, such as lowering interest rates and establishing temporary U.S. dollar liquidity arrangements (swap lines), can affect the exchange rate market as well.

Second, we analyse the dynamics of gross risk spillovers to other markets from each of the five markets. There are two factors affecting the degree of gross spillovers from one market to others: correlation between markets due to common risk factors and contagion caused by investors’ panic and asset reallocation. The high risk spillovers of one market imply its strong risk contagion capacity and high systemic importance.

Fig. 7 shows the dynamics of the directional risk spillover index \( t_{ij} \) for five markets at different phases of COVID-19 spread. Similar to the directional risk spillover index \( d_{ij} \), there is no significant difference between Phase I (Pre-pandemic) and Phase II (High risk) in terms of gross risk spillovers to other markets from one market. After entering Phase III (Very High Risk), the trend of risk spillovers sent to other markets changes significantly compared with Phases I and II. In Phase III, although the intensity and duration of spillovers from each market are different, we can still find clear comovements of risk spillovers most of the time. In general, after the fourth triggering circuit breaker of the U.S. stock market, the short-term risk spillovers of each market to others have gradually returned to the pre-pandemic level, but the medium- and long-term spillovers remain significant. In other words, the risk spillovers from one market to others shift from short-term to medium- and long-term with the development of the COVID-19 pandemic.
Specifically, in terms of the short-term frequency, the directional risk spillover index $T_d^j$ of each market does not change significantly until the outbreak of panic in the market. Risk spillovers sharply increase and become extremely volatile during the period of four circuit breakers of the U.S. stock market (see the shaded area in Fig. 7). After the fourth circuit breaker, the short-term index falls back and stabilizes at a level slightly higher than that of Phase I and Phase II. From the perspective of medium-term frequency, the stock market spillovers sharply increase before the first circuit breaker. The other four markets have no significant difference in spillovers compared with Phase I and Phase II. During the period of circuit breakers, the magnitude of risk spillovers in the stock, crude oil, bond and foreign exchange markets increases significantly and remains at high levels. In contrast, gold market spillovers have only some marginal variations because of their safe-haven nature during the crisis. Since the beginning of April 2020, the risk spillovers of each market, except the foreign exchange market, have remained relatively stable but still higher than those in Phase I and Phase II. Surprisingly, the pattern of the long-term frequency risk spillovers is quite different from the short- and medium-term spillovers. After the circuit breaker period of the U.S. stock market, the risk spillovers of all five markets sharply increase, reaching peaks, and become extremely volatile. From the beginning of April 2020, the risk spillovers of all the markets remain stable, and the magnitude of risk spillovers in the stock market, crude oil market, and bond market are higher than those in Phase I and Phase II, while the level of risk spillovers in the gold and foreign exchange markets are similar to those in Phase I and Phase II.

The results of the directional risk spillover index $T_d^j$ show that the stock market, crude oil market and bond market are more influential on other markets, which can be explained from the following three perspectives: investors’ asset reallocation activities, common risk factors, and risk amplification mechanisms (Bai et al., 2019; Hau & Lai, 2016).

5.1.3. Single market net spillovers

Inspired by Yang and Zhou (2013), we define one market as a “risk sender” if its risk spillovers to other markets are significantly greater than the risk it receives. In contrast, we define one market as a “risk receiver” if the risk spillovers received by this market are significantly greater than its risk spillovers to other markets. In addition, if a market’s directional risk spillover index $F_{dj}^r$ and $T_d^j$ are both high and their magnitudes are similar, then we define it as a “risk transfer station”. By observing the roles played by different markets, we can capture the main sources of risk in each period.

As shown in Fig. 8, the role of each market in risk transmission is relatively stable, and there is no significant change during the sample period at each frequency. The only exception is the oil market in the short term. The crude oil market mainly acted as a risk receiver of short-term risk spillovers, but during the period of four circuit breakers in March 2020, the net risk spillovers of the crude oil market reversed and became a risk sender due to the abnormal fluctuations of the crude oil market in this period.

From the perspective of medium- and long-term net spillovers, the stock and crude oil markets act as risk senders in Phase III (Very High Risk). Next, the gold and foreign exchange markets act as risk receivers. The directional risk spillover indexes $F_{dj}^r$ and $T_d^j$ of the bond market are both high and similar, indicating that the bond market can be viewed as a risk transfer station in the medium and long term.

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Fig. 8. Single market net spillovers at different frequencies. Notes: a. The horizontal axis represents the date variable, and the vertical axis represents the net risk spillover index $Net$ at different frequencies; b. Phases I, II and III represent the periods of Pre-pandemic, High Risk and Very High Risk, respectively; c. The shaded area indicates the period from March 9, 2020 to March 18, 2020, during which four circuit breakers were triggered on March 9, 12, 16 and 18 in the U.S. stock market.
5.1.4. Pairwise net spillovers

Overall, the absolute values of most pairwise net spillover indexes increase significantly in Phase III (Very High Risk). Therefore, it would be useful to investigate the dynamics of the spillover asymmetry between financial markets in Phase III (Very High Risk). From Fig. 9, the following findings are established.

First, the net spillovers from the stock market to the crude oil market are significant at the short-term frequency, whereas risk spillovers between the stock market and the other three markets (i.e., gold, bond and foreign exchange markets) are symmetrical. We also find that the stock market spreads more risk to the crude oil market than the other way around at the medium- and long-term frequencies during the period of the four circuit breakers in Phase III (Very High Risk). Moreover, the stock market has significantly higher risk spillovers to the gold, bond and foreign exchange markets in the medium and long term. Second, the crude oil market receives net risk spillovers at the short-term frequency from the other markets most of the time in Phase III, but this effect reverses during the circuit breaker period. Our results suggest that the other four markets are more influenced by the crude oil market than the other way around. At the medium- and long-term frequencies, the crude oil market spreads to the other four markets for most of Phase III. Third, the gold market receives more risk spillovers from other markets than it gives at the short-term frequency during the circuit breaker period. Moreover, the short-term risk spillovers between the gold market and the other four markets are symmetrical after the circuit breaker period. In the medium and long term, the gold market receives risk spillovers from the stock, crude oil and bond markets most of the time in Phase III. Before the end of the circuit breaker period, the gold market receives more risk spillovers from the foreign exchange market, but this effect reverses after this period. Fourth, the short-term risk spillovers received by the bond market are almost as large as those it sends to the stock and foreign exchange markets. Before and after the circuit breaker period in Phase III, the risk spillover at the short-term frequency between the bond market and the gold market is relatively symmetrical; however, during this period, the bond market spreads more risk than it receives from the gold market. From the medium- and long-term perspective, we find that the bond market spreads more risk to the gold and foreign exchange markets and receives more risk from the stock and crude oil markets throughout Phase III. Finally, the short-term risk spillovers from the foreign exchange market to the stock, gold, and bond markets are similar in magnitude to the spillovers from these markets. In other words, the short-term spillovers between these market pairs are symmetrical. At the medium- and long-term frequencies, the foreign exchange market is more influenced by the other markets than the other way around in Phase III.

Fig. 9. Pairwise net spillovers at different frequencies. Notes: a. The horizontal axis represents the date variable, and the vertical axis represents the pairwise risk spillover index $Pairwise$ at different frequencies; b. Phases I, II and III represent the periods of Pre-pandemic, High Risk and Very High Risk, respectively; c. The shaded area indicates the period from March 9, 2020 to March 18, 2020, during which four circuit breakers were triggered on March 9, 12, 16 and 18 in the U.S. stock market.
5.2. Risk spillover networks of global financial markets

In this subsection, we construct risk spillover networks of global financial markets based on the spillover relationships between each market pair at different frequencies (i.e., short-, medium- and long-term). To further explore the shock of COVID-19 on the structure of risk spillover networks, we construct networks using two subsamples: pre- and during the COVID-19 outbreak.

Specifically, the risk spillovers from one market to other markets ($T_{ij}^d$) are represented by the size of the node, and the spillovers to this market from other markets ($F_{jk}^m$) are represented by the color of the node. A larger node represents a higher degree of spillovers sent to other markets, while a darker color represents a higher degree of spillovers received from other markets. The directed lines connecting the nodes represent spillover paths between financial markets, and the width of the directed lines represents the risk spillover intensity ($n_{ij}$) between financial markets. The location of each node is determined by the ForceAtlas2 layout algorithm of Jacomy et al. (2014). This algorithm assumes that the nodes repulse each other like charged particles, and edges attract nodes like a spring. The force attracting nodes is proportional to the average pairwise spillovers between two markets. The closer the distance between two nodes, the greater the average spillovers between the two markets. To study the shock of COVID-19 on the structure of risk spillover networks, we use the date when the WHO upgregates the global risk level of COVID-19 to “high” on January 26, 2020 as a breakpoint to split our sample into two subsamples: pre- and during the COVID-19 outbreak. Therefore, we can obtain two risk spillover networks across global financial markets before and after the COVID-19 outbreak (see Figs. 10 and 11).

We have several general findings from Figs. 10 and 11: the size of the nodes increases in general after the outbreak of COVID-19. The distance between nodes decreases during the COVID-19 crisis. The width of the directed lines becomes wider in the time of COVID-19. All of these results indicate that the global spread of COVID-19 significantly erodes market confidence and therefore increases risk spillovers across financial markets.

From the perspective of risk spillovers received by one market from others (node color), we find that the crude oil market is the largest receiver of the short-term risk before and after the pandemic. At the medium-term frequency, the bond market is the largest receiver of risk spillovers among all the markets before the outbreak of COVID-19, while the foreign exchange market becomes the largest one during the COVID-19 period. In the long term, the gold and foreign exchange markets receive the most risk among all markets before and after the COVID-19 crisis, respectively.

From the perspective of risk spillovers from one market to others (node size), we find that the stock, bond, and gold markets are strong risk senders in the short term before and after the outbreak of the pandemic. The stock, bond, and gold markets are strong risk senders at the medium-term frequency before and after the outbreak of COVID-19. The crude oil market has the smallest medium-term spillovers among all markets before the pandemic but becomes the main risk sender after the pandemic. In the long run, the foreign exchange market is the largest risk sender before the pandemic and the smallest risk sender after the outbreak of COVID-19. Overall, the stock, bond and crude oil markets are the main contributors to risk spillovers during the pandemic crisis.

Overall, our results indicate that the continued spread of the COVID-19 pandemic around the world caused widespread panic in financial markets, and investors tended to switch from risky assets (stocks and crude oil) to safe-haven assets (US Treasury bond, gold, and the US dollar) to overcome COVID uncertainty. Therefore, the stock and crude oil markets act more as risk senders, and the gold, bond and foreign exchange markets act more as risk receivers. In addition, the bond market also acts as a risk sender. In response to the liquidity crisis caused by COVID-19 financial turmoil, the Federal Reserve has taken multiple policy actions (e.g., cutting interest rates, offering forward guidance, and repurchase agreement operations), which have led to fluctuations in interest rates and bond prices. Therefore, the bond market acts as both a risk sender and a risk receiver (a transfer station of risk).

Next, we show the risk spillover paths between financial markets at different frequencies according to the risk spillover networks. The paths of risk spillovers before and during COVID-19 are presented in Table 7. To show the path of risk spillovers more clearly, we use thresholds to select the most significant paths. Specifically, we only select and report the short- and medium-term spillovers that are greater than 5 and the long-term spillovers that are greater than 3 in Table 7.

First, there is no significant change between short-term risk spillover paths in global financial markets before and during COVID-19. Specifically, in the short-term spillover network, the stock and bond markets are the main risk senders to other markets, and the crude oil market receives the most risk from other markets. In addition, there are strong two-way spillovers between the stock and bond markets. Second, the medium-term spillover intensity across financial markets significantly increases during the COVID-19 pandemic. This is not surprising because it is a stylized fact that markets are more connected in turbulent or volatile times. Compared with the short-term shock, the COVID-19 pandemic has had a profound impact on the real economy and financial markets. Therefore, more effective policies should be implemented to mitigate mid-to-long term cross-market contagion. The stock market has two-way risk spillovers with the bond and gold markets. Finally, the stock market is the main risk sender to the foreign exchange and the gold markets in the long term.

6. The effect of economic stimulus and financial stabilization policies on global risk spillovers

In this section, we investigate the effect of the US government’s economic stimulus and financial stabilization policies in response to COVID-19.

Fig. 12a presents the effect of expansionary monetary policy on total risk spillovers, which seems insignificant in general. This indicates that expansionary monetary policy is ineffective in mitigating risk contagion across markets during the COVID-19 crisis. Fig. 12b shows the lagging effect of expansionary fiscal policy on market risk spillovers. Specifically, the significant mitigation effect on total risk spillovers does not occur until six months after the implementation of expansionary fiscal policy. Fig. 12c presents a
considerable mitigation effect of containment and health response on risk spillovers across markets on the 5th trading day after its implementation. Overall, our results show that containment and health response could effectively mitigate risk spillovers of global financial markets in the short term, while expansionary fiscal policy is more effective in reducing risk spillovers in the medium and long term.

7. Conclusion

The COVID-19 pandemic has caused a significant negative impact on the world economy and financial markets due to its global nature and severity. In this paper, we provide an analytical framework to capture the dynamics of global financial spillovers and the spillovers from developed markets to regional financial markets in the context of the COVID-19 crisis. Finally, we analyse the heterogeneous frequency (short-, medium- and long-term) risk spillovers across global financial markets due to the shock of COVID-19.

First, we find that the deterioration of the COVID-19 pandemic significantly raises the risk of the global stock, bond, crude oil, and foreign exchange markets sequentially in the short term. The Federal Reserve’s loose monetary policy played a role in mitigating the deterioration of risks on the day it took effect, with the exception of the gold market. We also find that this mitigation effect on the market became invalid four to five trading days after the policy was announced, and the impact of the COVID-19 pandemic on the
market continued to increase. Second, we show that the COVID-19 pandemic increases risk linkages among global financial markets in the medium and long term, and the magnitude of the risk spillovers is highly correlated with the degree of investor panic in financial markets. Third, from the perspective of the risk transmission mechanism, we find that the stock market and the crude oil market act

Fig. 12a. The effect of expansionary monetary policy on total risk spillovers.

Fig. 12b. The effect of fiscal monetary policy on total risk spillovers.

Fig. 12c. The effect of containment and health response on total risk spillovers. Note: This figure presents the effect of economic stimulus and financial stabilization policies in response to COVID-19 implemented by the U.S. government on total risk spillovers.
more as risk senders, the gold market and the foreign exchange market act more as risk receivers, and the bond market serves as a transfer station of risk. Finally, we find that containment and health responses can effectively mitigate risk spillovers of global financial markets in the short run, while expansionary fiscal policy can reduce them more effectively in the medium and long run.

Our findings have important implications for policymakers and investors. First, the magnitude of financial spillovers is closely linked to the severity of the COVID-19 outbreak. Thus, to mitigate risk spillovers and enhance market stability, it is crucial for policy makers to control and prevent the spread of COVID-19 and reduce the long-term uncertainty caused by the pandemic. Second, from the perspective of the long-term effects of COVID-19, the risk transmission channels should be monitored and controlled based on the role played by a market in the risk spillover process. In addition, investors should adjust their portfolios in a timely manner based not only on the severity of the pandemic but also on the response policies implemented by the government. Future research can extend our study to explore the mechanism of risk spillovers from one market to another. Another research direction is to investigate how investors manage their asset allocation in response to the negative shock of COVID-19.

Declaration of competing interest

We hereby declare that there is no known competing financial interests or personal relationships that could have appeared to influence the work reported in the paper entitled “Risk spillovers in global financial markets: Evidence from the COVID-19 crisis”.

Data availability

Data will be made available on request.

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