Oil prices and systemic financial risk: A complex network analysis

Fenghua Wen [a, b], Kangsheng Wang [a], Xu Gong [c,*]

[a] *School of Business, Central South University, Changsha 410083, China*

[b] *School of Finance, Shanghai Lixin University of Accounting and Finance, Shanghai, 201209, China*

[c] *School of Management, China Institute for Studies in Energy Policy, Xiamen University, Xiamen 361005, China*

Abstract: The risk associated with the dramatic volatility of oil prices has become an important factor affecting the stability of the financial system. Through a complex network viewpoint, this study uses firm-level data to investigate systemic financial risk contagion from the oil market to the financial markets. Our study considers the risk amplification effect in financial network and provides an in-depth empirical analysis of risk contagion among financial institutions under the oil market risk shock. According to the findings of this paper, systemic financial risk increases dramatically during oil crisis events. This paper also captures important characteristics of the network, including major risk receivers and risk transmitters, and finds that banks suffer more risk losses from the oil market. Furthermore, considering the important role of the financial system in the macro economy, the systemic financial risk caused by oil market risk has long-term negative effects on economic output.

Keywords: Systemic financial risk; Oil prices; Risk contagion; Complex network

JEL Codes: C32; E31; G01; G32

[*] Corresponding author: E-mail address: xugong@xmu.edu.cn (Xu Gong).

1. Introduction

The risk spillover between oil market risk and financial markets has become increasingly significant with the growing financialization of crude oil (Basher et al., 2016), and has become an important factor affecting financial stability (Zhang and Wang, 2019). International oil futures prices, in particular, fell substantially in early 2020, to the point of negative trade settlement prices. This event resulted in massive losses for financial institutions and harmed the financial system's stability (Devpura and Narayan, 2020). The risk spillovers from the oil market to financial institutions and the effects on financial stability have attracted extensive attention from scholars and regulators.

Although the impact of oil market risk has been widely examined in the literature (Kilian, 2009; Ma et al., 2021), little is known about how oil market risk affects financial stability through financial network risk contagion. A high degree of interconnectedness among financial institutions through lending, investment and other channels creates a financial network. If an institution becomes distressed or fails due to oil market risk, it can quickly spread losses to the entire financial system and affect financial stability through the financial network. In order to prevent oil market risk and maintain financial stability, it is necessary to understand the direction and size of oil market risk contagion among financial institutions. In this study, we fill this research gap from the perspective of financial networks and examine the impact of oil market risk on systemic financial risk.

As a crucial commodity in the world, oil plays a very important role in the economic operation (Ma et al., 2018; Roh et al, 2021). Theoretically, oil shocks have a major impact on financial risks primarily through two channels: directly through institutional asset portfolios and indirectly through macroeconomics. First, being a key source of global energy supply, oil prices generate pressure on production costs and impact company profitability. Meanwhile, fluctuates in oil prices are accompanied by changes in inflationary pressures and discount rates (Sari et al., 2010; Guesmi and Fattoum, 2014), which impact stock prices (Demirer et al, 2020) and the level of risk to financial institutions. Second, oil market risk shock has also an impact on financial markets. The value of various assets owned by financial institutions in the financial market may vary as a result of changes in oil prices, and this directly impacts the level of risk that the financial institution is exposed to. More importantly, fluctuations in the price of assets like stocks during oil market risk shock may cause an increase in reverse selection problems making borrowers more likely to delay loans (Bernanke and Gertler, 1995; Mishkin, 1999). Deteriorating balance sheets and a surge in bank bad loans are two examples.

Oil market risk may quickly spread across the financial system due to the interconnection of financial institutions. This causes the risk to show amplification effect in the financial system. This concept is often related with complex network theory (Battistion et al., 2012; Acemoglu et al., 2015). Therefore, unlike earlier studies (Mensi et al., 2017; Ji et al., 2020; Wen et al., 2020), we adopt a complex network technique to more effectively evaluate the systemic financial risk arising from oil market risk. This research extends and combines the LASSO-VAR variance decomposition model developed by Demirer et al. (2018) with the CoVaR approach proposed by Adrian and Brunnermeier (2016) to create a high-dimensional tail risk network. This method builds a system-wide financial network that describes how each institution's risks interact and is suitable for investigating the complex systemic features that appear during extreme crisis events (Diebold and Yilmaz, 2014; Demier et al., 2018).

Furthermore, we further the research for this paper. The financial market is vital to the economy. It serves as an intermediate between the supply and demand sides of money and has a natural link with all economic organizations (Rodrguez-Moreno et al., 2013). As a result, investigating the contagion link between systemic financial risk and the macro economy is both practical and academically significant. To that aim, we employ a vector autoregressive model (VAR) to investigate the impact of systemic financial risk caused by oil market risk on a variety of macroeconomic variables such as economic production, investment, and consumption. In this article, we analyze 59 financial organizations in China, including banks, brokerages, insurance, and trusts, from 2012 to 2021, taking data availability into consideration. We choose China as the paper's sample in particular. The key reason is that China has the second-largest economy. And, as the Chinese economy expands fast, the country has become increasingly reliant on oil (Xu et al., 2022). Heavy dependence on oil makes the stability of China's economy and financial system vulnerable to international oil prices. Therefore, China provides a good sample for our study.

Our study mainly includes the following results. First, this paper finds that during oil crisis events, systemic financial risk increases dramatically. And, the scope and intensity of risk contagion increases further after the negative oil futures price event. Second, this paper captures key network features, such as risk receivers and risk transmitters, and discovers that banks suffer more risk losses from the oil market banks play an essential role in transferring oil market risk. Importantly, this article discovers that financial institutions with higher centrality are more exposed to risk losses caused by oil market risk. Third, this paper discovers that systemic financial risk has a short-term positive impact on future economic production, investment, consumption, and employment. However, its effects are always negative in the long term. We uncover evidence that systemic financial risk is transferred to the macro economy by affecting investment and consumer demand.

Our study contributes to three streams of literature. First, it contributes to the oil market risk contagion literature. Much of the existing literature has explored the impact of oil market risk from different perspectives using Granger causality, DY, GARCH, and other methods (Du and He, 2015; Demirer et al.,2020; Tian et al.,2022). However, few scholars have explored the direction and size of oil market risk contagion among financial institutions or identified systemically important financial institutions that are exposed to oil market risk. This paper fills the gap in existing studies by constructing high-dimensional risk spillover networks using firm-level data with the Lasso-VAR methodology. Second, this paper also adds to the knowledge of how oil market risk affects systemic financial risk. In previous literature, some scholars have explored the impact of oil market risk on systemic risk (Shahzadet et al., 2018; Zhao et al., 2023). However, they neglected the amplification effect of oil market risk contagion in financial networks and underestimated the impact of oil market risk. This paper fills the existing gap through the perspective of complex networks and better estimates the systemic financial risk under oil market risk shock. Third, our study contributes to the existing literature on the economic effects of oil market risk (Gao et al.,2022). Prior early studies have focused on the macro-economic impact of oil market risk directly. Only a few studies have examined at the indirect macroeconomic impact of oil market risk, which is transmitted and magnified through financial networks. Our research contributes to the body of knowledge by investigating the macroeconomic impact of oil market risk from the perspective of systemic financial risk.

The rest of the paper is organized as follows. Section 2 shows the relevant literature. Section 3 provides empirical models used in this paper. Section 4 gives an introduction to the data and empirical analysis of this paper. In this section, we measure the level of systemic financial risk and estimate its impact on macroeconomics. Besides, corresponding robustness tests are also given. Section 5 is the conclusion and policy implications of this paper.

2. Review of literature

The effect of oil market risk on the financial system has been increasingly apparent as the financialization of oil has been strengthened over time. Numerous studies have examined the effects of oil market risk from a variety of perspectives (Hamilton, 2009; Guerrero Escobar et al., 2018), with a focus on the stock market (Zhao et al., 2023). Numerous academics have examined the effects of oil market risk on financial markets from the perspective of market interconnections in these papers. Du and He (2015), for instance, find a large risk spillover between sp500 and WTI using Granger causality. Demirer et al. (2020) investigate the direction and risk spillover of oil market risk on the stock and bond markets using the DY approach. They discover that the bond market is greatly impacted by oil market risk. Using the GARCH approach, Tian et al. (2022)

discovered that there is a significant risk spillover effect of oil market risk on stock markets around the world.

A number of academics have also looked at the effects of oil market risk from a micro viewpoint on financial institutions like banks. Oil market risk affects the profitability of financial institutions such as banks mainly indirectly through macroeconomic factors (Poghosyan and Hesse, 2016), thus generating a significant risk spillover relationship among financial institutions. And, this risk spillover relationship is more obvious in oil-exporting countries (Al-khazali and Mirzaei, 2017; Saif Alyousfi et al., 2018). The effect of oil market risk on Chinese banks and other financial institutions has also been investigated by several academics. Oil market risk can significantly affect bank performance and liquidity in China (Lee and Lee, 2019) and increase the risk level of banks (Ma et al., 2021). According to Hesse and Poghosyan (2016), the effect of this risk on banks will have an indirect effect on corporate lending and lower predicted corporate earnings. Furthermore, this impact will extend across the entire financial system, causing China's financial stress index to dramatically rise (Liu et al., 2021), which will have an important effect on the system's stability. Some scholars have conducted studies to investigate the influence of oil market risk on systemic financial risk. Using the CoVaR approach, Shahzadet al. (2018) discover that systemic financial risk is significantly impacted by oil market risk. Zhao et al. (2023) use the GARCH-EVT-Copula-CoVaR methodology, find that oil market risk significantly affects the systemic risk of the Chinese stock market when it rises and has a greater impact on the energy stock sector.

Most of the existing scholars in the above-mentioned field have investigated the impact of the oil market on the financial market, as well as systemic financial risk, utilizing financial market indices and methods such as Granger causality, CoVaR, DY, and GARCH. They did not, however, investigate the direction of oil market risk contagion among financial institutions, nor did they evaluate the amplification effect induced by risk contagion among financial institutions, resulting in an underestimation of the impact of oil market risk. Only a few scholars tried to fill the existing gap from the perspective of complex networks. Chen et al. (2023) used the DY technique to build a risk spillover network and discovered that oil price volatility accelerated the spread of global systemic financial risk. Elsayed et al. (2023) built a multilayered information spillover network (MISN) and discovered that oil price shocks had a major impact on systemic financial risk in the banking industry. Oil price shocks, according to the report, would have a major influence on systemic financial risk in the banking sector. Significant financial risk. They were unable to incorporate more financial institutions, however, and so underestimated the impact of oil market risk.

The Lasso-VAR approach is used in this paper to build a high-dimensional risk spillover network that includes more financial institutions and better measures the impact of oil market risk on the financial system. It is not only possible to describe the direction of oil market risk contagion in the financial system and identify both receivers and transmitters of risk by constructing a risk spillover network of financial institutions under oil market risk shocks, as in the Granger network approach (Billio et al., 2012), but it is also possible to measure the size of the risk contagion from financial institutions. This paper takes into account the amplification effect of risk contagion in the network and better estimates the magnitude of systemic financial risk under oil market risk shock. Furthermore, the paper demonstrates that banks are systemically important in the face of oil market risk shocks, providing some fresh insights into banks' vulnerability to oil market risk. The findings of this paper, in particular, demonstrate the interplay of risk contagion across banks and other financial institutions in the face of oil market risk shocks. These findings will assist regulators in mitigating the negative consequences of systemic financial risk originating from oil market risk by determining which banking institutions to focus on and mitigating the impact of banking institutions on other financial institutions.

3. Empirical models

In this research, we have built a high-dimensional risk network to better understand how oil market risks are further spread and amplified in the financial system, thereby affecting the stability of the financial system. The paper's empirical models are divided into two sections. First, referring to the CoVaR methodology in Adrian and Brunnermeier (2016) we estimate the risk losses of financial institutions under oil market risk shock. Second, the connections between financial institutions are taken into account. In this paper, we use the Lasso-VAR method to build a high-dimensional risk network. The methodology allows us to better understand the second round of risk losses due to contagion between financial institutions after they have experienced risk losses in the oil market.

3.1.VaR and CoVaR measurement

Classical measures of financial institution risk, such as value at risk (VAR) or expected shortfall (ES), are based on firm characteristics, or macroeconomic state variables that reflect the general state of the economy. In particular, the VaR of financial institution i at $\tau \in (0,1)$ is defined as:

$$P(X_{i,t} \leq VaR_{i,t,\tau}) \stackrel{\text{def}}{=} \tau \tag{1}$$

where τ represents the quantile, and $X_{i,t}$ is the logarithmic return of financial institution i at time t.

The CoVaR (Conditional Value at Risk) method proposed by Adrian and Brunnermeier (2016) is widely used to measure the systemic risk of financial institutions. The method takes into account spillover effects as well as the general state of the macroeconomy. Given $X_{i,t}$ at the level of $\tau \in (0,1)$ at time t, the CoVaR of financial institution j is defined as:

$$P(X_{j,t} \leq CoVaR_{j|i,t,\tau} | R_{i,t}) \stackrel{\text{def}}{=} \tau \tag{2}$$

where $R_{i,t}$ represents an information set, which contains $X_{i,t} = VaR_{i,t,\tau}$ and M_{t-1}. Note, M_{t-1} is a vector of macro state variables, which reflects the general state of the economy.

For the estimate of CoVaR, it is calculated by a two-step linear quantile regression:

$$X_{i,t} = \alpha_i + \gamma_i M_{t-1} + \varepsilon_{i,t}, \tag{3}$$

$$X_{j,t} = \alpha_{j|i} + \gamma_{j|i} M_{t-1} + \beta_{j|i} X_{i,t} + \varepsilon_{j|i,t}, \tag{4}$$

Adrian and Brunnermeier (2016) propose, in the first step, that the VaR of financial institution i is calculated using the quantile regression of the logarithmic return of financial institution i on some macro state variables. The $\beta_{j|i}$ in Eq. (4) is the standard coefficient of the linear regression, which represents the sensitivity of the logarithmic return of financial institution j to the change in the logarithmic return of financial institution i. In the second step, the CoVaR is estimated by adding the VaR of institution i at level τ calculated in (5) for into the Eq. (6).

$$\widehat{VaR}_{i,t,\tau} = \hat{\alpha}_i + \hat{\gamma}_i M_{t-1}, \tag{5}$$

$$\widehat{CoVaR}_{j|i,t,\tau} = \hat{\alpha}_{j|i} + \hat{\gamma}_{j|i} M_{t-1} + \hat{\beta}_{j|i} \widehat{VaR}_{i,t,\tau}. \tag{6}$$

Therefore, by calculating the macro state variables along with the VaR of financial institution i, we can calculate the risk of financial institution j. Here, the $\hat{\beta}_{j|i}$ in Eq. (6) reflects the degree of interaction between the two financial institutions. By setting j to be a financial institution and i to be the financial system, we can calculate each financial institution's risk exposure CoVaR, which is expressed as the degree to which a single financial institution is exposed to the overall risk of the system.

In this paper, $X_{i,t}$ stands for the return of the oil market, and $X_{j,t}$ for returns of financial institutions. We can therefore measure the CoVaR of each financial institution when the oil market is in extreme risk conditions ($\tau = 0.05$). In addition, in the macro variable M, we have selected six indicators that can reflect the temporal changes in asset returns and liquidity. These are the 3-Month Treasury Yield, the CSI 300 Index, the CSI 300 Real Volatility, the CSI 300 Banking Index, the Real Estate Index, and the SHIBOR, in that order.

3.2. Lasso-VAR connectedness

In order to clearly describe the network, we first define the sign of $CoVaR_{stock|oil}$. It is expressed as the loss of stock returns to financial institutions under oil market risk shock. Second, in order to construct the connection network of $CoVaR_{stock|oil}$, we use the Diebold-Yilmaz Connectedness Index (DY) method. The DY method relates the prediction error variance decomposition in vector auto-regression to edge weights in the network, providing a perspective of network estimation (Diebold and Yilmaz, 2009, 2012, 2014).

However, the number of estimated parameters rises dramatically as the number of variables increases. The general VAR method used in Diebold and Yilmaz (2014) may not be able to estimate so many parameters, because having too many variables to estimate will lead to the curse of dimensionality and estimation error in optimization. To overcome this problem, Demirer et al. (2018) propose a DY network method based on the Lasso-VAR model, which can be used to construct a high-dimensional network and improve the applicability of the model.

We put together the $CoVaR_{stock|oil}$ of the financial institution at time t to construct a vector y_t of n dimension. After that, we construct the vector autoregressive model y_t as follows.

$$y_t = \mu + \sum_{i=1}^{p} A_i y_{t-1} + \varepsilon_t, t = 1,2, \dots, T \tag{7}$$

We can repeatedly write Eq. (7) as n regression equations. According to the method of Demirer et al. (2018), we add the elastic-net penalty (Zou and Hastie, 2005) to each regression equation of the high-dimensional VAR model, and then estimate the coefficients equation by equation.

For each regression equation obtained from Eq. (7), we denote their independent variable as $\mathcal{Z}_t$ and the dependent variable as x_{jt}. After that, the elastic-net penalty regression solves the following optimization problem:

$$min_{(\beta_0,\beta)\in\mathbb{R}^{np+1}}\left(\frac{1}{2T}\sum_{t=1}^{T}(\mathcal{Z}_t-\beta_0-\sum_{j=1}^{np}\beta_j x_{jt})^2+\lambda P_\alpha(\beta)\right. \tag{8}$$

where the elastic-net penalty function is $P_\alpha(\beta)=\sum_{j=1}^{np}(\frac{1}{2}(1-\alpha)\beta_j^2+\alpha|\beta|)$. It has two tuning parameters λ and $\alpha\in[0,1]$. The estimator is lasso when $\alpha=1$ and ridge when $\alpha=0$. In empirical analysis, α is usually set to 0.5 and no cross-validation is required. In addition, 10-fold cross-validation is used to estimate the value of λ (Bostanci and Yilmaz,2020).

After estimating n regression equations, we add the estimated coefficients to the framework of the VAR model, and then construct the connection network of financial institutions' $CoVaR_{stock|oil}$.

$$y_t=\mu+\sum_{i=1}^{p}A_i y_{t-i}+\varepsilon_t=\varphi+\sum_{j=0}^{\infty}B_j\varepsilon_{t-j}\,,t=1,2,\ldots,T, \tag{9}$$

where $B_j=\sum_{k=1}^{p}A_kB_{j-k}$, $j=1,2,\ldots$,with $B_0=I$ and $B_j=0$ for $j<0$.

Referring to the generalized error variance decomposition proposed by Pesaran and Shin (1998), we can obtain the element $d_{i,j}^{g^H}$ of the variance decomposition matrix as:

$$d_{i,j}^{g^H}=\frac{\sigma_{jj}^{-1}\sum_{h=0}^{H-1}(e_i'B_h\sum e_j)^2}{\sum_{h=0}^{H-1}(e_i'B_h\sum B_h'\,e_i)}\,,i,j=1,2,\ldots,n \tag{10}$$

The connectedness matrix constructed in this paper is shown in Table 1. According to the connection matrix in Table 1, we can define some measures with reference to the methods of Diebold and Yilmaz (2014) and Demirer et al. (2018).

[Insert TABLE 1 here]

(1) The pairwise directional connectedness from financial institution j to financial institution i is denoted as

$$C_{i\leftarrow j} = \tilde{d}_{i,j}^{g^H} \tag{11}$$

(2) The total directional connectedness from others to financial institution i (incoming) is denoted as

$$C_{i\leftarrow \cdot} = \sum\nolimits_{i=1,i\neq j}^{n} \tilde{d}_{i,j}^{g^H} \tag{12}$$

(3) The total directional connectedness to others from financial institution j (outgoing) is denoted as

$$C_{\cdot\leftarrow j} = \sum\nolimits_{i=1,i\neq j}^{n} \tilde{d}_{i,j}^{g^H} \tag{13}$$

(4) The total connectedness level of the system of the financial institution (total) is denoted as

$$TCI = \frac{1}{n}\sum\nolimits_{i=1,i\neq j}^{n} \tilde{d}_{i,j}^{g^H} \tag{14}$$

In Demirer et al. (2018) paper, the authors use the methodology to study the global bank risk spillover network and the total connectivity index (TCI) is represented as the systemic financial risk index. Therefore, referring to Demirer et al. (2018), in this paper we use the TCI index to represent the systemic financial risk index under oil market risk shock.

4. Empirical analysis

4.1. Data

We gather daily stock price data for 59 financial institutions from the CSMAR database based on data availability. Based on the China Securities Regulatory Commission's 2012 industry categorization standard, we group 59 Chinese financial institutions into four industry categories: (1) Banks, (2) Securities Brokers, (3) Insurance Institutions, (4) Trust Organizations and others. Our study spans the years January 4, 2011 to December 31, 2021. Referring to Adrian and Brunnermeier (2016), 6 macro-state variables are selected for calculating CoVaR in this paper. These are the 3-Month Treasury Yield, the CSI 300 Index, the CSI 300 Real Volatility, the CSI 300 Banking Index, the Real Estate Index, and the SHIBOR. All of this information comes from the CSMAR database. In addition, this paper constructs annual risk spillover networks and explores some characteristics of network risk contagion. We also choose a variety of financial indicators from financial firms' balance sheets. These statistics contain yearly frequencies acquired from the CSMAR database, such as ROA and ROE. WTI and Brent futures are considered benchmark crude oil prices for worldwide crude oil pricing standards. We concentrate on WTI in this research for the following reasons. First, it is the first futures contract in the crude oil market and has a longer history. Second, with a daily trading volume of 1.2 million barrels (Känzig, 2021), it is the biggest and most liquid crude oil contract. WTI data is derived from the FRED database.

This paper also explores the macroeconomic impact of systemic financial risk in the context of oil market risk shock. For this purpose, the paper uses the moving average method to convert the TCI index into monthly or quarterly frequency. We gather some macroeconomic benchmark data. These data include typical measures general economic activity, such as GDP, unemployment rate, investment (amount of completed fixed asset investment), and consumption (total retail sales of social consumer items). We use PPI and CPI to investigate the influence of systemic financial risk on consumer pricing. These are seasonally adjusted statistics from the CSMAR database. The specifics of the aforementioned data can be found in Appendix Tables A1 and A2.

4.2.Network estimation results

As we all know, the risk of the oil market can have a significant impact on financial institutions. However, one interesting question is how the systemic financial risk will change as oil prices fluctuate. We quantify the systemic financial risk across the whole sample period to answer this issue. Figure 1 shows the total connectedness index (TCI), as well as the oil price. We can clearly see from Figure 1 that the TCI in this paper, namely systemic financial risk, responds to changes in oil prices.

[Insert FIGURE 1 here]

Focusing on specific oil crisis events makes sense because it can help us understand the significant impact that oil market risk has on systemic financial risk. When oil prices fell in June 2014, oil market risks surged. Meanwhile, systemic financial risks increased dramatically. Oil prices have fallen due to a supply glut, as Saudi Arabia has said that it would not cope with increased oil supplies from other suppliers, but OPEC has decided to maintain the output quotas (Arezki and Blanchard, 2015). Oil market risk, similarly, is at an all-time high in 2018 as a result of the trade war between the United States and China. However, it does not result in a major increase in systemic financial risk. This is mostly owing to many rounds of trade discussions between China and the United States, which have decreased the negative impact of oil market risk. Global oil demand has suffered a severe setback by the sharp rise in economic damage caused by the COVID-19 pandemic. As the cost of crude oil transportation and storage keeps exceeding the actual value of oil, oil trading has experienced its first negative settlement price in history on April 20, 2020. Market panic continues to spread and intensify as a result of this event. The systemic financial risk has continued to grow at a rapid rate. Then, as the gradual rise in oil prices came back to previous levels, systemic financial risk has declined. According to these findings, the systemic financial risk not only changes with oil prices but also rises dramatically during oil periods of crisis.

[Insert FIGURE 2 here]

Next, we give incoming and outgoing connectivity indices for the banking, brokerage, insurance, and trust industries, respectively. The results are displayed in Figures 2 and 3. Incoming connections indices for these four sectors seem similar, with more connections apparent after the 2014 oil price drop and the 2020 negative oil futures price event. This demonstrates that the impact of oil market risk on the financial system is wide and powerful, with the financial industry suffering significantly. On average, the insurance industry receives more risks than the other three industries. Figure 4 shows that outgoing connections indices are more volatile than incoming connections indices. Not unexpectedly, the banking industry delivers more risk to the financial system than other sectors. However, the outgoing risk from the insurance sector is much lower than that of the other industries on average.

The insurance sector, like other financial sectors, is an important part of the financial system. It not only has a risk transfer function, but also plays the role of a financial intermediary (Kugler and Ofoghi, 2005). In recent years, the insurance sector has also increasingly engaged in activities similar to those of other financial institutions, such as derivatives trading, financial guarantees and securities lending (Billio et al., 2012). These activities have significantly increased connections between other financial institutions, such as the banking sector, and the insurance sector. When the oil market is in high volatility, oil market risk can have a significant adverse impact on financial institutions such as banks. Since the insurance sector serves as an important financial intermediary, this adverse effect is indirectly transmitted to the insurance sector, which makes the insurance sector accept more risk. Moreover, the core business of the insurance sector has a risk transfer function (Abberger et al., 2016), making the insurance sector transmit less risk.

[Insert FIGURE 3 here]

The Total Connectivity Index (TCI) suggests a significant rise in systemic financial risk following a negative oil futures price. It also shows that negative oil price events have an important impact on the structure of the risk network. We illustrate the risk network in 2019 and 2020 in Figure 4.

By analyzing the network structure in 2019, we can see that significant changes happened. First, in contrast to 2019, the event leads in a reduction in the importance of banks, while there is still a cluster across banking sectors. This result is supported by a decrease in the number of pairwise relationships between banks. Second, after the event of the crisis, the number of financial institutions with a high number of connections decreases (as seen by the color and size of the nodes). Simultaneously, the number of edges with greater pairwise directional connections also decreases. These conclusions suggest that a crisis event will lead to stronger linkages between one financial institution and more financial institutions, not just a few financial institutions with greater linkages[1]. This reflects the fact that an oil crisis event will increase the intensity and scope of oil market risk contagion among financial institutions.

We can also obtain some significant findings by exploring into the specifics. Figure 4 clearly shows that after the event occurrence, CL (China Life Insurance Company) and PAI (Ping An Insurance (Group) Company of China) dramatically extended their connections with other financial institutions. It confirms the previous conclusion that the occurrence of extreme crisis events will result in larger losses for the insurance sector (Billio et al., 2012). We can observe that EVS (Everbright Securities) created significant risk contagion to financial institutions after the event. It also demonstrates that EVS (Everbright Securities) is a highly regulated institution. These findings are important because they indicate the direction and size of oil market risk propagation for each financial institution after a crisis event, as well as which institutions should be regulated.

[1] The network constructed in this paper is a complete graph, and the sum of the weights of a node connected to all other nodes is 1. Since only the edges with the top 25% of weights are shown in this paper, as more edges have weights close to the mean, the number of edges with larger weights and nodes with larger degrees will decrease in the graph.

[Insert FIGURE 4 here]

The analysis of the risk network above provides us with an overall comprehension of which financial institutions matter in certain networks. However, one of the primary purposes of financial regulation is to identify systemically important financial institutions (Battiston et al., 2016). For this reason, it is important to consider whether institutions in the center of the network will suffer greater oil market risk losses. Following Freeman (1978) and Liao et al. (2017), we investigate the potential of various types of network centrality to explain an institution's conditional value at risk (CoVaR). For verification, we employ the panel regression model shown below.

$$y_{i,t} = \beta_0 + \beta_1 Cen_{i,t} + \beta_2 Z_{i,t} + \epsilon_{i,t} \tag{15}$$

where $y_{i,t}$ is the conditional value at risk (CoVaR) for financial institution i, and it is calculated by Eq. (6). β_0 is a constant term. $Cen_{i,t}$ is the network centrality of the financial institution. We use several typical centrality measures, which are closeness centrality(clo), betweenness centrality(bet), eigenvector(evc), and Pagerank, respectively. In addition, $Z_{i,t}$ are control variables in the panel regression model, including total assets (Asset), book-to-market ratio (Mtb), return on assets (ROE), return on net assets (ROA), shareholders' equity ratio (Equity Ratio), current assets ratio (Curttoast), total asset growth rate (Totassgrrt). $\epsilon_{i,t}$ is the random error term.

Table 2 shows that, expect for betweenness centrality (bet), all centrality and CoVaR have a significant relationship. According to the findings, institutions with higher centrality are more likely to transmit risk or be exposed to risk from other institutions. In other words, when a financial institution has a large number of network connections, it is exposed to the risk that comes from the oil market. Furthermore, because a financial institution is at the center of the network, it may quickly transmit oil market risk to the whole financial system. The results of the above tell us that we should focus on financial institutions that are at the center of the network, which is especially important for regulators.

[Insert TABLE 2 here]

Following that, we use network centrality to represent the systemic importance of financial institutions from 2012 to 2021. Figure 5 shows the Pagerank for each financial institution in each year. Among these financial institutions, we can clearly see that some large banking institutions, such as ICBC (Industrial and Commercial Bank of China), are especially important. This is in line with the "too-big-to-fail" feature of the Chinese financial system (Cao et al., 2021). Thus, Chinese regulators should pay attention to the banking institutions, especially large ones. We also find that a few financial firms have key systemic importance between 2012 and 2022. CS (Changjiang Securities), EMI (East Money Information), and HHI (Harbin Hatou Investment) are a few examples. It is worth mentioning that the insurance institutions, such as PAI (Ping An Insurance (Group) Company of China), has grown significantly in importance after the negative oil price event of 2020. This demonstrates that the insurance companies face larger losses during the oil crisis (Billio et al., 2012).

To limit the impact of oil market risks on financial institutions such as banks, regulators should take steps to ensure the financial system's stability. They should, in particular, strengthen bank regulation. First, authorities should examine and monitor financial institutions' exposure to oil market risks, and banks should be required to implement more effective risk management systems. Banks' credit risk assessment of exposures relating to the oil and energy sectors, for example, should be improved. Second, conduct regular stress tests on banks to uncover weaknesses in their balance sheets and assess their ability to absorb oil market risk shocks. Finally, banks' liquidity management and capital adequacy regulations should be strengthened to guarantee they have adequate liquidity and capital adequacy ratios to safeguard and hedge against oil market risks.

[Insert FIGURE 5 here]

4.3. Additional test

The financial market is crucial in economic operations because it acts as a middleman between capital supply and demand. As a result, we must consider how the systemic financial risk related to oil market risk may impact the macroeconomy. To this end, this paper uses prediction regression equations for different time windows and vector autoregressive model (VAR) to conduct research.

[Insert TABLE 3 here]

Through prediction regression, we first investigate the relationship between systemic financial risk (denoted as TCI) and macroeconomic factors. The regression model is illustrated below:

$$y_{t+j} = const + \alpha_h TCI_t + \gamma_h Z_t + error_{t,t+j} \quad for\ j \geq 0, \tag{16}$$

where y_{t+j} is a series of macroeconomic variables. TCI_t is the TCI that we measured. Z_t stands for some control variable. Referring to the practice of Gao et al. (2022), we choose WTI oil price returns, oil implied volatility (OVX), and oil supply as control variables. We start running regressions on each macroeconomic variable and the results are shown in Table 3. This table shows that within one year, the TCI shock has a significant positive correlation with consumption and GDP, respectively. In contrast, the TCI shock shows a persistent negative relationship with current and future CPI and unemployment rate. These results suggest that the TCI shock still has significant effects on current and future economic activity when we control for the effects of oil price returns, oil price volatility, and oil supply.

However, in order to better understand how systemic financial risk arising from oil market risk is transmitted to the macroeconomic, we examine a variety of macroeconomic indicators. Applying the VAR model, we can measure the impact of the TCI. The relevant results are shown in the picture below. The point estimations are shown by the solid red lines. Based on 10,000 bootstrap replications, the point estimates are shown as red solid lines. Referring to Känzig, D. R. (2021), we chose 68% and 95% as the confidence levels for the VAR model, which are shaded, respectively. The lag order of the VAR model is selected based on the AIC (Akaike Information Criterion).

The systemic financial risk arising from oil market risk is a shock to the economy. We expect that it will pass through several predicted factors, such as economic policy uncertainty (EPU) and the macroeconomic outlook. The reaction of EPU to the TCI shock is shown on the left side of Figure 6. Surprisingly, the EPU responded positively during this period, growing. According to Matousek et al. (2020), this indicates that the level of uncertainty keeps increasing during the crisis. The right side of Figure 6 shows the response of the macroeconomic outlook to the TCI shock. The macroeconomic outlook has responded positively in the early stages. However, as the impact of TCI increases, concern about future economic policies grows. There is pessimism about future economic development due to the adverse effects of economic policy uncertainty on the actual economy (Pastor et al., 2012; Kelly et al., 2016). As a result, the macroeconomic outlook starts getting worse after roughly a year.

[Insert FIGURE 6 here]

Notably, because inflation is a key policy variable, the effect of a TCI shock on inflation expectations is of particular importance. However, direct measuring of inflation is difficult, thus the Consumer Price Index (CPI) and the Industrial Producer Price Index (PPI) are two alternatives. These findings are shown in Figure 7. We can observe that the TCI shock will cause a big and quick decline in CPI. This is consistent with the fact that China is one of the net oil importers, making it especially sensitive to oil market risk. Following then, the CPI fell for approximately a year. PPI fell momentarily as a result of the TCI shock, but then began to rise slowly and steadily.

The TCI shock will cause a significant and lasting decline in the CPI, but how will other CPI categories be affected? Figure 7 also shows these findings for several CPI categories: food, clothes, transportation, and living. Transportation, as predicted, reacts more strongly to the TCI shock since it is more dependent on oil prices. In contrast, clothes do not respond considerably in the short run. The impact of the shock is greatest on transportation, which will reach roughly 20% after half a year, followed by food (12%), living (4%), and clothes (2%). These findings also reveal that the impact of the shock is rapid for transportation and living, but takes longer for food and clothes.

The TCI shock has a significant impact on transportation and living since they are energy-dependent industries with high energy demand. This implies that regulatory authorities should pay attention to and take appropriate measures to mitigate the impact of oil market risks on many industries, particularly those that rely on energy. To begin, they should increase R&D investment in new energy and energy-saving technologies to encourage energy-dependent industries to diversify their energy sources and reduce their reliance on oil, thereby mitigating the impact of volatile oil prices on residents' transportation and living expenses. Second, policymakers should give financial assistance and incentives, such as subsidies or low-interest loans, to encourage energy-dependent sectors to invest in technology that lessen the risk of oil market volatility. Finally, authorities should implement a flexible regulatory framework, such as dynamic oil price adjustment, to assist energy-dependent companies in better managing energy costs during periods of oil market volatility. At the same time, energy-intensive sectors should be encouraged to use financial risk management methods such as risk hedging to assist them deal with the instability of the oil market.

[Insert FIGURE 7 here]

Figure 8 shows that the GDP responds positively in the first year after the TCI shock. This result may be consistent with the assumption that decreased oil prices may help oil importers in the short run (Känzig, 2021). Following that, the GDP begins to decrease rapidly and repeatedly. GDP, however, is merely one indicator of economic activity. To gain a better understanding of how the TCI shock affects the economy, we examine a variety of monthly or quarterly indices of economic activity, such as investment, consumption, and the unemployment rate. Figure 8 depicts the reactions of these economic activity indices. For the monthly economic activity data, we can observe that investment and consumption rise for a brief period of time, then decline weakly and continue. These economic effects of the TCI shock are also confirmed by looking at quarterly economic indicators.

[Insert FIGURE 8 here]

These findings confirm the hypothesis that the major transmission path of systemic financial risk caused by oil market risk is through a disruption in consumer and investment expenditure on goods and services (Hamilton, 2008; Edelstein and Kilian, 2009). This is supported by examining the responses of various CPI categories. In the short term, consumers have significantly increased their spending on food and transportation, probably due to an increase in personal disposable income due to a strong decline in CPI. Short-term increase in consumption and investment also decreases unemployment, improving GDP. However, a period of time has passed after the incidence of systemic financial risk, negative implications begin to appear. For example, economic policy uncertainty continues to increase, whereas the CPI has been declining for a long period. These factors eventually lead to fewer investment and consumption, increased unemployment, and lower GDP.

Through the previous research we have found that the systemic financial risk caused by the oil market risk has a long-term negative impact on the economy. And, with the gradual increase of China's dependence on oil (Xu et al., 2022), the development of China's economy is vulnerable to the impact of oil prices. Therefore, regulatory authorities should pay attention to the impact of oil market risk and formulate risk management policies. First, they should increase R&D investment in new energy technologies and energy-saving technologies and encourage diversification of energy use to reduce dependence on oil. Second, strategic oil reserves should be increased to provide a buffer against oil supply disruptions and drastic changes in oil prices, to stabilize the oil market and mitigate the negative impact on the economy. Finally, develop risk management strategies to respond to dramatic short-term changes in oil prices. Financial institutions can develop risk management strategies such as risk hedging and petroleum insurance products to mitigate the impact of oil market risk.

4.4.Robustness checks

Following that, we will go over detailed robustness tests against the key empirical findings. We investigate the differences in results with different parameters and lag orders.

We first examine if our conclusions are robust to the TCI shock computed using various parameters. The method we use is similar to change the value in Eq. (8) to 1. Meanwhile, the rolling window size has been adjusted to 52 weeks. The re-estimated TCI shock all follow the same pattern as our benchmark results (see Figure B1 in Appendix B). They clearly illustrate that the systemic financial risk has increased significantly during oil crisis events. Second, we investigate if the lag order in the vector autoregressive model (VAR) influences our findings. Our findings are not affected by adopting alternative lag orders for the dependent variable. Most of the macroeconomic variables show a similar trend to the VAR model's baseline results (Figures B1, B2, B3, and B4 in Appendix B).

5. Conclusion and Policy implications

5.1.Conclusion

With the increasing development in the financialized of oil, oil market risk has become a significant element influencing financial stability. The dramatic drop in international oil prices in early 2020, in particular, resulted in massive losses for financial institutions and seriously damaged the financial system's stability. Scholars and regulators have paid close attention to the risk spillovers from the oil market to financial institutions and the impact on financial stability. Financial networks, in particular, arise as a result of the high degree of interconnectedness among financial institutions. If one institution experiences a loss as a result of oil market risk, that loss can swiftly spread throughout the financial network and damage financial stability. However, in the existing literature, little is known about how oil market risk affects financial stability through risk contagion among financial individuals. In this study, we fill this research gap from the perspective of financial networks.

This study builds a high-dimensional risk network and investigates the direction and size of oil market risk contagion among financial institutions. At the same time, this paper demonstrates that systemic financial risk arising from oil market risk may have an impact on key macroeconomic indicators such as economic production. During the oil crisis event, we find that systemic financial risk increases significantly. The intensity and scope of risk contagion increase during negative oil price events. Second, we identify critical network characteristics such as risk receivers and risk transmitters， and discover that financial institutions at the network's core suffer greater risk losses. We find that banks, in particular, play a major role in spreading oil market risk. Regulators should concentrate on bank regulation. Finally, our empirical findings imply that systemic financial risks resulting from oil market risk increase economic output, investment, and consumption in the short run. However, these impacts are adverse in the long run. We also discover that systemic financial risks resulting from oil market concerns are passed to the macroeconomy via influencing investment and consumer demand.

5.2.Policy implications

In response to the above findings, the following recommendations are made.

(1) Real-time monitoring of oil market risks for early prevention and recognition. First, regulators should build and strengthen data monitoring systems to track oil market data, such as price volatility, in order to examine the implications of these factors on

financial markets in real-time. Second, monitor risks of systemically important financial institutions, e.g., liquidity risk. Oil price volatility influences financial asset liquidity, and monitoring liquidity risk can assist in detecting possible danger areas. Finally, evaluating the financial networks produced by financial institutions as a result of their connections and establishing a risk early warning system. The early warning system monitors the direction and size of oil market risk contagion in the financial network in real-time, and risk warning signals are delivered to market participants on time.

(2) Assessing financial institution connections to prevent risk contagion from expanding. To begin, data monitoring techniques are employed to examine financial institution connections in order to capture the direction of oil market risk contagion in the financial network. Second, scenario analyses are used to estimate the level of oil market risk contagion in the financial network and to measure financial institutions' exposure to oil market risk events such as extreme oil price volatility and geopolitical risks. Finally, authorities should deploy risk monitoring systems to detect early signs of oil market risk contagion in financial networks to prevent risk contagion from expanding.

(3) Enhance risk management strategies for dealing with emergencies like oil crises. To begin, regulatory authorities should preserve and expand strategic oil reserves in order to stabilize the oil market during oil crisis events and decrease the impact on systemic financial risk. Second, authorities should devise contingency plans to deal with the negative impact on financial stability that risky events in the oil market, such as geopolitical risks, have on the market. Then, to decrease their exposure to oil market risks, investors diversify their investments. Diversification reduces the impact of oil market risk on assets. Finally, investors employ financial instruments such as futures contracts, options, and other derivatives to mitigate oil market risks.

(4) Increase the regulation of systemically important financial institutions, notably banks. First, regulatory authorities should regularly examine and monitor financial institutions' exposure to oil market risks, as well as build an effective risk management

system. Banks' credit risk assessment methods for oil-related exposures, for example, should be improved. Second, do frequent stress tests on banks to uncover financial issues and measure their resilience to oil market risks. Finally, banks' liquidity management and capital adequacy criteria should be strengthened to guarantee that they have enough liquidity and capital to face oil market risk shocks.

Acknowledgments

This work is supported by the National Natural Science Foundation of China (Nos. 72131011; 72071166).

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TABLES

TABLE 1 The connectedness matrix based on generalized error variance decomposition.

	y_1	y_2	…	y_n	From
y_1	$\tilde{d}_{1,1}^{g^H}$	$\tilde{d}_{1,2}^{g^H}$	$\cdots$	$\tilde{d}_{1,n}^{g^H}$	$\sum_{j=1,j\neq 1}^{n} \tilde{d}_{1,j}^{g^H}$
y_2	$\tilde{d}_{2,1}^{g^H}$	$\tilde{d}_{2,2}^{g^H}$	$\cdots$	$\tilde{d}_{2,n}^{g^H}$	$\sum_{j=1,j\neq 2}^{n} \tilde{d}_{2,j}^{g^H}$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
y_n	$\tilde{d}_{n,1}^{g^H}$	$\tilde{d}_{n,1}^{g^H}$	$\cdots$	$\tilde{d}_{n,n}^{g^H}$	$\sum_{j=1,j\neq n}^{n} \tilde{d}_{n,j}^{g^H}$
To	$\sum_{i=1,i\neq 1}^{n} \tilde{d}_{i,1}^{g^H}$	$\sum_{i=1,i\neq 2}^{n} \tilde{d}_{i,2}^{g^H}$	$\cdots$	$\sum_{i=1,i\neq n}^{n} \tilde{d}_{i,n}^{g^H}$	$\frac{1}{n}\sum_{i,j=1,i\neq j}^{n} \tilde{d}_{i,j}^{g^H}$

TABLE 2 The relationship between network centrality and CoVaR.

	(1)	(2)	(3)	(4)
VARIABLES	CoVaR	CoVaR	CoVaR	CoVaR
clo	0.029**			
	(2.15)			
bet		0.014		
		(1.23)		
evc			0.003***	
			(3.22)	
PageRank				0.078***
				(3.38)
Asset	-0.001**	-0.001*	-0.001	-0.001
	(-1.98)	(-1.67)	(-1.54)	(-1.37)
Mtb	0.003**	0.002*	0.002	0.002
	(2.18)	(1.88)	(1.43)	(1.54)
ROE	-0.001	-0.001	-0.002	-0.001
	(-0.61)	(-0.67)	(-1.10)	(-0.83)
ROA	0.003	0.003	0.004	0.004
	(0.62)	(0.60)	(1.03)	(0.85)
Equity Ratio	-0.003*	-0.003*	-0.003*	-0.003*
	(-1.76)	(-1.87)	(-1.97)	(-1.88)
Curttoast	-0.003	-0.003	-0.002	-0.002
	(-1.45)	(-1.50)	(-1.32)	(-1.35)
Totassgrrt	0.000	0.000	0.000	0.000
	(0.39)	(0.42)	(0.50)	(0.47)
Constant	0.059***	0.061***	0.060***	0.059***
	(9.55)	(10.04)	(9.84)	(9.66)
Company FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
R-squared	0.036	0.026	0.054	0.057
Observations	368	368	368	368

Notes: The table reports the regression results between the risk loss CoVaR and network centrality of financial institutions. clo, bet, evc, and PageRank represent the four measures of network centrality, respectively. The t-statistics in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$

TABLE 3 The predictive regression of systemic financial risk on macroeconomic variables.

	Consumption			CPI		
	Slope	t	R-squared	Slope	t	R-squared
current	0.1426***	3.14	0.099	-0.0023	-1.04	0.056
1m ahead	0.1458***	3.07	0.113	-0.0039*	-1.81	0.040
3m ahead	0.1404***	3.11	0.100	-0.0026	-1.16	0.018
6m ahead	0.1461***	3.07	0.117	-0.0040**	-2.16	0.055
9m ahead	0.1774***	4.12	0.181	-0.0016	-0.84	0.012
12m ahead	0.2217***	7.86	0.282	-0.0015	-0.67	0.026
	GDP			Unemployment		
	Slope	t	R-squared	Slope	t	R-squared
current	0.1645*	(1.86)	0.175	-0.0006	(-0.42)	0.054
1q ahead	0.1818**	(2.04)	0.216	-0.0016	(-1.28)	0.057
2q ahead	0.2280**	(2.72)	0.314	-0.0025**	(-2.29)	0.145
3q ahead	0.3048***	(6.42)	0.476	-0.0029**	(-2.62)	0.139
4q ahead	0.2790***	(5.45)	0.438	-0.0022*	(-1.99)	0.068

Notes: The table reports the predicted regression results of the systemic financial risk on current and future macroeconomic variables, controlling for current and lagged oil price returns, oil implied volatility (OVX), and oil supply. Consumption and CPI data are monthly, while the economic output (GDP) and unemployment are quarterly. The sample period is from January 2013 to December 2021. Robust t-statistics in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

FIGURES

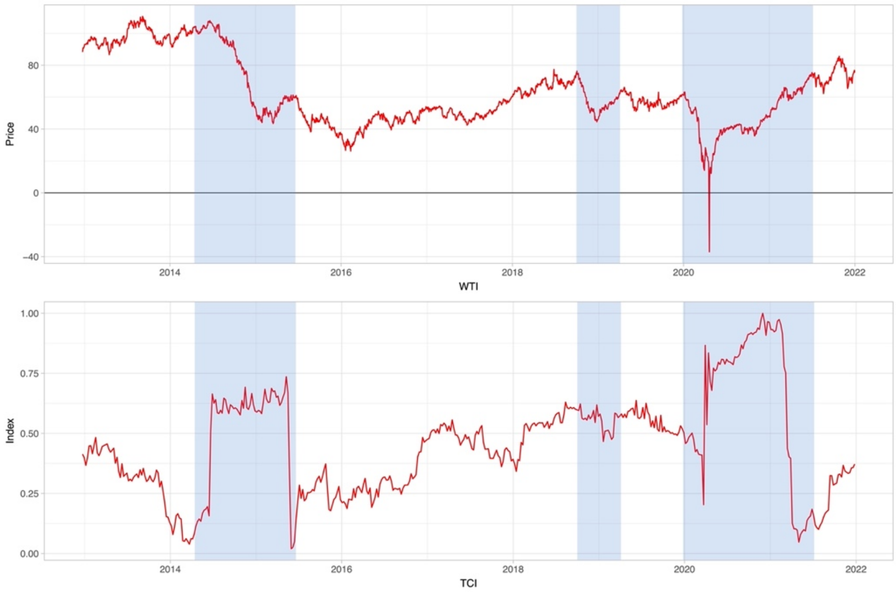

FIGURE 1 WTI Oil Price and Total Connectivity Index (TCI).

Notes: The total connectivity index (TCI) for 59 financial institutions. The time period is from December 23, 2012 to December 31, 2021, τ is 0.05, and the rolling window size is 48 weeks. The shaded areas in the figure represent important events. They are the collapse in oil prices in 2014, the China-US trade war in 2018, and the negative oil price event in 2020, respectively.

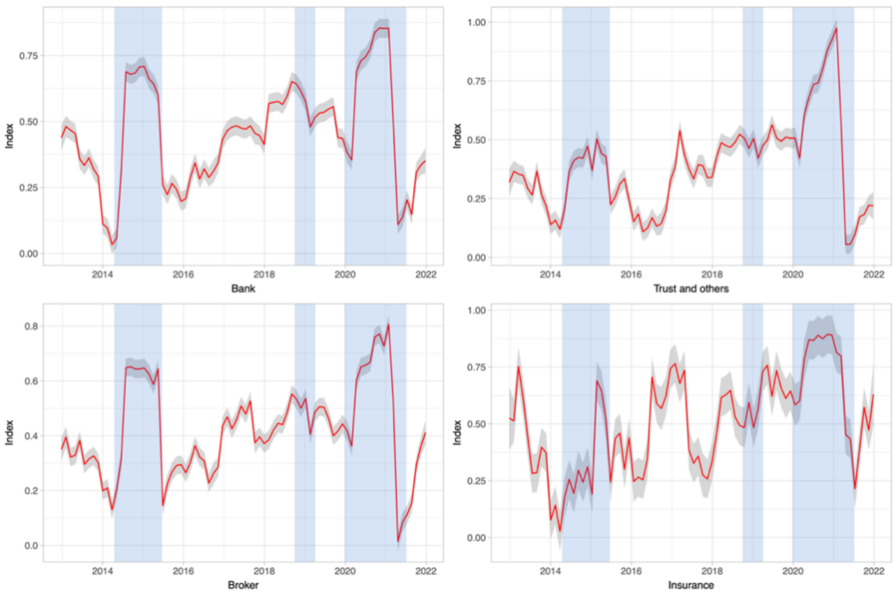

FIGURE 2 Incoming connections index.

Notes: The figure plots the incoming connectivity index for the bank, insurance, broker, and trust industries, respectively. The rolling window size for the estimation is 48 weeks, and τ is 0.05. The blue shaded areas in the figure represent important events. They are the collapse in oil prices in 2014, the China-US trade war in 2018, and the negative oil futures prices event in 2020, respectively. To show the trend of the incoming connectivity index more clearly, we perform smoothing. The gray shaded area in the figure represents the confidence interval of the smoothing.

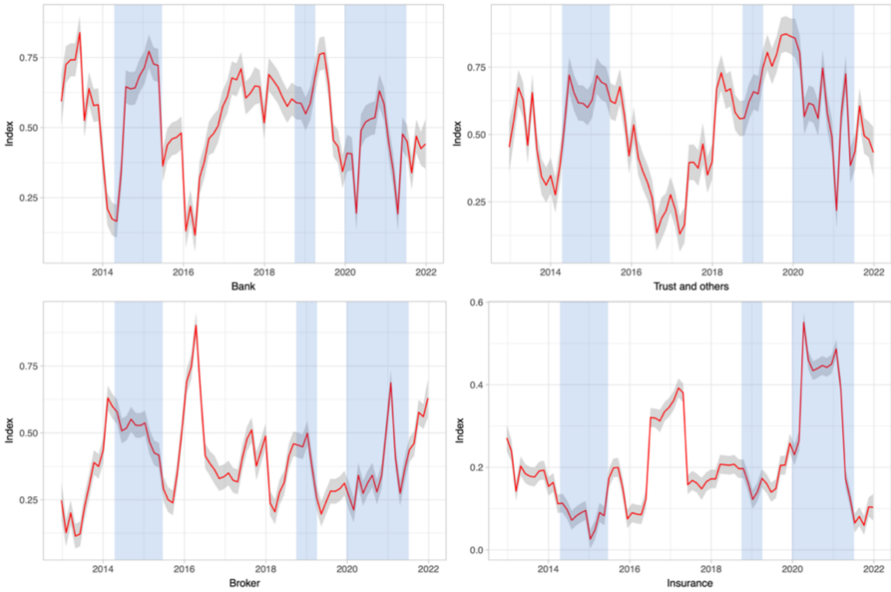

FIGURE 3 Outgoing connections index.

Notes: The figure plots the outgoing connectivity index for the bank, insurance, broker, and trust industries, respectively. The rolling window size for the estimation is 48 weeks, and τ is 0.05. The blue shaded areas in the figure represent important events. They are the collapse in oil prices in 2014, the China-US trade war in 2018, and the negative oil futures prices event in 2020, respectively. In order to show the trend of the incoming connectivity index more clearly, we perform smoothing. The gray shaded area in the figure represents the confidence interval of the smoothing.

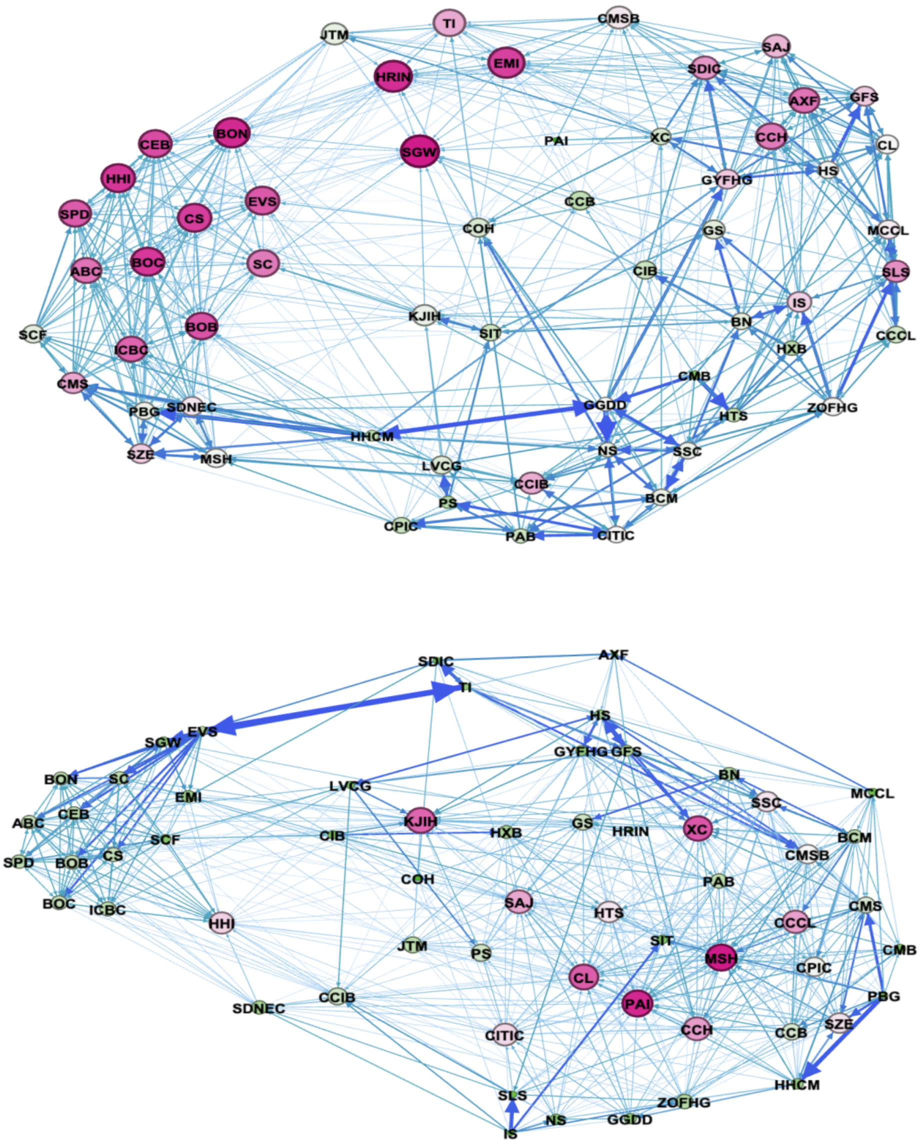

FIGURE 4 Network of financial institutions during negative oil price events.

Notes: In this Figure, from top to bottom, is the network diagram of financial institutions in 2019 and 2020, respectively. See Appendix A.2 for a list of the included financial institutions. See Appendix A.2 for a list of the included financial institutions. In order to show the basic features of the network structure more clearly, the largest top 25% edges in the network will be displayed, which is only a visual choice of the network graph. In this graph, we use the features of nodes and edges to convey information that is difficult to identify in the network. The weighted degree is denoted by the node color, and heavier weights are shown by darker hues. The degree of representation is given as the size of the node, where larger nodes have higher degrees of representation. The edge color and edge thickness are expressed as average pairwise directional connectivity. Greater pairwise directional connection is indicated by thicker, darker-colored edges. The position of the node represents the strength of the average pairwise directional connectedness. In other words, the larger mutual influence of risk spillovers across nodes, the closer their locations are to one another. The position of the node is determined by the ForceAtlas2 algorithm proposed by Jacomy et al. (2014).

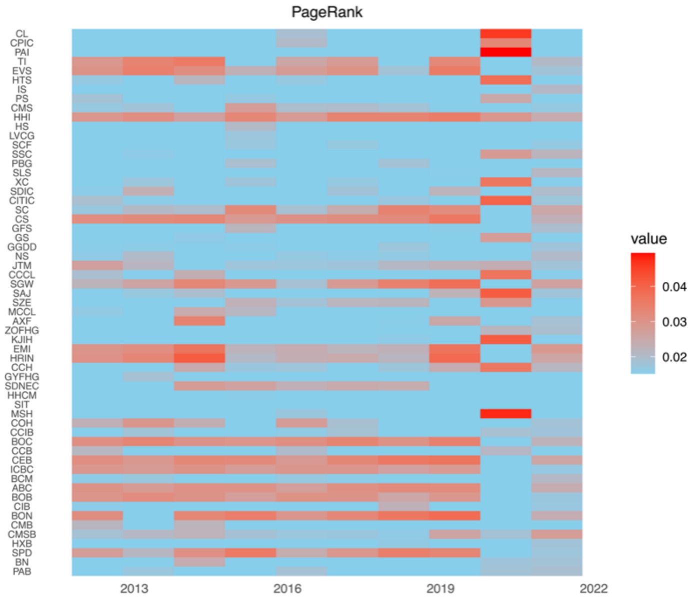

FIGURE 5 Network centrality of financial institutions.

Notes: The graph shows the network centrality of each financial institution from 2012 to 2021, which is measured using Pagerank. See Appendix A for a list of the included financial institutions. To more clearly show how the network centrality of financial institutions changes over time, we only show the results of the top 50% of the network centrality ranking.

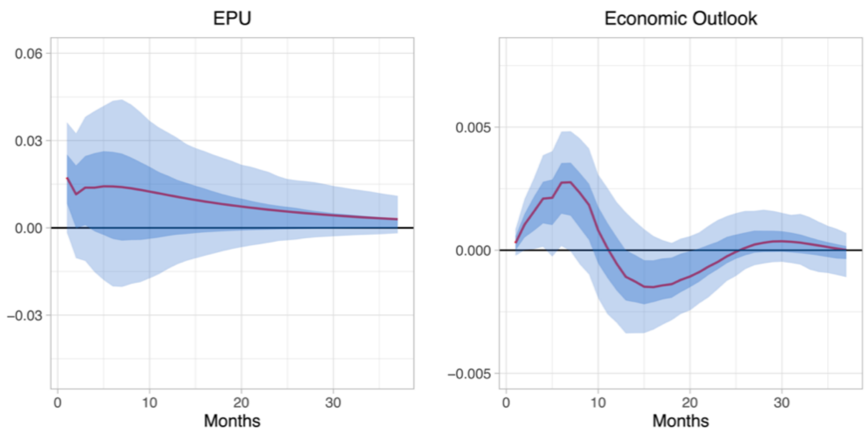

FIGURE 6 Uncertainty and expectation.

Notes: Responses of uncertainty and expectations. Based on 10,000 bootstrap replications, the shaded regions represent the 68% and 95% confidence intervals, respectively. The lag order of the VAR model is selected according to AIC (Akaike information criterion).

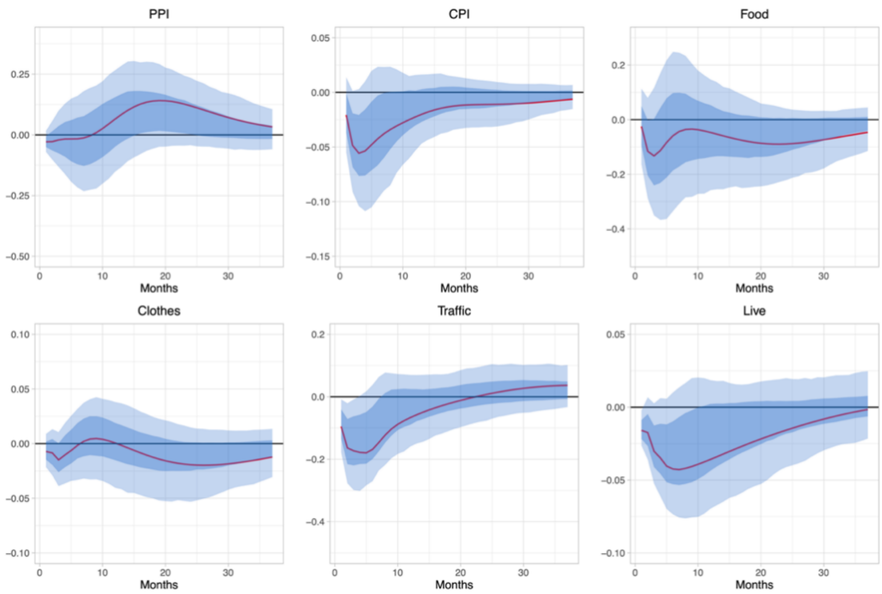

FIGURE 7 Consumer prices

Notes: Responses of different measures of consumer prices (CPI). Based on 10,000 bootstrap replications, the shaded regions represent the 68% and 95% confidence intervals, respectively. The lag order of the VAR model is selected according to AIC (Akaike information criterion).

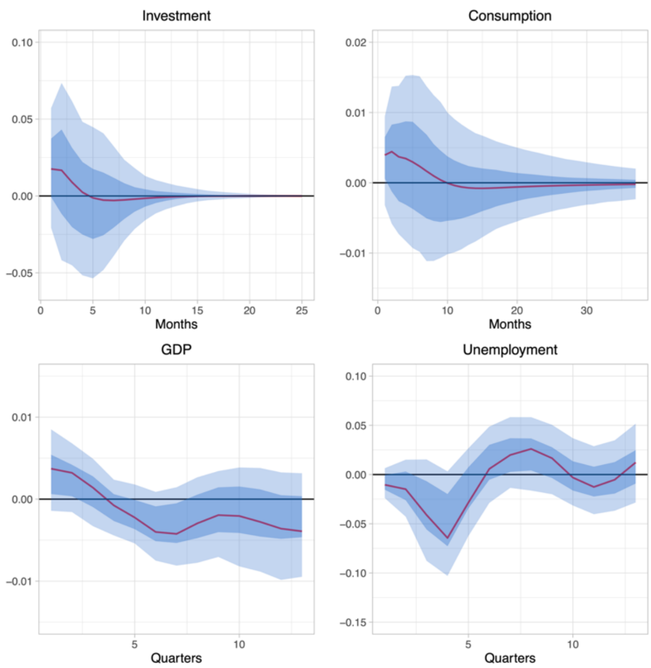

FIGURE 8 Economic activity.

Notes: Responses of different measures of economic activity. Based on 10,000 bootstrap replications, the shaded regions represent the 68% and 95% confidence intervals, respectively. The lag order of the VAR model is selected according to AIC (Akaike information criterion).

Appendix A

TABLE A1 Data description and sources.

Variable	Description	Source
Baseline variables		
Oil Price	Crude Oil Futures Prices: West Texas Intermediate (WTI), Dollars per Barrel, Daily	FRED
Stock Price	Stock Price Data of 59 Financial Institutions, daily, China	CSMAR
Macro State Variables		
CSI Index	The CSI 300 index, Daily, China	CSMAR
CSI Index Bank	The CSI 300 bank index, Daily, China	CSMAR
CSI Index RV	The CSI 300 realized volatility, Daily, China	CSMAR
Real Estate Index	The real estate index, Daily, China	CSMAR
SHIBOR	Shanghai interbank lending overnight rate, Daily, China	CSMAR
Bond	The 3-month treasury bond yield, Daily, China	CSMAR
Corporate Accounting Variables		
Asset	Total asset, Yearly, China	CSMAR
Mtb	Book-to- Market ratio, Yearly, China	CSMAR
ROE	Return on Assets, Yearly, China	CSMAR
ROA	Return on net assets, Yearly, China	CSMAR
Equity Ratio	Shareholders' Equity ratio, Yearly, China	CSMAR
Curttoast	Current asset ratio, Yearly, China	CSMAR
Totassgrrt	Total asset growth rate, Yearly, China	CSMAR
Macroeconomic Variables		
EPU	The Economic Policy Uncertainty Index, Monthly, China	
Economic outlook	The Macroeconomic Outlook Index, Monthly, China	CSMAR
PPI	The Industrial Producer Price Index, Monthly, China	CSMAR
CPI	The Consumer price index, China, Monthly, China	CSMAR
Food	The Consumer Price Index classification: Food, Monthly, China	CSMAR
Clothes	The Consumer Price Index classification: Clothing, Monthly, China	CSMAR
Traffic	The Consumer Price Index classification: Transportation, Monthly, China	CSMAR
Live	The Consumer Price Index classification: Residential, China, Monthly, China	CSMAR
Investment	Fixed asset investment completed amount, China, Monthly, China	CSMAR
Consumption	Total retail sales of social consumer goods, Monthly, China	CSMAR
GDP	Gross domestic product, Quarterly, China	CSMAR
Unemployment	Urban registered unemployment rate, Quarterly, China	CSMAR
OVX	CBOE Crude Oil ETF Volatility Index, Daily or quarterly, Index	FRED
Oil supply	OPEC Crude Oil Supply, Monthly or quarterly	EIA

TABLE A2 Analyzed financial institutions.

Name	Code	Name	Code
Banks (16)		Shanghai Chinafortune Co., Ltd.	SCF
PingAn Bank Co., Ltd.	PAB	Luxin Venture Capital Group Co., Ltd.	LVCG
Bank of Ningbo Co., Ltd.	BN	Haitong Securities Co., Ltd.	HS
Shanghai Pudong Development Bank Co., Ltd.	SPD	Harbin Hatou Investment Co., Ltd.	HHI
Hua Xia Bank Co., Limited	HXB	China Merchants Securities Co., Ltd.	CMS
China Minsheng Banking Corp., Ltd.	CMSB	The Pacific Securities Co., Ltd.	PS
China Merchants Bank Co., Ltd.	CMB	Industrial Securities Co., Ltd.	IS
Bank of Nanjing Co., Ltd.	BON	Huatai Securities Co., Ltd.	HTS
Industrial Bank Co., Ltd.	CIB	Everbright Securities Co., Ltd.	EVS
Bank of Beijing Co., Ltd.	BOB	**Insurance (4)**	
Agricultural Bank of China Limited	ABC	Tianmao Industry (Group) Co, Ltd.	TI
Bank of Communications Co., Ltd.	BCM	Ping An Insurance (Group) Company of China, Ltd.	PAI
Industrial and Commercial Bank of China Limited	ICBC	China Pacific Insurance (Group) Co., Ltd.	CPIC
China Everbright Bank Co., Ltd.	CEB	China Life Insurance Company Ltd.	CL
China Construction Bank Corporation	CCB	**Trusts and others (16)**	
Bank of China Limited	BOC	China Oceanwide Holdings Limited	COH
China CITIC Bank Corporation Limited	CCIB	Minsheng Holdings Co., Ltd.	MSH
Brokers (23)		Shaanxi International Trust Co., Ltd.	SIT
CNPC Capital Company Limited	CCCL	HAINAN HAIDE CAPITAL MANAGEMENT CO., LTD.	HHCM
Jingwei Textile Machinery Co., Ltd.	JTM	SPIC Dongfang New Energy Corporation	SDNEC
Northeast Securities Co., Ltd.	NS	Guangzhou Yuexiu Financial Holdings Group Co., Ltd.	GYFHG
Guangdong Golden Dragon Development Inc.	GGDD	COFCO CAPITAL HOLDINGSCO., LTD	CCH
Guoyuan Securities Co., Ltd.	GS	Hithink Royalflush Information Network Co., Ltd.	HRIN
GF Securities Co., Ltd.	GFS	East Money Information Co., Ltd.	EMI
Changjiang Securities Co., Ltd.	CS	Kunwu Jiuding Investment Holdings Co., Ltd.	KJIH
Shanxi Securities Co., Ltd.	SC	Zhejiang Orient Financial Holdings Group Co., Ltd.	ZOFHG
CITIC Securities Co., Ltd.	CITIC	Anhui Xinli Finance Co., Ltd.	AXF
SDIC Capital Co., Ltd	SDIC	Minmetals Capital Co., Ltd.	MCCL
XIANGCAI CO., LTD	XC	Shanghai Zhixin Electric Co., Ltd.	SZE
Sinolink Securities Co., Ltd.	SLS	Shanghai AJ Group Co., Ltd.	SAJ
Polaris Bay Group Co., Ltd.	PBG	Shanghai Great Wisdom Co., Ltd.	SGW
Southwest Securities Co., Ltd.	SSC		

Appendix B

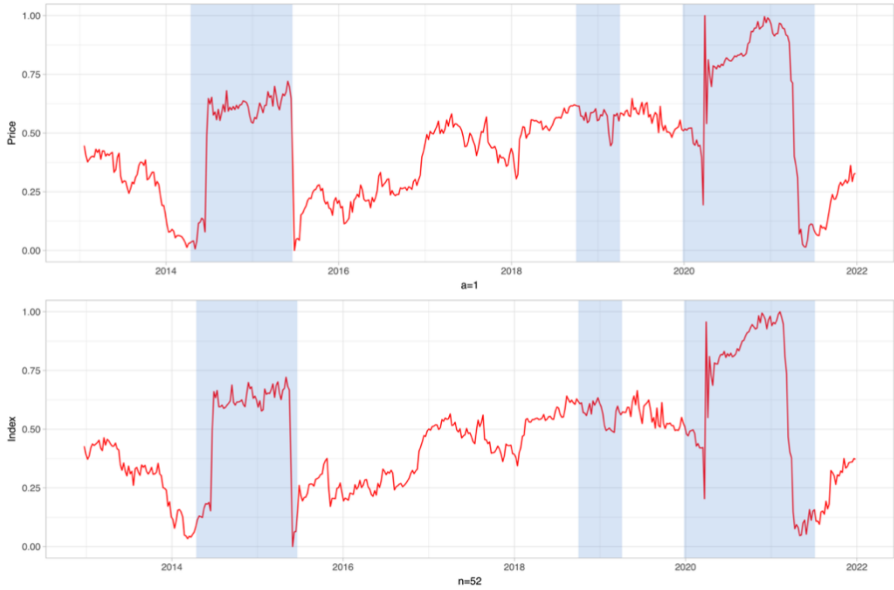

FIGURE B1 Total connectivity index (TCI).

Notes: The figure shows the total connectivity index under different parameter estimates, respectively. They are respectively in the elastic-net penalty function, parameter α is 1, and the rolling window size is 52 weeks. The shaded areas in the figure represent important events. They are the collapse in oil prices in 2014, the China-US trade war in 2018, and the negative oil futures prices event in 2020.

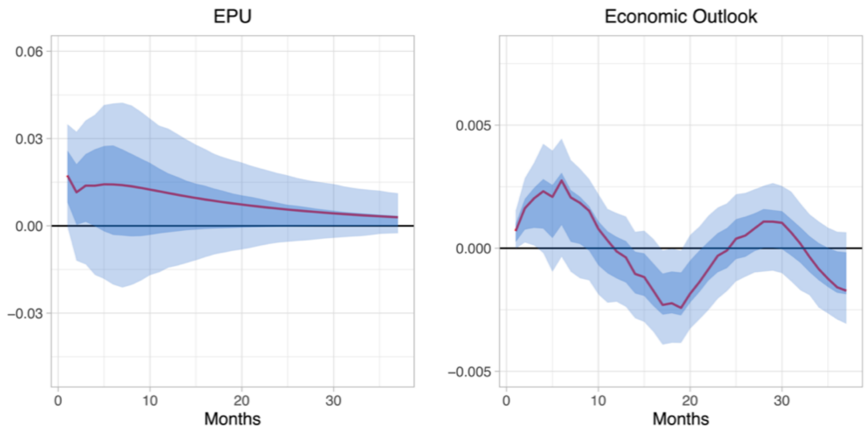

FIGURE B2 Uncertainty and expectation.

Notes: Responses of uncertainty and expectations. Based on 10,000 bootstrap replications, the shaded regions represent the 68% and 95% confidence intervals, respectively. The lag order of the VAR model is selected according to SC (Schwarz Criterion).

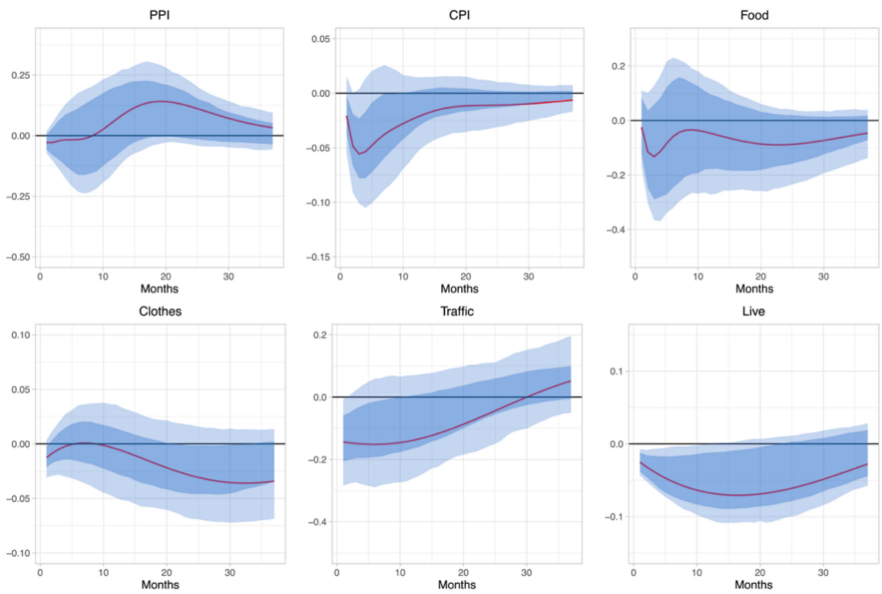

FIGURE B3 Consumer prices.

Notes: Responses of different measures of consumer prices. Based on 10,000 bootstrap replications, the shaded regions represent the 68% and 95% confidence intervals, respectively. The lag order of the VAR model is selected according to SC (Schwarz Criterion).

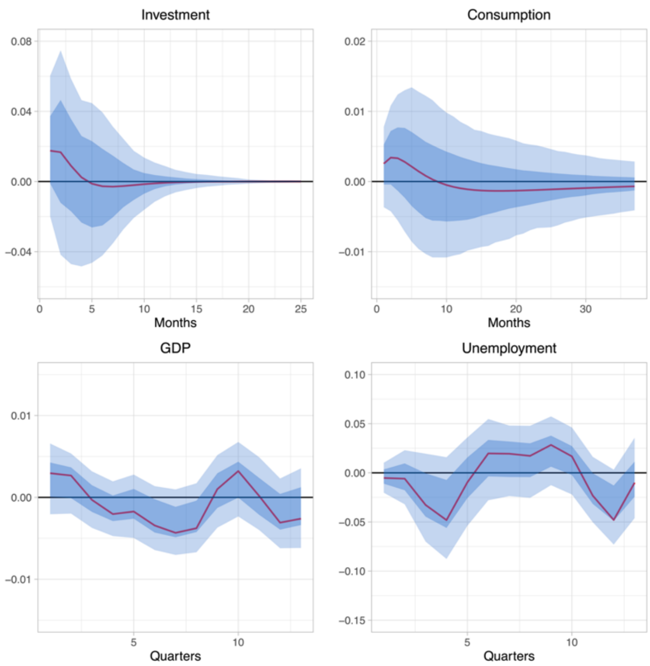

FIGURE B4 Economic activity.

Notes: Responses of different measures of economic activity. Based on 10,000 bootstrap replications, the shaded regions represent the 68% and 95% confidence intervals, respectively. The lag order of the VAR model is selected according to SC (Schwarz Criterion).