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Network diffusion of international oil volatility risk in China's stock market: Quantile interconnectedness modelling and shock decomposition analysis

Jionghao Huang [a], Ziruo Li [b], Xiaohua Xia [a,c,*]

[a] School of Applied Economics, Renmin University of China, Beijing, 100872, China
[b] Institute of Industry and Culture, School of Economics, Peking University, Beijing, 100871, China
[c] Institute of China's Economic Reform and Development, Renmin University of China, Beijing, 100872, China

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ABSTRACT

This paper aims to investigate whether oil volatility risks could diffuse through the linkage of industry returns and even further contribute to global crisis throughout the stock market. To highlight such sectoral financial interconnectedness which may serve as a key channel for oil volatility diffusion, we first apply the partial cross-quantilogram (PCQ) approach to detect the directional predictability between returns of 26 industries in China's stock market across different quantiles. We construct the corresponding network to provide a more comprehensive picture of such sectoral interconnection, which is shown to vary prominently under different market states and lag order specifications. Utilizing the spatial autoregressive (SAR) model for panel data, we further assess the possibility of the oil volatility risk diffusion by decomposing the aggregate effect of oil volatility shocks into direct shocks, and indirect shocks transmitting through the estimated network linkage of industries. The empirical results point to the significantly heterogeneous pattern of oil volatility risk diffusion among networks with different lag selections under various market states. Considering the financial linkage of industries within 5 traded days under extreme market states, there exist significant indirect effects contributing to larger oil volatility shocks on industry returns, which confirms risk contagion effects of monthly oil volatilities. It indicates that the network linkage of financial assets might be an important diffusion mechanism for oil volatility risks, which should not be neglected in the research of the oil-stock nexus.

1. Introduction

The consistently growing evidence of drastic volatilities in international crude oil prices and subsequent variations in stock prices attract much attention of financial investors, policymakers, and academic researchers (Joo & Park, 2017; Smyth & Narayan, 2018; Mishra et al., 2019). The underlying mechanism of how oil price fluctuations may impact equity returns can be roughly concluded by three dimensions, i.e. production cost effects with crude oil being one of the most important input factors (Apergis & Miller, 2009; Arouri & Nguyen, 2010; Jones and Leiby, 2004), oil-induced inflation effects (Jones & Kaul, 1996; Zhou et al., 2019), and oil market financialization effects (Basher & Sadorsky, 2016; Ma et al., 2019, 2021).

Traditionally, the international crude oil price volatility is generally considered as an exogenous structural shock to which the

* Corresponding author. School of Applied Economics, Renmin University of China, Beijing, 100872, China.
E-mail address: xiaxh.email@gmail.com (X. Xia).

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entire financial system is directly exposed. Most of the existing literature mainly focus on the direct spillover effect of crude oil price fluctuations into stock markets (Ji et al., 2018; Tiwari et al., 2019; Xiao et al., 2019; Ahmed and Huo., 2021). For example, Xiao et al. (2019) spot the co-movement of the oil market volatility and the overall stock market volatility. Ahmed and Huo (2021) confirm the volatility spillovers from crude oil prices to equity returns in China's stock market. Nevertheless, few of existing studies consider the scenario that shocks from oil price volatilities might not only directly spillover into the equity market, but can also diffuse between different industries throughout the stock market, and even further generate global crisis. In fact, with the global financial crisis in 2007–2009 and the domino effect triggered by the bankruptcy of Lehman Brothers, it reveals the possibility that shocks, irrespective of their sizes and scopes, might propagate throughout the financial system and eventually contribute to global crises (Acemoglu et al., 2012). Further, growing literature argues that the interconnection between different firms and sectors might serve as a potential propagation mechanism of shocks (Acemoglu et al., 2015; Ozdagli & Weber, 2017). Therefore, it is possible that oil price volatility risks may also propagate and spread among financial institutions and assets through their internal connections. However, such possibility is considerably discarded in existing models examining the oil-stock nexus. Take the input-output network for example, the input-output linkage between sectors and firms may facilitate the propagation of oil price shocks throughout the production network. To elaborate, with an unexpected surge in oil prices, firms may decrease the purchase of oil-related intermediate goods so as to control production costs. Because the input into their production is the output of firms in other sectors, the producers of oil-related intermediate goods have to decrease production, which further leads to a reduction in demand for goods of upstream sectors in the production network. The aggregate effect of oil price volatilities could therefore be divided into direct impacts on related companies and sectors, and indirect impacts on other companies and sectors due to various types of connection with those directly exposed. It illustrates that shocks brought by oil price fluctuations could spread to other firms and industries, and even further, the entire financial system. Hence, in this paper, we mainly study whether the interconnection between different industry returns may serve as a potential channel of oil volatility risk diffusion throughout the stock market. The question mainly concerned here is whether and in what direction indirect effects lead to the aggregate risk of oil volatilities through the interconnectedness of financial institutions and assets. Specifically, does such financial connectivity exaggerate oil price shocks and thus displaying a risk contagion effect, or play a role of risk absorber to mitigate shocks and therefore stabilize the system?

A natural starting point could be the issue of capturing the interconnectedness of different industry returns, which could be dealt with by applying the complex network analysis. In fact, researchers explore several network models to depict such financial interconnectedness. Billio et al. (2012) suggest the mean-mean Granger causality approach to identify the statistical dependence between asset returns and further establish corresponding networks so as to depict the interconnection between financial assets. However, Bonaccolto et al. (2019) point out that the network formation based on the traditional Granger causality test has certain limitations since it may only assess the statistical dependence between asset returns in the mean of their distributions. From the perspective of risk diffusion or financial contagion effects, what we usually focus on is not the mean or median correlation, but the correlation at extreme quantiles with the distribution of most financial asset returns displaying a fat-tail feature (Cont, 2001). Besides, since the interconnection of assets may serve as a potential mechanism for oil volatility diffusion, we are also interested in whether such interconnection, and more importantly, the network diffusion of oil price shocks, may display certain heterogeneous patterns under various market conditions. As the traditional Granger causality based network may fail to provide the most accurate picture of the internal linkage of assets, we are motivated to investigate the financial interconnection by examining the causal relationship between asset returns at different quantile levels. By applying the partial cross-quantilgoram (PCQ) model of Han et al. (2016), we identify the directional predictability across different quantiles of stock returns for 26 industries in China's stock market, and further estimate the quantile causality based network to capture the financial interconnectedness between different industries under various market conditions with different lag selections.

Before further investigating the network diffusion of oil price shocks in China's stock market, we would like to underline a key issue that the strict exogeneity assumption of oil price might not hold, which may be due to the existence of reverse causality that the stock market might also have an impact on the oil market (Barsky & Kilian, 2004). At the same time, crude oil prices and stock returns may also be driven by same macroeconomic factors. For example, an increase in global aggregate demand may push up oil prices and stock prices simultaneously. Such endogeneity problem may severely hinder the efficient identification of the oil-stock interaction (Kilian, 2009). Therefore, in addition to the daily Cboe Crude Oil ETF Volatility Index (OVX) published by Chicago Board Options Exchange (CBOE), we also apply the structural VAR (SVAR) model of Kilian (2009) to obtain exogenous oil price shocks based on the monthly Brent crude oil spot price data. As shown in the empirical results, the impact of oil price volatilities on stock returns varies prominently between these two volatility measurements.

To proceed, with the estimated quantile causality based network which depicts the financial interconnectedness between industries, we further apply the spatial autoregressive (SAR) model (Elhorst, 2003; LeSage & Pace, 2009) to decompose the aggregate impact of oil price shocks into direct impacts, and indirect impacts transmitting through the network connection of industries, so as to assess the specific pattern of network diffusion for oil price volatility risks in China's stock market. And empirical evidence indicates significantly heterogeneous patterns of oil volatility diffusion in accordance with the different network linkage characteristics under various market states with different lag order specifications.

We make several possible contributions to the literature, as follows. First, we highlight the possibility of the financial linkage between different industries serving as a crucial mechanism of oil volatility diffusion. Particularly, to depict such financial interconnectedness, we apply the partial cross-quantilogram (PCQ) model proposed by Han et al. (2016) to examine the directional predictability between returns of 26 industries in China's stock market across various quantile levels with different lag order specifications. Many studies adopt the traditional Granger causality approach limitedly focusing on the mean correlation between asset returns. And few of them pays attention to the lag order specification with which the statistical dependence should be detected to confirm the existence of the financial linkage, which may fail to provide the most well-rounded picture of such network interconnectedness. By constructing the quantile causality based network and further comparing the network structure under various market conditions with different lag order specifications, we are able to more comprehensively capture the internal linkage of 26 industries in China's stock market which might otherwise be hidden. This work also paves the way for further detecting the possible network diffusion of oil volatility risks through such interconnectedness.

Second, most of the existing literature rarely takes into consideration the network diffusion of international oil price volatility risks throughout the financial system. To the best of our knowledge, this paper is one of the first to address the network diffusion of oil volatility risks by applying the SAR model to decompose the impact the of oil price fluctuations on China's stock market into direct effects, and indirect network effects through the financial linkage between industries. This work may contribute to the reveal of the potential mechanism of oil price shock diffusion, which may be essentially important for a better understanding of the oil-stock interaction. The results show that industries are more prevailingly connected under extreme market conditions and significant risk contagion effects of oil volatilities are spotted with corresponding network specifications, which suggests that the network diffusion of oil volatility risks may play an important role in the oil-stock nexus.

Third, applying the daily OVX as well as the monthly exogenous oil price shocks identified from the SVAR model (Kilian, 2009), we measure the oil price volatility for different time scales to deal with the potential endogeneity problem brought by the daily oil volatility measurement. And the results of oil price shocks are shown to vary greatly between different the two volatility measurements.

The rest of the paper proceeds as follows: Section 2 provides a review of relevant literatures. Data, summary statistics and methodology are presented in Section 3. The empirical results and relevant discussion are presented in Section 4. Finally, Section 5 concludes the paper.

2. Literature review

Being one of the most crucial input factors and traded commodities in the world, crude oil, especially its price fluctuations, may have a huge impact on the economic and financial sectors through various mechanisms (Jones and Leiby, 2004; Apergis & Miller, 2009; Kilian, 2009; Arouri & Nguyen, 2010; Zhou et al., 2019). Understanding the uncertainty of crude oil prices is crucial for both crude oil exporters and importers, regulators, as well as for institutional and individual investors. Therefore, a growing strand of studies commit to better forecasting the oil price volatility and analyzing its complex interaction with various economic variables. The GARCH-type model (Sadorsky, 2006; Cheong, 2009; Wang & Wu, 2012; Wei et al., 2017; Herrera et al., 2018; Zhang et al., 2019; Marchese et al., 2020) and the HAR-type model (Wen et al., 2016; Degiannakis & Filis, 2017; Gong & Lin, 2017; Ma et al., 2018; Meng & Liu, 2019) are the two most popular and developed approaches to forecasting the oil price uncertainty with various economic predictors. For example, Marchese et al. (2020) apply fractionally integrated multivariate GARCH models to study prices of crude oil and its refined products from a forecasting and risk management perspective. Gong and Lin (2017) propose several HAR-type models to forecast the good and bad uncertainties of crude oil prices. They further investigate whether augmenting HAR models with the investor fear gauge (IFG) may help forecast the volatility of crude oil futures (Gong & Lin, 2018). Other economic variables such as the economic policy uncertainty (Wei et al., 2017), macro uncertainties (Bakas & Triantafyllou, 2019), the investor sentiment and leverage effect (Yang et al., 2019), structural breaks (Luo et al., 2020), financial stress (Gkillas et al., 2020) and market infections (Liu & Gong, 2020) are also believed to present predictability of oil price volatilities.

Kilian (2014) concludes that oil price shocks can transmit into the real economy through a supply channel and a demand channel. Specifically, a supply channel of shock transmission is based on oil-induced changes in terms-of-trade (Kim & Loungani, 1992) and capital-energy interactions (Atkeson & Kehoe, 1999; Finn, 2000). And a demand channel comes from the income effect (Dhawan & Jeske, 2008), the reallocation effect and the uncertainty effect (Edelstein & Kilian, 2009). As for the oil-stock nexus, the underlying mechanism of oil price fluctuations interacting with the stock market returns could be approximately concluded by the following aspects. First, surges in oil prices may directly lead to rises in firms' production costs, impairing enterprises' profitability (Jones and Leiby, 2004), thus downgrading firms' expected future cash flows and share prices (Apergis & Miller, 2009; Arouri & Nguyen, 2010). Second, the heavy inflationary pressure brought by a surge in oil prices and the following tightening currency policies may restrict the market liquidity and thus exerting downward pressures on stock prices (Miller & Ratti, 2009; Zhou et al., 2019). Moreover, the cash flow hypothesis suggests that enterprises take interest rate into account when discounting future expected cash flow and consequently a rise in interest rates may prejudice firms' earnings, dividends as well as equity returns (Jones & Kaul, 1996). Third, being a hedging tool that is nowadays much more frequently used to diverse stock market risks, crude oil shows increasingly stronger financial attributes, which enhances the interaction between the oil market and the stock market though the direction of such interconnectedness may still remain indistinct (Fattouh et al., 2013; Broadstock & Filis, 2014; Basher & Sadorsky, 2016; Ma et al., 2019, 2021; Ji et al., 2020). For example, Ma et al. (2019) argue that, among various factors, the effect of oil financialization strongly contributes to the crude oil volatility since the 2008 global financial turmoil. Ji et al. (2020) discover that the safe-haven role of WTI crude oil futures no longer exists during the recent financial crisis caused by the global COVID-19 pandemic. Ma et al. (2021) spot that the effect of commodity market financialization plays an important role in driving commodity return co-movement, especially in energy markets. The drastically growing trend of oil financialization may strengthen the volatility spillover of oil markets into stock markets which can further diffuse between assets and cause large scale market turbulence.

Empirically, numerous researchers explore various types of relationship between the crude oil market and the stock market with the application of different price measures (Sadorsky, 1999; Barsky & Kilian, 2004; Bhar & Nikolova, 2009; Caporale et al., 2015; Boldanov et al., 2016; Joo & Park, 2017; Smyth & Narayan, 2018; Mishra et al., 2019). Kling (1985) is the first scholar to study the interaction between oil price fluctuations and stock returns and suggests that the rise in international oil prices is not conducive to the US stock market returns. Despite considerable evidence supporting the negative impact of oil price shocks on stock returns (Sadorsky, 1999; Chen, 2010), some researchers indicate the contrary (Cong et al., 2008; Zhang & Chen, 2011; Zhu et al., 2014) while some other scholars also spot the nonlinear relationship between the oil price volatilities and equity returns in China's stock market (Wei & Guo, 2017; Luo & Qin, 2017). Singhal and Ghosh (2016), along with Bagchi (2017), Boubaker and Raza (2017) as well as Ji et al. (2018), suggest that oil price shocks may spillover to stock returns in emerging markets. Xiao et al. (2019) further identify the spillover effect of implied oil volatility index (OVX) on the implied volatility index of the Chinese stock market while Ahmed and Huo (2021) demonstrate significant bidirectional shocks spillover effect between oil market and China's stock market. On the one hand, many researchers confirm the existence of conditional mean spillover effects between oil markets and stock markets (Aloui et al., 2012; Gupta & Modise, 2013; Fang & You, 2014; Reboredo & Ugolini, 2016; Zhu et al., 2016). On the other hand, there is a growing trend of quantile causality based approach being applied in the investigation on the oil-stock relationship at different quantile levels, indicating that the bivariate nexus may be asymmetric under different market conditions. For example, by proposing the quantile on quantile (QQ) approach, Sim and Zhou (2015) investigate the relationship between oil prices and US equity returns, which indicates an asymmetric oil-stock nexus at different quantile levels. With the application of the cross-quantilogram (CQ) model of Han et al. (2016), Zhou et al. (2019) indicate the different impact of oil price shocks on stock returns under different market conditions. Tiwari et al. (2019) also spot long-term quantile dependence between crude oil prices and equity returns of emerging markets.

Nonetheless, as existing studies mostly pay attention to assessing the direct spillover effect of oil price volatilities on stock markets, how oil volatilities risk may diffuse throughout the stock market through the financial interconnectedness between different industries still remains in vague. As this paper mainly focuses on the network diffusion of oil price shocks, we also relate to researches investigating possible channels for shock diffusion throughout the financial system. Since the 2007–2009 global financial crisis, more and more scholars suggest that the interconnection of different firms, sectors and financial institutions could play a crucial role in shock diffusion and risk contagion. There are various types of such interconnection, such as input-output relationships (Acemoglu et al., 2012; Ozdagli & Weber, 2017; Herskovic et al., 2020), ownership relationships or those based on bilateral physical contracts (Blasques et al., 2016; Silva et al., 2018; Brunetti et al., 2019) as well as those based on the statistic correlation between sequences of stock returns in the Granger causality sense (Billio et al., 2012; Feng et al., 2018; Bonaccolto et al., 2019; Deev et al., 2020). On this basis, scholars begin to characterize such interconnection from a systematic perspective by applying the complex network theory. A network can be established to describe the structure of complex multivariate relationships between financial institutions and assets, and thus helping to investigate the potential risks of financial system and trace the sources of risk spillover effects (Wang et al., 2017; Baumöhl et al., 2018; Lyócsa et al., 2019). By identifying and depicting the interconnectedness of financial institutions and assets, the complex network analysis prevails to be a powerful method to detect possible financial crises (Brunetti et al., 2019), shock transmission and propagation (Silva et al., 2018), as well as systemic risks (Bisias et al., 2012; Acemoglu et al., 2015; Lyócsa et al., 2019). Therefore, a growing strand of literature starts to propose theoretical methods for financial network formation. A network can be established mainly based on physical interconnectedness such as input-output relationships, ownership relationships or bilateral exposures. For example, with the application of input-output networks, Acemoglu et al. (2012) demonstrate that microeconomic shocks to firms may spread through their linkages with other firms, which might eventually generate global fluctuations. Establishing a network of 67 industrial sectors in the United States based on their input-output relationships, Ozdagli and Weber (2017) apply the SAR model to decompose the impact of monetary policy shocks into direct and indirect effects. Herskovic et al. (2020) also indicate contagion network effects that shocks may diffuse among firms through their customer-supplier interconnectedness and even contribute to larger firm volatilities. Moreover, networks can also be established based on the statistical correlation of equity return series (Bonaccolto et al., 2019; Deev & Lyócsa, 2020). Compared with the former two types of network based on actual relationships, networks based on the statistic correlation of stock market returns may enable us to depict the latent interconnectedness of financial institutions and assets that may otherwise be hidden. To give a typical example, if the stock returns of two banks are significantly correlated, it's likely that both of them are sensitive to similar risk factors which might be due to their similar investment preferences. However, networks only focusing on physical relationships may fail to capture such internal linkage if the two banks don't directly conduct business with each other (Wang et al., 2017; Deev & Lyócsa, 2020). Accordingly, Feng et al. (2018) apply the GARCH-BEKK model to construct a directional mean spillover effect network for China's stock market. Utilizing daily closing price data of stock markets in 40 countries, Lyócsa et al. (2019) construct a financial network based on the mean Granger causality between equity returns and further investigate the topological structure and time-varying characteristics of the network. However, when considering the fat-tail characteristic of most asset return distributions (Cont, 2001), the traditional Granger causality based network has its own deficiency as it can only examine the mean dependence. Besides, it may also fail to comprehensively capture the financial interconnectedness which may demonstrate distinct characteristics under different market conditions (i.e. bearish, normal, or bullish). Consequently, based on the Quantile Regression model proposed by Koenker and Bassett (1978), Bonaccolto et al. (2019) further apply the parametric and non-parametric quantile on quantile (QQ) approach of Nicholas and Shahzad, Hernandez, Rehman, Al-Yahyaee, and Zakaria (2018) to construct a composite financial network, which describes the interconnectedness of 48 US industry portfolios, 25 banks and 25 insurance companies with the highest market value at their different quantiles. Applying the cross-quantilogram (CQ) model by Han et al. (2016), Shahzad, Hernandez, Rehman, Al-Yahyaee, and Zakaria (2018) investigate the complex network characteristics of stock markets in 58 countries under different market conditions. Deev and Lyócsa (2020) also construct CQ networks to identify the statistical dependence between stock market returns of 205 European financial institutions which shows to vary greatly across different quantile levels.

It's worth noticing that the network analysis is growingly integrated with methods of spatial econometrics such as SAR-type models. As the notion of spatial interconnection is not limited to geographical proximity but includes various types of complex relationships (i.e. social, economic or political relationships), a network can be easily characterized by a spatial weighted matrix so as

Table 1
Codes and IDs for shenwan hongyuan securities first level industry index.

Industry	Code	ID	Industry	Code	ID
Chemicals	CH	1	Agriculture	AG	14
Steel	ST	2	Food & Beverage	FB	15
Nonferrous Metal	NM	3	Leisure Industry	LI	16
Construction Materials	CM	4	Health Care	HC	17
Architectural Ornament	AO	5	Utilities	UT	18
Electrical Equipment	EE	6	Transportation	TR	19
Machinery Equipment	ME	7	Real Estate	RE	20
Defense	DEF	8	Electronics	EL	21
Automobile	AU	9	Computers	COMP	22
Household Appliance	HA	10	Media	MED	23
Textile & Apparel	TA	11	Communications Industry	CI	24
Light-industry Manufacturing	LIM	12	Commercial Banks	CB	25
Commerce	COM	13	Non-bank financials	NBF	26
			Wind All China Index	WA	27

provide the explicit picture of the multivariate interconnectedness. With the integration of network analysis and spatial models, researchers are able to extend the classic asset pricing models and to further study the risk diffusion channel of asset returns in financial markets (Asgharian et al., 2013; Billio et al., 2012; Chen et al., 2020; Debarsy et al., 2018; Fernandez, 2011; Jiang & Jin, 2020; Kou et al., 2018; Milcheva & Zhu, 2018; Ozdagli & Weber, 2017). Fernandez (2011) formulates a spatial capital asset pricing model (S-CAPM) while Kou et al. (2018) propose a spatial arbitrage pricing theory (S-APT), both highlighting the important role of the spatial interconnection between different assets in asset pricing and risk management. Further, Asgharian et al. (2013) apply spatial panel models to spot that, among various countries' economic and geographical interactions, the bilateral trade relationship is the most important linkage for the transmission of shocks between 41 stock markets. Through developing a spatio-temporal dynamic panel model, Jiang and Jin (2020) capture the endogenous spatial interaction of stock return volatility to study the shock of investor sentiment to the stock market, indicating that a sentiment shock could be expanded between firms through the spatial spillover effect thus resulting in a larger magnitude of stock volatility. Milcheva and Zhu (2018) employ the four-factor S-CAPM and show that during the global financial crisis, the spatial interconnection between 14 countries drastically strengthens, triggering a strong risk contagion effect which can account for 60% of overall asset risk. And Ozdagli and Weber (2017) attribute 50%–85% of the overall effect of monetary shocks on firms' stock returns to the indirect network effect through the input-output channel. Therefore, incorporating the network analysis with spatial statistics may be conducive to investigating whether the interconnectedness between assets may act as an important mechanism of oil volatility risk transmission.

It's also noteworthy that there is a growing trend of applying the network analysis to identify connectedness between energy markets and other markets (An et al., 2018; Bali et al., 2019; Geng et al., 2020, 2021; Han et al., 2019; Hu et al., 2020; Xia et al., 2019). Hu et al. (2020) establish a dynamic connectedness network to examine whether several macro-factors such as economic policy uncertainty can contribute to the realized volatility of crude oil markets. Geng et al. (2020) apply the time-frequency connectedness network model to depict the dynamic information connectedness between natural gas markets, uncertainties and stock markets. Geng et al. (2021) construct the returns and volatility networks of the global new energy companies to explore the information spillover among these companies. Although a few researches do apply the complex network analysis to investigate the impact of oil price volatilities on stock market returns (An et al., 2018; Han et al., 2019), how oil price shocks may diffuse and propagate between industries through their financial linkages, is considerably discarded in existing models examining the oil-stock relationship. Therefore, the main purpose of this paper is to examine whether and how oil price shocks may diffuse through the financial linkage of industries throughout the stock market under various market scenarios.

3. Data and methodology

3.1. Data

This paper employs two measurements of the oil price volatility, including the daily CBOE Crude Oil ETF Volatility Index (OVX) and the exogenous oil price shocks based on the monthly Brent crude oil spot price. Published by Chicago Board Options Exchange (CBOE), the OVX measures the market's expectation price of 30-day volatility of crude oil by applying the VIX methodology to United States Oil Fund which spans a wide range of strike prices. OVX gradually prevails to be a potent measure of oil price volatilities as it contains both the historical volatility information and investors' expectations of future oil market conditions (Maghyereh et al., 2016; Dutta et al., 2017; Zhou et al., 2019). In addition to OVX, we also identify the exogenous oil price shocks based on the SVAR model of Kilian (2009) to address the concern that the impact of OVX on stock markets might not be strictly exogenous with reversal causality and common trend effects (Barsky & Kilian, 2004; Kilian, 2009). Moreover, with the combination of the daily OVX and monthly oil price shocks, we are able to assess whether it may present a heterogeneous diffusion pattern for oil volatility risks at different time scales.

We investigate stock returns for different industries in China's stock market based on Shenwan Hongyuan Securities First Level Industry Index (a total of 26 industries). We define daily and monthly stock returns as the first-order logarithmic difference of stock indices, $\ln(PID_t/PID_{t-1})$ and $\ln(PIM_t/PIM_{t-1})$, where PID_t and PIM_t are daily and monthly closing prices of the stock price index for

Table 2
Descriptive statistics results for the daily data sample.

	Mean	Standard deviation	Skewness	Kurtosis	Jarque-Bera	PP	KPSS
OVX	37.8130	19.4901	4.5860	40.1434	188000***	−68.5522***	0.4134*
CH	0.0006	0.1281	0.2341	40.3580	179000***	−3636.0315***	0.1104
ST	0.0004	0.1384	0.2961	47.7143	257000***	−3627.9416***	0.0811
NM	0.0007	0.1880	0.1310	43.9401	215000***	−3663.4104***	0.0914
CM	0.0008	0.1432	0.0421	41.9910	195000***	−3584.2149***	0.0842
AO	0.0007	0.1091	0.4641	33.1181	117000***	−3628.1945***	0.1621
EE	0.0006	0.1274	0.0102	31.7643	106000***	−3652.2729***	0.1364
ME	0.0007	0.1380	0.1684	33.1652	117000***	−3712.3448***	0.1383
DEF	0.0008	0.1693	0.0001	42.1361	197000***	−3708.9524***	0.1231
AU	0.0007	0.1593	0.1140	40.5050	181000***	−3703.4706***	0.0982
HA	0.0011	0.1402	−0.3922	39.1704	168000***	−3757.5205***	0.1084
TA	0.0003	0.1352	0.2091	36.3751	143000***	−3627.6941***	0.0991
LIM	0.0005	0.1412	0.0930	40.6113	182000***	−3647.9304***	0.1032
COM	0.0006	0.1332	0.2664	36.2201	142000***	−3703.7844***	0.1643
AG	0.0007	0.1180	0.2193	27.9740	80100***	−3809.2821***	0.1324
FB	0.0011	0.1363	−1.8971	62.3004	453000***	−3923.3842***	0.1004
LI	0.0008	0.1461	−0.2784	46.1932	239000***	−3671.7039***	0.0974
HC	0.0008	0.1191	−0.7732	41.7902	193000***	−3803.8015***	0.1224
UT	0.0004	0.1081	0.3471	44.5401	222000***	−3505.6040***	0.0993
TR	0.0004	0.1290	0.1692	43.9513	215000***	−3635.0921***	0.0760
RE	0.0009	0.1514	0.2582	37.2572	151000***	−3593.5203***	0.1210
EL	0.0005	0.1461	−0.0760	33.3523	118000***	−3855.1242***	0.0553
COMP	0.0006	0.1282	−0.2263	31.4330	104000***	−3868.2047***	0.1013
MED	0.0003	0.1292	0.1001	31.7372	106000***	−3913.2531***	0.1030
CI	0.0005	0.1160	0.1323	29.6704	91300***	−3732.2221***	0.0914
CB	0.0010	0.1252	−0.0503	44.1953	218000***	−3695.7708***	0.1140
NBF	0.0012	0.1521	0.4212	38.3191	160000***	−3657.7346***	0.1181
WA	0.0008	0.1311	0.0994	40.2781	180000***	−3643.3308***	0.1150

Notes: PP are test statistics to test the null hypotheses of unit root, while KPSS are test statistics to test the null hypotheses of no unit root. *, **, *** denotes statistical significance at the 10%, 5% and 1% level respectively. PP tests and KPSS tests show that all 26 series of industry returns are strictly stationary.

each industry at time t, respectively. For the SVAR model applied to identify the monthly exogenous oil price shocks later on, we define the first-order logarithmic difference of monthly Brent crude oil spot price as percentage changes of real oil price. The monthly Brent crude oil spot price and the global crude oil production data can be obtained from the official website of U.S. Energy Information Administration. Derived from Bulk Dry Cargo Shipping Rates for measuring the intensity of global economic activities in the SVAR model, Kilian Index (Kilian, 2009; Kilian & Zhou, 2018) can be obtained from Professor Lutz Kilian's personal homepage. Daily and monthly closing stock prices for 26 industries as well as the Wind All China Index can be obtained from the WIND database. The daily time series sample ranges from May 10th, 2007 to June 5th, 2020, while the monthly sample period ranges from February 2001 to May 2020.

Table 1 displays the corresponding codes and IDs for the Shenwan Hongyuan Securities First Level Industry Index for 26 industries while Table 2 provides the descriptive statistics results for the daily data sample and Table 3 for the monthly data sample. The key requirement for using the PCQ method is that series of relevant variables follow a stationary stochastic process, which is confirmed by the results of PP test (Phillips & Perron, 1988) and KPSS test (Shin & Schmidt, 1992), as presented in Table 2.

3.2. *Methodology*

3.2.1. *Partial cross-quantilogram*

In this paper, we mainly focus on whether the financial sectoral linkage may serve as a potential diffusion channel for oil volatility shocks. To capture such interconnectedness of 26 industries in China's stock market, we examine the directional quantile dependence between the daily series of 26 industry returns by applying the partial cross-quantilogram model (PCQ) of Han et al. (2016). The cross-quantilogram (CQ) of Han et al. (2016) provides a correlation statistic of quantile hit processes, which examines the directional dependence between any quantile ranges of two industry returns rather than just at the median. Consequently, it enables us to focus on the fat-tail feature of asset returns (Cont, 2001), and to further investigate whether the network diffusion of oil price shocks may display certain heterogeneous patterns through the sectoral linkage under various market conditions (i.e. different quantile levels). Moreover, as an extended version of the CQ model, the PCQ approach enables us to control the effects of common behavior factors that might jeopardize the effectiveness of causality identification as suggested by Billio et al. (2012) and later by Bonaccolto et al. (2019). Assume $\{x_{it}, t \in \mathbf{Z}\}, i = 1, 2$ to be the two strictly stationary time series(i.e. the daily stock returns for different industries). As $F_i(\cdot)$ denotes the distribution function of x_{it} with density function $f_i(\cdot)$, we define the quantile function of the time series x_{it} as $q_i(\alpha_i) = inf\{\nu : F_i(\nu) \geq \alpha_i\}$, $\alpha_i \in (0,\ 1)$ and $\widetilde{\alpha}$ as the range of quantiles we are interested in, where $\widetilde{\alpha} \equiv \widetilde{\alpha}_1 \times \widetilde{\alpha}_2$, $\widetilde{\alpha}_i = [\underline{\alpha}_i, \overline{\alpha}_i]$, $0 < \underline{\alpha}_i < \overline{\alpha}_i < 1$. The

Table 3
Descriptive statistics results for the monthly data sample.

	Mean	Standard deviation	Skewness	Kurtosis	Jarque-Bera	PP	KPSS
CH	0.0004	0.0881	−0.4543	4.3953	26.9131***	−229.4316***	0.0723
ST	−0.0014	0.0974	−0.5280	5.2162	58.5030***	−245.8135***	0.0841
NM	0.0004	0.1111	−0.3723	4.4291	25.2119***	−225.8427***	0.0862
CM	0.0033	0.0984	−0.1492	4.8480	34.0403***	−239.0710***	0.0901
AO	−0.0009	0.0902	0.2671	4.3064	19.3205***	−242.1942***	0.1233
EE	0.0038	0.0913	−0.1384	4.1070	12.6420***	−224.0647***	0.1142
ME	0.0022	0.0951	−0.4340	4.6313	33.1137***	−235.1833***	0.0954
DEF	0.0028	0.1071	0.0784	4.7941	31.4715***	−218.2627***	0.0900
AU	0.0022	0.0960	−0.4970	4.6652	36.5203***	−218.5311***	0.0794
HA	0.0062	0.0872	−0.2651	3.8570	9.8631***	−224.0724***	0.2061
TA	−0.0015	0.0951	0.0900	5.3651	54.6233***	−225.5034***	0.0992
LIM	−0.0004	0.0932	−0.4272	5.1340	51.2727***	−207.7832***	0.1063
COM	0.0015	0.0890	−0.1071	4.5761	24.5544***	−208.2322***	0.1180
AG	0.0014	0.0940	−0.2693	3.9653	11.8618***	−233.1913***	0.2151
FB	0.0090	0.0803	−0.3742	3.8941	13.2030***	−235.2826***	0.1640
LI	0.0048	0.0942	−0.4593	4.6650	35.0946***	−225.7934***	0.1254
HC	0.0061	0.0840	−0.1620	4.3304	18.2018***	−224.5437***	0.1744
UT	−0.0011	0.0792	−0.0483	5.2202	47.9541***	−249.7709***	0.0820
TR	−0.0004	0.0834	−0.3824	5.3871	61.0035***	−235.6738***	0.0732
RE	0.0018	0.0952	0.0091	4.1470	12.7732***	−230.5527***	0.0964
EL	0.0022	0.1010	−0.2994	4.0354	13.8646***	−220.0849***	0.1910
COMP	0.0046	0.0994	−0.1612	4.1571	14.0129***	−213.8308***	0.1531
MED	0.0015	0.0991	−0.1583	3.5170	3.5635	−247.4203***	0.0803
CI	0.0004	0.0882	−0.3554	4.5502	28.2245***	−242.1031***	0.1002
CB	0.0034	0.0854	0.0870	4.9170	35.9725***	−211.0111***	0.0694
NBF	0.0027	0.1182	0.1494	4.5603	24.4910***	−230.5923***	0.0672
SVAR Model							
KI	0.1066	0.7463	0.8234	4.0092	10.2272***	−12.1415	0.7333**
$\Delta prod$	0.0002	0.0133	−6.9481	83.1714	63700***	237.8015***	0.2792
Δrop	−0.0020	0.1040	−1.2132	10.0561	535.8444***	−164.0336***	0.2361
MOS	−0.0003	0.0092	−0.3820	7.4882	199.5048***	−224.7521***	0.2011

Notes: PP are test statistics to test the null hypotheses of unit root, while KPSS are test statistics to test the null hypotheses of no unit root. *, **, *** denotes statistical significance at the 10%, 5% and 1% level respectively. For the SVAR model to obtain the exogenous oil price shocks, $\Delta prod$ denotes the percentage change in global crude oil production. *KI* stands for Kilian Index which measures the intensity of actual global economic activity and thus changes in global aggregate demand. Δrop represents the percentage change of real crude oil price. *MOS* is the monthly exogenous oil price shocks identified from the SVAR procedure (Kilian, 2009).

PCQ model measures the quantile dependence between two events $\{x_{1,t} \leq q_{1,t}(\alpha_1)\}$ and $\{x_{2,t-k} \leq q_{2,t-k}(\alpha_2)\}$, controlling for intermediate events between t and $t-k$ represented by $\mathbf{z}_t \equiv [\psi_{\alpha_3}(x_{3t} - q_{3,t}(\alpha_3)), \ldots, \psi_{\alpha_l}(x_{lt} - q_{l,t}(\alpha_l))]^\top$, where $l = 3, \ldots, n$ and $\psi_a(u) \equiv 1[u < 0] - a$. The correlation matrix of the quantile hit processes and its inverse version therefore are $R_{\overline{\alpha}} = E[h_t(\overline{\alpha})h_t(\overline{\alpha})^\top]$ and $P_{\overline{\alpha}} = R_{\overline{\alpha}}{}^{-1}$, respectively, where $h_t(\overline{\alpha}) = [\psi_{\alpha 1}(y_{1t} - q_{1,t}(\alpha_1)), \ldots, \psi_{\alpha l}(y_{lt} - q_{l,t}(\alpha_l))]^\top$ stands for the quantile hit process. The PCQ conditional on $\mathbf{z}_t$ therefore is defined as:

$$\rho_{\overline{\alpha}|\mathbf{z}} = -\frac{p_{\overline{\alpha},12}}{\sqrt{p_{\overline{\alpha},11} p_{\overline{\alpha},22}}} \tag{1}$$

where $p_{\overline{\alpha},ij}$ represents the (i,j) element of $P_{\overline{\alpha}}$, with the lag order k suppressed without loss of generality (Han et al., 2016). And the corresponding sample analogue of the PCQ can be presented as:

$$\widehat{\rho}_{\overline{\alpha}|\mathbf{z}} = -\frac{\widehat{p}_{\overline{\alpha},12}}{\sqrt{\widehat{p}_{\overline{\alpha},11} \widehat{p}_{\overline{\alpha},22}}} \tag{2}$$

after constructing the estimator for the correlation matrix as well as its inverse version as $\widehat{R}_{\overline{\alpha}} = \frac{1}{T} \sum_{t=1}^{T} \widehat{h}_t(\overline{\alpha}) \widehat{h}_t(\overline{\alpha})^\top$ and $\widehat{P}_{\overline{\alpha}} = \widehat{R}_{\overline{\alpha}}{}^{-1}$ through replacing $h_t(\overline{\alpha})$ by its sample analogues $\widehat{h}_t(\overline{\alpha})$.

By construction, $\widehat{\rho}_{\overline{\alpha}|\mathbf{z}} \in [-1, +1]$, where $\widehat{\rho}_{\overline{\alpha}|\mathbf{z}} = 0$, indicates the two unrelated quantile hit processes and $\widehat{\rho}_{\overline{\alpha}|\mathbf{z}} \neq 0$ suggests the contrary for a given lag k. To be specific, if the PCQ test statistics $\widehat{\rho}^{\,i,j}_{\overline{\alpha}|\mathbf{z}}$ is significantly distinct from 0, series i can significantly predict series j at the α quantile level controlling the effect of other variables represented by $\mathbf{z}$. To assess whether $\widehat{\rho}_{\overline{\alpha}|\mathbf{z}}$ is statistically distinct from 0, we use $100[\%] \times \left(1 - \frac{\lambda}{N-1}\right)$ confidence intervals to avoid an excessive overall type I error (Han et al., 2016; Lyócsa et al., 2019), where $\lambda = 0.05$ is the significance level with N industries. We utilize the stationary bootstrap method suggested by Politis and Romano

(1994) for the construction of confidence intervals and estimate the optimal block using the procedure of Politis and White (2004) as well as Patton et al. (2009), as suggested by Han et al. (2016).

3.2.2. Network formation

The network is essentially a collection of interconnected vertexes by which a financial system can be characterized (Billio et al., 2012; Bonaccolto et al., 2019). There are basically two types of network. One is the physical network that captures the actual linkage among different entities such as input-output relationships, ownership relationships or interconnections based on bilateral contracts. The other depicts the statistic correlation between sequences of their equity returns in the Granger causality sense. We here specify the statistically estimated network based on the PCQ approach to capture the sectoral linkage out of following considerations. Firstly, compared with the network based on actual relationships, the statistically estimated network may provide a more comprehensive picture of the latent sectoral linkage that may otherwise be hidden. To elaborate, stock returns of two industries might be significantly correlated with them both sensitive to similar risk factors or due to their similar development trends, which might not be captured by physical networks if the two industries don't directly link to each other. (Deev & Lyócsa, 2020; Wang et al., 2017). Secondly, networks that depict the directional dependence between industry returns at different quantiles make it possible for us to emphasize the fat-tail feature of the stock market and to see how such linkage might evolve under various market states. Most importantly, as we aim to investigate whether the sectoral linkage may be an important mechanism for oil volatility diffusion throughout the stock market, it enables us to further examine the potential heterogeneous characteristic of the oil volatility diffusion through the sectoral linkage under different market conditions.

The vertexes of the network represent financial assets, and the shock on an individual asset could be transmitted to those connected to it. Specifically, given a certain lag order $k = p$, a quantile causality based financial network $G_{p,\alpha} = (V, E)$ can be regarded as a collection of vertexes V and their edges E, where each element of E represents the interconnection between financial assets V. A financial network may also be represented by an adjacency matrix W. We start from a binary matrix in which each element w_{ij} can only take two values, 1 or 0. When w_{ij} is 1, vertex j is associated with vertex i indicating that financial asset i has an impact on financial asset j. Otherwise, there is no impact. We do not consider self-influence here with the diagonal element of W being 0. At the same time, the adjacency matrix W is directed, that is, $w_{ij} \neq w_{ji}$, which means the correlation between vertexes may be asymmetric. The significant influence of financial asset j on financial asset i does not mean that the reverse causality is also true. Such asymmetry could be appropriately dealt with by the PCQ model which can detect the directional predictability between two time series. Furthermore, the value of w_{ij} depends on whether the returns of financial asset i can significantly predict those of financial asset j at a certain quantile level at a given lag order k, that is, whether the PCQ test statistics $\widehat{\rho}^{i,j}_{\overline{\alpha}|\mathbf{z}}$ is significantly distinct from 0. Particularly, the value of w_{ij} is determined by:

$$w_{ij} = \begin{cases} 1 \text{ if } i \text{ can predict } j \left(i.e.\ \widehat{\rho}^{i,j}_{\overline{\alpha}\,\mathbf{z}} \neq 0 \right) \\ 0 \text{ if } i \text{ cannot predict } j \left(i.e.\ \widehat{\rho}^{i,j}_{\overline{\alpha}\,\mathbf{z}} = 0 \right) \end{cases} \tag{3}$$

It's noteworthy that in the empirical application of specifying the value of w_{ij}, and therefore the existence of the financial interconnection between industries, only very a few researchers address the lag order specification with which we should detect the statistical dependence between asset returns. For example, by detecting the quantile dependence at 3, 6 and 9 lags based on the seasonal characteristic of the tourism sector, Lyócsa et al. (2019) construct the CQ network to depict the interconnection of international tourism demand in European countries. Bonaccolto et al. (2019) specify lags equaling to 1, 5 and 10, respectively, while Deev and Lyócsa (2020) focus on the contemporaneous dependence (i.e. $k = 0$) of 205 financial institutions in Europe, but neither of them explains the specific criteria or the economic theory foundation of such lag order specifications. In this paper, to depict the financial linkage between industries with the corresponding networks, we examine the significance of the PCQ test statistics $\widehat{\rho}^{i,j}_{\overline{\alpha}|\mathbf{z}}$ between industry returns at one lag order as well as within 5 lags, respectively. The latter specification means that it is sufficient to confirm the financial interconnection with the quantile dependence being significant at any lag order k with $k \leq 5$. Such lag order specification is out of the consideration that returns of industries may correlate to each other at more than one lag and it may also take a relatively short period (i.e. within 5 traded days) for oil price shocks to impact relevant industries and further affect other industries through their network interconnectedness.

Further, the application of the PCQ model not only enables us to better capture the directional predictability between two industry returns under different market conditions (i.e. bearish, normal and bullish), but also allows us to emphasize the fat-tail characteristic and thus the risk dimension of financial asset returns (Cont, 2001). We specify the quantile level at 0.05, 0.10, 0.50, 0.90 and 0.95, respectively and let $\alpha_i = \alpha_j$ for each quantile level (Han et al., 2016), to examine if the financial interconnectedness of industries, and more importantly, the corresponding pattern of oil volatility risk diffusion, may vary under different market conditions.

3.2.3. Identification of the exogenous oil price shocks: SVAR modeling

Before we proceed, it should be noted that the strict exogeneity assumption of oil prices might fail to hold as the stock market might reversely have an impact on the oil market (Barsky & Kilian, 2004). Besides, oil prices and stock returns may be driven by the same economic factors (Kilian, 2009). For example, an increase in aggregate demand may simultaneously push up oil prices and stock prices. In order to obtain oil price shocks that are not confounded by reverse causality or common trend factors, a SVAR model is applied to

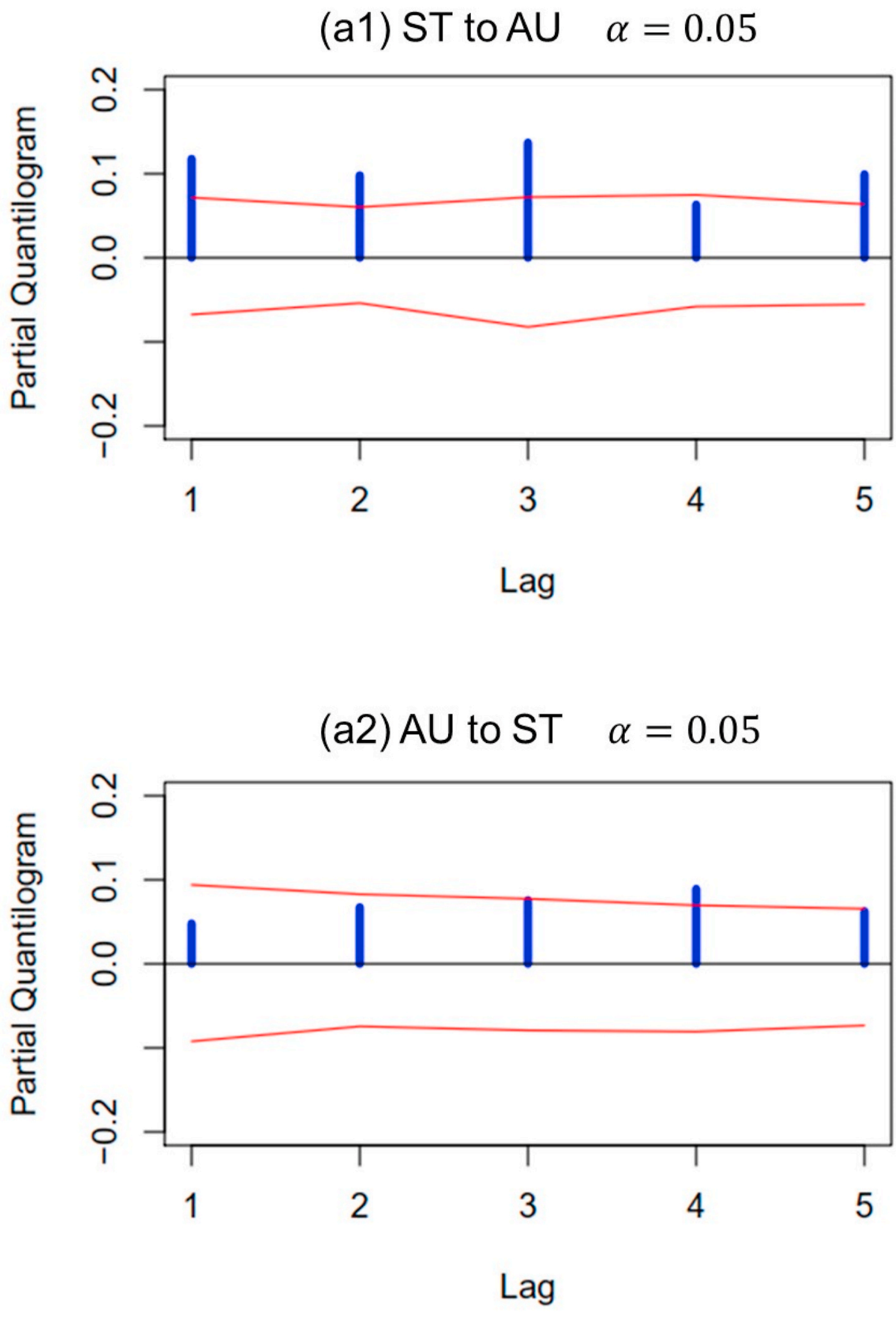

Fig. 1. The estimated partial cross-quantilogram (PCQ) results at 0.05 quantile level after controlling the returns of Wind All China Index. The result in (1a) examines the directional predictability from steel industry returns to automobile industry returns at given lags, while (1b) detects the directional predictability from automobile industry returns to steel industry returns. The blue bar graphs represent sample PCQs and the area between the two red lines are the 95% bootstrap confidence intervals constructed by 1000 bootstrapped replications. The blue bar exceeding the area between two red lines indicates significant directional predictability at corresponding lags. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

decompose the sources of oil price fluctuations. Kilian (2009) proposes a SVAR model to decompose oil price fluctuations into shocks from insufficient actual oil production, shocks from shifts in global demand, and shocks caused by changes in the preventive crude oil demand. The preventive crude oil demand reflects people's concerns about the increasing likelihood of oil supply shortage in the future. Shocks due to the changes in such preventive oil demand are regarded as the exogenous oil price shocks excluding the effects of oil production and global economic activities. Therefore, in addition to the daily OVX, the SVAR model of Kilian (2009) is also applied

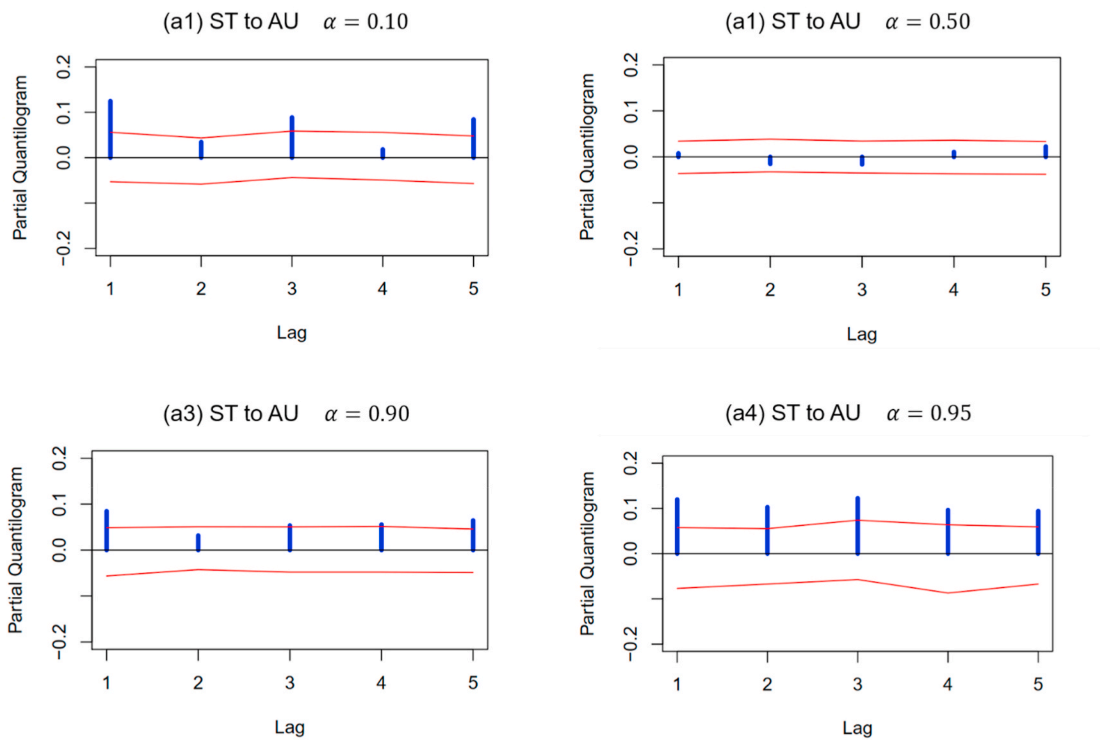

Fig. 2. The estimated partial cross-quantilogram (PCQ) results at different quantile levels (0.10, 0.50, 0.90, 0.95) after controlling the returns of Wind All China Index. The result in (2a) examines the directional predictability from steel industry returns to automobile industry returns at 0.10 quantile level, while (2b), (2c) and (2d) detect the directional predictability from steel industry returns to automobile industry returns at 0.50, 0.90 and 0.95, respectively. The blue bar graphs represent sample PCQs and the area between the two red lines are the 95% bootstrap confidence intervals constructed by 1000 bootstrapped replications. The blue bar exceeding the area between two red lines indicates significant directional predictability at corresponding lags. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

to identify the exogenous oil price shocks.

The three key variables of SVAR model include the percentage change in global crude oil production $\Delta prod_t$, followed by Kilian index KI_t representing changes in global aggregate demand, and followed by the percentage change of real crude oil price Δrop_t. Let $\mathbf{R}_t$ be the vector of these three variables, $\mathbf{R}_t = (\Delta prod_t \quad KI_t \quad \Delta rop_t)^T$, then the SVAR model can be expressed as:

$$A_0\mathbf{R}_t = \alpha + \sum_{i=1}^{p} A_i\mathbf{R}_{t-i} + \boldsymbol{\mu}_t \tag{4}$$

where $\boldsymbol{\mu}_t$ is assumed to be a vector of structural shocks that is not mutually or sequentially correlated. The number of lag terms i is determined by Akaike Information Criterion (AIC). If $\mathbf{e}_t$ represents a vector of reduced VAR residuals, the relationship between the structural impact vector $\boldsymbol{\mu}_t$ and the VAR residual $\mathbf{e}_t$ can be expressed as $\mathbf{e}_t = A_0^{-1}\boldsymbol{\mu}_t$. Therefore, in order to identify $\boldsymbol{\mu}_t$, we need to impose some constraints on the structure of A_0^{-1}. We assume a lower triangular structure on A_0^{-1} (Kilian & Park, 2009; Sim & Zhou, 2015), and thus the relationship between the reduced VAR error vector ($\mathbf{e}_t$) and the structural impact vector ($\boldsymbol{\mu}_t$) can be expressed as:

$$\mathbf{e}_t = \begin{pmatrix} e_{1t} \\ e_{2t} \\ e_{3t} \end{pmatrix} = \begin{bmatrix} a_{11} & 0 & 0 \\ a_{21} & a_{22} & 0 \\ a_{31} & a_{32} & a_{33} \end{bmatrix}^{-1} \begin{pmatrix} \mu_{1t} \\ \mu_{2t} \\ \mu_{3t} \end{pmatrix}. \tag{5}$$

Among them, μ_{1t} μ_{2t} and μ_{3t} are the structural shocks to global oil production, global economic activities and actual oil prices, respectively. The lower triangular structure of A_0 comes from three identification constraints which allow us to use μ_{3t} as the impact of preventive oil demand changes on the actual oil price (Kilian, 2009). The first identification constraint assumption is that the supply of crude oil is inelastic within a month since short-term adjustments to oil production may be highly costly. Therefore, global oil production will not be affected by the impact of actual global activities and oil prices within one month. The second identification constraint hypothesis is that the actual global economic activity responds relatively slowly to changes in oil prices, and therefore will not respond to changes in actual oil prices driven by demand shocks within one month. In this case, after the global oil production

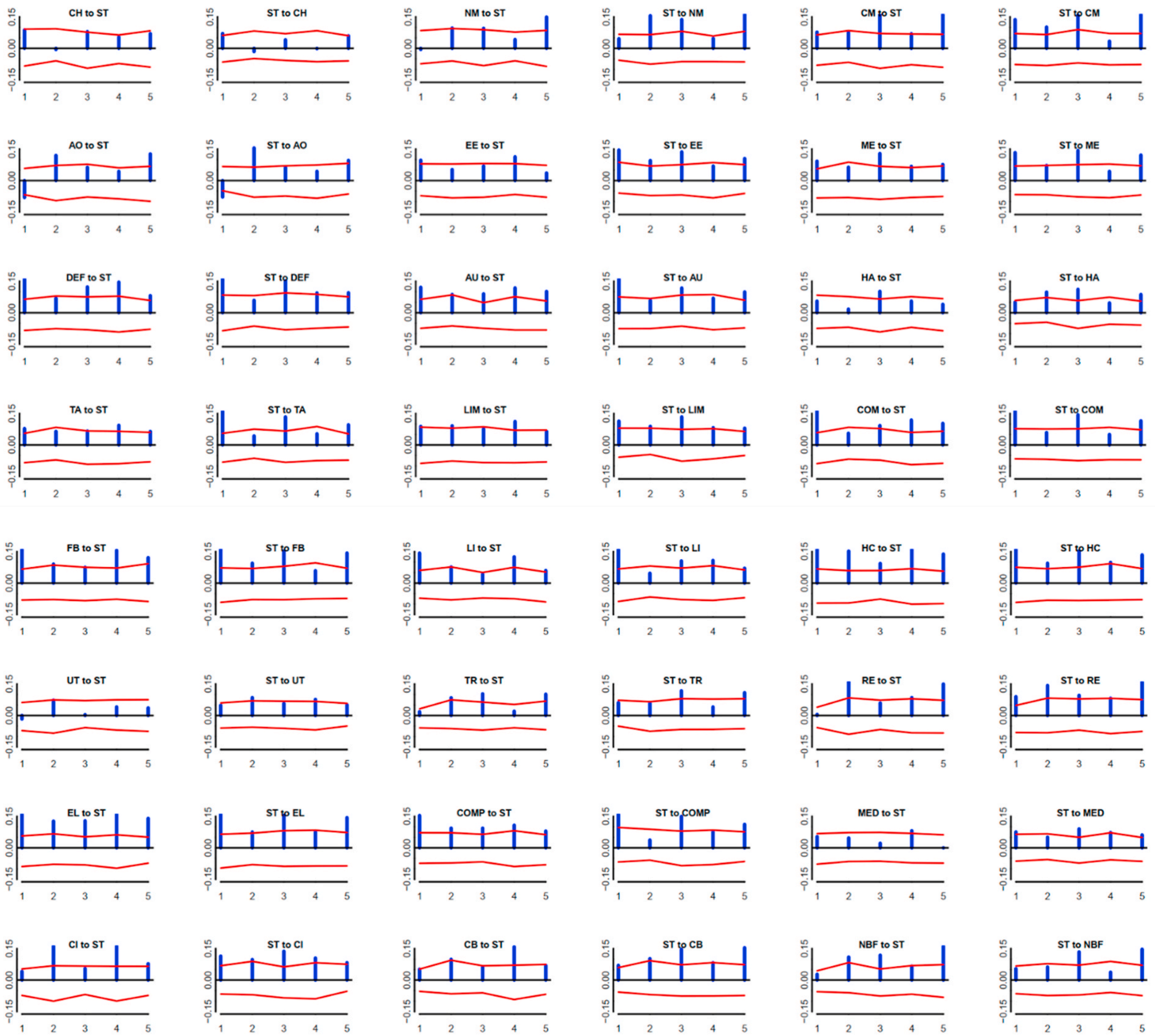

Fig. 3a. The estimated partial cross-quantilogram (PCQ) results for the directional predictability between returns of steel industry and returns of the rest 24 industries in both directions fixed at 0.05 quantile levels, after controlling the returns of Wind All China Index. The blue bar graphs represent sample PCQs and the area between two red lines are the 95% bootstrap confidence intervals constructed by 1000 bootstrapped replications. The blue bar exceeding the area between the two red lines indicates significant directional predictability at corresponding lags. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

shock (μ_{1t}) is decomposed and identified, the simplified form error e_{2t} can be used to identify the structural shock (μ_{2t}) to the actual global economic activities. The final constraint is that the preventive demand-driven shock to the actual oil price (μ_{3t}), as the main variable concerned, is neither derived from the shock of oil production nor from the shock to actual global economic activities. This assumption implies that the oil price shock driven by preventive demand can be obtained by eliminating the crude oil supply shock (μ_{1t}) and the global demand shock (μ_{2t}) from the simplified form error e_{3t}. With the introduction of equation (5) in SVAR, we are able to exclude the information about the impact of global aggregate demand fluctuations on oil prices, which enables us to avoid the endogeneity problem. Along with the control for oil production shocks, the structural shock μ_{3t} can represent the oil price changes that are not affected by oil production or global economic cycles but derived from changes in the preventive demand, which is referred as the exogenous demand-driven oil price shock by Kilian (2009).

3.2.4. Spatial autoregressive model and shock decomposition

With the application of the SAR model (Elhorst, 2003; LeSage & Pace, 2009) to decompose the overall stock market reaction to oil price shocks into a direct effect, and indirect effects transmitting through the financial interconnectedness of industries, we further examine how shocks from oil price volatilities may diffuse throughout the financial network. The SAR model is given by:

$$x_t = \beta os_t + \rho W' x_t + \varepsilon_t, \tag{6}$$

Table 4
The network density which captures the popularity of the financial interconnectedness with different specifications.

	$\alpha = 0.05$	$\alpha = 0.10$	$\alpha = 0.50$	$\alpha = 0.90$	$\alpha = 0.95$	Ave.
$k = 1$	0.4123	0.2908	0.0862	0.3585	0.5462	0.3388
$k \leq 5$	0.9507	0.9000	0.3724	0.9692	0.9338	0.8252
Difference	0.5384	0.6092	0.2862	0.6107	0.3876	0.4864

which indicates the data-generating process:

$$\begin{aligned} & x_t = (II_n - \rho W')^{-1}\beta os_t + (II_n - \rho W')^{-1}\varepsilon_t \\ & \varepsilon_t \overset{N}{\sim} (0, \sigma^2 II_n) \end{aligned}, \tag{7}$$

where x_t represents a vector of n industry stock returns, $os_t$is a vector of oil volatility shocks, and W' is a row-normalized version (Elhorst, 2003) of the previously estimated directed spatial matrix by applying the PCQ approach. To better comprehend the economic implication of the coefficients of the SAR model, we draw on the practice of Ozdagli and Weber (2017) by using equations (8) and (9):

$$O(W') = (II_n - \rho W')^{-1} = II_n + \rho W' + \rho^2 (W')^2 + \ldots, \tag{8}$$

$$SL(W') = O(W')\beta, \tag{9}$$

to rewrite equation (7) into equation (10):

$$x_t = SL(W')os_t + O(W')\varepsilon_t, \tag{10}$$

and consider a simple example of 3 industries and focus on industry 2 as presented by equation (11) and equation (12):

$$\begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix} = \begin{pmatrix} SL(W')_{11} & SL(W')_{12} & SL(W')_{13} \\ SL(W')_{21} & SL(W')_{22} & SL(W')_{23} \\ SL(W')_{31} & SL(W')_{32} & SL(W')_{33} \end{pmatrix} \times \begin{pmatrix} os \\ os \\ os \end{pmatrix} + O(W')\varepsilon, \tag{11}$$

$$x_2 = SL(W')_{2,1}os + SL(W')_{2,2}os + SL(W')_{2,3}os + O(W')_2\varepsilon, \tag{12}$$

where $SL(W')_{ij}$ denotes the ij^{th} element of the matrix $SL(W')$ and $O(W')_i$ denotes the i^{th} row of matrix $O(W')$.

It can be seen from equation (12) that the response of industry 2's return x_2 to oil price fluctuation os depends on the response of other industries to the same shock. In particular, $SL(W')_{2,2}$is the direct impact of oil price fluctuations on the returns of industry 2. $SL(W')_{1,2}$ shows that with industry 1 is the only industry directly affected by the shock, industry 2 is affected by oil price fluctuations due to its association with industry 1, which can be measured as the spillover or indirect impact of oil volatility on industry 2. Similarly, $SL(W')_{2,3}$ is used to measure the indirect impact of oil price fluctuations on industry 2 due to its connection to industry 3. The aggregate impact of oil price volatility on industry returns depends on the row-normalized version of the matrix W constructed by the PCQ model to describe the causal relationship between industry returns at different quantiles. The parameter β represents the strength of direct exposures to oil prices shocks. The parameter ρ, together with β, determines the strength of the indirect spillover effect through the network linkages. The diagonal elements of $SL(W')$ stand for the direct impact of oil volatility shocks on industry returns, while the non-diagonal elements represent indirect impacts transmitting through the financial interconnection. Although some industries may not be directly exposed to oil price shocks, significant indirect effects indicate that they are still influenced due to their linkages with other industries that are directly and/or indirectly affected by oil price volatilities. Therefore, significant indirect effects indicate that oil price shocks may diffuse through the network interconnectedness. Further, in terms of the specific pattern of network diffusion for oil volatility risks, it implies risk contagion effects when direct effects and indirect effects evolve in the same direction and contribute to greater total effects, indicating that shocks from oil price volatilities on industries intensify through the network diffusion. Otherwise, risk absorbing effects are indicated with direct oil price shocks being mitigated and diversified as indirect effects demonstrate the reverse direction. Particularly, we estimate the following empirical form of the SAR model to investigate how oil price shocks might diffuse throughout the financial system:

$$x_t = \beta_0 + \beta_1 \times os_t + \rho \times W' \times x_t + \varepsilon_t, \tag{13}$$

where x_t represents a vector of returns of 26 industries in China's stock market, os_t denotes a vector of oil price shocks measured respectively by the OVX, and the monthly exogenous oil price shocks (MOS) identified from the SVAR procedure (Kilian, 2009).

Fig. 3b. The estimated partial cross-quantilogram (PCQ) results for the directional predictability between returns of steel industry and returns of the rest 24 industries in both directions fixed at 0.10 quantile levels, after controlling the returns of Wind All China Index. The blue bar graphs represent sample PCQs and the area between two red lines are the 95% bootstrap confidence intervals constructed by 1000 bootstrapped replications. The blue bar exceeding the area between the two red lines indicates significant directional predictability at corresponding lags. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

4. Empirical results and discussion

4.1. Empirical results

4.1.1. Partial cross-quantilogram causality analysis

The PCQ approach is applied to detect the directional predictability and thus the financial interconnectedness between industries. To have a better understanding of the PCQ approach that detects the directional predictability between two series at given quantiles, we start from the result of steel industry returns (ST, ID = 2) and automobile industry returns (AU, ID = 9) as a simple example. Fig. 1 provides the estimated partial cross-quantilogram (PCQ) $\widehat{\rho}^{i,j}_{\overline{\alpha}|z}$ results at 0.05 quantile level after controlling the returns of Wind All China Index. The results in (1a) show the directional predictability from steel industry returns to automobile industry returns at given lag orders. And the results in (1b) display the directional predictability from automobile industry returns to steel industry returns. The blue bar graphs represent the sample PCQs and the area between the two red lines are the 95% bootstrap confidence intervals constructed by 1000 bootstrapped replications (Han et al., 2016). The blue bar exceeding the area between the two red lines indicates the significant directional predictability at corresponding lags. On the one hand, considering the case with a fixed lag order mode $k = 1$, significant quantile dependences are indicated from stock returns of steel industry to those of automobile industry, which means the

Fig. 3c. The estimated partial cross-quantilogram (PCQ) results for the directional predictability between returns of steel industry and returns of the rest 24 industries in both directions fixed at 0.50 quantile levels, after controlling the returns of Wind All China Index. The blue bar graphs represent sample PCQs and the area between two red lines are the 95% bootstrap confidence intervals constructed by 1000 bootstrapped replications. The blue bar exceeding the area between the two red lines indicates significant directional predictability at corresponding lags. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

corresponding entry of the adjacent matrix, w_{29}, equal to 1. However, an asymmetric effect emerges as the reverse predictability does not hold as the PCQ estimate from automobile industry returns to steel industry returns at one lag is not significantly distinct from 0, which means $w_{92} = 0$. Therefore, the corresponding adjacent matrix is directed as the quantile causality may be asymmetric. On the other hand, however, when it comes to a more flexible lag order mode (i.e. $k \leq 5$), the significant quantile dependence is suggested in both directions as the PCQ estimate from AU to ST is significant at $k = 4$, which indicates $w_{29} = w_{92} = 1$ in this case.

Moreover, the PCQ approach excels the traditional Granger test as it can detect the directional predictability at the quantile levels of interest instead of only focusing on the mean dependence. Fig. 2 provides the results of PCQ estimates at different quantile levels (0.10, 0.50, 0.90, 0.95) after controlling the returns of Wind All China Index. Results in (2b) show the directional predictability from steel industry returns to automobile industry returns at 0.50 quantile level, while results in (2a), (2c) and (2d) demonstrate the directional predictability from steel industry returns to automobile industry returns at 0.10, 0.90 and 0.95 quantiles, respectively. Along with the result from Fig. 1, it indicates that returns of steel industry can significantly predict those of automobile industry under

Fig. 3d. The estimated partial cross-quantilogram (PCQ) results for the directional predictability between returns of steel industry and returns of the rest 24 industries in both directions fixed at 0.90 quantile levels, after controlling the returns of Wind All China Index. The blue bar graphs represent sample PCQs and the area between two red lines are the 95% bootstrap confidence intervals constructed by 1000 bootstrapped replications. The blue bar exceeding the area between the two red lines indicates significant directional predictability at corresponding lags. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

extreme market conditions (i.e. 0.05/0.10 quantile, bearish; and 0.90/0.95 quantile, bullish), while little predictability is confirmed at any lags under the normal market condition (i.e. 0.50 quantile). Furthermore, Fig. 3(a)-3(e) display the results for the estimated PCQs to detect the directional predictability between returns of steel industry and those of the rest 24 industries in both directions across different quantiles.[1] In general, the results are essentially similar to the case of the directional predictability between returns of steel industry and automobile industry. Firstly, steel industry shows significant quantile correlations with considerable industries not at the first lag, but at more than one lag orders. Secondly, there is very little evidence of directional predictability between steel industry and the rest 24 industries at any lags in both directions under the normal market condition (i.e. 0.50 quantile), while steel industry shows much more connections with other industries at extreme quantiles. It suggests that industries may link to each other at more than one lag order and such financial interconnectedness is much more prevailing under extreme market conditions. As a result, the corresponding network depicting such statistical linkage may also vary across different quantiles with different lag order specifications.

[1] The full results for PCQ estimates across all quantiles for 26 industries are suppressed here to save space and are available upon request. Generally, the results are essentially similar to the case of the directional predictability between returns of steel industry and returns of the other 25 industries.

Fig. 3e. The estimated partial cross-quantilogram (PCQ) results for the directional predictability between returns of steel industry and returns of the rest 24 industries in both directions fixed at 0.95 quantile levels, after controlling the returns of Wind All China Index. The blue bar graphs represent sample PCQs and the area between two red lines are the 95% bootstrap confidence intervals constructed by 1000 bootstrapped replications. The blue bar exceeding the area between the two red lines indicates significant directional predictability at corresponding lags. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

4.1.2. Quantile causality network formation

By examining the directional predictability between returns of 26 industries through the PCQ approach, we may specify the value of each entry w_{ij} for $i, j = 1, 2, \ldots, 26; i \neq j$ with $w_{ii} = 0$. This work enables us to construct the 26×26 spatial matrix W and thus the corresponding quantile causality network that depicts the financial interconnection of 26 industries at given quantiles with different lag order specifications.[2] We first apply the network density measurement proposed by Wasserman and Faust (1994) and later Bonaccolto et al. (2019), to capture the popularity of the financial linkage between industries. The network density represents the actual number of connections between vertexes relative to the maximum number of such connections, which can be defined as $D = \frac{E}{V(V-1)}$, where E denotes the total connections between industries actually captured by the network and V corresponds to the number of industries. Therefore, a higher network density means larger number of linkages between industry returns, indicating that industries are more widely interconnected. And such financial interconnectedness may serve as a potential channel for the oil price shock diffusion.

[2] The results for the spatial matrix W based on the PCQ causality analysis detecting the quantile directional predictability between returns of 26 industries under different specifications are provided in the appendix, as presented in Fig. A1-Fig. A5.

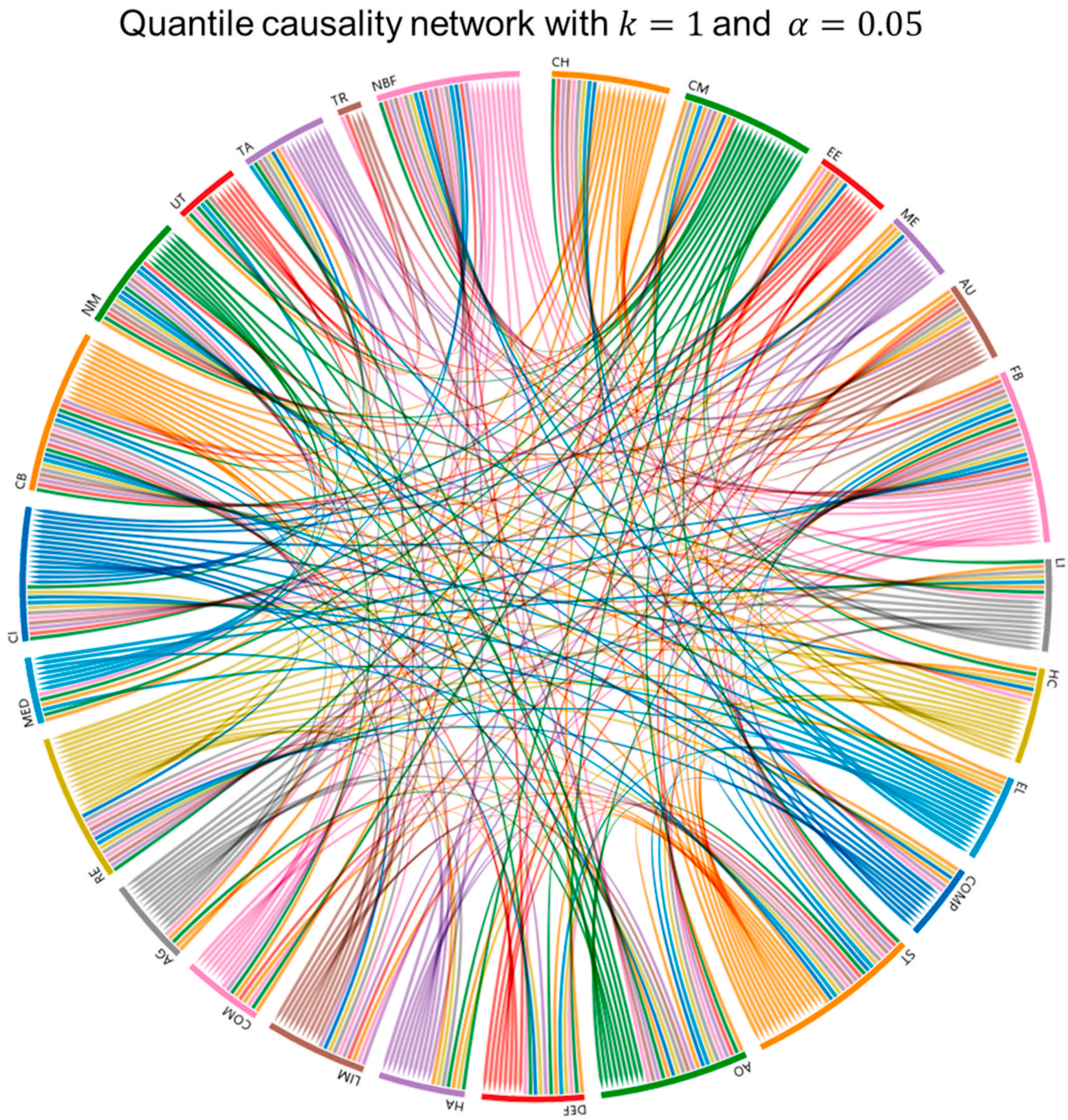

Fig. 4a. The quantile causality network depicting the financial interconnectedness between 26 industries at one lag with the quantile level $\alpha = 0.05$. The edge starting from industry i with an arrow pointing to j represents the significant directional predictability from i to j, and thus the financial interconnectedness with i having an influence on j at one lag at given quantile level $\alpha = 0.05$.

Table 4 reports the network density across different quantiles with different lag order specifications. For networks depicting the financial linkage at a fixed lag order $k = 1$, results show that industry returns most relate to each other at their 0.95 quantile level with the corresponding network density being 0.5462, while such financial interconnection can rarely be observed in the network at 0.50 quantile level as the corresponding network density is only 0.0862. For a relatively flexible lag order constraint ($k \leq 5$), industries are most interconnected at their 0.90 quantile level ($D = 0.9692$), while the network density at 0.50 quantile level ($D = 0.3724$) is again considerably less than that at other extreme quantiles. Overall, it is noteworthy that industries are more widely interconnected under extreme market conditions while the popularity of such financial interconnectedness drops drastically in the mean of their distribution. Moreover, the prominent variation of network density between two lag order modes (average 0.4864) suggests that a fairly large number of industries link to each other at more than 1 lag, and such interconnectedness might remain latent if we only consider the quantile dependence at a fixed lag order $k = 1$.

To provide a more comprehensive understanding of the financial interconnectedness between different industries, Figs. 4(a)–8(b) depict the structure of corresponding networks across different quantiles with different lag order specifications. The edge of a network starting from industry i with an arrow pointing to j represents the significant directional predictability from i to j, and thus the financial interconnectedness with i having an influence on j at given quantiles with corresponding lag order specifications. For example, Fig. 4

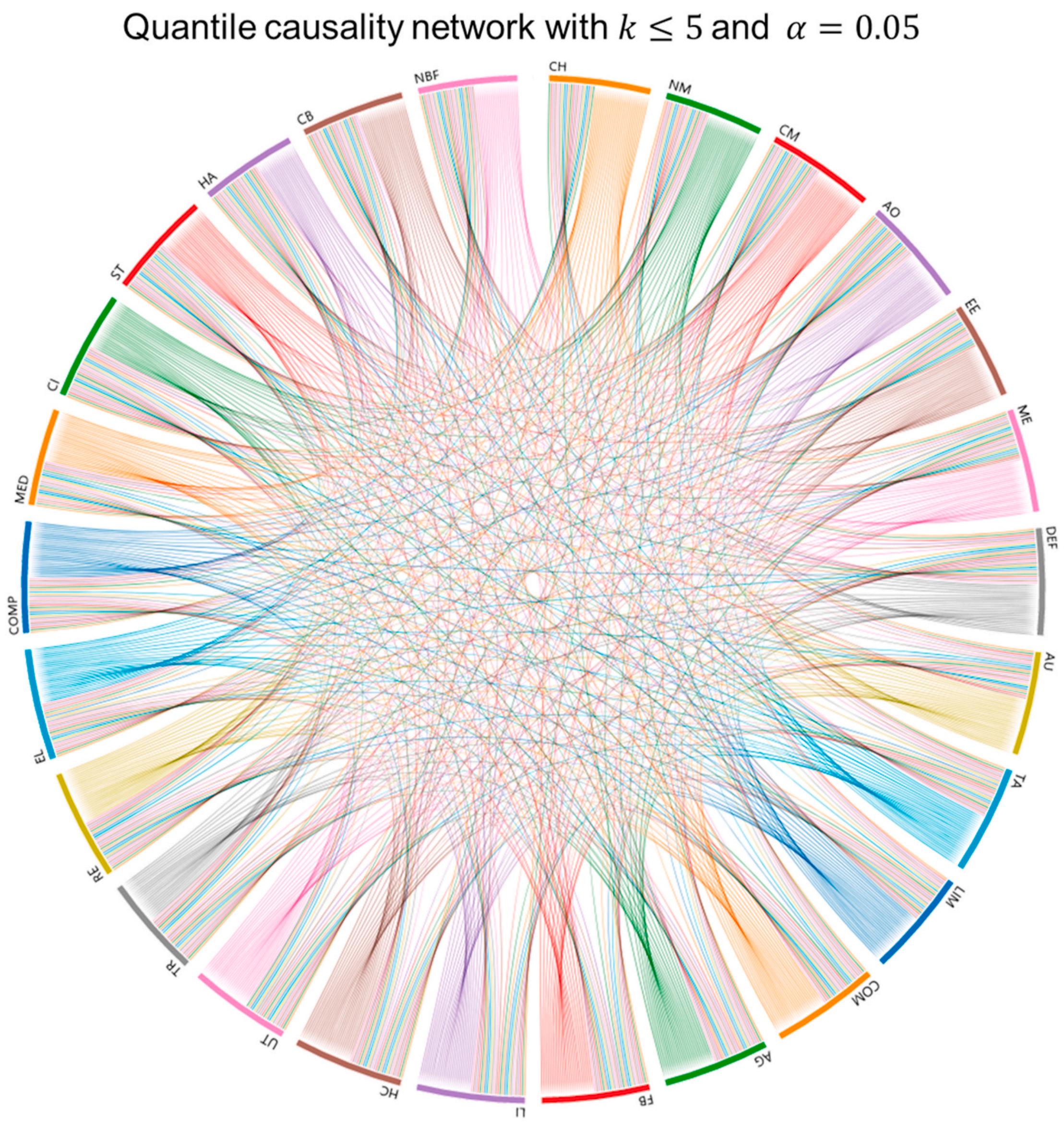

Fig. 4b. The quantile causality network depicting the financial interconnectedness between 26 industries with a more flexible lag mode ($k \leq 5$) at 0.05 quantile. Represented by an edge starting from industry *i* with an arrow pointing to *j*, the significant directional predictability from *i* to *j* (and thus the financial interconnectedness with *i* having an influence on *j*) is sufficiently confirmed as long as the corresponding PCQ estimate is significantly distinct from 0 at any lags within 5 at a given quantile level $\alpha = 0.05$.

(a) captures the financial interconnectedness between 26 industries at the first lag (i.e. $k = 1$), while Fig. 4(b) depicts the sectoral linkage within 5 traded days (i.e. $k \leq 5$) at 0.05 quantile. For starters, networks depicting the financial linkage at 0.50 quantile under both lag order specifications, as shown in Fig. 6(a) and (b), demonstrate considerably lower network density compared with those at extreme quantiles for both lag order modes. Along with the results in Table 4, it suggests that networks only focusing on the mean dependence may fail to capture the whole picture as the financial interconnectedness between industries demonstrates distinct characteristics under various market states. Besides, networks with a relative flexible lag order mode show markedly higher density than those with a fixed one lag order mode, which is again in accordance with the results shown in Table 4. It indicates that industry returns may connect to each other at more than one lag. It is also possible that it may take a relatively short period (i.e. within 5 traded days) for the oil price shock to exert a direct influence on the relevant industries and further affect other industries due to their linkages. Therefore, considering such time lag effect, a relative flexible lag order mode may also be necessary to capture the financial interconnectedness which may serve as a key mechanism of oil price shock diffusion.

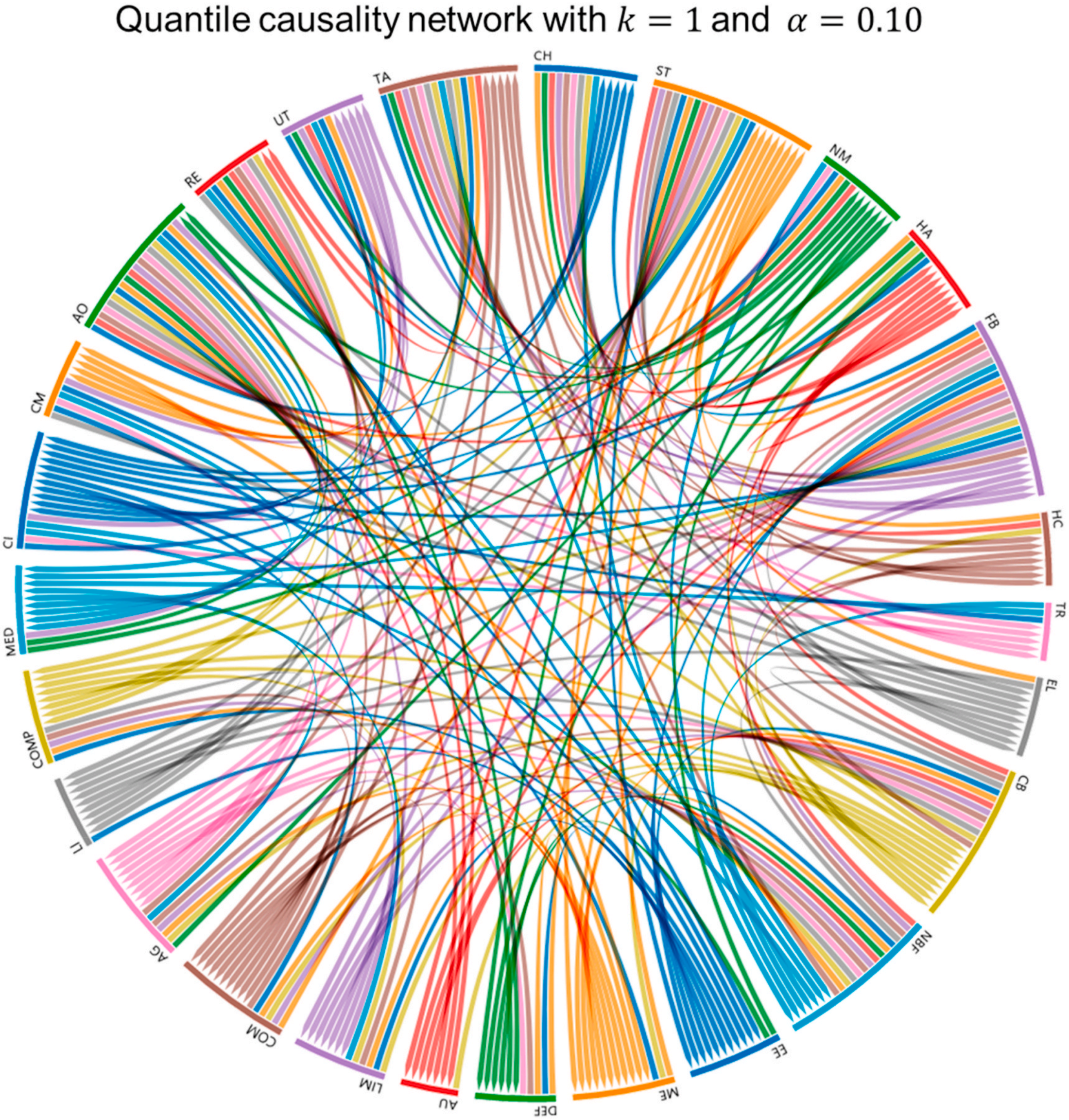

Fig. 5a. The quantile causality network depicting the financial interconnectedness between 26 industries at one lag with the quantile level $\alpha = 0.10$. The edge starting from industry i with an arrow pointing to j represents the significant directional predictability from i to j, and thus the financial interconnectedness with i having an influence on j at one lag at given quantile level $\alpha = 0.10$.

4.1.3. SAR model: oil price shock decomposition and network diffusion

With the quantile causality network and the corresponding adjacent matrix estimated in the previous section, we proceed by empirically estimating the SAR model to decompose the impact of oil price shocks on the returns of 26 industries in China's stock market. Particularly, by examining how indirect effects through the network linkage between industries contribute to aggregate oil price shocks, we investigate whether and in what direction oil price shocks may diffuse throughout the financial network under different market conditions with different lag order specifications.

Table 5 shows the results of the SAR model based on the PCQ networks depicting the sectoral financial interconnectedness at 0.05 quantile (i.e. bearish market condition). The first two columns report the results for the daily oil price shocks measured by OVX while column (3) and column (4) show the results for the monthly oil price shocks identified from the SVAR model. We first focus on the impact of daily oil volatilities on the industry returns. In terms of the network with a fixed lag order $k = 1$ (i.e. we only consider the

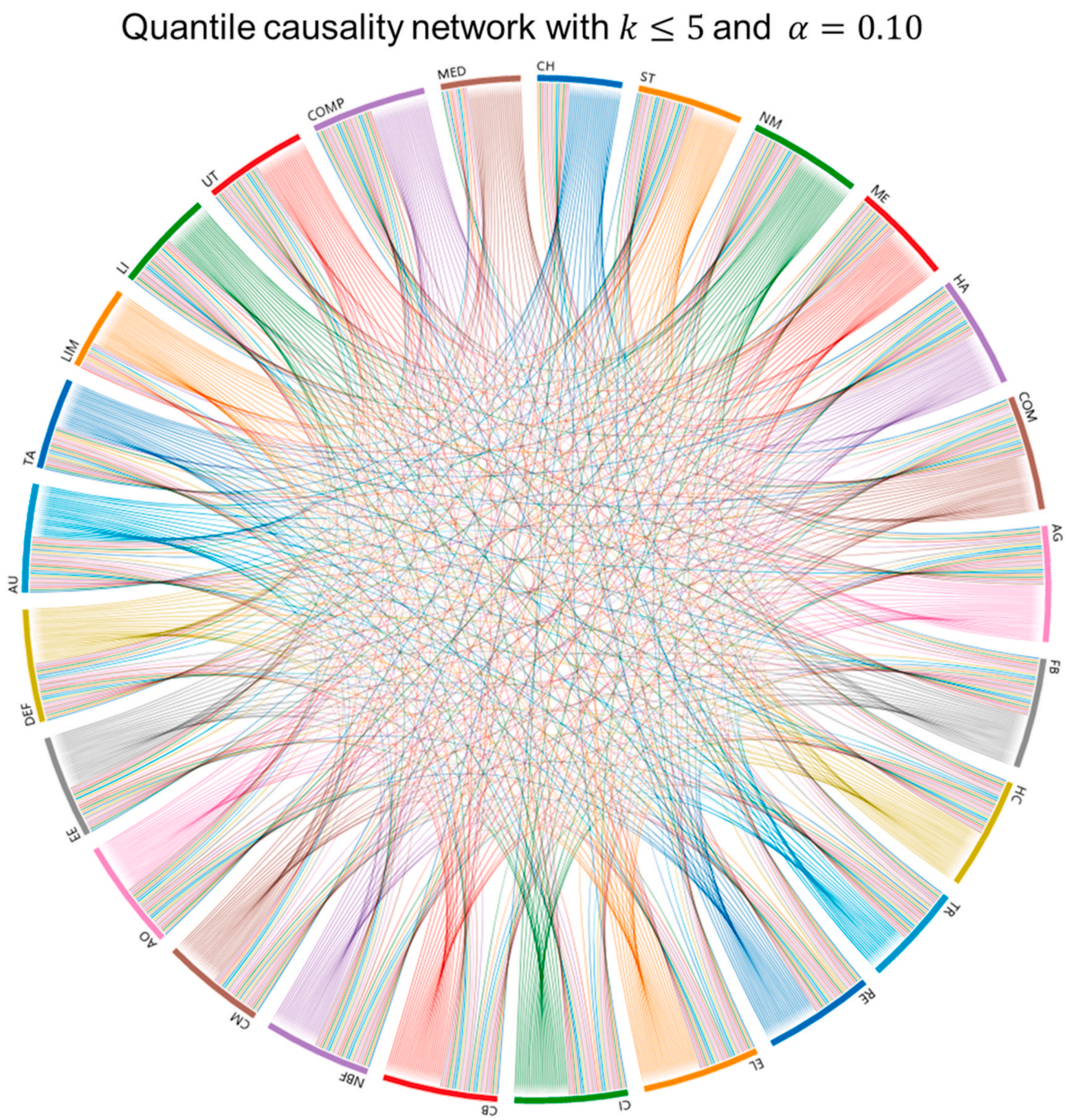

Fig. 5b. The quantile causality network depicting the financial interconnectedness between 26 industries with a more flexible lag mode ($k \leq 5$) at 0.10 quantile. Represented by an edge starting from industry i with an arrow pointing to j, the significant directional predictability from i to j (and thus the financial interconnectedness with i having an influence on j) is sufficiently confirmed as long as the corresponding PCQ estimate is significantly distinct from 0 at any lags within 5 at a given quantile level $\alpha = 0.10$.

quantile interconnection between returns at the first lag), the results in column (1) from Panel A show that the estimate for β is slightly significant while its magnitude is quite small (0.0042), indicating that the OVX may directly have a positive but relatively weak effect on the industry returns. Although the estimate for ρ is significantly negative, the results for the shock decomposition in Panel B suggest that the industry returns react relatively weakly to the daily oil price volatilities both directly and indirectly. With insignificant indirect effects, there is no evidence for the network diffusion of oil price shocks. For a relatively flexible lag order constraint ($k \leq 5$, which means we consider the quantile interconnection between returns within 5 traded days), the significantly positive but relative small β means a rise in OVX could faintly raise the industry returns. But still, there is little sign of network diffusion of oil price shocks despite the significantly negative estimate for ρ. Such counterintuitive patterns of the shock diffusion as well as the relatively small magnitude of the impact may be due to the noise brought by the daily data sample and the endogeneity problem of the daily oil price volatility

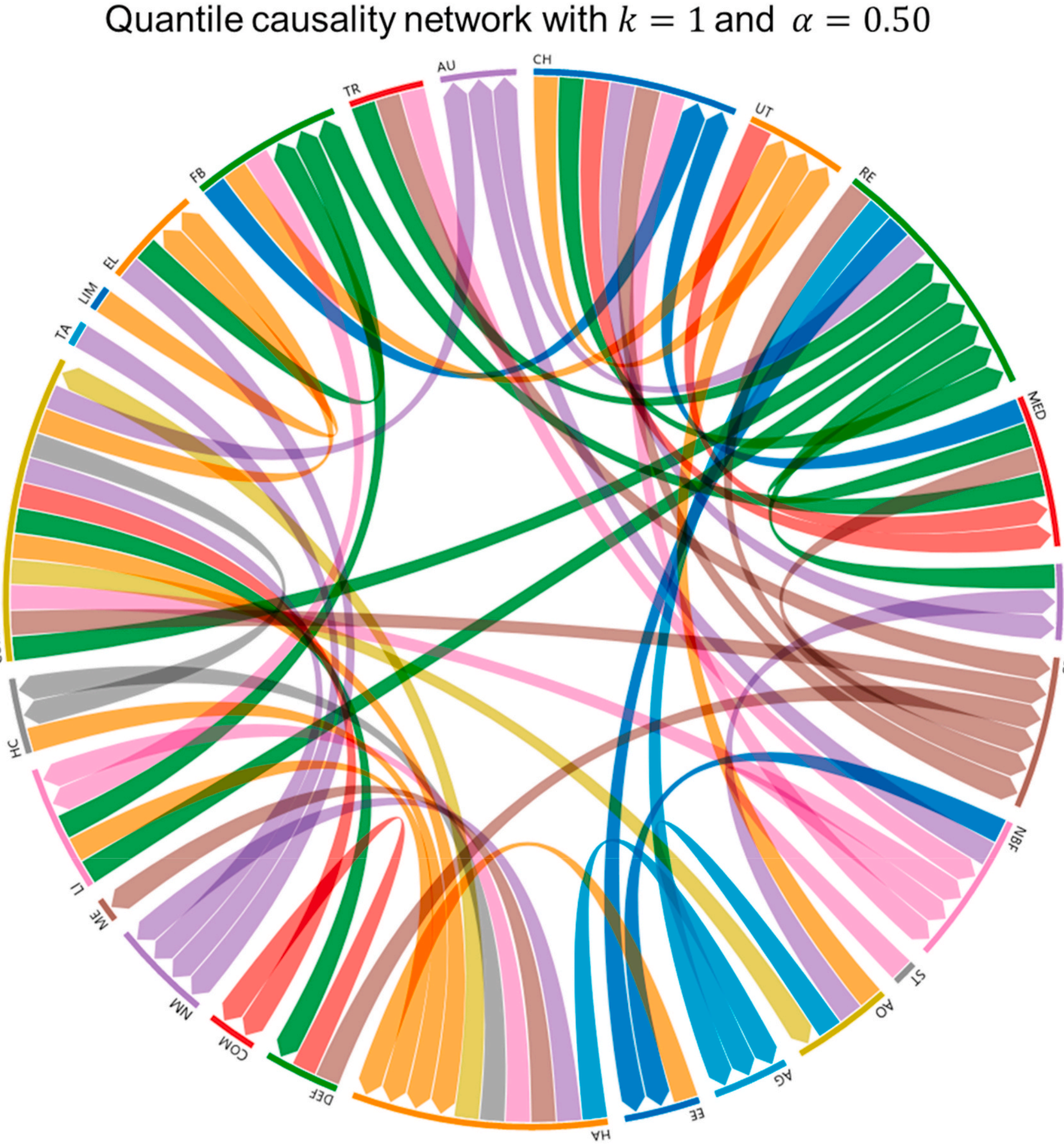

Fig. 6a. The quantile causality network depicting the financial interconnectedness between 26 industries at one lag with the quantile level $\alpha = 0.50$. The edge starting from industry i with an arrow pointing to j represents the significant directional predictability from i to j, and thus the financial interconnectedness with i having an influence on j at one lag at given quantile level $\alpha = 0.50$.

measure (OVX) resulted from the reverse causality and common trend factors.

Therefore, we turn to the responses of the monthly industry returns to the exogenous oil price shocks identified from the SVAR model. Column (3) in Table 5 shows that, for the network depicting the sectoral network linkage at a fixed lag order $k = 1$, the estimate for β is still significantly positive with a relatively larger magnitude (0.6235), indicating that positive oil price shocks could stimulate the industry returns. As the estimated for ρ remains indistinct from 0, along with the result of shock decomposition from Panel B, it suggests that the impact of oil price shocks on industry returns mostly come from the direct effect and oil price shocks scarcely transmit among industries. However, when considering the financial linkage between industries within 5 traded days ($k \leq 5$), the estimates of β and ρ are both positive and statistically significant. Furthermore, the significantly positive direct and indirect effect from the shock decomposition indicate that, oil price shocks not only directly boost industry returns, but also propagate within the financial system. With significantly positive indirect network effects contributing to an additional rise in industry returns, it indicates

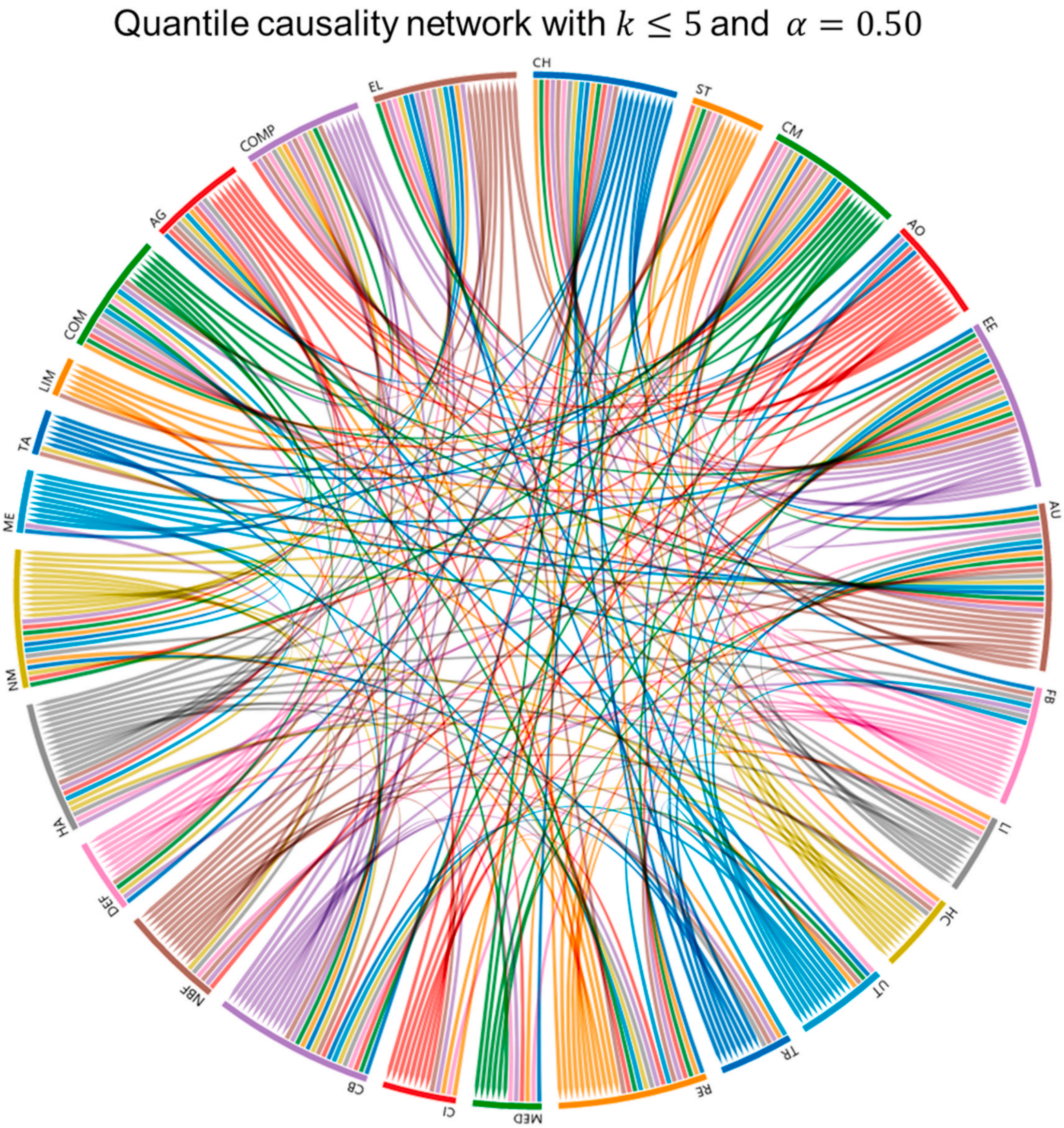

Fig. 6b. The quantile causality network depicting the financial interconnectedness between 26 industries with a more flexible lag mode ($k \leq 5$) at 0.50 quantile. Represented by an edge starting from industry *i* with an arrow pointing to *j*, the significant directional predictability from *i* to *j* (and thus the financial interconnectedness with *i* having an influence on *j*) is sufficiently confirmed as long as the corresponding PCQ estimate is significantly distinct from 0 at any lags within 5 at a given quantile level $\alpha = 0.50$.

the possibility of a risk contagion effect for oil volatility diffusion. To elaborate, adopting a similar procedure as Ozdagli and Weber (2017), Zhu and Milcheva (2018) as well as Jiang and Jin (2020), we further calculate the magnitude of such risk contagion effect with the ratio of the absolute value of the indirect effect versus the total effect as $Magnitude = \frac{|Indirect\ effect|}{|Total\ effect|}$. And here indirect effects through the sectoral financial linkage can account for 12.94% of the overall effect of oil price shocks on industry returns. As the pattern of network diffusion varies prominently between two lag specifications, it also provides certain support for the previous assumption that industries may link to each other at more than one lag and it may take a relatively short period for the oil price shock to impact the relevant industries and further affect other industries through their internal linkages. Such interconnectedness, serving as the potential channel for the oil price shock diffusion, might remain latent if we only consider the quantile dependence at a fixed lag order $k = 1$.

Table 6 shows the results of the SAR model based on the PCQ networks depicting the linkage between industry returns under

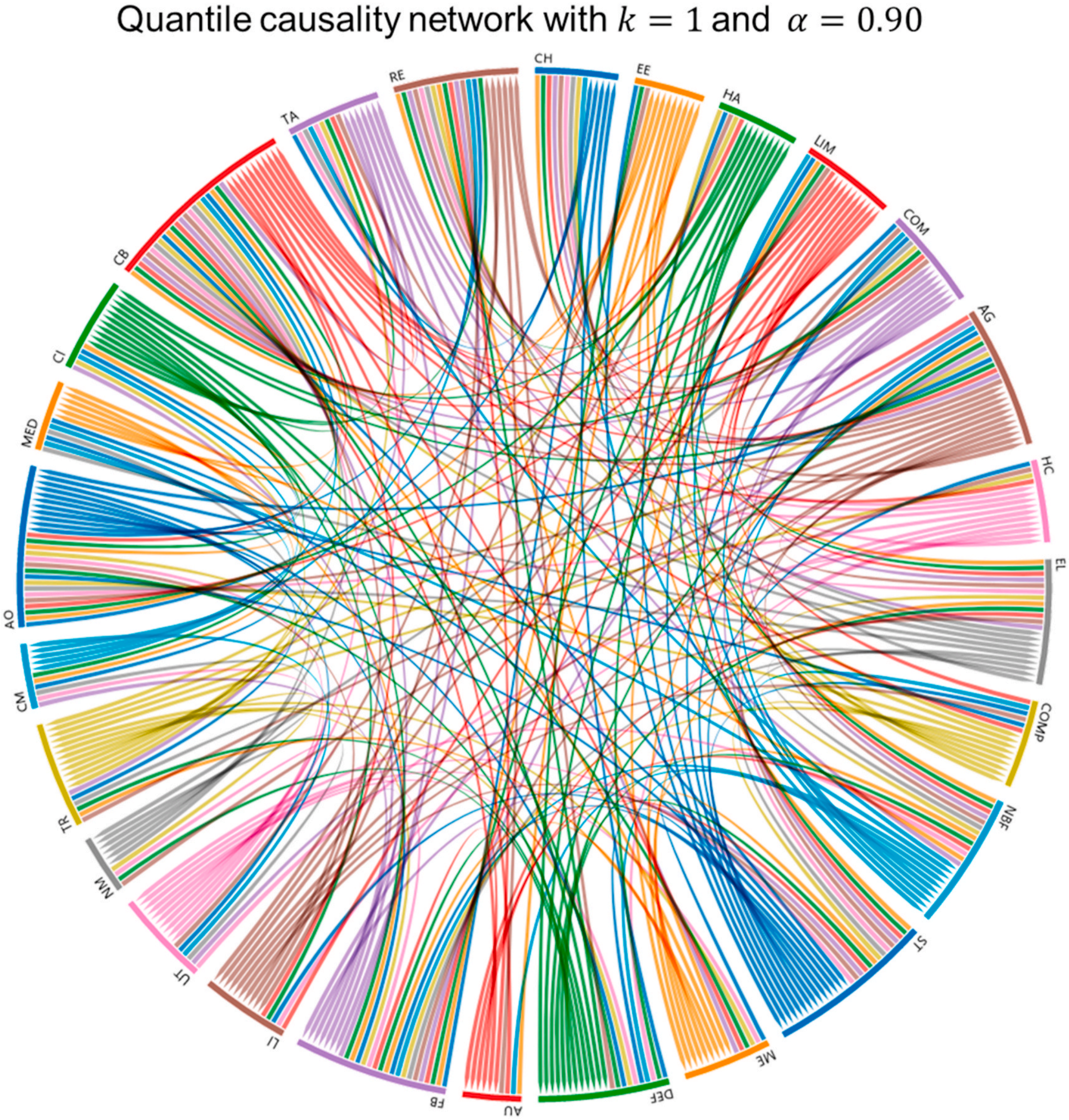

Fig. 7a. The quantile causality network depicting the financial interconnectedness between 26 industries at one lag with the quantile level $\alpha = 0.90$. The edge starting from industry i with an arrow pointing to j represents the significant directional predictability from i to j, and thus the financial interconnectedness with i having an influence on j at one lag at given quantile level $\alpha = 0.90$.

normal market condition (i.e. 0.50 quantile). The first two columns report the results for the daily oil price shocks measured by OVX while column (3) and column (4) show the results for the monthly oil price shocks identified from the SVAR model. We first focus on the impact of daily oil volatilities on the industry returns. When we only consider the quantile interconnection between returns at the first lag (i.e. $k = 1$), results from the Panel A in column (1) show that the estimate for β is insignificant, although the estimate for ρ is significantly negative. Further, the results for the shock decomposition in Panel B suggest that the impact of daily oil price volatilities on industry returns is negligible both directly and indirectly. And the insignificant indirect shocks indicate that there might not be network diffusion of oil volatilities. Nonetheless, the results based on the quantile interconnections between returns within 5 traded days indicate the opposite, as shown in column (2). The significantly positive but relatively small β indicates positive oil price fluctuations could slightly raise the industry returns while the significantly negative ρ suggests the possible negative network effects of oil

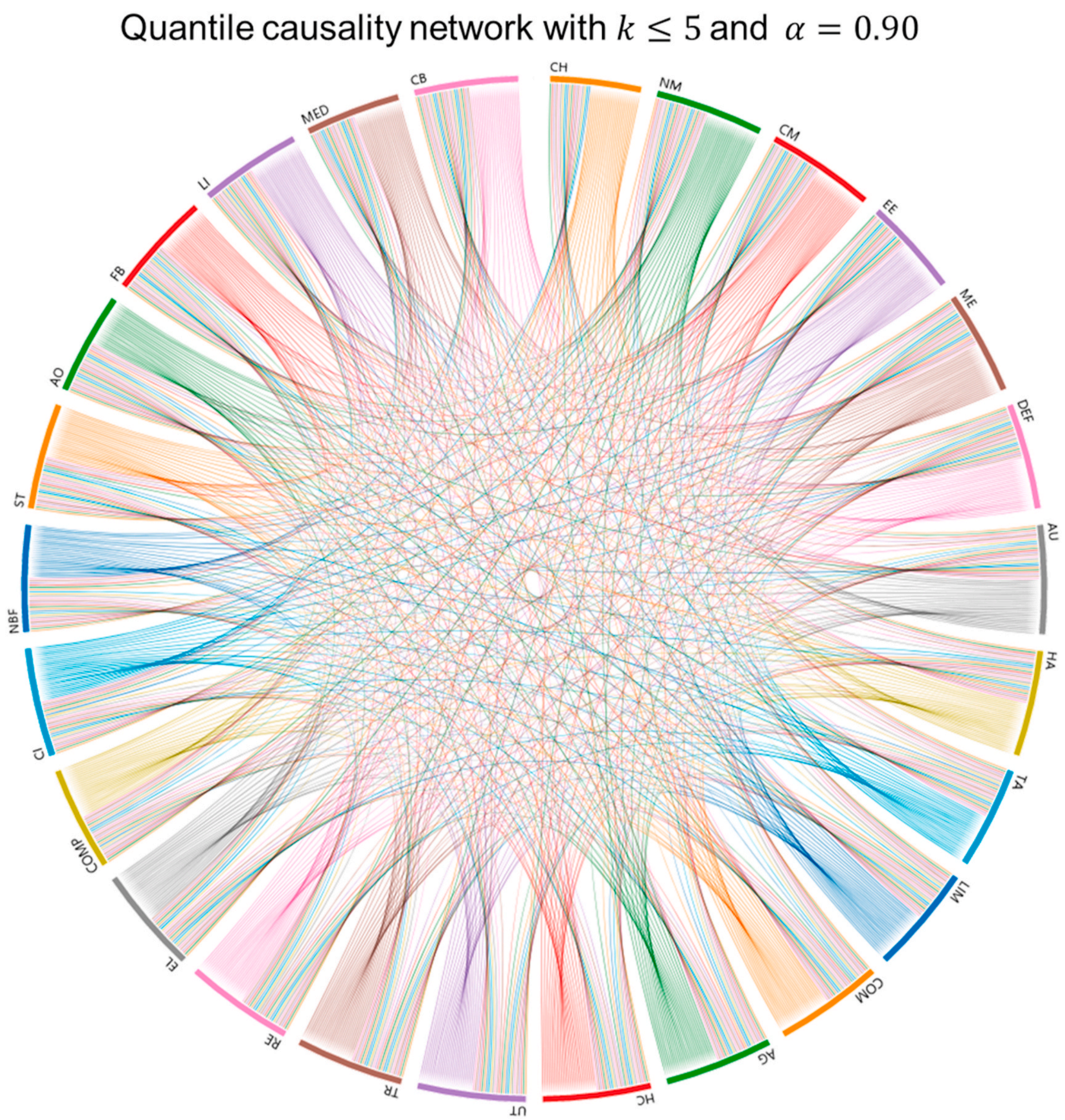

Fig. 7b. The quantile causality network depicting the financial interconnectedness between 26 industries with a more flexible lag mode ($k \leq 5$) at 0.90 quantile. Represented by an edge starting from industry i with an arrow pointing to j, the significant directional predictability from i to j (and thus the financial interconnectedness with i having an influence on j) is sufficiently confirmed as long as the corresponding PCQ estimate is significantly distinct from 0 at any lags within 5 at a given quantile level $\alpha = 0.90$.

price volatilities. Moreover, the significantly negative indirect effect from the shock decomposition indicate that, as oil price shocks may directly push up industry returns, such positive influence might be mitigated by the significant indirect effects through the network diffusion, which points to the possibility of the risk absorbing effect. Although indirect effects can explain 18.92% of the overall effect of oil price shocks on industry returns, the absolute value (0.0007) and significance (only significant at 10% level) of such risk absorbing effect are seemingly limited, which may be due to the noise brought by the daily data sample and the endogeneity problem of the daily oil price volatility measure (OVX).

Therefore, we further assess the responses of the monthly industry returns to the exogenous oil price shocks identified from the SVAR model. Column (3) and (4) in Table 6 show similar results for both lag order specifications. The estimates for β are both significantly positive, indicating the positive correlation between oil price shocks and industry returns, while the estimates for ρ under

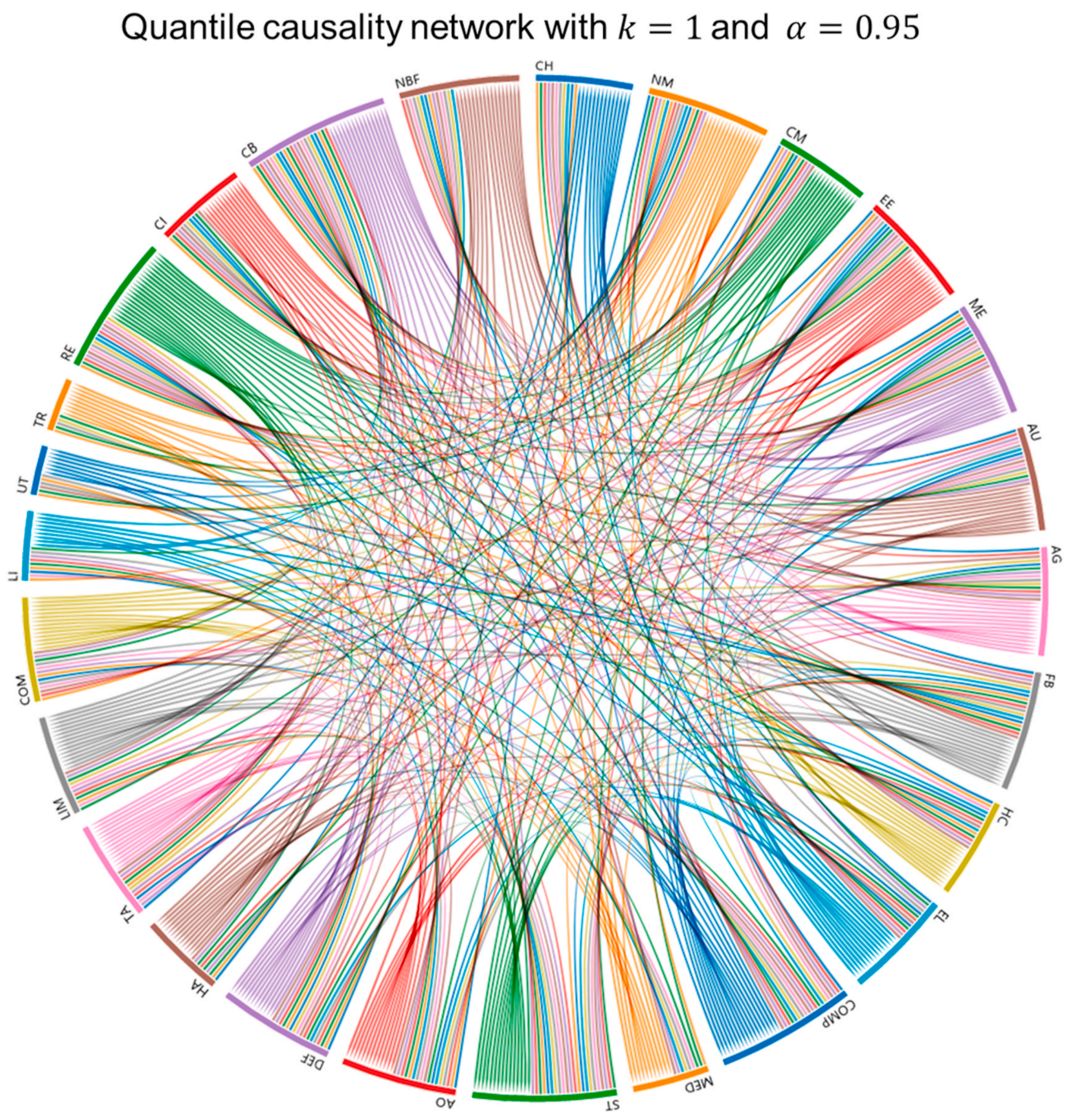

Fig. 8a. The quantile causality network depicting the financial interconnectedness between 26 industries at one lag with the quantile level $\alpha = 0.95$. The edge starting from industry i with an arrow pointing to j represents the significant directional predictability from i to j, and thus the financial interconnectedness with i having an influence on j at one lag at given quantile level $\alpha = 0.95$.

both lag specifications remain insignificant. Along with the result of shock decomposition from Panel B, it suggests that the impact of oil price shocks on industry returns mostly derives from the direct effect, while oil price shocks hardly diffuse among industries with indirect impacts of oil price shocks being insignificant. Compared with those under extreme market conditions, the prominently lower network density under normal market condition may serve as an explanation of the lack of oil volatility diffusion. A network with lower density suggests rare connection of industries, which might significantly reduce the possibility of network diffusion of oil volatility risk.

The results of the SAR model based on the PCQ networks depicting the network linkage between industries at 0.95 quantile level (i. e. bullish market condition) are presented in Table 7. We first focus on the impact of daily oil volatilities on the industry returns, as shown in the first two columns. Column (1) shows the results based on the quantile interconnection between returns at the first lag. The slightly significant but small (0.0043) estimate for β indicates that the OVX may directly have a positive but relatively faint effect on industry returns. Although the estimate for ρ is significantly negative, the shock decomposition in Panel B suggests insignificant impact

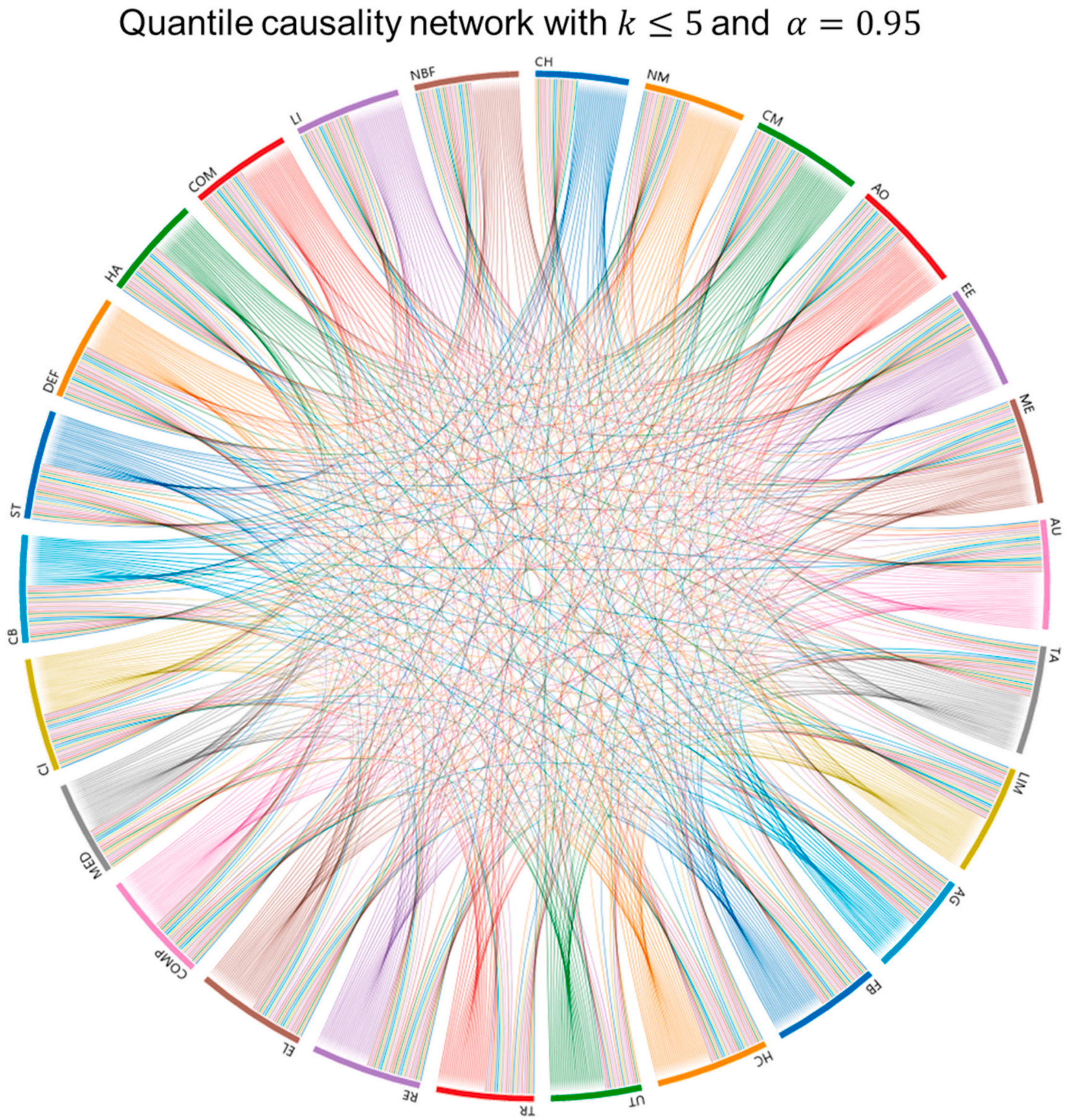

Fig. 8b. The quantile causality network depicting the financial interconnectedness between 26 industries with a more flexible lag mode ($k \leq 5$) at 0.95 quantile. Represented by an edge starting from industry i with an arrow pointing to j, the significant directional predictability from i to j (and thus the financial interconnectedness with i having an influence on j) is sufficiently confirmed as long as the corresponding PCQ estimate is significantly distinct from 0 at any lags within 5 at a given quantile level $\alpha = 0.95$.

of the daily oil price volatilities both directly and indirectly, and thus little evidence of network diffusion of daily oil price shocks. For a relatively flexible lag order constraint ($k \leq 5$, which points to the network based on the quantile interconnection between industry returns within 5 traded days), as presented in column (2), the significantly positive β again shows evidence for the positive correlation between OVX and industry returns. But still, no significant sign of network diffusion of oil price shocks is identified despite the significantly negative estimate for ρ.

Further, we turn to the responses of the monthly industry returns to the exogenous oil price shocks identified from the SVAR model. Column (3) in Table 7 shows the results for the network depicting the financial linkage at 1 lag order. The estimate for β is still significantly positive with a relatively larger magnitude, indicating that positive oil price shocks could boost the industry returns, while

Table 5
Spatial autoregressive model results for shock decomposition and network diffusion of oil price shocks on industry returns at 0.05 quantile.

	Daily oil price shocks (OVX)		Monthly oil price shocks (From SVAR)	
	(1)	(2)	(3)	(4)
	$k = 1$	$k \leq 5$	$k = 1$	$k \leq 5$
	$\alpha = 0.05$	$\alpha = 0.05$	$\alpha = 0.05$	$\alpha = 0.05$
Panel A: Point Estimates				
β	0.0042*	0.0050**	0.6235***	0.6324***
	(0.0025)	(0.0024)	(0.1340)	(0.1339)
ρ	−0.1780***	−0.9970***	0.0045	0.1280***
	(0.0084)	(0.0227)	(0.0288)	(0.0395)
Constant	−0.0007	−0.0005	0.0018	0.0017
	(0.0010)	(0.0011)	(0.0012)	(0.0012)
Adjusted R^2	0.0068	0.0578	0.0035	0.0060
Observations	80080	80080	6006	6006
Panel B: Shock Decomposition				
Direct effect	0.0042	0.0060	0.6162***	0.6331***
	(0.0025)	(0.0051)	(0.1329)	(0.1363)
Indirect effect	−0.0006	0.0184	0.0289	0.0941**
	(0.0004)	(0.1182)	(0.0215)	(0.0385)
Total effect	0.0035	0.0243	0.6450***	0.7272***
	(0.0021)	(0.1226)	(0.1408)	(0.1602)
Panel C: Network Diffusion				
Network diffusion	NO	NO	NO	YES
Risk contagion	NO	NO	NO	YES
Risk absorbing	NO	NO	NO	NO
Magnitude	/	/	/	12.94%

Notes: *, **, *** denotes statistical significance at the 10%, 5% and 1% level respectively. Significant indirect effects from Panel B suggest that industries are still affected due to their connections with other industries, even though they may not be directly exposed to oil price shocks, indicating network diffusion of oil price shocks. Further, significant indirect effects with the same sign as direct effects indicate oil price shocks intensify and point to the oil volatility risk-contagion effect, while indirect effects with the opposite sign point to the risk-absorbing effect with shocks being diversified through network diffusion, as shown in Panel C.

ρ still remains indistinct from 0. Along with the result of shock decomposition from Panel B, it suggests that the impact of oil price shocks on industry returns mostly come from the direct effect and oil price shocks scarcely transmit among industries. However, the estimates of β and ρ are both positive and statistically significant in the case of the financial linkage within 5 traded days ($k \leq 5$). Furthermore, with the direct and indirect effect being significantly positive, it indicates that oil price shocks not only directly boost industry returns but also propagate within the financial system contributing to larger impacts of oil volatilities, which points to the possibility of the oil volatility risk contagion effect. Moreover, indirect effects can account for 12.81% of the overall effect of oil price shocks on industry returns, which is similar to the case of 0.05 quantile market state. It also provides certain support for the previous assumption that industries connect to each other at more than one lag and it may take a relatively short period for the oil price shocks to impact the relevant industries and further affect other industries through their internal linkages.

The results of the SAR estimations for networks that depict the sectoral financial interconnectedness at 0.10 quantile and 0.90 quantile (as the paralleled measures for bearish and bullish market conditions, respectively) are presented in Table 8 and Table 9, which are essentially similar to the case at 0.05 quantile and 0.95 quantile.

4.2. Discussion

We further have a discussion on several interesting findings from the empirical analysis above. Firstly, the commonly positive relationship between the exogenous oil price shocks and industry returns may be due to the situation that the exogenous oil price shocks identified from the SVAR procedure, not only reflect the preventive demand changes (Kilian, 2009), but may also reflect the impact of financial speculation in the oil market (Broadstock & Filis, 2014; Wang & Liu, 2016). The increasing trend of hedging operations, as well as the rapid development of financial derivatives of crude oil, may reinforce the connection between international crude oil prices and stock indexes in the same direction (Fattouh et al., 2013; Basher & Sadorsky, 2016).

Secondly, for the daily oil price volatilities measured by the OVX, there is no significant evidence for network diffusion of oil

Table 6
Spatial autoregressive model results for shock decomposition and network diffusion of oil price shocks on industry returns at 0.50 quantile.

	Daily oil price shocks (OVX)		Monthly oil price shocks (From SVAR)	
	(1)	(2)	(3)	(4)
	$k = 1$	$k \leq 5$	$k = 1$	$k \leq 5$
	$\alpha = 0.50$	$\alpha = 0.50$	$\alpha = 0.50$	$\alpha = 0.50$
Panel A: Point Estimates				
β	0.0041	0.0043*	0.6235***	0.6254***
	(0.0025)	(0.0025)	(0.1340)	(0.1340)
ρ	−0.0380***	−0.2020***	0.0020	0.0209
	(0.0053)	(0.0076)	(0.0193)	(0.0262)
Constant	−0.0008	−0.0008	0.0019	0.0019
	(0.0011)	(0.0011)	(0.0012)	(0.0012)
Adjusted R^2	0.0007	0.0105	0.0036	0.0037
Observations	80080	80080	6006	6006
Panel B: Shock Decomposition				
Direct effect	0.0042	0.0044*	0.6218***	0.6276***
	(0.0025)	(0.0025)	(0.1351)	(0.1299)
Indirect effect	−0.0001	−0.0007*	0.0012	0.0144
	(0.0001)	(0.0004)	(0.0132)	(0.0183)
Total effect	0.0040	0.0037*	0.6230***	0.6420***
	(0.0024)	(0.0021)	(0.1357)	(0.1345)
Panel C: Network Diffusion				
Network diffusion	NO	YES	NO	NO
Risk contagion	NO	NO	NO	NO
Risk absorbing	NO	YES	NO	NO
Magnitude	/	18.92%	/	/

Notes: *, **, *** denote the statistical significance at the 10%, 5% and 1% level respectively. Significant indirect effects from Panel B suggest that industries are still affected due to their connections with other industries, even though they may not be directly exposed to oil price shocks, indicating network diffusion of oil price shocks. Further, significant indirect effects with the same sign as direct effects indicate oil price shocks intensify and point to the oil volatility risk-contagion effect, while indirect effects with the opposite sign point to the risk-absorbing effect with shocks being diversified through network diffusion, as shown in Panel C.

volatilities across all quantiles with both lag order modes, except that it shows a slight risk absorbing effect in the network diffusion when considering the financial linkage under normal market condition (0.05 quantile level) within 5 traded days ($k \leq 5$). However, such risk absorbing effect is relatively weak and only slightly significant (at 10% significance level), which might be due to the noise brought by the daily sample data as well as the endogeneity problem of the daily OVX measure.

Thirdly, for the monthly exogenous oil price shocks identified from the SVAR procedure (Kilian, 2009), the results vary significantly between two different lag order modes across different quantiles. To elaborate, with the networks that only depict the directional predictability between industry returns at the first lag, the positive impact of oil price shocks on industry returns mostly results from the direct effect, while the negligible indirect effect provides little evidence for network diffusion of oil price shocks. However, with the networks capturing the financial interconnection between industries within 5 traded days, it shows that direct and indirect effects of oil price shocks are both significantly positive under extreme market conditions, which suggests risk contagion effects of the oil volatility risk as indirect network effects contribute to greater oil price shocks on industry returns. Besides, with the evident variation of the network diffusion pattern between the two lag specifications, it indicates a time lag effect that industries may link to each other at more than one lag, and it may take a relatively short period (i.e. within 5 traded days) for the oil price shock to directly influence relevant industries and further affect other industries due to their internal connections. Therefore, a relative flexible lag order mode may be necessary when we depict the interconnectedness between industries and further investigate the oil price shock diffusion through such sectoral interconnection. And last but not least, it is suggested that the oil volatility risk hardly diffuse within the network under normal market condition (0.50 quantile). Nevertheless, when it comes to extreme market conditions, the significant network diffusion provides evidence for the risk contagion effect with indirect effects contributing to larger oil volatility shocks. It might be explained by the fact that industries connect to each other much more prevailingly under extreme circumstances than they do under the normal state. And such interconnection may serve as an important channel for oil volatility diffusion throughout the financial system. Moreover, we further calculate the magnitude of such risk contagion effect with the ratio of the absolute value of the indirect effect versus the total effect, where indirect effects through the sectoral financial linkage can approximately account for 12–13% of the

Table 7
Spatial autoregressive model results for shock decomposition and network diffusion of oil price shocks on industry returns at 0.95 quantile.

	Daily oil price shocks (OVX)		Monthly oil price shocks (From SVAR)	
	(1)	(2)	(3)	(4)
	$k = 1$	$k \leq 5$	$k = 1$	$k \leq 5$
	$\alpha = 0.95$	$\alpha = 0.95$	$\alpha = 0.95$	$\alpha = 0.95$
Panel A: Point Estimates				
β	0.0043*	0.0050**	0.6262***	0.6328***
	(0.0025)	(0.0024)	(0.1340)	(0.1338)
ρ	−0.2130***	−0.9940***	0.05100	0.1310***
	(0.0104)	(0.0218)	(0.0338)	(0.0395)
Constant	−0.0007	−0.0005	0.0019	0.0017
	(0.0011)	(0.0010)	(0.0012)	(0.0012)
Adjusted R^2	0.0089	0.0573	0.0041	0.0060
Observations	80080	80080	6006	6006
Panel B: Shock Decomposition				
Direct effect	0.0042	0.0056	0.6184***	0.6332***
	(0.0026)	(0.0035)	(0.1319)	(0.1312)
Indirect effect	−0.0007	0.0072	0.0330	0.0930**
	(0.0005)	(0.0462)	(0.0240)	(0.0386)
Total effect	0.0035	0.0127	0.6513***	0.7262***
	(0.0021)	(0.4850)	(0.1412)	(0.1531)
Panel C: Network Diffusion				
Network diffusion	NO	NO	NO	YES
Risk contagion	NO	NO	NO	YES
Risk absorbing	NO	NO	NO	NO
Magnitude	/	/	/	12.81%

Notes: *, **, *** denote the statistical significance at the 10%, 5% and 1% level respectively. Significant indirect effects from Panel B suggest that industries are still affected due to their connections with other industries, even though they may not be directly exposed to oil price shocks, indicating network diffusion of oil price shocks. Further, significant indirect effects with the same sign as direct effects indicate oil price shocks intensify and point to the oil volatility risk-contagion effect, while indirect effects with the opposite sign point to the risk-absorbing effect with shocks being diversified through network diffusion, as shown in Panel C.

overall effect of oil price shocks on industry returns. The magnitude of such risk diffusion effect may seem limited, which might be due to the portfolio diversification effects as well as strong administrative regulations and constraints on capital flows in China's stock market.

Overall, the results point to the distinct characteristics of the financial linkage between industries, and accordingly, the prominently heterogeneous oil volatility diffusion under different market states. While the traditional Granger causality based network may only capture the mean-mean sectoral correlation, the quantile causality based network enables us to explicitly depict the financial interconnectedness of industries under various market scenarios. Consequently, to comprehensively capture such financial linkage which may serve as a key mechanism for oil volatility risks, the quantile causality based network formation may be more appropriate than that based on the mean-mean Granger causality.

5. Concluding remarks

The global financial crisis unveils the possibility that shocks may diffuse throughout the financial system and even trigger global crisis. Particularly, it is possible that oil price shocks may also propagate and intensify, or alleviate and diminish among financial institutions and assets through their interconnectedness. However, such scenario is considerably neglected in existing models examining the oil-stock interaction, which may severely hinder the comprehensive interpretation of this bivariate relationship. To address this issue, we first highlight the financial interconnectedness that may serve as a key mechanism for oil volatility diffusion by applying the partial cross-quantilogram (PCQ) model of Han et al. (2016) to establish networks that depict the quantile dependence between returns of 26 industries in China's stock market. Further, utilizing the spatial autoregressive (SAR) model to decompose the aggregate impact of oil price volatilities, we investigate whether oil price shocks may diffuse throughout the estimated quantile causality based networks, and whether it shows a risk contagion effect or a risk absorbing effect. Besides, by combining the daily OVX and the monthly exogenous oil price shocks identified from the SVAR procedure by Kilian (2009), we deal with the potential

Table 8
Spatial autoregressive model results for shock decomposition and network diffusion of oil price shocks on industry returns at 0.10 quantile.

	Daily oil price shocks (OVX)		Monthly oil price shocks (From SVAR)	
	(1)	(2)	(3)	(4)
	$k = 1$	$k \leq 5$	$k = 1$	$k \leq 5$
	$\alpha = 0.10$	$\alpha = 0.10$	$\alpha = 0.10$	$\alpha = 0.10$
Panel A: Point Estimates				
β	0.0042*	0.0050**	0.6227***	0.6277***
	(0.0025%)	(0.0024%)	(0.1340)	(0.1339)
ρ	−0.1400***	−0.9940***	0.0310	0.1210***
	(0.0065)	(0.0205)	(0.0229)	(0.0389)
Constant	−0.0008	−0.0005	0.0019	0.0018
	(0.0011)	(0.0011)	(0.0012)	(0.0012)
Adjusted R^2	0.0062	0.0567	0.0039	0.0057
Observations	80080	80080	6006	6006
Panel B: Shock Decomposition				
Direct effect	0.0042	0.0056	0.6170***	0.6364***
	(0.0025)	(0.0035)	(0.1347)	(0.1328)
Indirect effect	−0.0005	0.0084	0.0200	0.0889**
	(0.0003)	(0.0458)	(0.0158)	(0.0375)
Total effect	0.0036	0.0140	0.6371***	0.7253***
	(0.0022)	(0.0483)	(0.1394)	(0.1549)
Panel C: Network Diffusion				
Network diffusion	NO	NO	NO	YES
Risk contagion	NO	NO	NO	YES
Risk absorbing	NO	NO	NO	NO
Magnitude	/	/	/	12.26%

Notes: *, **, *** denote the statistical significance at the 10%, 5% and 1% level respectively. Significant indirect effects from Panel B suggest that industries are still affected due to their connections with other industries, even though they may not be directly exposed to oil price shocks, indicating network diffusion of oil price shocks. Further, significant indirect effects with the same sign as direct effects indicate oil price shocks intensify and point to the oil volatility risk-contagion effect, while indirect effects with the opposite sign point to the risk-absorbing effect with shocks being diversified through network diffusion, as shown in Panel C.

endogeneity problem of daily oil price volatility measurement.

Overall, the response of industry returns to oil price volatilities as well as the pattern of network diffusion vary greatly between different oil volatility measures and different lag order specifications across different quantiles. For the daily OVX, industry returns generally react weakly to the oil price volatilities both directly and indirectly except for the case under normal market condition (0.50 quantile level) where it shows a slight risk absorbing effect of network diffusion. Moreover, with respect to the monthly exogenous oil price shocks, the significant positive impact of oil price shocks on industry returns mainly comes from the direct effect instead of indirect network effects if we only focus on the quantile linkage between industry returns at one lag. However, it is suggested that industries may significantly link to each other at more than one lag. Taking such possibility into account, significant network diffusion of oil price shocks is spotted. Specifically, considering the financial interconnectedness of industries within 5 traded days, it suggests that indirect network effects significantly contribute to greater oil price shocks, which points to a risk contagion effect of oil volatilities. Last but not least, empirical results show that industries relate to each other under extreme market conditions (bearish and bullish) much more prevailingly than they do under normal market condition. Accordingly, it further points to the prominently heterogeneous pattern of oil volatility diffusion, as significant risk contagion effects of oil volatilities are indicated at extreme quantiles while the oil volatility risk scarcely transmit under normal market condition.

As the role of the interconnection between different assets is growingly emphasized in augmented asset pricing models and risk hedging (Fernandez, 2011; Jiang & Jin, 2020; Kou et al., 2018), investors are suggested to take into account the distinct characteristics of the financial linkage between industries under different market conditions for investment optimization and risk identification. Moreover, it demonstrates a significant positive relationship between the monthly exogenous oil price shocks and industry returns, as well as risk contagion effects of oil volatilities where the sectoral financial interconnectedness may serve as an important channel for risk propagation. It might be explained by the situation that the exogenous oil price shocks identified from the SVAR procedure not only reflect preventive demand changes, but may also reflect the impact of financial speculation in the oil market. With the increasingly stronger interconnection between the oil market and the stock market, policymakers and investors are suggested to deal with the reverse impact of oil price volatility from a network perspective by taking the risk diffusion effect into consideration. What's

Table 9
Spatial autoregressive model results for shock decomposition and network diffusion of oil price shocks on industry returns at 0.90 quantile.

	Daily oil price shocks (OVX)		Monthly oil price shocks (From SVAR)	
	(1)	(2)	(3)	(4)
	$k = 1$	$k \leq 5$	$k = 1$	$k \leq 5$
	$\alpha = 0.90$	$\alpha = 0.90$	$\alpha = 0.90$	$\alpha = 0.90$
Panel A: Point Estimates				
β	0.0042	0.0049**	0.6229***	0.6328***
	(0.0025)	(0.0024)	(0.1340)	(0.1338)
ρ	−0.2330***	−0.9970***	0.0020	0.1310***
	(0.0082)	(0.0231)	(0.0193)	(0.0395)
Constant	−0.0006	−0.0005	0.0019	0.0017
	(0.0011)	(0.0010)	(0.0012)	(0.0012)
Adjusted R^2	0.0011	0.0551	0.0043	0.0062
Observations	80080	80080	6006	6006
Panel B: Shock Decomposition				
Direct effect	0.0042	0.0063	0.6291***	0.6407***
	(0.0026)	(0.0070)	(0.1354)	(0.1300)
Indirect effect	−0.0008	0.0189	0.0336	0.0980**
	(0.0005)	(0.0960)	(0.0219)	(0.0397)
Total effect	0.0034	0.0252	0.6626***	0.7387***
	(0.0021)	(0.1023)	(0.1448)	(0.1550)
Panel C: Network Diffusion				
Network diffusion	NO	NO	NO	YES
Risk contagion	NO	NO	NO	YES
Risk absorbing	NO	NO	NO	NO
Magnitude	/	/	/	13.27%

Notes: *, **, *** denote the statistical significance at the 10%, 5% and 1% level respectively. Significant indirect effects from Panel B suggest that industries are still affected due to their connections with other industries, even though they may not be directly exposed to oil price shocks, indicating network diffusion of oil price shocks. Further, significant indirect effects with the same sign as direct effects indicate oil price shocks intensify and point to the oil volatility risk-contagion effect, while indirect effects with the opposite sign point to the risk-absorbing effect with shocks being diversified through network diffusion, as shown in Panel C.

more, the continuously speeding process of capital flow liberalization and financial integration may make the financial system much more exposed to structural risks. As a result, policy makers should not neglect the possibility of oil volatility diffusion throughout the financial network, especially under extreme market states, so as to avoid the underestimation of various shocks with proper macro-prudential risk handling measures.

Credit authorship statement

Conceptualization:Jionghao Huang,Xiaohua Xia; Methodology: Jionghao Huang,Xiaohua Xia; Resources: Xiaohua Xia; Investigation:Jionghao Huang, Ziruo Li, Xiaohua Xia; Data Curation: Jionghao Huang, Ziruo Li, Xiaohua Xia; Software:Jionghao Huang,Xiaohua Xia; Formal analysis: Jionghao Huang, Ziruo Li, Xiaohua Xia.

Writing -Original Draft: Jionghao Huang,Xiaohua Xia; Writing -Review & Editing: Jionghao Huang, Ziruo Li, Xiaohua Xia; Visualization:Jionghao Huang, Ziruo Li, Xiaohua Xia; Validation:Jionghao Huang, Ziruo Li, Xiaohua Xia; Supervision: Xiaohua Xia; Project administration: Xiaohua Xia; Funding acquisition: Xiaohua Xia.

Approval of the version of the manuscript to be published: Jionghao Huang, Ziruo Li, Xiaohua Xia.

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Appendix

This section provides the results for the spatial matrix W corresponding to the network presented in section 4.1.2 based on the PCQ causality analysis. For each w_{ij} in the spatial matrix, it can only take two values, 1 or 0, where $w_{ij} = 1$ suggests the significant directional predictability from i to j, and thus the financial interconnectedness with i having an influence on j with corresponding lag order specifications at give quantiles. Otherwise, $w_{ij} = 0$ indicates little predictability and therefore the absence of the financial interconnectedness from i to j. We do not consider self-influence here with the diagonal element of W being 0.

Spatial matrix with $k=1$ and $\alpha=0.05$																										
	CH	ST	NM	CM	AO	EE	ME	DEF	AU	HA	TA	LIM	COM	AG	FB	LI	HC	UT	TR	RE	EL	COMP	MED	CI	CB	NBF
CH	0	0	0	1	0	1	1	0	1	0	0	0	0	0	1	1	1	0	0	0	1	1	0	0	0	0
ST	0	0	0	1	1	1	1	1	1	1	0	1	1	1	1	1	1	0	0	1	1	1	1	1	1	0
NM	1	0	0	1	1	1	0	0	1	1	0	1	1	0	0	1	1	1	0	0	1	1	1	1	0	0
CM	1	1	0	0	0	0	0	0	0	1	0	1	0	0	0	1	1	1	0	1	1	0	0	1	1	0
AO	1	1	1	1	0	1	1	0	0	1	1	1	0	1	1	1	1	0	1	1	1	1	0	1	1	1
EE	1	1	0	0	0	0	0	1	0	0	0	0	0	1	1	0	0	0	0	1	0	0	0	1	0	0
ME	1	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0
DEF	1	1	1	1	1	0	0	0	0	1	0	0	0	0	1	0	1	0	0	1	1	0	0	1	0	1
AU	1	1	0	0	0	0	0	1	0	0	1	1	0	1	0	0	0	0	0	1	0	0	0	0	1	0
HA	0	1	0	1	1	0	0	0	0	0	0	0	0	1	0	0	1	0	0	1	0	0	0	0	1	0
TA	0	0	0	0	1	0	0	0	0	0	0	1	0	1	0	0	0	0	0	1	1	0	0	1	1	1
LIM	0	1	0	0	0	0	1	1	0	1	1	0	1	1	1	0	0	0	0	1	0	0	0	1	0	0
COM	1	1	1	1	0	0	0	1	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	1	1
AG	1	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1
FB	1	1	0	0	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	0	1
LI	0	1	1	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	1	0	1	1
HC	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	1	1
UT	1	0	1	1	1	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	1	0	0	0
TR	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0
RE	0	0	0	1	0	0	1	0	1	1	0	1	1	1	1	1	1	0	0	0	1	1	0	1	0	0
EL	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0
COMP	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	0	0	0	1	1	1
MED	1	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	1
CI	0	0	1	1	0	1	1	0	1	0	0	0	0	0	1	1	1	0	0	1	1	1	0	0	0	0
CB	0	0	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	0	0	1	1	1	1	0	0
NBF	0	0	0	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	1	1	1	1	0	0

Fig. A1a. The results for the adjacent matrix W based on the PCQ causality analysis depicting the financial interconnectedness between 26 industries at 1 lag order with the quantile level $\alpha = 0.05$. $w_{ij} = 1$ suggests the significant quantile directional predictability from i to j, and thus the financial interconnectedness with i having an influence on j at 1 lag order with the quantile level $\alpha = 0.05$.

Spatial matrix with $k<=5$ and $\alpha=0.05$																										
	CH	ST	NM	CM	AO	EE	ME	DEF	AU	HA	TA	LIM	COM	AG	FB	LI	HC	UT	TR	RE	EL	COMP	MED	CI	CB	NBF
CH	0	0	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0
ST	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
NM	1	1	0	1	1	1	0	0	1	1	1	1	1	0	1	1	1	1	0	1	1	1	1	1	1	1
CM	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
AO	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
EE	1	1	1	0	1	0	1	1	1	0	1	1	1	1	1	1	1	1	0	1	1	1	0	1	0	0
ME	1	1	1	1	1	1	0	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1
DEF	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
AU	1	1	1	1	1	1	1	1	0	0	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	0
HA	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
TA	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1
LIM	1	1	0	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	0
COM	1	1	1	1	1	1	1	1	1	0	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1
AG	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	0	1	1
FB	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1
LI	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1
HC	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1
UT	1	0	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	0	1	1	1	1	1	1	0	0
TR	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1
RE	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1
EL	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1
COMP	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1
MED	1	1	1	1	0	1	1	0	1	1	1	1	1	1	0	1	1	1	0	1	1	1	0	1	1	1
CI	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1
CB	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1
NBF	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0

Fig. A1b. The results for the adjacent matrix W based on the PCQ causality analysis depicting the financial interconnectedness between 26 industries within 5 lags with the quantile level $\alpha = 0.05$. $w_{ij} = 1$ suggests the significant quantile directional predictability from i to j, and thus the financial interconnectedness with i having an influence on j within 5 traded days with the quantile level $\alpha = 0.05$.

Spatial matrix with $k=1$ and $\alpha=0.10$																										
	CH	ST	NM	CM	AO	EE	ME	DEF	AU	HA	TA	LIM	COM	AG	FB	LI	HC	UT	TR	RE	EL	COMP	MED	CI	CB	NBF
CH	0	1	1	0	0	0	0	0	0	1	0	0	0	0	1	0	1	0	1	0	1	0	0	0	1	1
ST	0	0	0	0	0	1	1	1	1	1	0	1	1	1	1	1	1	0	0	0	1	1	1	1	0	0
NM	0	0	0	1	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	1	0	1
CM	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	1	0	0	1	0	1	1	0	0
AO	1	0	0	1	0	1	1	1	1	1	0	1	1	1	0	1	1	1	1	0	1	1	1	1	1	0
EE	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
ME	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0
DEF	0	1	0	0	0	1	1	0	0	0	0	0	1	1	0	0	0	0	0	0	0	0	0	0	0	0
AU	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
HA	0	1	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0
TA	1	0	1	1	0	0	0	0	0	1	0	0	0	0	1	1	1	0	1	1	1	1	0	1	1	1
LIM	0	0	0	0	0	1	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	1	0	1	0
COM	0	1	0	0	0	0	1	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	1	1	0
AG	0	0	1	0	0	0	1	0	0	0	1	1	1	0	0	0	0	0	0	0	0	0	1	0	1	0
FB	1	1	0	0	0	1	1	0	1	1	1	1	1	1	0	1	1	1	1	0	1	1	1	1	0	1
LI	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
HC	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
UT	1	0	1	1	0	0	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	1	1	0	0
TR	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	1
RE	0	0	0	0	0	1	1	1	1	0	0	0	1	1	0	1	0	0	0	0	1	1	0	0	0	1
EL	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
COMP	0	0	0	0	0	1	1	0	0	0	0	1	1	0	0	1	0	0	0	0	0	0	0	0	0	0
MED	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0
CI	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	1	0	0	1
CB	0	0	0	0	0	1	1	0	1	1	1	1	1	1	0	1	1	0	0	0	1	1	0	0	0	0
NBF	0	0	0	1	0	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	1	1	0	0	0	0

Fig. A2a. The results for the adjacent matrix W based on the PCQ causality analysis depicting the financial interconnectedness between 26 industries at 1 lag order with the quantile level $\alpha = 0.10$. $w_{ij} = 1$ suggests the significant quantile directional predictability from i to j, and thus the financial interconnectedness with i having an influence on j at 1 lag order with the quantile level $\alpha = 0.10$.

Spatial matrix with $k<=5$ and $\alpha=0.10$																										
	CH	ST	NM	CM	AO	EE	ME	DEF	AU	HA	TA	LIM	COM	AG	FB	LI	HC	UT	TR	RE	EL	COMP	MED	CI	CB	NBF
CH	0	1	1	0	0	0	1	0	0	1	0	0	1	1	1	0	1	0	1	1	1	0	0	1	1	1
ST	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
NM	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1
CM	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	0	1	1	0	1	1	1	1	1	1	1
AO	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
EE	1	0	1	1	1	0	1	1	1	1	0	1	1	1	1	1	1	1	0	1	1	1	1	1	1	0
ME	0	1	1	0	0	1	0	1	0	1	1	1	1	1	1	0	1	1	0	1	1	1	1	1	1	1
DEF	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
AU	1	0	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
HA	1	1	1	1	1	1	1	1	1	0	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1
TA	1	0	1	1	1	0	1	1	0	1	0	1	1	0	1	1	1	0	1	1	1	1	0	1	1	1
LIM	0	0	0	0	0	1	1	1	1	1	0	0	1	1	0	0	1	0	0	0	1	1	1	0	1	0
COM	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1
AG	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1
FB	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1
LI	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	0	0	1	1	1	1	1	1	1	1	1
HC	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1
UT	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	1	1	1	1	1	0	0
TR	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1
RE	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	1	1	1	1	1	1
EL	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1
COMP	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1
MED	0	0	1	0	1	1	0	0	1	0	0	1	0	1	0	0	0	1	1	0	1	1	0	0	1	0
CI	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1
CB	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1
NBF	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0

Fig. A2b. The results for the adjacent matrix W based on the PCQ causality analysis depicting the financial interconnectedness between 26 industries within 5 lags with the quantile level $\alpha = 0.10$. $w_{ij} = 1$ suggests the significant quantile directional predictability from i to j, and thus the financial interconnectedness with i having an influence on j within 5 traded days with the quantile level $\alpha = 0.10$.

Spatial matrix with $k=1$ and $\alpha=0.50$																										
	CH	ST	NM	CM	AO	EE	ME	DEF	AU	HA	TA	LIM	COM	AG	FB	LI	HC	UT	TR	RE	EL	COMP	MED	CI	CB	NBF
CH	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	1	1	1	1
ST	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1
NM	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
CM	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
AO	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	1	0	0
EE	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
ME	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
DEF	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0
AU	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
HA	0	0	1	0	0	0	1	0	0	0	0	0	0	1	0	1	1	0	0	0	0	1	0	0	0	0
TA	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
LIM	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
COM	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
AG	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
FB	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	0	0	0	0	0	0
LI	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0
HC	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
UT	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0
TR	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	1
RE	0	0	0	0	0	1	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	0
EL	0	0	1	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
COMP	0	0	1	0	1	0	0	1	1	1	0	0	1	0	0	0	1	0	0	1	1	0	0	0	1	1
MED	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	1	0
CI	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0
CB	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
NBF	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Fig. A3a. The results for the adjacent matrix W based on the PCQ causality analysis depicting the financial interconnectedness between 26 industries at 1 lag order with the quantile level $\alpha = 0.50$. $w_{ij} = 1$ suggests the significant quantile directional predictability from i to j, and thus the financial interconnectedness with i having an influence on j at 1 lag order with the quantile level $\alpha = 0.50$.

Spatial matrix with $k<=5$ and $\alpha=0.50$																										
	CH	ST	NM	CM	AO	EE	ME	DEF	AU	HA	TA	LIM	COM	AG	FB	LI	HC	UT	TR	RE	EL	COMP	MED	CI	CB	NBF
CH	0	1	0	1	1	1	0	0	1	0	0	0	0	0	1	1	1	1	1	1	0	0	1	1	1	1
ST	0	0	0	0	1	0	0	1	0	1	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	1
NM	0	0	0	1	1	0	1	0	0	1	1	1	1	1	0	0	1	0	1	1	0	1	0	0	0	0
CM	0	0	1	0	1	1	1	1	0	1	1	1	0	1	1	1	1	0	1	1	0	0	0	0	1	1
AO	1	0	0	0	0	1	0	0	0	0	1	0	0	1	0	0	0	1	0	0	0	0	0	1	0	0
EE	1	0	1	1	1	0	1	1	1	1	0	1	1	1	0	0	1	1	1	1	1	1	1	1	0	1
ME	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0
DEF	1	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	1	0
AU	1	1	1	1	0	1	1	0	0	1	1	0	1	1	1	1	0	1	1	1	1	1	1	1	0	1
HA	0	0	1	0	0	1	1	0	0	0	0	0	0	1	1	1	1	0	0	0	1	1	0	0	0	0
TA	0	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
LIM	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
COM	0	1	1	1	1	1	1	1	1	0	0	0	0	0	1	1	0	1	0	0	1	1	1	0	0	0
AG	1	0	0	0	1	0	0	0	1	1	0	0	0	0	0	1	1	1	0	1	0	0	0	1	1	0
FB	1	0	0	0	0	0	1	0	1	1	0	0	0	0	0	1	0	1	0	0	0	0	0	0	1	0
LI	0	1	0	0	0	0	0	1	0	1	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0
HC	0	1	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1
UT	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	1	0	0	0	1	0	0	1
TR	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	1	0	0	0	0	1	1
RE	1	1	1	1	1	1	1	0	1	1	0	0	1	1	0	0	0	1	0	0	1	0	0	1	1	0
EL	0	0	1	1	1	1	1	1	0	1	1	1	0	0	1	0	1	1	1	0	0	1	0	0	1	1
COMP	0	0	1	0	1	1	0	1	1	1	0	0	1	0	1	1	1	0	0	1	1	0	0	0	1	1
MED	1	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	1	1	0
CI	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	1	1
CB	1	0	1	1	1	0	0	0	0	0	1	1	1	0	1	1	1	1	1	0	1	1	0	1	0	1
NBF	0	0	1	0	1	1	0	0	1	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0

Fig. A3b. The results for the adjacent matrix W based on the PCQ causality analysis depicting the financial interconnectedness between 26 industries within 5 lags with the quantile level $\alpha = 0.50$. $w_{ij} = 1$ suggests the significant quantile directional predictability from i to j, and thus the financial interconnectedness with i having an influence on j within 5 traded days with the quantile level $\alpha = 0.50$.

Spatial matrix with $k=1$ and $\alpha=0.90$																										
	CH	ST	NM	CM	AO	EE	ME	DEF	AU	HA	TA	LIM	COM	AG	FB	LI	HC	UT	TR	RE	EL	COMP	MED	CI	CB	NBF
CH	0	0	0	0	0	1	0	0	0	1	0	1	1	1	0	0	1	0	0	0	1	1	0	0	0	1
ST	0	0	0	0	0	1	1	1	1	1	0	1	1	1	1	1	1	1	0	0	1	1	0	0	0	0
NM	0	0	0	0	0	0	0	1	0	0	0	0	0	1	0	0	0	1	1	0	0	0	0	0	0	0
CM	0	0	1	0	1	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	1	1	0	0
AO	1	1	0	0	0	1	0	1	0	1	0	1	0	1	0	1	1	1	1	0	1	1	1	1	1	0
EE	0	1	0	0	0	0	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
ME	0	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	1	0	0	0	0	1	1	0
DEF	1	1	0	0	1	0	0	0	0	1	0	0	0	0	0	0	1	1	1	1	0	0	0	1	0	1
AU	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	1
HA	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	1	0	0	1	0
TA	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	0	0	1	1	1
LIM	0	1	0	0	0	0	1	1	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	1	1
COM	1	1	1	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	1	0	0	0	1	1	1
AG	0	1	0	0	1	0	1	1	0	0	1	1	1	0	1	0	0	0	1	1	0	0	0	1	1	1
FB	1	1	0	0	1	1	1	1	1	1	1	1	1	1	0	0	0	1	1	0	1	1	1	1	0	1
LI	0	1	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	0	0	0	0	0	0	1	1	0
HC	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	1	0
UT	0	0	1	1	1	0	0	0	0	0	0	0	0	0	1	0	1	0	0	1	0	0	0	0	0	0
TR	0	0	1	0	1	0	1	1	0	0	1	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0
RE	0	0	0	1	1	1	1	1	1	1	0	0	1	1	1	1	1	0	0	0	1	1	0	1	0	0
EL	0	0	0	0	0	1	1	1	1	1	1	1	1	1	0	1	1	0	0	0	0	1	0	0	0	0
COMP	0	1	0	0	1	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	1	1
MED	0	1	1	1	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1
CI	0	0	0	1	1	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	1	0	0	0
CB	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	0	0
NBF	0	0	0	0	0	1	1	1	1	1	1	1	1	1	0	0	0	1	0	0	1	1	1	0	0	0

Fig. A4a. The results for the adjacent matrix W based on the PCQ causality analysis depicting the financial interconnectedness between 26 industries at 1 lag order with the quantile level $\alpha = 0.90$. $w_{ij} = 1$ suggests the significant quantile directional predictability from i to j, and thus the financial interconnectedness with i having an influence on j at 1 lag order with the quantile level $\alpha = 0.90$.

Spatial matrix with $k<=5$ and $\alpha=0.90$																										
	CH	ST	NM	CM	AO	EE	ME	DEF	AU	HA	TA	LIM	COM	AG	FB	LI	HC	UT	TR	RE	EL	COMP	MED	CI	CB	NBF
CH	0	0	1	1	0	1	1	1	1	1	1	1	1	1	0	0	1	1	1	1	1	1	0	1	0	1
ST	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
NM	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
CM	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
AO	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
EE	0	1	1	1	1	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	1	1	0
ME	1	1	1	1	0	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
DEF	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
AU	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
HA	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
TA	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1
LIM	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1
COM	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1
AG	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1
FB	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1
LI	1	1	1	1	0	1	1	1	1	1	0	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1
HC	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1
UT	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1
TR	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1
RE	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1
EL	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	0	1
COMP	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1
MED	0	1	1	1	1	1	1	0	1	0	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1
CI	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1
CB	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1
NBF	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0

Fig. A4b. The results for the adjacent matrix W based on the PCQ causality analysis depicting the financial interconnectedness between 26 industries within 5 lags with the quantile level $\alpha = 0.90$. $w_{ij} = 1$ suggests the significant quantile directional predictability from i to j, and thus the financial interconnectedness with i having an influence on j within 5 traded days with the quantile level $\alpha = 0.90$.

Spatial matrix with $k=1$ and $\alpha=0.95$																										
	CH	ST	NM	CM	AO	EE	ME	DEF	AU	HA	TA	LIM	COM	AG	FB	LI	HC	UT	TR	RE	EL	COMP	MED	CI	CB	NBF
CH	0	0	1	1	0	1	1	0	1	0	0	0	0	1	1	0	1	0	0	0	1	1	1	0	0	0
ST	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0
NM	1	0	0	1	1	1	1	0	0	1	0	1	0	0	0	1	1	1	1	1	1	0	1	1	1	0
CM	1	1	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	1	1	0	0	1	1	1	1
AO	1	1	1	0	0	1	0	0	0	1	1	1	0	0	1	1	1	0	1	1	1	1	0	1	1	1
EE	1	1	1	0	0	0	0	1	1	1	1	1	1	1	1	0	0	0	0	1	1	1	0	0	0	1
ME	1	1	1	1	0	1	0	1	0	1	1	1	1	1	0	0	0	0	0	1	1	1	0	1	1	1
DEF	1	1	1	1	1	1	0	0	0	1	1	0	1	0	1	0	0	1	1	1	1	0	0	1	1	1
AU	1	0	0	0	0	1	1	1	0	1	1	1	1	1	1	0	0	0	0	1	1	1	0	0	1	1
HA	1	1	1	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	1	1
TA	1	0	0	0	1	0	1	1	0	0	0	0	1	1	0	0	0	0	1	1	0	1	0	1	1	1
LIM	0	1	0	1	1	0	0	1	0	0	1	0	1	1	0	0	0	0	0	1	0	0	1	0	1	1
COM	0	0	1	0	0	1	0	1	1	0	1	1	0	1	1	0	0	0	0	1	0	1	1	0	1	1
AG	1	1	0	0	0	1	0	1	1	0	1	1	1	0	0	0	1	0	0	1	0	1	0	1	1	1
FB	1	1	0	0	1	1	1	0	1	0	0	1	1	0	0	1	1	1	1	1	1	1	1	1	0	1
LI	0	1	1	0	1	0	0	1	0	0	0	1	0	1	0	0	0	0	0	1	0	1	1	0	0	0
HC	1	1	1	0	1	0	0	0	0	1	0	0	0	1	0	1	0	0	1	1	1	1	0	1	1	1
UT	0	0	1	1	0	0	0	0	1	0	0	1	0	0	1	0	0	0	0	0	0	0	1	0	0	0
TR	0	0	1	1	0	0	0	0	0	0	0	0	0	0	1	0	1	0	0	1	0	0	0	0	0	0
RE	0	0	1	1	1	1	1	1	1	1	1	0	1	1	1	0	1	0	0	0	1	1	0	0	0	0
EL	1	1	0	1	1	0	1	0	0	1	0	0	0	0	1	0	0	1	0	1	0	1	0	1	1	1
COMP	1	1	0	0	1	1	1	1	1	1	1	1	1	1	0	1	1	0	0	1	1	0	0	1	1	1
MED	0	1	1	1	0	0	0	0	0	0	1	1	1	0	0	1	0	0	0	0	0	0	0	0	1	1
CI	0	0	1	1	0	1	1	0	1	0	0	0	0	0	1	0	1	0	0	1	1	1	0	0	0	1
CB	0	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	0	0
NBF	0	0	0	0	0	1	0	1	1	1	1	1	1	1	1	1	1	0	0	0	1	1	1	0	0	0

Fig. A5a. The results for the adjacent matrix W based on the PCQ causality analysis depicting the financial interconnectedness between 26 industries at 1 lag order with the quantile level $\alpha = 0.95$. $w_{ij} = 1$ suggests the significant quantile directional predictability from i to j, and thus the financial interconnectedness with i having an influence on j at 1 lag order with the quantile level $\alpha = 0.95$.

Spatial matrix with $k<=5$ and $\alpha=0.95$																										
	CH	ST	NM	CM	AO	EE	ME	DEF	AU	HA	TA	LIM	COM	AG	FB	LI	HC	UT	TR	RE	EL	COMP	MED	CI	CB	NBF
CH	0	0	1	1	1	1	1	0	1	0	1	1	0	1	1	0	1	1	1	1	1	1	1	1	1	0
ST	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
NM	1	1	0	1	1	1	1	1	1	1	1	1	1	0	0	1	1	1	1	1	1	0	1	1	1	0
CM	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
AO	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
EE	1	1	0	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	0	1	0	1
ME	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1
DEF	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
AU	1	1	1	0	1	1	1	1	0	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1
HA	1	1	1	1	1	1	1	1	1	0	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1
TA	1	0	1	1	1	1	1	1	1	1	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1
LIM	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1
COM	0	1	1	1	1	1	1	1	1	0	1	1	0	1	1	1	1	1	0	1	1	1	1	1	1	1
AG	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1
FB	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1
LI	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	0	0
HC	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1
UT	0	1	1	1	1	1	0	0	1	0	1	1	1	0	1	1	1	0	0	1	0	1	1	1	0	0
TR	1	1	1	1	1	1	1	1	1	0	1	1	1	0	1	1	1	0	0	1	1	1	1	1	1	1
RE	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1
EL	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1
COMP	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1
MED	0	1	1	1	1	1	0	0	1	1	1	1	1	0	0	1	1	1	1	0	1	1	0	1	1	1
CI	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1
CB	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1
NBF	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0

Fig. A5b. The results for the adjacent matrix W based on the PCQ causality analysis depicting the financial interconnectedness between 26 industries within 5 lags with the quantile level $\alpha = 0.95$. $w_{ij} = 1$ suggests the significant quantile directional predictability from i to j, and thus the financial interconnectedness with i having an influence on j within 5 traded days with the quantile level $\alpha = 0.95$.

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