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# The risk spillover effect of the COVID-19 pandemic on energy sector: Evidence from China

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ABSTRACT

Detecting the adverse effects of major emergencies on financial markets and real economy is of great importance not only for short-term policy reactions but also for economic and financial stability. This is the lesson we learnt from the COVID-19 pandemic. This paper focuses on the risk spillover effect of the COVID-19 on Chinese energy industry using a high-dimensional and time-varying factor-augmented VAR model. The results show that the net volatility spillovers of the pandemic remain positive to all underlying energy sectors during January to June of 2020 and February to April of 2021. For the former sub-period, the volatility spillover of the COVID-19 is not only the highest, but also lasts longest for oil exploitation sector, followed by the power and gas sectors. While for the latter sub-period, the COVID-19 has relatively higher volatility spillovers to the power, coal mining and petrochemical sectors. These findings suggest that the COVID-19 has significant risk spillover effects on Chinese energy sectors, and the effects vary among different energy sub-sectors and across different periods of time.

## 1. Introduction

Over the past two decades, a series of major emergencies have broken in the world. For example, the SARS pandemic in 2003, the Indian ocean tsunami in 2004, the Chinese Wenchuan earthquake in 2008, the Japan earthquake in 2011 and the ensuing Fukushima nuclear power plant leakage, the Ebola virus in 2014, and the novel coronavirus disease in 2019 (COVID-19) (See Fig. A1 in the Appendix). Such major emergencies not only pose a serious threat to the safety of public life and property, but also negatively affect the social and economic stability of all countries. Especially for the COVID-19, it has been declared as a "public health emergency of international concern" by World Health Organization (WHO), with the fastest transmission rate, the widest scope of infection and the greatest difficulty in prevention. Such an incident has imposed serious adverse impacts on firms and households in a very short period of time, and also triggered a significant volatility in global financial markets (Baker et al., 2020; Kinateder et al., 2021). Compared to the impacts of other types of emergencies, the impact of the COVID-19 is more widespread and lasts much longer. It has produced a high degree of uncertainty and huge challenges to the development of the global economy, causing severe impacts on the global industrial chain, supply chain and capital chain. The production and business activities of the affected regions and countries have been forced to stagnate, and the volume of global trade has declined sharply. Especially the complexity and changeability of the evolution of the pandemic once leaded to the failure of virus detection in time, which in turn weaken the decision making of governments, and caused a great deal of damaging effects on real economy, financial markets and people's healthy and lives. In fact, how to ensure economic and financial stability and prevent potential systemic risks during the COVID-19 has attracted great attention from Chinese policymakers. Within the first 2 weeks of the COVID-19 outbreak in China, Chinese stock market has never been gloomier, with the volatility index reached a 5-year high since the 2015 stock market crash. On February 23, 2020, the Chinese government emphasized that it is extremely urgent to prevent economic growth sliding out reasonable interval, and to prevent short-term shocks evolving into long-term trends in the context of the pandemic. For this reason, it is of critical importance to quantify the impacts of the COVID-19 on China's macroeconomy and financial markets, and conduct in-depth analyses of the direction and contagion intensity of the risk spillover of the pandemic to real economy and financial system. A better knowledge of the impacts of the COVID-19 will not only help improve

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the effectiveness of governments' policy response mechanisms and risk prevention measures compatible with "major incidents", but also help avoid potential systemic risks across different sectors and different markets.

As for China, the COVID-19 pandemic has posed serious impacts on its economic development and social security. Energy industry is one of the most essential pillar industries of Chinese economy, and thus how to improve the economic performance of energy industry is one of the main focuses of the Chinese government. In the pre-COVID period, there had been a rising expansion in energy imports but a much slower growth in energy exports in China, resulting in energy consumption being highly dependent on imported energy products and in turn, exerting a lot of pressure on energy security. The COVID-19 pandemic has affected the energy industry on all fronts (Huang and Liu, 2021; Nguyen et al., 2021; Ramelli and Wagner, 2020). The spread of COVID-19 not only significantly influences energy prices (Devpura and Narayan, 2020; Narayan, 2020; Prabheesh et al., 2020), but also leads to lower energy demand and consumption due to human mobility and economic activity lockdown (Liu et al., 2020; Norouzi et al., 2020). Moreover, investors' future expectations have been generally pessimistic in the context of COVID-19, and their investment strategies have altered accordingly (Mazur et al., 2021; Wen et al., 2021). In particular, since the COVID-19 is steadily worsening the demand and disrupting energy supply, the energy market, especially the crude oil market, is full of uncertainties and fluctuation, resulting in huge negative shocks for the energy and stock markets (Aydın and Ari, 2020; Štifanić et al., 2020). Thus, additional evidence shows that the COVID-19 is associated with lower stock returns and heighted stock volatility in energy market, and the risk contagion between energy and stock markets has significantly increased during the COVID-19. However, it should be noted that not all energy sub-sectors are homogeneously affected by the pandemic, given that the isolation and lockdown policy has greatly altered the patterns of energy demand and consumption of households and enterprises. Moreover, the effects of the COVID-19 on energy consumption vary among different economic sectors (Zhang et al., 2021), which would in turn result in heterogeneous impacts on different energy sub-sectors. An extensive literature has been devoted to assess the impacts of the COVID-19 on energy market from various perspectives, but lacks a a detailed sector-level analysis of the risk contagion between the pandemic and heterogeneous energy sectors especially for China.

This paper thus aims to quantify how the outbreak of the COVID-19 impacts Chinese energy industry, and on this basis, to depict the risk transmission path of the pandemic to heterogeneous energy sectors. We hypothesize that the COVID-19 has significant risk spillover effects on Chinese energy sectors, and the effects vary among different energy sub-sectors and across different periods of time. Due to the ever-increasing linkage between different energy sub-sectors, markets and industries, the impact of major emergencies, including the COVID-19, shows somewhat "accelerator" and "ripple" features, similar to the phenomenon of "resonance". In other words, when an individual energy sub-market is affected, the negative effects will be gradually transmitted to other markets and at last, generates systemic risk (Baruník and Křehlík, 2018). Moreover, in the face of extreme shocks, the commodity and financial markets are likely to "overreact", and in turn, produce large abnormal shocks in the short term (Lasfer et al., 2003), which will further aggravate economic fluctuations and cause risk contagion between financial institutions or markets. These facts increase the difficulty of risk prevention and triggers as well a number of related studies regarding macro-prudential policies, local government debt, and cross-market contagion of extreme risks (Ballester et al., 2016; Maggio et al., 2017; Guidolin et al., 2019; Zhang et al., 2020).

In order to test the above risk spillover hypotheses, this study uses daily stock price data on Chinese energy market from January 20, 2020 to April 20, 2021, and utilizes a higher-dimensional time-varying factor-augmented VAR (HD-TVP-FAVAR) model which allows us to capture potential high-dimensional and time-varying features existed in economic and financial risk network. In particular, we consider nine energy sub-sectors and employ the spillover index approach based on the HD-TVP-FAVAR model to estimate the risk spillover effects of the COVID-19 to all energy sectors and to each energy sector we consider. The empirical results show that the net volatility spillovers of the pandemic remain positive to all concerned energy sectors during January to June of 2020 and February to April of 2021, the two most serious stages of the spread of the pandemic in China. For the former sub-period, the volatility spillover of the COVID-19 is not only the highest, but also lasts longest for oil exploitation sector, followed by the power and gas sectors. While for the latter sub-period, the COVID-19 has relatively higher volatility spillovers to the power, coal mining and petrochemical sectors. The COVID-19 shock could induce volatility co-movement in Chinese energy markets through affecting oil exploitation sector and then spilling over into other energy sectors. Our findings not only have important implications for the governments to prevent the risks brought by major events to spread across different energy sectors, but also are relevant for investors regarding diversification and safe-haven investments.

Compared with the existing studies, the marginal contributions of this paper are twofold. First, unlike existing studies employing traditional linear methods or dynamic correlation analysis between the COVID-19 pandemic or other types of major emergencies and macroeconomic and financial variables, this paper uses the HD-TVP-FAVAR model and the spillover index approach based on the model to quantify the effects of COVID-19 on Chinese energy markets. Specifically, we simultaneously estimate the dynamic impulse response and spillover effects of nine selected energy sectors to the COVID-19 shock. For a more detailed analysis and also for a robust test, we also construct the adjacency matrix to include tail event covariates and further find that the network effect between the COVID-19 and energy markets is more pronounced when the pandemic related uncertainty is relatively high. Our findings suggest that the HD-TVP-FAVAR model we employed can not only quantify the volatility spillover effects of the pandemic across different energy sectors, but also capture substantial time-variations in the spillover effects.

Second, despite a growing literature on the impacts of COVID-19 on energy industry, limited work pays special interest in the potential sectoral heterogeneity of risk contagion between COVID-19 and heterogeneous energy sectors. In fact, different energy sub-sectors are likely to be affected heterogeneously by the COVID-19. Meanwhile, during different stages of the COVID-19, the impacts on the same energy sector may also be differential. Taking account of this, the main focus of this paper is to perform a detailed sector-level analysis of the risk contagion between the pandemic and heterogeneous energy sectors for China from a time-varying perspective. Our empirical findings confirm that relative to other concerned energy sectors, oil exploitation sector, followed by the power and gas sectors, are affected the most by the pandemic owing to negative supply and demand shocks and high uncertainty shock in oil, power and gas sectors during the most serious stage of the COVID.

The remainder of the paper proceeds as follows. Section 3 presents the HD-TVP-FAVAR model and the connectedness index approach. Section 4 introduces data and variables. Section 5 shows the empirical results and analyzes the impacts of the COVID-19 on different Chinese energy sectors. Section 6 summarizes the main conclusions.

## 2. Literature review

If one country's governments have not taken effective measures to deal with major emergencies in a timely manner, its economy would face great downward pressure in the short and long terms, and its financial markets are likely to experience violent fluctuations, which could in turn lead to systemic risks and even induce economic crisis. A growing number of studies have been undertaken to focus on the evolving mechanism of major emergencies, including their occurrence, development and spreading rules. In particular, some studies have investigated the occurrence mechanism of specific major emergencies mainly include the evolution law of natural disasters (Cheung et al., 2003), and the uncertainty induced by natural disasters using probabilistic techniques (Apel et al., 2006). In addition, a chain reaction model of events is used to investigate the linkages among major emergencies. Helbing et al. (2006) utilize semi-parametric and non-parametric techniques to achieve a risk assessment of the chain reaction of public emergencies, and show that the chain reaction was not only helpful to evaluate the evolving rules and characteristics of major emergencies, but also to assess the effectiveness of emergency management measures of governments. Willis et al. (2007) estimate the uncertainty of major emergencies so as to provide theoretical support for short-term emergency preparedness in changeable environments. In methodology, the existing literature often employs event intervention model (Goh and Law, 2002; Deryugina et al., 2018), event study method and natural experiment method (Boehm et al., 2019) to conduct comparative analysis of economic conditions before and after the outbreak of major events, given the low frequency of the occurrence of events and the difficulty of data statistics. Pacini and Marlett (2001) find that insurance companies with hurricane risk exposure had more positive responses to stock prices, by employing generalized least square method and non-parametric event study technique. Ragin and Halek (2016) focusing on 43 disasters since 1970 that caused the largest insurance loss, present that insurance brokers received abnormal stock returns on the day of the event.

In addition, there is another stand of studies focusing on the impact of major emergencies on real economy and financial market fluctuations based on other advanced econometric models. For example, Bai et al. (2018) construct a dynamic stochastic general equilibrium (DSGE) model including heterogeneous multi-sector and considering the impact of rare disaster, and analyze the unconventional impact of unexpected events on firm value, with the results showing that the asset pricing portfolio model (CAPM) containing abnormal shocks can better predict stock market volatility. Lanfear et al. (2019) evaluate the abnormal disturbance of the US hurricanes on stock returns and illiquidity across portfolios of stocks sorted during 1990–2017, and document that such events do have substantial negative impacts on stock market. In particular, White et al. (2015) note that under the shock of major emergencies, there is a significant risk contagion and spillover effect across different markets.

However, most of these earlier studies focus on the impact of natural disasters such as earthquakes and hurricanes on real economy and financial markets. Due to relatively short duration of such events, empirical analysis based on traditional methods is likely to induce the problem of "Curse of dimensions" (Marcellino and Sivec, 2016). As a consequence, it is difficult to achieve a comprehensive analysis of the economic impacts of major events (Galariotis et al., 2018). Therefore, most existing studies rely on constructing specific risk indicators and following the comparative analysis paradigm, neglecting the network structure consisting of heterogeneous markets. Moreover, the event intervention model, event study method or quasi-natural experiments employed by existing studies are only suitable for conducting comparative analysis of the short-term effects before and after the event, which is not conducive to monitoring the unconventional impacts of major emergencies and depicting the risk contagion between heterogeneous market.

Since the outbreak of the COVID-19, a large number of studies have emerged to focus on the economic effects of the pandemic. Altig et al. (2020) and Salisu and Akanni (2020) find that the COVID-19 pandemic and the ensuing economic fallout led to sharp uncertainty jumps. By employing daily data of 20 selected countries, Szczygielski et al. (2021) further present that the uncertainty regarding the COVID-19 has a negative impact on energy stock returns for all countries but is related to heightened volatility in most. Kinateder et al. (2021) document a significant degradation of correlation within the major asset classes, i.e., sovereign bonds, commodities and major exchange rates. A number of studies have found the evidence that energy sector has been particularly impacted by the pandemic. Liu et al. (2020) find that the COVID-19 pandemic leads to lower energy consumption due to human mobility and economic activity lockdown. Zhang et al. (2021) find that the COVID-19 had a significant impact on the spillover effect between energy and stock market, with the extent of risk acceptance of the energy market increased after the COVID-19 outbreak. Al-Awadhi et al. (2020) observe that the growth in COVID-19 cases and deaths had a negative impact on Chinese stock returns with the effect more pronounced for larger firms. Huang and Liu (2021) present firm-level evidence that the COVID-19 has decreased the stock price crash risk of energy firms in China. However, although these studies have evaluated the impacts of the COVID-19 on energy market from various perspectives, but still lacks a detailed sector-level analysis of the risk contagion between the pandemic and heterogeneous energy sectors.

## 3. Methodology

### 3.1. High-dimensional time-varying factor-augmented VAR model

Under the impacts of unexpected external shocks, economic and financial variables are likely to have the characteristics of short-memory and long-memory. Especially when the types, magnitudes and directions of the impacts are different, the relationship among the variables probably evolves with time. Taking account of these stylized facts, Primiceri (2005) and Koop and Korobilis (2013) propose a time-varying parameter factor-augmented model including stochastic volatility. Following the two studies, we further extend the model into a high-dimensional time-varying factor-augmented VAR (HD-TVP-FAVAR) model as follows:

$$x_t^n = \lambda_t^y y_t + \lambda_t^f f_t + \mu_t \tag{1}$$

$$\begin{bmatrix} y_t \\ f_t \end{bmatrix} = c_t + \theta_{t,1} \begin{bmatrix} y_{t-1} \\ f_{t-1} \end{bmatrix} + \ldots + \theta_{t,p} \begin{bmatrix} y_{t-p} \\ f_{t-p} \end{bmatrix} + \delta_t \tag{2}$$

where Eq.(1) is the measuring equation and Eq.(2) is the HD-TVP-FAVAR equation with $p$-lags; $x_t^n$ is the $n \times 1$ vector matrix consisting of $n$ endogenous variables; $y_t$ is the $s \times 1$ observable factor matrix consisting of $s$ observable variables in the period $t$ and $f_t$ is the potential explanatory factor of the target macroeconomic variable included in $x_{tj}$. Therefore, $\lambda_t^y$and $\lambda_t^f$ correspond to $y_t$ and $f_t$ respectively, representing regression coefficients and observable factor loading matrix. In Eq. (2), $c_t$ denotes the intercept and $\theta_{t,\,p}$ for $t = 1, \ldots, T$, $i = 1, \ldots, p$ denotes the time-varying coefficient matrix. $\mu_t$ and $\delta_t$ are the Gaussian perturbation terms with zero means and time-varying covariance matrixs $V_t$ and $Q_t$, respectively. By using multivariate model system as well as the potential target explanatory factor, we can predict macroeconomic variables and examine the dynamic relationship among variables. All parameters in the HD-TVP-FAVAR model are assumed to be time-varying given the possible time-variations in the data generating process of variables.

In order to ensure the completeness of the model, we further define the the loading vectors and the time-varying coefficients and as follows:

$$\lambda_t = \left( \left(\lambda_t^y\right)', \left(\lambda_t^f\right)' \right)' \tag{3}$$

$$\beta_t = \left( c_t', vec\left(\theta_{t,1}\right)', \ldots, vec\left(\theta_{t,p}\right)' \right)' \tag{4}$$

where both Eqs. (3) and (4) are separately subjected to the following random walk processes:

$$\lambda_t = \lambda_{t-1} + v_t \tag{5}$$

$$\beta_t = \beta_{t-1} + \eta_t \tag{6}$$

where $v_t \sim N(0, W_t)$ and $\eta_t \sim N(0, \Xi_t)$ are uncorrelated disturbance terms with time-varying covariance matrixs $W_t$ and $\Xi_t$, respectively.

Koop and Korobilis (2013) point that the efficiency of the parameter estimation of the TVP-FAVAR model with MCMC algorithm is low and the parameter estimation tends to be biased. Moreover, since financial variables tend to change dramatically in the face of extreme shocks, the assumption of long memory of the variables probably works poorly. On the other hand, when the economy encounters a sudden and unconventional shock such as the COVID-19 pandemic, the dynamic relationship of the variables and the driving factors of the dynamic impacting process may change across different regimes. Therefore, in order to accommodate the characteristics of fast forgetting and slow forgetting of financial variables, following Doz et al. (2011) and Koop and Korobilis (2013), this paper uses the Kalman Filtering algorithm with forgetting factor and makes a reference of the Exponentially Weighted Moving Average in Primiceri (2005) to estimate the error covariance matrix ($V_t, Q_t, W_t, \Xi_t$) and ensure the large sample property of the parameter estimation.

Specifically, we embed the dynamic model selection (DMS) and dynamic model average (DMA) into the above model. Especially, DMS is a special example of DMA model. In doing so, we intend to automatically achieve different forgetting speed according to different market conditions, avoiding the subjective error of artificial selection parameters. We now work with $M_j$, $j = 1, 2, \dots, J$ models as follows:

$$x_t^{(j)} = \lambda_t^f f_t^{(j)} + \lambda_t^y y_t + \mu_t \tag{7}$$

$$\begin{bmatrix} y_t \\ f_t^{(j)} \end{bmatrix} = c_t + \theta_{t,1}\begin{bmatrix} y_{t-1} \\ f_{t-1}^{(j)} \end{bmatrix} + \dots + \theta_{t,p}\begin{bmatrix} y_{t-p} \\ f_{t-p}^{(j)} \end{bmatrix} + \delta_t' \tag{8}$$

where $x_t^{(j)}$ is subset of $x_t$; $f_t^{(j)}$ is the potential factor extracted from the corresponding $x_t^{(j)}$. Because $x_t^n$ consists of $n$ variables, DMA consists of $2^n - 1$ variable combinations used to extract the forgetting factor, which can avoid artificial selection.

We define $\pi_{(t|t-1,j)} = Pro(L_t = j|Y^{t-1})$, in which $Y^{t-1} = \{y_1, \dots, y_{t-1}\}$, representing the probability that model $j$ applies in the period $t$. $L_t$ refers to each concrete variable combination, and $L_t = j$ represents that the $j$ variable combination is selected. In order to simplify the calculation and ensure the fitting accuracy, this paper is based on the fast recursive algorithm similar to Kalman Filtering adopted by Poole and Raftery (2000), in which, we assume the initial value of $\pi_{(t|t-1,j)}$ is $\pi_{(0|0,j)}(j = 1, 2, \dots, J)$, introduce the forgetting factor$\alpha(0 < \alpha \le 1)$, and get the simplified probability prediction model and updated equation:

$$\pi_{t|t-1,j} = \frac{\pi_{t-1|t-1,j}^{\alpha}}{\sum_{l=1}^{J}\pi_{t-1|t-1,l}^{\alpha}} \tag{9}$$

$$\pi_{t|t,j} = \frac{\pi_{t|t-1,j} f_j\left(y_t|Y^{t-1}\right)}{\sum_{l=1}^{J}\pi_{t|t-1,l} f_l\left(y_t|Y^{t-1}\right)} \tag{10}$$

where $f_j(y_t|Y^{t-1})$ is a measure of fit of model $j$. According to Koop and Korobilis (2013), we assume the initial values for the factor $f_t$, the time-varying coefficient in the state equation $\lambda_t$ and$\beta_t$, the time-varying covariance matrix $V_t$and $Q_t$ as well as $\pi_{t|t-1,j}$ are $f_0$, $\lambda_0$, $V_0$, $\beta_0$, $Q_0$ and$\pi_{0|0,j}$, respectively. These intial values are set as follows:

$$f_0 \sim N(0,4), \lambda_0 \sim N\left(0, 4 \times I_{n(s+1)}\right), \beta_0 \sim N(0, V_{MIN}), \tag{11}$$

$$V_0 = 1 \times I_n, Q_0 = 1 \times I_{s+1}, \pi_{0|0,j} = \frac{1}{J} \tag{12}$$

### 3.2. Connectedness based on high-dimensional time-varying factor-augmented VAR model

In order to quantitatively analyze the fluctuation characteristic across markets and sectors from the perspective of spillover, Diebold and Yilmaz (2009, 2012) proposed the measure between total volatility and directional volatility correlation, which can reveal the level of volatility spillover in different markets. We first express the generalized prediction error variance decomposition (GFEVD) in the sense that:

$$(\Theta_H)_{j,k} = \frac{\sigma_{kk}^{-1}\sum_{h=0}^{H}\left((\Psi_h\Sigma)_{j,k}\right)^2}{\sum_{h=0}^{H}(\Psi_h\Sigma\Psi_h')_{j,j}} \tag{13}$$

where $\sigma_{kk} = (\Sigma)_{k,\ k}$ is the standard deviation of the error term, this equation represents the contribution of $k$ variable about the prediction error variance of element $j$ at the horizontal $h$, we standardized it according to the row and can get the following result:

$$\left(\widetilde{\Theta}_H\right)_{j,k} = \frac{(\Theta_H)_{j,k}}{\sum_{k=1}^{N}(\Theta_H)_{j,k}} \tag{14}$$

where $\sum_{j=1}^{N}\left(\widetilde{\Theta}_H\right)_{j,k} = 1$ and $\sum_{j,k=1}^{N}\left(\widetilde{\Theta}_H\right)_{j,k} = N$, Diebold and Yilmaz (2012) define the total correlation as the share of the error in the prediction except for the error itself.

$$C^H = 100 \cdot \frac{\sum_{j\ne k}\left(\widetilde{\Theta}_H\right)_{j,k}}{\sum\widetilde{\Theta}_H} = 100 \cdot \left(1 - \frac{Tr\left\{\widetilde{\Theta}_H\right\}}{\sum\widetilde{\Theta}_H}\right) \tag{15}$$

where $Tr\{\cdot\}$ is the rank operator; $\sum\widetilde{\Theta}_H$ refers to the sum of all the elements in the $\widetilde{\Theta}_H$ matrix. The total correlation is the relative contribution of the other variables in the system to the prediction variance. In other words, the contagion effects of other variables on j and the contagion effects of variable $j$ on other variables can be expressed as follows:

$$C_{j\leftarrow\cdot}^H = 100 \cdot \frac{\sum_{k=1,k\ne j}^{N}\left(\widetilde{\Theta}_H\right)_{j,k}}{\sum\widetilde{\Theta}_H} \tag{16}$$

$$C_{j\rightarrow\cdot}^H = 100 \cdot \frac{\sum_{k=1,k\ne j}^{N}\left(\widetilde{\Theta}_H\right)_{k,j}}{\sum\widetilde{\Theta}_H} \tag{17}$$

Therefore, the total net directional spillover effect among heterogeneous variables can be expressed as follows:

$$C_j^H = C_{j\rightarrow\cdot}^H - C_{j\leftarrow\cdot}^H \tag{18}$$

where $C_j^H$ helps determine whether variable $j$ is driving the network (if $C_j^H > 0$) or driven by the network (if $C_j^H < 0$).

Finally, we break down the net total directional spillover index to examine the bidirectional network spillover by computing the net pairwise directional spillovers.

$$C_{jk}^H = 100 \cdot \frac{\left(\widetilde{\Theta}_H\right)_{k,j} - \left(\widetilde{\Theta}_H\right)_{j,k}}{\sum\widetilde{\Theta}_H} \tag{19}$$

If $C_{jk}^H > 0(C_{jk}^H < 0)$, then variable $j$ is a net transmitter (receiver) of spillover effect to (from) variable $k$.

By employing the spillover index approach based on the high-dimensional time-varying factor-augmented VAR model, we can study the volatility spillover effects of the COVID-19 on energy markets at different time periods. Moreover, the extended high-dimensional time-varying factor-augmented VAR model employed in this paper can not only describe the volatility spillover effect in different variables in a better way, but also distinguish the heterogeneity characteristics of the spillover effect in different period.

## 4. Data

In order to explore the impact of the COVID-19 on Chinese energy industry as well as the potential features of the impact, we obtain the original data of the number of the accumulated confirmed COVID-19 cases as well as the stock prices of nine energy sub-sectors in China. These energy sub-sectors include oil exploitation (*OE*), coal mining (*CM*), other mining (*OM*), petrochemical (*PE*), power supply equipment (*PSE*), electrical automation equipment (*EAE*), power (*POW*), gas (*GAS*) and optoelectronics sectors (*OPT*). Note that we define these industries as energy sectors according to the Shenwan Industry Classification Standard of China.

In particular, we use the stochastic volatility (SV) model proposed by Chan and Grant (2016) to estimate the stock price volatility for the above nine energy sectors. Since the SV model is directly related to the diffusion process of financial and economic variables, it is assumed that time-varying variance follows an unobservable random process and does not completely depend on past observations. Therefore, the volatility sequence measured by the SV model is more robust to misspecification and to dramatic changes in the time series than the GARCH model, and it can better describe the fat-tailed characteristics of high-frequency variables. Next, we briefly introduce the SV model as follow:

$$r_t = \mu^r + \varepsilon_t^r, \varepsilon_t^r \sim N\left(0, e^{h_t}\right) \tag{20}$$

$$h_t = \mu_h + \chi_h(h_{t-1} - \mu_h) + \varepsilon_t^h, \varepsilon_t^h \sim N\left(0, \omega_h^2\right) \tag{21}$$

where $r_t$ denotes one specified energy sector's stock returns given by $r_t = \ln p_t - \ln p_{t-1}$, in which $p_t$ represents stock prices; $\varepsilon_t^r$ and $\varepsilon_t^h$ are normally distributed disturbance terms; $\mu_h$ is an conditional mean, and $h_t$ is the log-volatility of an energy sector's stock price. Eq. (20) is the observation equation, while Eq. (21) is the conditional variance equation of SV model. The log volatility of estimated from the SV model are employed in this study to measure stock price volatility for the nine Chinese energy sub-sectors.

For the measurement of the COVID-19 pandemic, we make use of the growth rate of the number of the accumulated confirmed COVID-19 cases. Finally, our sample period spans from January 20, 2020 to April 20, 2021 and all original data are obtained from the Wind database of China.

Table 1 presents descriptive statistics of all concerned series. The statistics show that four volatility series, i.e., the stock price volatility of other mining (*OM*), power supply equipment (*PSE*), electrical automation equipment (*EAE*) and optoelectronics sectors (*OPT*) have relatively higher mean values than the other volatility series, proving that the stock prices of the four sectors have higher volatilities than those of the other energy sectors on average during the sample period. Furthermore, the results from the skewness, kurtosis and *JB* tests show that all variables except the stock price volatility of electrical automation equipment (*EAE*) sector are non-normally distributed. In addition, *Q* (20), $Q^2$ (20) and *LM* (20) tests indicate that nine stock price volatility series we consider are autocorrelated and exhibit ARCH errors, and the results from ADF test show that all concerned series are stationary at the significance level of at least 10%. All these results support choosing a HD-TVP-FAVAR model.

Table 2 presents the pairwise correlation coefficients and shows that the COVID-19 pandemic tends to positively correlate with the stock price volatility series of the concerned nine energy sectors. Moreover, the COVID-19 pandemic shows stronger correlations with oil exploitation, electrical automation equipment and gas sectors, providing preliminary evidence of closer relationship between the COVID-19 shock and the three energy sectors. Nevertheless, simple correlation analysis could be misleading because of temporal instability of correlation coefficients and cannot directly uncover the hidden causal structures. Therefore, in the following empirical analysis, we use the HD-TVP-FAVAR model to make a more profound exploration of the dynamic impact of the COVID-19 on the Chinese energy markets.

## 5. Empirical results

First, we use Bayesian multi-step moving Gibbs sampling method to implement parameter estimations of the HD-TVP-FAVAR model. Specifically, we set the sampling frequency to 11,000 times, and use the results of the first 1000 times as "burn-in" with the aim of avoiding the influence of the initial value on the parameter estimation. The impulse responses of the nine Chinese energy sectors to the COVID-19 are thus estimated and shown in Fig. 1.

We find from Fig. 1 that the COVID-19 pandemic aggravates the fluctuations of all concerned energy sectors, but there is significant heterogeneity in the impact on different sectors. Specifically, the COVID-19 pandemic has the greatest impact on the oil exploitation sector, followed by the power sector. When in the face of one standard deviation shock from the pandemic, the stock price volatility for the oil exploitation and power sectors increases by 0.2 and 0.1 percentages respectively at the first day, and takes almost 13 days to converge to zero. On the contrast, the impact of the COVID-19 pandemic on the petrochemical and power supply equipment sectors is relatively small. The maximum magnitude of the response of the stock price volatility in these two sectors to the COVID-19 is less than 0.02. In addition, we also conclude that the impact of the COVID-19 pandemic on the stock price volatility of all concerned energy sectors is mainly at the short-term, and

**Table 1**
Summary statistics for all variables.

| | *OE* | *CM* | *OM* | *PE* | *PSE* | *EAE* | *POW* | *GAS* | *OPT* | *COVID* |
|---|---|---|---|---|---|---|---|---|---|---|
| Mean | 1.26 | 1.734 | 1.938 | 1.288 | 2.502 | 1.984 | 1.09 | 1.431 | 2.245 | 1.77 |
| Variance | 0.16 | 0.18 | 0.248 | 0.124 | 0.284 | 0.166 | 0.132 | 0.156 | 0.273 | 352.953 |
| Skewness | 1.024*** | 0.500*** | 0.284** | 0.922*** | −0.074 | 0.015 | 1.140*** | 0.605*** | 1.348*** | 16.329*** |
| | (0.000) | (0.001) | (0.043) | (0.000) | (0.590) | (0.912) | (0.000) | (0.000) | (0.000) | (0.000) |
| Kurtosis | 0.776** | −0.477** | −1.008*** | 0.144 | −0.969*** | −0.538** | 0.850** | 0.726** | 0.908*** | 273.676*** |
| | (0.021) | (0.039) | (0.000) | (0.488) | (0.000) | (0.014) | (0.014) | (0.027) | (0.010) | (0.000) |
| JB | 60.151*** | 15.375*** | 16.779*** | 42.873*** | 12.048*** | 3.638 | 74.252*** | 24.996*** | 101.476*** | 9527.238*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.002) | (0.162) | (0.000) | (0.000) | (0.000) | (0.000) |
| Q(20) | 983.025*** | 1677.113*** | 1727.787*** | 1737.236*** | 2251.364*** | 2134.914*** | 1822.337*** | 1705.299*** | 2435.743*** | 20.133** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.016) |
| $Q^2(20)$ | 642.631*** | 1239.093*** | 1310.382*** | 1326.796*** | 2015.174*** | 1575.056*** | 1436.834*** | 978.698*** | 2353.257*** | 0.006 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (1.000) |
| LM(20) | 230.945*** | 179.570*** | 63.005*** | 221.880*** | 218.445*** | 59.123*** | 134.183*** | 94.971*** | 38.267*** | 0.024 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (1.000) |
| ADF | −4.197*** | −2.952** | −2.893** | −2.669* | −4.807*** | −5.985*** | −6.251 | −5.456*** | −3.828*** | −40.250*** |
| | (0.005) | (0.041) | (0.047) | (0.081) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |

Note: This table provides descriptive statistics (namely, mean, variance, skewness, kurtosis, JB, Q (20), $Q^2$ (20), LM (20) and ADF for each variable used in our empirical analysis. *COVID* represents the growth rate of $^{\text{cumulative}}$ confirmed cases of COVID-19; *OE, CM, OM, PE, PSE, EAE, POW, GAS* and *OPT* denote stock price volatility series of oil exploitation, coal mining, other mining, petrochemical, power supply equipment, electrical automation equipment, power, gas and optoelectronics sectors, respectively. *, ** and *** indicate the significance levels of 10%, 5% and 1%, respectively. The numbers in parentheses are corresponding *p*-values.

**Table 2**
Correlation coefficients among the key variables.

| | *OE* | *CM* | *OM* | *PE* | *PSE* | *EAE* | *POW* | *GAS* | *OPT* | *COVID* |
|---|---|---|---|---|---|---|---|---|---|---|
| *OE* | 1.000 | 0.499 | 0.666 | 0.784 | 0.298 | 0.435 | 0.346 | 0.501 | 0.455 | 0.217 |
| *CM* | 0.499 | 1.000 | 0.784 | 0.532 | 0.549 | 0.548 | 0.493 | 0.628 | 0.179 | 0.149 |
| *OM* | 0.666 | 0.784 | 1.000 | 0.730 | 0.556 | 0.677 | 0.513 | 0.656 | 0.414 | 0.195 |
| *PE* | 0.784 | 0.532 | 0.730 | 1.000 | 0.470 | 0.572 | 0.428 | 0.462 | 0.467 | 0.132 |
| *PSE* | 0.298 | 0.549 | 0.556 | 0.470 | 1.000 | 0.838 | 0.558 | 0.623 | 0.357 | 0.072 |
| *EAE* | 0.435 | 0.548 | 0.677 | 0.572 | 0.838 | 1.000 | 0.628 | 0.783 | 0.440 | 0.220 |
| *POW* | 0.346 | 0.493 | 0.513 | 0.428 | 0.558 | 0.628 | 1.000 | 0.715 | 0.262 | 0.194 |
| *GAS* | 0.501 | 0.628 | 0.656 | 0.462 | 0.623 | 0.783 | 0.715 | 1.000 | 0.581 | 0.280 |
| *OPT* | 0.455 | 0.179 | 0.414 | 0.467 | 0.357 | 0.440 | 0.262 | 0.581 | 1.000 | 0.196 |
| *COVID* | 0.217 | 0.149 | 0.195 | 0.132 | 0.072 | 0.220 | 0.194 | 0.280 | 0.196 | 1.000 |

Note: This table presents the correlation coefficients among the main concerned variables. *COVID* represents the growth rate of cumulative confirmed cases of COVID-19; *OE, CM, OM, PE, PSE, EAE, POW, GAS* and *OPT* denote stock price volatility series of oil exploitation, coal mining, other mining, petrochemical, power supply equipment, electrical automation equipment, power, gas and optoelectronics sectors, respectively.

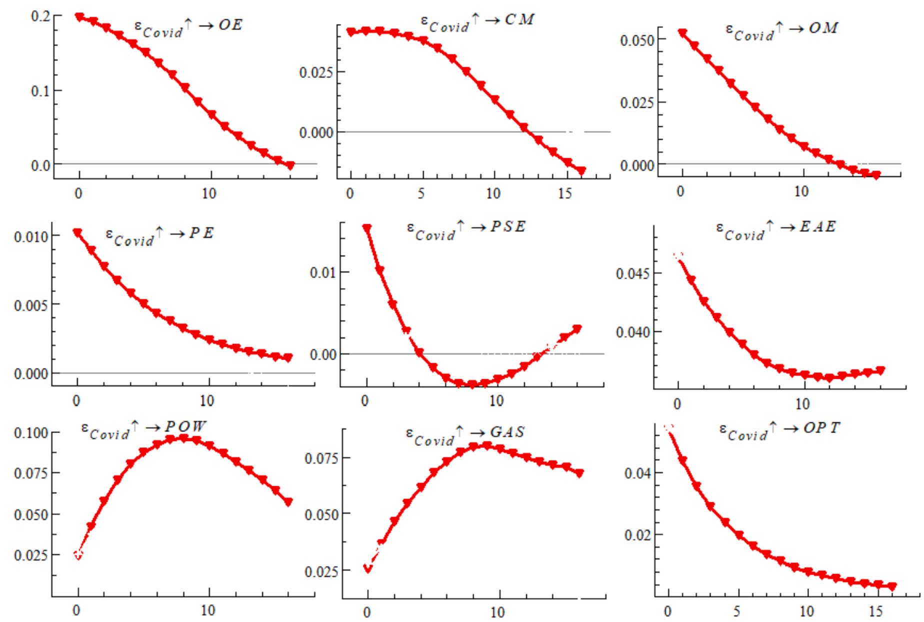
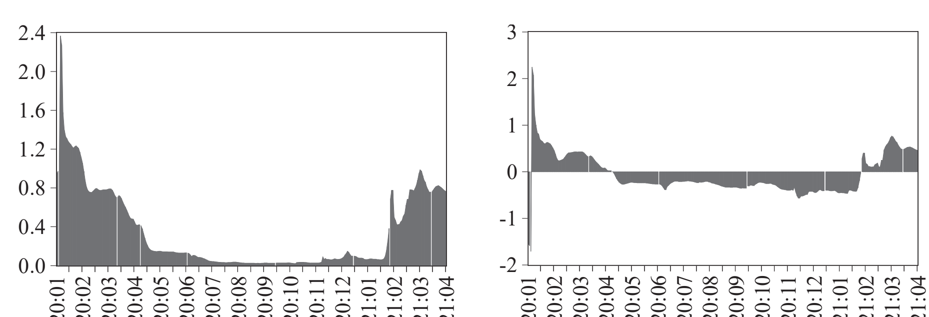



**Fig. 1.** The impulse responses of heterogeneous energy sectors to the COVID-19 pandemic. Note: *Covid* ↑ → means the response to the COVID-19 pandemic shock. *OE, CM, OM, PE, PSE, EAE, POW, GAS* and *OPT* denote stock price volatility of oil exploitation, coal mining, other mining, petrochemical, power supply equipment, electrical automation equipment, power, gas and optoelectronics sectors, respectively.

the fluctuations of each industry show a trend of first rising and then falling, which further implies that the COVID-19 pandemic has caused significant risk spillover effects among various energy sectors of China. In other words, the COVID-19 pandemic is likely to trigger a risk co-movement phenomenon in energy markets, which would intensify potential systemic risks.

Next, in order to intuitively observe the magnitude of the spillover effect of the COVID-19 pandemic on heterogenous energy sectors, we turn to estimate the dynamic spillover index between the COVID-19 and all concerned energy sectors based on the high-dimensional time-



a) Total spillover effects of COVID-19

b) Net spillover effects of COVID-19

**Fig. 2.** The total and net spillover effects of COVID-19 to all energy sectors. Note: The gray areas provide spillovers. Total spillovers of COVID-19 represent directional 'to' spillovers to all energy sectors, and net spillovers are further calculated by directional 'to' spillovers from directional 'from' spillovers. If net spillovers are positive, then the COVID-19 is a net transmitter of spillovers.

varying factor-augmented VAR model. The results of the total and net spillover effects of COVID-19 on all energy sectors are displayed in Fig. 2. It is clear that during January to June of 2020 and February to April of 2021, i.e., the two sub-periods when the confirmed COVID-19 cases sharply increase in China, the total and net spillovers of the COVID-19 pandemic to all energy sectors are obviously higher than the other sub-periods. This suggests a significant time-varying risk transmission from the COVID-19 to Chinese energy market. Furthermore, we also find that such spillovers in the former sub-period are larger than those in the latter sub-period, indicating the COVID-19 pandemic has imposed an unconventional impact on energy markets when there is a dramatic rise in panic due to the first outbreak of the pandemic.

We further estimate the pairwise net volatility spillovers of COVID-19 to each energy sector, in order to determine whether the COVID-19 shock is a net transmitter of spillover effect to individual energy sectors. The corresponding results are shown in Fig. 3. The overall evidence confirms that the responses of energy sectors to the pandemic shock are time-varying. We still observe that the net volatility spillovers of the pandemic remain positive to all underlying energy sectors during the two above-mentioned sub-periods, while are negative for the other sub-periods. On the other hand, we also find that the responses of different energy sectors are obviously heterogenous. For the first sub-period, i.e., from January to June of 2020, there are positive net pairwise volatility spillovers of the COVID-19 pandemic to all nine energy sectors except the power supply equipment sector. This implies that the COVID-19 pandemic serves as a risk transmitter to eight out of nine concerned energy sectors in this sub-period. Moreover, the volatility spillover is not only the highest, but also lasts longest for oil exploitation sector, followed by the power and gas sectors. While for the second sub-period, i.e., from February to April of 2021, the COVID-19 pandemic serves as a risk transmitter to all underlying energy sectors except the gas sector, and has relatively higher volatility spillovers to the power, coal mining and petrochemical sectors. These findings support the heterogeneous impacts of the COVID-19 on different energy sectors, and confirm the time-varying nature of the impacts. In fact, due to the skyrocketing infection rate for the early stage of the COVID-19, the restriction of the population from outdoor activities has severely affected the energy consumption in different areas, including business, industries, tourism, manufacturing, transportation and the residential sectors. The demand and prices for oil and gas have been affected the most under the gloomy scenario and lockdown policy, which turns to be increased uncertainty and higher spillovers from the COVID-19 for these energy sectors.

We also plot the net directional volatility spillover network topologies among all concerned series for the two above-mentioned sub-periods in Figs. 4 and 5, respectively. As shown in Fig. 4, we intuitively observe that five energy sectors, namely the oil exploitation, gas, electrical automation equipment, petrochemical and power sectors, are the domain risk transmitters within the risk network model consisting of nine concerned energy sectors during January to June of 2020. Meanwhile, we have concluded that the COVID-19 remains positive

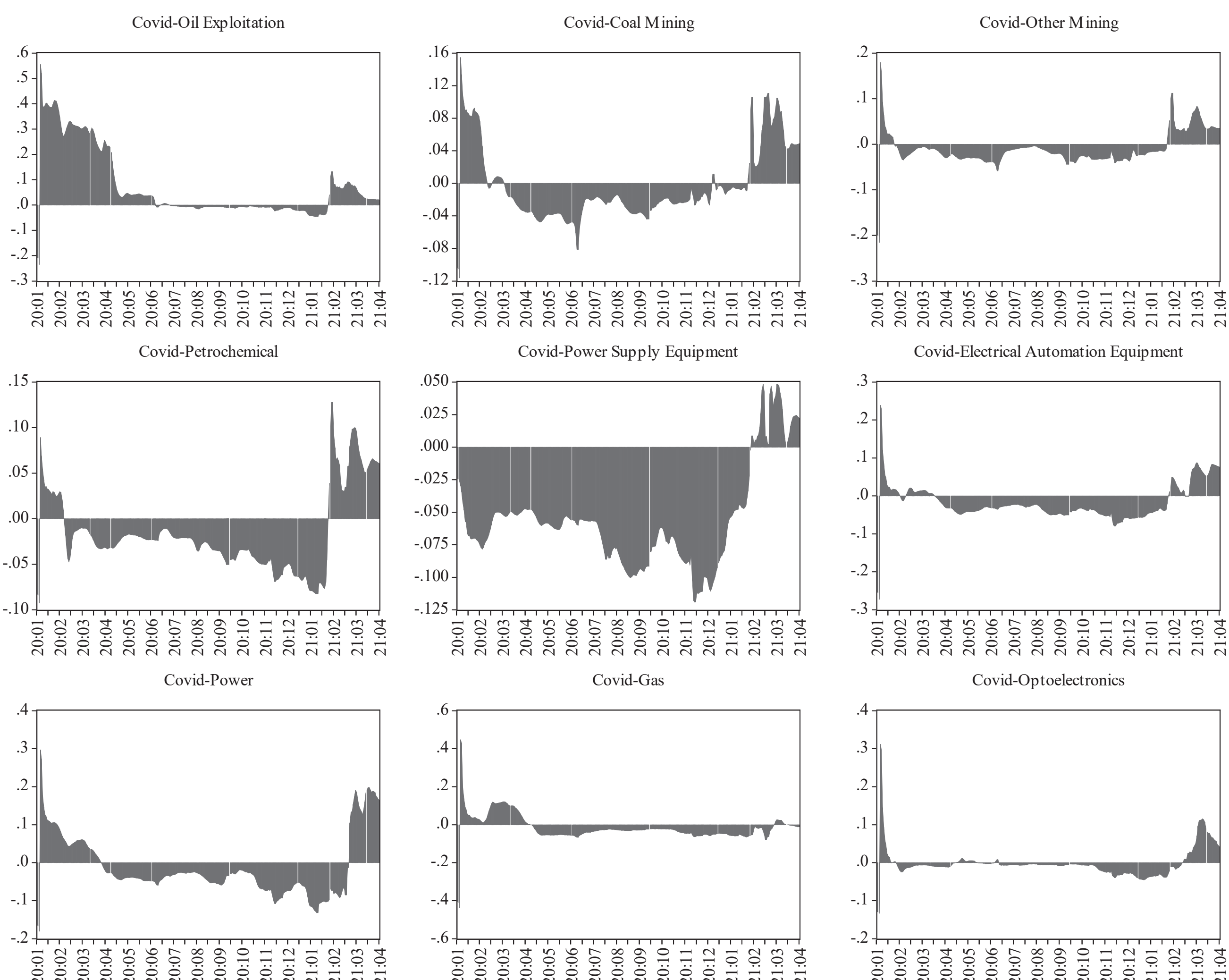



**Fig. 3.** The pairwise net spillover effects of COVID-19 to each energy sector. Note: The gray areas in the figure provide pairwise net spillovers. Positive ones indicates that the COVID-19 is a net transmitter of spillovers to specified energy sub-sector.

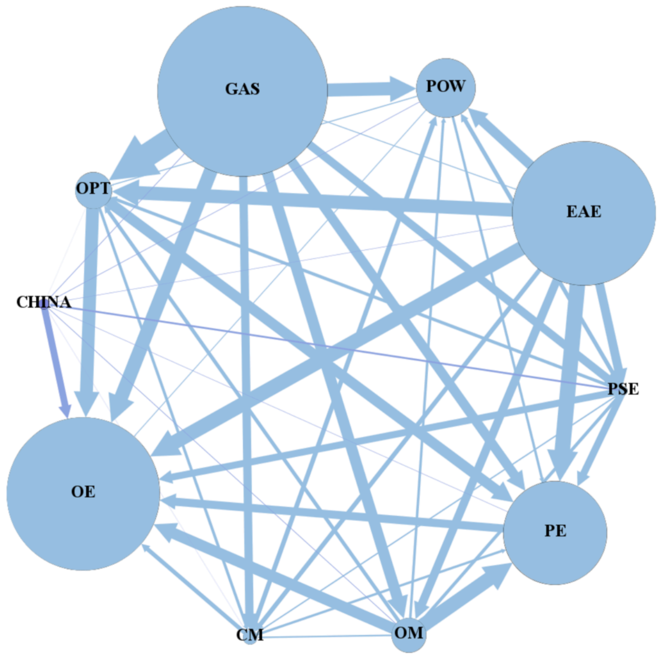



**Fig. 4.** The risk transmission network of COVID-19 and Chinese energy sectors during 2020M1 to 2020M6. Note: The size of the nodes reflects the strength of the total net spillovers. The larger the node, the stronger the net spillover effect. The thickness of the line and the size of the arrow indicates the strength of the pairwise net spillovers.

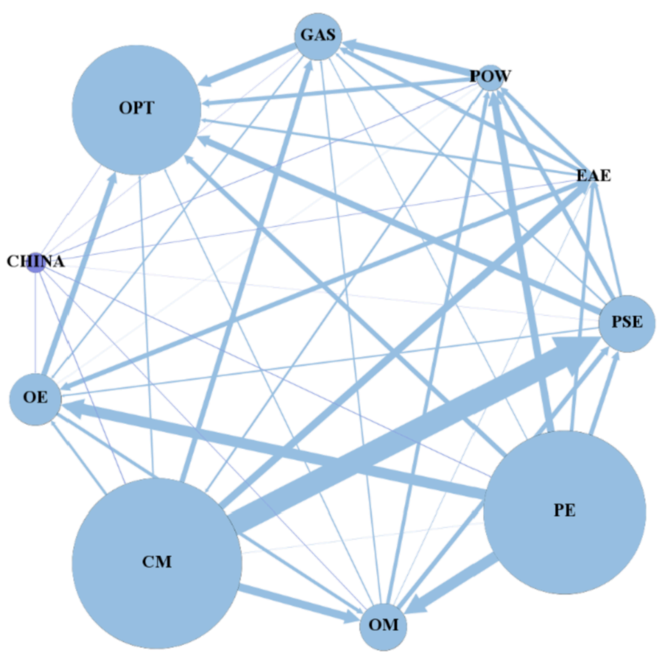



**Fig. 5.** The risk transmission network of COVID-19 and Chinese energy sectors during 2021M2 to 2021M4. Note: The size of the nodes reflect the strength of the total net spillovers of the COVID-19 shock. The larger the node, the stronger the net spillover effect. The thickness of the line and the size of the arrow indicates the strength of the pairwise net spillovers.

directional net spillovers for these five energy sectors, especially the oil exploitation and gas sectors. This further suggests that the uncertainty shock originated from the COVID-19 pandemic could be ultimately transmitted to all energy sectors through the five sectors, resulting in possible risk contagions across different energy markets. However, the results differs greatly when it comes to the sub-period from February to April of 2021. The domain risk transmitters within the risk network model consisting of nine concerned energy sectors turn to be another four energy sectors, including coal mining, petrochemical and opto-electronics sectors. The COVID-19 pandemic shock is likely to induce volatility co-movement in the Chinese energy markets through first spilling over into these four sectors.

The risk correlation among the heterogeneous departments is also measured based on the similarity matrix and the adjacency matrix. In particular, we measure the cosine correlation of each time node based on the risk characteristics of the covariates, and accurately screen the characteristics of the risk curve. Fig. 6 displays the characteristics of heterogeneous cross-sector risk correlations at specific time points during the sub-period of January to June of 2020. It is obvious that during the sub-period, with the intensification of the COVID-19 pandemic, the correlation among the nine energy markets selected in this paper has increased significantly. In particular, in February and March when the spread of the pandemic was the most serious, the color of the similar matrix was gradually covered by yellow, which fully reflected that the dependence among different energy sub-sectors was significantly increased. As the COVID-19 pandemic was brought under control in April 2020, the number of newly diagnosed also showed a downward trend, and meanwhile, the duration of the co-movement among different markets also exhibits a declining trend to a certain extent. However, with the intensification of overseas imported risks, some regions (e.g., Heilongjiang, Jilin, Beijing and Xinjiang) of China experienced a second outbreak of the COVID-19 from May to June of 2020. As expected, the color of the similar matrix turned yellow, suggesting that risk contagion between the energy sub-sectors happens when the pandemic comes back. These findings confirm previous results that energy sectors were indeed affected by the pandemic, and the risk contagion among different energy sectors has a significant time-varying nature, with the risk contagion highly sensitive to the COVID-19 related uncertainty.

Furthermore, we construct the network effect of risk into a unified confidence interval, and evaluates its nonlinearity or deviation from ordinary linear regression, thereby forming risk differences among heterogeneous markets. However, it should also be pointed out that, when describing the risk resonance characteristics among different markets during the COVID-19 pandemic period, we found that different markets did not show the same shock characteristics. In other words, the impact of the pandemic on different markets has asymmetric characteristics. However, because the systemic risk is caused by the positive correlation among heterogeneous sectors, that is, the increase in the positive dependence of heterogeneous market risk tends to aggravate the systemic risk. In order to further describe the asymmetric characteristics of cross-market risk spillover effect, we divide risk transmission into "direct co-action, uncertainty co-action and inverse co-action", and the specific results are shown in Fig. 7. As shown, during the period from January to March 2020, the number of white grids shows a trend of gradual increase, which means that the risk spillover effect among heterogeneous energy sectors presents a significant positive correlation. As the interest rate in the inter-bank lending market can be regarded as the proxy variable of monetary policy, its adjustment process is mainly counter-cyclical regulation. Therefore, for the interest rate market marked with 10, its correlation with other markets is mainly black, which also reflects the realistic characteristics of counter-cyclical regulation of China's monetary policy. As mentioned above, under the strong leadership of the CPC Central Committee with Secretary Xi Jinping at its core, and the arduous efforts of the people across the country with great sacrifices, major strategic achievements have been achieved in the prevention and control of the COVID-19 pandemic. The number of newly diagnosed patients in China dropped to the lowest level. At this time, nodes in the network graph gradually show negative correlation during April 2020, that is, the earlier implied risk aggregation phenomenon begins to scatter, that is, the color of the graph in April 2020 is

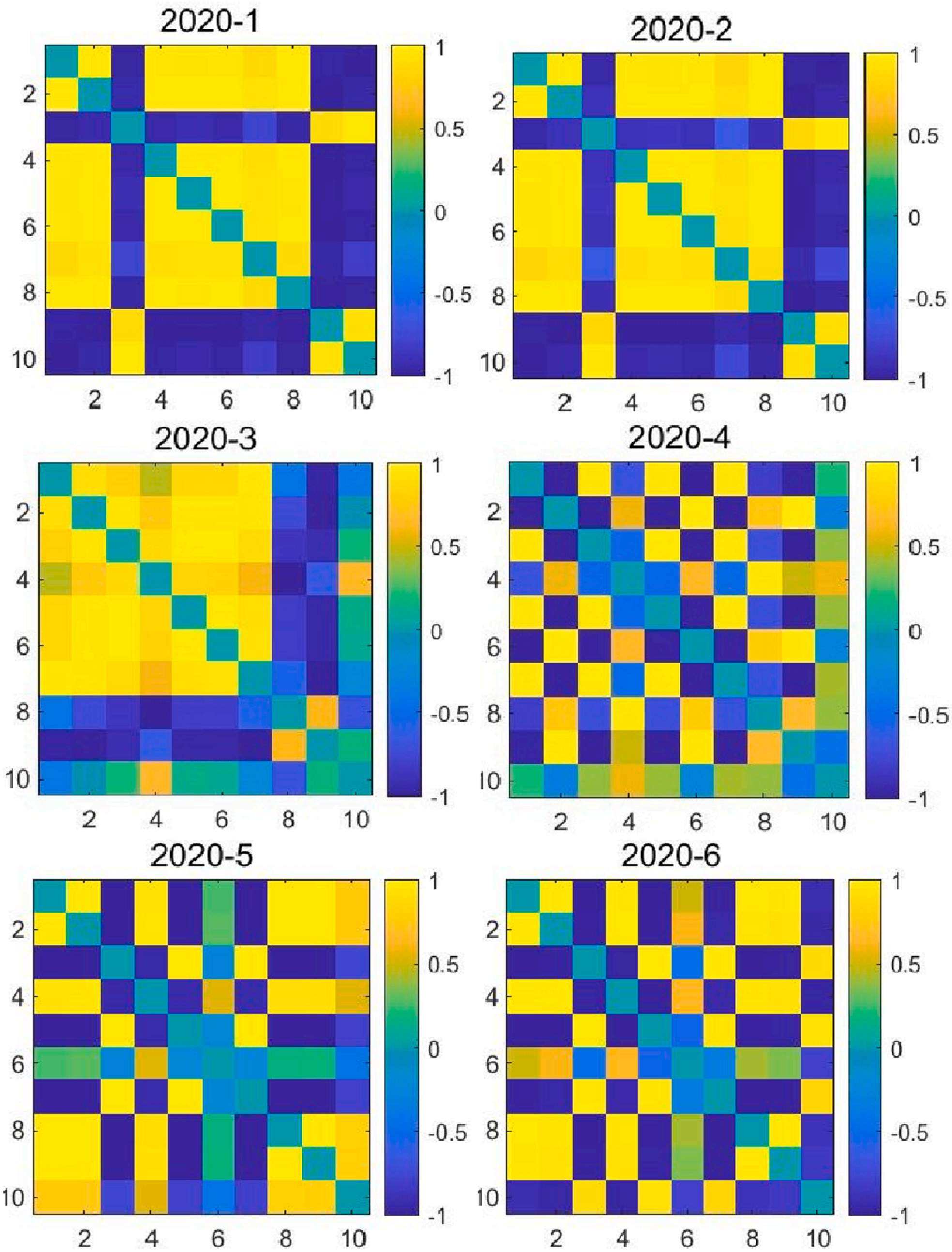



**Fig. 6.** The risk similarity matrix of heterogeneous energy sectors and the COVID-19 pandemic during 2020M1 to 2020M6. Note: The colors used to represent the degree of similarity vary from negative (blue) to positive correlation (yellow) in the grids. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

gray. However, due to the adverse impact of overseas imported risks, the COVID-19 pandemic in May–June 2020 began to rebound, which made the risks among different markets begin to show positive linkage and strong "resonance" spillover effect.

## 6. Conclusions

The unconventional shocks originated from major emergencies not only pose a great threat to life safety and health of people, but also cause negative impacts on production and consumption and bring huge challenges to social and economic stability. Therefore, effectively monitoring the impacts of major emergencies on the real economy and financial markets, and capturing the transmission direction, magnitude and path of the shocks between heterogenous markets are not only helpful to improve governments' response mechanism and risk prevention, but also help to avoid systemic risks due to risk contagion across sectors and markets and finally, to maintain economic development and social stability.

This paper employs the COVID-19 pandemic that broke out in early 2020 as an unconventional pandemic shock, and utilizes a HD-TVP-FAVAR model to assess the dynamic impacts of the COVID-19 pandemic on the nine energy sub-markets in China. In particular, this study analyzes the time-varying volatility spillover effects of the pandemic to these energy sub-industries. We find that the net volatility spillovers of the pandemic remain positive to all underlying energy sectors during January to June of 2020 and February to April of 2021, supporting the presence of the risk spillover effect of the COVID-19 to energy markets. In addition, our empirical evidence also suggests that

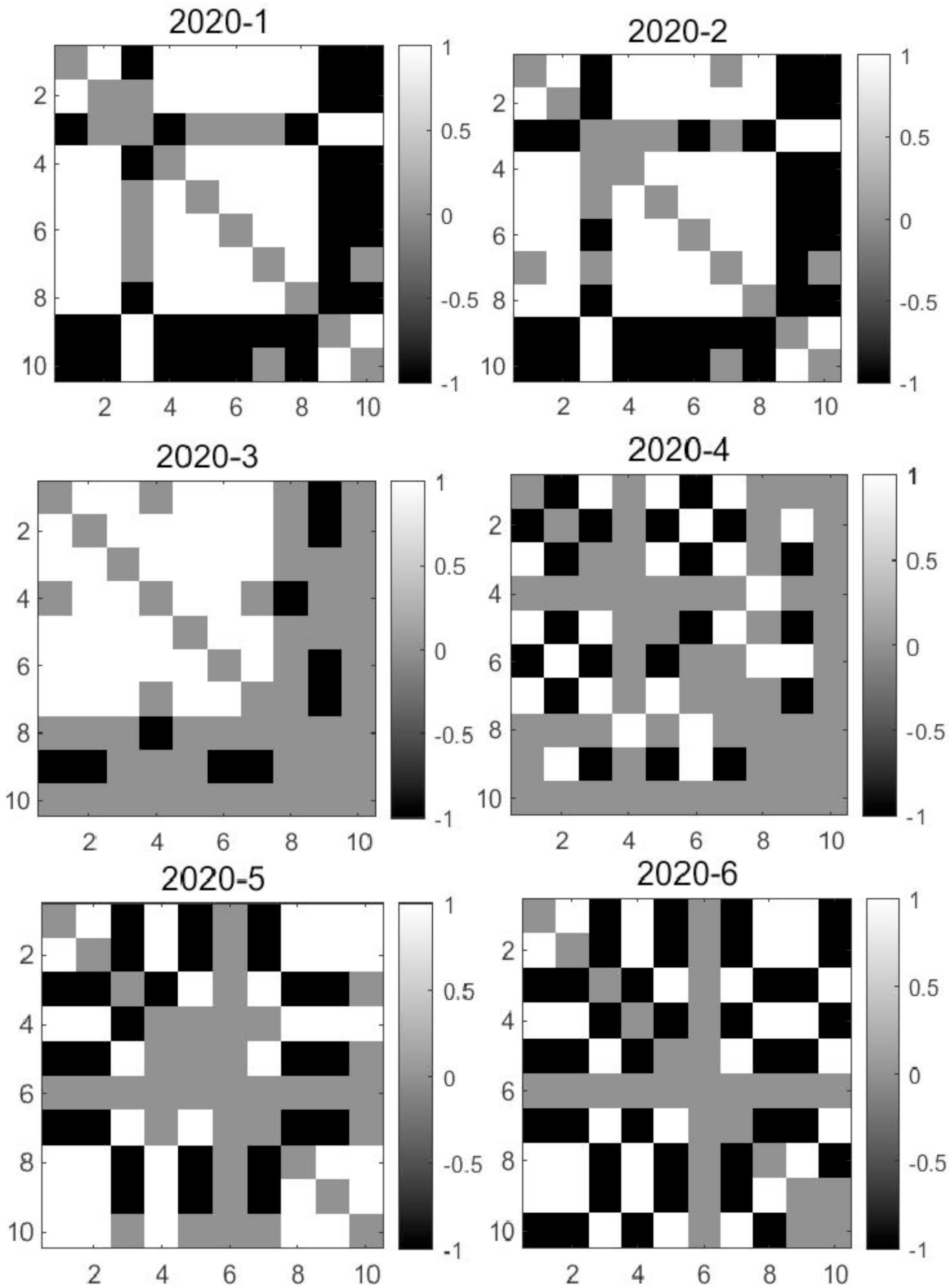



**Fig. 7.** The risk adjacency matrix of heterogeneous energy sectors and COVID-19 during 2020M1 to 2020M6. Note: the highly positive correlation (in white), the highly negative correlation (in gray) and the weak correlation (in black) are shown for each month of interest.

the spillover effects vary among different energy sub-sectors. For the sub-period of January to June of 2020, the volatility spillover of the COVID-19 is not only the highest, but also lasts longest for oil exploitation sector, followed by the power and gas sectors. The finding is in line with recent evidence that the oil exploitation sector, followed by the power and gas sectors, is affected the most by the pandemic owing to negative supply and demand shocks and high uncertainty shock in oil, power and gas sectors during the most serious stage of the COVID. While for the latter sub-period, i.e., February to April of 2021, the COVID-19 turns to impose relatively higher volatility spillovers to the power, coal mining and petrochemical sectors.

This study has several policy implications. First, given that energy markets could be largely affected by extreme events including COVID-19, the Chinese governments should take appropriate energy policies to avoid possible energy insecurity and poverty, and to improve energy price mechanism, and to encourage the transition to a more renewable and sustainable energy system. Second, the spillover effects could be strengthened in the short term, and are heterogeneous among different energy sub-sectors and across different periods of time, governments should comprehensively consider different development stages of both energy industries and major emergencies, and thus purposefully adjust policy tools for risks from different sources to avoid negative impacts of improper policy implementation on real economy and financial markets. Third, since abnormal fluctuations in energy stock sectors, especially for those energy sectors highly sensitive to external uncertainty shocks, are easily contagious and could induce the resonance of the entire risk network during major emergencies, governments should monitor abnormal fluctuations in these sectors and effectively control the direction and intensity of policy tools, which is essential for reducing the risk of cross-contagion between different energy sectors.

The implications from our research can potentially instigate further research. The ongoing COVID-19 pandemic can impact energy industries profoundly and persistently. This is an important starting point. The next step, and possible extension, is to analyze the long-term effects of the COVID-19 on the investment and financial decisions as well as innovation activities of specific energy industries, given that the pandemic also could bring some dividends and opportunities to energy industries, like promoting the transition to a more renewable and sustainable energy system.

## Credit author statement

Deng-Kui Si: Data, Methodology, Software, Writing-Reviewing and Editing. Xiao-Lin Li: Conceptualization, Resources, Writing-Reviewing and Editing. XuChuan Xu: Supervision, Writing-Reviewing and Editing. All authors have read and agreed to the published version of the manuscript.

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## Appendix

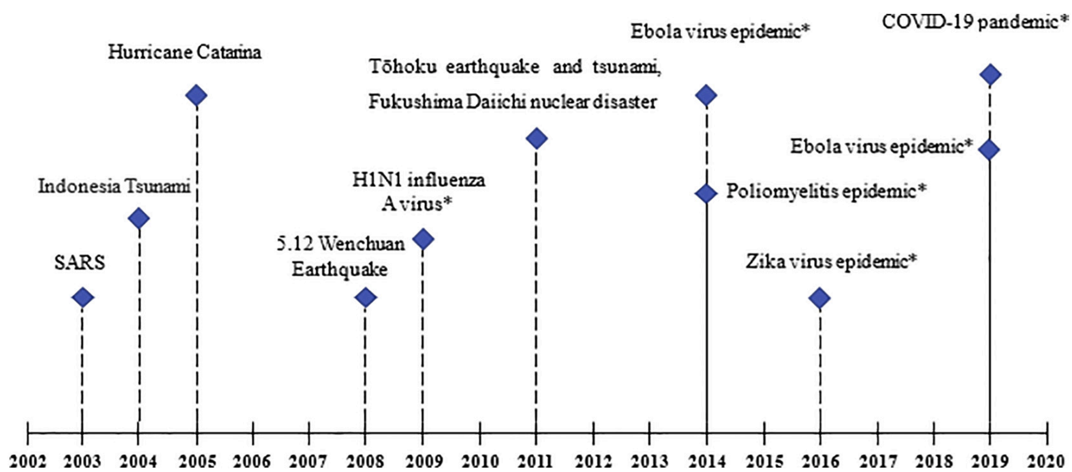


**Fig. A1.** The memorabilia of major emergencies over the past two decades.

## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2021.105498.

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