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Energy market reforms in China and the time-varying connectedness of domestic and international markets

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A R T I C L E I N F O

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A B S T R A C T

China is the world's largest energy consumer and a considerable force in international energy markets. Continuous market reforms in the country together with the ongoing energy transition due to the commitment to carbon neutrality have brought fundamental changes to Chinese energy markets and have resulted in new sources of uncertainty in international energy markets. It is therefore important to investigate market linkages between China and the world from a dynamic perspective. This paper adopts the time-varying parameter VAR (TVP-VAR) model and the network spillover approach to explore the time-varying linkages between China and the international energy markets. The results show that the marketization process in China has led to significant changes in spillover patterns between international energy markets and Chinese domestic markets. Dynamics in the Chinese energy markets have played an increasingly important role in affecting international energy price movements. There is also clear evidence that the energy transition process in China has driven risk spillovers from the country to the international energy markets.

1. Introduction

China is the largest energy consumer in the world, consuming 25% of the global energy in 2021.[1] Although China is also one of the largest energy producers in the world, the country is highly dependent on the international energy markets. For example, over 70% of the oil consumed in China is imported, whereas over 40% of natural gas consumption depends on international markets. As the demand for energy increases with the steady economic growth of the country, China's dependency on foreign oil producers may exceed 80% by 2030 (Wang et al., 2018).

Despite the huge energy demand, China is traditionally a price-taker in the global market. The lack of pricing power and the failure to be fully integrated into the international energy system are often considered the main reasons for paying relatively higher prices, termed the 'Asian premium' (Zhang et al., 2018a, 2018b). The situation has become more challenging in recent years due to fundamental changes in the international energy markets. Negative shocks, such as the COVID-19 pandemic (Akhtaruzzaman et al., 2021), the Russia–Ukraine war (Khudaykulova et al., 2022) and increasing geopolitical risks, have brought enormous risks in the energy sector, leading to higher price volatilities and energy crises. In addition, increasing focus on the climate crisis and associated transitions have caused considerable uncertainty in the global energy markets (Nam, 2021).

To better serve the fast economic growth in China and ensure energy security in the country, authorities have continuously restructured and reformed the energy sector. The core of these reforms is to introduce a fully functional market mechanism. One of the main pillars is to change the pricing mechanism from the central planning system to a more flexible market-based mechanism. For example, the current refinery oil pricing scheme is based on a series of reforms from 1998 and has evolved to the current price adjustment mechanism. This is to adjust prices according to a basket of international oil prices, namely those of Brent, Dubai and Mina. The new mechanisms can better reflect price dynamics in the international markets. In addition, China's LNG ex-factory prices are no longer controlled by the government since September 2014, and the trading centers in Shanghai, Chongqing, and Shenzhen are established to deregulate oil and gas prices.

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[1] https://yearbook.enerdata.net/total-energy/world-consumption-statistics.html

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Another main pillar of the reform is focusing on institutional changes, aiming at breaking down monopolies in the energy sector and allowing more market participants to be involved (see, for example, Yuan et al., 2020 and Wang et al., 2022a, 2022b for more details). In 2018, China established its own crude oil futures in the Shanghai International Energy Exchange, using Chinese currengy RMB to trade. This is another attempt to gain pricing power in the international energy markets, although there is still much more to be done (Ji and Zhang, 2019).

In general, these market reforms in China have changed the energy sector substantially and have led to closer domestic linkages among different sources of energy and also internationally with other benchmark prices (Ji et al., 2022). For example, the coal price in China has been fully determined by the market, while the oil-indexation pricing mechanism remains dominant in China's natural gas market (Miao et al., 2022). It is believed that there will be an obvious correlation between the price of natural gas and coal when natural gas marketization is completed (Li et al., 2017; Li et al., 2021). By closely integrating with the international markets, and considering the size of China's energy trade, the China factor has started to emerge in driving the dynamics of the international energy markets (Li et al., 2019).

Another critical change in China is the commitment to carbon neutrality, which inevitably leads to the transition to renewable energy (Jia and Lin, 2021; Wang et al., 2022b). Risks and uncertainties in this transition process (Chen et al., 2022) can have profound impacts on the traditional fossil fuel energy sector and can spill over to the international energy markets (Zhang et al., 2021), leading to extreme price fluctuations (Wang et al., 2022a).

Due to the effects of marketization reform and energy transition policies to achieve carbon neutrality, there is renewed interest in investigating how different energy forms link with each other in China and the role of the Chinese energy sector in the international energy markets. To explore these issues and allow for the dynamic patterns to be revealed, a time-varying network approach, such as that employed by Antonakakis et al. (2018, 2020), can be used. Specifically, we use the TVP-VAR model, together with the network approach employed by Diebold and Yilmaz (2014), to explore a series of energy price changes/volatilities. To that end, we include both China's domestic energy prices and international energy prices. For domestic energy prices, liquefied natural gas (LNG), diesel, gasoline and coal price are considered, whereas oil, coal and natural gas prices are used for international energy markets.

Our main contributions are as follows. First, we combine the TVP-VAR model with a network connectedness approach to capture the time-varying dynamic linkages between the Chinese domestic energy markets and international energy markets. The model allows us to explore the dynamic evolution of the system and thus enables us to comment on the changing role of China in the international markets. Under the "dual carbon" target, the energy market risks triggered by the contradiction between energy transition and fossil energy dependence will spread through the open economic environment, generating risk spillovers and contagion effects. The international energy risk contagion under special circumstances such as global economic crises, geopolitical conflicts, and during the post-COVID-19 epidemic era has been discussed intensively (e.g. Corbet et al., 2020; Gharib et al., 2021a, 2021b; Bouri et al., 2021a), but little attention has been paid to energy risk spillovers from China.

Second, the dynamic analysis allows us to examine the outcomes of China's marketization reform of its energy markets. According to the arguments above, energy market reforms in China seek to establish a market mechnism. On the one hand, this market mechnism connects different forms of energy within the Chinese energy markets. In other words, we would expect to see a higher level of price connectedness among different energy prices in China. On the other hand, marketization leads to a higher degree of integration between China and the international markets; therefore, stronger spillovers should be observed over time. Additionally, the dynamic analysis can show whether China's commitment to carbon neutrality makes any difference across markets.

Third, we explore both returns and volatility spillovers using daily frequency data. High-frequency energy price indices are available from the Shanghai petroleum and natural gas center (SHPGX). As part of the energy marketization process, trading centers were established in China to collect and disclose price information in China's refined oil and gas markets (Zeng et al., 2020). Such information can better reflect marketwide linkages and connections with the international markets and is therefore especially relevant to the main purpose of the current study. As our results show, marketization and energy transition have driven the spillover of Chinese energy price risk to international energy markets.

The remainder of this paper is organized as follows. Section 2 consists of a review of the relevant literature on the spillover effect in energy markets. Section 3 introduces the methodology and the data. Section 4 reports and discusses the empirical results. Section 5 concludes with policy implications.

2. Literature review

2.1. The price linkage between fossil fuels

Inter-fuel substitution dominates the price interactions between different energy types, and there are co-movements of crude oil, natural gas and coal prices in the international markets (Ferrari et al., 2021). Using a diagonal BEKK approach, Zolfaghari et al. (2020) find robust evidence of volatility spillover effects among coal prices, crude oil prices and natural gas prices in the U.S. market. Employing the frameworks by Diebold and Yilmaz (2012) and Baruník and Křehlík (2018), Asadi et al. (2022) suggest that although the coal market does not strongly connect with natural gas, volatility spillover between crude oil and coal is pronounced. The effect of natural gas on the volatility of crude oil is also noticeable in the US. Li et al. (2019) focus on China's inter-fuel substitution and inter-market contagion and demonstrated that China's coal market is a net volatility recipient of shocks from both the crude oil market and the international coal market.

The price relationship between refined oil and crude oil is related to their production modes. Specifically, gasoline and diesel are the main processed products of crude oil, and their prices are closely related to the price of crude oil (Liu et al., 2010; Storhas et al., 2020). Moreover, the news related to the supply of the international crude oil market also has a positive impact on the price of refined oil in some markets (Kang et al., 2019; Shioji, 2021). Focusing on the volatility spillovers of crude oil, gas oil, gasoline, heating oil and natural gas futures markets, Mensi et al. (2021a, 2021c) show that crude oil is the biggest net contributor of volatility spillovers to the other markets.

Initially, the price relationship between natural gas and crude oil is also related to the production modes. Natural gas is an associated product of oil field exploitation, and the high oil price is a main driving force for natural gas drilling and production decisions. The price return of crude oil and refined oil products are often information transmitters to natural gas in Europe and the US (e.g. Ji et al., 2018a; Gong et al., 2021). Shen et al. (2018) find asymmetric spillover patterns between oil and natural gas prices in the US; that is, the shocks in the oil market will significantly increase the volatility risk of the natural gas market, but there is no reverse impact. Evidence also shows that natural gas price is gradually decoupling from crude oil prices. For example, the large-scale development of shale gas in the US causes their natural gas prices to be more affected by fundamental market factors rather than crude oil prices (Jadidzadeh and Serletis, 2017; Wang et al., 2019). The market-based pricing approach based on trading centres also facilitates the decoupling of oil-gas prices (Zhang et al., 2018a, 2018b; Chai et al., 2019).

The price linkage between fossil fuels in the Chinese market is determined by the scale of trade and the degree of marketization. For example, the linkage between China's coal price and international crude oil prices mainly depends on the share of these two kinds of energy in

China's energy consumption structure, and its linkage with international coal price depends on the scale of coal trade (Li et al., 2019). The dependence structure between China's natural gas and oil markets is determined by the natural gas pricing mechanism linked to crude oil prices (Chai et al., 2019; Miao et al., 2022). In addition, it is necessary to adopt hub-based pricing in Asia so that gas pricing can fully reflect the fundamentals in gas markets (Wang et al., 2020a, 2020b).

Given the price linkage between China's coal and natural gas markets, Li et al. (2017, 2021) demonstrate that market-oriented reforms will promote the price correlation between coal and natural gas, and in the short-term coal prices have a more significant impact on natural gas prices than oil prices. A similar case is that when the coal price in China fluctuated greatly in 2021, the domestic oil and gas price indices, related derivatives and international coal prices all fluctuated significantly. In the context of marketization and energy transition, how the price risk of Chinese energy may spread across markets is worth studying to help enhance energy risk management.

2.2. The time-varying connectedness of energy prices

Economic crises, geopolitics, trade frictions and large-scale public health events are all shown to have significant impacts on risk contagion across energy markets (e.g. Corbet et al., 2020; Gharib et al., 2021a, 2021b; Bouri et al., 2021b). Based on Diebold and Yilmaz's connected framework and wavelet methods, Mensi et al. (2021c) show evidence of intensified risk spillovers among the crude oil, gas oil, gasoline, heating oil and natural gas futures markets during the global financial crisis, the oil price crash and the COVID-19 pandemic crisis. The risk spillover between Chinese and international crude oil futures also underwent dramatic changes in direction, intensity and durability during the COVID-19 pandemic (Yang et al., 2020; Fu and Qiao, 2021).

The combination of connectedness measures and a rolling window can further reveal the time-varying characteristics of the spillover effect (e.g. Geng et al., 2021; Ji et al., 2018a, 2018b, 2019; Mensi et al., 2021b; Wang et al., 2020a, 2020b). However, the dynamic change of the spillover effect based on vector autoregression (VAR) error decomposition will be affected by the size of the rolling window. In addition, there is a loss of observations in the calculation of the dynamic measures of connectedness. Antonakakis et al. (2018, 2020) improve the methodology and propose a dynamic connectedness approach based on time-varying parameter vector autoregression (TVP-VAR) with the result that spillover dynamics are not influenced by the rolling window size. A more accurate measurement of the volatility correlation of variables is proposed by Dai et al. (2022). In analyzing the time-varying volatility spillovers between the crude oil markets using the TVP-VAR method and the traditional rolling window method, Liu and Gong (2020) show that the volatility spillovers calculated by TVP-VAR are clearer, more stable and not outlier-sensitive. The time-varying characteristics of spillover effects between energy and various other assets (e.g. gold, stocks, currencies, bonds, metals, agriculture commodities, etc.) are also captured by the advantage of this new method (e.g. Mokni et al., 2020; Bouri et al., 2021a, 2021b; Balcilar et al., 2021; Song et al., 2021, 2022; Qin et al., 2021; Farid et al., 2022).

In combining the TVP-VAR model and the spillover method, Gong et al. (2021) point out that the volatility spillover indices across oil and natural gas futures markets show peaks and troughs during some periods, such as the shale gas revolution, financial crises and the oil price crash. Lin and Tong (2021) observe a dramatic increase in the total connectedness of U.S. energy markets following the outbreak of COVID-19. Chatziantoniou et al. (2022) also find the total connectedness across crude oil and refined petroleum product prices positively affected by the COVID-19 pandemic, while the integration of the European gas futures market was hit hard by the pandemic (Chen et al., 2022). Not only the spillover among energy markets, but the strong transmission of return shocks between energy, metals, and agriculture commodities is also found by Farid et al. (2022) during this period.

Focusing on China's energy market, Si et al., (2021) find that during the most serious stage of COVID-19, the oil exploitation sector has the highest volatility spillover effect with the longest duration, followed by the power and gas sectors. Based on the measure of stock price crash risk, Huang and Liu (2021) indicates that China's energy firms showed significantly lower crash risk than other firms. As for whether the epidemic has changed the structure of energy risk spillovers between China and international markets, further research is needed.

3. Methodology and data

3.1. The spillover framework based on TVP-VAR

We employ the spillover framework by Diebold and Yilmaz (2012, 2014) and the TVP-VAR method to analyse the dynamic correlation between China's energy commodity prices and international energy prices. Compared with the traditional spillover estimation via a rolling-window VAR approach, there is no need to choose the rolling-window size, and there is no loss of observations. Following Antonakakis et al. (2018, 2020), we estimate a TVP-VAR(1) model as suggested by the Bayesian information criterion (BIC):

$$\mathrm{Y_t} = \mathrm{A_t Y_{t-1}} + \varepsilon_t \ \varepsilon_t \ |\Omega_{t-1} \sim \mathrm{N}(0, \Sigma_t) \tag{1}$$

$$vec(\mathrm{A_t}) = vec(\mathrm{A_{t-1}}) + \xi_t \ \xi_t|\Omega_{t-1} \sim \mathrm{N}(0, \Xi_t) \tag{2}$$

where $\mathrm{Y_t}$ and $\mathrm{Y_{t-1}}$ are $\mathrm{K} \times 1$ dimensional endogenous variable vectors, ε_t denotes a $\mathrm{K} \times 1$ dimensional error vector, and Σ_t is a $\mathrm{K} \times \mathrm{K}$ dimensional variance–covariance matrix of ε_t. $\mathrm{A_t}$ and $\mathrm{A_{t-1}}$ are $\mathrm{K} \times \mathrm{K}$ dimensional matrices, and $vec(\mathrm{A_t})$ is the vectorisation of $\mathrm{A_t}$ which is an $\mathrm{K}^2 \times 1$ dimensional vector. ξ_t is a $\mathrm{K}^2 \times 1$ dimensional vectors, and Ξ_t is $\mathrm{K}^2 \times \mathrm{K}^2$ dimensional variance–covariance matrix of ξ_t. Moreover, Ω_{t-1} represents the information available at $t - 1$. $\mathrm{Y_t}$, the vector of endogenous variables, contains 8 variables ($\mathrm{K} = 8$), which are eight energy price indices that we are interested in.

Based on the generalized forecast error variance decompositions (GFEVD) and the generalized impulse response function (GIRF), the time-varying coefficients and the time-varying variance–covariance matrices can be used to estimate the generalized connectedness procedure. To calculate the GIRF and GFEVD, the TVP-VAR is transformed into its vector moving average (VMA) representation based on the Wold theorem, shown as follows:

$$\mathrm{Y_t} = \sum\nolimits_{i=1}^{p} \mathrm{A_{i,t} Y_{t-1}} + \varepsilon_t = \sum\nolimits_{j=0}^{\infty} \mathrm{B_{j,t}} \varepsilon_{t-j} \tag{3}$$

Then, combined with the KPSS variance decomposition matrix (Koop et al., 1996; Koop and Korobilis, 2014), the H-step error variance in forecasting $\mathrm{y_i}$ that is due to shocks of $\mathrm{y_j}$ at time t is given by:

$$RC_{j\to i,t}(H) = \frac{\sum_{t=1, i\neq j}^{H-1}\left(\sum\limits_{ij,t}^{-\frac{1}{2}} B_{H,t}\sum\limits_{t}\varepsilon_{\mathrm{ij,t}}\right)^2}{\sum\limits_{i=1}^{K}\sum_{t=1}^{H-1}\left(\sum\limits_{ij,t}^{-\frac{1}{2}} B_{H,t}\sum\limits_{t}\varepsilon_{\mathrm{ij,t}}\right)^2}, \tag{4}$$

where Σ_t is the covariance matrix for the error vector $\varepsilon_{\mathrm{ij},\,t}$, $0 \le RC_{j\to i,\,t}(H) \le 1$, $\sum_{j=1}^{K} RC_{j\to i,t}(H) = 1$, and $\sum_{i,j=1}^{K} RC_{j\to i,t}(H) = K, i, j = 1, 2, \cdots, K$. The larger size of $RC_{j\to i,\,t}(H)$, the higher the spillover effect from y_j to y_i is at this moment. Such a process ensures that all variables explain 100% of variable i's forecast error variance.

Following Diebold and Yilmaz (2012, 2014), we also construct the total connectedness index $TSI_t(H)$, the directional volatility spillover received by variable i from all other variables, denoted as $SI_{\to i,\,t}(H)$, and the directional volatility spillover transmitted from variable i to all other variables, denoted as $SI_{\mathrm{i}\to,t}(H)$.

$$TSI_t(H) = \frac{\sum_{i,j=1,i\neq j}^{K} RC_{j\rightarrow i,t}(H)}{\sum_{i,j=1}^{K} RC_{j\rightarrow i,t}(H)} \times 100 = \frac{\sum_{i,j=1,i\neq j}^{K} RC_{j\rightarrow i,t}(H)}{K} \times 100 \quad (5)$$

$$SI_{\rightarrow i,t}(H) = \frac{\sum_{j=1,i\neq j}^{K} RC_{j\rightarrow i,t}(H)}{\sum_{i,j=1}^{k} RC_{j\rightarrow i,t}(H)} \times 100 = \frac{\sum_{j=1,i\neq j}^{K} RC_{j\rightarrow i,t}(H)}{K} \times 100 \quad (6)$$

$$SI_{i\rightarrow,t}(H) = \frac{\sum_{j=1,i\neq j}^{K} RC_{i\rightarrow j,t}(H)}{\sum_{i,j=1}^{k} RC_{i\rightarrow j,t}(H)} \times 100 = \frac{\sum_{j=1,i\neq j}^{K} RC_{i\rightarrow j,t}(H)}{K} \times 100 \quad (7)$$

The net volatility spillover from variable i to all the others is simply the difference between $SI_{i\rightarrow,t}(H)$ and $SI_{\rightarrow i,t}(H)$:

$$NSI_{i,t}(H) = SI_{i\rightarrow,t}(H) - SI_{\rightarrow i,t}(H). \quad (8)$$

The net pairwise volatility spillover from y_j to y_i can be defined as:

$$NPS^{H}_{j\rightarrow i,t} = \left(\frac{RC_{j\rightarrow i,t}(H)}{\sum_{i,k=1}^{K} RC_{k\rightarrow i,t}(H)} - \frac{RC_{i\rightarrow j,t}(H)}{\sum_{j,k=1}^{K} RC_{k\rightarrow j,t}(H)} \right) \times 100 \quad (9)$$
$$= \left(\frac{\mathrm{RC_{j\rightarrow i,t}(H) - RC_{i\rightarrow j,t}(H)}}{\mathrm{K}} \right) \times 100$$

Finally, the static spillover effect among variables in the sample interval can be calculated as the mean value of these dynamic indicators. For example, $\mathrm{RC_{j\rightarrow i}(H)}$ is the mean value of $\mathrm{RC_{j\rightarrow i,\ t}(H)}$, indicating the static H-step error variance in forecasting $\mathrm{y_i}$ that is due to shocks on $\mathrm{y_j}$. Meanwhile, the static indices $\mathrm{SI_{\rightarrow i}(H)}$ and $\mathrm{SI_{i\rightarrow}(H)}$, calculated by the mean value of $\mathrm{SI_{\rightarrow i,\ t}(H)}$ and $\mathrm{SI_{i\rightarrow,\ t}(H)}$ respectively, measure the static directional spillovers between all markets and market i. The static net volatility spillover from the market i to all other markets can also be calculated as the difference between $\mathrm{SI_{i\rightarrow}(H)}$ and $\mathrm{SI_{\rightarrow i}(H)}$. These static spillover indicators are shown in Table A.1 in the Appendix.

3.2. Data

3.2.1. Data and summary statistics

The dataset used in this study is from 25 November 2016 to 31 December 2021 at daily frequency. China's gasoline, diesel, and LNG price indices are collected from the Shanghai Petroleum and Natural Gas Trading Center (SHPGX), which was established in 2015 and started to publish these indices from 25 November 2016. Brent and WTI crude oil prices are used to measure international oil price, and the Newcastle port coal price (NEWC) in Australia is used to measure international coal price (Li et al., 2019). Considering the low level of integration of the global natural gas markets (Chai et al., 2019), the daily settlement prices of natural gas futures on the New York Mercantile Exchange (NG_NYMEX) and International Petroleum Exchange (NG_IPE) are introduced to represent the international natural gas markets. The China LNG ex-factory price national index (LNG), diesel wholesale price index (Diesel), gasoline wholesale price index (Gasoline) and the Qinhuangdao Q5500 thermal coal market price (QHD) are used to measure the energy prices in the Chinese market.

Frist, the LNG ex-factory price index is exclusively published by the SHPGX, which focuses on monitoring nearly 50 LNG plants and terminals in 14 regions in China. It is calculated based on the transaction data of the trading centre, supplemented by the quotations of the trading centre's shareholder and cooperative information agencies and mainly reflects the LNG price trend in the Chinese market. Second, China's gasoline and diesel wholesale price indices are jointly released by the SHPGX, the China Economic Information Service of the Xinhua news agency and the CNPC Economic and Technical Research Institute, based on the collection and calculation of wholesale price data of major business units and social business units (excluding refineries) nationwide. It is an authoritative index product reflecting the overall situation of China's gasoline and diesel wholesale market. Third, the port of Qinhuangdao is the largest coal trans-shipment port in China and plays an important strategic role in ensuring China's coal supply security. The fluctuation of coal prices at this port reflects the overall performance of China's coal market (Fan et al., 2016; Guo et al., 2016).

While energy price returns directly gauge the return on energy investment (Ji et al., 2018a, 2018b; Mensi et al., 2021a, 2021b, 2021c), the variance of the residual series generated by autoregression captures the volatility of time series data and reflects the price fluctuation risk in the energy markets (Geng et al., 2021; Umar et al., 2021). This study discusses the spillover effects between both energy price returns and volatilities. We calculate energy price returns using $\mathrm{R_t} = (\ln(\mathrm{y_t}) - \ln(\mathrm{y_{t-1}})) \times 100$. Referring to Broadstock et al. (2020), we then adopt the conditional variance in a standard GARCH (1,1) model $\sigma_t^2 = \alpha + \delta\sigma_{t-1}^2 + \gamma\varepsilon_{t-1}^2$ to estimate the price volatility risk of each variable. ε_t is the residual generated in the autoregressive process of returns $R_t = c + \beta R_{t-1} + \varepsilon_t$, $\varepsilon_t \sim N(0, \sigma_t^2)$, and α, δ, γ and c are parameters to be estimated in the model.

The summary statistics of the daily returns for energy prices are reported in Table 1-A. Notably, the average returns are all positive, and all return series show excess kurtosis. International crude oil (Brent and WTI) and natural gas future prices (NG_IPE and NG_NYMEX) show relatively high standard deviations; Chinese refined oil (Gasoline and Diesel) shows relatively low standard deviations; and the standard deviations of coal (QHD and NEWC) and LNG stand between them. The skewness value is positive for gasoline, NG_IPE and NG_NYMEX and is negative for the others. The Jarque–Bera (JB) statistics rebut the normality of the unconditional distribution. All return series are stationary at the 1% level of significance, as evidenced by the augmented Dickey–Fuller (ADF) test results.

The summary statistics of the volatility series are shown in Table 1-B. Both international oil (Brent and WTI) and natural gas futures prices (NG_IPE and NG_NYMEX) show high levels of average volatility with relatively high standard deviations, which corresponds with the high standard deviations of these variables' return series exhibited in Table 1-A. Relatively low levels of average volatility and standard deviation are reported for variables Diesel and Gasoline, implying that the Chinese oil and gas markets are less exposed to price volatility risk relative to the international markets. All volatility series show positive skewness and Gasoline has the highest kurtosis value. All volatility series are stationary, except for NEWC.

3.2.2. Correlation analysis

Fig. 1 shows the correlation coefficients between variables. For the return correlations shown in Fig. 1-A, the coal price return in China (QHD) is strongly correlated with the NEWC. China's coal price has been fully determined by the market, so it is not surprising that the coal price return and fluctuation are significantly correlated with those in the international market, evidenced by the high correlation between QHD and NEWC. Gasoline and diesel, on the other hand, are the main processed products of crude oil, while natural gas is also an associated product of oil field exploitation. Due to the substitutability between fossil energy sources, the high prices of both crude oil and coal are the main driving force of the production of refined oil and natural gas. This can be observed in Fig. 1-A that China's refined oil price indices (Gasoline and Diesel) are significantly and positively correlated with the international crude oil prices and China's coal and LNG prices.

Unlike crude oil, natural gas does not follow any global price index but is divided into three regional markets: North America, Europe, and Asia. Due to distinct pricing mechanisms in these regions, China's LNG price return is not shown to be correlated with the European ((NG_IPE) or the US natural gas future market (NG_NYMEX). Meanwhile, SHPGX's gasoline and diesel price returns are not significantly correlated with international gas market returns represented by NG_IPE and NG_NYMEX. Instead, significant correlations are found between international gas market returns (NG_NYMEX and NG_IPE), between NG_IPE and the international crude oil returns, as well as between NG_IPE and both Chinese and the global coal market returns (QHD and NEWC).

Fig. 1-B shows the volatility correlations between the variables.

Table 1-A
Descriptive statistics (return).

	Mean	Max.	Min.	St. Dev.	Skewness	Kurtosis	JB	ADF
Brent	0.037	22.951	−42.977	3.059	−2.134	41.381	98,519.553***	−10.23***
WTI	0.035	31.963	−60.168	3.476	−3.663	84.676	411,191.334***	−11.213***
Gasoline	0.026	6.631	−7.425	0.682	0.115	27.975	44,559.129***	−8.032***
Diesel	0.024	5.518	−6.752	0.648	−0.214	21.603	26,584.827***	−7.152***
LNG	0.043	15.995	−17.884	1.824	−0.622	22.863	29,850.886***	−8.267***
NG_IPE	0.1	34.335	−27.898	4.185	0.392	8.084	3758.734***	−10.02***
NG_NYMEX	0.015	17.833	−18.441	3.134	0.14	4.841	1340.965***	−11.104***
QHD	0.027	10.732	−18.268	1.319	−2.499	44.773	115,540.188***	−9.675***
NEWC	0.042	12.222	−19.557	1.821	−0.664	22.614	29,219.496***	−10.272***

Note: Brent indicates Brent crude oil price; WTI indicates West Texas Intermediate crude oil price; Gasoline is China's gasoline wholesale price index; Diesel is China's diesel wholesale price index; LNG indicates China's LNG ex-factory price index; NG_NYMEX indicates the settlement prices of natural gas futures on the New York Mercantile Exchange; NG_IPE indicates the settlement prices of natural gas futures on the International Petroleum Exchange; NEWC indicates Newcastle port coal price in Australia; QHD indicates the Qinhuangdao Q5500 thermal coal market price. ***, ** and * denote the significance at the 1%, 5% and 10% levels, respectively.

Table 1-B
Descriptive statistics (volatility).

	Mean	Max.	Min.	St. Dev.	Skewness	Kurtosis	JB	ADF
Brent	8.338	268.703	1.818	21.384	6.633	51.93	163,522.302***	−3.691**
WTI	12.029	560.015	1.659	43.627	8.218	77.143	354,116.414***	−5.809***
Gasoline	0.55	35.239	0.187	1.686	13.274	217.375	2,729,616.844***	−9.688***
Diesel	0.432	4.29	0.188	0.393	4.484	26.318	44,009.362***	−6.256***
LNG	4.655	52.357	0.139	7.453	2.797	8.661	6054.015***	−4.096***
NG_IPE	18.477	185.107	2.151	20.738	3.133	13.988	13,376.826***	−4.09***
NG_NYMEX	10.38	64.199	1.634	9.561	1.942	4.614	2071.666***	−4.523***
QHD	1.964	101.81	0.079	7.032	8.424	88.155	458,506.994***	−5.337***
NEWC	3.366	15.594	0.987	2.474	2.892	10.114	7730.579***	−1.549

Note: Brent indicates Brent crude oil price; WTI indicates West Texas Intermediate crude oil price; Gasoline is China's gasoline wholesale price index; Diesel is China's diesel wholesale price index; LNG indicates China's LNG ex-factory price index; NG_NYMEX indicates the settlement prices of natural gas futures on the New York Mercantile Exchange; NG_IPE indicates the settlement prices of natural gas futures on the International Petroleum Exchange; NEWC indicates Newcastle port coal price in Australia; QHD indicates the Qinhuangdao Q5500 thermal coal market price. ***, ** and * denote the significance at the 1%, 5% and 10% levels, respectively.

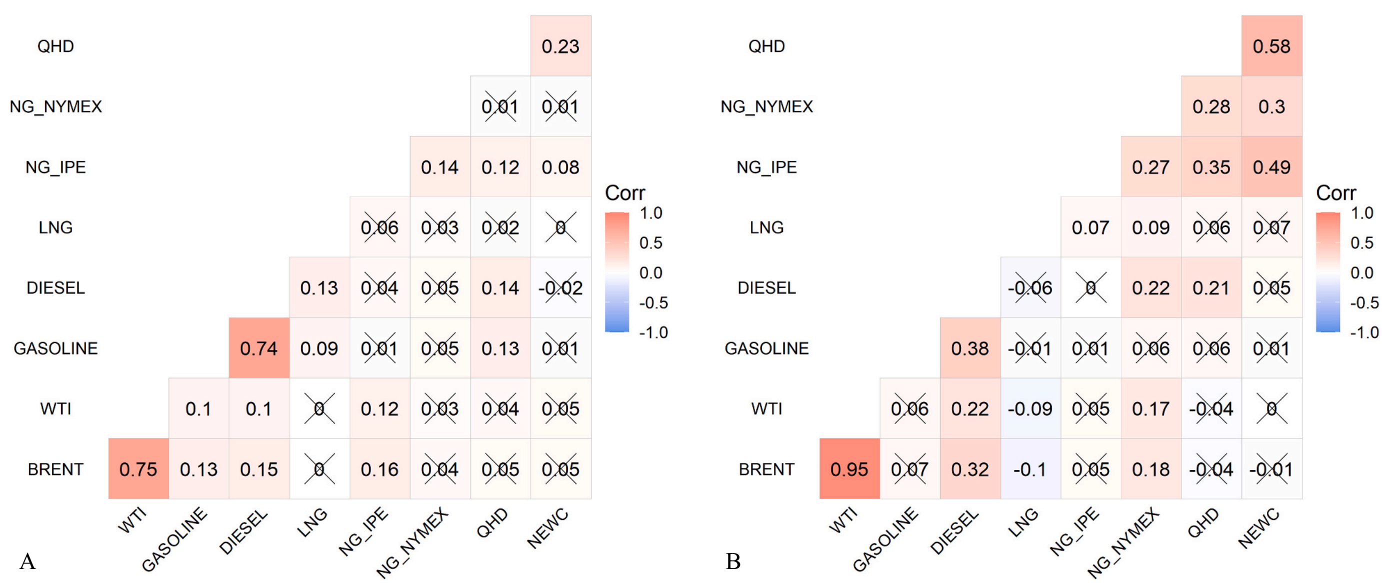

Fig. 1. (A) Correlation of energy returns. (B) Correlation of energy price volatility.
Note: BRENT indicates Brent crude oil price; WTI indicates West Texas Intermediate crude oil price; GASOLINE indicates China's gasoline wholesale price index; DIESEL indicates China's diesel wholesale price index; LNG indicates China's LNG ex-factory price index; NG_NYMEX indicates the settlement prices of natural gas futures on the New York Mercantile Exchange; NG_IPE indicates the settlement prices of natural gas futures on the International Petroleum Exchange; NEWC indicates Newcastle port coal price in Australia; QHD indicates the Qinhuangdao Q5500 thermal coal market price. × indicates not significant at the 99% confidence interval.

Volatility measures the risk arising from price fluctuations in the energy markets, and marketization can promote risk contagion between energy prices. From the perspective of volatility, Chinese LNG price shows significant negative correlations with international crude oil and positive correlations with European and US natural gas future prices. The price volatilities of NG_IPE, NG_NYMEX, and the Chinese and international coal markets (QHD and NEWC) are positively correlated with each other. Compared to Europe and China's natural gas prices, the price volatility of North America's natural gas, which is a fully competitive market, is much more correlated with the international oil price volatility.

Based on the above information, the impact of international crude oil price fluctuations is greater on China's refined oil product prices than on its coal and LNG prices. The QHD coal price is significantly correlated with international coal prices. While China's LNG price return is closely correlated with the domestic refined oil product returns, its volatility is more influenced by the international crude oil and natural gas market volatilities. For the global oil-gas links, price returns in the international crude oil markets significantly affect the European natural gas market, but the volatility risks in the international crude oil markets are significantly and positively correlated with the US natural gas market volatility.

4. Empirical results

The empirical study includes both static connectedness analysis and dynamic spillover analysis. Each contains the analysis of energy price returns and volatility and encompasses the discussion of total spillover, net spillover, and interaction spillover. Considering the many graphs involved, the research design and corresponding tables and figures are tabulated in Table A.2 for the reader's convenience.

4.1. Connectedness analysis

Table 2 reports the connectedness matrix of the eight energy price returns. WTI and Brent, the two international benchmark oil prices, are shown to be increasingly decoupled due to geopolitical tensions and the evolving situation in the international crude oil market (Mastroeni et al., 2021). We therefore use Brent and WTI to represent the international crude oil price for the main analysis and the robustness test, respectively.

4.1.1. Return connectedness network

As mentioned above, Brent is used to represent the international crude oil price for the main analysis. The results of return connectedness across the eight energy types are reported in Table 2.

As shown in Table 2, the proportion of each variable's self-contribution is generally large. NG_NYMEX has the largest self-explanatory power, with 92.5% arising from its own variations, followed by NEWC (90.5%), LNG (90.1%) and Brent (89.9%). The self-explanatory ability of Gasoline and Diesel is relatively weak (around 60%), but the interactive spillovers between them are both >30%, leading to their high spillover effects in terms of both receiving "From others" and transmitting "To others". QHD also has relatively high spillover values, receiving 15.6% from the others and transmitting 14% to the others. Considering the country's long-standing heavy dependence on coal consumption, it is not surprising to observe such an important role of QHD in the risk spillover network as both significant risk receiver and transmitter. Regarding China's LNG, it receives the most spillover from Diesel and then QHD, implying the significant impacts from the domestic oil and coal sides on the natural gas market returns.

The total spillover index, which measures the contribution of interactions across eight energy returns to the total forecast error variance, reaches 18.5%. The net spillover is derived by deducting the contributions "From others" from the contributions "To others". As shown in the last row of Table 2, the positive net spillover values of Brent (1.9%), Gasoline (2.6%), NG_IPE (1.5%) and NG_NYMEX (0.4%) support their roles as information transmitters in the return connectedness network, while Diesel (−0.2%), LNG (−1.8%), QHD (−1.6%) and NEWC (−2.9%) are net information receivers. These findings remain robust when using WTI to replace Brent in the robustness test (Table A.3), except for the relatively high self-explanatory power of WTI (90.7%).

Net pairwise spillover shows the direction of return spillover across energy prices. As shown in Fig. 2 and Fig. A.1, international crude oil price, whether being Brent or WTI, acts clearly as an information transmitter in the whole connectedness network, mainly transmitting information to China's refined oil markets represented by Diesel and Gasoline, which then transmit the information further down to China's domestic coal and LNG markets. Fig. 2 clearly depicts the spillover path from the international oil market to the Chinese domestic oil side and then further to its coal and natural gas markets, highlighting international crude oil as a significant source of risk along the spillover chain. For international energy markets, the correlation between crude oil and natural gas markets is relatively weak, and NEWC is the net recipient of all other indicator information, especially NG_IPE.

4.1.2. Volatility connectedness network

Table 3 reports the volatility connectedness matrix across the energy prices using Brent to represent the international crude oil market. The contribution from the volatility interactions across the eight energy prices to the total volatility forecast error variance amounts to 34.1%, which is higher than the total connectedness of the return series (18.5%). To interpret the difference between these two findings, one should be aware that returns measure the gains from energy investments, while volatility is a measure of risk. Higher volatility generally corresponds to higher risk and implies the potential for high returns. With the financialization of energy markets, which has caused energy prices to change more dramatically, speculation and arbitrage can stimulate the spread of price volatility risks across spots, futures, stocks and other financial markets. Therefore, it is not entirely surprising to observe increasing risk linkages and volatility spillover across these markets (Ji et al., 2018b). Correspondingly, the self-explanatory power

Table 2
Connectedness matrix of energy returns (Brent representing international crude oil price).

	Brent	Gasoline	Diesel	LNG	NG_IPE	NG_NYMEX	QHD	NEWC	From others
Brent	89.9	2.1	2.3	0.5	2.5	1.4	0.9	0.5	10.1
Gasoline	3	59.3	31	1	1	1.1	2.9	0.8	40.7
Diesel	3.2	32.5	55.7	1.9	1	0.7	4.3	0.6	44.3
LNG	0.6	1.5	2.9	90.1	1.7	0.4	1.8	1.1	9.9
NG_IPE	2.5	0.8	0.7	1.4	89.2	3.1	1.1	1.1	10.8
NG_NYMEX	1.3	1	0.6	0.5	2.9	92.5	0.6	0.6	7.5
QHD	0.8	4.1	5.7	1.7	0.9	0.4	84.4	1.9	15.6
NEWC	0.6	1.3	0.9	1.2	2.3	0.7	2.5	90.5	9.5
To others	12	43.3	44.1	8.1	12.3	7.8	14	6.6	TSI
Net spillover	1.9	2.6	−0.2	−1.8	1.5	0.4	−1.6	−2.9	18.5

Note: "From others" measures spillovers received by one market from all the other markets; "To others" measures spillovers transmitted from one market to all the others; Net spillover measures the net spillover effect of a given variable, being the difference between "To others" and "From others"; TSI indicates the total connectedness index. Brent indicates Brent crude oil price; Gasoline is China's gasoline wholesale price index; Diesel is China's diesel wholesale price index; LNG indicates China's LNG ex-factory price index; NG_NYMEX indicates the settlement prices of natural gas futures on the New York Mercantile Exchange; NG_IPE indicates the settlement prices of natural gas futures on the International Petroleum Exchange; NEWC indicates Newcastle port coal price in Australia; QHD indicates the Qinhuangdao Q5500 thermal coal market price.

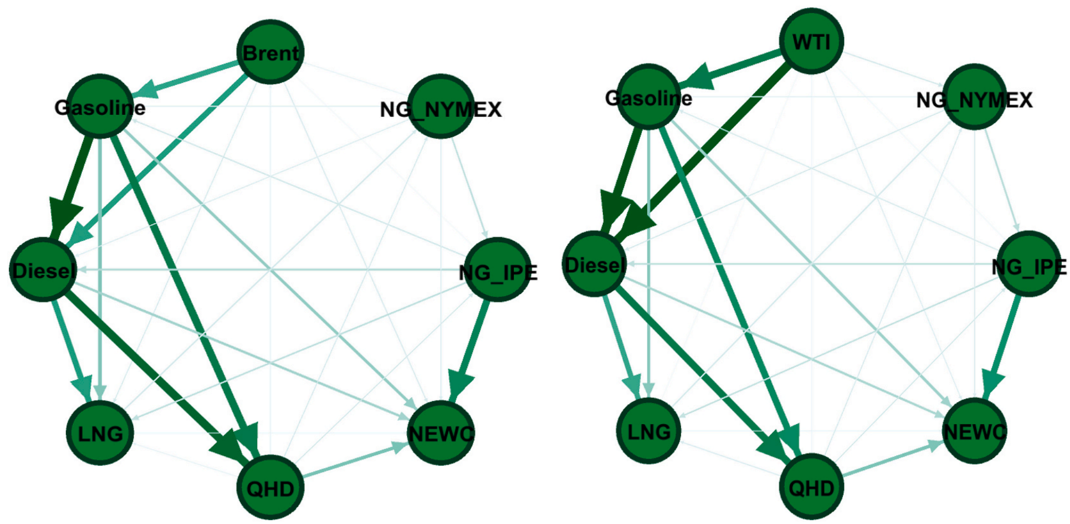

Fig. 2. Net pairwise spillover of energy returns.
Note: Arrows point from risk transmitters to risk receivers. Thicker and darker arrows indicate stronger spillover effects. Brent and WTI respectively represent Brent and West Texas Intermediate crude oil prices; Gasoline and Diesel respectively denote China's gasoline and diesel wholesale price indices; LNG is China's LNG ex-factory price index; NG_NYMEX is the settlement prices of natural gas futures on the New York Mercantile Exchange; NG_IPE is the settlement prices of natural gas futures on the International Petroleum Exchange; NEWC is Newcastle port coal price in Australia; QHD is the Qinhuangdao Q5500 thermal coal market price.

Table 3
Connectedness matrix of energy price volatilities (Brent representing international crude oil price).

	Brent	Gasoline	Diesel	LNG	NG_IPE	NG_NYMEX	QHD	NEWC	From others
Brent	76.3	1.7	3.3	0.7	3.5	5.3	2.7	6.5	23.7
Gasoline	4	64.2	22.5	0.8	1.8	3.1	1.4	2.2	35.8
Diesel	8.6	17.4	41.8	2	4.9	8.5	6	10.8	58.2
LNG	4.2	0.5	1.5	78.4	3.6	4.9	4.2	2.7	21.6
NG_IPE	2.6	0.8	1.4	2.7	68.7	7.6	5.5	10.7	31.3
NG_NYMEX	9.4	0.9	1.5	1.4	6.8	68.2	5.8	6	31.8
QHD	2.3	0.8	1.8	1	3.7	3.2	74.8	12.3	25.2
NEWC	4.9	0.7	2.5	2.2	11.4	10.5	12.7	55.1	44.9
To others	36	22.9	34.6	10.8	35.7	43.2	38.2	51.1	TSI
Net spillover	12.3	−12.9	−23.7	−10.8	4.4	11.4	13	6.2	34.1

Note: "From others" measures spillovers received by one market from all the other markets; "To others" measures spillovers transmitted from one market to all the others; Net spillover measures the net spillover effect of a given variable, being the difference between "To others" and "From others"; TSI indicates the total connectedness index. Brent indicates Brent crude oil price; Gasoline is China's gasoline wholesale price index; Diesel is China's diesel wholesale price index; LNG indicates China's LNG ex-factory price index; NG_NYMEX indicates the settlement prices of natural gas futures on the New York Mercantile Exchange; NG_IPE indicates the settlement prices of natural gas futures on the International Petroleum Exchange; NEWC indicates Newcastle port coal price in Australia; QHD indicates the Qinhuangdao Q5500 thermal coal market price.

of the volatility series is mostly lower than that reported for the return series. Similar to the results based on energy returns, Diesel still has the lowest self-explanatory power, and the top pairwise volatility connectedness is still between Gasoline and Diesel. The volatility connectedness results using WTI instead of Brent confirm the robustness of above conclusions, as shown in Tables A.3 and A.4.

When looking at the net spillover effects and net pairwise connectedness, the results based on volatility series are distinct from those based on returns for several markets. Crude oil is shown to be the top net transmitter of price volatility, with WTI in particular having a net spillover effect of 55.6% (shown in Table A.4). In both the Brent and WTI scenarios, the top net receiver of volatility is Diesel, while Gasoline becomes a net receiver of volatility information, which is a net information transmitter in the return connectedness network. Table 3 also shows that QHD and NEWC become net information transmitters in the volatility connectedness network. NG_NYMEX is still an information transmitter in the volatility spillover network, while NG_IPE becomes a net receiver of volatility spillover in the network based on WTI price (see Table A.4).

Fig. 3 visualizes the net pairwise spillover in terms of energy price volatility. WTI is not negligible as a net transmitter of volatility spillover for all the other energy types. Similar to the findings based on energy returns, volatility spillover in the Chinese market is shown to be from the coal market (QHD) to the refined oil markets (Diesel and Gasoline), rather than from the opposite direction. China's LNG market is mainly prone to the volatility spillovers from international crude oil markets, the US natural gas market (NG_NYMEX) and domestic coal market (QHD), but not from domestic refined oil markets (Gasoline and Diesel), which is similar to the return-based findings shown in Fig. 2.

We could therefore argue that crude oil still plays a leading role in transmitting the price volatility risk across the whole energy network, while the refined oil product markets in China are highly susceptible to those volatility spillovers from the international crude oil markets. Meanwhile, the risk-transmitting role of China's domestic coal market should also not be neglected. These findings add new evidence to the related literature on the risk spillover between coal, crude oil and other energy types (Li et al., 2017; Mensi et al., 2021a, 2021b, 2021c; Asadi et al., 2022) and indirectly confirms the evidence in the literature of the fundamental role of coal during China's economic development (Guo et al., 2016).

On the whole, from the perspective of return spillover, China's refined oil acts as an intermediary for the transmission of international

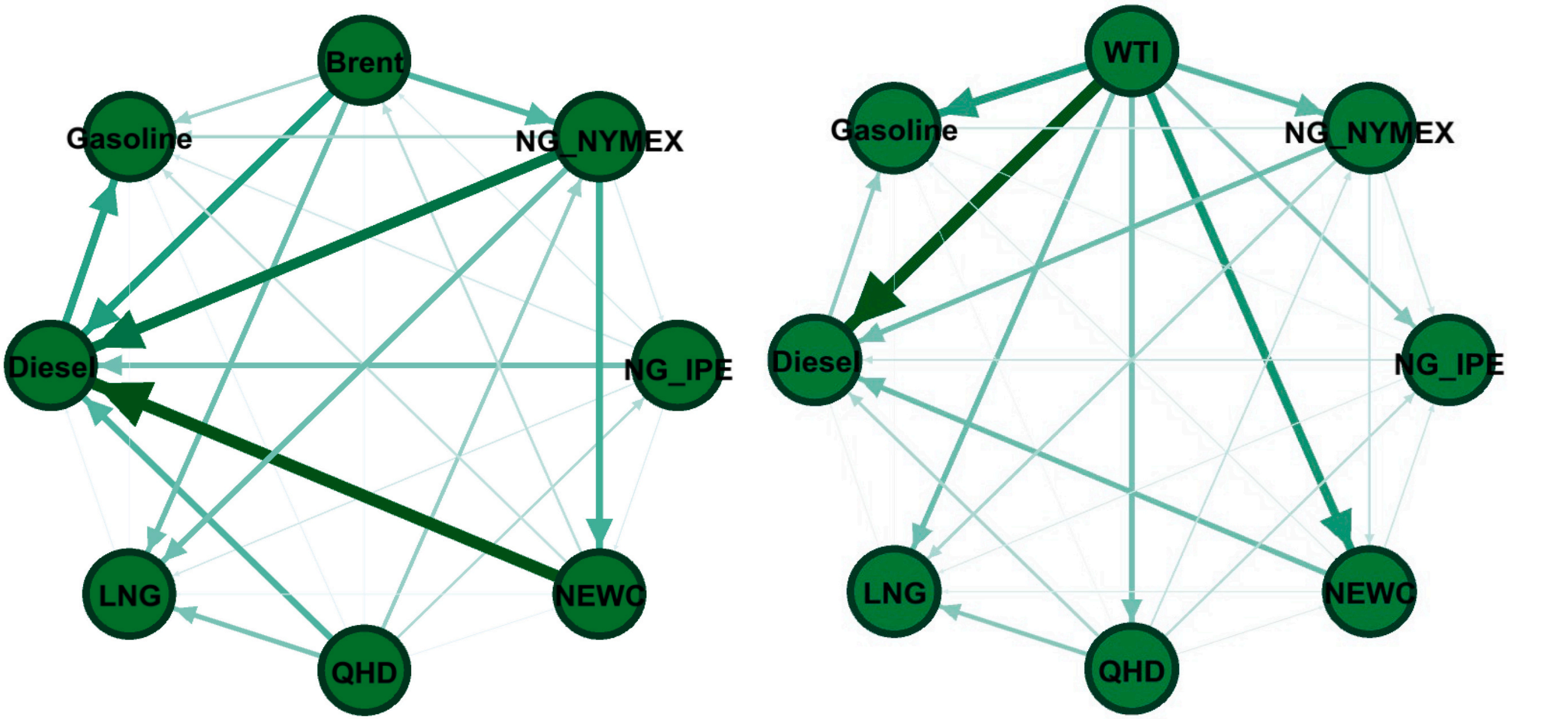

Fig. 3. Net pairwise spillover of energy price volatility.

Note: Arrows point from risk transmitters to risk receivers. Thicker and darker arrows indicate stronger spillover effects. Brent and WTI respectively represent Brent and West Texas Intermediate crude oil prices; Gasoline and Diesel respectively denote China's gasoline and diesel wholesale price indices; LNG is China's LNG ex-factory price index; NG_NYMEX is the settlement prices of natural gas futures on the New York Mercantile Exchange; NG_IPE is the settlement prices of natural gas futures on the International Petroleum Exchange; NEWC is Newcastle port coal price in Australia; QHD is the Qinhuangdao Q5500 thermal coal market price.

crude oil market information to domestic LNG and coal markets. The pricing mechanisms dominate the return spillover between China and international energy markets. However, from the perspective of volatility spillover, SHPGX's gasoline and diesel price indices are net receivers of domestic and international energy market risks. On the other hand, the LNG price volatility in China is mainly directed by the risks in the domestic coal market and the international crude oil and natural gas markets. These findings suggest that the volatility correlations between China and international energy markets are significantly higher and more complex than their return correlations.

4.2. Dynamic total spillover and net spillover effects

The static spillover matrixes reported above reflect the full-sample spillover and interactions between the variables. To capture the dynamic changes of the spillover effect during the sample period, we adopt the TVP-VAR approach to estimate the time-varying changes of the total spillover index (TSI), shown in Fig. 4. Both return and volatility connectedness indices are shown to be time-varying. Comparing the magnitudes of TSI in the two scenarios, the TSI based on energy returns is constantly smaller than that based on volatility. Specifically, the total connectedness index of energy price returns ranges from 10% to 30% during the sample period, lower than that range of TSI based on volatility (15% to 60%).

This implies that the dynamic spillover effect is more pronounced in the network constructed based on volatility connectedness rather than by return connectedness. The stronger volatility spillover effect relative to return spillover over time suggests that the former type of risk is more likely to spread through the energy network and thus has more potential to trigger greater market reactions and even systemic events. It also reflects that these energy markets are more sensitive to the risk information embedded in energy price volatility relative to pure returns. When looking at the net spillover index (NSI) for each type of energy, this phenomenon is even more pronounced. Except for the initial period of the full sample interval, the net spillover of the return series (see Fig. 5) ranges between −2% and 2% for a long time, while the net spillover effect of energy price volatility (see Fig. 6) is generally much higher. For risk management purposes, more attention should therefore be paid to the volatility dynamics of the key energy assets in an investor's portfolio.

Seen in Figs. 4 and 6, in March 2020, against the background of the COVID-2019 pandemic, the risk of slumping international oil prices caused by sluggish market demand quickly spreads to the entire energy market. The total spillover effect increases significantly, and crude oil shows the highest net volatility spillover effect during this period. The volatility spillover effect from WTI reaches up to over 40% in early 2020, corresponding to the high oil price volatility and price crash triggered by the unprecedented drop in energy demand during the onset of the COVID−19 pandemic (Akhtaruzzaman et al., 2021) and the negative bubble in oil price arising from pandemic-related negative news (Gharib et al., 2021). Both international and Chinese coal markets and natural gas markets are recipients of market information during the onset of the COVID-19 pandemic, consistent with the view of Si et al. (2021) that the COVID-19 pandemic has triggered a phenomenon of risk co-movement in energy markets and crude oil is the main transmitter of market information during this period.

The volatility spillover effect of the Chinese domestic coal market represented by QHD also peaks at >20% in 2019 and 2021. This can be linked back to increasing uncertainties and risks in the Chinese coal industry arising from China's coal capacity cut policies, with the government's intention to curb the use of coal to facilitate the country's energy transition and achieve its carbon neutrality goal (Zhang et al., 2021). Concurrent with several rounds of policy adjustments and shocks in China's coal market since late 2018, the total volatility spillover index rises sharply. As the net spillover effects of all the other energy types are negative during this period, the strong positive net spillover effect of China's coal market (over 20%) alone can explain the tightening volatility connectedness in the whole spillover network. Similarly, the soaring total spillover effects of returns and volatility in October 2021 may also derive from China's coal market dynamics. As shown in Fig. 5 and Fig. 6, the net return and volatility spillover of QHD are both positive in 2021 and significantly higher than those of other energy types.

Still shown in Fig. 4, before the outbreak of the COVID-19 pandemic, the overall connectedness of energy price volatility shows a gradual downward trend, and there is a period of fluctuation at the end of 2018. The dynamic changes of each variable's net volatility spillover indices are distinct, as shown in Fig. 6. The net spillover effects of international crude oil prices and the natural gas futures prices decline before the COVID-19 epidemic. An opposite trend is observed when looking at the net spillover effect of China's refined oil product markets represented by Gasoline and Diesel. Both return and volatility spillover effects in these markets gradually rise and reverse from negative to approach zero, implying the change in their roles from risk receivers to risk transmitters. Combining these results, we could argue that the decline in the total volatility spillover index before the COVID-19 pandemic is mainly caused by the declining risk spillover effects in the international oil and natural gas markets.

Moreover, Fig. 4 also shows that different benchmark oil prices exhibit different levels of risk spillover effects. Irrespective of returns or volatility, the spillover networks built with WTI have higher levels of total spillover effects relative to their counterparts with Brent.

4.3. Dynamic pairwise spillover effects

4.3.1. Dynamic pairwise spillover effects in energy returns

After analyzing the general spillover trends and each market's

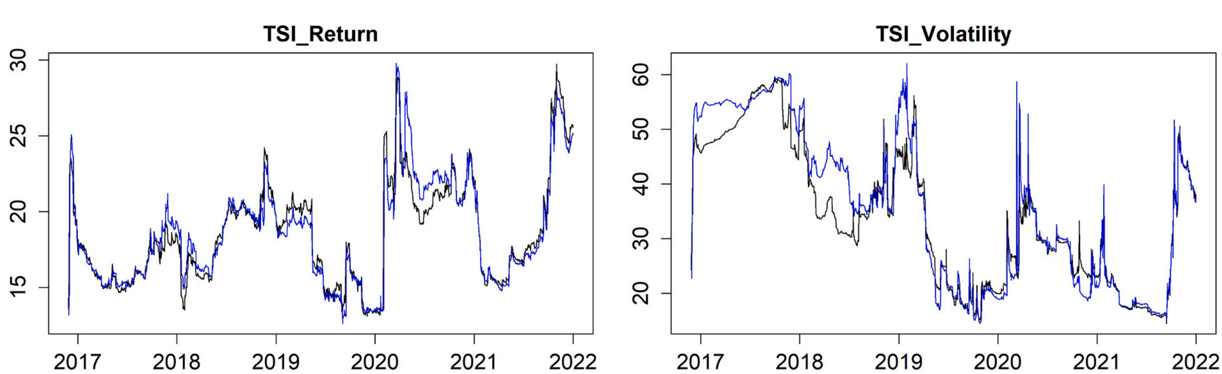

Fig. 4. Dynamics of total spillover index (TSI).
Note: TSI_Return indicates the total spillover index based on return series; TSI_Volatility indicates the total spillover index based on volatility series. The black and blue lines indicate the results using Brent and WTI to represent the international crude oil price, respectively.

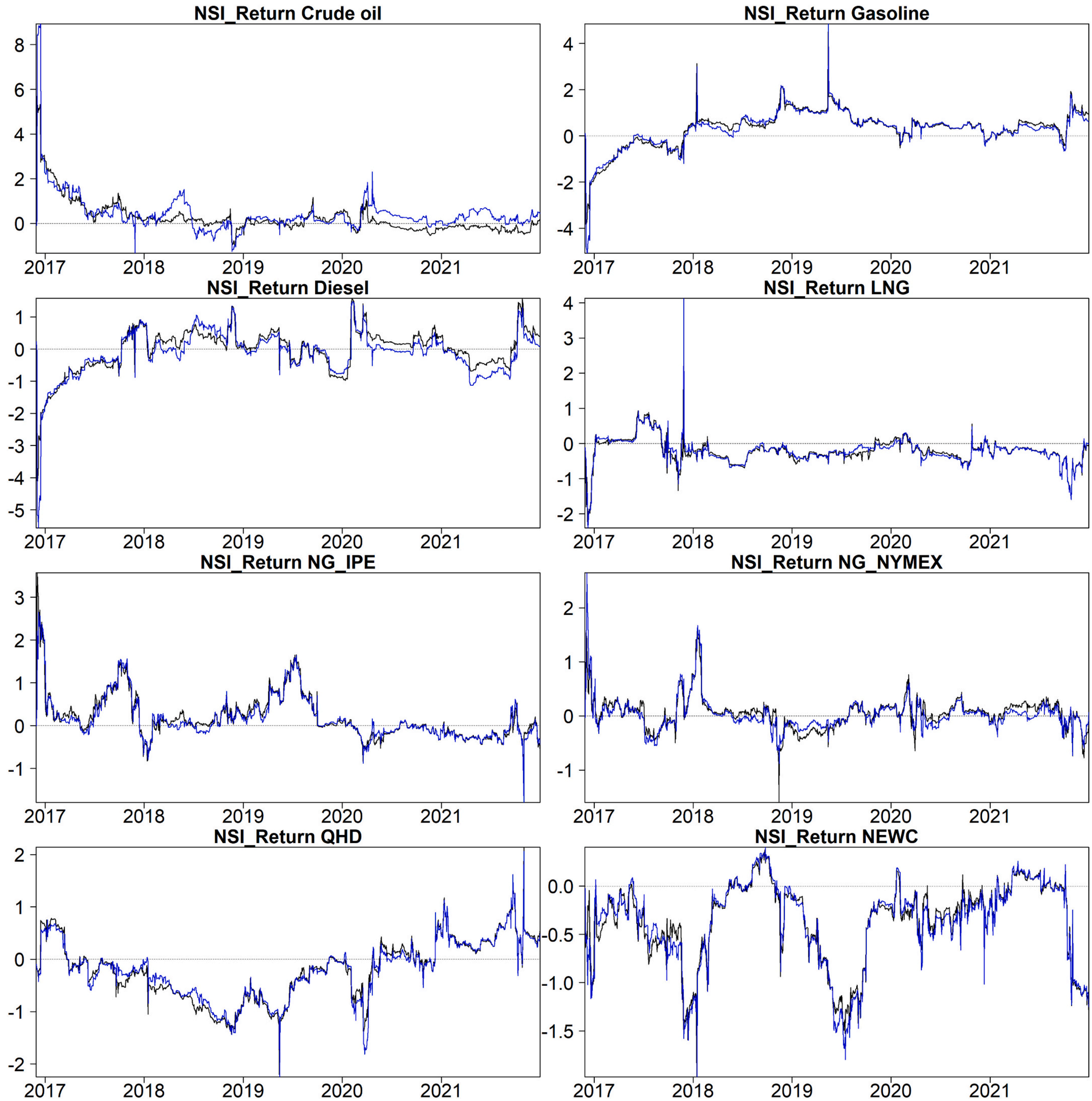

Fig. 5. Dynamics of net spillover index (return series).
Note: NSI_Return indicates the net spillover index based on return series. The black and blue lines indicate the results using Brent and WTI to represent the international crude oil price, respectively. Gasoline and Diesel respectively denote China's gasoline and diesel wholesale price indices; LNG is China's LNG ex-factory price index; NG_NYMEX is the settlement prices of natural gas futures on the New York Mercantile Exchange; NG_IPE is the settlement prices of natural gas futures on the International Petroleum Exchange; NEWC is Newcastle port coal price in Australia; QHD is the Qinhuangdao Q5500 thermal coal market price.

contribution, we proceed to discuss the pairwise spillover effects over time in the risk spillover networks. This section focuses on the interactions across the energy types to find out their pairwise risk relationships. Similar to the results of TSI and NSI, the dynamic pairwise spillover effects are higher in magnitudes when calculated by volatility relative to by returns (see Figs. 7 and 8).

We first look at the return spillover from the international crude oil markets. Although the pricing of refined oil products in China is linked with international oil prices, the net spillover effects from the international crude oil market to China's refined oil market (Gasoline and Diesel) is $<0.5\%$ for most of sample period (see Fig. 7-A). The international oil price shock in 2020 causes a significant return shock to the Chinese coal market, as the spillover effect from crude oil to QHD soars in the same year. From 2021 onwards, however, the trend reverses. The risk spillover from the international crude oil market to China's coal market become negative, indicating that the huge fluctuations in China's coal prices in turn transmit to the global crude oil market. Chinese coal market also becomes a risk transmitter to the international coal market

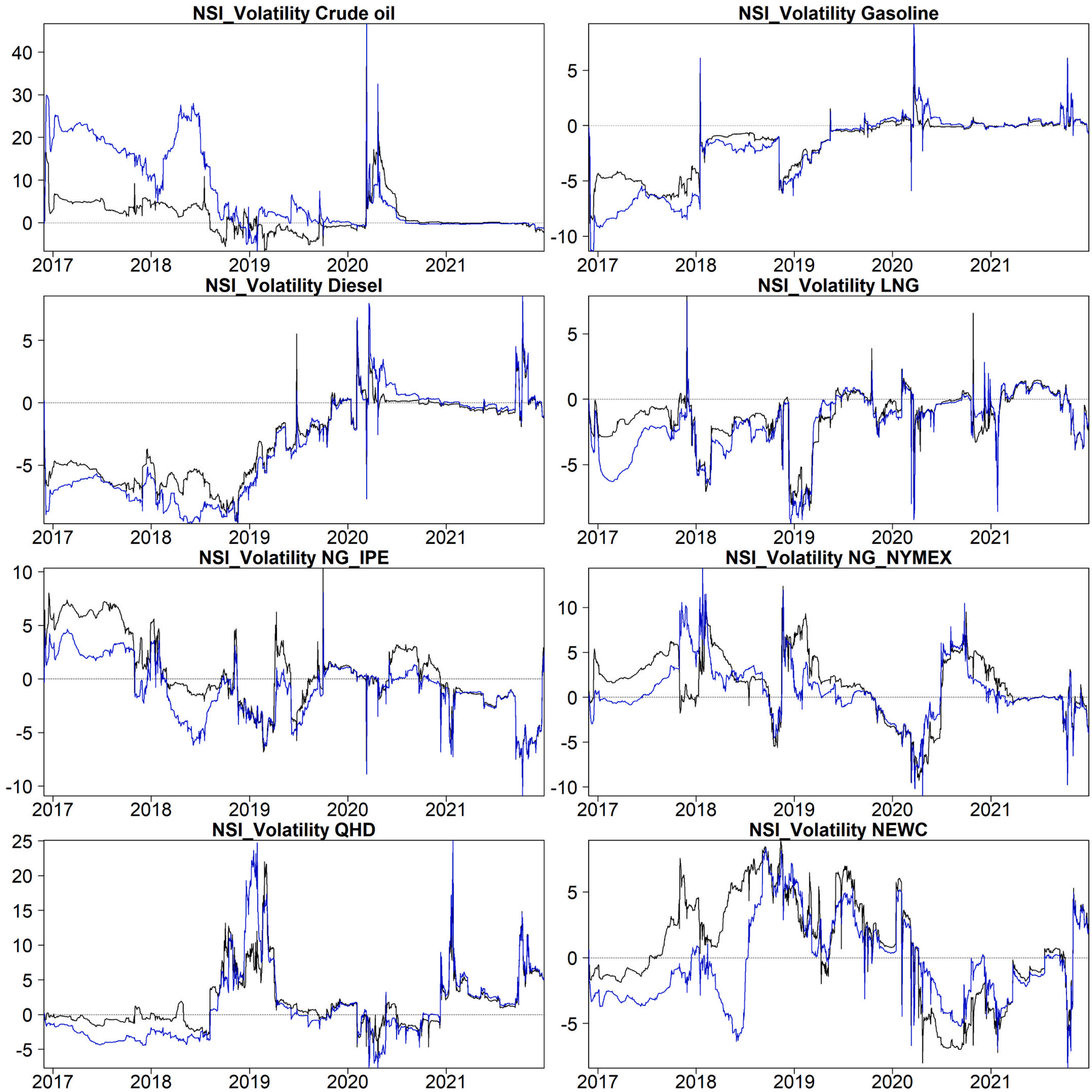

Fig. 6. Dynamics of net spillover index (volatility series).
Note: NSI_Volatility indicates the net spillover index based on volatility series. The black and blue lines indicate the results using Brent and WTI to represent the international crude oil price, respectively. Gasoline and Diesel respectively denote China's gasoline and diesel wholesale price indices; LNG is China's LNG ex-factory price index; NG_NYMEX is the settlement prices of natural gas futures on the New York Mercantile Exchange; NG_IPE is the settlement prices of natural gas futures on the International Petroleum Exchange; NEWC is Newcastle port coal price in Australia; QHD is the Qinhuangdao Q5500 thermal coal market price.

in terms of return spillovers during the same period, evidenced by the negative spillover from NEWC to QHD in 2020 (Fig. 7-A). Its return spillover to the international natural gas markets (NG_IPE, NG_NYMEX) is also emerging from 2020 (Fig. 7-B). These results jointly suggest that the coal market in China, which used to be a risk receiver, plays an increasing role in the transmitting risks that arise from its exposure to significant policy changes and uncertainties, to the global energy risk spillover network.

Fig. 7-B also shows return spillovers between China's refined oil, gas and the international natural gas market. At the early stage since SHPGX's establishment, China's refined oil and LNG price indices act as net recipients of return spillovers from the international gas markets (NG_IPE and NG_NYMEX). These spillover effects then decrease over time in some Chinese energy markets, for example, Gasoline and LNG. By the end of the sample period, the return information of the SHPGX's price indices show the trend of spillover to the international natural gas futures markets.

Regarding the spillover effects across the Chinese energy market returns, the net spillover effects from the refined oil markets (Gasoline and Diesel) to the domestic coal and gas markets (QHD and LNG) are

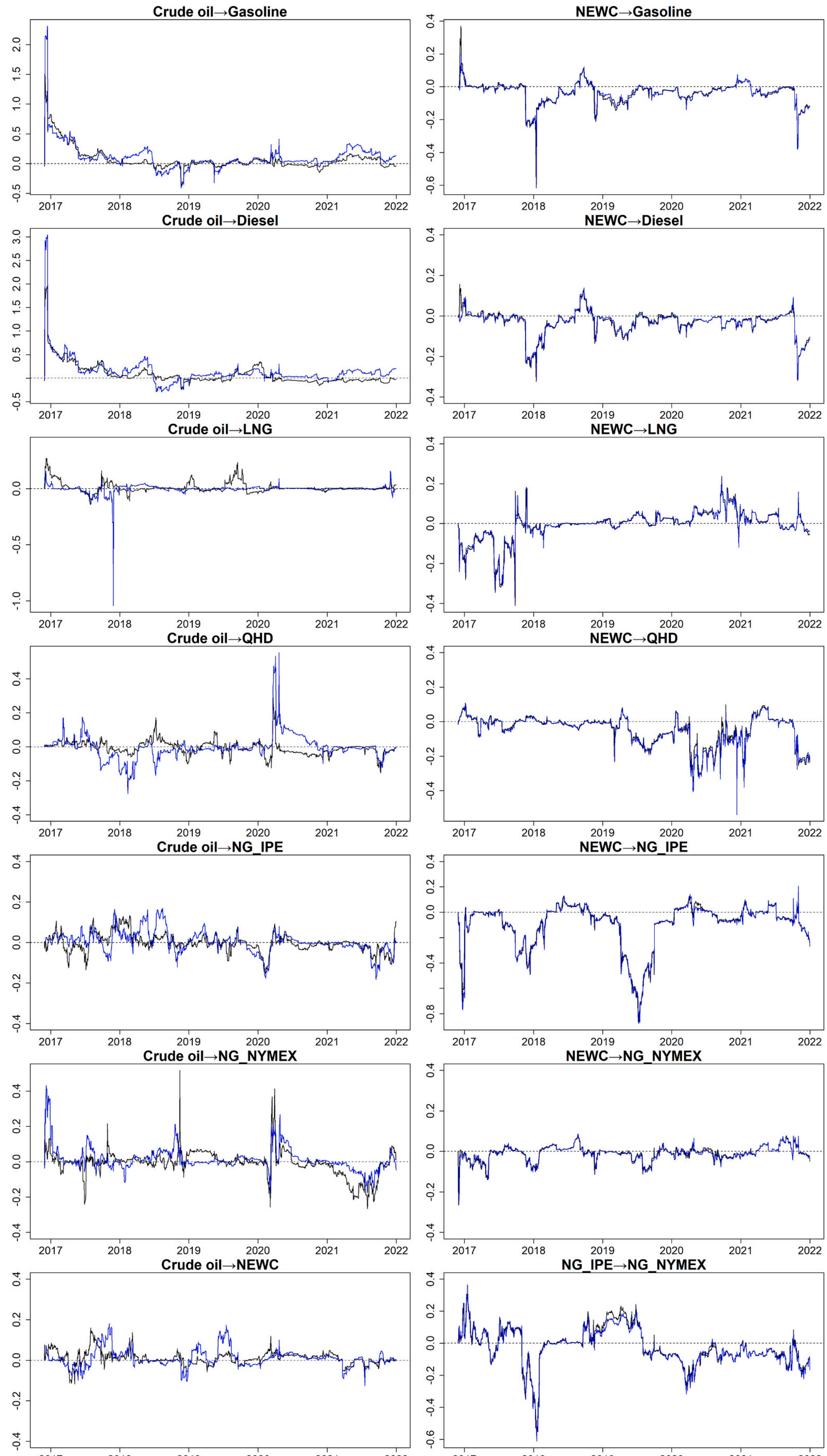
Crude oil→Gasoline
NEWC→Gasoline
Crude oil→Diesel
NEWC→Diesel
Crude oil→LNG
NEWC→LNG
Crude oil→QHD
NEWC→QHD
Crude oil→NG_IPE
NEWC→NG_IPE
Crude oil→NG_NYMEX
NEWC→NG_NYMEX
Crude oil→NEWC
NG_IPE→NG_NYMEX
2017
2018
2019
2020
2021
2022

Fig. 7. (A) Dynamic pairwise net spillover from international crude oil and coal markets to other energy markets (return series). (B) Dynamic pairwise net spillover from international natural gas markets to Chinese energy markets (return series). (C) Dynamic pairwise net spillover across Chinese energy markets (return series). Note: The black and blue lines indicate the results using Brent and WTI to represent the international crude oil price, respectively. Crude oil denotes the international crude oil price; Gasoline and Diesel respectively denote China's gasoline and diesel wholesale price indices; LNG is China's LNG ex-factory price index; NG_NYMEX is the settlement prices of natural gas futures on the New York Mercantile Exchange; NG_IPE is the settlement prices of natural gas futures on the International Petroleum Exchange; NEWC is Newcastle port coal price in Australia; QHD is the Qinhuangdao Q5500 thermal coal market price. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

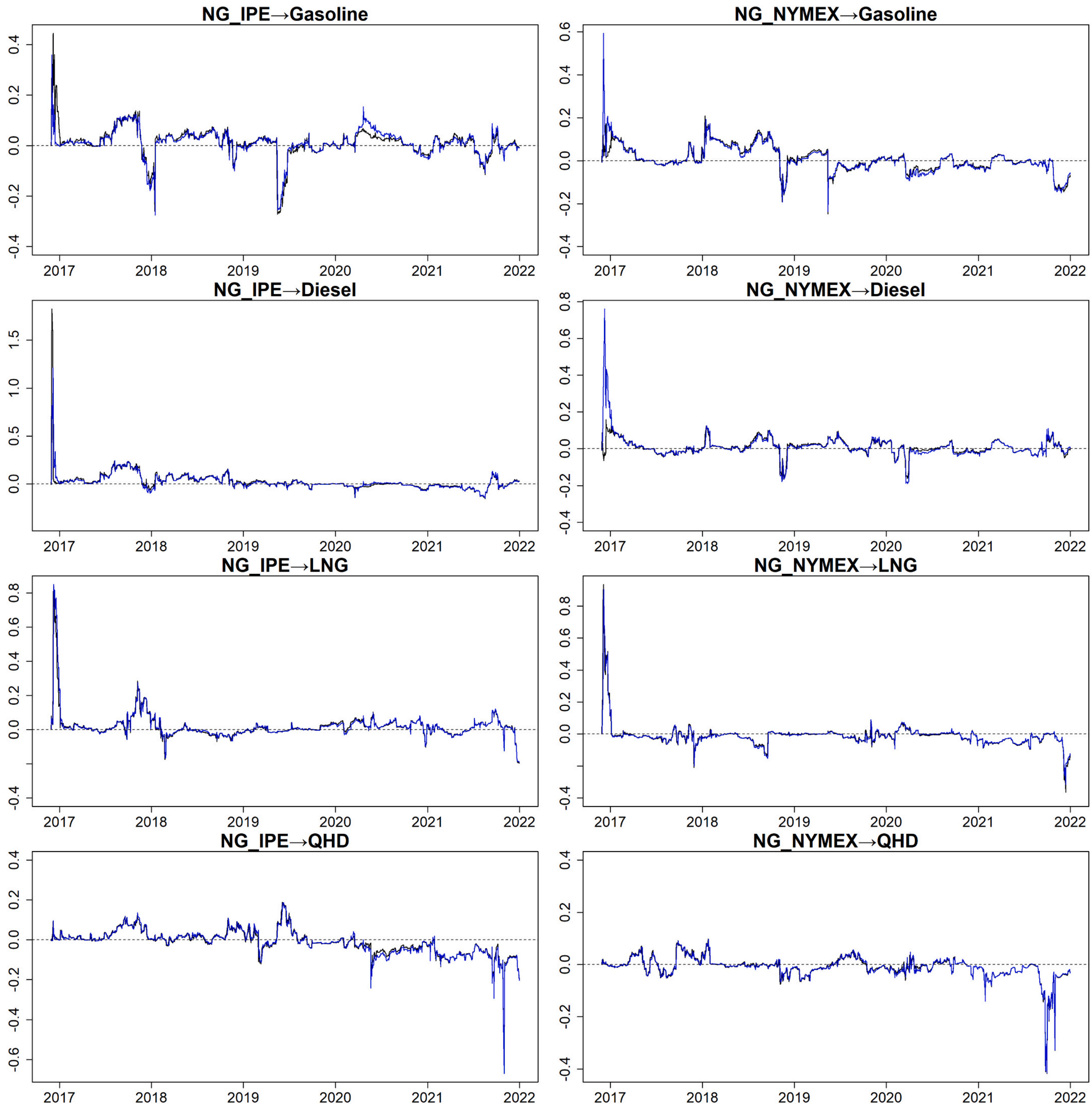

Fig. 7. (*continued*).

mostly positive (see Fig. 7-C). LNG and QHD appear to be the major net receivers of domestic return spillover from the oil side. As Gasoline and Diesel are processed products of petroleum, and the prices of China's refined oil products are linked to the international crude oil prices, China's wholesale price indices of diesel and gasoline are naturally exposed to the risk spillover from the international crude oil markets. Combining these findings and facts, it is not hard to understand the role of China's refined oil market as an information bridge connecting the international crude oil markets and China's LNG and coal markets.

4.3.2. Dynamic pairwise spillover effects in energy price volatility

We first notice that in Fig. 8-A, the volatility spillover from WTI to

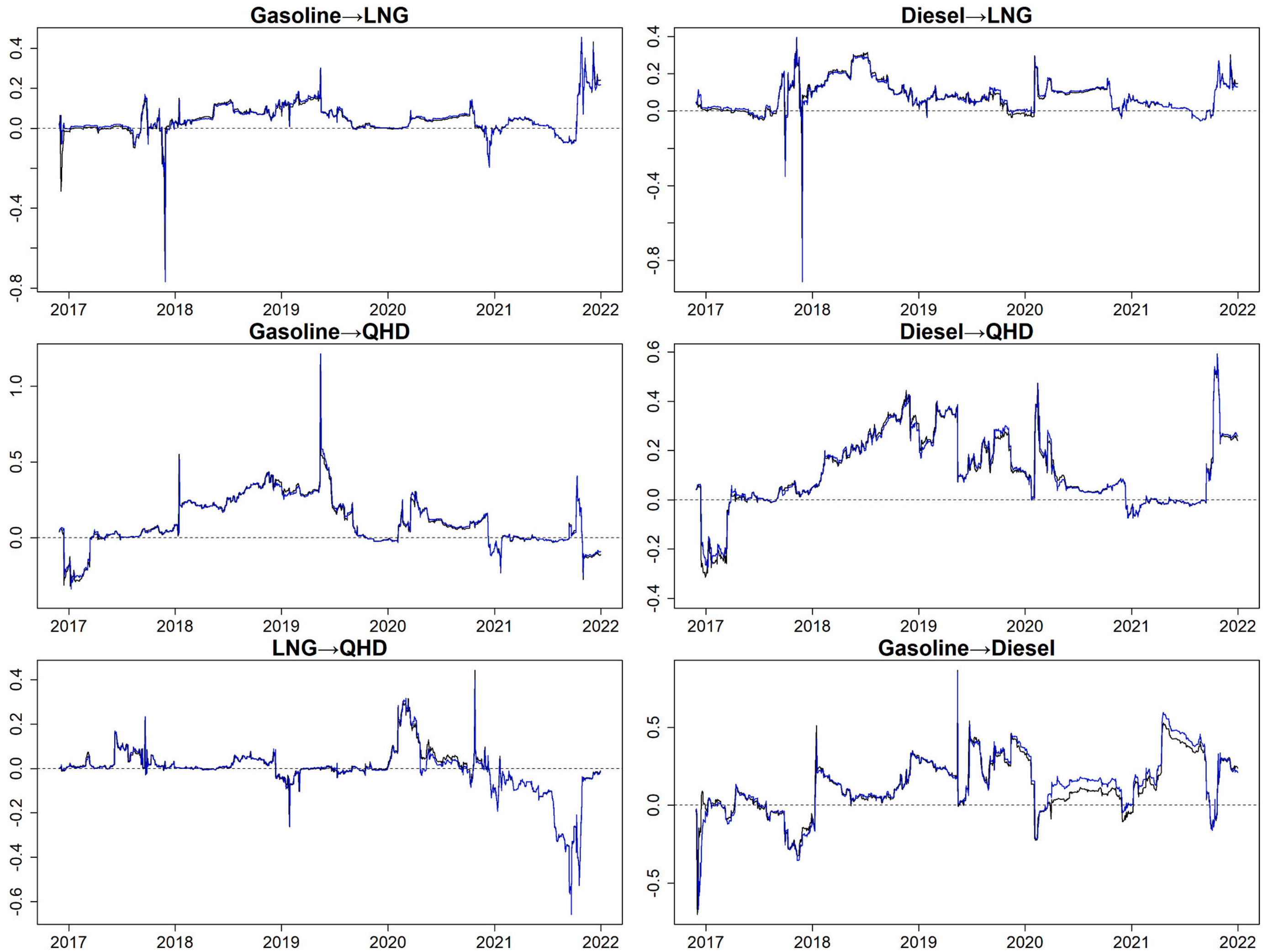

Fig. 7. (*continued*).

other series is slightly higher than that from Brent. Then, we see that the net spillover from international crude oil markets to China's refined oil and LNG markets (Gasoline, Diesel and LNG) all shows obvious downward trends before 2019. The spillover of volatility risks from the international crude oil markets to all the other markets peaks but with notable fluctuations during the onset of the COVID-19 pandemic in early 2020, which is a new trend compared to the findings based on return series. This indicates that the pandemic-induced volatility in the international crude oil markets is highly contagious in the whole energy network, but its contagion shows a high level of instability. We can observe that during this period, the spillover effects from both international coal (NEWC) and gas market (NG_NYMEX) also fluctuate, as well as the cross-market spillovers in China (Shown in Fig. 8-B and Fig. 8-C), suggesting mounting uncertainties and potential reshaping of the risk connectedness structure during this period.

After this period, the international crude oil markets are no longer the dominant net transmitter of volatility risks in the network, confirmed by the results that net volatility spillover from crude oil to other series approaches zero, among which the Crude oil-to-LNG spillover even becomes negative by the end of 2021. The net volatility spillover from the international coal and natural gas markets to the Chinese refined oil market also converges to zero after the outbreak of COVID-19, and the SHPGX price indices act as transmitters of volatility risks in the international natural gas market since 2021 (see Fig. 8-B). The international influence of the Chinese energy trading centre is initially revealed.

The motivation of China to establish its energy trading centres is to facilitate energy marketization. Previous studies show that marketization promotes price interactions between domestic energy markets (Zhang et al., 2021a), and the connection between China's coal and LNG markets is expected to become closer. Figs. 8-A, B and C show that the huge volatility in China's coal prices in October 2018 transfers the volatility risks to the entire energy system. QHD, which represents the Chinese coal price, becomes a volatility transmitter to other domestic markets including Gasoline, Diesel and LNG in October 2021. Moreover, China's coal market has developed into a net transmitter to the international coal (NEWC) and natural gas (NG_IPE, NG_NYMEX) markets. This provides reverse evidence to the exiting findings in the literature, which finds that China's coal market receives the most price spillovers from international coal markets and the contribution of the Australian market to others is the highest (Batten et al., 2019).

Under China's Dual Carbon target, reducing coal consumption is going to be a major trend. China has continued to promote coal decapacity since 2016. At present, the proportion of coal consumption in primary energy consumption has fallen to 56%. However, coal is still the main energy resource in China. The excessive reduction of the coal supply has led to the imbalance of coal supply and demand, and the coal price in China rose sharply in 2021. Its price risk has been found contagious in not only the domestic oil and gas markets, but also the international coal and natural gas markets. To this end, we could argue

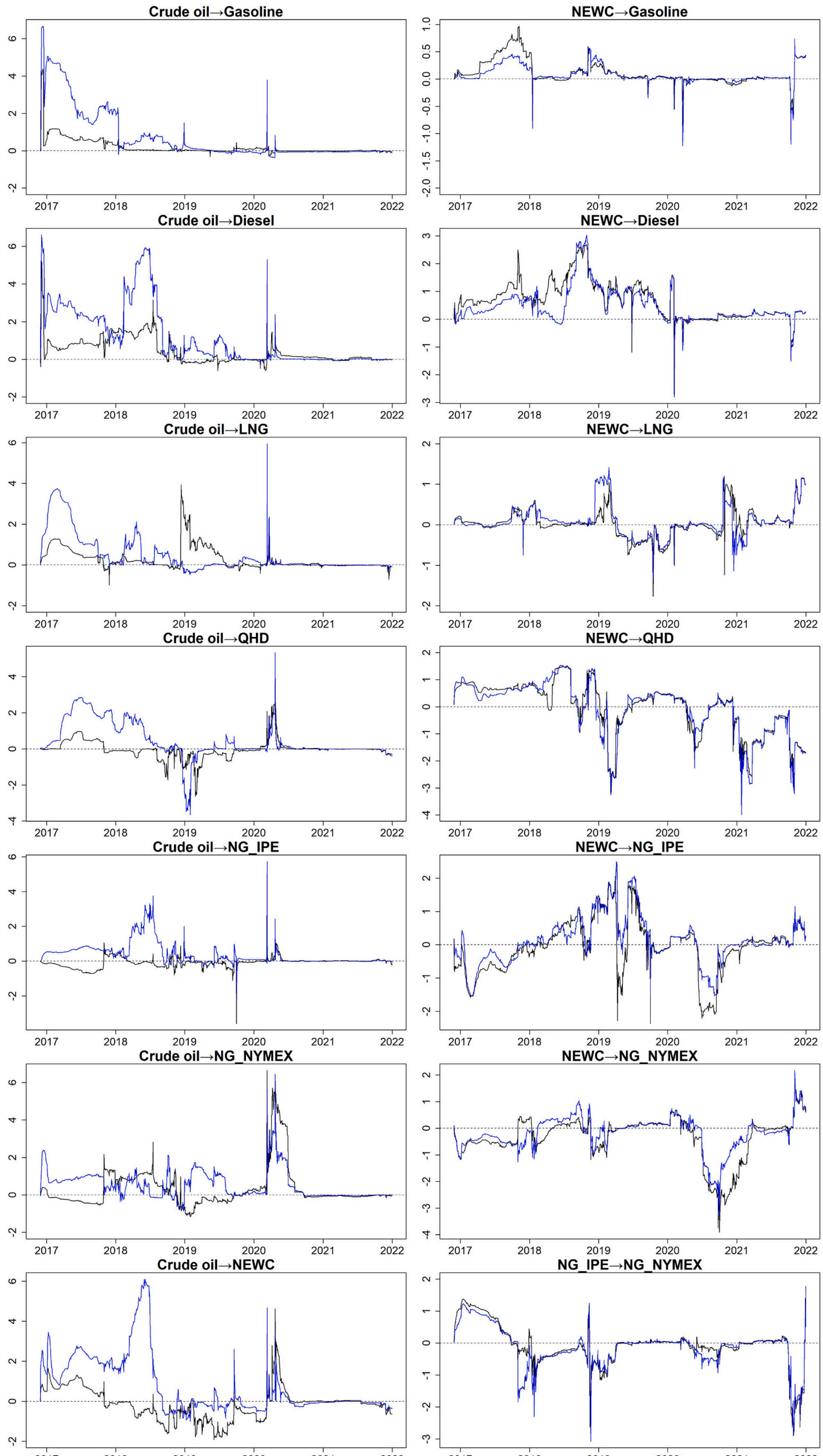
Crude oil→Gasoline
NEWC→Gasoline
Crude oil→Diesel
NEWC→Diesel
Crude oil→LNG
NEWC→LNG
Crude oil→QHD
NEWC→QHD
Crude oil→NG_IPE
NEWC→NG_IPE
Crude oil→NG_NYMEX
NEWC→NG_NYMEX
Crude oil→NEWC
NG_IPE→NG_NYMEX
2017
2018
2019
2020
2021
2022

Fig. 8. (A) Dynamic pairwise net spillover from international crude oil and coal markets to other energy markets (volatility series). (B) Dynamic pairwise net spillover from international natural gas markets to Chinese energy markets (volatility series). (C) Dynamic pairwise net spillover across Chinese energy markets (volatility series).

Note: The black and blue lines indicate the results using Brent and WTI to represent the international crude oil price, respectively. Crude oil denotes the international crude oil price; Gasoline and Diesel respectively denote China's gasoline and diesel wholesale price indices; LNG is China's LNG ex-factory price index; NG_NYMEX is the settlement prices of natural gas futures on the New York Mercantile Exchange; NG_IPE is the settlement prices of natural gas futures on the International Petroleum Exchange; NEWC is Newcastle port coal price in Australia; QHD is the Qinhuangdao Q5500 thermal coal market price. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

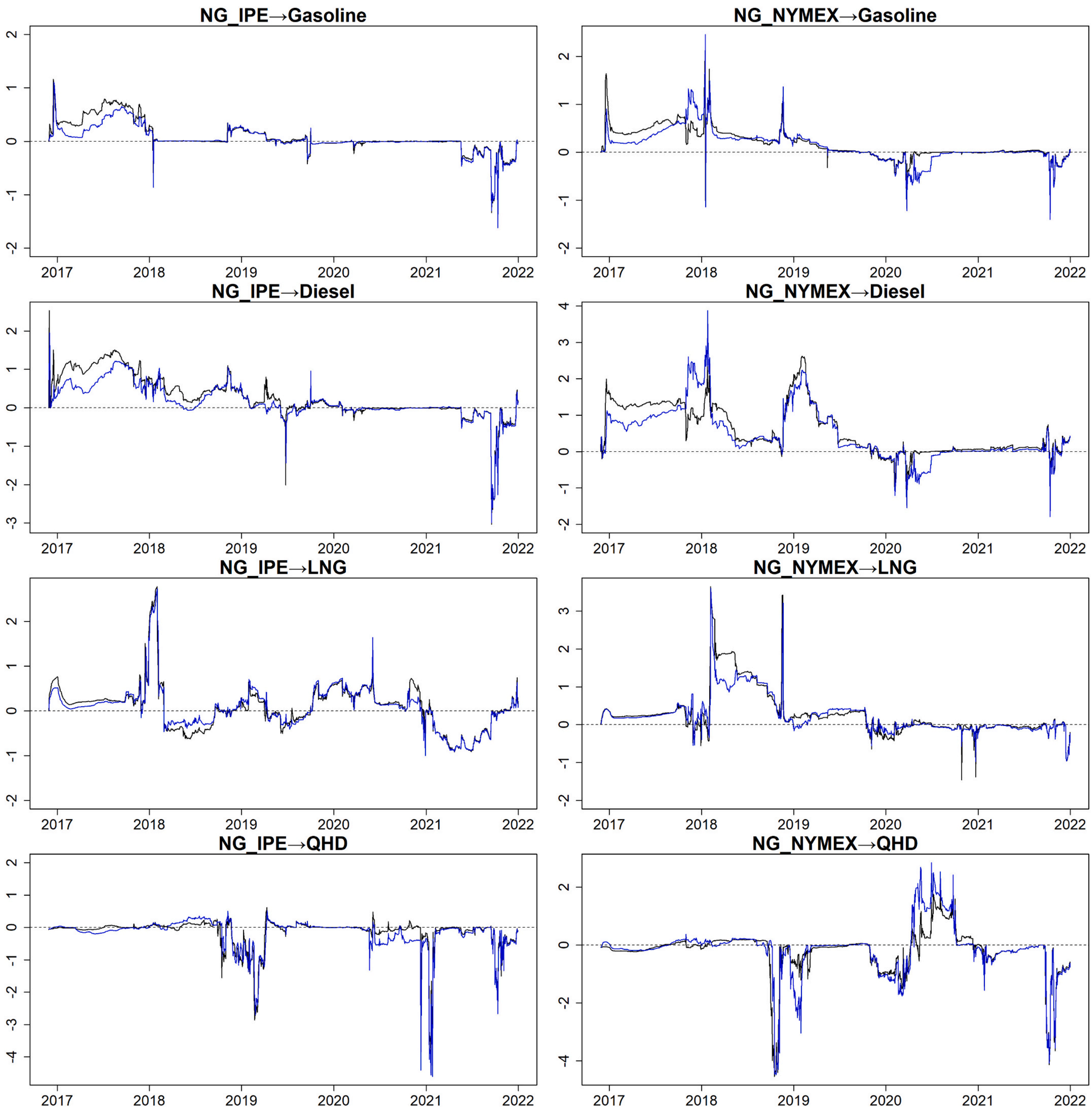

Fig. 8. (*continued*).

that energy transition in China has driven spillover of the country's energy price risks to international energy markets. Particularly in 2021, China's energy price risks arising from the frictions between energy transition and energy demand created several rounds of record high risk spillovers to international energy markets. Despite its necessity and environmental contribution, the energy transformation in China has increased the price volatility risk spillover from China's energy market to the international market.

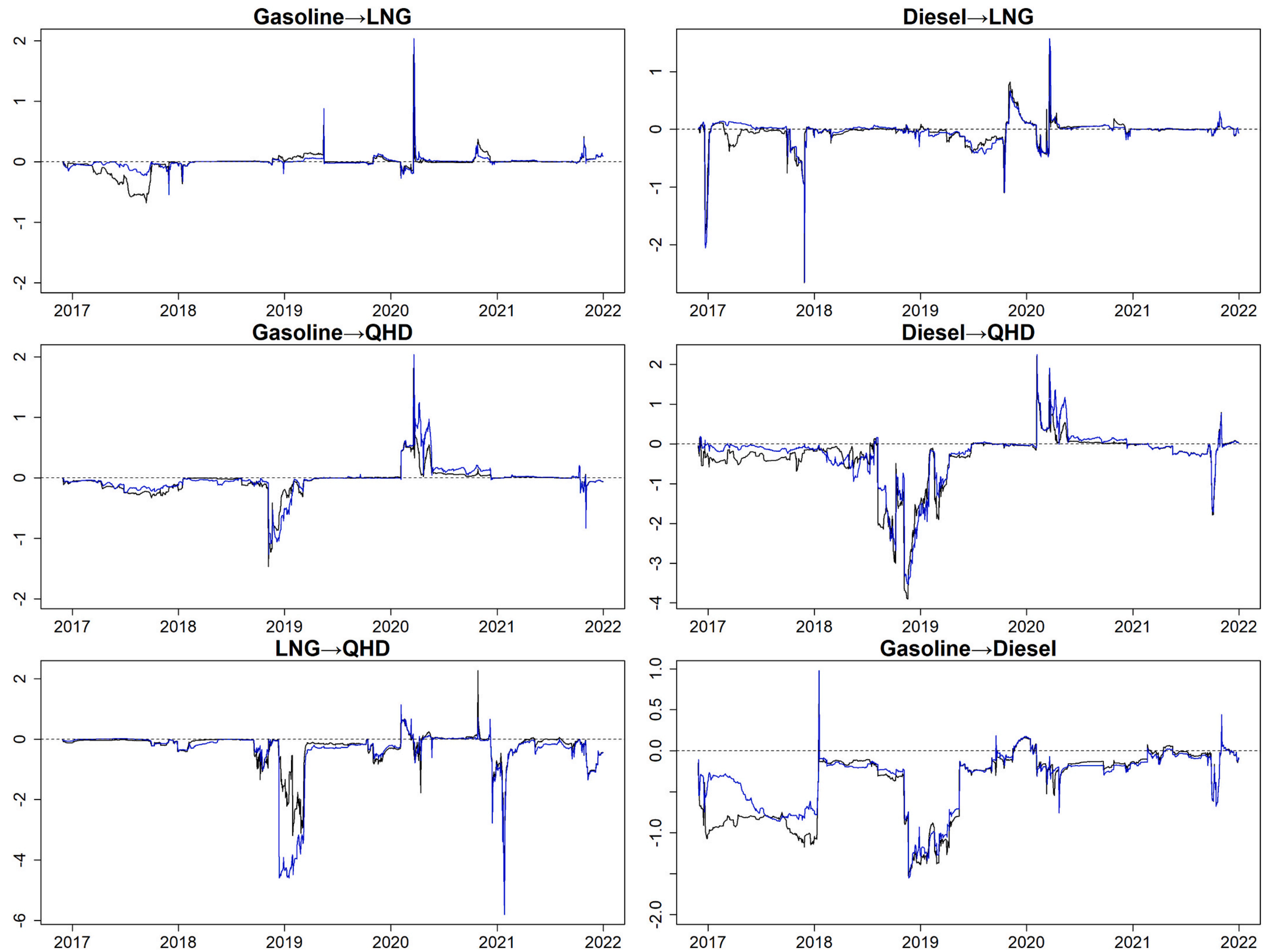

Fig. 8. (*continued*).

4.3.3. Further analysis: Dynamic spillover from Chinese market

To further analyse the changes in the influence of the Chinese energy market during the country's energy transition and reform process, we calculate the total spillover effects[2] of the Chinese energy market to the international crude oil, coal and natural gas markets. As shown in Fig. 9, both in return and volatility, the net spillover effects of Chinese energy on the international crude oil, coal and natural gas markets are negative at the initial stage of SHPGX establishment, followed by an upward trend (except for the mostly positive spillover effect on international coal return). Although the net return spillover from Chinese energy markets to international energy markets is currently relatively weak, the establishment of SHPGX has obviously increased the international influence of the Chinese energy markets.

In particular, after the carbon neutrality target was proposed in September 2020, the net spillover effect of the international crude oil market on China's energy market reaches zero, and China has developed into a net risk transmitter to the international coal markets as well as European and US natural gas futures markets, especially in 2021 when China's energy price risks as a result of the friction between energy transition and demand exacerbated risk spillovers to the international energy markets to record high levels. The energy transformation in China has so far accelerated the spillover of the country's energy price risks to the international market.

[2] We sum the net pairwise spillover from Diesel, Gasoline, LNG and QHD to the target market (namely, crude oil, NEWC, NG_IPE and NG_NYMEX).

5. Conclusion and implications

This study adopts the TVP-VAR approach and the Diebold and Yilmaz (2014) network typology to study the dynamic risk spillovers between Chinese domestic energy markets and international energy markets. The dynamic framework allows us to evaluate the impacts of China's on-going energy market reforms on its domestic market and its risk linkages with the international energy markets.

From a static perspective, China's refined oil products are the top information receivers of return spillover from the international crude oil markets. In contrast, the return spillover between the global crude oil markets and natural gas markets (either US and European natural gas futures markets or Chinese LNG market) is not significant. Gasoline and Diesel are processed products of petroleum, and the pricing of Chinese refined oil products is linked to international oil prices. All these lead to the phenomenon that crude oil markets tend to first transmit risks in returns to China's refined oil markets and further down to China's coal and LNG markets. In terms of volatility spillover, the crude oil price volatility risk can directly transmit to all other energy markets, and the price volatility risk in the international natural gas markets and China's coal market also shows significant spillover effect on China's refined oil and natural gas markets.

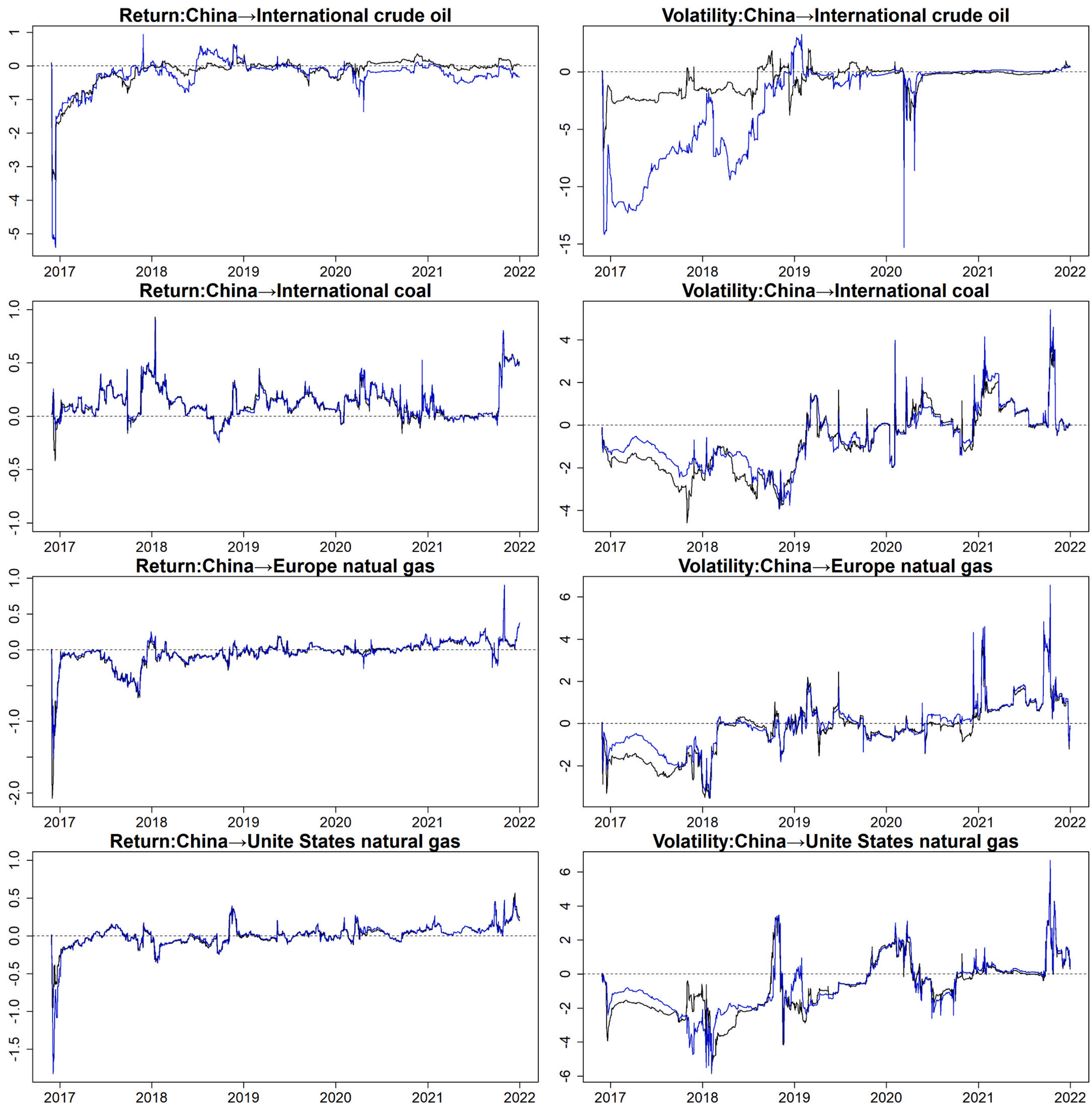

Fig. 9. Dynamic spillover effects from Chinese energy market to global markets.
Note: The black and blue lines indicate the results using Brent and WTI to represent the international crude oil price, respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

A notable finding from the dynamic spillover analysis is that the net spillover effects of international crude oil and natural gas future prices on China's energy markets are diminishing over time, while the risk spillover from Chinese eneryg markets to the world markets becomes increasingly pronounced during the sample period. The oil-linked pricing mechanism for refined products and natural gas in China has made the SHPGX's price indices net receivers of global crude oil prices during the earlier stage after China's energy trading centre was first established. As the operation of the trading center goes on track, risk contagion from international energy markets to SHPGX's price indices is shown to be decreasing. However, Zeng et al. (2020) argue that the market information transparency and price discovery efficiency of the SHPGX indices are still inadequate. Relevant institutions should be implemented to continue to promote energy marketization, deregulate the prices of refined oil and natural gas, to give full play to the role of oil and gas trading hubs, such as Shanghai, Chongqing and Shenzhen.

The results confirm that growing risk spillover from China's energy markets to the global energy markets. Whether to international crude oil, natural gas futures or coal market, the net risk spillover from China's energy markets has turned from negative to positive over the full sample. In particular, the large volatility of Qinhuangdao thermal coal prices in 2021 had a significant spillover effect on domestic and international energy markets. The price spillover between SHPGX's price indices and the international energy markets also showed significant fluctuations during that period. Relevant investors cannot ignore the risk transmitting role of China's energy markets when making venture capital investments in the international energy markets.

Our study offers some recommendations for policymakers. Energy transition is an important step for China to achieve the goal of carbon peak and carbon neutralization. Reducing coal consumption and increasing natural gas and renewable energy consumption are the main aspects of the energy transition. However, coal will remain a critical energy source over a long period given the natural endowments of China. Marketization is considered to accelerate energy transition over the long run (Zhang et al., 2021), and the promotion of marketization will also further strengthen the price links between coal and the domestic oil and gas markets (Li et al., 2017, 2021). China should further liberalize the price controls, promote the market-oriented reforms of refined oil products and natural gas, and make full use of the trading center to enhance the international influence of China's energy markets.

Another issue that has contributed to the increasing risk spillover from China's energy markets to the world market is the conflict between the country's energy transition goals and the existing energy consumption structure. To achieve the carbon neutrality goal, policy measures have been implemented to reduce the country's dependence on coal, leading to high voaltiltiy and increasing uncertainties in the coal market. Such price risk in the single market is not only contagious across energy markets but also in economic and financial markets. It is expected that energy transition and marketization will further complicate the risk spillover of energy prices. In the future, there is a strong need to keep monitoring energy market risks and focus on the interactive spillover effects between China's domestic markets and international energy markets.

A limitation of this study is that the influence of the Russia-Ukraine conflict on energy price risk contagion is not considered, due to sample limitation. Geopolitical conflicts are known to have the potential to cause substantial uncertainties and changes to cross-market risk spillover. Especially after the Nord Stream pipeline was bombed, international coal and natural gas prices all rose sharply. The soaring energy prices favor the development of the renewable energy sector (Maghyereh et al., 2019; Corbet et al., 2020). Continued strong fossil energy prices may present many opportunities for China's energy transition under the dual carbon target. A possible direction of future study could be the evolution of energy risk spillover characteristics under geopolitical conflicts.

CRediT authorship contribution statement

Tiantian Wang: Formal analysis, Investigation, Validation, Data curation, Visualization, Writing – original draft. **Fei Wu:** Validation, Investigation, Writing – review & editing. **Dayong Zhang:** Conceptualization, Validation, Writing – original draft, Writing – review & editing, Supervision, Project administration, Funding acquisition. **Qiang Ji:** Methodology, Formal analysis, Investigation, Project administration, Funding acquisition.

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Appendix A. Appendix

Table A.1
Static spillover based on the TVP-VAR-DY model.

	y_1	y_2	⋯	y_K	From others
y_1	${RC_{11}}^H$	${RC_{12}}^H$	⋯	RC_{1K}^H	$SI_{\rightarrow 1}(H)$
y_2	${RC_{21}}^H$	${RC_{22}}^H$	⋯	RC_{2K}^H	$SI_{\rightarrow 2}(H)$
⋮	⋮	⋮	⋱	⋮	⋮
y_K	${RC_{K1}}^H$	${RC_{K2}}^H$	⋯	RC_{K3}^H	$SI_{\rightarrow K}(H)$
To others	$SI_{1\rightarrow}(H)$	$SI_{2\rightarrow}(H)$	⋯	$SI_{K\rightarrow}(H)$	$TSI(H)$
Net spillovers	$NSI_1(H)$	$NSI_2(H)$	⋯	$NSI_i(H)$	

Note: "From others" measures spillovers received by one market i from all the other markets, calculated by the mean value of $SI_{\rightarrow i,\ t}(H)$; "To others" measures spillovers transmitted from one market i to all the others, calculated by the mean value of $SI_{i\rightarrow,t}(H)$; "Net spillover" measures the net spillover effect of a given market i, calculated as the difference between $SI_{i\rightarrow}(H)$ and $SI_{\rightarrow i}(H)$; $RC_{ji}(H)$ is the mean value of $RC_{j\rightarrow i,\ t}(H)$, indicating the H-step error variance in forecasting y_i that is due to shocks on y_j.

Table A.2
Tabulation of empirical results.

	Spillover indicators	Energy price return	Energy price volatility
Static spillover effect	Total spillover Net spillover From/To others Pairwise spillover	Table 2 & Table A.3	Table 3 & Table A.4
	Net pairwise spillover	Fig. 2	Fig. 3
Dynamic spillover effect	Total spillover	Fig. 4	
	Net spillover	Fig. 5	Fig. 6
	Net pairwise spillover	Fig. 7 (A,B,C)	Fig. 8 (A,B,C)
	Spillover from China	Fig. 9	

Table A.3
Connectedness matrix of energy price returns (WTI representing international crude oil price).

	WTI	Gasoline	Diesel	LNG	NG_IPE	NG_NYMEX	QHD	NEWC	From others
WTI	90.7	2.2	1.9	0.4	2.1	0.9	0.8	0.9	9.3
Gasoline	3.7	58.9	30.8	1	1	1.1	2.8	0.8	41.1
Diesel	3.7	32.5	55.3	1.9	1.1	0.8	4.2	0.5	44.7
LNG	0.3	1.6	2.9	90.2	1.6	0.4	1.8	1.1	9.8
NG_IPE	2.2	0.9	0.8	1.4	89.2	3.2	1.2	1.1	10.8
NG_NYMEX	1.1	1.1	0.7	0.5	2.9	92.6	0.6	0.5	7.4
QHD	0.8	4.1	5.7	1.7	1	0.4	84.4	1.9	15.6
NEWC	1	1.2	0.9	1.2	2.3	0.7	2.6	90.1	9.9
To others	12.7	43.5	43.7	8.1	12.1	7.6	14	6.9	TSI
Net spillover	3.4	2.4	-1	−1.7	1.4	0.2	−1.6	−3	18.6

Note: "From others" measures spillovers received by one market from all the other markets; "To others" measures spillovers transmitted from one market to all the others; Net spillover measures the net spillover effect of a given variable, being the difference between "To others" and "From others"; TSI indicates the total connectedness index. Brent indicates Brent crude oil price; Gasoline is China's gasoline wholesale price index; Diesel is China's diesel wholesale price index; LNG indicates China's LNG ex-factory price index; NG_NYMEX indicates the settlement prices of natural gas futures on the New York Mercantile Exchange; NG_IPE indicates the settlement prices of natural gas futures on the International Petroleum Exchange; NEWC indicates Newcastle port coal price in Australia; QHD indicates the Qinhuangdao Q5500 thermal coal market price.

Table A.4
Connectedness matrix of energy price volatility (WTI representing international crude oil price).

	WTI	Gasoline	Diesel	LNG	NG_IPE	NG_NYMEX	QHD	NEWC	From others
WTI	85.9	1.8	2	0.7	1.7	2.9	1.6	3.2	14.1
Gasoline	10.9	59.9	21.3	0.6	1.3	2.9	1.4	1.7	40.1
Diesel	16.2	17.1	39.5	1.9	3.6	7.7	5.5	8.6	60.5
LNG	6.6	0.5	1.5	74.8	3.4	4.6	5.7	3	25.2
NG_IPE	6.5	0.8	1.6	2.5	65	7.8	5.6	10.2	35
NG_NYMEX	9.6	1.2	1.9	1.5	6.1	66.9	5.8	7	33.1
QHD	7.2	1.1	2.2	1	3.2	4	70.3	10.9	29.7
NEWC	12.7	0.7	2.6	2.1	8.7	9.1	11.6	52.5	47.5
To others	69.7	23.4	33.2	10.2	28.1	39.1	37.3	44.5	TSI
Net spillover	55.6	−16.7	−27.4	−15.1	−6.9	6	7.6	−3	35.7

Note: "From others" measures spillovers received by one market from all the other markets; "To others" measures spillovers transmitted from one market to all the others; Net spillover measures the net spillover effect of a given variable, being the difference between "To others" and "From others"; TSI indicates the total connectedness index. Brent indicates Brent crude oil price; Gasoline is China's gasoline wholesale price index; Diesel is China's diesel wholesale price index; LNG indicates China's LNG ex-factory price index; NG_NYMEX indicates the settlement prices of natural gas futures on the New York Mercantile Exchange; NG_IPE indicates the settlement prices of natural gas futures on the International Petroleum Exchange; NEWC indicates Newcastle port coal price in Australia; QHD indicates the Qinhuangdao Q5500 thermal coal market price.

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2022.106495.

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