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Dynamic spillovers between energy and stock markets and their implications in the context of COVID-19

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ABSTRACT

This study combined time-varying parameter vector autoregression (TVP-VAR) and a spillover index model to analyze the static, total, and net spillover effects of energy and stock markets before and after the COVID-19 outbreak. A network method was also used to depict structural changes more intuitively. Furthermore, we calculated and compared changes in the hedge ratio, optimal portfolio weights, and hedge effectiveness to guide investors to adjust portfolio strategies during COVID-19. The main findings were as follows: First, COVID-19 had a significant impact on spillover effects, and the average value of total spillover index increased by 19.94% compared with that before the epidemic. Second, the energy market was an important risk recipient of the stock market before COVID-19, and the extent of risk acceptance increased after the COVID-19 outbreak. Third, the hedging ratio, optimal portfolio weights, and hedge effectiveness showed huge changes after the COVID-19 outbreak, requiring investors to adjust their portfolio strategies.

1. Introduction

The linkage between energy markets and stock markets has been extensively investigated to gain a better understanding of the price fluctuations and investment attributes of energy markets (Batten, Kinateder, Szilagyi, & Wagner, 2019; Lin & Su, 2020; Peng, Wen, & Gong, 2020). The nexus between energy prices and the stock index was significantly altered during the global financial crisis (GFC), the European debt crisis (EDC), and the Great Crash of the stock market (GCS) (Aromi & Clements, 2019; Wen, Xu, Ouyang, & Kou, 2019; Wen, Yuan, & Zhou, 2020). Recently, energy and stock markets have experienced a huge shock as a result of COVID-19. For example, using Granger causality tests, Sharif, Aloui, and Yarovaya (2020) found that oil prices have had a significant effect on US markets during COVID-19. Moreover, job security, business operations, and essential services have been directly affected by COVID-19 (Sharif et al., 2020). Investors' future expectations have been generally negative in the face of COVID-19, and their strategies have changed accordingly, causing huge negative shocks for the energy and stock markets (Hetkamp et al., 2020; Mazur, Dang, & Vega, 2020; Wen, Li, Sha, & Shao, 2020). Meanwhile, the international trade of crude oil has been seriously affected, and the spot energy market has been greatly affected as well, which will inevitably cause additional fluctuations in future energy prices. Yet, there are two important problems that have not been sufficiently addressed in the research. First, from the perspective of systemic risk, the impact of COVID-19 on information spillover effects in the energy and stock markets remains unclear. Second, in terms of asset allocation, changes in the hedging ability of energy during COVID-19 remain unclear as well.

A spillover effect can be understood as a fluctuation in financial markets that transfers from one market (asset) to another (asset). To address the first abovementioned problem, we can refer to relevant research on dynamic spillovers across markets. Since the 2008 GFC, researchers have paid increasing attention to spillover effects between energy markets and other markets. Adams and Glück (2015) suggested that the GFC could have magnified information spillovers between the energy market and other financial markets. Using Granger causality testing, Du and He (2015) found a positive spillover from Brent crude oil to the S&P 500 index and a negative spillover in the opposite direction. Meanwhile, using vector autoregression and the pseudo quantile impulse response function, Wen, Wang, Ma, and Wang (2019) found that the spillover effect between crude oil and stock markets was significant in the upside quantiles, and this spillover effect increased after the GFC. Ashfaq, Tang, and Maqbool (2020) tested the spillover effects between crude oil prices and Asian stock markets using a VAR-DCC-GARCH

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model and found that strong spillover relations existed.

It is clear that major events such as COVID-19 can greatly alter the relationships between markets. Existing research on the GFC can be instructive in this regard given the similarities between the GFC and COVID-19. Both events have had lasting and serious effects on the whole economy. As with the GFC in 2008, the interconnectedness and spillovers between energy prices and other markets have likely been changed during COVID-19 (Xu, 2020; Yong & Laing, 2020). However, COVID-19's effects on the energy and stock markets are slightly different than those of the GFC, EDC, and GCS. The three latter events were initiated by a specific negative event (e.g., the Lehman bankruptcy in 2008), and then the shock was transmitted to the whole financial market (Gong, Wang, & Shao, 2020; (Saeed & Ridoy, 2020)Shehzad, Xiaoxing, & Kazouz, 2020; Shibata, 2020). COVID-19, meanwhile, was initially underestimated, and financial markets were not seriously affected at first. As the epidemic worsened, however, its negative effects began to be experienced around the world.

Related studies typically use GARCH models. However, constructing a GARCH model that reflects both the direction and temporality of spillover effects is complex. Diebold and Yilmaz (2008, 2012, 2014) proposed a spillover index model (called the DY model) that measures the direction and temporality of spillover effects in financial markets. Investigating temporal spillover effects between oil and stocks in the US, UK, and Japan, Zhang and Ma (2019) found that the one-way spillover of Brent crude oil and stock markets only appeared during the event period while a two-way spillover effect appeared significantly all of the time. Tiwari, Trabelsi, Alqahtani, and Raheem (2020) measured risk transmission between oil and G7 stock markets based on conditional value-at-risk and the copula method; they found that the crude oil market can be a good choice for diversifying risk in the US and Japan.

Spillover effect can also be seen as a systemic risk that transfers from one market to another and includes direct and temporal spillover effects (He, Wang, & Yin, 2020; Xiao, Hu, Ouyang, & Wen, 2019). However, existing research has had difficulty in analyzing spillover effects considering both directionality and time variability. In this regard, Diebold and Yilmaz (2008, 2012, 2014) proposed a simple framework for exploring the degree of correlation between different markets. This is an effective tool for estimating the connectivity of the system as a proxy measure of system risk level, and it includes the directionality and time variability of spillover effects. Antonakakis, Chatziantoniou, and Gabauer (2020) and Liu and Gong (2020) proposed nonparametric estimation based on the DY and TVP models, called TVP-DY; this is an effective method for analyzing systematic spillover effects. Therefore, the present study used the TVP-DY model to measure the total and net spillover effects. Moreover, to explore the effects of COVID-19 in detail, we compared statistical characteristics based on TVP-DY before and after the outbreak. Structural changes in the spillover network are also examined, wherein we intuitively observe changes in the spillover effect using network theory.

Regarding the second problem that we mentioned earlier, some studies have found that the energy market is being financialized and can hedge the risks of other assets. Thus, some researchers have paid attention to proper portfolio strategies between energy and stock markets. Kim, Rahman, and Shamsuddin (2019) found that the ability of energy prices to predict US stock returns was different under different portfolio strategies; they also found that the effect of energy prices on stock returns changed from negative to positive as a result of the GFC. Using asset pricing and factor models, Azimli (2020) found that Brent crude oil had negative portfolio returns for the US market and positive returns for the Asia-Pacific market. Other studies have suggested that the hedge effectiveness of portfolios can be improved by considering correlations and information spillovers between assets. Mensi, Boubaker, Al-Yahyaee, and Kang (2018) found that investors and speculators could design better portfolio strategies when they considered net spillover effects between assets. As mentioned earlier, COVID-19 may have altered the spillovers between the energy and stock markets, and investors may need to adjust their portfolio strategies accordingly (Ji, Zhang, & Zhao, 2020). In addition, the international energy trade has been hit hard by COVID-19, and energy producers and trading companies might also need more hedging to deal with the coming production risks (Ji, Bahloul, Geng, & Gupta, 2020). To create a more accurate portfolio, based on spillover effects, we constructed a one-dollar long position in the energy market (or stock market) and a short position in the stock market (or energy market) to explore the differences in hedge ratio, optimal portfolio weights, and hedging effectiveness before and after COVID-19.

This study makes the following contributions. First, although many studies have investigated the relationship between energy prices and the stock market, there is a lack of work on the systemic spillovers of the energy and stock markets under the effects of COVID-19. Thus, we systematically analyzed three different energy markets and 10 main stock markets using a TVP-DY framework. We further analyzed the similarities and differences in the information spillover effects between the three types of energy markets and the different stock markets. Second, we investigated the structural changes caused by COVID-19 by comparing the spillover index before and after the outbreak. A network method was used to more intuitively examine these structural changes in the market. Third, previous studies have only considered the spillover relationship between the energy and stock markets; our study, however, further analyzed the hedging strategy between the energy and stock markets. We compared the hedging ability of energy markets against stock markets and vice versa, suggesting proper portfolio strategies for investors. We also compared hedging ability before and after COVID-19, which can also provide reference for investors to adjust their portfolio strategies.

2. Method

2.1. TVP-DY method

In order to solve the systematic spillover among financial markets, Diebold and Yilmaz (2008, 2012, 2014) proposed a dynamic spillover index framework called the DY model based on forecast error variance decomposition calculated by a generalized N-variables vector autoregression (VAR) model. A rolling-window size is needed to set up in DY model to evaluate the parameters in the model, which would lose the estimation of the rolling-window length at the beginning of the sample. Antonakakis et al. (2020) constructed a new spillover model–based DY model called TVP-DY, which replaced rolling-window estimation the parameters of VAR with the TVP-VAR model. In order to reveal the spillover effect between energy and stock markets, we used the TVP-DY model in this paper. According to Antonakakis et al. (2020) and Evrim Mandacı, Cagli, and Taşkın (2020), we built a TVP-VAR model at the beginning as follows:

$$Y_t = \sum_{i=1}^{p} \beta_t Y_{t-1} + \varepsilon_t, \varepsilon_t \sim N(0, S_t) \tag{1}$$

$$\beta_t = \beta_{t-1} + v_t, v_t \sim N(0, R_t) \tag{2}$$

with

$$Y = \begin{pmatrix} y_1 \\ y_2 \\ \dots \\ y_N \end{pmatrix} \beta_t' = \begin{pmatrix} \beta_{1t} \\ \beta_{2t} \\ \dots \\ \beta_{pt} \end{pmatrix}$$

where Y_t is a $N \times 1$ vector representing the object set of this research. y_1, y_2, …, y_N represents the single energy and stock market. p is the optimal lag length of TVP-VAR model measured by AIC and SC. ε_t and v_t represent the noise term. ε_t is a $N \times 1$ vector, and v_t is a $N^2p \times 1$ vector, whereas the time-varying variance-covariance matrices S_t and R_t are $N \times N$ and $N^2p \times N^2p$, respectively. β_t is an $N \times Np$ matrices, which represents the estimated coefficients of each variable at time t. The detailed model setting and derivation process can be seen in Antonakakis et al. (2020), and we can get the H-step ahead generalized forecast error variance decompositions as follows:

$$d_{ij}(h) = \frac{\sigma_{jj}^{-1} \sum_{0}^{H-1} \left(e_i' A_h \sum e_j\right)^2}{\sum_{0}^{H-1} \left(e_i' A_h \sum A_h' e_i\right)} \tag{3}$$

where Σ represents the covariance matrix of ε_t, σ_{jj}^{-1} is the standard error of ε_t, e_j represents a vector with the j-th unit value 1. Furthermore, the variance decompositions matrix $D_{ij}(h)$ reflects the spillover effect from market j to market i, which can be written as:

$$D_{ij}(h) = \begin{Bmatrix} d_{11} & d_{12} & \dots & d_{1N} \\ d_{21} & d_{22} & \dots & d_{2N} \\ \dots & \dots & \dots & \dots \\ d_{N1} & d_{N2} & \dots & d_{NN} \end{Bmatrix} \tag{4}$$

In order analyze the spillover effect, we standardized the total spillover effect of each row as 1, and we defined the standard of $d_{ij}(h)$ as $l_{ij}(h)$ with the detail format as Eq. (6).

$$l_{ij}(h) = \frac{d_{ij}(h)}{\sum_{j}^{N} d_{ij}(h)} \tag{5}$$

Here comes the total connectedness (or spillover) index (TCI) as follows:

$$TCI(h) = 100 \times \frac{\sum_{i,j=1, i \neq j}^{N} l_{ij}(h)}{\sum_{i,j=1}^{N} d_{ij}(h)} \tag{6}$$

We can calculate the net pairwise directional connectedness (NPDC) as follows:

$$NPDC_{i \leftarrow j} = l_{ij} - l_{ji} \tag{7}$$

2.2. Hedge strategy framework

We followed Guhathakurta, Dash, and Maitra (2020)' work, and constructed hedge strategy between energy and stock markets. The hedge ratio can be written as (Kroner & Sultan, 1993):

$$\beta_{oil,stock} = \frac{h_{oil,stock}}{h_{stock,stock}}, \tag{8}$$

where $\beta_{oil,\ stock}$ ($\beta_{stock,\ oil}$) represents the hedge portfolio with one-dollar long position in energy markets (stock markets) and short position in stock markets (energy markets). $h_{oil,\ stock}$ represents the conditional covariance between energy markets and stock markets, and $h_{stock,\ stock}$ represents conditional variance of stock markets.

The optimal portfolio weights between energy and stock markets can be gotten when the risk is minimal, and the formula is following (Kroner & Ng, 1998).

$$w_{oil,stock} = \frac{h_{stock,stock} - h_{oil,stock}}{h_{oil,oil} - 2h_{oil,stock} + h_{stock,stock}} \tag{9}$$

with

$$w_{oil,stock} = \begin{cases} 0, & 0 < w_{oil,stock} \\ w_{oil,stock}, & 0 \leq w_{oil,stock} \leq 1 \\ 1, & w_{oil,stock} < 1 \end{cases} \tag{10}$$

We can also get the hedge effectiveness (HE) as follows:

$$HE_{oil,stock} = \frac{h_{unhedged} - h_{oil,stock}}{h_{unhedged}} \tag{11}$$

where $h_{unhedged}$ represents the conditional variance of energy or stocks without hedging strategies, and $h_{oil,\ stock}$ is the total variance of the hedged portfolio with the optimal investment weights between energy and stock markets.

3. Data and preliminary analysis

3.1. Data

We focused on connectedness, directional spillover effects, and portfolio strategies between energy and stock markets in the context of COVID-19. Following Bekiros, Nguyen, Sandoval Junior, and Uddin (2017) and Qin, Hong, Chen, and Zhang (2020), we referred to the NYMEX heating oil, NYMEX natural gas, and Brent crude oil energy markets. Regarding international stock markets, based on the literature (Labidi, Rahman, Hedström, Uddin, & Bekiros, 2018; Wilms, Rombouts, & Croux, 2021), we chose the S&P 500 (US), DAX (Germany), FTSE 100 (UK), CAC 40 (France), Nikkei 225 (Japan), HSI (Hong Kong), SSE (China), KOSPI 200 (Korea), Ibovespa (Brazil), and RTS (Russia). We chose daily data for observations of energy and stocks from January 4, 2011, to August 11, 2020. Daily frequency returns were employed in this study. Stock indexes and energy prices were taken from the Wind database. Returns can be calculated by $R_t = \ln(P_t) - \ln(P_{t-1})$, and P_t is the closing price at t. According to Forbes and Rigobon (2002), we improved the daily analysis by observing the average between two subsequent days avoiding contamination arising from the differences between the opening time zones of the studied markets. Sandoval and Franca (2012) filled in missing values of holidays using Random Matrix Theory, which need to have a lot of time series in the research. However, according to Callot, Kock, and Medeiros (2017), the reliability of the analysis results is not affected by the data processing process when the proportion of missing data is relatively low. Hence, this study deleted data that does not match the timing of transactions in each market and used the "common trading window" for empirical analysis. Given that the date of the earliest COVID-19 case remains unclear, and little attention was paid in the early stages, we set January 1, 2020, as the cut-off time point before and after the COVID-19 outbreak in line with Aslam, Aziz, Nguyen, Mughal, and Khan (2020). In this paper, the TVP-DY model, hedging rate, hedging efficiency, and other indicators are calculated by R language, and the spillover networks are drawn by Gephi software.

3.2. Preliminary analysis

According to the returns series shown in the Fig. 1, the fluctuations in stock markets (in both developed and emerging countries) and energy markets were significant during 2015, 2016, and from January 1, 2020, to August 11, 2020 (the most recent date). The first fluctuation is mainly attributable to the stock market crash of 2015 and 2016, and the last large fluctuation was caused by COVID-19 and the fusing of the US stock market. We can observe intuitively that energy markets were also affected by the catastrophe in the stock markets. There is also a slight fluctuation between September 10, 2018, and March 1, 2019, which may have been caused by a series of events in the stock or energy markets.

Table 1 shows descriptive statistics for energy and stock returns. The returns for heating oil, natural gas, Brent crude oil and RTS are negative. The main reason is that the world economy was negatively affected by the epidemic, and energy and stock markets saw huge drops. The stock means for some countries is positive, implying that some good information appeared in those countries. We can also see that most daily returns are positive according to the median values, which implies that

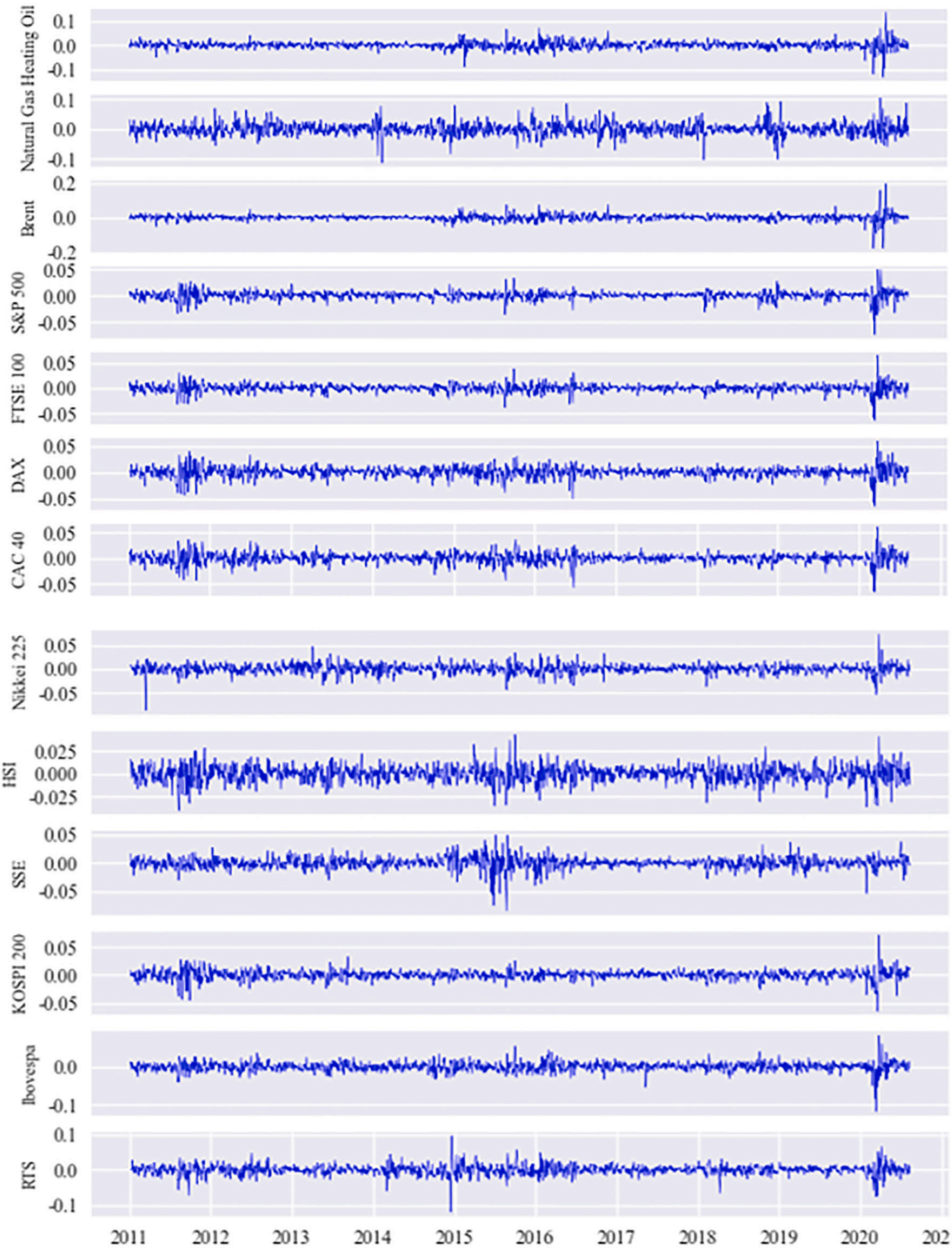


Fig. 1. Returns of each energy and stock.

these markets still had investment properties, despite the stock market crash and the spread of the epidemic. According to the null hypothesis of zero skewness, greater-than-three kurtosis, and the Jarque–Bera test (J-B test), all returns have nonnormal distribution, which implies the existence of high peaks and fat tails. Based on the augmented Dicky–Fuller (ADF) and Phillips–Perron (PP) tests, all observations have stationarity.

4. Empirical results and discussion

4.1. Static spillover effect analysis

Table 2 shows the static spillover index for energy and stock returns with a total spillover index of 62.7%. We can obtain five main important results from Table 2. First, the net contributors and recipients can be reflected by the value of the net directional connectedness. We can intuitively judge that stocks in developed economies are high net spillover contributors, while those in emerging economies are important net

Table 1
Descriptive statistics of energy and stock returns.

	Mean	Median	Max	Min	Std. Dev.	Skew	Kurt	J-B test	ADF	PP
Heating oil	−0.0003	0.0002	0.1361	−0.1328	0.0147	−0.35	15.50	14,790.98***	−11.93***	−26.33***
Natural gas	−0.0003	−0.0006	0.1055	−0.1145	0.0199	0.11	6.04	876.63***	−14.63***	−25.94***
Brent	−0.0003	0.0002	0.1950	−0.1792	0.0173	0.02	28.81	62,824.64***	−9.09***	−25.17***
S&P 500	0.0004	0.0008	0.0496	−0.0741	0.0073	−0.87	13.70	11,079.88***	−12.99***	−25.94***
FTSE 100	0.0000	0.0004	0.0644	−0.0630	0.0075	−0.58	12.04	7838.70***	−9.59***	−25.12***
DAX	0.0003	0.0008	0.0596	−0.0649	0.0096	−0.60	8.26	2751.58***	−8.87***	−24.87***
CAC 40	0.0001	0.0007	0.0616	−0.0662	0.0095	−0.64	8.87	3400.81***	−11.72***	−24.76***
Nikkei 225	0.0003	0.0005	0.0733	−0.0866	0.0095	−0.46	9.85	4510.66***	−12.79***	−24.66***
HSI	0.0000	0.0006	0.0425	−0.0398	0.0085	−0.24	4.98	391.37***	−10.73***	−25.51***
SSE	0.0001	0.0002	0.0501	−0.0843	0.0101	−0.93	10.67	5872.08***	−9.00***	−26.18***
KOSPI 200	0.0001	0.0004	0.0709	−0.0644	0.0079	−0.58	11.30	6623.64***	−10.72***	−24.72***
Ibovespa	0.0002	0.0001	0.0820	−0.1173	0.0113	−0.49	12.35	8340.27***	−8.30***	−27.20***
RTS	−0.0001	0.0001	0.0960	−0.1188	0.0135	−0.58	10.06	4828.84***	−10.01***	−25.26***

Notes: *** indicates significance at the 1% confidence level.

Table 2
Static spillover index.

	Heating Oil	Natural Gas	Brent	S&P500	FTSE 100	DAX	CAC40	Nikkei 225	HSI	SSE	KOSPI 200	Ibovespa	RTS	FROM
Heating Oil	41.1	1.6	30.4	3.7	2.6	3.7	3	1.2	1.6	1.3	1.3	3.5	5.1	58.9
Natural Gas	2.9	83	1.9	1.8	1.1	1.1	1.1	1.3	0.9	1.2	1.2	1.5	1.1	17
Brent	27.8	0.9	40.4	4.8	2.8	4.3	3.5	1.1	1.6	1.5	1.4	4.1	6	59.6
S&P500	2.3	0.5	3.4	33.2	12.3	12	13.3	2.8	3.1	1	2.8	7.7	5.6	66.8
FTSE 100	2.6	0.4	3.3	14	15	24.6	17.1	2.5	4.3	1.1	3.1	6.1	6	75.4
DAX	1.7	0.4	2.1	12.9	25.3	15.4	21.4	2.8	3.7	1	3.1	4.5	5.7	74.7
CAC40	2	0.4	2.7	13	19.9	16.2	24.2	2.8	3.7	1	3	5.1	6	75.8
Nikkei 225	1.8	0.7	2.1	14.1	10.6	8.9	11.5	29.2	5.4	1.9	5.1	3.9	4.8	70.8
HSI	2	0.5	2.5	10	8.4	9.5	9	4	25.2	7.1	7.6	7.8	6.3	74.8
SSE	1.6	0.5	2.1	4.5	3.9	4.6	4	3.1	15	50.6	3.9	3.2	3	49.4
KOSPI 200	2	0.6	2.7	10.8	9.3	8.7	9.6	4.5	9.3	2.4	28.6	6.1	5.5	71.4
Ibovespa	3.2	0.9	4.2	10.7	6.1	7.6	7	1.3	3.8	1.2	2.3	45.1	6.6	54.9
RTS	5.4	0.6	7.5	8.7	7.4	8.4	8.2	1.7	4.5	1.8	2.7	8.3	34.9	65.1
To	55.4	7.9	64.9	109	99.4	100.1	108.5	29	57	22.6	37.5	61.7	61.7	814.8
NET	−3.5	−9.2	5.3	42.2	24.7	24.7	32.7	−41.7	−17.8	−26.9	−33.9	6.8	−3.4	62.7

Notes: The row "To" represents the total spillover from one certain market to another market, and the column "From" represents the total spillover from other markets to one certain market. The row "NET" represents the net spillover from one certain market to other markets, which calculates "To" minus "From".

spillover recipients. This is in line with Yoon, Al Mamun, Uddin, and Kang (2019)—namely, that stock markets of often play a transmitter role in spillover effects. This means that financial risk shifts from developed countries to emerging ones and to energy markets, playing an important role in financial markets when bad events arise. Our study further confirmed the study by Diebold and Yilmaz (2008), which found that the US stock market was the biggest spillover contributor. Notably, European stock markets such as CAC 40, DAX, and FTSE 100 were also very high transmitters to other markets. Two important events may have contributed to spillover effects between European stock markets and other markets. First, the EDC produced a huge systematic spillover to the global economy, increasing the effect of European stock markets on other stock markets. Second, the financial transaction tax (FTT) proposed in 2011 limited high-frequency speculative trading, reduced volatility, and created financial stability (Colliard & Hoffmann, 2017). Kang, Maitra, Dash, and Brooks (2019) also suggested that FTT increased the spillover effect of European stock markets on other markets.

Second, natural gas had the highest spillover (83%) on its own markets, and heating oil and Brent crude oil had about a 40% spillover on their own markets. Energy markets are mainly influenced by their own markets from a static perspective, which implies that energy markets were still relatively independent of the stock markets for the whole period. In addition to the energy markets, stocks in emerging countries had more influence on their own countries compared to the case in developed countries. For example, China and Brazil's stock markets spill over about 50% and 45% of their own markets. This may be due to the limited degree of the financialization of energy markets and stock markets in emerging countries. We take SSE as an example to explain this phenomenon. Zhou, Zhang, and Zhang (2012) found that the SSE was a slight net recipient based on a sample before 2009. However, Wang, Xie, Jiang, and Eugene Stanley (2016) found that Chinese stock markets were influenced by the GFC and EDC based on a sample ranging from 2005 to 2015. Further, Cheng and Xiong (2014) found that the financialization of energy markets had been deepening, indicating that the spillover effect between the energy and stock markets was limited.

Third, energy markets are the basis of modern economies, and energy returns are affected by financial markets. Stocks markets, conversely, are also affected when fluctuations appear in energy markets. We found that the spillover effect was stronger from developed stock markets to energy markets than in the reverse situation. This is because energy markets have both commodity and financial attributes, and commodity attributes can weaken the effect of stock markets on energy markets, which is consistent with Kang et al. (2019). We also found that the spillover effect from energy markets to emerging countries is slightly higher than that by contraries. There are two possibly reason. The first one is that compared with the developed countries, the stock market of emerging countries is immature, and the fluctuation of stock indexes are more difficult to transmit to the energy market. The last one is that energy markets are more needed in emerging countries for economic development, creating a higher impact on stock markets in emerging countries and regions.

Fourth, the spillover between heating oil and Brent crude oil was approximately 30%. Heating oil is refined from crude oil, which creates a close relationship between returns of heating oil and Brent crude oil. This is in line with some existing studies. For example, Hammoudeh, Li, and Jeon (2003) found a strong causal relationship between crude oil and heating oil; this is further supported by (Scheitrum, Carter, & Revoredo-Giha, 2018) and Ederington, Fernando, Lee, Linn, and Zhang (2020). This high spillover effect between Brent crude oil and heating oil should be noted by market regulators, producers, and investors because price fluctuations in one market always leads to fluctuations in the other. Another concern is that the net spillovers of Brent crude oil to heating oil and natural gas are 2.6% and 1% contributing the net transmitter of Brent crude oil.

Fifth, compared to others, natural gas had much lower spillovers to and from others, indicating that natural gas has little relationship with other markets. Hailemariam and Smyth (2019) found that natural gas price volatility was primarily driven by demand shocks, which implies that the market is not strongly affected by others. Natural gas has also been a continuous oversupply market in recent years, which strengthens the results.

4.2. Dynamic total spillover effect analysis

Fig. 2 reports the dynamic total spillover index, showing spillover effects among energy and stock markets from a time-varying perspective. Four large peaks can be observed in Fig. 2. The first appears at the beginning of 2012, mainly as a result of the EDC. The second peak is in early 2016, with the fusion of A-shares in China, followed by Britain exiting from the EU and a series of significant political, economic, and terrorist incidents. The third coincides with the stock market crash of early 2018, which has had an ongoing influence. The last one, in early 2020, is the highest peak, coinciding with the outbreak of COVID-19 and the US stock fusion. Although some studies have investigated the first three peaks, few have investigated the COVID-19 peak in relation to stock and energy markets.

With the global outbreak of COVID-19, international trade practically halted, and the economic system was on the verge of collapse. The stock market began to plummet as the situation worsened. We calculated the average spillover index during and before COVID-19 with values of 61.89% and 74.23%, respectively. We can observe that COVID-19 had an unprecedented effect on energy markets and stocks, making the total spillover index 19.94% higher than the average. Fortunately, as we can see, the total spillover index continued to decline after March 24, 2020, at the highest value of 80.27%. As the understanding of COVID-19 increased and US stocks stabilized, fluctuations in the energy and stock markets tended to stabilize, and the economic downturn slowed down. Furthermore, COVID-19 has been more or less controlled in certain areas, such as China, and economies have begun to recover.

4.3. Dynamic spillover effect analysis for each market

Fig. 3 shows the dynamic evolution of the “To spillover” and “From spillover” index of each energy market, and the differences between “from others” and “to others” reflect the net spillover effect. We can define a certain market as a net transmitter (recipient) when its net spillover index is positive (negative). As we can see in Fig. 3, natural gas markets have been net recipients of stock markets since January 5, 2011, implying that natural gas returns are much more affected by stock returns, especially during periods of negative events, from a dynamic perspective. When bad events occur, investments are transferred from the stock market to the natural gas market, causing additional fluctuations in energy markets. Investors have perceived huge risks in the financial market during COVID-19, and natural gas markets have, to some extent, become a safe haven. We can observe that the net spillover of natural gas during COVID-19 has continued to be high, albeit with a slight drop, suggesting that the influence of COVID-19 is still noteworthy.

The net spillover behaviors of Brent crude oil and heating oil markets are very similar. For example, they are all net transmitters during 2015 and late 2018 when the oil prices plummeted, but they are all net recipient in the other period. However, the spillover effect of Brent crude oil is much higher than heating oil not only as net transmitters but also as net recipients. We can judge that both Brent crude oil and heating oil are higher net recipients than COVID-19 outbreak even though heating oil transfer to net transmitter in the recent time. A higher net recipient means that hedging ability may be better when we take energy markets as the long position in a given portfolio.

Even though the change of net spillover effect of each energy market is slight difference caused by COVID-19, the “To spillover” and “From spillover” effect are sudden increasing. The higher “To spillover” and “From spillover” means that the risk is easier to transmit among stock or energy markets.

As for stock markets in developed countries, as shown in Fig. 4, the “To spillover” of S&P 500, FTSE 100, DAX, and CAC 40 are significantly higher than “From spillover”, as a role of net transmitters. Consistent with previous studies, the net spillover of the S&P 500 is always high during the whole sample. The net spillovers of DAX, FTSE 100, and CAC 40 were very high during the European debt crisis, while the net

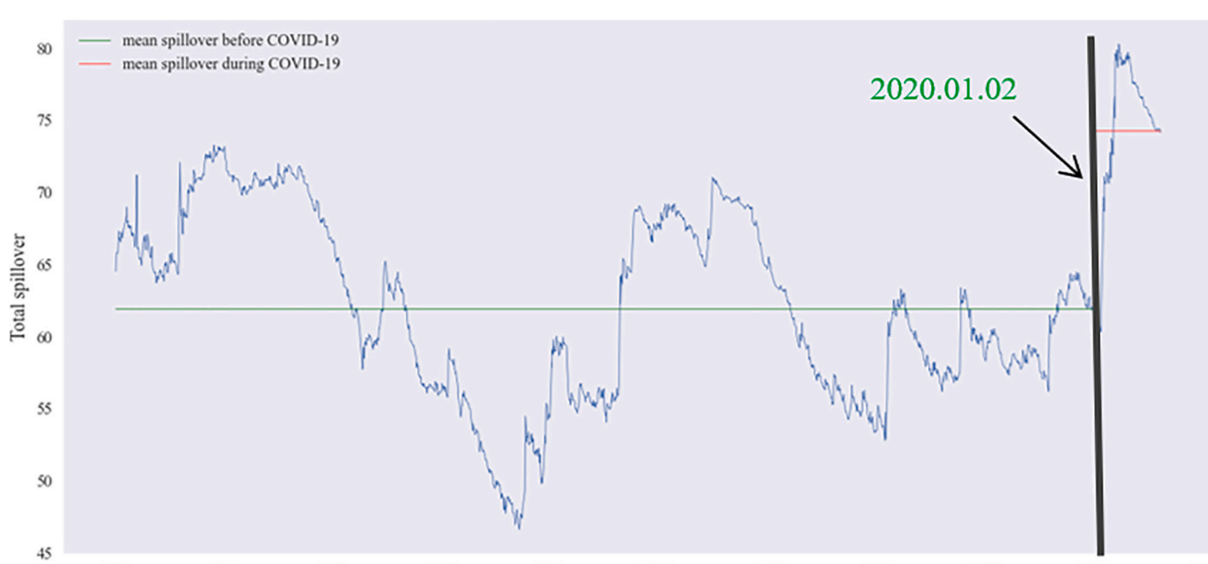


Fig. 2. Dynamic total spillovers among energy and stock markets.

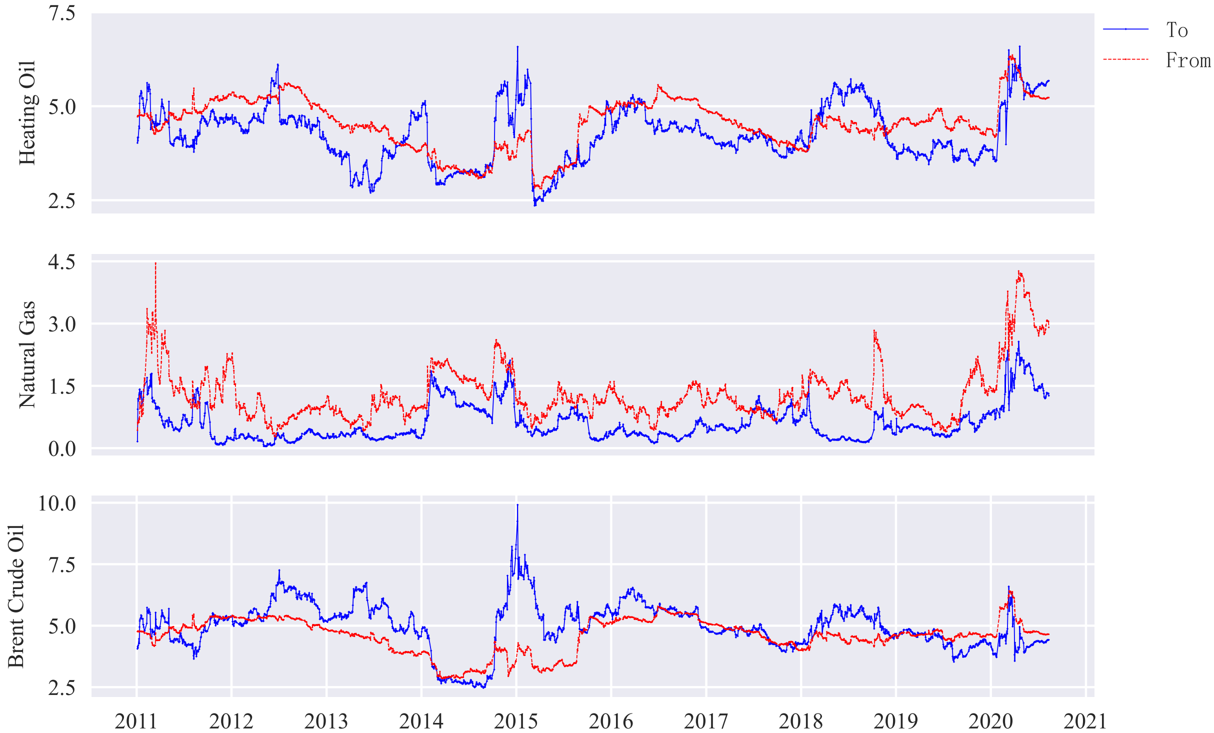


Fig. 3. To and from spillover effect of each energy.

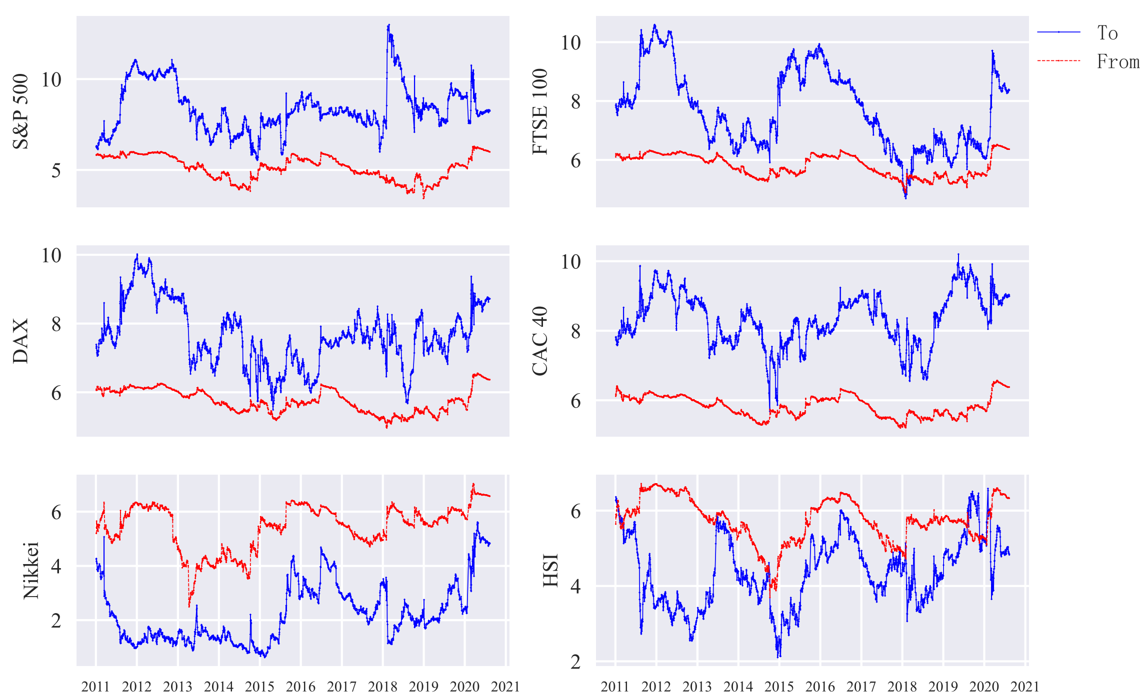


Fig. 4. To and from spillover effect of each developed country or region.

spillovers were slight lower at the other time. These four markets all maintained above average spillover levels during COVID-19 outbreak. Furthermore, the "From spillover" of these four stock indexes just have a slight change during COVID-19, while the "To spillover" have a huge increase. It further implied that S&P 500, FTSE 100, DAX, and CAC 40 are important risk transmitters.

The Nikkei 225 and HSI have always played the role of net recipient, which is exceptions among developed countries or regions. The "From spillover" of Nikkei and HSI are similar to S&P 500, FTSE 100, DAX, and CAC 40, but the "To spillover" of Nikkei and HSI are much lower. It could be that the influence of Nikkei and HSI's stock markets on world economy are limited and implied that the Japanese economy and Chinese Hong Kong are relatively dependent on the US and European economies, whose markets are a good option when bad events occur around the world. As we can see, the COVID-19 caused a huge shock on Nikkei and HSI index, and the "To spillover" of Nikkei increased sharply.

The "To spillover" of HSI had a sudden decrease at the beginning of COVID-19 outbreaking and increased later. The possible reason is that the stock markets and macroeconomics in Hong Kong is dependent on Chinese Mainland, and the fluctuation behavior of HSI is similar to SSE in recent years.

As shown in Fig. 5, overall, the spillover effect of emerging countries is quite different from developed countries or regions. Compared to traditional developed countries and regions, the stock markets in emerging countries are immature, and the "To spillover" is much lower than traditional countries and regions. Obviously, the spillover effect between SSE, KOSPI 200 and Ibovespa, RTS is quite different. The possible reason is follows: Firstly, from "To spillover" perspective, the economics of Brail and Russia are all reliant on resources (Mensi, Hernandez, Yoon, Vo, & Kang, 2021), which leads to a higher "To spillover" of Ibovespa and RTS. For example, Brazil is an important exporter of iron ore and agricultures, and Russia is an important exporter of crude oil. The change of global resources demand could be easily impacted by resource export-oriented countries, which are more likely to have an impact on the global macro-economy (Mensi et al., 2021). Secondly, from "From spillover" perspective, the "From spillover" of these emerging countries are similar. More specifically, China is the second largest economy with an immature stock market, which reduced the "From spillover" from other markets. As a result, SSE is slightly lower than other three countries.

As we can see in Fig. 5, the impact of COVID-19 on emerging countries in "From spillover" is similar. At the beginning of COVID-19 outbreak, the "From spillover" of each country ascended moderately and descended gradually. However, the "To spillover" of emerging countries rose suddenly when COVID-19 outbroke, and the "To spillover" of each country had different degrees of decline.

In theory, the net spillover effect of each energy and stock market can be useful for guiding investors' portfolios. According to Kang et al. (2019), with a long position on a net recipient market and a short position on a net transmitter market, an investor can obtain a better portfolio strategy. As we can see, energy markets have a higher increase on "From spillover" and stock markets have a higher increase on "To spillover", which implies a better hedging ability with long position on energy and short position on stocks after COVID-19 outbroke.

4.4. Spillover network analysis

To further analyze the structural changes of spillover effects, we took each market as a node and the average net spillover index between markets as the connection matrix to construct a spillover network during COVID-19 (January 1, 2020, to August 11, 2020 and before COVID-19 (January 5, 2011, to December 31, 2019). Fig. 6 depicts the network with all the connections, which is less clear because of the large pairwise connections. We calculated and compared 25%, 50% and 75% quantiles before and after COVID-19 outbreak. We found that the 25%, 50% and 75% quantiles before the epidemic were 0.052, 0.113 and 0.230, respectively, but after the epidemic, they were 0.074, 0.146 and 0.277. As you can see, the pairwise spillover increased at each quantile due to the COVID-19. This implies that the connections during COVID-19 are much closer than those before COVID-19. To simplify unimportant connections and retain more information from the spillover network, we set the threshold value as 0.113, which is the same as the 50 quantile (median value) connection before COVID-19.

Fig. 7 shows the spillover network with threshold connections. Intuitively, the connections during COVID-19 are much more in line with the conclusions based on TVP-DY model. Before COVID-19 outbreak, the spillover effect between energy markets and stock markets were low. Brent crude oil market was the only market that has spillover effect with stock markets through Russia stock market. This is because Russia is an important crude oil producer and consumer, and its economic development is closely related to the crude oil industry. Even under normal market conditions, RTS and the crude oil market will be closely related. In addition, heating oil and natural gas did not have directed spillover effect with stock markets.

Fig. 8 reflected the in degree and out degree of each energy and stock market before and after COVID-19. The in degree of heating oil, natural gas and brent crude oil had a significant increase caused by COVID-19. It means that more investors shift capital from the stock markets to the energy markets to reduce the risk of the portfolio, leading to the returns fluctuation risk transmit from stock markets to energy markets due to COVID-19. As for S&P 500, FTSE 100, CAC 40, and DAX, intuitively, these four markets always maintain a high out degree and a low in degree not only before COVID-19 but also after COVID-19. Comparatively,

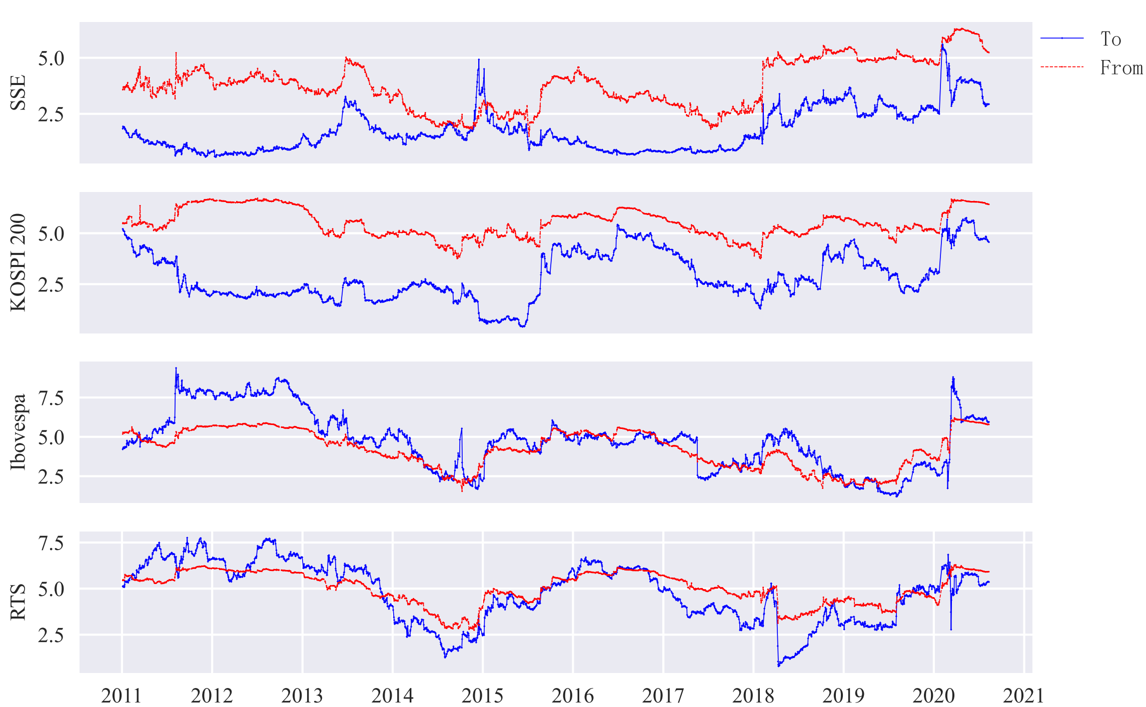
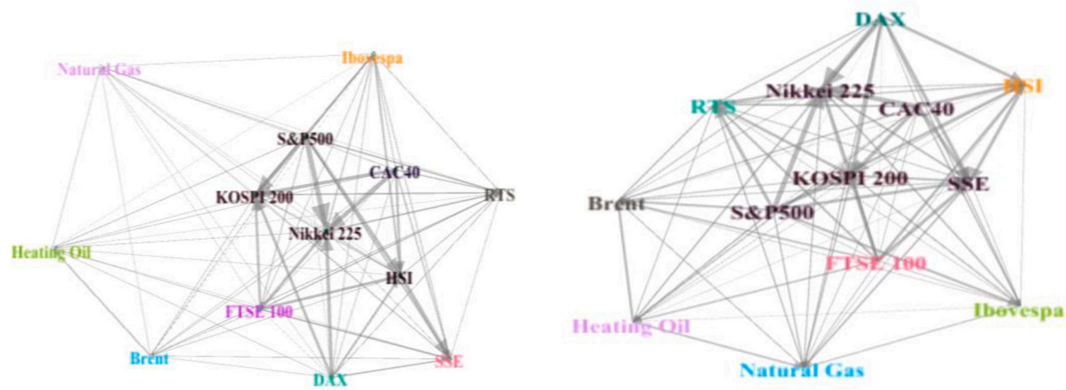
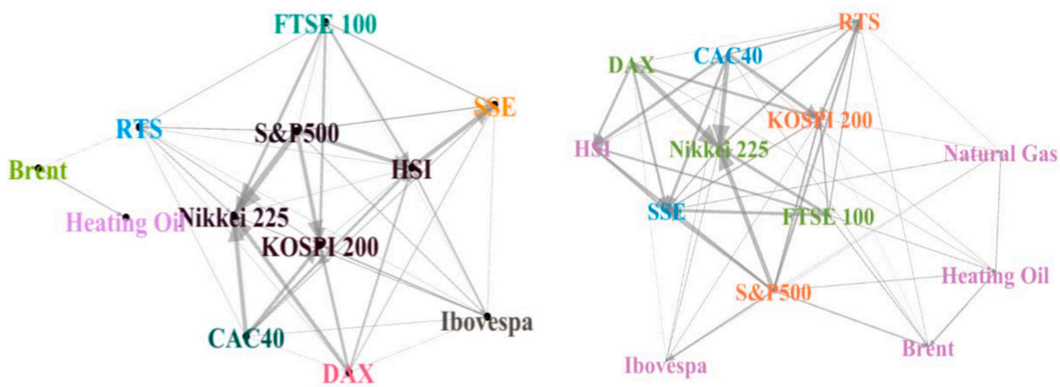


Fig. 5. To and from spillover effect of each emerging country.



(a) before COVID-19 (b) during COVID-19

Fig. 6. Spillover network of all connections.



(a) before COVID-19 (b) during COVID-19

Fig. 7. Spillover network of threshold connections.

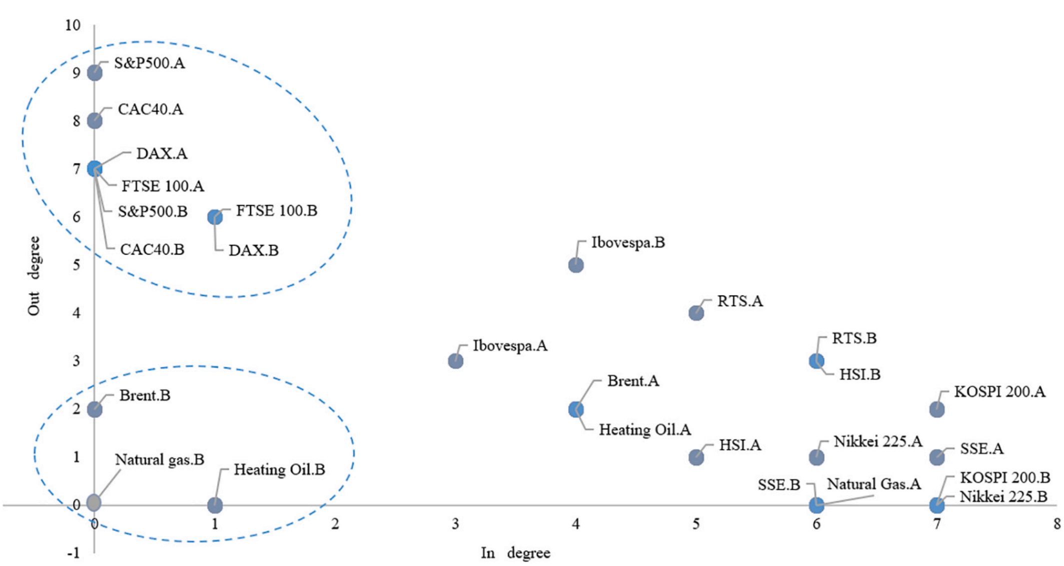


Fig. 8. The changes of in degree and out degree for each energy and stock market. Notes: Energy.B and Stock.B represent energy and stock markets before COVID-19 outbroke, respectively, and Energy.A and Stock.A represent energy and stock markets after COVID-19 outbroke, respectively.

the out degrees of these markets were higher after COVID-19 erupted. As the economic development of Russia and Brazil relies heavily on resource exports, the in degrees and out degrees of these countries are relatively balanced. As for Nikkei 225, HSI, SSE and KOSPI 200, they always play a role of recipients because in degrees of them are larger than out degrees no matter before or after the epidemic.

Above all, heating oil, natural gas, and Brent crude oil played important roles in financial network risk. When the market is normal, heating oil, natural gas, and Brent crude oil are relatively independent to stock markets and slightly share market risk. However, the role of these markets rises sharply when big shocks take place in the market. Energy markets are considered safe assets compared to stock markets, and they tend to be added to portfolio strategies when huge fluctuations and uncertainties appear in financial markets.

4.5. Portfolio implications before and after COVID-19

To achieve better hedging effectiveness and portfolio diversification returns, investors need to understand the co-movements, interdependencies, and spillovers between various markets or assets. Previous studies have found spillover effects and connectedness between energy and stock markets, which may affect investors' portfolio strategies for risk diversification in asset allocation. Following Nikolaos Antonakakis, Cunado, Filis, Gabauer, and Perez de Gracia (2018) and Kang et al. (2019), we assume that portfolio managers can use spillover information (net receivers and net transmitters) to design effective asset allocation and portfolio diversification strategies. We therefore constructed a long–short position hedge trading strategy to explore the hedging ability of energy markets and stock markets. Based on TVP-DY and network analysis, we found that spillover effects and connectedness were seriously affected by COVID-19. Hedging effectiveness between energy and stock markets may be seriously affected by COVID-19, and investors need to adjust their portfolios during the outbreak.

Table 3 shows the hedge ratio, optimal portfolio weights, and hedging effectiveness for each energy–stock pair before and after COVID-19. Compared Panel A and Panel B, we could find that a strategy with long position on energy and short position on stock is much more effective than the strategy with short position on energy and long position on stock. Panel A shows the statistics with a one-dollar long position in energy markets and a short position in stock markets. Before COVID-19, except long position on heating oil, brent crude oil and short position on Ibovespa, RTS, the hedging rate of other hedging strategies were very low (less than 0.2) and the hedge efficiency were very high (more than 0.6). For example, the top three hedge effectiveness are S&P 500, KOSPI 200, and HSI for natural gas with values of 89%, 86%, and 83%, respectively. This means that investors could hedge most risk from energy with long position by a small cost. However, the hedge ratio of heating oil/Ibovespa and Brent/Ibovespa were 0.23 and 0.24, with the hedge effectiveness of 0.46 and 0.5. The hedging ratio and effectiveness of RTS seem to be worse. The reasonable explanation is that Brazil and Russia rely on resources exports for their macro-economy and are not suitable for hedging under normal market conditions. Unlike Brazil, Russia exports crude oil and heating oil directly, which makes it less efficient for RTS hedging crude oil and heating oil. Furthermore, the hedge ratio of stocks that hedge against natural gas are generally less than heating oil and Brent crude oil. This implies that stocks have better risk diversification for natural gas compared to heating oil and Brent crude oil. The same conclusion can be drawn for hedging efficiency in that we can get higher hedging efficiency with most natural gas–stock pairs.

There are huge changes in the hedge ratio, optimal portfolio weights, and hedging effectiveness after COVID-19. First, in addition to Ibovespa and RTS, the hedge ratio is higher, and investors need more costs to hedge risks in energy markets. For example, the hedge ratio of heating oil/SSE increased from 0.09 to 0.14. It is worth noting that the hedge ratio of Ibovespa and RTS hedging heating oil and RTS were lower, which implied that lower hedging cost for these "energy-stock" pairs. Second, there are significant differences not only between countries but also among energy markets in the optimal portfolio weights and hedging effectiveness. Optimal portfolio weights and hedging effectiveness were higher after COVID-19 in heating oil and Brent crude oil. This suggests that stock markets became a better hedging asset for heating oil and Brent crude oil markets during COVID-19. Third, as we can see in the Table 3, the hedge effectiveness for long position on natural gas and short position on stocks are all more than 0.69. There was no obvious change in hedging effect for stock hedging natural gas, which might be because hedging efficiency is too high to improve.

Panel B reports the results with a one-dollar short position in energy markets and a long position in stock markets. As we can see, the hedging rate is generally high and the hedging efficiency is low, and the hedge ability become worse due to COVID-19. It implied that the "short position in energy markets and a long position in stock markets" portfolio strategy is inappropriate for investment to reduce their portfolio risk. For example, the top three hedge effectiveness were heating oil for RTS, Ibovespa, and SSE, with values of 0.33, 0.31, and 0.30, respectively. This means that short positions on heating oil and long position on stocks can only reduce portfolio risk not more than 33%.

Combined with the results of the spillover analysis, we can conclude that a long position in the energy market and a short position in stock markets, such as S&P 500 and DAX, are the great choices for investors to adopt proper hedge portfolio strategies.

5. Conclusions

This study aimed to analyze the effects of COVID-19 on spillover effects and asset allocations between energy and stock markets. First, we used a TVP-DY framework to reveal the dynamic spillover effects between the two markets and compared the statistics before and after COVID-19. Next, we constructed a spillover network based on the pairwise spillovers before and after COVID-19 to explore structural changes in the energy market–stock market system. Finally, we calculated and compared the hedge ratio, optimal portfolio weights, and hedging effectiveness before and after COVID-19 to investigate the change in hedging ability between the energy and stock markets. The main findings were summarized below.

First, there was a significant spillover effect between energy and stock markets, and heating oil, natural gas, and crude oil were all significant net recipients against stock markets. Natural gas was the highest net recipient among the three energy markets, and the spillover behaviors between heating oil and crude oil were very similar. COVID-19 had a huge impact on the spillover effect between energy and stock markets, and the spillover of each energy market effect became higher compared to the period before COVID-19. The highest total spillover effect arose during COVID-19 with a value of 80.27%, and the average spillover index increased by about 19.94% compared to the average spillover before COVID-19.

Second, based on the network analysis, we found that energy markets were relatively independent to stock markets before COVID-19. This implies that normal price fluctuations in stock markets have little effect on energy markets. However, the degree, especially indegree, became extremely high, implying that energy markets have faced a lot of systemic risks from stock markets during COVID-19. Our network analysis suggests that investors need to further adjust their portfolio management.

Third, heating oil, natural gas, and crude oil markets were more suitable as long positions against short positions in stock markets before COVID-19; this changed after COVID-19. A higher hedging effectiveness can be obtained in between long positions on heating oil or t crude oil and short positions on stock markets. There was no obvious change in hedging effectiveness for portfolios with a long position on natural gas and a short position on each stock market. However, the hedging efficiency remained at a high level before and after the outbreak. Moreover,

Table 3
The comparison of hedge ratio, optimal portfolio weights, and hedging effectiveness before and after COVID-19 outbreak.

Portfolio Pairs	Before COVID-19			After COVID-19			Portfolio Pairs	Before COVID-19			After COVID-19		
	Hedge Ratio	Optimal Portfolio Weights	HE	Hedge Ratio	Optimal Portfolio Weights	HE		Hedge Ratio	Optimal Portfolio Weights	HE	Hedge Ratio	Optimal Portfolio Weights	HE
Panel A: Energy as long position							Panel B: Energy as short position						
Heating oil/S&P 500	0.14	0.84	0.74	0.19	0.89	0.75	S&P 500/Heating oil	0.54	0.16	0.11	0.97	0.11	0.06
Heating oil/FTSE 100	0.16	0.83	0.71	0.19	0.89	0.74	FTSE 100/ Heating oil	0.52	0.17	0.11	0.87	0.11	0.05
Heating oil/DAX	0.16	0.69	0.60	0.20	0.82	0.68	DAX/Heating oil	0.30	0.31	0.23	0.64	0.18	0.11
Heating oil/CAC 40	0.18	0.71	0.60	0.20	0.85	0.70	CAC 40/Heating oil	0.35	0.29	0.22	0.73	0.15	0.07
Heating oil/Nikkei 225	0.10	0.66	0.60	0.12	0.85	0.76	Nikkei 225/ Heating oil	0.19	0.34	0.29	0.54	0.15	0.11
Heating oil/HSI	0.12	0.70	0.62	0.12	0.85	0.76	HSI/Heating oil	0.26	0.30	0.24	0.61	0.15	0.10
Heating oil/SSE	0.09	0.66	0.61	0.14	0.85	0.75	SSE/Heating oil	0.16	0.34	0.30	0.95	0.15	0.11
Heating oil/KOSPI 200	0.11	0.77	0.69	0.10	0.85	0.77	KOSPI 200/ Heating oil	0.35	0.23	0.17	0.55	0.15	0.11
Heating oil/ Ibovespa	0.23	0.58	0.46	0.19	0.74	0.61	Ibovespa/Heating oil	0.31	0.42	0.31	0.46	0.26	0.18
Heating oil/RTS	0.33	0.53	0.38	0.25	0.75	0.58	RTS/Heating oil	0.38	0.47	0.33	0.58	0.25	0.15
Natural gas/S&P 500	0.00	0.89	0.89	0.03	0.81	0.80	S&P 500/Natural gas	−0.02	0.11	0.12	0.09	0.19	0.18
Natural gas /FTSE 100	−0.01	0.76	0.76	0.03	0.81	0.79	FTSE 100/Natural gas	−0.02	0.24	−0.16	0.08	0.19	0.03
Natural gas /DAX	0.00	0.81	0.81	0.02	0.77	0.75	DAX/Natural gas	−0.03	0.19	0.19	0.07	0.23	0.22
Natural gas /CAC 40	0.00	0.81	0.82	0.02	0.79	0.77	CAC 40/ Natural gas	−0.01	0.19	0.19	0.10	0.21	0.20
Natural gas /Nikkei 225	0.01	0.80	0.80	0.03	0.83	0.81	Nikkei 225/ Natural gas	0.02	0.20	0.20	0.11	0.17	0.15
Natural gas /HSI	0.00	0.82	0.83	0.01	0.83	0.82	HSI/Natural gas	−0.01	0.18	0.18	0.06	0.17	0.17
Natural gas /SSE	0.01	0.79	0.79	0.02	0.85	0.83	SSE/Natural gas	0.03	0.21	0.20	0.11	0.15	0.14
Natural gas /KOSPI 200	0.00	0.87	0.86	0.03	0.83	0.81	KOSPI 200/ Natural gas	0.04	0.13	0.14	0.12	0.17	0.15
Natural gas /Ibovespa	0.03	0.76	0.74	0.07	0.72	0.69	Ibovespa/Natural gas	0.09	0.24	0.23	0.12	0.28	0.25
Natural gas /RTS	0.03	0.71	0.69	0.05	0.70	0.67	RTS/Natural gas	0.06	0.29	0.28	0.11	0.30	0.28
Brent/S&P 500	0.14	0.88	0.77	0.15	0.94	0.83	S&P 500/Brent	0.68	0.12	0.08	1.08	0.06	0.02
Brent/FTSE 100	0.15	0.86	0.74	0.16	0.94	0.82	FTSE 100/Brent	0.61	0.14	0.08	1.01	0.06	0.03
Brent/DAX	0.15	0.74	0.64	0.15	0.89	0.77	DAX/Brent	0.34	0.26	0.20	0.67	0.11	0.07
Brent/CAC 40	0.18	0.75	0.63	0.16	0.92	0.79	CAC 40/Brent	0.42	0.25	0.17	0.82	0.08	0.04
Brent/Nikkei 225	0.10	0.69	0.63	0.08	0.89	0.83	Nikkei 225/Brent	0.22	0.31	0.26	0.56	0.11	0.08
Brent/HSI	0.11	0.74	0.66	0.10	0.90	0.82	HSI/Brent	0.27	0.26	0.21	0.70	0.10	0.07
Brent/SSE	0.09	0.69	0.64	0.12	0.88	0.80	SSE/Brent	0.18	0.31	0.27	1.24	0.12	0.09
Brent/KOSPI 200	0.09	0.80	0.73	0.09	0.90	0.83	KOSPI 200/Brent	0.35	0.20	0.15	0.67	0.10	0.07
Brent/Ibovespa	0.24	0.64	0.50	0.16	0.84	0.72	Ibovespa/Brent	0.39	0.36	0.25	0.59	0.16	0.09
Brent/RTS	0.31	0.60	0.42	0.23	0.86	0.68	RTS/Brent	0.46	0.40	0.27	0.76	0.14	0.07

heating oil, natural gas and crude oil markets were not suitable for hedging risk as short positions, neither before or after COVID-19.

Our results can help market regulators understand changes in spillover effects caused by COVID-19 and develop policies to control systemic spillover effects during the outbreak. Energy market regulators need to not only guard against the effects of COVID-19 but also be aware of spillover effects from other markets. Our findings are also meaningful for investors, portfolio managers, and energy-related manufacturing enterprises, all of whom can decrease investment risks through a hedging strategy with a long position in energy markets and a short position in stock markets. In particular, proper hedging strategies and positional choices are highly affected by COVID-19. Investors should therefore adjust their hedging strategies between energy markets and stock markets, such as SSE and HSI.

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