Journal of Economics and Public Finance
ISSN 2377-1038 (Print) ISSN 2377-1046 (Online)
Vol. 8, No. 2, 2022
www.scholink.org/ojs/index.php/jepf

Original Paper

Analysis of the Linkage between International Crude Oil and Chinese Industry Sector Indices under the COVID-19

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Received: March 10, 2022 Accepted: March 25, 2022 Online Published: March 31, 2022

doi:10.22158/jepf.v8n2p26 URL: http://dx.doi.org/10.22158/jepf.v8n2p26

Abstract

The sudden epidemic has a huge impact on the global economy. This paper takes the International crude oil and the SSE Industry Index as the research objects to explore the linkage between the two markets under COVID-19. We use DCC-GARCH to study the dynamic correlation between the two markets before and after the outbreak. The PCA-GARCH model is further used to verify whether there is a spillover effect between the two markets, and finally the time-varying spillover index is used to quantify the spillover effect. The results show that the epidemic has strengthened the overall connection between the two markets. In particular, the correlation between SSE Public and International crude oil has the greatest impact. During the epidemic, crude oil has the most volatility, and most of the volatility series can reach the peak state. There are positive spillover effects among SSE Material, SSE Energy, and SSE Industry. In the total spillover index table, the conclusion of the PCA-GARCH model is verified, that is, the spillover index value is larger when there is a spillover effect. After the outbreak, the total spillover index rose by 10%. Before and after the outbreak, crude oil changed from a volatility sender to a receiver.

Keywords

DCC-GARCH, COVID-19, International crude oil, industry index, PCA-GARCH, time-varying spillover index

1. Introduction

The outbreak of COVID-19 at the end of 2019 has had a significant impact on the global economy. In the short term, production activities have stagnated and the overall economic level has declined. The outbreak of the epidemic has also caused fluctuations in the stock market. The International crude oil market has also been affected by the epidemic as a global market. Its impact has penetrated almost all industries. In this context, the impact of international crude oil prices on the stock market will be magnified, and the stock market will be more susceptible to shocks. Therefore, in the context of COVID-19, it is of greater significance to study the linkage between international crude oil and stock markets. For example, Gao et al. (2021) used a new wavelet-based quantile-to-quantile method to compare the impact of COVID-19 and oil price changes on the Chinese and US stock markets. Compared with changes in oil prices, COVID-19 has a greater impact on the U.S. stock market. Some scholars have revealed the connection between the implied volatility of these markets. For example, Dutta (2018) used the Chicago Board Options Exchange's implied volatility index to assess the connection between global oil and the U.S. energy sector stock market, the results show that there is a long-term relationship between oil and the stock market implied volatility index, taking Granger causality test, there is a short-term lead-lag relationship between the implied volatility of international crude oil and the US energy sector stock market. Liu et al. (2020) used the implied volatility index released by the Chicago Stock Exchange to study the dynamic correlation between the oil market and the U.S. stock market, and the results showed that there is a time-varying positive correlation between oil and stock implied volatility returns, during the global financial crisis, the correlation between oil and the stock market increased significantly.

Stock market supervision plays an important role in the stock market, and international crude oil market investors are all over the world, this market has strong information transmission and price discovery capabilities. This article selects 10 industry sectors of the Shanghai Stock Exchange when studying the stock market. On the one hand, considering that the analysis of different industries has a more comprehensive correlation with international crude oil. On the other hand, the financialization of International crude oil has strengthened the linkage with the stock market year by year. The industry sector market can measure the changes in the stock market from a micro perspective. Understanding the linkage between International crude oil and Chinese industry sectors will help the stock market to monitor the industry sector market trends, improve the efficiency of the government's supervision of the stock market, help ensure the stability and development of China's industry sector markets, and study the spillover effect of International crude oil and China's industry sector market can help investors to reasonably hedge their risk when oil price rises or falls sharply.

This study explores the volatility spillover effect and dynamic correlation between oil price volatility and price volatility in China's industry sector stock markets (SSE Energy, SSE Material, SSE Finance, etc.) from January 2016 to March 2021. To this end, based on the background of COVID-19, on the one hand, we establish a dynamic conditional correlation (DCC-GARCH) model, which can identify the dynamic correlation and volatility between crude oil prices and the stock market, on the other hand, using the PCA-GARCH model verify whether the volatility spillover effect between the two markets exists. When it does, the time-varying spillover index is further used to calculate the specific spillover index value between international crude oil and industry sectors.

2. Literature Review

In the past research, some scholars paid more attention to the impact of the international crude oil market on the capital market, especially the impact of the stock market. Among them, by investigating the correlation between the crude oil market and the stock market, it is proved that oil prices and oil price fluctuations will affect actual stock returns (Sadorsky, 1999). Early research focused on whether the crude oil market will affect the stock market changes. For example, Broadstock et al. (2012) used time-varying condition correlation and asset pricing models to study how the crude oil market affects China's energy market. On the basis of adding structural instability factors, considering the outbreak of the financial crisis in 2008, the conditional correlation between markets has increased sharply, reflecting that the energy market is more sensitive to fluctuations in crude oil. Qi and Zhu (2011) used the VAR model to prove that international crude oil has a greater impact on the US stock market, but crude oil has a smaller impact on the Chinese stock market, and both stock markets have a co-integration relationship with international crude oil. Shahzad et al. (2018) used the CoVaR model to analyze the upward and downward risk spillovers and dependence structures between five Islamic stock markets and oil market participants, and the results show that there is a time-varying low-tail dependence between oil and the Islamic stock market. Rui et al. (2017) combined the VAR model, univariate and multivariate GARCH model to study the return rate and volatility spillover effects between the Shanghai Stock Exchange Index and the Hong Kong Hang Seng Index. The results prove that the Shanghai-Hong Kong Stock Connect has indeed strengthened the importance of the Chinese mainland stock market, and at the same time, it has also led to an increase in the variance of the two market conditions. In addition, the Shanghai-Hong Kong Stock Connect highlights the leading role of the Shanghai Composite Index by overflowing yield and volatility. The risk level has been affected and the effectiveness of the Shanghai Stock Exchange market has been improved. Ji et al. (2020) combined structural VAR and the Copula-GARCH-CoVaR model to study the risk spillover effect and dynamic correlation between the international crude oil market and the international stock market. When Yousaf and Hassan. (2019) studied the volatility spillover effect between crude oil and emerging Asian stock markets during the Chinese stock market crash, they found that crude oil has a positive spillover effect on most stock markets, and volatility can be transmitted from oil to other stock markets. In addition, during the Chinese stock market crash, oil's weight in the oil stock portfolio has declined, and oil assets should be reduced to reduce the risk of the investment portfolio. The researches of the above scholars all analyze the linkage between the stock market and the crude oil market from a macro level.

In the analysis of the impact of the International crude oil market on the industry level. Hammoudeh et al. (2010) used the standard GARCH model to study the impact of changes in world stock returns, oil prices, federal funds rate, and industry-specific variables (such as price-to-earnings ratio and trading volume) on the volatility of stock returns in 27 industries in the United States. Some scholars have used two-factor multivariate GARCH to study the impact of international crude oil on China's 14 industry sector indexes (Jin et al., 2010). The results show that different industries are affected by crude oil in different degrees. When studying the relationship between International crude oil and the Chinese and American stock markets and the impact of crude oil on China's industry sector indexes, in order to compare the interdependence between international crude oil and the Chinese and American stock markets, Yu et al. (2018) used the vine copula model to study it, the study found that there is a significant difference between the two markets. The correlation between the Chinese industry sector index and international crude oil is generally weaker than the correlation between the US industry sector index and international crude oil. Peng et al. (2018) adopted a nuclear-based non-parametric method to test the Granger causality between quantile and quantile between crude oil and corporate income. The results show that the relationship between crude oil and corporate fixed income is asymmetrical, positive spillovers are more serious than negative spillovers, especially in top-down spillovers. Differences between industries affect the risk transmission of oil price shocks to company returns. Further considering the conditions of the epidemic, Bouri et al. (2021) used a multivariate GARCH model and regression analysis to study the impact of the three measures taken by the government on the epidemic on the stock returns of 14 industries. Among them, the technology, medical and real estate industries have relatively small fluctuations.

In the analysis of the dynamic correlation and spillover effects between the oil market and the stock market. Singhal and Ghosh (2018) analyzed the crude oil market and the Indian stock market as a whole and the industry (7 industries including automobile, energy, finance, etc.) by constructing the VAR-DCC-GARCH model and the GARCH cluster model (standard, threshold and index). The results found that the dynamics are significant, the volatility continues, the spillover effect of the crude oil market on the Indian stock market is weak, and the spillover effect of crude oil on certain industries is significant. However, most of them use the DCC-GARCH/MGARCH model and spillover index for analysis. For example, Hassan et al. (2019) studied the linkage between the oil market and the BRIC Islamic Index, they found that during the financial crisis, The correlation between the two assets is stronger than that between the Chinese and Indian stock markets. Compared with the volatility spillover between traditional indices and oil, the error prediction variances of the five indices are all derived from spillovers. However, the study did not highlight the changes in the total spillover index before and after the financial crisis. Jiang Yonghong et al. (2019) used the DCC-GARCH model to describe the dynamic correlation between the crude oil market and Chinese industry stocks, and calculated conditions and marginal value at risk on this basis. And raw materials have the greatest degree of risk spillover, however, there are changes in the dynamic research model. Jiang et al. (2019) used the DCC-GJR-GARCH model to empirically analyze the internal relationship between the global oil market and the Chinese commodity sector. Maitra et al. (2021) adopted the GJR-GARCH-DECO model to analyze the correlation between the crude oil market and the stock returns of international transportation and logistics companies, the spillover effect is still selected for calculation of the spillover index. The results show that the correlation between WTI and logistics company stock returns is always positive, the analysis of spillover effects emphasizes the impact of the financial crisis, and the total spillover effect has risen sharply during the financial crisis.

Through analysis, it is found that the previous research has the following shortcomings: (1) Most of the researches on the overall correlation of the stock market, most of them combine the GARCH cluster model to carry out volatility research, and use the static spillover index to measure the spillover effect. (2) When studying spillover effects, the spillover index is directly used for calculation, and there is no demonstration of spillover effects between markets; (3) When conducting spillover effect analysis and dynamic analysis between markets, the impact of major events such as the epidemic was not considered. Based on the above-mentioned existing literature research, this article has the following contributions when studying the linkage between the international crude oil market and the Chinese industry sector market: a. Dynamic test, use the DCC-GARCH model to measure the dynamic dependence between the two markets, and estimate the volatility; b. Spillover effect test, first use PCA-GARCH to estimate the volatility spillover effect between the international crude oil and the Shanghai Stock Exchange industry index, and combine Antonakakis (2020) to use time-varying spillover on the basis of existing research Exponential model for quantitative estimation of spillover effects.

3. Method

This article will use the DCC-GARCH model and the PCA-GARCH model to study the dynamics and spillover effects between the International crude oil and the Chinese industry sector market. On the basis of existence the spillover effects, the time-varying spillover index is used for quantification.

3.1 DCC-GARCH and PCA-GARCH Model

Compared with the commonly used multivariate GARCH model, the DCC-GARCH model has more advantages in parameter estimation, economic significance of the model and dynamic measurement, and a more comprehensive description of the volatility series. Based on this, this article uses the DCC-GARCH model to explore the dynamic correlation between the two markets.

The DCC-GARCH model expression is as follows:

$$r_t = \mu_t + e_t, \quad e_t \sim N(0, H_t), \tag{1}$$

$$H_t = D_t R_t D_t, \tag{2}$$

$$R_t = diag(Q_t)^{-1/2} Q_t diag(Q_t)^{-1/2}, \tag{3}$$

$$Q_t = (1 - \sum_{n=1}^{N} \alpha_n - \sum_{m=1}^{M} \beta_m)\bar{Q} + \sum_{n=1}^{N} \alpha_n \mu_{t-n} \mu_{t-n}^T + \sum_{m=1}^{M} \beta_m Q_{\text{t-m}}, \tag{4}$$

$$\bar{Q} = T^{-1} \sum_{t=1}^{T} \mu_{t-1} \mu_{t-1}^T, \tag{5}$$

(1) is the mean value equation of the rate of return, r_t is the rate of return sequence, μ_t is the conditional mean of the rate of return sequence, e_t is the residual term, which obeys the mean value

of 0, and the covariance matrix is the normal distribution of H_t, and the matrix H_t can be decomposed into $D_t R_t D_t$, $D_t = diag(\sqrt{h_{it}})$, h_{it} is the conditional variance of the return sequence, R_t is the time-varying correlation coefficient matrix (while the correlation coefficient matrix in CCC-GARCH is time-invariant), in order to further simplify the model, rewrite R_t as (3) and (4), $\overline{Q}$ is the correlation coefficient matrix of the standardized residual, which is obtained after the residual term is standardized, that is $\mu_t^T = D_t^{-1} e_t$, α_n、β_m are a non-negative dynamic correlation coefficient and satisfy $\alpha_n + \beta_m < 1$. Among them, m and n are determined by the GARCH model.

If DCC-GARCH is to study the dynamics between markets, then the PCA-GARCH model can further explore the spillover effect mechanism on the basis of dynamics. The volatility spillover effect between markets refers to the mutual influence between the volatility of different market returns, that is, volatility may be transmitted from one market to another. In this article, it refers specifically to the volatility sequence generated by the GARCH model. This article will use the PCA-GARCH model verifies whether there is a volatility spillover effect between markets, in order to explore the impact of volatility between international crude oil and industry sectors.

The analysis steps of the PCA-GARCH model are as follows:

In the first step, assuming there are n+1 markets, fit the GARCH(p,q) model to the n+1 return series as follows:

$$h_{n+1,t} = \alpha_0 + \sum_{j=1}^{q} \alpha_j \varepsilon_{t-j,n+1}^2 + \sum_{i=1}^{p} \beta_i h_{n+1,t-i} + v_t \tag{6}$$

Where $h_{n+1,t}$ represents the volatility sequence of the n+1th industry sector at time t.

In the second step, take the n+1th volatility sequence as an example, perform principal component analysis on the remaining n volatility sequences, and select k principal components $(p_1, p_2, ..., p_k)$ with a cumulative variance contribution rate of more than 85%, where k<n.

The third step is to add the extracted k principal components as exogenous variables into the volatility equation of the n+1th GARCH.

$$h_{n+1,t} = \alpha_0 + \sum_{j=1}^{q} \alpha_j \varepsilon_{t-j,n+1}^2 + \sum_{i=1}^{p} \beta_i h_{n+1,t-i} + \sum_{l=1}^{k} \theta_l p_{lt} + v_t \tag{7}$$

p_{lt} represents the l principal components extracted at time t ($l = 1, 2, ..., k$).

The fourth step is to use the t-test to test the significance of the parameter θ_l. If θ_l is significant, it means that the l-th principal component has a volatility spillover effect on the n+1th industry. If it is not significant, it means that the spillover effect is weak or does not exist.

3.2 Time-varying Volatility Spillover Index

The TVP-VAR method extends the volatility connectivity method proposed by Diebold and Yilmaz (2014). On this basis, it improves the shortcomings of arbitrary selection of the rolling window, and effectively avoid the loss of valuable observations. According to the research conclusion of Koop and Korobilis (2014), the variance-covariance matrix is allowed to estimate the change through Kalman filter with forgetting factor. In addition, Koop and Korobilis (2014) pointed out that the heteroscedastic process is better than the homoscedastic process.

We transform TVP-VAR into its vector moving average (VMA) representation based on the Wold representation theorem. Retrieving VMA means that it can be explained by recursive replacement:

$$y_t = J^T(M_t(z_{t-2}+\eta_{t-1})+\eta_t \tag{8}$$

$$= J^T(M_t^{k-1}z_{t-k-1}+\sum_{j=0}^{k}M_t^j\eta_{t-j})$$

$$M_t=\begin{pmatrix} A_t & \\ I_{m(p-1)} & 0_{m(p-1)\times m}\end{pmatrix},\ \eta_t=\begin{pmatrix}\varepsilon_t & 0 & \cdots & 0\end{pmatrix}^T,\ J=\begin{pmatrix}I & 0 & \cdots & 0\end{pmatrix}^T$$

M_t and η_t represent $mp\times mp$ and $mp\times 1$ dimensional matrices, respectively, J is a dimensional $mp\times m$ matric, when $k\to\infty$

$$y_t=\lim_{k\to\infty}J^T(M_t^{k-1}z_{t-k-1}+\sum_{j=0}^{k}M_t^j\eta_{t-j})=\sum_{j=0}^{\infty}\mathrm{B}_{jt}\varepsilon_{t-j},\ \mathrm{B}_{jt}=J^TM_t^jJ,\ j=0,1\ldots \tag{9}$$

B_{jt} is an $m\times m$ dimensional matric, $GIRFs(\Psi_{ij,t}(H))$ indicates the response of all variables j after the impact of variable i, Since we don't have a structural model, we calculated the difference between the H-step forward predictions, the difference can be attributed to the shock in variable i, which can be calculated by the following formula.

$$GIRF_t(H,\delta_{j,t},\Omega_{t-1})=E(y_{t+H}\,|\,e_j=\delta_{j,t},\Omega_{t-1})-E(y_{t+J}\,|\,\Omega_{t-1}) \tag{10}$$

$$\Psi_{j,t}(H)=\frac{B_{H,t}\Sigma_t e_j}{\sqrt{\Sigma_{jj,t}}}\frac{\delta_{j,t}}{\sqrt{\Sigma_{jj,t}}},\ \delta_{j,t}=\sqrt{\Sigma_{jj,t}}$$

$$\Psi_{j,t}(H)=\frac{B_{H,t}}{\sqrt{\Sigma_{jj,t}}}\Sigma_t e_j$$

e_j is an $m\times 1$ dimensional column vector, The m-th position element is 1, and the remaining position elements are 0. in turn, calculate the $GFEVD(\phi_{ij,t}(H))$, which represents the connectivity of the two directions from j to i, and from the perspective of the prediction error variance share, the influence of variable j on variable i is explained, then standardize these variance shares so that each row adds up to 1, which means that all variables together can explain 100% of the variance of the prediction error of the variable.

$$\phi_{ij,t}(H)=\frac{\sum_{t=1}^{H-1}\Psi_{ij,t}^2}{\Sigma_{j=1}^{m}\sum_{t=1}^{H-1}\Psi_{ij,t}^2} \tag{11}$$

$\sum_{j=1}^{m}\phi_{ij,t}(H)=1,\sum_{i,j=1}^{m}\phi_{ij,t}(H)=m$, the denominator represents the cumulative effect of all shocks, and the numerator represents the cumulative effect of the shock in variable i.

(1) Total volatility spillover index

$$C_t(H)=\frac{\sum_{i,j=1,i\neq j}^{m}\phi_{ij,t}(H)}{\sum_{i,j=1}^{m}\phi_{ij,t}(H)}\times 100=\frac{\sum_{i,j=1,i\neq j}^{m}\phi_{ij,t}(H)}{m}\times 100 \tag{12}$$

(2) Directional spillover index

variable i comes from all other variables j :

$$C_{i\leftarrow j,t}(H)=\frac{\sum_{j=1,i\neq j}^{m}\phi_{ij,t}(H)}{\sum_{i=1}^{m}\phi_{ij,t}(H)}\times 100 \tag{13}$$

variable i to all other variables j :

$$C_{i\rightarrow j,t}(H)=\frac{\sum_{j=1,i\neq j}^{m}\phi_{ji,t}(H)}{\sum_{j=1}^{m}\phi_{ji,t}(H)}\times 100 \tag{14}$$

(3) Net spillover index

$$C_{i,t}=C_{i\rightarrow j,t}(H)-C_{i\leftarrow j,t}(H) \tag{15}$$

If $C_{i,t}>0$ means that the influence of variable i on other variables is greater than its own influence, otherwise, the variable i is driven by other variables.

3.3 Data Selection

This article selects the daily closing price of China's industry sector index and the International crude oil price index as the research objects. The industry sector data includes (SSE Energy, SSE Material, SSE Telecom, SSE Finance, SSE Optional, SSE Consumption, SSE Industry, SSE Public, SSE Information, SSE Medicine), use the above-mentioned index to measure the changes in the stock market of China's stocks in various industries and the trend of changes in crude oil. The data comes from the Wind database and the U.S. Energy Information Administration (EIA). The sample sampling period is from January 5, 2016 to March 2, 2021, including the turbulent period of the COVID-19 outbreak. Excluding the time when the two markets are not open at the same time, there are 1183 samples remaining. Taking into account that the country has officially adopted measures on January 23, the arrival of the Spring Festival did not have much impact on the stock market, so this article chooses February 3, 2020 to April 17, 2020 as the Mid-outbreak period, The specific time segment is shown in Table 1.

Table 1. Division of the Three Time Periods

period	time interval	n
Before the epidemic	2016.1.5-2020.1.23	950
Mid-outbreak period	2020.2.3-2020.4.17	52
Epidemic alleviation	2020.4.21-2021.3.2	202

Since the closing price of stocks is not stable, we will log-differentiate the closing price of the sequence day.

$$r.sn_t=100\times(\ln sn_t-\ln sn_{t-1}),t=1,2,...,1183 \tag{16}$$

sn_t represents the closing price of SSE Material on day t, and $r.sn_t$ represents the rate of return of SSE Material on day t.

Table 2 shows the one-to-one correspondence between the names and symbols of the 10 industry sector indexes of the Shanghai Stock Exchange.

Table 2. Symbol Description

Sequence of returns	International crude oil	SSE Energy	SSE Material	SSE Telecom	SSE Industry	SSE Finance	SSE Optional	SSE Consumption	SSE Information	SSE Medicine	SSE Public
symbol	***r.yy***	***r.sn***	***r.sc***	***r.sd***	***r.sg***	***r.sj***	***r.sk***	***r.sx***	***r.sxx***	***r.sy***	***r.sgy***

4. Result

It can be seen from Figure 1 that the return rate series of the 10 SSE industry indexes and the crude oil price index fluctuate uniformly. At the beginning of 2020, most of the return rate series will drop to the lowest. Table 3 shows the basic statistical description of sequence returns. The SSE Consumption has the highest rate of return, and the SSE Public has the lowest rate of return. From the perspective of volatility, International crude oil has the largest volatility (3.8174), and the SSE Public has the smallest volatility (1.0248). At the 1% significance level, the results of the Jarque-Bera normality test for 11 sequences all rejected the null hypothesis of normal distribution, and the distribution of all sequences showed a “spike and thick tail”. Except for SSE Finance, the remaining series are left-biased.

Table 3. Descriptive Analysis Table

	mean	**median**	**max**	**min**	**std**	**skew**	**kurt**	**J-B**	**P**
r.yy	0.04091	0.2487	31.963	-60.168	3.8174	-3.053	69.609	224447.5	0
r.sn	-0.0172	0.0196	9.4316	-8.8154	1.4274	-0.407	9.0713	1882.364	0
r.sc	0.04982	0.0531	6.2402	-9.0402	1.605	-0.555	6.8341	799.1879	0
r.sd	-0.0029	0.0482	6.8822	-10.525	1.9238	-0.681	6.8993	855.9596	0
r.sg	0.01326	-0.013	6.9155	-9.4609	1.3873	-0.633	9.2197	2021.063	0
r.sj	0.02164	-0.002	12.364	-7.5567	1.3025	0.4998	12.415	4497.299	0
r.sk	0.02007	0.0382	9.0796	-9.3363	1.4543	-0.733	8.6873	1730.414	0
r.sx	0.09698	0.0845	4.9231	-7.8145	1.5484	-0.58	5.6666	424.2031	0
r.sxx	0.00339	-0.007	7.1711	-10.227	1.9978	-0.423	5.5359	358.4562	0
r.sy	0.03724	0.0413	5.0821	-8.6847	1.5294	-0.532	5.4554	359.151	0
r.sgy	-0.0246	0.0018	4.5176	-7.9886	1.0248	-1.253	11.792	4192.484	0

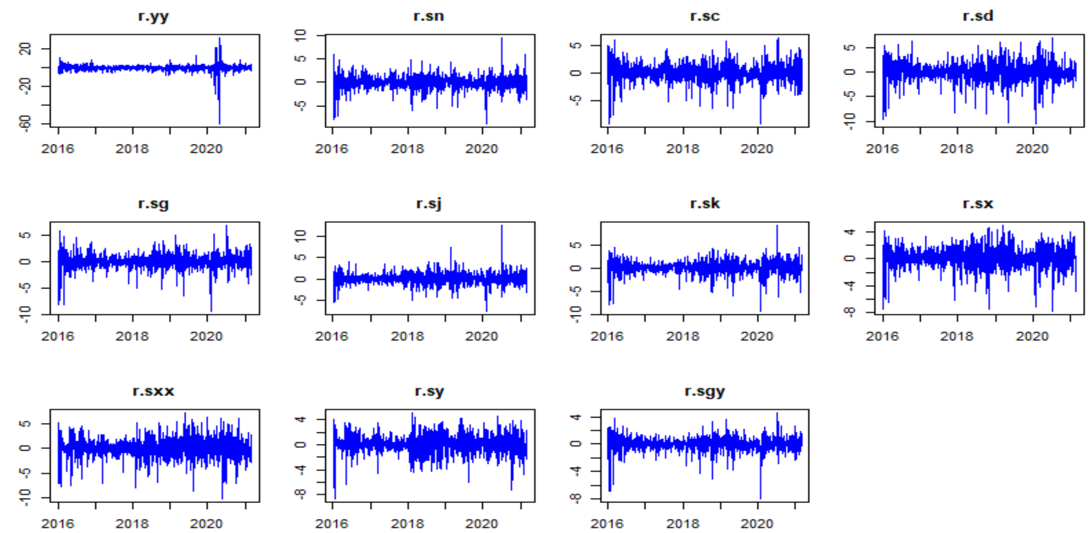

Figure 1. Timing Diagram of the Rate of Return Series

Our empirical research includes two steps. In the first step, we use the DCC-GARCH model to analyze the dynamic correlation between the International crude oil market and the Chinese stock industry sector market, and study the dynamic dependence of the two markets in the context of the epidemic. It reveals the volatility of International crude oil and the Shanghai Stock Exchange industry sector index; the second step is to establish PCA-GARCH model to study the spillover effect mechanism in two markets, and further calculate the time-varying spillover index to quantify the spillover effect under the epidemic situation.

Before establishing the model, first perform a stationarity test on the return sequences. On the basis of the significance level of 5%, the p-value of all return sequences is less than 0.05, which means that all return sequences are stable and can be carried out, the next step is to analyze.

4.1 Dynamic Correlation

To study the dynamic correlation between International crude oil and the Shanghai Stock Exchange Industry Sector Index during the epidemic, this article uses the DCC-GARCH model for analysis. Since the analysis object of the DCC-GARCH model is the volatility of the industry index, it is considered that the volatility has autocorrelation. Therefore, before establishing the DCC-GARCH model, the following tests are required: (1) Autocorrelation test of residuals, fitting the ARMA model to 11 return rate series, and using LB statistics to test the autocorrelation of the residual series generated by the ARMA model; (2) The heteroscedasticity test is performed on the return (testing the ARCH effect). After the LM test, it is found that both the international crude oil and the Shanghai Stock Exchange Industry Sector Index have the ARCH effect, which means the variance of the return residual term depends on the variance of the previous period.

After the above test, the hypothesis of the GARCH model is satisfied, the GARCH model can be fitted, and GARCH(1,1) is selected according to the minimum information criterion, and finally the dynamic correlation coefficient is estimated. The parameter estimation is shown in Table 4.

Table 4. DCC-GARCH Model Parameter Estimation Table

sequence	α_1	β_1	$\alpha_1+\beta_1$
r.yy/r.sn	0.017357	0.92327	0.940627
r.yy/r.sc	0.027854	0.905285	0.933139
r.yy/r.sd	0	0.921828	0.921828
r.yy/r.sg	0.01765	0.909821	0.927471
r.yy/r.sj	0.026929	0.866017	0.892946
r.yy/r.sk	0.054588	0.306768	0.361356
r.yy/r.sx	0.030453	0.000004	0.030457
r.yy/r.sxx	0.073744	0.600652	0.674396
r.yy/r.sy	0.079263	0.572923	0.652186
r.yy/r.sgy	0.029799	0.901615	0.931414

According to the results of the DCC-GARCH parameter estimation, the sum of the dynamic correlation coefficients between the international crude oil and the SSE industry sector index is less than 1, but the sum of the correlation coefficients between the international crude oil and the SSE consumption index and the SSE optional index is much less than 1. It shows that the linkage between international crude oil and the two indices is relatively weak, and the dynamic linkage between other industries and International crude oil is relatively strong.

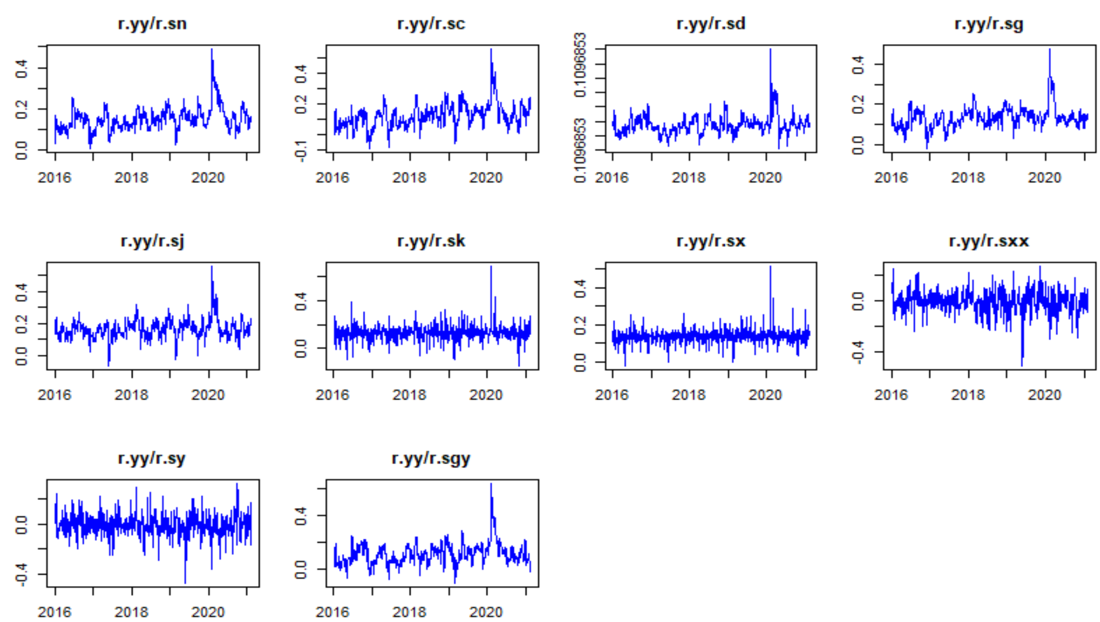

Figure 2. Dynamic Correlation Diagram of International Crude Oil and China Industry Sector Index

It can be seen from Figure 2 that the correlation coefficient between International crude oil and China's industry sector index is not constant, and its changes are dynamic, and there are clusters of changes. When the epidemic broke out (February-April 2020), The correlation coefficients of International crude oil and the 10 industry sector indexes of the Shanghai Stock Exchange have reached the maximum. The dynamic correlation coefficients of International crude oil and SSE Energy, SSE Material, SSE Telecom, SSE Industry, and SSE Public Index have similar trends. The dynamic changes between International crude oil and SSE optional and SSE consumption are also similar. The dynamic correlation coefficients of international crude oil, SSE Information, and SSE Medicine reached the lowest in 2019.

Table 5. Average Dynamic Correlation Coefficients of International Crude Oil and 10 Industry Indexes of Shanghai Stock Exchange

sequence	Early-stage of the outbreak	Mid stage of the outbreak	Late stage of the outbreak
r.yy/r.sn	0.1428	0.3071	0.1522
r.yy/r.sc	0.1120	0.3151	0.1274
r.yy/r.sd	0.1097	0.1097	0.1097
r.yy/r.sg	0.1280	0.2720	0.1268
r.yy/r.sj	0.1614	0.2943	0.1562
r.yy/r.sk	0.1288	0.1728	0.1289
r.yy/r.sx	0.1377	0.1531	0.1390
r.yy/r.sxx	-0.0049	-0.0397	-0.0138
r.yy/r.sy	-0.0081	-0.0396	-0.0096
r.yy/r.sgy	0.1029	0.3254	0.1027

As can be seen from Table 5, due to the impact of the epidemic, the correlation between international crude oil and the Shanghai Stock Exchange's 10 industry sector indexes has strengthened.

The correlation coefficient between the international crude oil and the Shanghai Stock Exchange Utility Index has increased the most, indicating that the correlation is most affected by the epidemic, and the fluctuations in the crude oil market will have a greater impact on the public utility industry in the Shanghai securities market. During the outbreak period, the dynamic correlation between WTI and the SSE Information Index was the weakest, the dynamic correlation between SSE Telecom and International crude oil was almost unaffected, and the range of changes was the smallest. That is to say, the impact of volatility between the crude oil market and the telecommunications industry, information technology industry on the Shanghai securities market will not increase or decrease due to the epidemic.

There is a negative correlation between International crude oil, SSE Information and SSE Medicine, and the correlation is low. To verify the conclusion of the previous DCC coefficient test, crude oil fluctuations have little impact on the SSE Medicine industry and the information technology industry.

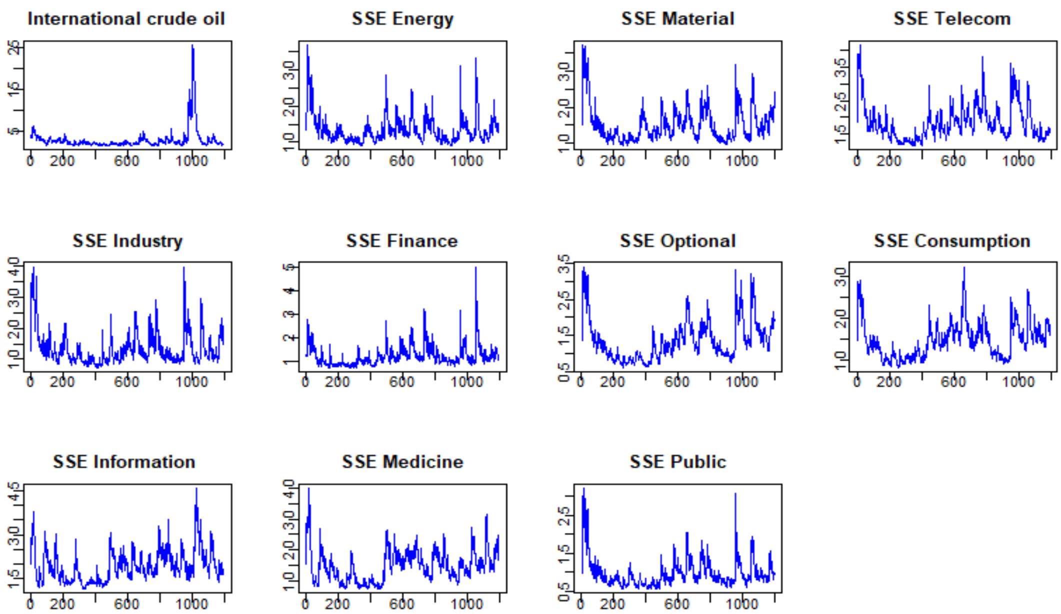

Figure 3. The Volatility of Each Series under the DCC-GARCH Model

After the DCC-GARCH model is fitted, the volatility of 11 series is obtained. It can be seen from Figure 3 that in about 1000 observations (corresponding to the outbreak of the epidemic period), most of the series estimated by DCC-GARCH have too high volatility in this period and reach a peak. During the entire period, the international crude oil fluctuates the most, its volatility reaches its highest during the epidemic, and the fluctuations are relatively stable after the epidemic. However, the volatility of the 10 industry series of the Shanghai Stock Exchange is relatively small.

4.2 Initial Proof of Spillover Effect—Based on the PCA-GARCH Model

The DCC-GARCH model verifies the dynamic correlation between the two markets, and then further explores the spillover effect mechanism of the two markets, and uses the PCA-GARCH model to verify whether there is a spillover effect between the two markets.

To investigate whether there is a spillover effect of International crude oil, SSE Material and SSE Public indices on SSE Energy, for example, a GARCH model is first fitted to 11 return series, here a GARCH(1,1) is fitted to each rate of return series and the 11 volatility series after the model fit are extracted.

where SSE Energy corresponds to the GARCH(1,1) volatility equation (each parameter passes the significance test).

$$h_{sn,t} = 0.0977 + 0.84965 * h_{sn,t-1} + 0.10625 * \varepsilon^2_{sn,t-1}$$

Next, the volatility of the series of SSE Material, SSE Public index and international crude oil are subjected to principal component analysis, in which the cumulative contribution of the variance of the first three principal components reaches 85%, then the extraction of the first three principal components (respectively p_1、p_2、p_3) has been able to represent the vast majority of the information of the original volatility, and the principal component coefficient matrix is as follows:

$$P = \begin{pmatrix} 0.084917 & 0.045299 & 0.940187 \\ 0.369782 & -0.16636 & -0.10071 \\ 0.351941 & -0.09308 & 0.227936 \\ 0.372959 & -0.13991 & -0.07732 \\ 0.330071 & -0.1175 & -0.13952 \\ 0.386191 & -0.0578 & 0.050723 \\ 0.353611 & -0.01996 & -0.00729 \\ 0.153625 & 0.711072 & 0.005716 \\ 0.211112 & 0.640951 & -0.11906 \\ 0.376549 & -0.08972 & -0.10805 \end{pmatrix}$$

The first principal component p_1 is mainly related to SSE Material, SSE Telecom, SSE Industry, SSE Optional, SSE Consumption, and SSE Public. The second principal component p_2 is related to SSE Information and SSE Medicine. The third principal component p_3 is mainly related to international crude oil. The extracted three principal component series are added to the volatility equation of SSE Energy as three exogenous variables, and finally, we analyze whether there is a volatility spillover effect of the three principal component series on the SSE Energy industry.

$$h_{sn,t} = 0.0104 + 0.6689 * h_{sn,t-1} + 0.000139 * \varepsilon^2_{sn,t-1} + 0.001317 * p_1 + v_t$$

(0.000618) (0.000) (0.007924) (0.038015)

v_t denotes the residual term that is not explained by the model. The value in parentheses is the p value of the t-test. All of the above parameters passed the significance test and were positive at a significance level of 0.05. The first principal component extracted has a strong positive volatility spillover effect on the SSE Energy, probably because with the development of the economy, SSE Material, SSE Telecom, SSE Industry, SSE Optional, SSE Consumption, and SSE Public are becoming more and more closely linked and strongly correlated with SSE Energy, while the second and third principal components do not have a significant volatility spillover effect on SSE Energy.

Similarly, the spillover effects of the 10 series on SSE Material, SSE telecom, ..., and international crude oil are studied separately.

In the same way, the spillover effects of 10 sequences on the SSE Material, SSE Telecom, and International crude oil sequences are studied respectively.

$$h_{sc,t} = 0.011458 + 0.702158 * h_{sc,t-1} + 0.000484 * \varepsilon^2_{sc,t-1} + 0.001343 * p_1 + \nu_t$$

(0.000) (0.000) (0.04284) (0.046846)

$$h_{sd,t} = 0.013095 + 0.666775 * h_{sd,t-1} + 0.0002 * \varepsilon^2_{sd,t-1} + 0.001407 * p_1 + \nu_t$$

(0.000) (0.000) (0.0057) (0.003865)

$$h_{sg,t} = 0.016230 + 0.663295 * h_{sg,t-1} + 0.005 * \varepsilon^2_{sg,t-1} + 0.002045 * p_1 + \nu_t$$

(0.000) (0.000) (0.000) (0.000)

$$h_{sj,t} = 0.012279 + 0.672891 * h_{sj,t-1} + 0.000014 * \varepsilon^2_{sj,t-1} + 0.001052 * p_1 + \nu_t$$

(0.000) (0.000) (0.000) (0.000)

$$h_{sk,t} = 0.010994 + 0.710034 * h_{sk,t-1} + 0.001 * \varepsilon^2_{sk,t-1} + 0.002177 * p_1 + \nu_t$$

(0.000) (0.000) (0.0067) (0.000045)

$$h_{sxx,t} = 0.018129 + 0.693295 * h_{sxx,t-1} + 0.0001 * \varepsilon^2_{sxx,t-1} + 0.001298 * p_3 + \nu_t$$

(0.000) (0.000) (0.000) (0.0045)

$$h_{sgy,t} = 0.006615 + 0.691619 * h_{sgy,t-1} + 0.006 * \varepsilon^2_{sgy,t-1} + 0.001044 * p_1 + \nu_t$$

(0.000) (0.000) (0.0061) (0.0045)

All the above parameters pass the significance test at a significance level of 0.05. In the study of the spillover effect of the 10 series on the SSE Information index, the third principal component extracted (mainly related to SSE Medicine and SSE Finance) has a positive spillover effect on the SSE Information index, and in the spillover analysis of the remaining indices, the first principal component has a positive spillover effect on the volatility series, and the SSE Energy, Telecom, Public, Industry, Optional, and Consumption have positive spillover effects on each other.

4.3 Time-varying Volatility Spillover Index

After the PCA-GARCH model detects a positive volatility spillover effect between certain industries, and secondly, in order to explore the impact of COVID-19 on the spillover effect of the two markets, for this purpose we use a time-varying spillover index to compare the volatility spillover indices of the three periods and further analyze the volatility spillover between the Chinese industry sector index and WTI, this allows us to capture the spillover index metric across multiple industries.

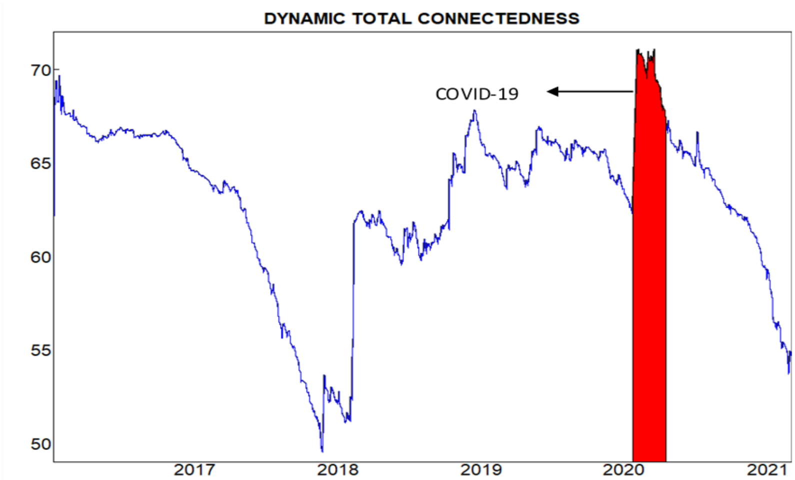

Figure 4. Total Spillover Effect of International Crude Oil and SSE 10 Industry Sectors

Figure 4 shows two main cycles of volatility transmission. The first is from the beginning of the analysis to the end of 2017, during this period, the volatility spillover index reached between 49% and 69%, a period that coincided with a significant drop in oil prices, which notably weakened after the drop. A possible explanation could be that low oil prices dampened the development of the SSE sectoral indices, and after 2017, the volatility spillover effect gradually increased, and due to the emergence of the new crown epidemic, the volatility spillover effect increased again in early 2020. After the outbreak, the volatility spillover reaches a level higher than the previous peak (73.6%), after which the spillover between the two markets gradually decreases as the outbreak is contained.

The diagonal element corresponds to its own variance share, which is the highest value in the table. The "FROM" column corresponds to the share of volatility shocks received from other industries, and the "TO" row is the total share of the industry's shocks to other industries and the international crude oil market. Finally, the "NET" row shows the difference between the sum of the column sum of each industry and the sum of the row of the industry, which is the net volatility shock share provided for all other industries. TCI is the total spillover index.

Table 6. Total Spillover Index Table(%)

	r.yy	r.sn	r.sc	r.sd	r.sg	r.sj	r.sk	r.sx	r.sxx	r.sy	r.sgy	FROM
r.yy	87	1.9	1.7	1.1	1.5	1.6	1.7	1.5	0.4	0.2	1.4	13
r.sn	2	23.2	15.8	7.5	12.5	9.8	9.9	6.7	0.4	0.4	11.8	76.8
r.sc	0.9	14.8	21.9	9.2	13.1	8.3	11.7	9	0.2	0.3	10.7	78.1
r.sd	0.5	8.8	11.4	27	12.3	6.5	13.5	9.2	0.2	0.2	10.4	73
r.sg	0.5	11.1	12.5	9.3	20.7	10	13.2	9.3	0.3	0.3	12.8	79.3
r.sj	0.9	11	10	6.3	12.7	27.8	11.9	8.2	0.5	0.5	10.2	72.2
r.sk	0.5	9	11.4	10.5	13.5	9.3	21	13.1	0.2	0.2	11.2	79

r.sx	0.6	7.6	10.8	9	11.9	7.9	16.3	26.1	0.2	0.3	9.3	73.9
r.sxx	0.3	1.1	0.6	0.6	0.9	1.6	0.8	0.7	65	27.5	0.9	35
r.sy	0.4	1	0.9	0.9	1.1	1.3	1.1	0.9	27.3	64.2	0.9	35.8
r.sgy	0.8	11.7	11.4	8.9	14.1	8.9	12.3	8.1	0.3	0.3	23.2	76.8
TO	7.3	77.9	86.5	63.4	93.8	65.3	92.2	66.7	30	30.2	79.7	TCI
NET	-5.7	1.1	8.4	-9.6	14.5	-6.9	13.2	-7.2	-4.9	-5.6	2.9	63

The share of variance of the 11 series corresponding to themselves is the largest during the whole sample period, with the SSE Material and SSE Public sectors as the main volatility senders, while the SSE telecom and SSE Consumption sectors are the main volatility receivers, i.e., the raw materials sector and the utility sector have the greatest influence on the overall market, while the telecom business sector and the main consumer sectors are most vulnerable to other sectors and the crude oil market. Table 6 shows that the volatility spillover of SSE's 10 industry sector indices to WTI is weak, verifying the conclusion that the 10 industry sector indices have insignificant impact on International crude oil obtained in the preliminary evidence of spillover effect. Secondly, SSE Energy itself has the highest share of variance (23.2%), and SSE Public (11.7%), SSE Material (14.8%), and SSE Industry (11.1%) all have larger spillover indices on SSE Energy, confirming the positive spillover effect of these industries on the SSE Energy sector, and the total spillover index table verifies the validity of the PCA-GARCH analysis of the spillover effect. In addition, Table 6 also shows that the spillover effect of crude oil on SSE Energy reaches 1.9%, while the spillover effect of SSE Energy on crude oil accounts for 2%.

Table 7. Spillover Index before the Epidemic(%)

	r.yy	r.sn	r.sc	r.sd	r.sg	r.sj	r.sk	r.sx	r.sxx	r.sy	r.sgy	FROM
r.yy	88.1	1.4	1.4	1.1	1.4	1.8	1.3	1.3	0.6	0.4	1.3	11.9
r.sn	1.4	23.6	16.3	7.7	12.3	8.8	10.3	7.6	0.4	0.5	11.1	76.4
r.sc	0.5	15.3	22.3	9.6	12.7	7.7	11.7	9.2	0.2	0.3	10.4	77.7
r.sd	0.3	8.7	11.5	26.4	12.2	5.7	13.9	10.3	0.3	0.2	10.5	73.6
r.sg	0.4	10.9	12.0	9.6	21.1	9.6	13.3	9.5	0.3	0.4	12.8	78.9
r.sj	0.7	10.2	9.6	6.0	12.5	29.0	12.1	9.0	0.4	0.6	9.9	71.0
r.sk	0.3	9.1	11.0	10.9	13.1	9.0	20.6	13.6	0.2	0.3	11.8	79.4
r.sx	0.4	8.3	10.5	9.8	11.4	8.1	16.5	25.0	0.3	0.3	9.4	75.0
r.sxx	0.4	0.9	0.7	0.8	0.9	1.2	0.9	0.9	62.6	29.8	1.0	37.4
r.sy	0.2	1.0	0.9	0.9	1.3	1.5	1.3	1.1	29.3	61.5	1.0	38.5
r.sgy	0.5	11.0	11.0	9.2	14.1	8.3	13.2	8.5	0.4	0.4	23.5	76.5
TO	5.0	76.9	84.8	65.7	91.9	61.7	94.5	71.0	32.5	33.2	79.1	TCI
NET	-6.9	0.5	7.1	-7.9	13.0	-9.3	15.2	-4.0	-4.9	-5.3	2.5	63.3

Table 8. Spillover Index in Mid-outbreak Period(%)

	r.yy	r.sn	r.sc	r.sd	r.sg	r.sj	r.sk	r.sx	r.sxx	r.sy	r.sgy	FROM
r.yy	61.3	4.3	4.1	8.8	3.9	3.8	4.7	4.2	0.5	0.4	4	38.7
r.sn	2.7	15.8	12.6	6.3	13.3	12.6	11.4	10	1.2	0.9	13.3	84.2
r.sc	1.4	12.3	15.5	7.3	13.1	12.3	12.7	11.3	1.2	1	11.9	84.5
r.sd	4.7	9.3	11	23.4	9.9	9	13.7	8.3	0.1	0.6	10.1	76.6
r.sg	1.4	12.9	12.9	6.6	15.3	13.1	12.5	10.7	1.1	0.6	12.8	84.7
r.sj	4.3	12.1	12.1	5.9	13	15.2	12.5	11.5	1	0.6	11.9	84.8
r.sk	1.4	11.3	12.8	9.2	12.8	12.9	15.7	11.4	0.8	0.2	11.4	84.3
r.sx	1.8	10.9	12.6	6.1	12	13	12.5	17.1	0.9	0.5	12.6	82.9
r.sxx	4.5	4.7	4.7	0.9	4.9	4.1	3.3	3.5	52.9	11.6	4.8	47.1
r.sy	19.4	4.1	4.3	4.7	3.2	2.9	2.6	2.5	10.6	42.6	3.1	57.4
r.sgy	3	13.1	12	6.9	13	12	11.3	11.4	1.3	0.5	15.5	84.5
TO	44.6	95	99.1	62.7	99	95.6	97.1	85	18.7	17	95.8	TCI
NET	5.9	10.8	14.6	-14	14.3	10.8	12.9	2.1	-28	-40	11.3	73.6

Table 9. Spillover Index in Epidemic Alleviation(%)

	r.yy	r.sn	r.sc	r.sd	r.sg	r.sj	r.sk	r.sx	r.sxx	r.sy	r.sgy	FROM
r.yy	96.8	0.9	1	0	0.2	0.1	0.4	0.3	0	0.1	0.2	3.2
r.sn	2.9	28.1	14.8	6.7	11.2	13.9	5	0.8	1.1	0.4	15.1	71.9
r.sc	1.5	13.6	26.1	8.2	15.2	7.9	10.1	6.5	0.3	0.5	10.2	73.9
r.sd	0.9	8	10.9	32.3	13.5	8.8	11.1	4.5	0.3	0.4	9.2	67.7
r.sg	0.2	9.4	14.1	9.6	24	9.7	13.8	8	0.3	0.5	10.5	76
r.sj	0.6	15	9.2	7.9	12.3	30.5	8.4	1.3	2.5	0.7	11.6	69.5
r.sk	0.4	5.4	11.6	9.4	16.8	8.1	29.7	11.7	0.3	0.4	6.3	70.3
r.sx	1	1.3	10.8	6.1	14.2	2	16.9	42.7	0.3	0.3	4.4	57.3
r.sxx	0.1	2.8	0.7	0.2	0.8	5.7	0.6	0.1	69.6	18.4	1	30.4
r.sy	2.3	1.8	1.4	0.8	1.2	2.3	0.7	0.6	19.9	68.3	0.7	31.7
r.sgy	0.4	15.8	11.6	8.3	13	11.2	6.4	3.3	0.9	0.4	28.8	71.2
TO	10.2	73.9	86	57.2	98.4	69.7	73.3	37.1	26	22	69.2	TCI
NET	7	2	12.1	-11	22.3	0.3	3	-20	-4.4	-9.7	-2	56.6

From Table 7 to Table 9 demonstrates the volatility spillover between the International crude oil and industry sector markets during the three phases, the total spillover index (TCI) increases from 63.3% to 73.6% and decreases to 56.6% when the epidemic subsides, which indicates a high dependence between volatility during the epidemic, mainly concentrated on the directional spillover index (FROM and TO), compared to this pre-epidemic period (from 11.9% to 79.4%), the FROM connectivity varies between 38.7% and 84.8%, and similarly, the T0 spillover index increases from a maximum of 94.5% (SSE Optional index) before the epidemic to 99.1% (SSE Material index) during the outbreak period.

Throughout the process, the volatility-connected properties of WTI are transformed by the epidemic, from the initial volatility receiver to the volatility sender, that is, the outbreak of the epidemic increases the volatility shock to WTI from the SSE sector index, and continues to maintain its volatility sender status when the epidemic enters a calm period, consistent with the findings of Wang et al. (2019), when the identity of the crude oil market changes when a major sexual event such as a stock market crash or an epidemic occurs.

5. Discussion

In this paper, we first study the dynamic correlation between International crude oil and Chinese industry sector market by DCC-GARCH model, on the basis of which we verify the existence of spillover effect between the two markets by the PCA-GARCH model, and further use time-varying spillover to refer to quantitative spillover effect, after the above research analysis, we get the following conclusions:

First, in terms of dynamic correlation analysis, (1) there is dynamic correlation between International crude oil and all industry indices, while for SSE Telecom and International crude oil, the dynamic changes are smaller; (2) the linkage between International crude oil and SSE industry sector indices is different at different stages, and with the outbreak of the epidemic, the linkage between the two markets has gradually strengthened, especially between international crude oil and SSE Public Index, however, the epidemic has little impact on the fluctuations between the crude oil market and the telecommunications industry, information technology industry in the Shanghai securities market. In addition, crude oil shows negative and weak correlation with SSE Information and SSE Medicine; (3) the volatility series estimated by DCC-GARCH shows the largest ups and downs for international crude oil and smaller volatility for 10 industry indices, with most of the volatility series peaking in 1000 observations.

Second, in the analysis of spillover effect analysis, PCA-GARCH model and time-varying spillover index were used to evaluate the spillover effect mechanism between the two markets. (1) PCA-GARCH model was first used to initially prove the positive spillover effect between SSE Energy, SSE Material, SSE Optional, SSE Public, SSE Industry, and SSE Telecom sectors with each other, and further quantified by time-varying spillover index. spillover effects between International crude oil and Chinese industry sectors; (2) the calculation of spillover indices in the full sample interval verifies the results of the PCA-GARCH model, the series that generate spillover effects correspond to larger spillover indices, and the series that do not have spillover effects correspond to values close to 0 in the total spillover index table, the raw material industry and the utility industry have the greatest impact on the overall market, while the telecom business industries and major consumer industries are the most vulnerable to other industries and the crude oil market; (3) further considering the factors of the epidemic, the spillover effect mechanisms of the two markets are compared and analyzed for three time periods. Before and after the epidemic, the total spillover index changes by about 10%, and international crude oil also transforms from a volatility receiver to a volatility sender, and as the epidemic tends to ease, international crude oil continues to maintain its volatility sender.

The results of this study demonstrate the importance of selecting multiple industry markets to study the linkages between international crude oil and industry segments, highlighting the heterogeneity within industry segment markets, which has important implications for investors and policy makers. The existence of strong spillover effects in certain industry sectors with strong intra-industry linkages is pointed out. A limitation of this study is the industry sectors selected, and an important extension might be to consider the inclusion of other country industry sectors and analyze the linkages between the entire international equity industry sector index and International crude oil in order to have a more comprehensive understanding of the linkages.

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