Dynamic Linkages Between Global Oil Price Volatility and Fertilizer Stock Indices in China on Pre and During Covid-19 Pandemic

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Abstract: This study firstly detects the dynamic linkage between WTI oil price and Chinese fertilizer stock indices, namely potash, phosphorus, and nitrogen fertilizer, respectively. Results indicate a weak long-term interdependence and the time-varying pathway of connectedness between WTI oil price and fertilizer indices using a connectedness technique. Then, BEKK, CDCC, and GARCH models are used to display time-varying changes of dynamic conditional correlations on pre and during Covid-19 pandemic, and a significant increase of linkage can be identified at the beginning of the pandemic. Finally, response impulse and historical variance decomposition techniques are employed to analyze the response of fertilizer stock indices from the effect of the magnitude of oil price. Results help to diversify investment portfolios for investors.

1 INTRODUCTION

The global fertilizer industry has been shocked due to the effects of the Covid-19 pandemic in many countries and regions. Because fertilizers are key nutrients that are beneficial to improve agricultural productivity and maintain food supply to satisfy global population growth, we can understand that the supply security of fertilizer is correlated with the food security in the globe. Moreover, the oil price has affected the fertilizer industry because extraction of phosphate rock and potash, the production of integrated chemical complexes, transportation, etc. are greatly impacted by energy use. In past studies, despite the much literature focusing on the nexus of oil and major stock indices in the world, the related empirical research on the nexus of oil price and fertilizer indices is extremely limited. More importantly, China is the largest producer and predominant exporter in the global fertilizer industry, so it is essential to estimate the dynamic impact of oil price and fertilizer stock indices to given rise to focus on detecting the dynamic linkage of oil and fertilizer stock indices, also provide possible evidence to facilitate the diversification strategies for investors.

This study contributes to extend previous studies in several regards. First, this is the first empirical study to display the time-varying dynamics of WTI oil price and fertilizer stocks in China, namely potash, phosphorus, and nitrogen, using the most recent data, including the pre and during performance Covid-19 pandemic. Second, we use BEKK, CDCC and GO-GARCH models to display the time-varying performance of dynamic conditional correlations on pre and during Covid-19 pandemic. Third, this study explores the impulse response and historical variance decomposition analysis to show the shock and impact of the pandemic.

The remainder of this paper is analyzed as follows. Section 2 provides the data and preliminary analysis. Section 3 provides econometric methods. Section 4 presents the empirical results. Section 5 discusses conclusions.

2 DATA AND PRELIMINARY TEST

This study uses the closing price data obtained from Choice system. (http://choice.eastmoney.com/) An essential contribution of this study spans the most recent period from August 4, 2014, to July 23, 2021, which covers the recent period of pre and during the Covid-19 pandemic with high fluctuations in global financial markets due to the pandemic. Daily closing price returns were calculated by the logarithmic difference, and all assets return show a characteristic

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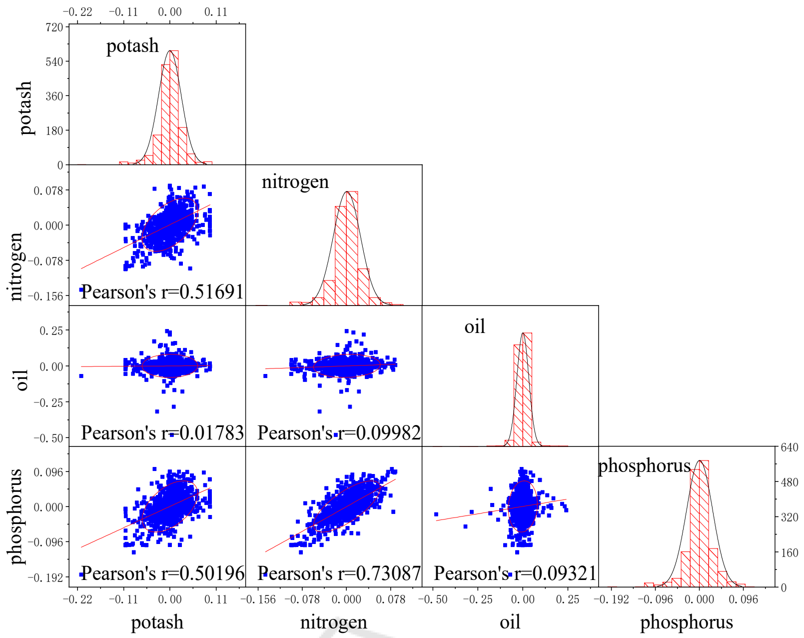

Figure 1: Scatter matrix graph between WTI oil price and Chinese fertilizer stock indices returns.

of more volatile clustering. The results of preliminary statistics indicate that WTI oil return shows the highest standard deviations and volatility clustering pattern. Kurtosis results indicate that all series probability distributions exist in fat tails, and Jarque-Bera (J-B) shows a normal distribution does not exist. Augmented Dickey-Fuller (ADF) test and KPSS test support all assets series are stationary at/ the 1% significance. The ARCH-LM (20) test confirms the ARCH effects for all returns. Fig. 1 visually shows the correlation of different assets return by using a scatter-matrix graph. It is observable that a weak positive correlation exists between oil price and fertilizer indices, and the highest value exists between oil price and nitrogen return.

3 ECONOMETRIC METHODS

3.1 Net Pairwise Connectedness

Connectedness technique was proposed by Diebold and Yilmaz (2012) (Diebold, 2012) to estimate directional and net connectedness. We only provide a simple introduction of the method. Detailed introduction can be seen in many previous studies. The generalized forecast error variance decomposition of the H-step ahead error variance in forecasting the j-th following shocks from the k-th variable can be expressed as follows:

$$\Theta_{ij}(H) = \frac{\sigma_{kk}^{-1}\sum_{h=0}^{H-1}(e_i^T\Omega_h\Sigma e_j)^2}{\sum_{h=0}^{H-1}(e_i^T\Omega_h\Sigma\Omega_h^T e_i)} \tag{1}$$

$\Theta_{ij}(H)$ captures the contribution of the H-step ahead error variance.

The directional connectedness received by market i (or j) from all other markets j (or i) is given by

$$TD_{i-j} = 100 \times \frac{\sum_{i,j=1\, i\neq j}^{N}\widetilde{\Theta}_{ij}(H)}{\sum_{i,j=1}^{N}\widetilde{\Theta}_{ij}(H)} = 100 \times \frac{\sum_{i,j=1\, i\neq j}^{N}\widetilde{\Theta}_{ij}(H)}{n} \tag{2}$$

$$TD_{j-i} = 100 \times \frac{\sum_{i,j=1\, i\neq j}^{N}\widetilde{\Theta}_{ji}(H)}{\sum_{i,j=1}^{N}\widetilde{\Theta}_{ij}(H)} = 100 \times \frac{\sum_{i,j=1\, i\neq j}^{N}\widetilde{\Theta}_{ji}(H)}{n} \tag{3}$$

Thus, a net connectedness index for variable i can be identified as

$$NES_i(H) = TD_{i-j} - TD_{j-i}. \tag{4}$$

3.2 BEKK, CDCC, and GO-GARCH Models

Following Ahmad et al. (2018) (Ahmad, 2018), Kang et al. (2017) (Kang, 2017), and Sadorsky et al. (2014) (Sadorsky, 2014), we provide the dynamic conditional correlations depend on BEKK, CDCC, and GOGARCH models. Previous studies have provided detailed equations, and we introduce a simple review of methods in the study. Previous studies have provided a very detailed introduction. BEKK-GARCH model defines a positive H_t without imposing an explicit restriction for coefficients. H_t can be indicated by Eq. (1) and construct a diagonal BEKK by 2 X 2 matrices A and B.

$$H_t = C'C + C'u_{t-1}u'_{t-1} + B'H_{t-1}B \qquad (5)$$

$$C = \begin{bmatrix} C_{ss} & C_{sf} \\ 0 & C_{ff} \end{bmatrix}, A = \begin{bmatrix} a_{ss} & 0 \\ 0 & a_{ff} \end{bmatrix}, \ B = \begin{bmatrix} b_{ss} & 0 \\ 0 & b_{ff} \end{bmatrix} \qquad (6)$$

where C denotes an upper triangular of 2 X 2 matrices

An orthogonal method of GO-GARCH model, assuming the residuals of $\varepsilon_t = ze_t$, and z denotes linear map and e_t is uncorrelated section. the conditional covariance matrix H_t is given by

$$H_t = Z'ZG_t \qquad (7)$$

The GO (1, 1) is indicated as:

$$G_t = C'C + A'e_{t-1}e'_{t-1} + B'G_{t-1}B \qquad (8)$$

Engle (2002) (Engle, 2002) proposed a two-step procedure of dynamic conditional correlation (DCC) model. A matrix of conditional correlations γ_t can be shown as:

$$\gamma_t = \left(\mathrm{diag}({\xi_t}^*)\right)^{-1/2} \xi_t \left(\mathrm{diag}({\xi_t}^*)\right)^{-1/2}, with\ {\xi_t}^* = diag[\xi_t]. \qquad (9)$$

ξ_t denotes the symmetric positive-definite matrix and can be shown as:

$$\xi_t = (1 - \alpha - \beta)\bar{\xi} + a\varepsilon_{t-1}\varepsilon'_{t-1} + b\xi_{t-1},$$

with a, b > 0, and a+b<1. (10)

Aielli (2013) (Aielli, 2013) proposed a corrected version of the correlation process as in Equation (11):

$$\xi_t = (1 - \alpha - \beta)S + \alpha(\xi_{t-1}^{*1/2}\varepsilon_{t-1}\varepsilon'_{t-1}\xi_{t-1}^{*1/2}) + \beta Q_{t-1}\kappa_1,$$

$$\kappa_2 > 0, \text{ and } \kappa_1 + \kappa_2 < 1. \qquad (11)$$

4 RESULTS

4.1 Connectedness Analysis

Fig. 2 plots the total connectedness index (TCI) by employing Diebold and Yilmaz (2012). We calculate based on a 200-day rolling technique and 10-day forecasting horizon. The results show that TCI was 22.3% and a weak interdependence between oil and fertilizer indices, but potash, phosphorus, and nitrogen stock return seems easily transmitted. From a time-varying perspective, the TCI shows as high as 30-40% during 2014-2016 then decline rapidly, and about 22%-36% during the Covid-19 pandemic.

As shown in Table 1, Potash and Phosphorus stock index contributed the statistically larger of TCI

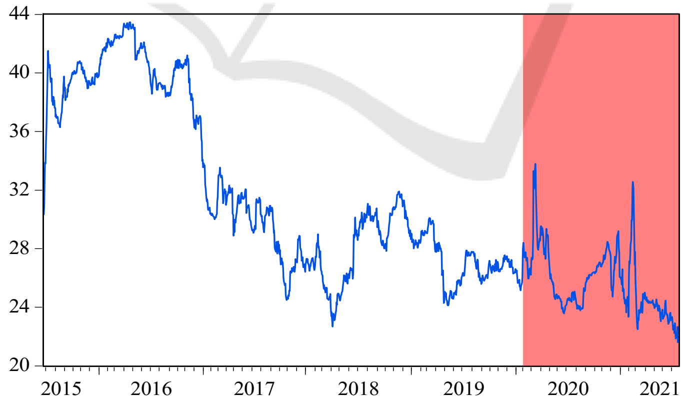

Figure 2: The dynamics of the total connectedness index.

Table 1: Total connectedness index (TCI) and net pairwise connectedness results.

	Oil	*Potash*	*Phosphorus*	*Nitrogen*	*From*
Oil	98.8	0.4	0.6	0.3	1.2
Potash	1.0	97.8	0.5	0.7	2.2
Phosphorus	1.9	25.3	72.2	0.5	27.8
Nitrogen	2.7	26.6	28.8	41.9	58.1
Contribution to.	5.7	52.3	29.9	1.4	89.3
Contribution including	104.4	150.1	102.1	43.3	22.3%

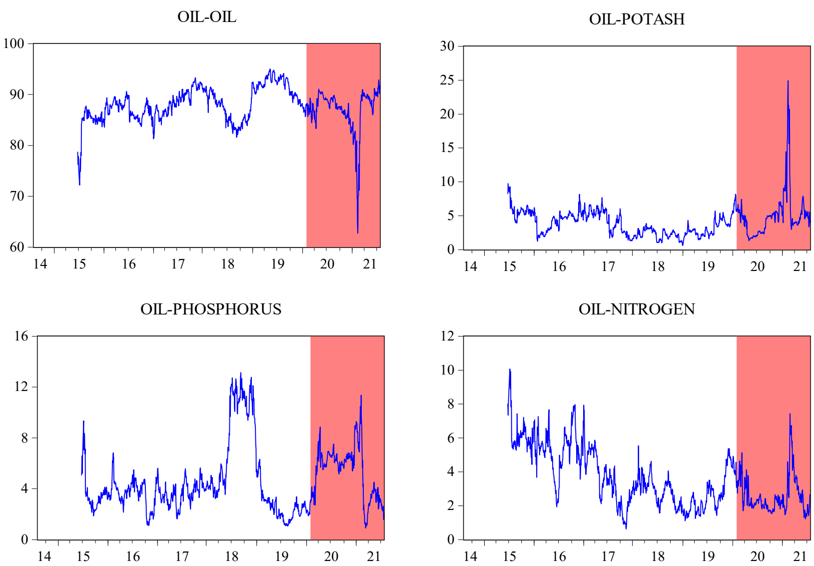

Figure 3: Dynamic pairwise connectedness between WTI oil price and WTI oil price, potash, phosphorus and nitrogen returns (red shaded area is the period of Covid).

to other assets, with 52.3% and 29.9%, and received spillovers from others with 2.2% and 27.8%, respectively. Oil transmitted 5.7% of the shocks to others and received 1.2% from others, implying oil return is the net transmitter but weak interconnected with Chinese fertilizer stock indices. It is worthy to note that Phosphorus stock index have a important role during assets. Phosphorus stock index contributed 29.9% to others, and receive about 27.8% from others. Nitrogen stock index is the biggest receiver among all assets, and received 58.1% from other assets.

The dynamic trajectory of the net pairwise TCI of WTI oil price and fertilizer indices is indicated in Fig.3. We can observe that transmission from WTI oil price to fertilizer stock indices was not highly influenced.

The pairwise connectedness of oil-phosphorus and oil-nitrogen have higher performance on the pre-Covid-19 pandemic, and oil-potash shows the weakest. During the Covid-19 period, we can observe that the pairwise connectedness is highly volatile for all pairs, and the potash stock index is more sensitive to oil shocks. The findings have implications of indicating the connectedness of oil and potash stock s have a significant increase during Covid-19, and investors can consider possible strategies based on the time-varying path of the connectedness.

4.2 Dynamic Conditional Correlations

Fig. 4 displays the time-varying changes of dynamic conditional correlations of WTI oil price and fertilizer stock indices on pre and during Covid-19 pandemic by comparing three multivariate GARCH models (BEKK, CDCC and Go-GARCH).

Overall, the findings confirm there is a weak integration between WTI oil price and the Chinese fertilizer industry, implying oil price has a weak impact on the fertilizer industry in China. Moreover, BEKK and CDCC-GARCH models have a similar performance of capturing the co-movements and dynamic conditional correlations, and the results of GO-GARCH are significantly different. Most importantly, during the Covid-19 pandemic, a significant clustering and increase can be observed for all pairs, and oil-potash shows a sudden increase. In the case of the WTI oil price and phosphorus stock index pair, the conditional correlation stayed more stable, with an average of 0.147 over the sample period. The Covid-19 pandemic also increase the linkage of WTI oil price, and shows a correlation of 0.2. It is observable that the strongest linkage between oil and phosphorus stock was shown at the begging of the Covid-19, also implying the sudden crisis have significant news impact on stock market. Nitrogen stock index shows a stronger co-movement with oil price compared to other stock indices. In the covid-19 period, the correlation is 2 times more than pre-Covid-19, which is averaged of 0.245.

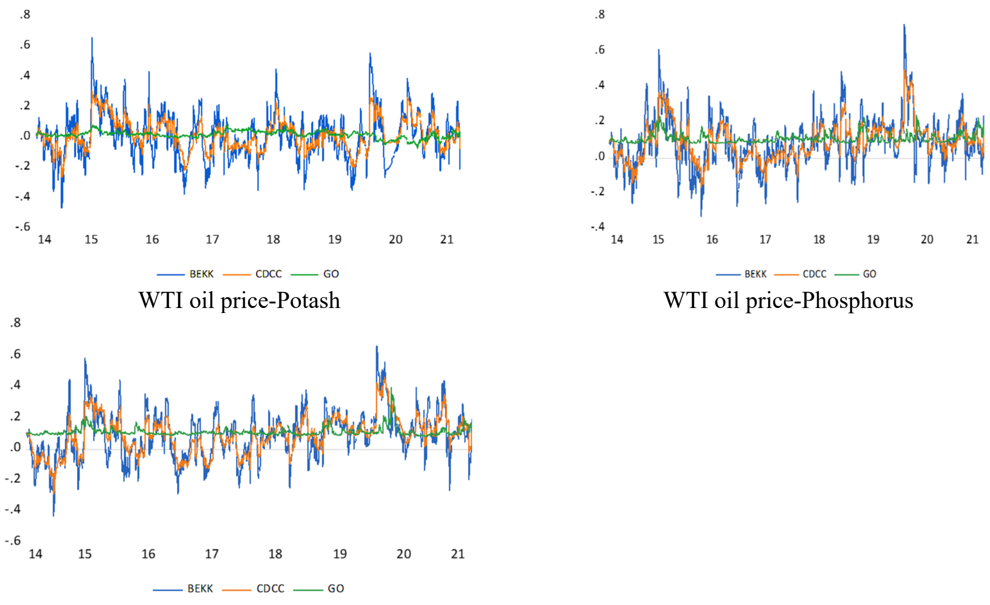

Figure 4: Time-varying dynamic conditional correlations of WTI oil price and Chinese fertilizer stocks indices.

Table 2: Mean and average value of the dynamic conditional correlation from different methods.

	BEKK	*CDCC*	*GO*	*Average*
Oil-Potash				
all	0.011	0.018	0.023	0.026
Pre-Covid	0.000	0.006	0.030	0.018
During Covid	0.047	0.054	-0.004	0.048
Oil-Phosphorus				
all	0.090	0.093	0.112	0.147
Pre-Covid	0.076	0.076	0.109	0.131
During Covid	0.135	0.144	0.122	0.200
Oil-Nitrogen				
all	0.091	0.091	0.114	0.148
Pre-Covid	0.062	0.062	0.111	0.117
During Covid	0.176	0.185	0.129	0.245

4.3 Impulse Response and Historical Variance Decomposition

We conduct an impulse response to show the dynamics of WTI oil price on the Potash, Phosphorus, and Nitrogen fertilizer index over 10 periods, respectively. A new technique of bootstrapping with a 95% confidence interval is used to show the results.

Fig. 5 presents the response of Potash, Phosphorus, and Nitrogen from WTI oil price to display the impact of oil shocks. The results indicate the impact exists shortly for all indexes, and the impact is relatively weak from WTI oil price. There is only a positive impact on all fertilizer stock index from first to third year, and the peak year exists in the second year. And positive effect from the fourth year, then gradually decline after the eighth year.

In order to indicate the different performance of oil price shocks, in the following, we use generalized weights of historical variance decomposition of fertilizer stock indices from WTI oil return. The output is very similar to previous results. The Covid-19 pandemic has an essential impact on the correlation of oil and fertilizer stocks. Moreover, it is observable that the impact is minimal and only exists at the beginning of the Covid-19 pandemic (See in Fig.6)

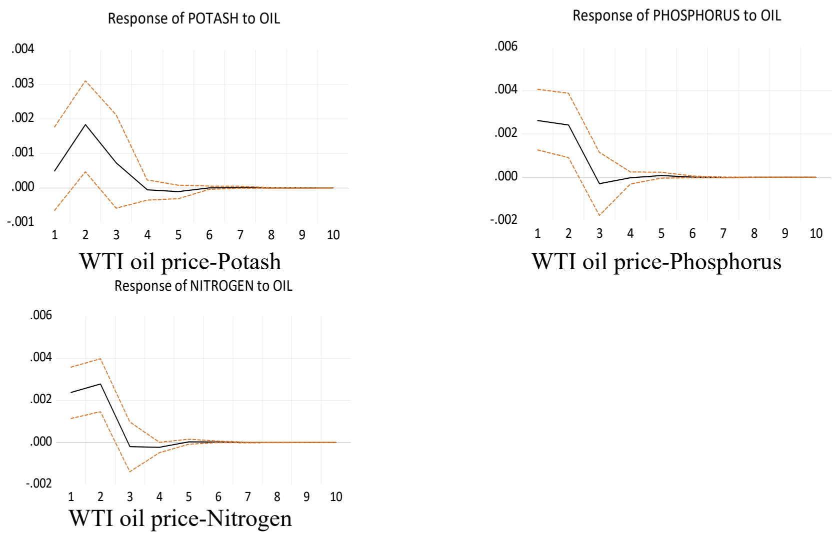

Figure 5: Response of Chinese fertilizer stock indices to WTI oil price.

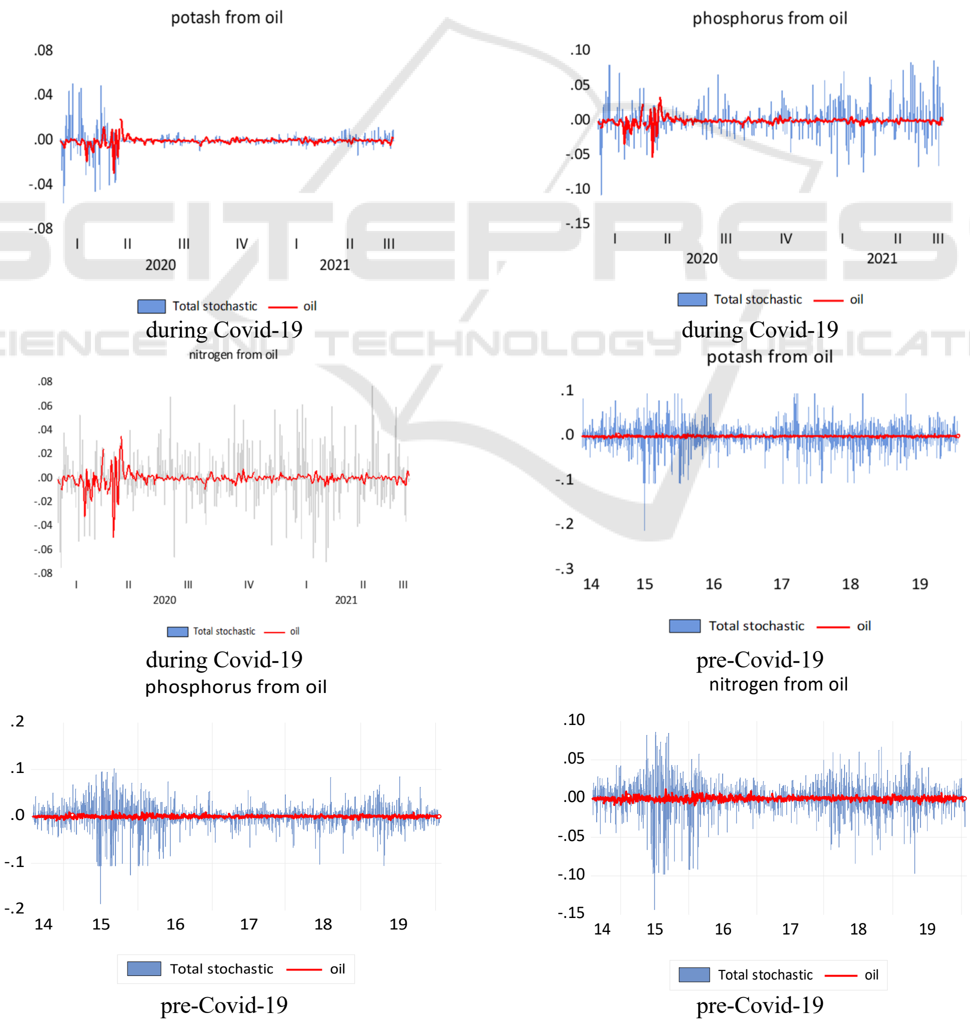

Figure 6: Historical variance of decompositions of fertilizer stock indices from WTI oil price on pre and during Covid-19 pandemic.

5 CONCLUSIONS

The empirical results of the study firstly provide the evidence to extend previous works of literature to examine the nexus of WTI oil price and fertilizer stocks in China. Several conclusions can be obtained. First, the total connectedness index was 22.3%, implying a weak interdependence between oil and fertilizer indices. From a hedging strategy perspective, it is not an ideal asset to hedge the risk for energy markets. WTI oil has a fragile impact on the fluctuations of the others, and the potash stock index was a significant contributor, and the nitrogen stock index was a receiver in the long run. Second, primarily positive dynamic conditional correlations between the WTI oil price and stock indices were observable pre and during the Covid-19 period. More importantly, it can be obtained the Covid-19 had a significant impact on fertilizer stock indices at the beginning of the pandemic. Oil-Nitrogen showed a higher dynamic linkage during the sampling period, and Oil-Potash showed a weaker performance. The findings from Impulse response and Historical variance decomposition analysis also are consistent with the results. The impact of the Covid-19 on the nexus of Oil price and fertilizer stock indices only exists at the beginning of the pandemic, then shows a rapid decline. The results are beneficial to investors and portfolio managers to assess risk management to optimize portfolios if they consider the nexus of the energy market and fertilizer industry. Moreover, policymakers can use this analysis to monitor the changes in energy costs in the fertilizer industry.

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