The Risk Spillover Relationship Between Major Agricultural Commodities in China and the US

Zhibo Fan*

Economics School, Jilin University, Changchun, Jilin, 130012, China

*Corresponding author: 492755142@qq.com

Abstract. As economic globalization continues to deepen, fluctuations in international commodity prices have had significant impacts on economies worldwide. As China, the major importer of commodities, is particularly noteworthy in terms of the risk spillover between its agricultural prices and international commodity prices. This paper employs D-Y methodology based on vector autoregressive (VAR) model to examine the spillover effects of major agricultural commodities in China and the US. Results indicate that there is a significant spillover effect of international commodity price fluctuations on China's agricultural product prices, with a marked response to black swan events such as the COVID-19 pandemic and the Russo-Ukrainian conflict.

Keywords: Risk spillover; Commodity Prices; Agricultural products

1 Introduction

Economic globalization, which has evolved into an unstoppable trend, now sees economies worldwide interconnected and mutually affecting. Financial crises, the COVID-19 pandemic, the Russo-Ukrainian war – all have unleashed a series of black swans and grey rhinos that have sent global commodity prices into a rollercoaster ride, thereby causing significant disruptions to global supply chains and value chains, and affecting the global socioeconomic development in multiple ways. As one of the major importers of various commodities, China's reliance on foreign sources for crude oil, minerals, and other raw materials is high. Price fluctuations in these commodities can further impact the production costs of agricultural products and primary processed goods. How to mitigate the negative impact of international commodity price fluctuations on China's economy has become a topic of widespread concern. Agriculture holds a fundamental position in China's national economy, serving as the foundation for the country's survival. Ensuring the healthy and stable development of agriculture, as well as food security, is of paramount significance to China's economic growth and national security. In particular, maintaining price stability in agricultural products is conducive to increasing farmers' incomes, playing a significant role in mitigating systemic risks in major commodity markets, and serving as a key factor for promoting the healthy and stable development of China's agriculture. In this context, where the complexity of the global

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economic situation is further exacerbated, studying the risk spillover relationship between international commodity price fluctuations and China's major agricultural product prices, as well as their dynamic evolutionary trends, holds significant importance in mitigating and warning against the risks associated with price fluctuations of China's agricultural products.

This paper employs the risk spillover network analysis method, exploring the relationship between China's major agricultural product prices and international major commodity prices. It further conducted a time-varying study through a sliding window approach, analyzing the systemic risks in China's agricultural market and the main external shock factors.

Beginning with a comprehensive review of literature in the second part, the third section delves into the data and modeling methodologies employed in this study. The fourth section presents the empirical analysis results, followed by a conclusion and recommendations.

2 Literature Review

In the realm of commodity price volatility, scholars both domestically and internationally have carried out a series of research efforts aimed at exploring the risk spillovers between different types of commodity markets. In the context of risk spillovers across typical commodity markets, Ji and Fan (2012) investigated price volatility spillovers between oil markets, agricultural products markets, and metal markets prior to and after the 2008 financial crisis by constructing a bivariate EGARCH model with time-varying correlations[1]. The study revealed that there was a significant volatility spillover effect from the oil market onto non-energy commodity markets. Mensi et al. (2014) employed the VAR-BEKK-GARCH and VAR-DCC-GARCH models to discuss dynamic volatility spillovers in international energy and grain commodity markets, finding significant correlations between daily spot prices of eight major commodities including WTI crude oil, Brent crude oil, gasoline, heating oil, barley, corn, sorghum, and wheat[2]. Wei et al. (2023) employed quantile-time domain and frequency-domain static and dynamic spill-over effects methods to investigate the relationship between crude oil prices, carbon emissions permits, and agricultural commodity futures, finding that the total spillover volume between these commodities far exceeded the normal spill-over volume under extreme market conditions[3]. Naeem et al. (2024) investigated extreme downside risk propagation in commodity markets utilizing the CAViaR model and assessed the impact of various crises such as the COVID-19 pandemic and the Russo-Ukrainian conflict on the dynamic relationships between different commodity markets[4] .They observed that during different crisis periods, these markets exhibited heterogeneous interconnected patterns.

In terms of the risk spillovers from other major commodities to agricultural markets, Cao and Cheng (2021) employed the BK frequency-domain spill-over index and rolling window method to investigate the spill-over effects between food and crude oil markets under the influence of COVID-19, comparing changes in the spill-over effects before and after the pandemic[5]. They found that the food and crude oil market systems exhibited the strongest short-term spill-over effect, with the spillover effect during the pandemic significantly weaker than that during the financial crisis. Hanif et al. (2021) employed static and dynamic binary composite algorithms, VaR and CoVaR methodologies, to investigate the dynamic nonlinear dependence between oil prices and world food prices, as well as down-and-up risk spillovers[6]. They found that oil prices move independently of food total prices indexed by the World Food Price Index during market fluctuations, yet exhibited a positive and negative tail dependency when observed in relation to grain, vegetable oil, and sugar prices.

In study on risk spillovers between domestic and international agricultural commodity markets as well as those for different types of commodities, Feng et al. (2023) employed multifractal methods to investigate the cross-correlation dynamics under a series of exogenous shocks in the US-China corn futures market post-2020, with particular attention paid to the impact of international crude oil prices on this relationship[7]. Their findings revealed that after 2020, the cross-correlation significantly strengthened across multiple time scales, but its uncertainty and complexity decreased. Zhou et al. (2024) introduced a novel tail dependence analysis framework, combining Copula-CVaR methodology with ARMA-GARCH-skewed Student-t models, to investigate the pre-and-post-pandemic tail dependence structure and extreme risk spillovers in commodity futures and spot markets [8].They found that the tail dependence structures of soybeans, corn, wheat, and rice futures and spot markets exhibited significant responses to the Russia-Ukraine conflict.

From existing literature studies, it can be discerned that the risk spillover relationship between major agricultural commodities and other commodity markets has long been a topic of academic interest. However, existing research largely focuses on international markets, examining the risk spillovers between various commodity market prices in those markets. As an important energy importer, China's domestic agricultural product market prices are influenced by both international market prices and domestic supply-demand relationships, as well as other factors such as climate. However, there is a dearth of research that has focused on the spillover effects of external commodity prices on China’s agricultural market. Consequently, this paper will focus on several typical agricultural product markets in China, examining the spillover effects of international crude oil prices, natural gas prices, and other major commodity prices on the Chinese agricultural market.

3 The Construction of Risk Spillover Models

In this research, we employ an innovative approach to quantifying volatility spillovers across financial markets using a Generalized Vector Autoregressive (GVAR) model framework (DY, 2009)[9]. This methodology is distinguished by its robustness to the ordering of variables, ensuring that the variance decompositions are consistent regardless of the sequence in which variables are arranged. The model's capacity to decompose the forecast error variance into distinct components attributable to various shocks renders it a powerful tool for dissecting the intricate dynamics of financial systems.

In the context of a covariance-stationary N-variable Vector Autoregression (VAR(p)) model, the system can be articulated as follow：

$$x = \sum_{i-1}^{P} \Phi_{\mathrm{i}} x_{t-i} + \varepsilon_t \tag{1}$$

Here, ε_t is a vector of independently and identially distributed (i.i.d.) disturbances, characterized by a mean vector of zero and a positive definite covariance matrix$\sum$, denoted as $\varepsilon_t \sim N(0, \Sigma)$.

The corresponding Moving Average (MA) representation of the system is given by: $x_t = \sum_{i-0}^{\infty} A_i \varepsilon_{t-i}$.

In this representation, the coefficient matrices Ai of dimension N×N are determined by the following recursive relationship: $A_i = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + \ldots + \Phi_p A_{i-p}$

with the initial condition A_0being an identity matrix of size N×N, and it is stipulated that A_i=0 for all i＜0.

Let us proceed to delineate the concept of variance shares in the context of an N-variable VAR(p) model. Variance shares are defined as the proportions of the H-step-ahead forecast error variances attributable to shocks within the system itself, specifically to the variable x_i, for i=1,2...N. Conversely, cross variance shares, or spillovers, are the proportions of the H-step-ahead forecast error variances that result from exogenous shocks to a different variable x_j, with the constraint $i \neq j$ for $i, j = 1,2,\ldots,N$. The Generalized Impulse Response (KPSS) H-step-ahead forecast error variance decompositions are denoted by$\theta_{ij}^{g}(H)$, for H=1,2,..., and can be mathematically expressed as:

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e'_i A_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e'_i A_h \Sigma A'_h e_i)} \tag{2}$$

In this equation Σ represents the covariance matrix of the error vector ε . σ^{jj} is the standard deviation associated with the error term of the j^{th}equation. e_i is the selection vector that isolates the i^{th} element of a vector. To facilitate a comprehensive understanding of the variance decomposition matrix, we proceed to standardize each matrix entry by its corresponding row sum. This normalization is executed as follows:

$$\tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)} \tag{3}$$

Note that, by construction $\sum_{j=1}^{N} \tilde{\theta}_{ij}^{g}(H) = 1$ and $\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H) = N$.

Utilizing the insights derived from the KPPS variance decomposition, we can articulate a measure that encapsulates the total impact of volatility spillovers within the system. This metric, known as the total volatility spillover index, is delineated as follows:

$$S^g(H) = \frac{\sum_{\substack{i,j=1 \\ i\neq j}}^{N} \tilde{\theta}_{ij}^g(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^g(H)} \cdot 100 = \frac{\sum_{\substack{i,j=1 \\ i\neq j}}^{N} \tilde{\theta}_{ij}^g(H)}{N} \cdot 100 \tag{4}$$

For market i, the directional volatility spillovers received from all other markets j(where i≠j) are measured by the following index:

$$S_{i.}^g(H) = \frac{\sum_{\substack{j=1 \\ j\neq i}}^{N} \tilde{\theta}_{ij}^g(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^g(H)} \cdot 100 = \frac{\sum_{\substack{j=1 \\ j\neq i}}^{N} \tilde{\theta}_{ij}^g(H)}{N} \cdot 100 \tag{5}$$

Conversely, the directional volatility spillovers transmitted by market i to all other markets j are measured by the following index:

$$S_{.i}^g(H) = \frac{\sum_{\substack{j=1 \\ j\neq i}}^{N} \tilde{\theta}_{ji}^g(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ji}^g(H)} \cdot 100 = \frac{\sum_{\substack{j=1 \\ j\neq i}}^{N} \tilde{\theta}_{ji}^g(H)}{N} \cdot 100 \tag{6}$$

Finally, to quantify the net impact of volatility spillovers from a specific market i to all other markets j, we derive a measure as：

$$S_i^g(H) = S_{.i}^g(H) - S_{i.}^g(H) \tag{7}$$

To capture the evolving nature of financial interconnections, we employ a rolling-sample technique, which allows us to track changes in spillover patterns over time.

4 Estimates of the Spillover Effects of Large-scale Commodity and Agricultural Market Fluctuations

4.1 Data

This study selected the futures prices of corn (corn_C), soybeans (soy_C), crude oil (oil_C) in China, and US corn (corn_A), soybeans (soy_A), and WTI crude oil (oil_W) from January 1, 2019 to December 29, 2023 as experimental data. The Chinese data originated from Eastmoney, while the American data came from Yingwei Finance.

4.2 Overall Analysis of Systematic Risk Spillover

Table 1 presents the static risk spill-over matrix for the entire sample, with the data in the y^{th} row of the i^{th} column indicating the directional spillover of i's corresponding commodity price volatility on y's corresponding commodity price.

Table 1. Static Risk Spillover Matrix

	corn_C	soy_C	oil_C	oil_W	soy_A	corn_A	From
corn_C	93.91	3.26	0.28	0.07	1.18	1.30	6.09
soy_C	3.46	94.59	0.46	0.06	1.01	0.41	5.41
oil_C	0.53	0.39	85.69	7.92	3.29	2.18	14.31
oil_W	0.08	1.42	1.37	95.20	0.92	1.01	4.8
soy_A	0.53	0.18	0.40	0.78	77.76	20.35	22.24
corn_A	0.62	0.24	0.68	1.04	20.46	76.97	23.03
TO	5.21	5.48	3.19	9.88	26.85	25.26	
NET	-0.87	0.07	-11.12	7.08	4.62	2.22	TCI/12.65

In Table 1, the column sums (TO) exclude the self-effects, representing the impact of the price fluctuations of this major commodity on the prices of all other commodities in the sample, and the row sums (FROM) indicate the total influence of the prices of all other commodities on the price of this commodity. The difference between "TO" and "FROM" constitutes the net volatility overflow (NET). From Table 1, one can obtain the overall and net directional spillovers for price fluctuations of various commodities.

The overall directional spillovers show that China's three categories of commodity prices exhibit smaller directional spillovers on other categories of goods compared to those of the United States. Specifically, the three categories of commodity prices of US exhibit larger overall directional spillovers, with data from the "FROM" column indicating that corn and soybean prices in China are less affected by other commodity prices, while US soybean and corn prices as well as Chinese crude oil prices are more influenced by other commodities. For US soybean and corn, the respective directional spillovers were found to be 22.24% and 23.03%, whereas the corresponding directional spillover for Chinese crude oil was 14.31%. Upon further analysis of Table 1 data, it becomes evident that the primary cause for the larger risk spillover index between US soybeans and corn is the strong correlation between their prices. Specifically, the overall directional volatility spillover from US corn prices onto US soybean prices stands at 20.35%, while the corresponding figure for US soybean prices onto US corn prices is 20.46%. As for pure volatility spillovers, the most significant impact on other commodity prices is from WTI crude oil, while China's crude oil price, which is most affected by other commodity prices, is -11.12%.

4.3 Dynamic Risk Spillover Analysis

This analysis spans the period from early 2019 to the end of 2023, during which two major shock events occurred globally – the COVID-19 pandemic and the Russo-

Ukrainian conflict – that had a significant impact on the global commodities market. The partially constructed static risk overflow matrix and the overflow index, while enabling analysis of the mutual influence of commodity price fluctuations, fail to capture the changes in volatility overflow over specific timeframes. Therefore, employ a 200-day rolling sample to estimate volatility spillovers, and assess the extent of time-varying volatility spillovers through corresponding time series.

Fig. 1. Dynamic Total Risk Spillover Index

As depicted in Fig. 1, the trend of the dynamic total overflow index can be divided into three cycles. The first cycle spanned from early 2020 to the first quarter of 2021. In early December 2019, the first case of novel coronavirus infection was discovered in Wuhan, followed by a global pandemic that became one of the most severe public health crises of the 21st century. The slowdown in global economies and reduced demand have contributed to dramatic fluctuations in commodity markets, with the Total Outlier Index entering an upward cycle during this period. At the beginning of 2020, after experiencing a brief period of fluctuations, the overall overflow index soared to nearly 40%, before subsequently declining to below 20% within the second quarter of that same year. Subsequently, the total overflow index gradually increased, returning to levels between 25% and 30% in mid-2021. The second cycle spanned from the first quarter of 2021 to early 2022, during which global efforts in controlling the pandemic began to show tangible results, and international relations remained relatively stable. The overall excess index fluctuated within the range of 27%-30%, marking a period of stability throughout the entire sample time frame. The third cycle began in February 2022 with the outbreak of the Russia-Ukraine conflict, which rapidly deteriorated Russia's relations with Western Europe and the United States. This led to volatility in the oil market, spilling over into other commodity markets, particularly those of agricultural products. The total index of spillage rose to approximately 36% before declining to 25%, fluctuating around that level.

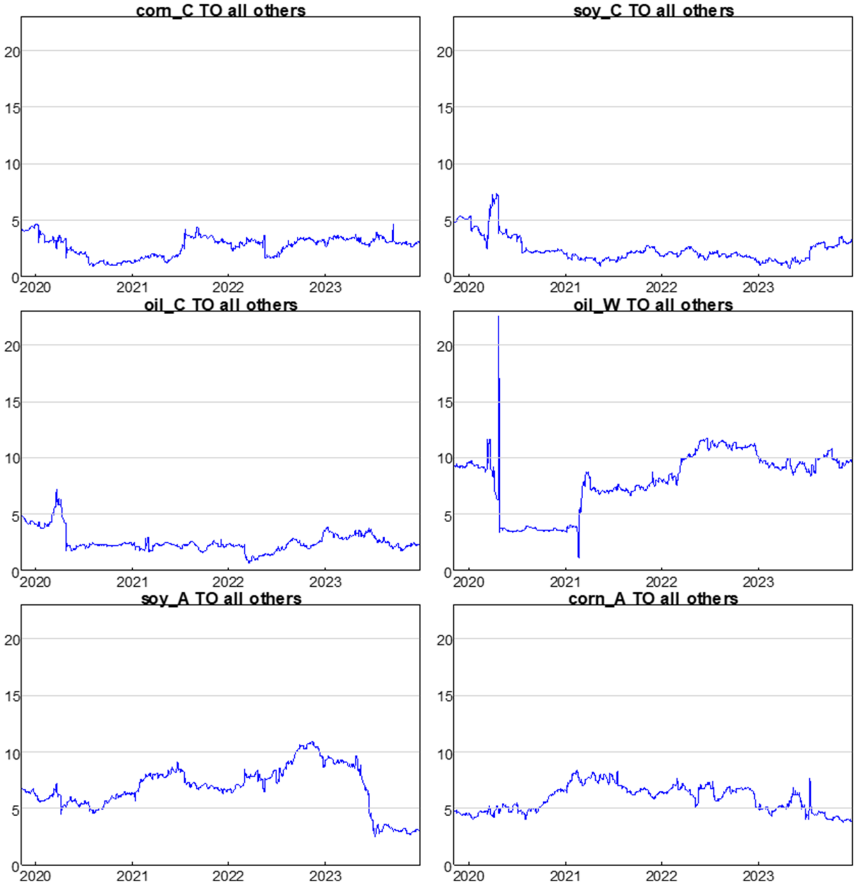

Fig. 2. Directional risk spillovers across different commodity markets

To delve further into the extent to which different commodity prices influence one another over the sample period, Fig. 2 reveals the dynamic changes in directional risk spillovers across six major commodities. One can observe that China's three major commodity prices exhibit smaller directional risk spillovers to other commodity prices, with the majority of the sample period falling below 5%. The fluctuations in the prices of three major commodities in the US have a significant impact on other commodity categories in the sample. Among them, the directional volatility surges in US soybeans and corn were consistently above 5% for most of the time, with WTI crude oil's fluctuations remaining stable around 7% except during the pandemic when it experienced a significant jump, after which it settled at an elevated level of around 10%.

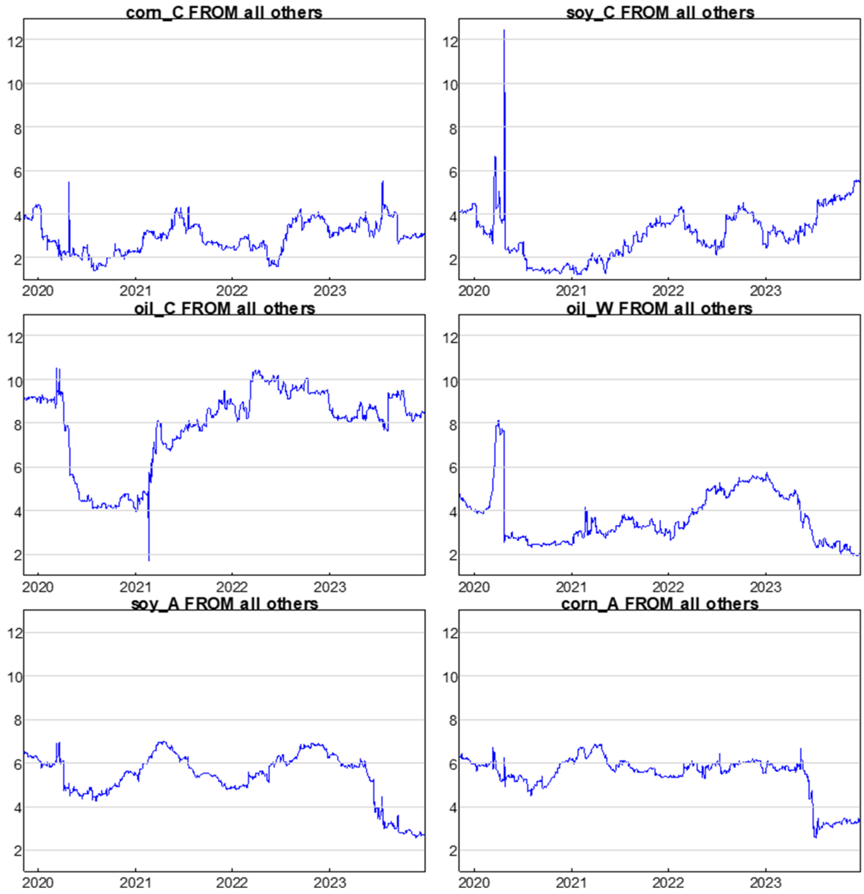

Fig. 3. Directional risks spillovers in different commodity markets

As depicted in Fig. 3, the directional spillovers of commodity price fluctuations on other commodities indicate the extent to which the prices of these goods are influenced by changes in the prices of other commodities. Similar to directional spillovers in other commodity prices, during tranquil periods, China's corn and soybean prices exhibit lower levels of spill-over from other commodities compared to those in the US, hovering around 3%, while the US consistently maintains a level of around 6%. Whereas for crude oil, a major commodity, the conclusion is the opposite. Apart from the pandemic period, China's crude prices have been affected by fluctuations in other commodities at a rate of 9%, far higher than that of the US. Of particular note is that in the second half of 2023, prices for three major commodity groups in the US fell to low levels of around 3% or less, reflecting a decoupling from other commodity price fluctuations.

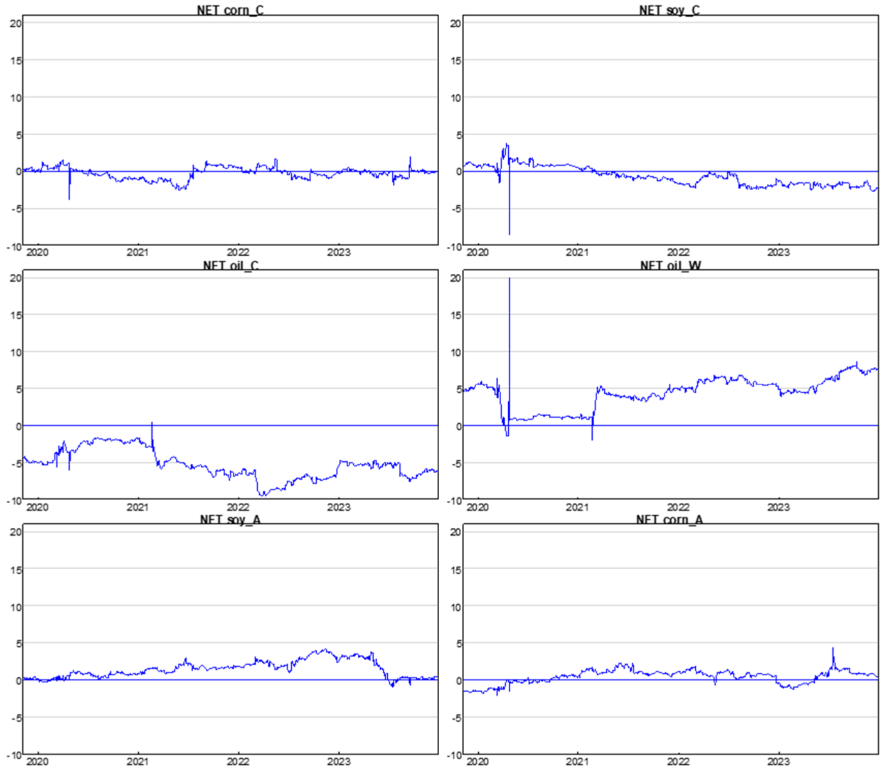

Fig. 4. The net risk imbalances in various commodity markets

As shown in Fig. 4, the net volatility spillovers for China's two major commodities – corn and soybeans – were mostly below 3% during most periods, excluding the brief spike during the pandemic. In both cases, the US also exhibited similar dynamics, with the absolute value of net volatility spillovers never exceeding 5%. The net volatility outliers in corn between the two countries were mainly around zero during the sample period, while the net volatility outliers for soybeans in China were all negative after 2021. In the United States, the net volatility outliers for soybeans were almost positive until mid-2023. When examining the crude oil data of both countries, it can be observed that China's crude oil finds itself on the receiving end of net volatility overflow effects, while US crude oil primarily plays a role in providing volatility overflow to other markets. During the pandemic's global spread, the net fluctuations' absolute values were relatively small.

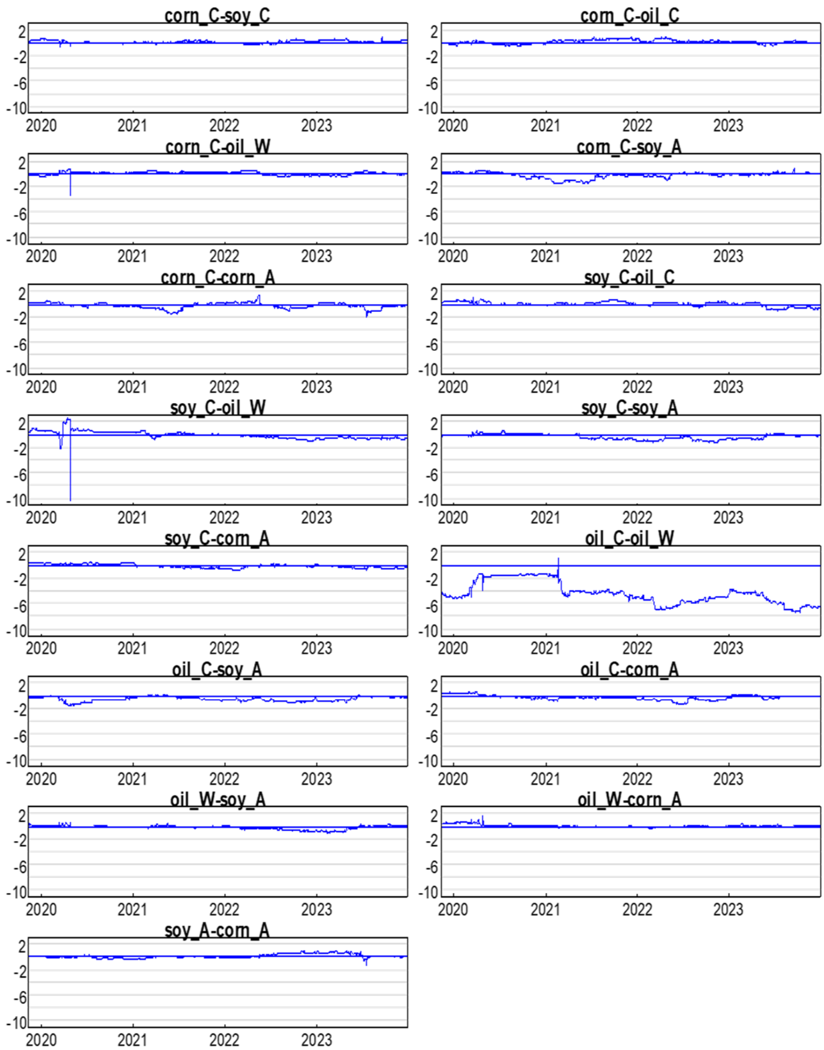

Fig. 5. Net pairwise volatility spillovers

As illustrated in Fig. 5, when examining the net directional impact of risk spillage, oil_C's warning direction for other markets was largely negative, indicating that China's crude oil prices were mostly absorbing the fluctuations in the price of three major commodities from the US, particularly those affected by WTI crude oil, with an average absolute value ranging between 4% to 5%. During the pandemic, due to the implementation of related isolation control policies on transportation industries, this figure dropped to around 2%. Following the outbreak of the Russia-Ukraine conflict, the WTI crude oil market exhibited a temporary decrease in its impact on China's crude oil market, but promptly recovered to normal levels. For China's two major agricultural commodities, soybeans and corn, the Chinese market for both has been largely influenced by fluctuations in the US market for these same crops. In the net risk overflow diagram from soy_C to oil_W, it can be seen that the majority of data was positive before 2022, while after that year, the vast majority of data was negative. This indicates a change in the net direction of risk overflow over the last few years.

5 Conclusion and Suggestion

By examining the risk spillover matrix derived from static risk overflows analysis, it can be observed that the interconnections between major agricultural commodities in China are less pronounced than those in the United States, with the net risk spillover index for corn and soybeans in China significantly lower than in the US, placing them in a passive position in international risk spillover relationships. By conducting a dynamic risk spillover analysis and focusing on its direction, it was discovered that during the COVID-19 pandemic, the risk spillovers for the six major commodities under study were significantly affected. This was due to the implementation of related isolation policies, which led to a significant decrease in the risk spillover indices between the six commodities studied here. Furthermore, the net risk spillover indices for China's two major agricultural commodities showed a downward trend during this period. At the early stages of the Russia-Ukraine conflict, China's net risk index for corn and soybeans both experienced a brief increase before returning to pre-event levels. Finally, focusing on the risk spillover direction of price fluctuations in similar agricultural products between China and the US, it was found that China is generally exposed to the impact of large-scale agricultural product price fluctuations from the US.

During the COVID-19 pandemic, China's agricultural supply faced regional shortages due to isolation policies, ringing alarm bells for the safety of Chinese agriculture. To ensure that one billion people have sufficient food to eat, mitigate systemic risks in major agricultural commodity markets, and promote the healthy and stable development of China's agriculture, it holds immense significance for China. Based on the analysis presented herein, we propose the following suggestions:

Firstly, the translated paragraph In agricultural commodity price risk management, it is crucial to closely monitor the dynamics of international commodity markets, as fluctuations in these markets often have significant implications for domestic agricultural prices. Especially for commodities of the same type that are more closely linked to international markets, such as soybeans and corn, their price fluctuations are more susceptible to changes in global supply and demand, policy interventions, currency fluctuations, and trade disputes.

Secondly, agricultural enterprises should actively engage in hedging through futures markets, locking in future sales prices or costs for their products, thus reducing the uncertainty brought about by fluctuations in spot market prices. In tandem, through hedging operations in futures markets, enterprises can effectively mitigate the risks associated with price fluctuations, ensuring the stability of their earnings. This extends beyond hedging against price fluctuations in a single commodity; it also entails managing price risks associated with other major commodities (such as fertilizers and energy) that are linked to agricultural production. Moreover, agricultural enterprises should also consider adopting diversified risk management strategies that integrate various financial instruments and non-financial tools in line with their unique production and operational characteristics. For instance, by adjusting procurement and sales strategies, optimizing inventory management, and participating in agricultural insurance programs, one can further diversify and mitigate risks.

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