Correlation between Agricultural Markets in Dynamic Perspective——Evidence from China and the U.S. Futures Markets

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Abstract

Emerging as the earliest futures markets, agricultural futures markets play an important role in risk aversion and price discovery. With the integration of global economy, the linkage between domestic and international futures markets becomes closer than ever. By using the thermal optimal path (TOP) method, this paper selects soybean, corn and wheat as the representatives to study the dynamic lead-lag relationship between the Chinese and American markets in both returns and volatility. The results indicate that: (1) For the futures return, different kinds of agricultural futures lead-lag relationship between China and the U.S. varied before 2014 both in direction and order in different time periods. However, China leads the U.S. for all the three kinds we study after 2014. (2) Agricultural commodities subject to less import restrictions and government regulations in China such as soybean are more susceptible to the fluctuations from the international markets. On the other hand, lower foreign trade openness and more government regulation species such as wheat are less affected by fluctuations from outside. (3) The volatility transmission from the U.S. to China wheat futures market takes longer time than soybean, which suggests that China's soybean futures market is more closely linked to the international agricultural futures market than wheat.

Keywords: Agricultural futures; Lead-lag relationship; Thermal optimal path method

1. Introduction

In recent years, China's agricultural markets have been growing rapidly, mainly due to the expanding trade with other countries. In 2011, China replaced the United States and became the world's largest importer of agricultural products. The total value of China's agricultural imports has increased dramatically to more than 1.1 trillion dollars in 2014. Despite the fact that the trading volume of China's agricultural products keeps growing, its trade position is not optimistic, meaning that the prices of China's most important agricultural products can only passively follow the international markets and do not have strong international pricing power. For example, wheat and corn as well as many others from China cannot compete with those from the U.S., Canada and other countries due to quality problems, resulted in an inferior international trade position. Traditional agricultural products such as soybeans and cotton have lost their advantages after China joined the World Trade Organization since they are no longer protected by domestic high tariffs. As a result, China has to import large quantities of agricultural products passively every year.

Under the planned economy system, the commodity futures market cannot perform its role of price discovery and hedging as the government controls the price of almost all commodities. Since the reform and open-up policy in 1970s, China began to release the price control and to reduce direct government intervention to allow the market to gradually build a socialist market economy. Since then the commodity prices began to fluctuate dramatically. Yet, a valid hedging market mechanism did not exist at that time and a large number of market participants suffered great loss from huge price fluctuations. For example, the Chinese "soybean crisis" in 2004 brought huge market risks for

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the operation and production of the whole soybean-related industrial chain. In recent years, with the integration of the global economy, the linkage between markets in China and other countries has become closer. In particular since 2007-2008, the prices of international agricultural commodities fluctuated significantly and brought new challenges for China's domestic agricultural markets that threatened people's livelihood.

Accordingly, the study on the linkage and transmission effects between domestic and foreign markets is essential in the trend of economic integration. The present work will not only help us understand the current situation of China's agricultural futures market deeper, but will also help us carry out proper strategies to compete in the international market, and to further improve China's pricing power of agricultural products among the international markets.

2. Literature Review

A perfect market system is a prerequisite for the healthy smooth operation of the market economy. Futures market, as an extension of stock market, is becoming an integral part in the contemporary financial markets due to its function of risk aversion and price discovery. A highly developed commodity futures markets can provide hedging tools for market participants.

In recent years, researchers have conducted research on futures markets from different perspectives including spot-futures price relationship, volume-price relationship and the linkage between different futures markets [1–6]. Early studies e.g., Garbade and Silber [1] presented a model to examine the price discovery mechanism of futures market and the effect of arbitrage on price changes in commodities spot-futures markets, extending the existing methodology to this area. Chan et al.[3] employed a bivariate GARCH model to study the intraday return relationship between Standard & Poor's stock index and its futures, and suggested that the volatility of the spot and futures returns has a strong inter-market dependence. On the contrary, other studies reported conflicting conclusions that there are no significant volatility spillovers from the spot market to the futures market [4]. Using the intraday five-minute interval data, Lihara [2] also proved that the information flow observed in the spot and futures market is unidirectional, which is different from the results given in Chan et al.[3].

The "instantaneous adjustment" property of an efficient market was put forward by Fama [7], which suggests that the history of the series cannot effectively predict its future. According to the efficient market hypothesis, the transmission effect does not theoretically exist across different financial markets since any useful information will be digested by the financial markets promptly. Yet, the spillover effect and inter-market information transmission has been observed and discussed in rich literatures and researchers began to pay more attention to the research of the linkage between different financial markets in recent years. The early works in this field mainly focus on the stock markets [8–11]. For example, Hamao et al.[8] examined the spillover effect between stock markets in the U.S., the U.K. and Japan, and the spillover effect shows an intriguing asymmetry. Similar evidence was observed by Susmel and Engle [9]. Contrary to the results in Ref. [8–11], Lin et al. [10] showed that cross-market interdependence in returns and volatility between the U.S. and the Japanese stock markets was bi-directional. Based on the conception of stock-markets integration, evidence has been found that some international stock markets share the same volatility process [11].

In the trend of global economy integration, the linkage between China and the world markets is becoming closer. China is more vulnerable to the fluctuations of the international markets in recent years. Previous studies [12–21] provide abundant resources to investigate the linkage between different financial markets in the world. These studies suggest that the U.S. plays a predominant role in information flow across international financial markets. For example, Xu and Fung [17] found that the US market played a more important role than the Japanese market by examining the cross-market price spillover effect of gold, silver and platinum futures. After the large swings of agricultural commodity prices between 2007 and 2008, Beckmann and Czudaj[20] found that a short-run volatility transmission process existed between the U.S. and China agricultural futures markets, but the impacts died out in the long-run. Zhang and Qu [21] studied the effect of global oil price shocks on six kinds of agricultural commodities in China, and found that the oil price shocks had different effects on different agricultural commodities.

One should be aware that most of the previous studies on futures markets employed linear parameter methods [22–24]. For example, based on the Johansen's co-integration approach, Wang and Ke[23] studied the efficiency of Chinese wheat and soybean futures markets, and came to different conclusions for the two species. Theories based on the linear framework such as the random walk theory, capital asset pricing model have been employed to study financial

markets. Since the financial market system is open and complex, linear methods alone cannot effectively explain the relationship between complex variables in the ever changing financial markets [25–28]. For example, Opong et al.[27] and Mckenzie [28] found strong evidence of nonlinearity characteristics in stock market. In recent years, researchers began to study the futures market by using nonlinear methods [29–36]. By employing the MF-DCCA method, He and Chen [37] examined the price-volume relationships in the U.S. and China agricultural commodity futures markets, and found that the nonlinear dependence in all price-volume relationships did exist. Beckmann and Czudaj[38] adopted a non-linear smooth transition approach to detect the relationship between futures prices of seven agricultural commodities, and the results revealed that important dynamics would be neglected in a linear framework.

Noting the nonlinearity and complexity of financial markets, we here adopt a nonlinear and non-parametric methodology called thermal optimal path (TOP) method to examine the lead-lag relationship. As a nonlinear and non-parametric estimation method, TOP offers a new approach to detect the dependence between two time series, and can intuitively uncover the dynamic lead-lag order between two time series.

The rest of this paper is organized as follows. Section 3 presents the TOP procedure. Section 4 describes the data of three representative agricultural future prices. Section 5 provides qualitative and quantitative analyses on the lead-lag relationship between the U.S. and China agricultural futures return and volatility by means of TOP method. Section 6 gives our conclusions and suggestions.

3. Methodology

Different from the previous studies, we here use the thermal optimum path (TOP) method to study the lead-lag relationship in return and volatility of the futures market between China and the U.S.. As a non-linear and non-parametric method, it was originally proposed by Sornette and Zhou[29] to test the dynamic evolution of the lead-lag structure between two time series. The approach has since been successfully improved and enables one to analyze the relationship between two economic or financial variables [30, 31, 39].

We now give a brief review of the TOP method. Suppose there are two time series $X(t_1)$ and $Y(t_2)$ ($t_1 = 1, 2, \dots, L$; $t_2 = 1, 2, \dots, L$), where L is the length of the series. We define a distance matrix $E_{X,Y}$ and $\varepsilon(t_1, t_2)$ is an element of $E_{X,Y}$ between X and Y .

$$\varepsilon(t_1, t_2) = |X(t_1) - Y(t_2)| \quad (1)$$

X and Y are the two time-series of the same length after standardization. Note that other forms of distance can be used [29], e.g. $\varepsilon(t_1, t_2) = |X(t_1) - Y(t_2)|^q$ ($q > 1$). But we will use the form in Eq.1 in the rest of the paper. The purpose of TOP method is to reveal the lowest energy path between two series.

Figure 1: Representation of the plane (t_1, t_2) and the rotated frame (t, x) as defined in Eq.2. The three arrows in red depict the three possible moves from any node in one step.

As shown in Fig.1, the distance matrix can be interpreted as the energy landscape in the plane (t_1, t_2) . The plane coordinate system (t_1, t_2) is the original distance matrix with t_1 and t_2 as the horizontal and vertical coordinates,

respectively. We get the new coordinates (t, x) by the following transformation

$$\begin{cases} t_1 = 1 + (t - x)/2 \\ t_2 = 1 + (t + x)/2 \end{cases} \quad (2)$$

After the rotation, the main diagonal direction of the original coordinate system becomes the t axis, which is perpendicular to the x axis. Obviously, the variable x quantifies the lead-lag relation between the series X and Y . Obviously, the variable x quantifies the lead-lag relation between the series X and Y . A positive (negative) x means that the series X leads (lags) the series Y . Here, the path from the neighboring node to a given node can only take one of the three possibilities, namely along the horizontal, vertical, or the main diagonal. The optimal path between two series can then be determined.

By employing statistical physics methods, we here take the Boltzmann factor $\exp[-\varepsilon(x, t)/T]$ as the weight to build the partition function G . The recursive equation of the partition function G can be defined as follows:

$$G(x, t + 1) = [G(x - 1, t) + G(x + 1, t) + G(x, t - 1)]e^{-\varepsilon(x, t)/T} \quad (3)$$

where $\varepsilon(t_1, t_2)$ is the matrix element in Eq.1 representing the energy value. The variable T is the temperature that quantifies the deviation of the optimal path from the minimum energy. For $t = 0$ and 1 , $G(x, t) = 0$. $G(x, t)$ is obtained recursively from Eq.3.

The larger the temperature T is, the larger the probability that the absolute deviation from the minimum energy is allowed. If we set the temperature T to 0, the problem will become a search for the absolute minimum value of x corresponding to each time t . In reality, the two sequences are not completely smooth since the distance matrix contains large quantity of noises. As a result, the optimal path could be very sensitive to the temperature T . For our purpose, we should choose a proper temperature which is neither too large nor too small, in order to avoid over-fitting or to prevent the loss of information.

We now calculate the optimal thermal average $\langle x(t) \rangle$. The probability of a path being x at time t is given by $G(x, t)/G(t)$. Note that $G(x, t)/G(t)$ also represents the probability of the distance from the point to the diagonal being x at time t . This probability will increase as the energy of this point at t decreases. Therefore, the optimal thermal average $\langle x(t) \rangle$ is defined as

$$\langle x(t) \rangle = \sum_x x G(x, t) / G(t) \quad (4)$$

where $\langle x(t) \rangle$ denotes the lead-leg order at each time t . By using the TOP method, the change of the lead-lag order can be visually observed.

4. Data

Daily data of the Chinese futures markets and the corresponding foreign markets are derived from Wind Database. We select a sample of 3 representative agriculture futures traded in the Chinese market: No.1 soybean futures, corn futures from China's Dalian Commodity Exchange (DCE), and strong gluten wheat futures from China's Zhengzhou Commodity Exchange (ZCE). There are several types of futures contracts according to different delivery months for each agriculture futures. We here take the closing price of the main futures contract for the period from Nov.5, 2008 till Sept.24, 2015. The main contract refers to the contract traded with the largest volume in a day. We match each of these Chinese futures with the most active futures contracts from the Chicago Board of Trade (CBOT). CBOT is currently the most influential agricultural futures market in the world, and the transaction prices of agricultural commodities in CBOT are more representative of the world prices. The closing price of futures traded in DCE and ZCE is conducted through an electronic trading system while that in CBOT is offered by the open outcry system.

One should also be aware that the trading hours of China and the U.S. futures markets are nonsynchronous. Beijing time leads the CST by 14 hours, and with daylight saving time, the time difference is 13 hours. The trading hours of CBOT are between 11:30 p.m. (same day) and 3:15 a.m. (next day) when converted to Beijing time. For daylight saving time, the trading hours of CBOT are between 10:30 p.m. (same day) and 2:15 a.m. (next day) in Beijing time.

Table 1: Futures contract specifications.

All the trading hours are converted to Beijing time. For contracts traded in CBOT, only floor trading hours are reported.

Contract	Open time	End time	Delivery Month
Soybean(DCE)	9:00a.m	3:00p.m. (Same day)	1,3,5,7,9,11
Soybean(CBOT)	11:30p.m. (For daylight saving: 10:30p.m.)	3:15a.m. (Next day) (For daylight saving time: Next day 2:15a.m.)	1,3,5,7,8,9,11
Corn(DCE)	9:00a.m.	3:00p.m. (Same day)	1,3,5,7,9,11
Corn(CBOT)	11:30p.m. (For daylight saving time: 10:30p.m.)	3:15a.m. (Next day) (For daylight saving time: Next day 2:15a.m.)	3,5,7,9,12
Wheat(ZCE)	9:00a.m.	3:00p.m. (Same day)	1,3,5,7,9,11
Wheat(CBOT)	11:30p.m. (For daylight saving time: 10:30p.m.)	3:15a.m. (Next day) (For daylight saving time: Next day 2:15a.m.)	3,5,7,9,12

From Table 1, we notice that the closing price of day t in China is affected by the closing price of day $t - 1$ in the U.S.. Therefore we match the U.S. futures price of day $t - 1$ with that of day t in China. Furthermore, by considering the difference in holidays between the two nations, we exclude the unmatched data and finally get 1305 pairs for each kind of futures, wheat, corn and soybean.

Using the closing price data, we denote $P_c(t)$ and $P_a(t)$ as the futures price at time t in China and the U.S. respectively. The return is expressed as the difference of the logarithmic prices, given by the following

$$\begin{cases} R_c(t) = \ln P_c(t) - \ln P_c(t-1) \\ R_a(t) = \ln P_a(t) - \ln P_a(t-1) \end{cases} \quad (5)$$

The return series of China's soybean, corn and wheat can be expressed as $R_{cs}(t), R_{cc}(t), R_{cw}(t)$, respectively, and the return series of the U.S. soybean, corn and wheat can be expressed as $R_{as}(t), R_{ac}(t), R_{aw}(t)$.

(a)

(b)

(c)

Figure 2: Time series of futures closing prices. This figure displays the time series of the closing prices of the soybean futures, corn futures and wheat futures. Panel (a) reports the trend of $R_{cs}(t)$ and $R_{as}(t)$, Panel (b) reports the trend of $R_{cc}(t)$ and $R_{ac}(t)$ and Panel (c) reports the trend of $R_{cw}(t)$ and $R_{aw}(t)$. The units of China and the US futures are CNY per metric ton and US dollars per bushel, respectively.

From the behavior of the price trend in Fig.2, we partition the sample period into three stages. During the first stage(2008.11-2010.08), the prices of agricultural commodities kept increasing rapidly in China while for the U.S., the agricultural commodities prices fluctuated slightly at a relatively low level. During the second stage(2010.09-2013.10), apparently, the agricultural commodities prices fluctuated sharply both in China and the U.S., when compared with other periods. During the third stage(2013.11-2015.09), the U.S. agricultural commodities prices began to fall back to the level before 2011 while the prices of agricultural commodities in China still remain at a high level till now, from which one can see that the price trend between China and the U.S. began to differentiate during this period. Despite the inconformity of China and the U.S. futures price series in some periods (especially after 2014), a certain correlation of the prices of the agricultural products between China and the U.S. can still be observed.

We next study the lead-leg relationship between the Chinese and the U.S. futures market and analyze the change of lead-leg order based on the three stages.

5. Empirical results and analysis

5.1. The lead-lag relationship between China and the U.S. agricultural commodity futures return

Taking the standardized return series $R_c(t)$ and $R_a(t)$ of the Chinese and U.S. agricultural futures as $X(t_1)$ and $Y(t_2)$. The positive (negative) optimal thermal average $\langle x(t) \rangle > 0 (< 0)$ means that the U.S. (China) agricultural commodity futures return leads that in China (the U.S.). The value of $\langle x(t) \rangle$ represents the order of the lead-lag relationship between China and the U.S.. Considering that the daily prices of an agricultural commodity contains great jumps and large quantity of noises, especially among international markets, we compare the results of the TOP method with those from the correlation coefficient method and find that the lead-lag order is more accurate when $T = 10$.

We therefore set $T = 10$ to test the lead-lag relationship between agricultural futures returns between China and the U.S. agricultural futures returns.

Figure 3: (Color online) Average lead-lag order between China and U.S. soybean futures return.(Unit: day)

Figure 4: (Color online) Average lead-lag order between China and U.S. corn futures return. (Unit: day)

Figure 5: (Color online) Average lead-lag order between China and U.S. wheat futures return.(Unit: day)

Figs.3 - 5 present the average optimal thermal lead-lag order between the futures returns of China and the U.S.. The vertical axis is the lead-lag order when $T = 10$. Overall, for soybean futures return, the U.S. market leads the Chinese market for about 4 days for most of the time before 2014. However, after 2014, China surprisingly began to lead the U.S.. For corn and wheat futures return, China led the U.S. for almost the whole sampling period.

During the first stage (2008.11-2010.08), the optimal thermal path curves for the three species of agricultural futures are relatively stable and the lead (lag) order are all small. The agricultural futures prices of China and the U.S. began to adjust and showed a strong correlation after the financial crisis in 2008. Corn and wheat futures return in China led the U.S. for 5 and 6 days respectively.

During the second stage (2010.09-2013.10), the optimal thermal average order for the three species of agricultural futures began to change significantly. For soybean, the lead-lag curve is relatively stable during the whole sampling period except at point A (around July6, 2013).

During the third stage (2013.11-2015.09), China led the U.S. for the return of the three species of the agricultural futures. In particular, the lead-lag direction between the Chinese and U.S. soybean futures prices reversed since 2014 (point B, Fig.3.). The main reason is that since 2014, China has begun to implement the target price subsidy system on soybean, replacing the previous purchase and storage policy. This policy promoted the price liberalization and had a significant impact on the soybean market as well as the whole agricultural commodity markets.

Around July 2013, the lead-lag relationship for the three species of agricultural futures between China and the U.S. had unusual spikes (point A, A', A''). This is mainly due to the fact that on Jun.13, 2013, Argentina, as one of the world's most important exporters of agricultural products claimed that it would suspend exporting crops for about one week to protest the government trade policy, which exerted a great impact on the U.S. soybean price as well as corn and wheat. Moreover, the trading volume of soybean exporting from the U.S. to China has decreased sharply after the implementation of target price subsidy policy in China, which had a tremendous effect on the lead-lag relationship between the two countries.

5.2. The lead-lag relationship between the Chinese and U.S. agricultural futures price volatilities

To further study the linkage between the Chinese and U.S. agricultural markets, we will perform a study on the lead-lag relationship between the Chinese and U.S. agricultural futures price volatilities in this section. The temperature parameter T remains to be 10, in analogy with our study on agriculture futures return in section 5.1.

There are different definitions of volatility in previous studies. Motivated by Bansal et al. [40], we here define the volatility using 5-trading day overlapping returns:

$$\sigma_t = \ln \sqrt{R_t^2 + R_{t+1}^2 + R_{t+2}^2 + R_{t+3}^2 + R_{t+4}^2} \quad (6)$$

where R_t is the daily returns of agriculture futures. We focus on the rolling weekly periods since this approach could mitigate some of the noises that would not be eliminated in a daily-volatility analysis. We evaluate rolling periods since this approach can more likely capture the return dynamics when using the available data and the benefit of using overlapping periods is quantified by Richardson and Smith [41].

Figs. 6 - 8 depict the lead-lag relationship between Chinese and U.S. soybean, corn and wheat futures price volatilities respectively.

Figure 6: (Color online) The optimal thermal average order between Chinese and U.S. soybean futures price volatilities (Unit: Day)

Figure 7: (Color online) The optimal thermal average order between Chinese and U.S. corn futures price volatilities (Unit: Day)

Figure 8: (Color online) The optimal thermal average order between Chinese and U.S. wheat futures price volatilities (Unit: Day)

From the TOP curves in Figs. 6 - 8, one can see that for the soybean futures price volatility, the U.S. leads China for about 8 days in almost the whole sampling period, in particular between 2011 and 2013. For the corn futures price volatility, the lead-lag relationship varies during our sampling period, China and the U.S. led each other for some time. For the wheat futures price volatility, the U.S. led China for most of the time. We summarize as follows.

During the first stage (2008.11-2010.08), the period when the financial crisis just ended and the agricultural futures prices began to adjust quickly. The lead-lag orders between Chinese and U.S. agricultural futures price volatilities of the three varieties were all relatively small, which indicate that the volatilities between the two countries transmitted fast during this period. However, the lead-lag order and direction differed for different species.

During the second stage (2010.09-2013.10), the optimal thermal average showed violent fluctuations and the lead-lag order of the three species enlarged when compared to the first stage. This is mainly due to the fact that during this period the large fluctuations appeared for the agricultural commodity prices in China and the U.S., which led to the unstable lead-lag order.

During the third stage (2013.11-2015.09), China began to lead the U.S. for soybean and corn. For wheat, the U.S. still led China, similar to the two previous stages. Furthermore, it can be clearly observed that the volatility transmission of wheat futures price between China and the U.S. took more time than soybean, which suggests that China's soybean market is more closely linked to the U.S. and the price information transmission between the Chinese and U.S. soybean markets conducts more rapidly than the wheat market.

6. Conclusion

By examining the lead-lag relationship between the Chinese and U.S. agricultural futures returns and price volatilities, we find that

- (1) For the lead-lag relationship between the Chinese and U.S. agricultural futures returns, agricultural commodities that are less subject to government regulations and trade restrictions in China (such as soybean) are more easily influenced by the U.S. markets. For the agricultural species that are heavily regulated and subsidized such as corn and wheat, China appears to lead the U.S. in our sampling period.

- (2) Although the U.S. led China most of the time for all the three species in agricultural futures price volatility, the volatility transmission of wheat between the Chinese and U.S. markets takes longer time than soybean and corn. The main reason is because China's wheat market is regulated by national policies, and the change of wheat price caused by exterior influence is not as sensitive as soybean and corn.
- (3) Since 2014, China has carried out the target price subsidy policy, taking cotton and soybean as pilots at the beginning, which had a tremendous impact on the lead-lag relationship between the U.S. and Chinese soybean markets. At the same time, the lead-lag order between the U.S. and Chinese corn prices as well as wheat also began to expand significantly, indicating that the contagion effect between different agricultural market prices does exist due to the transmission of information between different markets, and the agricultural futures prices of different species can to some extent influence each other.

In conclusion, the lead-lag relationship between the Chinese and U.S. agricultural commodity futures differs in different economic stages and policy situations. Relatively mature species of futures such as soybean are closely linked to the world markets, and thus have a certain impact on the international commodity futures prices. Policy-dominant species such as wheat suffer from severe government regulations, hence their domestic market prices are relatively isolated from the international markets.

From the above analysis, we conclude that the formulation and implementation of government policies play an extremely important role on agricultural commodity futures prices, and can even change the lead-lag relationship between the markets in the U.S. and China. As a rising economic power as well as a leading agricultural nation, China's agricultural production, consumption and volume of trade are all highly ranked in the world. It has the potential to be the world food price center and the ability of pricing in international commodity prices, rather than passive acceptance. National authorities should pay attention to policy making to guide the development and normal operation of China's agricultural market. Furthermore, one should pay more attention to China's agricultural products market pricing power in international markets. On one hand, we should protect the domestic agricultural market by fighting against illegal speculative funds from abroad. On the other hand, reducing government intervention in agricultural futures markets appropriately is necessary in order to make the Chinese agricultural commodity pricing power stronger, and to enhance the influence and competitiveness of the Chinese commodity futures markets among the international markets.

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