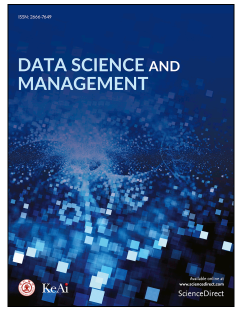
Journal Pre-proof



The dynamics of price discovery between US and Chinese soybean market: A wavelet approach to understanding the effects of Sino-U.S. trade conflict and COVID-19 pandemic

Xiang Gao, Apicha Insuwan, Ziran Li, Shuairu Tian

PII: S2666-7649(23)00047-4

DOI: https://doi.org/10.1016/j.dsm.2023.10.004

Reference: DSM 76

To appear in: *Data Science and Management*

Received Date: 15 May 2023

Revised Date: 8 October 2023

Accepted Date: 9 October 2023

Please cite this article as: Gao, X., Insuwan, A., Li, Z., Tian, S., The dynamics of price discovery between US and Chinese soybean market: A wavelet approach to understanding the effects of Sino-U.S. trade conflict and COVID-19 pandemic, *Data Science and Management* (2023), doi: https://doi.org/10.1016/j.dsm.2023.10.004.

The dynamics of price discovery between US and Chinese soybean market: A wavelet approach to understanding the effects of Sino-U.S. trade conflict and COVID-19 pandemic

Xiang GAO, Apicha INSUWAN, Ziran LI, and Shuairu TIAN

Xiang GAO, Professor of Finance
Research Center of Finance, Shanghai Business School, Shanghai, China.
gaoxiang@sbs.edu.cn
2271 West Zhong Shan Road, Shanghai 200235, China
(86) 21-64870020

Apicha INSUWAN, President
Payap University, Chiang Mai, Thailand.
aphicha@payap.ac.th
Payap University, Chiang Mai 50000, Thailand
(66) 53851478

Ziran LI, Associate Professor of Finance
School of Public Finance and Taxation, Southwestern University of Finance and Economics
lizr@swufe.edu.cn
555, Liutai Avenue, Wenjiang District, Chengdu, Sichuan 611130, China
(86) 28-87092239

Shuairu TIAN, Assistant Professor of Finance
Research Center of Finance, Shanghai Business School, Shanghai, China.
tiansr@sbs.edu.cn
2271 West Zhong Shan Road, Shanghai 200235, China
(86) 21-64870020

The dynamics of price discovery between US and Chinese soybean markets: A wavelet approach to understanding the effects of the Sino–U.S. trade conflict and the COVID-19 pandemic

Abstract: During geopolitical crises, the price stability of agricultural commodities is critical for national security. Understanding the dynamics of pricing power between the United States and China and how it varies over time can help smaller nations navigate unpredictable moments. This study uses a unified framework and wavelet approach to examine soybean price discovery in United States and China from the standpoints of price interdependence and information flows. We begin by illustrating the integrated link between the soybean futures markets in United States and China, which includes multiple structural breaks. The pricing difference between the two nations acts as the primary information spillover route for their integrated relationship. Furthermore, we show that the direction and degree of information spillover change dramatically in proportion to the strength of United States–Chinese soybean interaction. Finally, we find that China's recent retaliatory tax on U.S. soybeans gave the Chinese market a more powerful position in soybean futures price discovery. After the first-stage trade deal was reached, and during the epidemic phase of the coronavirus pandemic, the pricing power of United States soybean market showed no signs of full recovery.

Keywords: soybean markets; price discovery; wavelet; trade conflict; COVID-19 pandemic.

1. Introduction

The United States and China are the two largest producers, consumers, and traders of soybeans worldwide. Understanding the dynamics of soybean price discovery and the transmission of information between major markets is essential for market stability. As shown in Figure 1, China's soybean imports have grown dramatically over the last 30 years and now account for approximately 70% of the global soybean trade. In 2017, United States exported 59 million metric tons of soybeans, most of which went to China. Both United States and China have active soybean futures markets, and U.S. soybean futures have long been viewed as benchmarks for pricing on other exchanges. Market participants and policymakers must understand this spatial link between soybean prices in terms of how market integration and information spillovers affect policy effectiveness, especially since United States soybean export market share appears to be declining.

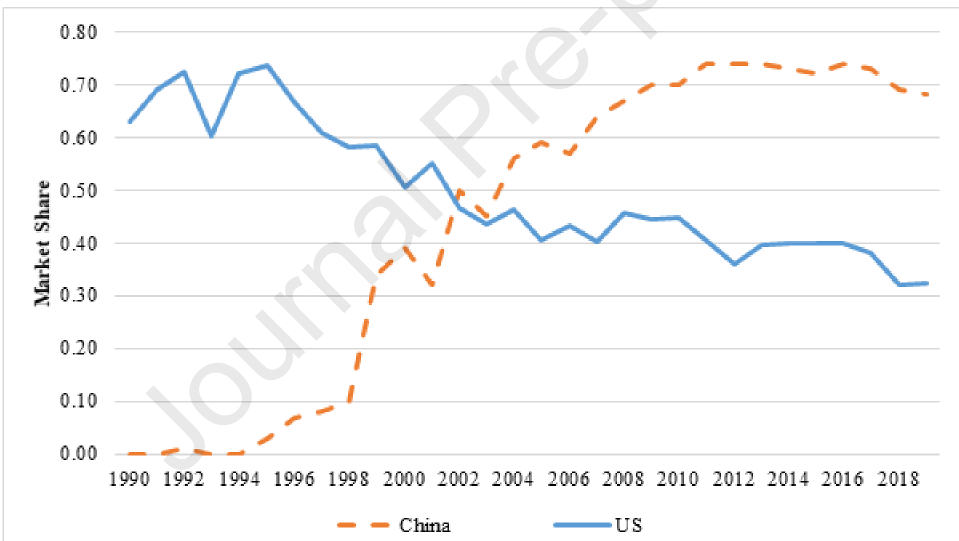


Fig.1. Annual Chinese imports and U.S. exports as a percentage of total global soybean trade, 1990-2019.

Data source: United States Department of Agriculture, Foreign Agricultural Service. https://www.fas.usda.gov/data.

The objective of this study was to investigate how price interdependence and directional information spillover between United States and Chinese soybean markets vary over time and across frequencies. Prior studies analyzing price relationships for agricultural futures typically relied on cointegration, error correction models, and Granger causality tests. However, these methods are sensitive to the sample periods and assume stable relationships. This study applied an innovative wavelet analysis approach to examine United States–China soybean price linkage. Wavelets can deal with nonstationarity and analyze correlations in both the time and frequency domains. This allows for the characterization of dynamic and cyclical relationships missed by conventional techniques.

Regarding the soybean market, recent studies have focused on contracting price adjustments that incorporate different forms of market (Chen et al., 2021; Hao et al., 2021; Li and Xiong, 2021), the high-frequency dimension (Wang et al., 2022; Zhou et al., 2023), and the one-way impact of trade wars (Bandyopadhyay and Rajib, 2023). However, we are among the first to analyze the extent of soybean price interdependence in two-sided markets and the structure of directional information spillovers over a 10-year period and across a range of frequencies. We examined the role of the price difference between the two futures markets as a possible information transmission channel. Finally, we examined the impacts of recent trade conflicts, trade agreements, and the COVID-19 pandemic on United States–China soybean price relationship.

How do the correlations and lead-lag relationships between U.S. and Chinese soybean futures prices evolve across short-, medium-, and long-term horizons? What role does the price difference between two countries play in transmitting information and guiding price discovery? How have recent major events such as United States–China trade war and COVID-19 impacted soybean price dynamics and information spillovers? In this study, we addressed these research questions.

This study used wavelet analysis to examine the dynamics of soybean price discovery and information transmission between United States and Chinese futures markets. We found that United States–China soybean price correlations varied over time and across short-, medium-, and long-term horizons. The relative price difference was identified as a key information channel. An analysis of the subperiods revealed that China gained more price discovery influence during the 2018 trade war tariff, but United States largely resumed dominance after the 2020 trade agreement. This study also examined the impact of COVID-19. Overall, this study demonstrates the advantages of wavelets in agricultural futures price analysis. The findings provide a nuanced characterization of United States–China soybean price relationship with implications for academic researchers, market participants, and policymakers.

This study makes several contributions to the existing literature. First, examining United States and China soybean price linkages using wavelets provides new insights compared to past literature that only focused on stable long-run relationships. Second, we considered the differences in trading hours in international markets and showed that short-term prices in international soybean markets are significantly correlated. Third, this study offers timely evidence of the influence of recent trade-policy shifts and global shocks on the vital global commodity market. Finally, we introduced new indicators, namely phase difference ratios, to investigate information spillovers conditional on the frequencies and degrees of strength of the relationship between two markets.

The remainder of this paper is organized as follows: Section 2 reviews the relevant literature. Section 3 introduces the wavelet methodology, effective price correlation, and causation measures. Sections 4 and 5 describe the data set and report the empirical results, respectively. Section 6 discusses the theoretical and methodological contributions and practical implications for academics, policymakers, and practitioners. Section 7 concludes.

2. Literature review

Many studies have examined the price-discovery mechanisms of futures contracts for the same underlying commodities on different exchanges. The consensus is that markets with higher liquidity tend to attract more trading activity, but traders sometimes trade liquidity to ensure hedging effectiveness (Silber, 1981). To investigate whether and how information is transmitted from one market to another, Granger causality (Granger, 1969) is often used to test the direction of information flow. Further, cointegration methods (Granger, 1981) have become the most popular tools for studying the joint relationships among multiple price series. An error correction model was also developed to formalize the data-generating processes of cointegration relationships (Engle and Granger, 1987). These methods are well suited for exploring price discovery in multiple areas of agricultural commodities. The economic intuition behind the co-integration relationship is the law of one price (Ardeni, 1989).

More recent literature focuses on price discovery between United States and Chinese soybean futures markets, as China has become an essential player in the international soybean market. Using an AR-GARCH model, Fung, Leung, and Xu (2003) found that United States and Chinese soybean futures markets are somewhat segmented, with United States playing a dominant role in information transmission. Liu and An (2011) examined the price spillover between U.S. and Chinese soybean futures from 2004 to 2009. They also demonstrated the importance of the two markets' trading hours in identifying price transmission patterns. Christofoletti, Silva, and Mattos (2012) studied soybean futures prices in United States, China, Brazil, and Argentina using a vector error correction model based on daily data from 2002 to 2011 and confirmed the leading role of United States in the world price discovery of soybeans. Using a similar methodology, Han, Liang, and Tang (2013) showed the existence of bidirectional causality between the Chicago Mercantile Exchange (CME) soybean futures returns and the returns of the Dalian Commodity Exchange (DCE) soybean futures traded in China from 2002 to 2011. Liu et al. (2015) used a GARCH model with a generalized error distribution and showed that information transmitted from the CME to the DCE's No. 1 soybean futures has weakened over time. Similarly, Merener (2015) concluded that supply-side shocks to soybeans outside United States have become more influential on CME soybean futures prices. However, Li and Hayes (2017) showed unidirectional causality between U.S. soybean futures prices and Chinese No. 1 soybean futures prices. They also identified structural breaks in this price relationship when the direction of information spillover changed or became insignificant. These related soybean literatures are summarized in table 1.

These studies were based on Granger co-integration methods, which seem relatively sensitive to the specific data periods examined and unknown structural breaks. This calls for new tools to analyze soybean price discovery more comprehensively across major markets. Jiang et al. (2016) used a cross-quantilogram analysis to examine the price relationships of agricultural futures between United States and China over different quantiles of daily price returns. Janzen and Adjemian (2017) employed microstructural methods with intraday high-frequency data to identify the locations of wheat price discoveries in Chicago, Kansas City, Minneapolis, and Paris.

Although empirical wavelet methods have been frequently applied to other financial markets, they are relatively new in the context of commodity futures. Past applications include the examination of the relationship between stock returns and inflation (Gençay, Selçuk, and Whitcher, 2005); comovement among international stock returns (Rua and Nunes, 2009); economic growth cycles in major European countries (Rua, 2010); and the effects of oil prices on real exchange rates (Uddin et al., 2013). Joseph, Siodia, and Tiwari (2015) used wavelet analysis to study the relationship between the spot and futures prices of Indian commodity futures.

Kristoufek, Janda, and Zilberman (2016) studied the price comovement of ethanol and its related product prices in Brazil and United States, and Nigatu and Adjemian (2020) examined the cointegration relationships between United States and international agricultural markets for several agricultural commodities. In contrast to previous studies, they found that short-term prices are not correlated in major agricultural markets. However, the authors analyzed daily closing prices while ignoring the differences in international markets' trading hours. Guo et al. (2022) investigated the linkage of soybean, soybean oil, and soybean meal futures between United States and China and showed that the Chinese market was unilaterally influenced by United States market after 2018. Lence, Moschini, and Santeramo (2018) demonstrated that there is an "inactive" period during which no price adjustments take place. In this case, the inactive period is caused by trading-hour differences, during which one market is open and the other is closed. Therefore, it should not be viewed as evidence of inefficiency in price transmission. We accounted for this in our dataset construction and provide a detailed explanation in Section 4. To establish a bird's-eye view of our study's contributions to the extant literature, we tabulated the differences in methods and results between relevant previous studies and this study.

Table 1

Summary of related literatures

Study	Methodology	Main Findings	Consistency or not with this paper	Reason for inconsistency
Fung, Leung, and Xu (2003)	AR-GARCH model	U.S. dominates price discovery, markets somewhat segmented	Partly	Found U.S. dominance but did not examine time-varying relationships
Han, Liang, and Tang (2013)	Granger causality	Bidirectional causality between U.S. and Chinese prices	Partly	Evidence of two-way spillovers but did not consider different frequencies
Liu et al. (2015)	GARCH model	Information flow from U.S. to China weakened over time	Partly	Declining U.S. price influence aligns with trade war results in

				this study
Li and Hayes (2017)	Threshold cointegration	Unidirectional causality from U.S. to China	No	Contradicts our finding of bidirectional spillovers
Nigatu and Adjemian (2020)	Cointegration	No price correlation in the short term	Partly	Documented a greater high-frequency linkage than what was found in this study
Guo et al. (2022)	Error correction model	Bidirectional causality before trade war. Dominant role of U.S. market after trade war	No	Contradicts our finding of bidirectional spillovers after trade war in 2018
Bandyopadhyay and Rajib (2023)	Information leadership share model; ARDL model	Influence of U.S. market decline in the trade war; China gained influence during trade war when tariff imposed	Partly	Investigation focused on macro factors and sentiment

3. The wavelet method

3.1. Wavelet theory

The wavelet method was used to comprehensively evaluate soybean price discovery between United States and Chinese futures markets with less strict assumptions than traditional time-series techniques. The wavelet method does not require a specific predetermined relationship between variables as in regression models and does not impose assumptions on the distributional characteristics of the variables. This section briefly explains the theoretical foundation of the wavelet approach and its flexibility and comprehensiveness in decomposing future time series into wavelets.

3.1.1. Definition of a wavelet series

A wavelet series is a useful mathematical tool for extracting information from data. It consists of a set of wavelet functions that decompose data without gaps into different frequency components. Denote each wavelet function as $\psi_{\tau,s}(t)$:

$$(1) \qquad \psi_{\tau,s}(t) = \frac{1}{\sqrt{|s|}}\psi\left(\frac{t-\tau}{s}\right)$$

where s is a scaling factor that controls the width of the wavelet, which is inversely related to the data frequency. τ is a location parameter and $\frac{1}{\sqrt{|s|}}$ is used to normalize the wavelet variance to 1, i.e., $\left\|\psi_{\tau,s}\right\|^2 = 1$. This normalization enables the wavelets to be comparable across different scales. We chose the commonly used Morlet wavelet (Goupillaud et al., 1984) as the "mother" wavelet that defines the functional form for $\psi_{\tau,s}(t)$ in Equation (1):

$$(2) \qquad \psi^M(t) = \frac{1}{\pi^{1/4}}e^{i\omega_0 t}e^{-t^2/2}$$

where ω_0 denotes the central frequency. We followed the literature by setting ω_0 equal to 6, which enables a balance between time and frequency localization (Grinsted et al., 2004; Rua and Nunes, 2009).

3.1.2. Continuous wavelet transform

This study used the continuous wavelet transform (CWT), which is efficient and flexible and allows the translation and scale parameters to vary continuously. Applying the CWT to a time series $y(t)$ yields

$$(3) \qquad W_{y;\psi}(\tau,s) = \int_{-\infty}^{\infty} y(t)\frac{1}{\sqrt{|s|}}\psi^*\left(\frac{t-\tau}{s}\right)dt$$

where superscript * denotes a complex conjugate defined in mathematics as a number with equal real and imaginary parts. The time series $y(t)$ can then be reconstructed from the inverse of the CWT $W_{y;\psi}(\tau,s)$, as follows:

$$(4) \qquad y(t) = \frac{1}{C_\psi}\int_0^\infty\left[\int_{-\infty}^{\infty} W_{y;\psi}(\tau,s)\,\psi_{\tau,s}(t)d\tau\right]\frac{ds}{s^2}$$

The energy of this time series $y(t)$ can then be written as

$$(5) \qquad \|y\|^2 = \frac{1}{C_\psi}\int_0^\infty\left[\int_{-\infty}^{\infty}\left|W_{y;\psi}(\tau,s)\right|^2 d\tau\right]\frac{ds}{s^2}$$

where $\left|W_{y;\psi}(\tau,s)\right|^2$ is the wavelet power spectrum (WPS), which serves as a proxy for the local variance of $y(t)$ across scales.

Grinsted et al. (2004) tested the statistical significance of a time-series generating process given by an AR (1) stationary process with a certain background power spectrum. They found that the local WPS distribution is given as follows:

$$(6) \qquad D\left(\frac{\left|W_{y,t}(s)\right|^2}{\sigma_y^2} < p\right) = \frac{1}{2} P_f y^2$$

where the so-called background power spectrum P_f denotes the mean spectrum at the Fourier frequency f, which in turn roughly equals the reciprocal of the wavelet scale s (i.e., $f \approx 1/s$).

3.1.3. Cross-wavelet transform, wavelet coherence, and phase difference

To study the interaction between soybean futures prices in United States and China, we extended the above wavelet setup to construct three wavelet measures of the relationships between the two time series. Hudgins et al. (1993) defined the CWT of two sequences, $x(t)$ and $y(t)$, as $W_{xy} = W_x W_y{}^*$, where W_x and W_y are the respective wavelet transforms of $x(t)$ and $y(t)$, and $W_y{}^*$ is the complex conjugate of W_y. The cross-wavelet power (XWP), which describes the high common-power area in the time-frequency space, is given by

$$(7) \qquad (XWP)_{xy} = \left|W_{xy}\right|$$

The XWP provides information on the scale-by-scale local covariance. Torrence and Compo (1998) derived a density function for the XWP:

$$(8) \qquad D\left(\frac{|W_{x,t}(s)W_{y,t}^*(s)|}{\sigma_x \sigma_y} < p\right) = \frac{Z_v(p)}{v}\sqrt{P_f^x P_f^y}$$

where P_f^x and P_f^y are the background power spectra corresponding to x and y, respectively, and $Z_v(p)$ is the confidence level with a given probability p for the probability density function characterized by the square root of the product of two χ^2 distributions.

Another measure of the relationship between two series is wavelet coherence, which is defined as the ratio of the cross-spectrum to the product of each series spectrum. Rua and Nunes (2009) showed that the wavelet squared coherence (WTC) can be written as

$$(9) \qquad R_{xy}{}^2 = \frac{|S(s^{-1}W_{xy})|^2}{S(s^{-1}|W_x|^2)S(s^{-1}|W_y|^2)}$$

where S is a smoothing operator in both time and scale, which ensures that the smoothed WTC returns a value between zero and one, i.e., $0 \leq R_{xy}{}^2 \leq 1$. Specifically, $R_{xy}{}^2$ close to zero indicates a weak relationship between x and y, while close to one suggests a strong relationship. We followed Grinsted et al. (2004) and used a Monte Carlo simulation to test the statistical significance of wavelet-squared coherence.

Our last measure of the phase difference is used to show whether the two series are positively or negatively correlated. Mathematically, the definition of phase difference ϕ_{xy} is defined as follows:

$$(10) \quad \phi_{xy} = \arctan\left(\frac{\Im\{S(s^{-1}W_{xy})\}}{\Re\{S(s^{-1}W_{xy})\}}\right), with\ \phi_{xy} \in [-\pi, \pi]$$

where $\Im$ and $\Re$ denote the imaginary and real parts of the CWT between x and y, respectively. So, the two series are said to move in phase (positively correlated) if $\phi_{xy} \in \left(-\frac{\pi}{2}, 0\right) \cup \left(0, \frac{\pi}{2}\right)$. Conditional on their moving in phase, $\phi_{xy} \in \left(0, \frac{\pi}{2}\right)$ means that y leads x and $\phi_{xy} \in \left(-\frac{\pi}{2}, 0\right)$ indicates that x leads y. Similarly, if $\phi_{xy} \in \left(-\pi, -\frac{\pi}{2}\right) \cup \left(\frac{\pi}{2}, \pi\right)$, the two series move in an anti-phase relationship—i.e., negatively correlated—and x leads y in this relationship when $\phi_{xy} \in \left(\frac{\pi}{2}, \pi\right)$, and vice versa.

3.2. Information spillover indicators for price discovery: Phase difference ratio

A wavelet phase difference is used to detect the information spillover between two series (Grinsted et al., 2004; Tiwari et al., 2013; Jiang et al., 2015). For a given frequency domain captured by the scale parameter s, one can define the conditional phase difference ratio (CPDR) as

$$(11) \quad CPDR_{x \to y|s} = \frac{1}{T}\sum_{t=1}^{T} I\left(\phi_{xy,t|s} \in \left(-\frac{\pi}{2}, 0\right) \cup \left(\frac{\pi}{2}, \pi\right)\right)$$

where x→y denotes that the information transmits from the market of x to the market of y. T denotes the sample period and I is an indicator variable. We can further condition the equation on two positively correlated series:

$$(12) \quad CPDR_{x \to y|s,in\ phase} = \frac{1}{T}\sum_{t=1}^{T} I\left(\phi_{xy,t|s} \in \left(-\frac{\pi}{2}, 0\right)\right)$$

A large value of the conditional phase difference ratio implies that the other market transmits a significant amount of information, given the defined direction of transmission and scale. We can also condition the phase difference ratio on the wavelet-squared coherence, ${R_{xy}}^2$ for a given interval:

$$(13) \quad CPDR_{x \to y|s,in\ phase,{R_{xy|s}}^2(a,b)} = \frac{1}{\sum_{t=1}^{T} I\left({R_{xy,t|s}}^2 \in F_{{R_{xy|s}}^2}(a,b)\right)} \times \sum_{t=1}^{T} I\left(\phi_{xy,t|s} \in \left(-\frac{\pi}{2}, 0\right), {R_{xy,t|s}}^2 \in F_{{R_{xy|s}}^2}(a,b)\right)$$

where $F_{R_{xy|s}^2}$ is the distribution function of the wavelet-squared coherence ${R_{xy,t|s}}^2$ conditional on scale s. Equation (13) was used to investigate the information spillover conditional on various degrees of strength of the relationship between the two series. For example, to examine the information transmission structure between two markets when their correlation is at the strongest 10% for a given frequency, we set the parameter range (a, b) equal to $(0.9, 1)$.

4. Data

United States price was sourced from the nearest-to-maturity soybean futures contracts traded on the CME and was rolled on the first trading day of the new maturity month. The Chinese market offers two types of soybean futures contracts listed on the DCE; we used the No. 1 soybean futures contracts because of their higher liquidity (Han, Liang, and Tang, 2013). Contract No. 1 is specified for non-GMO (genetically modified) soybeans, and contract No. 2 may contain GMO soybean crops that are mainly imported for crushing. Soybean marketing firms in China prefer to use No. 1 soybean futures for hedging because they can improve hedging effectiveness by reducing the basis risk. Unlike United States, where front-month contracts are traded most actively, soybean contracts in China within three months of maturities are the most liquid ones, as measured by open interest. Thus, we followed the financial practitioners' practice of using the so-called "dominant" contract, which is constructed by rolling into the most liquid contract that is within three months of maturity. We converted the quotation on DCE-traded soybean prices into U.S. dollars per bushel using spot exchange rates for comparability.

We also needed to adjust for the time differences between the two markets, as Dalian is 12 hours (13 hours when Daylight Saving Time is in effect) ahead of Chicago. The DCE also has a shorter trading period than the CME, and U.S. soybean futures are always traded as long as their Chinese counterparts' markets are open. To align the two price series as they occur concurrently, we divided the 24-hour daily return (close-to-close return) into overnight return (i.e., close-to-open return) and trading time return (i.e., open-to-close return). We then matched the trading time return in China with the overnight return in United States that ends on the same calendar day. Panel A of Fig. 2 provides a graphical illustration of this matching. Our sample period spanned January 2010 to August 2020, with 2,486 trading days, excluding non-open days and holidays, and contained 4,972 observations. It is worth noting that China started night trading of soybean futures in 2015. This is illustrated in Panel B of Figure 2. Although the introduction of night trading in China did not affect how the two series were matched, the synchronicity of the two markets became stronger. In the next section, we examine the possible impact of China's night trading on price spillovers. Finally, we constructed a return series of the price difference, which was equal to the soybean futures price in China minus that in United States This treatment is analogous to the co-integration method, which tests whether the same underlying economic forces partly govern the two prices.

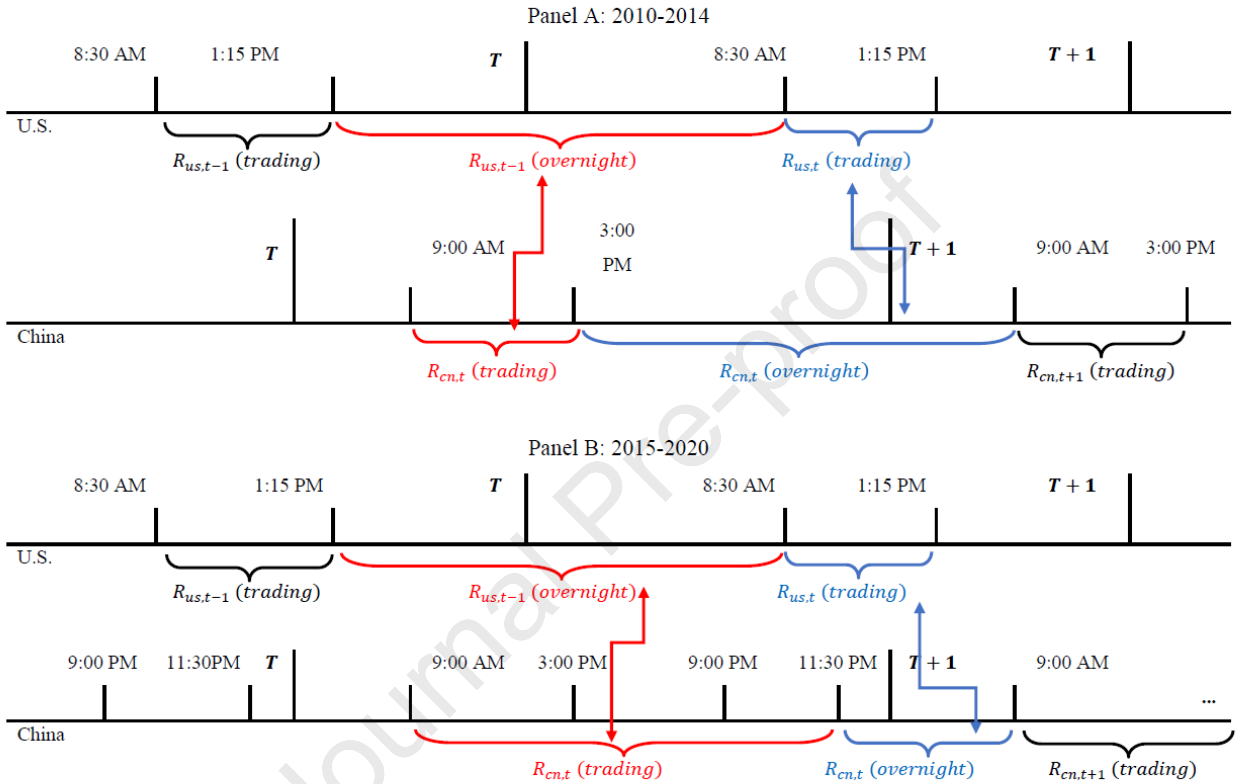


Fig. 2. Market trading hours in DCE (China) and CME (U.S.) markets.

Note: Time series for U.S. and Chinese soybean returns are constructed using both trading time and overnight returns. Trading time returns of Chinese markets are matched with overnight returns of U.S. markets, and vice versa.

The descriptive statistics for these return series are presented in Table 2. Neither series was distributed symmetrically at higher moments, which is evident from the large skewness and kurtosis estimates. The Jaque-Bera test rejected the normality assumption for all return distributions. This rejection supported our adoption of the wavelet method, which is suitable for analyzing price spikes and volatility jumps in data without making a priori distributional assumptions.

Table 2

Summary statistics of US and Chinese soybean futures returns, and price difference return between the two.

Variables	Mean	Std. Dev	Skew	Kurtosis	Max	Min	median	J-B
US	-5.45E-06	0.010	-0.946	16.284	0.065	-0.121	-1.74E-04	<0.001
CN	2.71E-05	0.008	0.330	17.746	0.099	-0.069	1.31E-04	<0.001
DIFF	7.46E-05	0.029	0.659	13.439	0.282	-0.184	-2.15E-04	<0.001

Note: US, CN, and DIFF denote returns of US soybean futures and Chinese soybean futures and their price differences, respectively. J-B represents the p-value for the Jarque-Bera normality test for returns distributions.

Figure 3(a) and (b) plot the price levels, daily returns, and wavelet power spectra for U.S. and Chinese soybean futures, respectively. As expected, Chinese No. 1 soybean futures commanded a premium over U.S. futures. This is because the Chinese contracts specified non-GMO soybeans. To some extent, the CME and DCE price series of futures contracts were correlated with visual inspection. Their higher volatility periods also seemed to coincide in large part before 2015, as illustrated by their respective wavelet power spectra; that is, the irregular black spots tended to cluster at approximately the same positions. Figure 3(c) plots the same set of figures for United States–Chinese soybean price difference, which seems to share high-volatility periods with the two markets, suggesting that the two price series do not comove strongly enough to cancel out price jumps. Consequently, the relative price movements contain additional information.

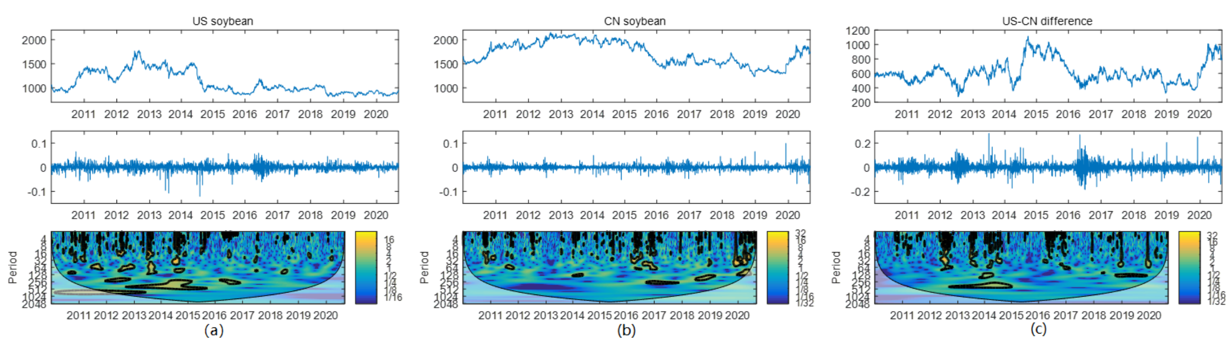


Fig. 3. Price levels, price returns, and wavelet power spectrum for US and Chinese soybean futures and changes in their price difference.

5. Empirical results

In this section, the following indicators are used to address the comprehensive relationship between United States and Chinese soybean markets.

(1) Wavelet coherence: This measures the strength of the relationship between two time series (U.S. and Chinese soybean futures prices) across different frequencies. It is used to analyze how the correlation between the two markets changes over time and across short-, medium-, and long-term frequencies.

(2) Phase difference: This indicates whether the two series are positively or negatively correlated, and the potential leads/lags between them. It estimates the direction of information flow and price discovery between two markets.

(3) Conditional phase difference ratio: This quantifies the relative importance of United States versus China in price discovery, conditional on the time period, frequency, and coherence strength. This approach provides a more nuanced view of bidirectional spillovers.

The main reason for using these wavelet-based indicators is that they allow us to analyze both the time and frequency domains together under one unified framework. This analysis provides a more complete picture than typical time-series methods such as vector autoregressive models. Wavelet tools do not require strict assumptions regarding the stationarity or distribution specifications. They are robust to the structural breaks and regime changes that potentially exist in these relationships.

Given China's rising importance in the global soybean market, being able to estimate time-varying and frequency-dependent price linkages with United States provides valuable economic insights. Wavelet indicators help quantify the lead-lag and correlation structure that may be obscured when looking only at aggregate relationships. They are particularly useful in agricultural commodities markets, which are globally connected but subject to policy shocks and volatility.

Table 3 presents the means and standard deviations of both the wavelet coherence and phase difference across scales, measuring the direction and strength of the price correlations. A larger scale indicates a lower frequency. Panel A depicts the relationship between U.S. and Chinese soybean futures returns. Panels B and C report the estimated coherence for the log differences of the two countries' price series when matching with U.S. soybean futures returns and Chinese soybean futures returns. Clearly, the estimated coherence is the strongest in D1 for all pairs, whereas the standard deviations remain relatively stable. The return series in one country's market is more closely correlated with the intercountry price difference series than with the return series in the other country's market. These findings suggest significant short-term arbitrage opportunities in international soybean markets by correctly predicting relative price levels. However, the phase difference estimates are statistically insignificant, indicating that the direction of information spillovers varies over time and frequencies.

Table 3

Coherence and phase difference estimates.

Scale			D1	D2	D3	D4	D5	D6
Panel A US-CN	Coherence	Mean	0.49	0.38	0.40	0.43	0.43	0.45
		Std	0.27	0.18	0.19	0.19	0.20	0.20
	Phase	Mean	-0.09	-0.09	-0.16	-0.15	-0.25	-0.04
		Std	1.78	0.99	0.85	0.79	0.79	0.85
Panel B US-DIFF	Coherence	Mean	0.66	0.58	0.50	0.47	0.46	0.43
		Std	0.27	0.21	0.23	0.21	0.20	0.20
	Phase	Mean	-0.13	-0.16	-0.32	-0.22	-0.43	0.03
		Std	2.42	1.43	1.30	1.33	1.21	1.29
Panel C CN-DIFF	Coherence	Mean	0.70	0.65	0.64	0.58	0.60	0.61
		Std	0.27	0.23	0.24	0.25	0.25	0.22
	Phase	Mean	-0.06	-0.07	-0.16	-0.07	-0.17	0.06
		Std	1.08	0.60	0.61	0.70	0.58	0.63

Note: US, CN, and DIFF denote the returns of US soybean futures and Chinese soybean futures and their price differences, respectively. D1, D2, D3, D4, D5, and D6 refer to 2-4, 4-8, 8-16, 16-32, 32-64, and 64-128 observations, respectively. Each trading day contains two observations.

Figure 4 visually depicts the dynamic relationship between United States and Chinese soybean markets, as well as their price differences. In all panels, the horizontal axis denotes the time dimension, the vertical axis plots the scale dimension, and the colors represent the relationship strength. The strength of the relationship between the two series weakens as the color shifts from bright yellow to dark blue. In addition, the thick black line enclosing the blue areas distinguishes the 5% significance portion of the WTC from the insignificant portion. Only areas inside the cone of influence can be interpreted as having economic meaning. The arrows represent the phase difference estimates and point to the right or left when both return series are in-phase (i.e., positively correlated) or anti-phase (i.e., negatively correlated).

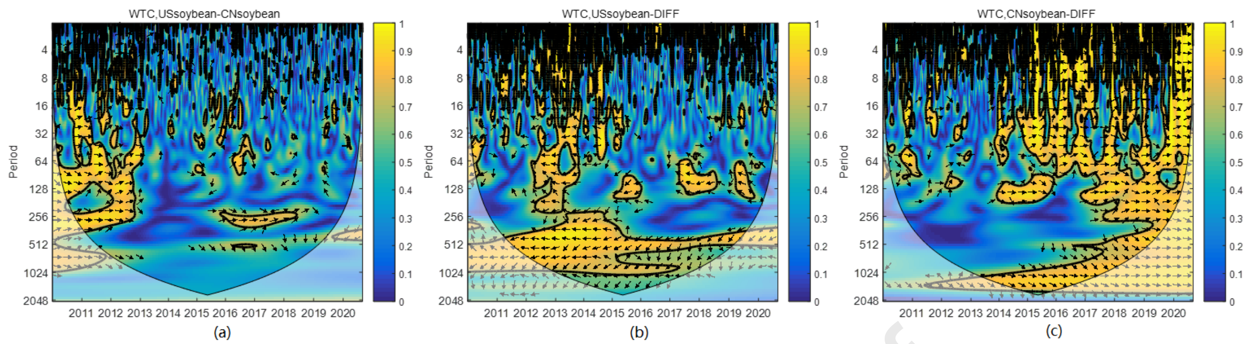


Fig. 4. Wavelet coherence between any two pairs of changes in the U.S. soybean futures price, China soybean futures price, and their price difference.

In Figure 4(a), it is immediately apparent that the daily returns of U.S. and Chinese soybean futures are closely correlated at higher frequencies, as indicated by the thick dark lines in the upper range of the graph. However, significant portions of the high-frequency area are disconnected, suggesting a time-varying short-term relationship between United States and Chinese soybean markets. As both the correlation and associated significance vary across different scales, this observation helps to explain why previous literature on U.S. and Chinese soybean futures often generated seemingly conflicting results, as they evaluated this relationship at different sample periods or frequencies. Along with Figure 4(b) and (c), we can see that both United States and Chinese soybean markets have stronger correlations with their price differences than with each other. Specifically, the bold black areas are distributed evenly in both the high- and low-frequency areas, suggesting that the two futures markets are connected and partially driven by price differences. Similarly, the significant portions are disconnected in the high-frequency area, indicating a frequently changing relationship between soybean prices and United States–China price difference in both markets. Such a fickle relationship may be attributed to short-term arbitrage, hedging, or behavioral reasons. By contrast, the significant portions in the mid- and long-term are continuous among these figures, suggesting stable long-term relationships. Figure 4(c) shows that the return series in China correlates more strongly with the price differences after 2019. At high frequencies, the relationships were maintained at a level that was more stable than that observed prior to 2019. This may be attributed to China's reliance on soybean imports from United States and its sensitivity to U.S.–China trade conflicts.

Looking at the arrows in the significant areas in Figure 4, most are pointing right. These results suggest positive correlations between United States and Chinese soybean prices as well as their price difference. In addition, these arrows indicate either up or down with similar possibilities, indicating the prevailing existence of bidirectional information spillovers.

5.1 Information spillover between United States and Chinese markets

In this subsection, we analyze the information spillover between United States and Chinese soybean futures markets. Note that the phase difference estimates in Table 3 are not statistically significant, owing to the higher variance. Therefore, we separated the phase difference ratios into four quadrants: either a positive (in-phase) or negative (anti-phase) relationship in terms of wavelet series correlations, and either a China-to-U.S. or U.S.-to-China relationship in terms of bidirectional information spillovers. Using Equation (12) in Table 4, we calculated and summarized the phase difference ratios in each quadrant, conditional on a range of scales. Because these ratios are based on counts of the observations in each cell, we interpreted them based on the relative importance (measured in percentages) of their corresponding quadrants at each frequency level rather than viewing them in terms of traditional statistical significance in an econometric sense.

As shown in Panel A of Table 4, the information flow between United States and Chinese soybean futures appears to be bidirectional and relatively symmetric, particularly at very high frequencies (e.g., D1), as the conditional phase difference ratios for the four quadrants are similar in terms of percentage share. Although United States and Chinese soybean futures return series are positively correlated most of the time, there are still a few sections in which the two markets interact negatively, especially in the relatively short term. These anomalies can be attributed to behavioral reasons such as mean reversion and overshooting in financial markets. Panels B and C of Table 4 illustrate the phase difference ratios between the price difference and each country. Note that the anti-phase indicates a positive (negative) correlation between the price difference and U.S. (Chinese) soybean futures.

Table 4

Conditional phase difference ratio estimates on the directions of correlations.

Scale	D1	D2	D3	D4	D5	D6

Panel A US-CN	Anti-phase US←CN	0.26	0.24	0.19	0.16	0.19	0.16
	In phase US←CN	0.25	0.25	0.27	0.32	0.26	0.34
	In phase US→CN	0.27	0.30	0.38	0.39	0.42	0.36
	Anti-phase US→CN	0.22	0.22	0.16	0.13	0.13	0.15
Panel B US-DIFF	Anti-phase US←DIFF	0.44	0.44	0.43	0.40	0.44	0.33
	In phase US←DIFF	0.09	0.09	0.12	0.12	0.12	0.14
	In phase US→DIFF	0.09	0.09	0.14	0.15	0.17	0.18
	Anti-phase US→DIFF	0.38	0.38	0.31	0.32	0.28	0.35
Panel C CN-DIFF	Anti-phase CN←DIFF	0.08	0.09	0.10	0.11	0.10	0.07
	In phase CN←DIFF	0.40	0.39	0.36	0.35	0.33	0.37
	In phase CN→DIFF	0.45	0.45	0.47	0.45	0.50	0.44
	Anti-phase CN→DIFF	0.08	0.07	0.07	0.10	0.07	0.11

Note: US, CN, and DIFF denote the returns of US soybean futures and Chinese soybean futures and their price differences, respectively. D1, D2, D3, D4, D5, and D6 refer to 2-4, 4-8, 8-16, 16-32, 32-64, and 64-128 observations, respectively.

Both United States and Chinese soybean markets are more likely to be positively correlated with price differences. Thus, our results imply that an increase (decrease) in soybean prices, irrespective of whether it occurs in U.S. or Chinese quotes, would increase (reduce) the spread between U.S. and Chinese prices due to inherent linkages between the three series. This result further suggests that relative price levels play a crucial role in driving U.S. soybean futures returns, and vice versa.

5.2 Conditional information spillover

We will show how the relative U.S.–China price level and returns on soybean futures affect each other. This subsection analyzes whether and to what extent such information spillover varies in response to the different strengths of the relationship between the two markets' returns, as well as to their correlations with the price difference. For this purpose, we computed and presented the results of the phase difference ratios conditional on four intervals of wavelet coherence ${R_{xy|s}}^2$: left tail $F_{{R_{xy|s}}^2}(0, 0.1)$, left body $F_{{R_{xy|s}}^2}(0.1, 0.5)$, right body $F_{{R_{xy|s}}^2}(0.5, 0.9)$, and right tail $F_{{R_{xy|s}}^2}(0.9, 1)$. The left and right tails indicate the weakest and strongest relationships, respectively. The phase difference ratios conditional on the wavelet coherence were calculated using Equation (13).

Table 5 reports the estimates of phase difference ratios conditioned on the quantiles of wavelet coherence between United States and Chinese soybean futures returns. In total, as the strength of their relationship is increasing (the coherence shifts up from Panels A to D), the two markets are more likely to be positively correlated (in phase). United States soybean market has an increasing influence on the Chinese soybean market, especially when their relationship is very strong. These results suggest that large shocks in soybean prices usually originate from the supply side (United States market), while the demand side (the Chinese market) is relatively stable. This phenomenon is intuitive: Chinese agricultural markets are heavily regulated by the government, and the major players in the agricultural industry are state-owned enterprises. As a result, we observed a less volatile soybean futures market in China than in United States, as shown in Table 2. On the other hand, in the short term (e.g., D1 and D2), a significant proportion of the two markets was negatively correlated, even when their relationship was the strongest, which suggests that market participants play significant roles in soybean pricing. However, in the mid to long term, supply and demand forces will dominate, as China is the world's largest importer of soybeans and United States is the largest soybean producer and exporter.

Table 5

Conditional phase difference ratio estimates on wavelet coherence quantiles between U.S. and Chinese soybean futures.

Scale	D1	D2	D3	D4	D5	D6
Panel A. Left tail of Coherence $F_{{R_{US-CN|s}}^2}(0, 0.1)$						
Anti-phase US←CN	0.27	0.24	0.27	0.27	0.31	0.29
In phase US←CN	0.26	0.25	0.25	0.21	0.19	0.23
In phase US→CN	0.21	0.24	0.22	0.21	0.16	0.17
Anti-phase US→CN	0.26	0.27	0.26	0.32	0.34	0.30
Panel B. Left part of Coherence $F_{{R_{US-CN|s}}^2}(0.1, 0.5)$						
Anti-phase US←CN	0.26	0.25	0.22	0.23	0.25	0.21
In phase US←CN	0.26	0.26	0.28	0.28	0.24	0.28

In phase US→CN	0.26	0.26	0.28	0.30	0.31	0.30
Anti-phase US→CN	0.22	0.24	0.21	0.19	0.19	0.21
Panel C. Right part of Coherence $F_{R_{US-CN\|s}{}^2}(0.5, 0.9)$						
Anti-phase US←CN	0.25	0.24	0.17	0.11	0.13	0.10
In phase US←CN	0.25	0.24	0.28	0.38	0.28	0.36
In phase US→CN	0.29	0.32	0.46	0.47	0.54	0.46
Anti-phase US→CN	0.21	0.20	0.10	0.05	0.05	0.08
Panel D. Right tail of Coherence $F_{R_{US-CN\|s}{}^2}(0.9, 1)$						
Anti-phase US←CN	0.24	0.20	0.09	0.03	0.03	0.01
In phase US←CN	0.22	0.22	0.21	0.34	0.34	0.35
In phase US→CN	0.30	0.42	0.66	0.63	0.63	0.62
Anti-phase US→CN	0.24	0.16	0.04	0.00	0.00	0.01

Note: US, CN, and DIFF denote the returns of US soybean futures and Chinese soybean futures and their price differences, respectively. D1, D2, D3, D4, D5, and D6 refer to 2-4, 4-8, 8-16, 16-32, 32-64, and 64-128 observations, respectively.

Tables 6 and 7 report the conditional phase difference ratios of the price difference with U.S. and Chinese soybean futures, respectively. As a basic interpretation of the results, we can state that, along with the increasingly strengthening relationship between the two markets, the price difference is more likely to be positively correlated with U.S. and Chinese soybean prices. These results suggest that an increase (decrease) in soybean prices would increase (decrease) United States–China soybean price difference. Unlike United States–China relationship in Table 5, the relationship between the price difference and United States and Chinese soybean markets displays a more definite feature. Negative correlations are rarely observed when the relationship is strong. This phenomenon indicates that price differences play a key role as a proxy for information spillovers between the two markets.

Table 6

Conditional phase difference ratio estimates on wavelet coherence quantiles between U.S. soybean futures and price difference.

Scale	D1	D2	D3	D4	D5	D6
Panel A. Left tail of Coherence $F_{R_{US-DIFF\|s}{}^2}(0, 0.1)$						
Anti-phase US←DIFF	0.22	0.19	0.22	0.20	0.22	0.19
In phase US←DIFF	0.31	0.31	0.32	0.30	0.33	0.30
In phase US→DIFF	0.27	0.29	0.29	0.28	0.23	0.36

Anti-phase US→DIFF	0.21	0.21	0.18	0.23	0.22	0.16
Panel B. Left part of Coherence $F_{R_{US-DIFF\|s}^2}(0.1, 0.5)$						
Anti-phase US←DIFF	0.38	0.39	0.30	0.32	0.31	0.29
In phase US←DIFF	0.14	0.12	0.18	0.18	0.17	0.17
In phase US→DIFF	0.13	0.13	0.22	0.21	0.23	0.26
Anti-phase US→DIFF	0.35	0.36	0.30	0.29	0.29	0.27
Panel C. Right part of Coherence $F_{R_{US-DIFF\|s}^2}(0.5, 0.9)$						
Anti-phase US←DIFF	0.52	0.53	0.54	0.47	0.57	0.40
In phase US←DIFF	0.02	0.02	0.04	0.05	0.04	0.10
In phase US→DIFF	0.02	0.02	0.07	0.10	0.12	0.09
Anti-phase US→DIFF	0.44	0.43	0.36	0.38	0.27	0.41
Panel D. Right tail of Coherence $F_{R_{US-DIFF\|s}^2}(0.9, 1)$						
Anti-phase US←DIFF	0.55	0.59	0.73	0.68	0.63	0.61
In phase US←DIFF	0.00	0.00	0.00	0.01	0.00	0.00
In phase US→DIFF	0.00	0.00	0.00	0.02	0.05	0.00
Anti-phase US→DIFF	0.45	0.41	0.26	0.30	0.32	0.39

Note: US, CN, and DIFF denote the returns of US soybean futures and Chinese soybean futures and their price differences, respectively. D1, D2, D3, D4, D5, and D6 refer to 2-4, 4-8, 8-16, 16-32, 32-64, and 64-128 observations, respectively.

Table 7

Conditional phase difference ratio estimates on wavelet coherence quantiles between China soybean futures and price difference

Scale	D1	D2	D3	D4	D5	D6
Panel A. Left tail of Coherence $F_{R_{CN-DIFF\|s}^2}(0, 0.1)$						
Anti-phase CN←DIFF	0.24	0.29	0.33	0.31	0.31	0.27
In phase CN←DIFF	0.21	0.20	0.19	0.22	0.21	0.19
In phase CN→DIFF	0.23	0.21	0.20	0.16	0.19	0.26
Anti-phase CN→DIFF	0.32	0.30	0.28	0.31	0.30	0.28
Panel B. Left part of Coherence $F_{R_{CN-DIFF\|s}^2}(0.1, 0.5)$						
Anti-phase CN←DIFF	0.12	0.13	0.14	0.16	0.16	0.11
In phase CN←DIFF	0.38	0.37	0.32	0.34	0.31	0.37
In phase CN→DIFF	0.40	0.41	0.45	0.34	0.43	0.36
Anti-phase CN→DIFF	0.10	0.10	0.08	0.16	0.10	0.17
Panel C. Right part of Coherence $F_{R_{CN-DIFF\|s}^2}(0.5, 0.9)$						
Anti-phase CN←DIFF	0.01	0.01	0.02	0.02	0.02	0.01

In phase CN←DIFF	0.43	0.45	0.41	0.41	0.37	0.40
In phase CN→DIFF	0.54	0.53	0.56	0.56	0.60	0.55
Anti-phase CN→DIFF	0.01	0.01	0.01	0.01	0.01	0.04
Panel D. Right tail of Coherence $F_{R_{CN-DIFF\|s}{}^2}(0.9, 1)$						
Anti-phase CN←DIFF	0.00	0.00	0.00	0.00	0.00	0.00
In phase CN←DIFF	0.51	0.46	0.50	0.27	0.31	0.45
In phase CN→DIFF	0.49	0.54	0.49	0.72	0.69	0.55
Anti-phase CN→DIFF	0.00	0.00	0.00	0.00	0.00	0.00

Note: US, CN, and DIFF denote the returns of US soybean futures and Chinese soybean futures and their price differences, respectively. D1, D2, D3, D4, D5, and D6 refer to 2-4, 4-8, 8-16, 16-32, 32-64, and 64-128 observations, respectively.

5.3 Impacts of the tariff, trade agreement, and COVID-19

The international trade of soybeans, which governs price relationships between countries, can occasionally be disrupted. In April 2018, China announced a retaliatory tariff on U.S. soybean exports, which was implemented in June 2018 and significantly disrupted U.S. soybean exports to China. In January 2020, United States and China reached a trade agreement. International trade between the two countries returned to normal, and the Chinese government guaranteed the import of more U.S. agricultural products. Moreover, the COVID-19 pandemic that began in January 2020 forced a lockdown in both countries and noticeably changed both supply and demand in soybean markets. Hence, it is of great interest to analyze the impact of these abnormal policies and the impact of the COVID-19 pandemic on United States–China soybean trade. For this purpose, we separated the entire sample into three sub-periods: pre-tariff, post-tariff, and post-trade agreement coinciding with the COVID-19 pandemic period.

Table 8 provides summary statistics for the three subsamples. It is worth noting that U.S. soybean volatility, proxied by the standard deviation, decreased and converged with that of China after the tariff. In agricultural markets, the volatility of futures returns is inversely correlated with the supply of the underlying commodities. After the imposition of the punitive tariff by China, United States was left with a large volume of soybeans for domestic use. This positive supply shock dampened the volatility of returns on U.S. futures contracts. This observation was corroborated by the decrease in kurtosis. The opposite is true for China, which had a soybean shortage. After the trade agreement was reached, we observed a reversal of this.

Table 8

Summary statistics for U.S. and Chinese soybean futures returns series and price difference series between the two during the three subsample periods.

Variable	Mean	Std. Dev	Skew	Kurtosis	Max	Min	median	J-B
Panel A. Pre-tariff period 2010.1.1~2018.4.4								
US	4.48E-06	0.011	-1.044	15.919	0.065	-0.121	-1.93E-04	<0.001
CN	1.73E-05	0.007	-0.139	10.412	0.049	-0.052	1.43E-04	<0.001
DIFF	3.72E-05	0.030	0.553	12.412	0.282	-0.184	-3.31E-04	<0.001
Panel B. Post-tariff period 2018.4.4~2020.1.15								
US	-8.50E-05	0.008	0.466	6.795	0.045	-0.030	0	<0.001
CN	-5.73E-06	0.008	3.578	43.373	0.099	-0.033	7.87E-05	<0.001
DIFF	1.15E-04	0.025	1.834	20.864	0.252	-0.118	2.07E-04	<0.001
Panel C. Post trade agreement and COVID-19 pandemic 2020.1.16~2020.8.31								
US	9.48E-05	0.007	-0.601	10.157	0.026	-0.043	0	<0.001
CN	2.51E-04	0.012	-1.009	12.506	0.047	-0.069	2.52E-04	<0.001
DIFF	4.48E-04	0.024	-0.758	10.541	0.095	-0.142	4.45E-04	<0.001

Note: US, CN, and DIFF denote the returns of US soybean futures and Chinese soybean futures and their price differences, respectively. D1, D2, D3, D4, D5, and D6 refer to 2-4, 4-8, 8-16, 16-32, 32-64, and 64-128 observations, respectively.

Table 9 presents estimates of pairwise coherence and phases between the three return series in the subsamples. In line with our expectations, the coherence, which measures the strength of the relationship between United States and Chinese soybean markets, weakened by around 30% on average across all frequencies after the tariff was imposed. In contrast, the relationship strength of the price difference with U.S. soybean futures returns remained relatively stable and even increased with Chinese soybean returns. After the trade agreement was reached, United States– price-difference relationship was weakened and the China–price-difference relationship was strengthened. That is because the trade war provoked by the Trump administration impeded the soybean trade, significantly increasing both the inventory of U.S. soybeans and the demand shortage in Chinese markets. Since the estimates of the average phase difference ratios were not significant, we turned to conditional phase difference ratios to detect potential changes in information spillovers between the two markets.

Table 9

Coherence and phase difference estimates during the three subsample periods.

Scale			D1	D2	D3	D4	D5	D6
Panel A. Pre-tariff period 2010.1.1~2018.4.4								
US-CN	Coherence	Mean	0.49	0.39	0.43	0.46	0.45	0.48
		Std	0.27	0.19	0.19	0.20	0.20	0.20
	Phase	Mean	-0.14	-0.15	-0.22	-0.18	-0.29	-0.01
		Std	1.74	0.96	0.82	0.74	0.76	0.80
US-DIFF	Coherence	Mean	0.67	0.59	0.51	0.48	0.47	0.46
		Std	0.27	0.21	0.23	0.22	0.21	0.19
	Phase	Mean	-0.20	-0.26	-0.43	-0.30	-0.51	0.07
		Std	2.44	1.44	1.30	1.32	1.19	1.32
CN-DIFF	Coherence	Mean	0.67	0.61	0.62	0.54	0.57	0.56
		Std	0.27	0.23	0.24	0.25	0.25	0.22
	Phase	Mean	-0.08	-0.11	-0.22	-0.11	-0.21	0.08
		Std	1.15	0.64	0.64	0.74	0.59	0.70
Panel B. Post-tariff period 2018.4.4~2019.9.30								
US-CN	Coherence	Mean	0.48	0.34	0.31	0.30	0.36	0.32
		Std	0.27	0.16	0.17	0.14	0.17	0.13
	Phase	Mean	0.08	0.15	0.01	0.01	-0.25	-0.34
		Std	1.93	1.08	0.91	0.91	0.84	0.81
US-DIFF	Coherence	Mean	0.67	0.58	0.50	0.40	0.47	0.29
		Std	0.24	0.19	0.21	0.15	0.16	0.15
	Phase	Mean	0.08	0.21	0.05	0.12	-0.26	-0.30
		Std	2.42	1.41	1.28	1.32	1.24	1.04
CN-DIFF	Coherence	Mean	0.77	0.73	0.66	0.65	0.62	0.71
		Std	0.24	0.19	0.20	0.21	0.21	0.14
	Phase	Mean	0.01	0.05	0.04	0.12	-0.03	0.01
		Std	0.87	0.45	0.50	0.55	0.56	0.32
Panel C. Post trade agreement and COVID-19 pandemic 2020.1.16~2020.8.31								
US-CN	Coherence	Mean	0.46	0.33	0.33	0.37	0.32	0.38
		Std	0.26	0.16	0.19	0.13	0.15	0.17
	Phase	Mean	0.08	0.02	0.11	-0.17	0.26	0.54
		Std	1.80	1.02	0.91	1.02	0.90	1.20
US-DIFF	Coherence	Mean	0.49	0.37	0.37	0.48	0.36	0.32

		Std	0.26	0.19	0.18	0.13	0.15	0.21
	Phase	Mean	0.12	0.04	0.11	-0.16	0.21	0.47
		Std	2.15	1.22	1.09	1.22	1.13	1.37
CN-DIFF	Coherence	Mean	0.89	0.92	0.94	0.89	0.88	0.87
		Std	0.13	0.08	0.05	0.06	0.09	0.07
	Phase	Mean	0.05	0.03	0.00	0.02	-0.07	-0.07
		Std	0.69	0.29	0.22	0.30	0.30	0.22

According to Panels A and B in Table 10, in the pre-tariff period, U.S. and Chinese soybeans were more likely to move in phase. However, after the tariff was imposed, the proportion of the anti-phase increased, suggesting that the two prices moved in opposite directions. This makes sense, as the tariff drove a wedge between the two countries' prices, whereby United States soybean price decreased due to oversupply and the Chinese soybean price increased for the opposite reason.

Moreover, United States soybean market was less likely to be influenced by price differences during the post-tariff and post-trade agreement periods. Intuitively, as United States soybean inventory significantly increased during the trade war, the price sensitivity of United States soybean market decreased. Due to a shortage in Chinese soybean demand, the Chinese soybean price became more closely correlated with the price difference. As a result, an increase in Chinese soybean prices would not necessarily cause an increase in U.S. soybean prices, widening the price gap between the two.

More interestingly, during the post-tariff period, the information spillovers from the Chinese soybean market to United States soybean market turned out to be much stronger than those flowing in the opposite direction, especially at mid to low frequencies. This suggests that the Chinese soybean futures market became more influential in price discovery during this period than the corresponding U.S. market. As China is the largest soybean importer, the Chinese tariff is the most important risk factor determining world soybean prices. Our results are in line with those of Elobeid et al. (2021), who found that the retaliatory tariff imposed by China reduced U.S. soybean exports by 31.2%. According to the results in Panel C in table 10, this considerable decline was mitigated by trade agreements, especially from a long-term cumulative perspective. United States market again gained pricing power after ordinary trade orders were restored. In summary, the Trump administration's trade war was a double-edged sword, as it damaged not only U.S. farmers but also United States financial industry.

Table 10

Conditional phase difference ratio estimates on the directions of correlations during the three subsample periods.

Scale	D1	D2	D3	D4	D5	D6
Panel A. Pre-tariff period 2010.1.1~2018.4.4						
Anti-phase US←CN	0.26	0.24	0.18	0.14	0.18	0.14
In phase US←CN	0.26	0.25	0.26	0.32	0.26	0.36
In phase US→CN	0.29	0.32	0.42	0.43	0.44	0.36
Anti-phase US→CN	0.20	0.19	0.14	0.11	0.12	0.14
Anti-phase US←DIFF	0.45	0.47	0.45	0.42	0.45	0.34
In phase US←DIFF	0.09	0.08	0.11	0.13	0.12	0.13
In phase US→DIFF	0.08	0.09	0.15	0.16	0.17	0.17
Anti-phase US→DIFF	0.38	0.36	0.29	0.30	0.25	0.37
Anti-phase CN←DIFF	0.09	0.10	0.11	0.12	0.11	0.09
In phase CN←DIFF	0.38	0.36	0.33	0.32	0.31	0.36
In phase CN→DIFF	0.45	0.45	0.49	0.45	0.51	0.42
Anti-phase CN→DIFF	0.08	0.08	0.07	0.11	0.07	0.13
Panel B. Post-tariff period 2018.4.4~2020.1.15						
Anti-phase US←CN	0.27	0.25	0.22	0.20	0.21	0.23
In phase US←CN	0.21	0.23	0.32	0.35	0.28	0.29
In phase US→CN	0.22	0.21	0.26	0.27	0.36	0.36
Anti-phase US→CN	0.30	0.31	0.20	0.19	0.15	0.12
Anti-phase US←DIFF	0.40	0.37	0.37	0.34	0.43	0.38
In phase US←DIFF	0.09	0.09	0.13	0.13	0.09	0.18
In phase US→DIFF	0.10	0.09	0.11	0.13	0.13	0.20
Anti-phase US→DIFF	0.41	0.45	0.39	0.40	0.34	0.24
Anti-phase CN←DIFF	0.04	0.04	0.06	0.06	0.09	0.03
In phase CN←DIFF	0.43	0.49	0.45	0.43	0.34	0.38

In phase CN→DIFF	0.47	0.42	0.42	0.42	0.47	0.55
Anti-phase CN→DIFF	0.06	0.05	0.07	0.09	0.10	0.05
Panel C. Post trade agreement and COVID-19 pandemic 2020.1.16~2020.8.31						
Anti-phase US←CN	0.22	0.24	0.19	0.33	0.17	0.09
In phase US←CN	0.32	0.27	0.28	0.20	0.24	0.19
In phase US→CN	0.24	0.25	0.28	0.20	0.31	0.37
Anti-phase US→CN	0.22	0.24	0.24	0.26	0.29	0.35
Anti-phase US←DIFF	0.33	0.33	0.27	0.41	0.28	0.18
In phase US←DIFF	0.18	0.17	0.21	0.10	0.16	0.15
In phase US→DIFF	0.13	0.16	0.20	0.13	0.20	0.28
Anti-phase US→DIFF	0.36	0.34	0.31	0.36	0.37	0.38
Anti-phase CN←DIFF	0.02	0.01	0.00	0.02	0.02	0.02
In phase CN←DIFF	0.53	0.50	0.52	0.44	0.51	0.54
In phase CN→DIFF	0.42	0.48	0.47	0.52	0.46	0.42
Anti-phase CN→DIFF	0.03	0.02	0.01	0.02	0.01	0.01

Note: US, CN, and DIFF denote the returns of US soybean futures and Chinese soybean futures and their price differences, respectively. D1, D2, D3, D4, D5, and D6 refer to 2-4, 4-8, 8-16, 16-32, 32-64, and 64-128 observations, respectively.

6. Discussions and implications

This study makes several methodological contributions to the literature on commodity market data. First, it demonstrated the advantages of using wavelet analysis to characterize complex cyclical relationships and time-varying correlations missed in typical cointegration and causality approaches. Second, the analysis established intercountry price differences as a key factor in soybean futures price discovery, based on theoretical notions of market integration. Third, examining the impacts of major exogenous events, such as political events, as represented by trade wars, and public health, as represented by pandemics, revealed a new application of the wavelet approach in data science. Therefore, this study expands the theoretical understanding of the evolution of soybean futures price dynamics between major soybean producers and consumers. The methodological innovation of applying wavelets in this context provides a valuable new tool for researchers seeking to better analyze datasets that share similar traits with commodity price series.

Our findings have important managerial implications for practitioners. A nuanced characterization of changing price correlations and discovery patterns should interest industry professionals involved in commodity trading, hedging, and investment decisions. The fact that China gained influence during the trade war suggests that geopolitical conditions matter in real rather than nominal ways. The price difference measure also offers a real-time monitoring tool. For policymakers, the evidence that trade disputes disrupt the traditional soybean price determination landscape highlights the interconnectedness of global commodity markets and their fragility. As China's market power grows, monitoring price dynamics is becoming prudent. The pricing impacts of tariffs and trade pacts found here may inform future cost-benefit policy choices. Overall, this study advances both the theoretical and empirical understanding of soybean futures markets while delivering practical insights valuable to market participants, risk managers, policymakers, and regulators.

7. Conclusion

This study used the wavelet method to analyze the dynamic relationship between U.S. and Chinese soybean futures. Recently, China has dramatically increased its soybean imports, and the soybean futures market in China has witnessed increasing trading volumes. Both developments have implications for soybean price discovery in United States and China. This study adds to the extant literature in the following three ways, helping to understand the price discovery dynamics between United States and China in the globally indispensable soybean market.

(1) Time-varying correlations between United States and China across frequencies. A central finding from the wavelet analysis was that the strength of the correlation between United States and Chinese soybean futures prices changed substantially over time and across frequencies. Periods of strong high-frequency comovement were interrupted by periods of disconnection. This time-varying relationship provides insights into the conflicting results found in the literature using more stable cointegration frameworks. The wavelet coherence measures revealed a complex cyclical linkage that was overlooked by standard time-series models.

(2) Role of relative price difference. The empirical analysis identified the price difference between United States and China as a persistent factor closely tied to each country's soybean price. This relative price level served as a key information transmission mechanism, even during recent major trade disputes. The price wedge likely reflects the underlying supply and demand conditions influencing both markets. Its stability indicates fundamental market integration.

(3) Impacts of the trade war and COVID-19. Examining the sub-periods around major political and public health events provided further evidence of evolving price dynamics. China gained greater influence over soybean price discovery in 2018 when it imposed retaliatory tariffs on U.S. exports. However, United States largely resumed its dominant role after the 2020 Phase-One Trade Agreement. Meanwhile, COVID-19 had mixed effects, increasing United States–China futures linkage but reducing U.S. price sensitivity.

The findings of this study are partly consistent with existing studies but provide several new insights. First, the use of wavelet analysis allowed the detection of time-varying, frequency-dependent relationships missed in studies using stable cointegration relationships. Second, this study established price differences as a key transmission mechanism. Third, the analysis of recent major events such as the trade war provided new evidence that China gained influence during the trade dispute. Overall, the wavelet approach led to a more nuanced characterization of the cyclical, evolving linkages between United States and Chinese soybean futures markets.

Future studies could extend this analysis to other internationally connected financial markets. Incorporating high-frequency intraday data and microstructure metrics, such as trading volumes, would also be worthwhile. Because major events shape global trade, applying wavelet techniques to examine the impact of other types of shocks or newly emerging hot events on commodity markets seems promising. Finally, it may be fruitful to relate the price dynamics uncovered to macroeconomic indicators, such as exchange rate fluctuations and monetary policy divergences between the two countries.

In summary, this study conducted a novel and complete characterization of the evolving price discovery patterns between the two major players in global agricultural commodity markets. The findings should interest academics, policymakers, and practitioners involved in monitoring and analyzing these economically vital links across countries.

References

Ardeni, P. G, 1989. Does the law of one price really hold for commodity prices? Am. J. Agric. Econ. 71(3), 661-669.

Bandyopadhyay, A., & Rajib, P, 2023. The impact of Sino-US trade war on price discovery of soybean: A double-edged sword? J. FUTURES MARKETS. 43(7), 858-879.

Chen, Z., Yan, B., Kang, H., et al., 2021. Asymmetric price adjustment and price discovery in spot and futures markets of agricultural commodities. Review of Economics Design. 27, 139-162.

Christofoletti, M. A. M., Silva, R. M. D., & Mattos, F., 2012. The increasing participation of China in the world soybean market and its impact on price linkages in futures markets. In Proceedings of the NCCC-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management.

Elobeid, A., Carriquiry, M., Dumortier, J., et al., 2021. China-U.S. trade dispute and its impact on global agricultural markets, United States economy, and greenhouse gas emissions. J. AGR. ECON. 72(3), 647-672.

Engle, R. F., & Granger, C. W., 1987. Co-integration and error correction: representation, estimation, and testing. ECONOMETRICA. 55(2), 251-276.

Fung, H. G., Leung, W. K., & Xu, X. E., 2003. Information flows between the US and China commodity futures trading. REV. QUANT. FINANC. ACC. 21(3), 267-285.

Gençay, R., Selçuk, F., & Whitcher, B., 2005. Multiscale systematic risk. J. INT. MONEY. FINANC. 24(1), 55-70.

Goupillaud, P., Grossman, A., & Morlet, J., 1984. Cycle-octave and related transforms in seismic signal analysis. Geoexploration. 23(1), 85-102.

Granger, C. W., 1969. Investigating causal relations by econometric models and cross-spectral methods. ECONOMETRICA. 37(3), 424-438.

Granger, C. W., 1981. Some properties of time series data and their use in econometric model specification. J. Econometrics. 16(1), 121-130.

Grinsted, A, Moore, J. C., & Jevrejeva, S., 2004. Application of the cross wavelet transform and wavelet coherence to geophysical time series. NONLINEAR. PROC. GEOPH. 11, 561-566.

Guo, J., Wu, D. D., Zhang, K., et al., 2022. Linkage relationship between China and US futures market during trade friction: The case of soybean, soybean oil and soybean meal. APPL. ECON. LETT. 30, 2647-2651.

Han, L., Liang, R., & Tang, K. E., 2013. Cross-market soybean futures price discovery: Does the Dalian Commodity Exchange affect the Chicago Board of Trade? QUANT. FINANC. 13(4), 613-626.

Hao, J., He, F., Liu-Chen, B., et al., 2021. Price discovery and its determinants for the Chinese soybean options and futures markets. FINANC. RES. LETT. 40, 101689.

Hudgins, L., Friehe, C. A., & Mayer, M. E., 1993. Wavelet transforms and atmospheric turbulence. PHYS. REV. LETT. 71(20), 3279.

Janzen, J. P., & Adjemian, M. K., 2017. Estimating the location of world wheat price discovery. Am. J. Agric. Econ. 99(5), 1188-1207.

Jiang, C., Chang, T., & Li, X., 2015. Money growth and inflation in China: New evidence from a wavelet analysis. INT. REV. ECON. FINANC. 35, 249-261.

Jiang, H., Su, J. J., Todorova, N., et al., 2016. Spillovers and directional predictability with a cross-quantilogram analysis: The case of US and Chinese agricultural futures. J. FUTURES MARKETS. 36(12), 1231-1255.

Joseph, A., Sisodia, G., & Tiwari, A. K., 2015. The inter-temporal causal nexus between Indian commodity futures and spot prices: A wavelet analysis. Theoretical Economics Letters. 5(02), 312.

Kristoufek, L., Janda, K., & Zilberman, D., 2016. Comovements of ethanol-related prices: Evidence from Brazil and the USA. GCB-Bioenergy. 8(2), 346-356.

Lence, S. H., Moschini, G., & Santeramo, F. G., 2018. Threshold cointegration and spatial price transmission when expectations matter. AGR. ECON. 49(1), 25-39.

Li, C., & Hayes, D. J., 2017. Price discovery on the international soybean futures markets: A threshold co‐integration approach. J. FUTURES MARKETS. 37(1), 52-70.

Li, M., & Xiong, T., 2021. Dynamic price discovery in Chinese agricultural futures markets. J. ASIAN. ECON. 76, 101370.

Liu, B. J., Wang, Y., Wang, J., et al., 2015. Is China the price taker in soybean futures? CHINA. AGR. ECON. REV. 7(3), 389-404.

Liu, Q., & An, Y., 2011. Information transmission in informationally linked markets: Evidence from US and Chinese commodity futures markets. J. INT. MONEY. FINANC. 30(5), 778-795.

Merener, N., 2015. Globally distributed production and the pricing of CME commodity futures. J. FUTURES MARKETS. 35(1), 1-30.

Nigatu, G., & Adjemian, M., 2020. A wavelet analysis of price integration in major agricultural markets. J. AGRIC. APPL. ECON. 52(1), 117-134.

Rua, A., 2010. Measuring comovement in the time-frequency space. J. MACROECON. 32(2), 685-691.

Rua, A., & Nunes, L. C., 2009. International comovement of stock market returns: A wavelet analysis. J. EMPIR. FINANC. 16(4), 632-639.

Silber, W. L., 1981. Innovation, competition, and new contract design in futures markets. J. FUTURES. MARKETS. 1(2), 123-155.

Torrence, C., & Compo, G. P., 1998. A practical guide to wavelet analysis. B. AM. METEOROL. SOC. 79(1), 61-78.

Uddin, G. S., Tiwari, A. K., Arouri, M., et al., 2013. On the relationship between oil price and exchange rates: A wavelet analysis. ECON. MODEL. 35, 502-507.

Wang, X., Zhang, L., Cheng, Q., et al., 2022. What drives risk in China's soybean futures market? Evidence from a flexible GARCH-MIDAS model. J. APPL. ECON. 25(1), 454-475.

Zhou, X., Bagnarosa, G., Gohin, A., et al., 2023. Microstructure and high-frequency price discovery in the soybean complex. J. COMMOD. MARK. 30, 100314.

The Dynamics of Price Discovery between the U.S. and Chinese Soybean Market: A Wavelet Approach to Understanding the Effects of Sino-U.S. Trade Conflict and COVID-19 Pandemic

Declarations of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.