Spillovers and Directional Predictability with a Cross-Quantilogram Analysis: The Case of U.S. and Chinese Agricultural Futures

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This paper examines the daily, overnight, intraday, and rolling return spillovers of four key agricultural commodities—soybeans, wheat, corn, and sugar, between the U.S. and Chinese futures markets via a newly developed quantile dependence measure called quantilogram. The results reveal significant bi-directional dependence between the two markets across commodities which is greater in extreme quantiles and moderately stronger from the United States to China. These findings offer valuable insights into investors' behavior, market integration, dissimilarity, and market efficiency in both countries. © 2016 Wiley Periodicals, Inc. Jrl Fut Mark 36:1231–1255, 2016

1. INTRODUCTION

The United States and China are two of the world's biggest players and trading partners in relation to agricultural commodities. The U.S. agricultural futures market, i.e., Chicago Board of Trade (CBOT) and Inter Continental Exchange (ICE), is the world's most active while the Chinese market, i.e., Dalian Commodities Exchange (DCE) and Zhengzhou Commodities Exchange (ZCE), is the world's fastest growing (Acworth, 2013). Hence, the interaction between these two markets is of significant importance as it would have an impact on other markets (Christofoletti et al., 2012; Han et al., 2013; Hernandez et al., 2014). Applying MGARCH, VAR, VECM, Granger Causality, Wavelet, and impulse response functions[1] to daily closing prices, the existing literature consistently demonstrates greater price discovery in the United States compared to China. However, there is a lack

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JEL Classification: C12, C13, C22, Q11, Q14

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[1] Section 2 provides a detailed literature review.

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of studies that systematically investigate the mechanism and dynamics of the spillovers between these two markets. Our study addresses this important knowledge gap.

This paper investigates the return spillovers between the U.S. and Chinese agricultural futures markets in relation to the four major commodities—soybeans, wheat, corn, and sugar, based on a newly developed methodology called quantilogram. Given the close connection between the United States and China in terms of trade and investment, we expect a significant bilateral dependence between the two markets. However, since the U.S. futures market is globally well-established and easily accessed by different types of investors whereas the Chinese futures market is more restricted to foreign participation (Talpsepp, 2011; Wang, 2012), we conjecture a stronger return spillover from the United States to China than vice versa.

This study makes three contributions to the empirical literature. First, the cross-quantilogram introduced by Han et al. (2014) offers the advantage of providing a comprehensive examination of return spillovers and directional predictability between the U.S. and Chinese futures markets as it allows the analysis of the relationship between the two markets at different quantiles, rather than just at the median. The recent Global Financial Crisis (GFC) and its aftermath have highlighted, once again, the imperative of understanding and modeling relationships between markets at the extremes of the return distributions rather than just at the center. Although there are other methods that can be used to analyze relationships between variables at different quantiles, for example, quantile regressions, the cross-quantilogram has advantages over them. As demonstrated by Han et al. (2014), the cross-quantilogram can detect the magnitude, duration, and direction of the relationship simultaneously, which cannot be done by means of a quantile regression. One can also select arbitrary quantiles for both time series, rather than preset ones. Furthermore, the stationary bootstrap is used to construct critical values and allows the use of large lags. The cross-quantilogram has been applied only to the equity market by Han et al. (2014). Thus, this paper is the first to apply this newly introduced and advantageous methodology in studying commodity markets.

Second, unlike existing research, this study analyzes the daily interaction between the U.S. and Chinese agricultural futures markets based on trading and non-trading parts of the day with an adjustment on cross-country nonsynchronous trading hours. Motivated by the extensive body of literature on market microstructure in relation to the stock market, which suggests that the market behaves differently during trading and non-trading periods (Barclay and Hendershott, 2008; Hong and Wang, 2000), in this paper, daily (close-to-close) returns are decomposed into overnight (close-to-open) and intraday (open-to-close) returns components. To the best of the authors' knowledge, the extant literature on agricultural futures is primarily based on daily (close-to-close) returns. Only one study (Fung et al., 2013) is found to have decomposed daily returns into overnight and intraday returns. However, this study differs from ours as it mainly focuses on the contemporaneous and lead–lag dynamic return transmissions in the conditional mean using a standard approach.

Third, different from other studies, our paper tests whether the movements in returns in each of the two countries are indeed driven more bilaterally rather than by their own historical returns. This is done by performing an autocorrelation analysis of each country's returns using the auto-quantilogram. Moreover, a rolling cross-quantilogram based on a rolling window of 2 years is examined to identify the stability and dynamics of the observed spillovers found in the entire sample.

With return series obtained from daily closing prices, the cross-quantilogram results show a significant short-lived (1 day) positive directional predictability for soybean, wheat, corn, and sugar futures from the United States to China across various quantiles. The transmission from China to the United States is also short-lived (1 day) for each of the four commodities; however, its magnitude is comparatively smaller, particularly for wheat, corn, and sugar. The results of the auto-quantilogram for the return series confirm the stronger cross-country return interactions. The analysis of the bilateral spillovers based on decomposed return components documents a consistent structure in the 1-day return transmission from the United States to China for all four commodities. Positive overnight return spillovers are the essential source of daily return spillovers and offset the insignificant negative intraday return spillovers. In contrast, the underlying transmission pattern from China to the United States varies across commodities. The overnight and intraday spillovers are both positive and reinforce each other, resulting in a more pronounced daily return transmission. Compared to other subsample periods, the rolling cross-quantilogram shows that the observed spillovers are most pronounced and asymmetric (stronger on the downside) during the GFC. The return movements in both the United States and China are mainly driven by external rather than local market dynamics, which can be interpreted as an indication of the integration of these two markets.

The structure of the paper is as follows. Section 2 provides a literature review of spillovers between the U.S. and Chinese agricultural commodities futures markets and the predictive power of the U.S. returns. Section 3 addresses the economic importance of soybeans, wheat, corn, and sugar, followed by an introduction of the agricultural futures markets in both countries and the hypotheses on return spillovers. Section 4 discusses the cross-quantilogram, the construction of returns, and the descriptive statistics. Section 5 presents the findings, and Section 6 concludes.

2. LITERATURE REVIEW

Most existing empirical studies on spillovers between the agricultural futures markets of the United States and China concern volatility, with soybeans, wheat, corn, and sugar being the most popular subjects. Although sample time intervals and research methodologies vary across the literature, in general, a stronger volatility spillover has been detected from the United States to China rather than in the opposite direction.

Studies demonstrating the predictive power of U.S. soybean futures include those of Liu (2009) who applied VAR and VECM models to daily closing soybean futures prices in both markets from 2004 to 2009, Liu and An (2011) who studied daily closing prices of soybean futures from the DCE and CBOT from 2004 to 2009 with a MGARCH model and Shi and He (2013) who used daily closing soybean futures prices from 2006 to 2011 with a bivariate GARCH-BEKK model. By applying MGARCH models to daily closing prices of soybean and wheat futures from 2004 to 2007 in the United States and China, Liu (2009) found that the United States acts as an information forerunner. With the application of a bivariate GARCH model to daily data from 1995 to 2001, Fung et al. (2003) examined the dominant role of the U.S. futures market in transmitting volatility to the Chinese market for soybeans and wheat. Christofoletti et al. (2012) detected significant volatility transmission from the United States to China for corn futures between 2002 and 2011 using an ECM. Based on Granger Causality tests for the U.S. and Chinese markets, Zhang and Tong (2012) suggested that the United States holds a dominant position in the sugar futures pricing mechanism.

In spite of the importance of China in the global agricultural futures market, few studies document bi-directional volatility spillovers between the United States and China. Hernandez et al. (2014) explored the dynamics across major exchanges for corn, wheat, and soybeans in the United States, Europe, and Asia with a multivariate GARCH approach. Their findings suggest that these markets are highly interrelated, with both local and cross-boundary volatility dependence among most of the exchanges. With daily futures data from the post crisis period (2011–2012), Yang and Liu (2013) utilized Wavelet, VAR, and GARCH-BEKK analysis to uncover soybean volatility spillovers between both markets but mainly from the CBOT to the DCE. Analyzing daily soybean futures prices from 2002 to 2011 with SVAR, VEC, and impulse response functions, Han et al. (2013) also detected information transfers between the DCE and CBOT in both directions.

In relation to the predictive power of the U.S. markets, a number of studies have analyzed the lead–lag relationships among various countries and the United States. Rapach et al. (2013) documented that the lagged U.S. stock returns have substantial predictive power for the equity markets of various non-U.S. industrialized countries, even after controlling for interest rates and dividend yields. The majority of studies addressing the influence of the United States on Chinese markets focus on equities. Goh et al. (2013) found a set of 14 U.S. economic variables that have significant predictive power for the returns of the Chinese stock market for the period after China's admission into the World Trade Organization (WTO). Zhang and Li (2014) examined co-movements between the Chinese and U.S. stock markets over the period of 2000–2012 using cointegration, DCC model, and quantile regression analysis. They uncovered a strong impact of the U.S. market on the Chinese market, especially when the latter undergoes extreme movements. Based on daily opening values of the S&P500, DJIA, NASDAQ, SSEC, and SZCI from 2000 to 2010, Ye (2014) documented a one way predictive power of the United States on China—daily returns in the U.S. equity market have significant predictive ability for Chinese stock market openings since 2006, whereas the Chinese stock market's daily returns have no ability to forecast U.S. stock market openings. In summary, in stock and agricultural commodities futures markets, the empirical evidence suggests that the United States drives markets in other economies, including China, more significantly than the other way around.

3. MARKEY BACKGROUND AND HYPOTHESIS

This section demonstrates the economic importance of soybeans, wheat, corn, and sugar in China through a discussion of their fundamentals and linkages to the United States via consumption and import. It also highlights some characteristics of the agricultural futures markets in the United States and China, in support of the hypothesis presented in Subsection 3.3.

3.1. Agricultural Commodities Demand

Figure 1 shows the annual level of consumption and the ratio to the world's annual level of consumption of the United States and China for soybeans, wheat, corn, and sugar from 2000/2001 to 2014/2015, as reported by the U.S. Department of Agriculture (USDA). China has dominated the world's demand for soybeans since 2008/2009 and for wheat since 2000/2001. In terms of the demand for corn and sugar, China ranks second globally, with the United States being the world's largest corn consumer. The line charts display a stable pattern in the world's consumption ratio from China for wheat, corn, and sugar, and a remarkable upsurge for soybeans, with the percentage almost doubling from approximately 15 to 30% from 2000/2001 to 2014/2015.

Furthermore, since the production year 2004/2005, more than 60% of the soybeans consumed locally in China have been imported, with the United States being the largest supplier (Tables I and II). The level of sugar imports in China is the second largest among the four commodities, with imports on average accounting for 22.95% of its local demand

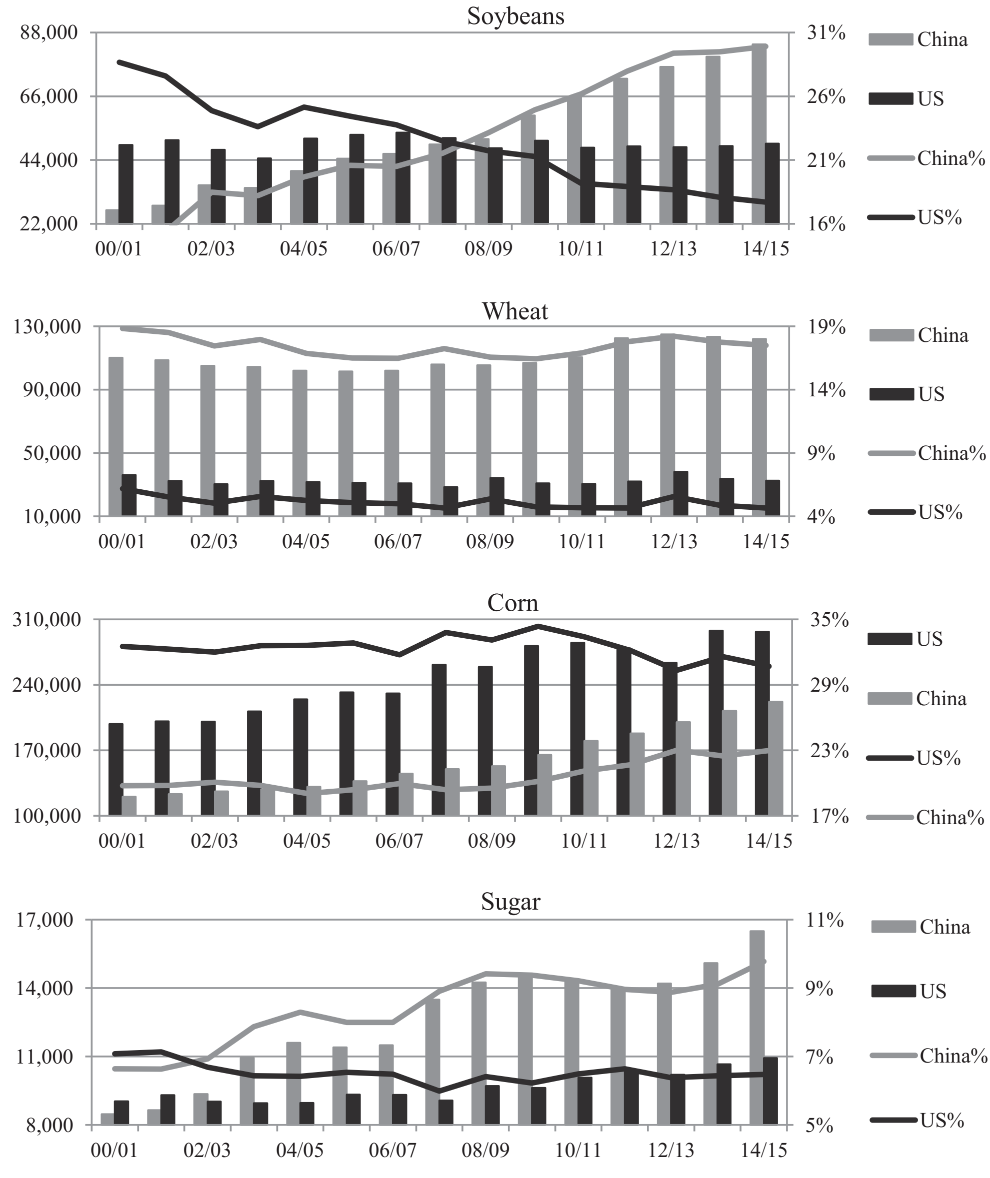


FIGURE 1

U.S. and Chinese Consumption and Consumption Ratios

Note. The bar charts represent the annual consumption of the United States and China for soybeans, wheat, corn, and sugar, with the scale on the left-hand side in 1000 ton. The line charts show the ratio of each country's consumption to the world's total consumption in the same production year, with the scale on the right-hand side in percentage.

Source. Bric database.

during the crop years 2010/2011–2013/2014. For wheat and corn, although the amount imported by China has been below 5% in the past 14 years, the United States is the second largest exporter of wheat and the largest exporter of corn to China. Given these facts, it is clear that China has a close trading partnership with the United States for soybeans, sugar, wheat, and corn.

TABLE I
Import and Import/Consumption for Soybeans, Wheat, Corn, and Sugar in China, 2000–2014

	Soybeans		*Wheat*		*Corn*		*Sugar*	
Year	*Imp*	*I/C*	*Imp*	*I/C*	*Imp*	*I/C*	*Imp*	*I/C*
00/01	13244	49.59%	423	0.38%	280	0.02%	1040	12.27%
01/02	10384	36.68%	911	0.85%	150	0.01%	1320	15.26%
02/03	21415	60.68%	373	0.35%	0	0.00%	800	8.55%
03/04	16933	49.26%	1752	2.86%	10	0.01%	1180	10.78%
04/05	25802	64.16%	8211	7.14%	20	0.02%	1290	11.12%
05/06	28317	63.72%	1324	1.30%	60	0.04%	1190	10.44%
06/07	28726	62.28%	384	0.38%	20	0.01%	1400	12.17%
07/08	37816	76.51%	150	0.14%	40	0.03%	920	6.81%
08/09	41098	80.18%	258	0.43%	50	0.03%	1020	7.16%
09/10	50342	84.78%	1362	1.31%	1300	0.79%	1480	10.21%
10/11	52339	79.42%	795	0.86%	1000	0.56%	2060	14.41%
11/12	59231	82.19%	2953	2.41%	5250	2.79%	4257	30.41%
12/13	59870	78.59%	2895	3.20%	2750	1.38%	3661	25.78%
13/14	68300	82.86%	7067	5.26%	4000	1.89%	3900	21.19%

Note. Year represents the crop year. Imp = Import; I/C = Ratio of Import to local Consumption. Unit for Imp is thousand ton.
Source. Bric Database.

3.2. Agricultural Futures Markets

The CBOT and ICE are well-established global agricultural futures markets and can be accessed by different types of participants: professional, proprietary, domestic, foreign, institutional, individual, etc. (Talpsepp, 2011; Wang, 2003). In contrast, due to the restriction on the RMB as an international settlement currency and the concerns about potential interference that foreign investors might cause, the Chinese futures market (DCE and ZCE) is more restricted by regulations, with over 95% of the investors being domestic (Wang, 2012). Most of the foreign participants are institutional investors and fund managers who get into the Chinese futures market through partnerships with the local companies. In contrast to the U.S. futures market, where over 70% of the participants are institutional investors, less than 10% of the local participants in the Chinese futures market are institutional investors, with the rest being individual investors, which stimulates speculative and noisy trades (Wang, 2012).

Although speculative activities provide liquidity, the Chinese futures market can be regarded as relatively unstable and likely to be affected by the U.S. market (Tan, 2009). The decision making of a great proportion of individual investors in China might be affected by

TABLE II
U.S. Export to China, Position and Percentage

	Soybeans	*Wheat*	*Corn*	*Sugar*
U.S. Position	1st	2nd	1st	10th
U.S. Export/CN Import	42.06%	29.23%	84.41%	0.0051%

Note. U.S. export/CN import measures the percentage of the total import amount in China contributed by the United States. Numbers are calculated as the average of 2000–2014.
Source. Bric database.

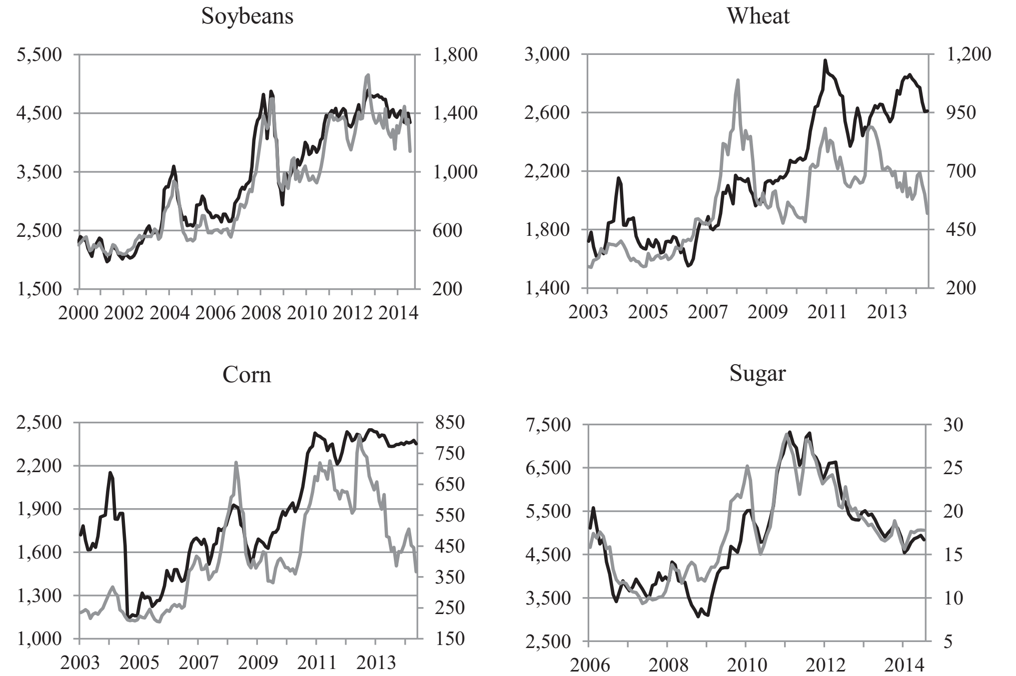


FIGURE 2

Monthly Averaged Closing Prices for the U.S. and Chinese Continuous Futures Contracts

Note. The closing prices are monthly averaged with the daily data, the sample size is up to July, 2014. For each of the four commodities, the monthly closing prices are presented with the black line for the Chinese futures market and the gray line for the U.S. futures market. The unit is RMB/ton for soybeans, wheat, corn, and sugar for the Chinese market, with the scale on the left-hand side. The unit is Cent/bushel for soybeans, corn, and wheat, Cent/pound for sugar in the U.S. market with the scale on the right-hand side.

Source. Bric database.

the actions of large speculators and institutional investors, who might also invest in the U.S. market and facilitate the flow of information (Wang, 2012).

Figure 2 plots the average monthly closing prices of the continuous futures contracts for soybeans, wheat, corn, and sugar. Clearly, the soybean and sugar prices in both the U.S. (in gray) and Chinese (in black) markets exhibit a very similar course, with price increases and declines occurring almost simultaneously. Despite some deviations in the corn and wheat markets, similar price development can be observed for these commodities as well.

3.3. Hypothesis

Based on the evidence documented in the extant literature on volatility spillovers between the U.S. and Chinese agricultural futures, the similarities in the historical price patterns of agricultural futures in the two countries, and the close connection that China has with the United States in terms of trade and investment, the main conjecture raised in this paper is that there will be a stronger daily return spillover from the United States to China than vice versa. Given the maturity and size of the U.S. futures market and the large proportion of institutional investors, it is expected that the U.S. market would be more efficient, whereas the large proportion of individual investors which account for more than 90% of the total amount of trade in China is likely to heavily reflect information inherent in recent U.S. futures prices.

4. METHODOLOGY

This study examines the spillovers and directional predictability between the returns of the U.S. and Chinese futures markets with regards to four major commodities—soybeans, corn, wheat, and sugar with the cross-quantilogram introduced by Han et al. (2014). The analysis is undertaken based on daily (close-to-close) returns, which are further decomposed into overnight (close-to-open) and intraday (open-to-close) returns. This section provides a detailed discussion of the cross-quantilogram, the data, as well as the construction and decomposition of return components.

4.1. The Cross-Quantilogram

The past few years witnessed vibrant theoretical developments in modeling multivariate lead–lag cross-correlations beyond the conditional mean, with methods such as the extremogram (Davis et al., 2009, 2012, 2013) and advanced statistics incorporating jumps (Bollerslev et al., 2013, 2014). The quantilogram (Linton and Whang, 2007) was developed to measure and test for directional predictability of a stationary time series at different quantiles. More recently, Han et al. (2014) extended the univariate quantilogram to the bivariate cross-quantilogram. The cross-quantilogram is a highly flexible and advanced method that estimates the lead–lag correlation between series for different quantiles and lags simultaneously.

Define $\{x_{i,t}, t \in \mathbb{Z}\}$, $i = 1, 2$ as two strictly stationary time series. In the context of this paper, $x_{1,t}$ and $x_{2,t}$ represent the returns of the continuous futures in China and the United States, respectively. Let $F_i(\cdot)$ and $f_i(\cdot)$ be the distribution function and the density function of the series $x_{i,t}$, respectively. The quantile of $x_{i,t}$ is $q_i(\alpha_i) = \mathit{inf}\{\upsilon : F_i(\upsilon) \geq \alpha_i\}$ for $\alpha_i \in (0, 1)$. For simplicity, q_α stands for the two-dimensional series of quantiles $(q_1(\alpha_1), q_2(\alpha_2))^T$ for $\alpha \equiv (\alpha_1, \alpha_2)^T$.

The cross-quantilogram for α-quantile with k lags is defined as

$$\rho_\alpha(k) = \frac{E[\psi_{\alpha_1}(x_{1,t} - q_1(\alpha_1))\psi_{\alpha_2}(x_{2,t-k} - q_2(\alpha_2))]}{\sqrt{E[\psi^2_{\alpha_1}(x_{1,t} - q_1(\alpha_1))]}\sqrt{E[\psi^2_{\alpha_2}(x_{2,t} - q_2(\alpha_2))]}}, \tag{1}$$

for $k = 0, \pm 1, \pm 2, \ldots$. Note that $\psi_a(u) \equiv 1[u < 0] - a$, $1[\cdot]$ is the indicator function and $1[x_{i,t} \leq q_i(\alpha_i)]$ is the quantile-hit (or quantile-exceedance) process. The cross-quantilogram in Equation (1) captures serial dependence between two series at different quantile levels. Taking $\alpha = (\alpha_1, \alpha_2) = (\alpha_{CN}, \alpha_{US})$ as an example, $\rho_\alpha(1)$ measures the cross-correlation between the Chinese market being above or below quantile $q_{CN}(\alpha_{CN})$ at time t and the U.S. market being above or below quantile $q_{US}(\alpha_{US})$ at time $t - 1$. Therefore, $\rho_\alpha(1) = 0$ implies that whether the U.S. market is above or below quantile $q_{US}(\alpha_{US})$ at time t does not help predict on average whether the Chinese market will be above or below quantile $q_{CN}(\alpha_{CN})$ on the next trading day. In contrast, if $\rho_\alpha(1) \neq 0$, there exists 1-day directional predictability from the United States to China at $\alpha = (\alpha_{CN}, \alpha_{US})$.

The sample counterpart of cross-quantilogram can be calculated as

$$\widehat{\rho}_\alpha(k) = \frac{\sum_{t=k+1}^{T} \psi_{\alpha_1}(x_{1,t} - \widehat{q}_1(\alpha_1))\psi_{\alpha_2}(x_{2,t-k} - \widehat{q}_2(\alpha_2))}{\sqrt{\sum_{t=k+1}^{T} \psi^2_{\alpha_1}(x_{1,t} - \widehat{q}_1(\alpha_1))}\sqrt{\sum_{t=k+1}^{T} \psi^2_{\alpha_2}(x_{2,t-k} - \widehat{q}_2(\alpha_2))}}, \tag{2}$$

for $k = 0, \pm 1, \pm 2, \ldots$. In Equation (2), $\widehat{q}_i(\alpha_i)$ is the unconditional sample quantile of $x_{i,t}$ defined as in Han et al. (2014).

Additionally, Han et al. (2014) propose a quantile version of the Ljung–Box–Pierce type statistic with $H_0 : \rho_\alpha(k) = 0$ for all $k \in 1, ..., p$ against the alternative $H_1 : \rho_\alpha(k) \neq 0$ for some $k \in 1, ..., p$:

$$\widehat{Q}_\alpha^{(p)} \equiv \frac{T(T+2)\sum_{k=1}^{p} \widehat{\rho}_\alpha^2(k)}{T-k}. \tag{3}$$

The portmanteau test $\widehat{Q}_\alpha^{(p)}$ can be used to test the directional predictability of returns from one time series to another for events up to p lags (p trading days) at a pair of quantiles $\alpha = (\alpha_1, \alpha_2)$.

As the asymptotic distribution of the cross-quantilogram is not free of nuisance parameters under the null hypothesis of no directional predictability, Han et al. (2014) suggest using the stationary bootstrap (SB) of Politis and Romano (1994) to approximate the null distribution and conduct inference. The SB is a block bootstrap procedure that takes into account the serial dependence inherent in the data. Unlike the usual block bootstraps, the SB procedure allows for random block lengths. Let $B_{K_i,L_i} = \{(x_{1,t}, x_{2,t-k})\}_{t=K_i}^{L_i-1}$ be the i-th block with block length L_i starting from K_i. Here, L_i is an *iid* variable with distribution $Pr(L_i = s) = \gamma(1-\gamma)^{s-1}$, $s = 1, 2...$ for some $\gamma \in (0, 1)$, and K_i is an *iid* sequence drawn from a uniform distribution on $\{1, 2, ..., T\}$. Because the upper limit of B_{K_i,L_i} may exceed the sample size T, when $t > T$, the pair $(x_{1,t}, x_{2,t-k})$ is replaced by $(x_{1,j}, x_{2,j-k})$ with $j = k + (t \bmod (T-k))$. The pseudo SB resample is constructed based on a sequence of blocks. The cross-quantilogram and associated portmanteau test statistic can be applied to the SB to obtain bootstrapped confidence intervals.

4.2. Data

This paper uses daily opening and closing prices[2] from the continuous futures contracts[3] for soybeans, corn, wheat, and sugar in China and the United States. Data were obtained from Beijing Bric Agricultural Information Science Co., Ltd. Price entries of zero and missing values are deleted. The daily continuous holding period return $R_{i,t}^D$ for country i on day t is calculated with the closing prices:

$$R_{i,t}^D = \ln\left(\frac{P_{i,t}^C}{P_{i,t-1}^C}\right), \tag{4}$$

where $i = CN, US$. $P_{i,t}^C$ represents the closing price of country i on day t. Return data are used only for days when both markets are open.

Details about the generated return series for each commodity are given in Table III. The start dates for the sample period are different across the four commodities given that these commodities were listed on the futures market in China later than in the United States at different dates. The end date of the sample period is August 25, 2014 for all commodities. Among the four commodities considered, soybean futures have the largest sample size (3566 obs), whereas sugar has the shortest sample period (1943 obs).

[2]The highest available frequency for the historical Chinese futures prices is daily.
[3]The continuous futures price series in the database record the price of the front contract. The roll-over from the front contract to the second nearby contract occurs in the month before the expiration of the front contract. This roll-over approach ensures that the price series are not affected by any erratic effects arising close to the contracts' expiration.

TABLE III
Sample Description

Futures	*Sample Period*	*Sample Size*
Soybeans	January 01, 1999–August 25, 2014	3566
Wheat	March 31, 2003–August 25, 2014	2552
Corn	March 31, 2003–August 25, 2014	2504
Sugar	January 01, 2006–August 25, 2014	1943

When analyzing data from markets in different time zones, special care needs to be taken in respect to nonsynchronous trading. Figure 3a illustrates the asynchronous trading hours for agricultural futures markets in China and the United States under the Greenwich Mean Time (GMT). On the same trading day, the futures trading in China opens at 1:00 GMT and ends at 7:00 GMT first, followed by the opening of floor trading in the United States at 13:00 GMT to 17:15 GMT. Clearly, there is no overlap in trading sessions between these two countries. As the Chinese futures market opens 12 hours ahead of the U.S. market on each trading day, when applying the cross-quantilogram to examine the daily return transmission accounting for the time zone difference, instead of a 24-hour effect, the spillover from the U.S. futures market to the Chinese market is actually a 12-hour impact[4]. In Figure 3a, the daily return spillover from the United States on day t to China on day $t+1$ is shown as from $R^D_{US,t}$ to $R^D_{CN,t+1}$. The cross-quantilogram has the advantage of estimating simultaneously the directional predictability for multiple days, i.e., $R^D_{US,t}$ to $R^D_{CN,t+1}$, $R^D_{CN,t+2}$, etc. In Section 5.1, spillovers from 1 to 20 days are assessed, with 20 representing roughly the average trading days per month.

To obtain comparable statistics, the 12-hour directional predictability should be investigated from China to the United States as well. Given that the Chinese futures market opens 12 hours before the U.S. market, when assessing the daily return spillovers, returns from the same trading day of both countries are used. In Figure 3a, the daily return spillover from China on day t to the United States on day t is represented as from $R^D_{CN,t}$ to $R^D_{US,t}$. The U.S. daily return series is lagged by 1day, i.e., positioning the U.S. daily return R_t for date t on day $t+1$[5]. The 2–day transmission is given as from $R^D_{CN,t}$ to $R^D_{US,t+1}$. The directional predictability from 1 to 20 days is also assessed in the case from China to the United States in Section 5.1.

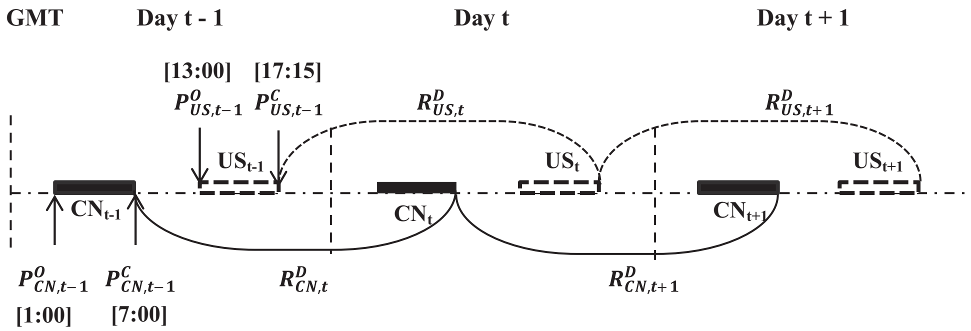
To identify the underlying mechanism of the 1-day-ahead return spillovers across commodities and countries, the close-to-close return of country i on day t ($R^D_{i,t}$) is decomposed into close-to-open overnight ($R^{OV}_{i,t}$) and open-to-close intraday ($R^{IN}_{i,t}$) return components in the following format[6]:

$$R^D_{i,t} = \ln\left(\frac{P^C_{i,t}}{P^C_{i,t-1}}\right) = \ln\left(\frac{P^O_{i,t}}{P^C_{i,t-1}}\right) + \ln\left(\frac{P^C_{i,t}}{P^O_{i,t}}\right) = R^{OV}_{i,t} + R^{IN}_{i,t}, \tag{5}$$

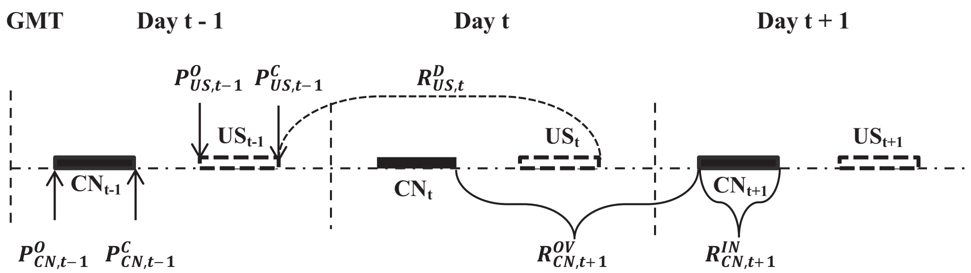
[4]For simplicity, we call it daily/1-day impact.

[5]Without shifting the U.S. return series, the cross-quantilogram method would assess a 36-hour effect from the Chinese futures market to the U.S. futures market. The statistics regarding the 36-hour impact from China to the United States are similar to those regarding the 12-hour impact but of a smaller magnitude. The results are not be reported to save space but are available upon request.

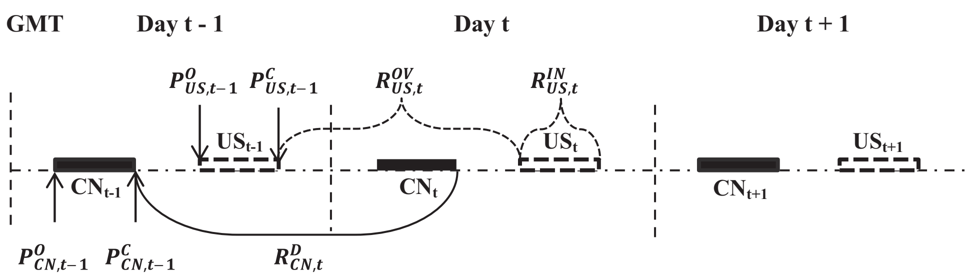
[6]The decomposition formula is identical for each commodity. For simplicity, no subscript is used to denote the commodity type.



(a) Bilateral daily return spillovers under GMT
(US to CN: $R^D_{US,t} \to R^D_{CN,t+1}, R^D_{CN,t+2}, \cdots$; CN to US: $R^D_{CN,t} \to R^D_{US,t}, R^D_{US,t+1}, \cdots$)



(b) Decomposed return spillovers from the US to China via overnight and intraday returns
($R^D_{US,t} \to R^{OV}_{CN,t+1}$ and $R^D_{US,t} \to R^{IN}_{CN,t+1}$)



(c) Decomposed return spillovers from China to the US via overnight and intraday returns
($R^D_{CN,t} \to R^{OV}_{US,t}$ and $R^D_{CN,t} \to R^{IN}_{US,t}$)

FIGURE 3

Return Spillovers Under GMT

Note. Figure 3a illustrates daily return spillovers considering nonsynchronous trading hours between the U.S. and Chinese futures markets with an example of 3 trading days, i.e., day t−1 to day t+1. Figure 3b and c illustrate the decomposition of daily return transmission via overnight and intraday returns between the U.S. and Chinese futures markets with an example of day t. GMT is the Greenwich Mean Time. Solid boxes represent the time when the Chinese futures market is open, dashed boxes represent the time when the U.S. futures market is open. $P^O_{i,t-1}$ and $P^C_{i,t-1}$, $i = US, CN$, are the opening and closing prices of country i at day t−1, respectively. $R^D_{i,t} = \ln(P^C_{i,t}/P^C_{i,t-1})$, $i = US, CN$, represents the daily return of country i at day t. $R^{OV}_{i,t} = \ln(P^O_{i,t}/P^C_{i,t-1})$, $i = US, CN$, represents the overnight return at day t for country i. $R^{IN}_{i,t} = \ln(P^C_{i,t}/P^O_{i,t})$, $i = US, CN$, represents the intraday return at day t for country i.

TABLE IV
Descriptive Statistics of Daily Returns

Futures	China						
	Mean	*Median*	*Min*	*Max*	*SD*	*Skewness*	*Kurtosis*
Soybeans	0.00011	−0.00024	−0.06501	0.08697	0.01181	0.29556	5.39962
Wheat	0.00014	0.00037	−0.12890	0.12213	0.01190	0.90195	38.11301
Corn	0.00008	0.00040	−0.12889	0.12213	0.01191	0.14235	38.92952
Sugar	−0.00014	−0.00016	−0.14276	0.08484	0.01305	−0.65741	10.98791
Futures	US						
	Mean	*Median*	*Min*	*Max*	*SD*	*Skewness*	*Kurtosis*
Soybeans	0.00032	0.00127	−0.11378	0.07866	0.01687	−0.74989	6.37366
Wheat	−2.3224*E*-6	−0.00135	−0.10362	0.11198	0.02185	0.09317	1.95005
Corn	0.00037	0.00027	−0.14481	0.08799	0.01921	−0.15036	2.94547
Sugar	0.00006	−0.00042	−0.11868	0.13903	0.02206	−0.25427	3.24595

with $i = US, CN$. $P^O_{i,t}$ is the opening price for country i on day t, and $P^C_{i,t}$ is, as defined previously, the closing price of country i on day t. Figure 3b shows the decomposition of daily return in China on day $t+1$ into overnight and intraday returns. The 1-day-ahead return transmission from the United States to China through overnight and intraday returns is represented as from $R^D_{US,t}$ to $R^{OV}_{CN,t+1}$ and $R^{IN}_{CN,t+1}$. In Figure 3c, the U.S. daily return on day t is decomposed into overnight and intraday returns, the 1-day-ahead daily return spillover from China to the United States via overnight and intraday returns is given as from $R^D_{CN,t}$ to $R^{OV}_{US,t}$ and $R^{IN}_{US,t}$.

Table IV reports the descriptive statistics of the daily returns for both the United States and Chinese markets. In general, the average daily returns for all commodities in China and the United States are close to zero, as expected. In China, the mean return is negative in the sugar market only (−0.014%). In addition, the sugar market in China has the largest minimum return (−14.276%) and the lowest maximum return (8.484%), associated with the greatest daily return variation. The bottom panel of the table presents statistics for the futures markets in the United States. Different than the futures market in China, the average daily return is negative only for wheat. The futures of soybean and corn have higher mean returns in the United States compared with China (0.032 and 0.037%, respectively). The magnitude of the standard deviations (SD) shows that the historical U.S. futures returns have a larger dispersion than the returns in China for the four commodities, and the daily return variation is the largest for the sugar futures in both countries.

5. RESULTS

This section is divided into five subsections with the results reported in Subsections 5.1–5.4. Subsection 5.1 describes the bi-directional daily return transmissions between the U.S. and Chinese agricultural futures markets. The auto-quantilogram results for the daily returns series in both countries are reported in Subsection 5.2. Subsection 5.3 discusses statistics of decomposed spillovers via the overnight and intraday return components. As a robustness check, the results from a rolling cross-quantilogram in Subsection 5.4 shed further light on the daily spillovers observed for the entire sample, followed by a discussion in subsection 5.5.

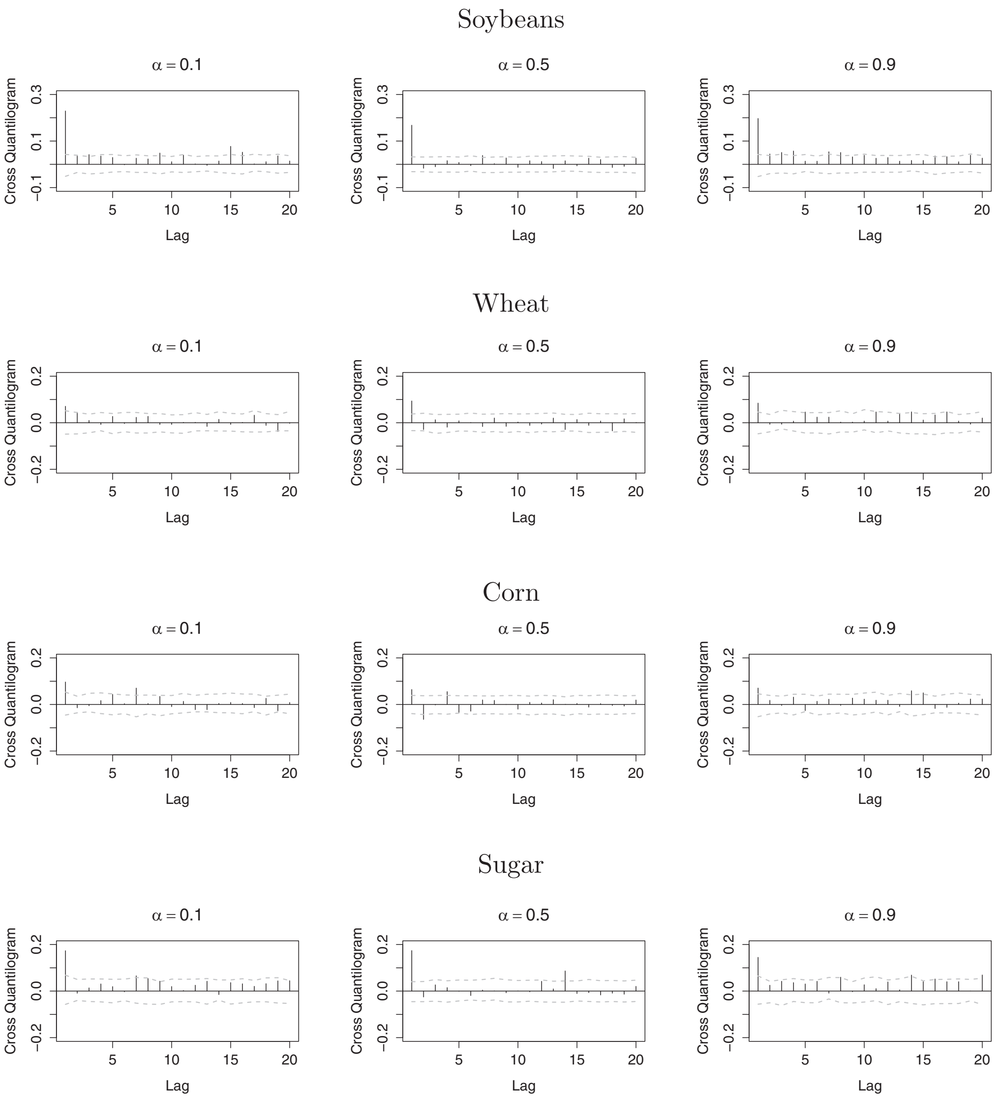


FIGURE 4

Daily Return Spillovers from United States to China

Note. Figure reports the sample cross-quantilogram of daily return spillovers from the United States to China when both markets take same quantiles. From the top to the bottom, the commodities are soybeans, wheat, corn, and sugar. Results for low quantile ($\alpha_{US} = 0.1$ to $\alpha_{CN} = 0.1$), median quantile ($\alpha_{US} = 0.5$ to $\alpha_{CN} = 0.5$), and high quantile ($\alpha_{US} = 0.9$ to $\alpha_{CN} = 0.9$) are given in the left, middle, and right panels, respectively. Lag p is 20, the average trading days per month. Gray-dashed lines represent the 95% bootstrapped confidence intervals for no directional predictability with 1,000 bootstrapped replicates.

5.1. Bilateral Daily Return Spillovers

This subsection provides results of the daily return spillovers for soybeans, wheat, corn, and sugar futures with lag k from 1 to 20 from the United States to China (Figure 4), followed by statistics in the same structure from China to the United States (Figure 5). For each of the four commodities, the cross-quantilogram results are reported when both markets are

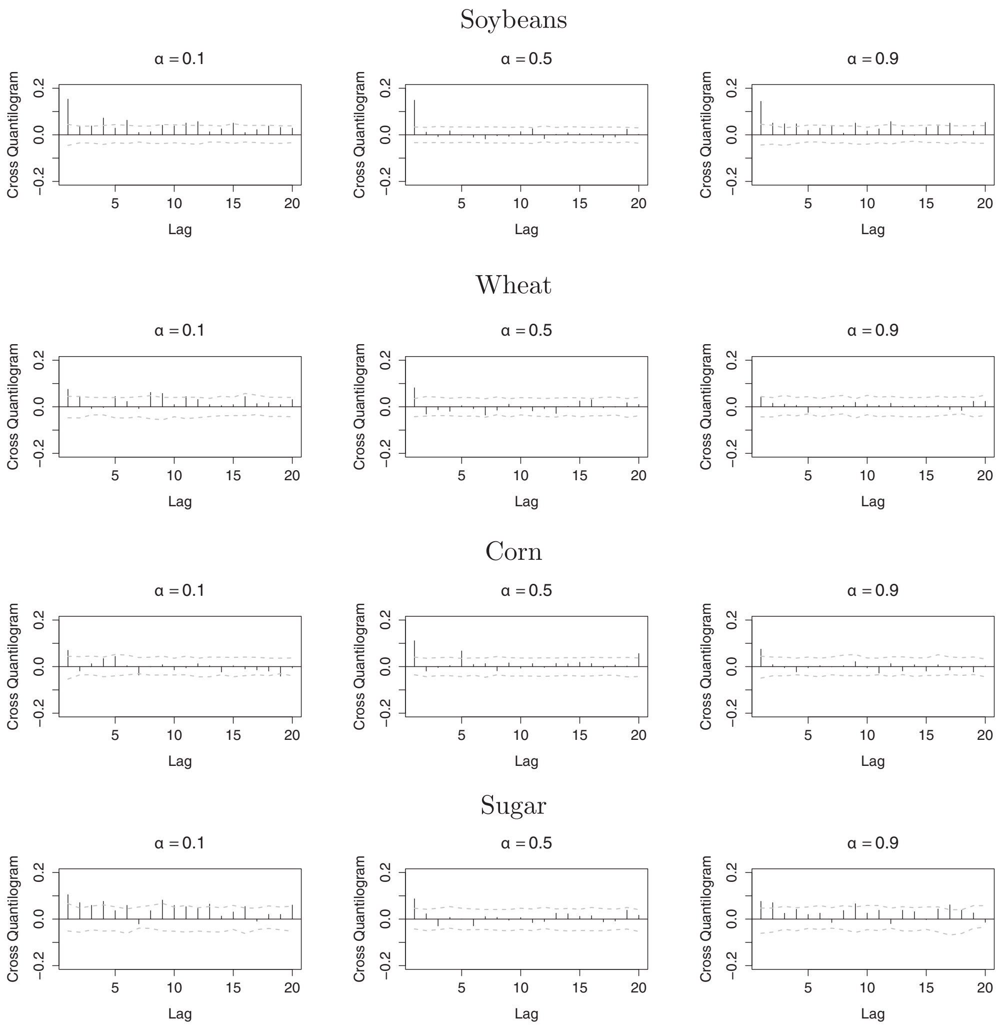


FIGURE 5

Daily Return Spillovers from China to United States

Note. Figure reports the sample cross-quantilogram of daily return spillovers from China to the United States when both markets take same quantiles. From the top to the bottom, the commodities are soybeans, wheat, corn, and sugar. Results for low quantile ($\alpha_{CN} = 0.1$ to $\alpha_{US} = 0.1$), median quantile ($\alpha_{CN} = 0.5$ to $\alpha_{US} = 0.5$), and high quantile ($\alpha_{CN} = 0.9$ to $\alpha_{US} = 0.9$) are given in the left, middle, and right panels, respectively. Lag p is 20, the average trading days per month. Gray-dashed lines represent the 95% bootstrapped confidence intervals for no directional predictability with 1,000 bootstrapped replicates.

in their low, median, and high quantiles, i.e., $\alpha_{US} = \alpha_{CN} = 0.1, 0.5$ and 0.9 from left to the right[7]. In each figure, the gray-dashed lines are the 95% bootstrapped confidence intervals for no predictability based on 1,000 bootstrapped replicates[8]. By choosing $\alpha_i = 0.1, 0.5$ and

[7]The corresponding portmanteau test $\hat{Q}_{\alpha}^{(p)}$ with 20 lags provides consistent results as the cross-quantilogram. Results are not reported here to save space.

[8]The tuning parameter used in this paper, $1/\gamma$, follows Han et al. (2014), who adapted the rule suggested by Patton et al. (2009). The critical bands generated with 2,000 bootstrapped replicates are similar to those generated with 1,000 bootstrapped replicates.

0.9 for $i = US, CN$, we aim to capture the patterns of the directional predictability of both extreme and median daily returns of one country to the other[9].

In terms of the daily return spillovers from the United States to China for soybeans, the cross-quantilogram results in Figure 4 show a significant, positive 1-day correlation for all three quantiles, i.e., $\hat{\rho}_{\alpha_{CN}}(1) = 0.23, 0.17$, and 0.20, and the correlation quickly drops off after 1 day. This implies a short-lived directional predictability: when the soybean futures return in the United States is low/moderate/high, it is very likely that the Chinese soybean futures will also experience a low/moderate/high return on the following trading day, respectively. It appears that the 1-day quantile correlation of return series is slightly stronger in the upper and lower quantiles than at the median. The portmanteau test statistics confirm the significance of the quantile correlations. The quantile correlations, again, are significant and positive only for 1 day in wheat, corn, and sugar markets. The magnitude of the 1-day lead–lag correlation seems to be similar across the three quantiles. The Q statistics confirm significant spillovers for all 20 lags of wheat, corn, and sugar futures, apart from the low quantile for wheat from the United States to China, with significance given for only up to 10 lags. Out of the four commodities, the spillover effects from the United States to China appear to be stronger for soybeans and sugar than in wheat and corn markets.

The results for daily return transmission from China to the United States (Figure 5) show a positive and significant 1-day predictability from China to the United States for soybean futures with a value $\hat{\rho}_{\alpha_{US}}(1) \approx 0.15$ for all three quantiles. Similar to the United States to China spillovers, the China to U.S. spillovers last only for 1 day. Different from soybean futures, the daily return transmissions from China to the United States are much weaker for wheat, corn, and sugar, with cross-quantilogram values of less than 0.1 in all cases, particularly for the high quantile ($\alpha = 0.9$).

In summary, the daily return spillovers appear to be bi-directional, in most cases, with a short-lived quantile correlation that is significant for 1 day, both from the United States to China and the other way round. The transmission from the United States to China is generally stronger than from China to the United States, and most pronounced for soybeans, followed by sugar, corn, and wheat. There are a few cases of a stronger correlation in the upper and lower quantiles as compared to the median, particularly for soybeans and sugar[10].

5.2. Auto-Quantilogram of Daily Return Series

Next, we examine the serial autocorrelation of daily return series for the four commodities in the United States and China with the auto-quantilogram of lag $k = 1, 2, ..., 20$[11]. As shown in Figure 6, regardless of the choice of quantiles, we can hardly discern any short-lived dependence of the daily U.S. returns on soybean, corn, wheat, and sugar futures. In other words, no conclusion can be drawn for the likelihood of the occurrence of a certain return, i.e., low ($\alpha_{US} = 0.1$), median ($\alpha_{US} = 0.5$), or high ($\alpha_{US} = 0.9$), for the U.S. market on the

[9]For the bilateral daily return spillovers between the United States and China, the cross-quantilogram and associated portmanteau tests were initially conducted for 15 quantile combinations, i.e., from $\alpha = 0.1, 0.5, 0.9$ to $\alpha = 0.1, 0.3, 0.5, 0.7, 0.9$ both from the United States to China and from China to the United States, for each of the four commodities. In general, the bi-directional spillovers are stronger between the same quantiles, i.e., $\alpha_{US} = \alpha_{CN} = 0.1, 0.5$ and 0.9, than between different quantiles, with a few non-substantial exceptions. To save space, this section only reports cross-quantilogram results from the same quantiles. The results for different quantiles are available upon request.

[10]To the best of our knowledge, there is no suitable test that assesses whether the difference of spillover in extreme quantiles is statistically significant or not. The design of the test is left to future research.

[11]The results from the portmanteau test $\hat{Q}_{\alpha}^{(p)}$ are available upon request.

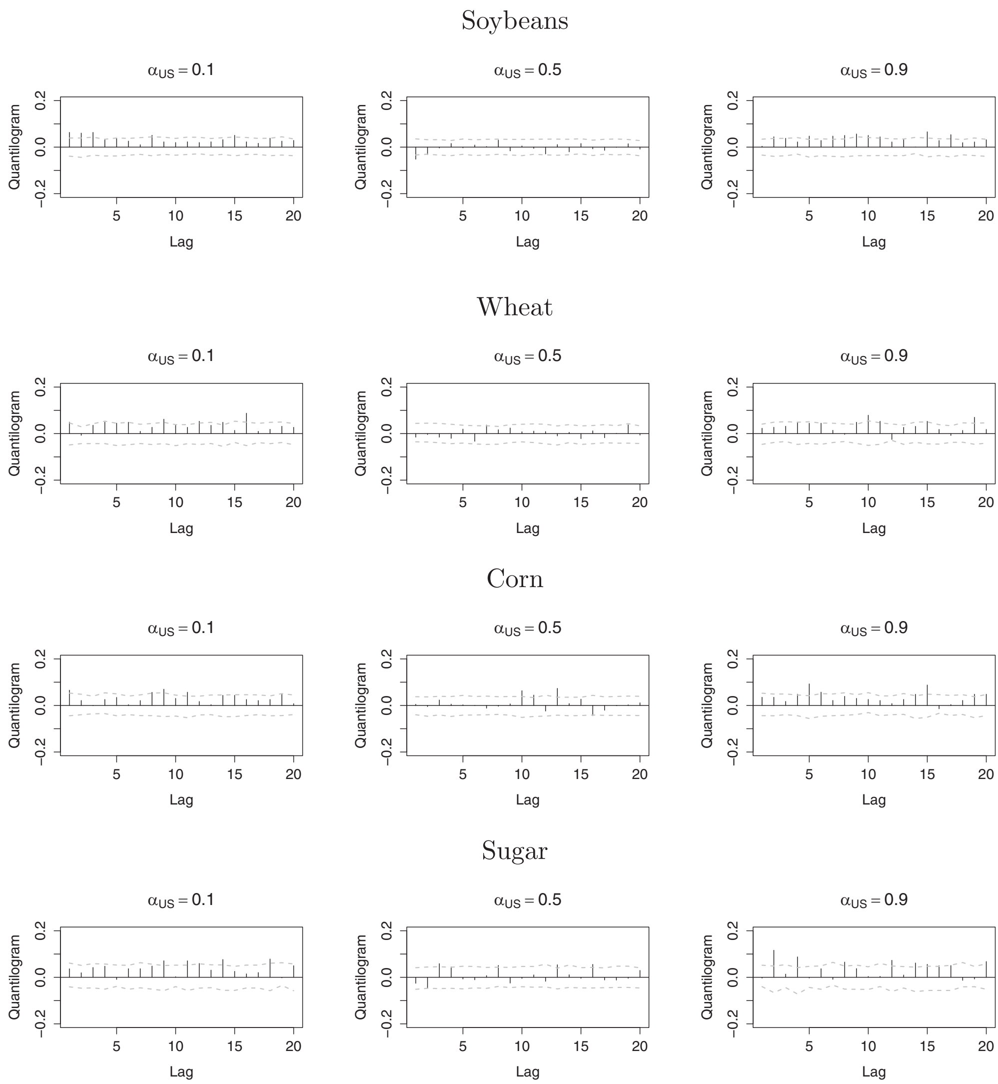


FIGURE 6

Auto-Quantilogram of Returns on U.S. Futures

Note. Figure reports the sample auto-quantilogram statistics for soybean, wheat, corn, and sugar futures daily return series with lag $k = 1, 2, \ldots, 20$ in the same quantiles for the United States. Quantilogram results for low $\alpha_{US} = 0.1$, median $\alpha_{US} = 0.5$, and high $\alpha_{US} = 0.9$ quantiles are given in left, middle, and right panels, respectively.

next trading day given the current return level in the U.S. market. In regard to the return transmission over longer periods, a significantly positive predictability can be detected for the fifth lag of corn and the second lag for sugar.

The auto-quantilogram pattern of daily return series for the Chinese futures market is quite different compared to the U.S. futures for the four commodities. As given in Figure 7, almost no 1-day spillovers can be identified when the return in Chinese market is either at the upper or lower quantile for soybeans, wheat, corn, and sugar. In the central quantile, however,

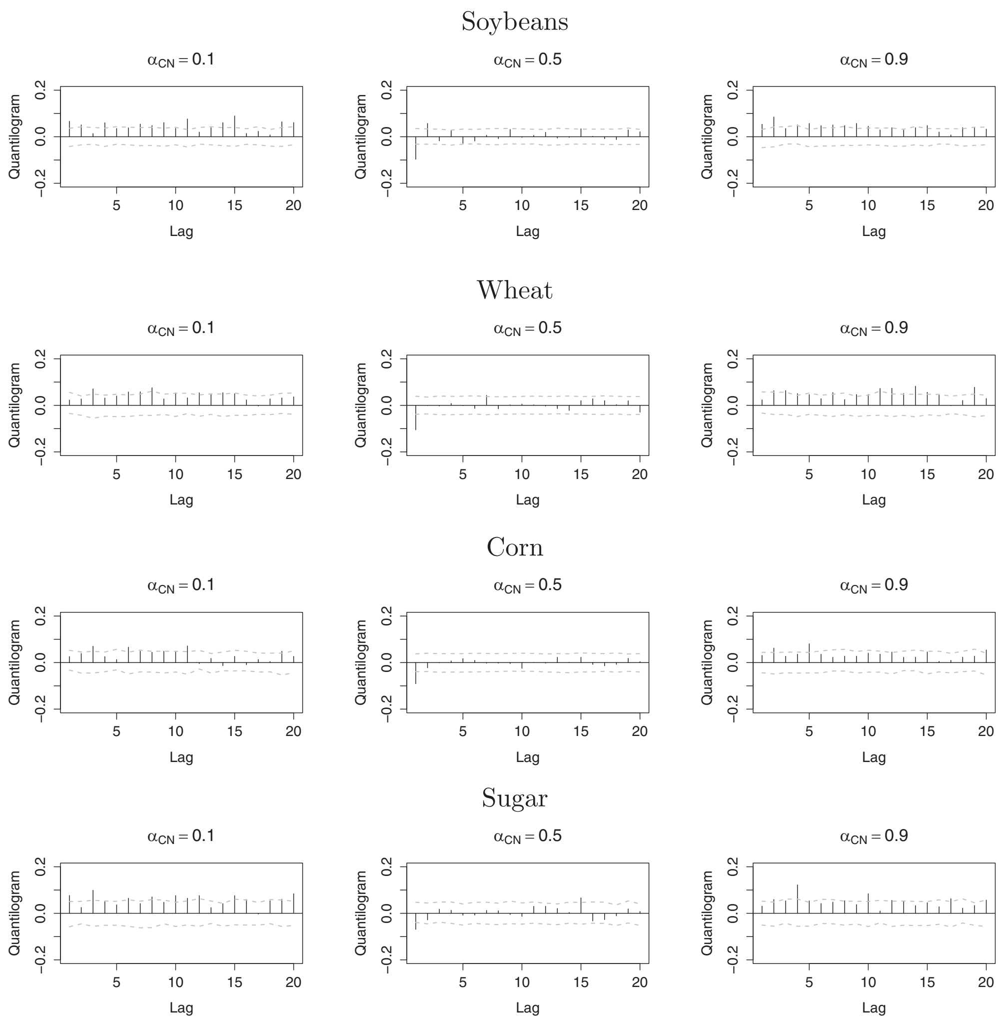


FIGURE 7
Auto-Quantilogram of Returns on Chinese Futures

Note. Figure reports the sample auto-quantilogram statistics for soybean, wheat, corn, and sugar futures daily return series with lag $k = 1, 2, \ldots, 20$ in the same quantiles for China. Quantilogram results for low $\alpha_{CN} = 0.1$, median $\alpha_{CN} = 0.5$, and high $\alpha_{CN} = 0.9$ quantiles are given in left, middle, and right panels, respectively.

a significantly negative return transmission with a value less than 0.1 can be documented for the first lag of the auto-quantilogram for the four commodities.

5.3. Overnight and Intraday Spillovers

Table V displays the cross-quantilogram statistics of the first lag (1 day) from the U.S. daily returns to the Chinese daily, overnight and intraday return components for soybeans, wheat, corn, and sugar, with the corresponding 95% bootstrapped confidence intervals. Apparently, for soybean futures, the daily spillovers ($R^D_{US,t}$ to $R^D_{CN,t+1}$) are stronger when the quantiles in both markets are either low or high, as demonstrated above. More importantly, after

TABLE V

Cross-Quantilogram of the First Lag, the U.S. Daily Return Spillovers via Chinese Daily and Decomposed Returns

	Daily R_{CN}^{D}			*Overnight* R_{CN}^{OV}			*Intraday* R_{CN}^{IN}		
		95% CI			*95% CI*			*95% CI*	
α_{US} *to* α_{CN}	*CQ*	*LB*	*UB*	*CQ*	*LB*	*UB*	*CQ*	*LB*	*UB*
					Soybeans				
0.1 to 0.1	0.2292*	−0.0541	0.0442	**0.4343***	−0.0577	0.0427	0.0014	−0.0295	0.0367
0.5 to 0.5	0.1680*	−0.0326	0.0320	**0.4592***	−0.0297	0.0286	−0.1158*	−0.0359	0.0348
0.9 to 0.9	0.1969*	−0.0551	0.0380	**0.3961***	−0.0515	0.0445	−0.0210	−0.0338	0.0256
					Wheat				
0.1 to 0.1	0.0708*	−0.0444	0.0471	**0.2923***	−0.0676	0.0598	0.0013	−0.0478	0.0337
0.5 to 0.5	0.0937*	−0.0416	0.0376	**0.3305***	−0.0314	0.0408	−0.0811*	−0.0361	0.0408
0.9 to 0.9	0.0844*	−0.0474	0.0485	**0.2715***	−0.0541	0.0539	−0.0117	−0.0337	0.0410
					Corn				
0.1 to 0.1	0.0967*	−0.0487	0.0524	**0.2826***	−0.0504	0.0612	−0.0096	−0.0402	0.0354
0.5 to 0.5	0.0643*	−0.0392	0.0400	**0.3456***	−0.0360	0.0360	−0.1059*	−0.0360	0.0392
0.9 to 0.9	0.0707*	−0.0478	0.0488	**0.2392***	−0.0480	0.0656	−0.0317	−0.0392	0.0314
					Sugar				
0.1 to 0.1	0.1734*	−0.0530	0.0616	**0.3444***	−0.0525	0.0783	−0.0033	−0.0404	0.0543
0.5 to 0.5	0.1740*	−0.0463	0.0412	**0.4521***	−0.0402	0.0381	−0.0680*	−0.0464	0.0443
0.9 to 0.9	0.1449*	−0.0513	0.0627	**0.3729***	−0.0571	0.0757	−0.0204	−0.0395	0.0456

Note. Table summarizes the results of cross-quantilogram from the U.S. daily return to the Chinese daily, overnight, and intraday returns with the first lag for soybean, wheat, corn, and sugar futures in the same quantiles. It measures the significance of the 1 day return spillovers from the United States to China. R_{CN}^{D} is the daily return of the Chinese market, which is further decomposed to overnight R_{CN}^{OV} and intraday R_{CN}^{IN} returns in China. α_{US} to α_{CN} represents the quantile selected from the U.S. market to the Chinese market. CQ represents the statistics of the cross-quantilogram for the first lag. 95% CI is the bootstrapped confidence interval for no predictability at a significance level of 5%. Statistics marked by an asterisk are significant at 5% significance level. Results printed in bold show the most significant decomposed return spillovers for each quantile from the United States to China.

decomposing daily returns R_{CN}^{D} into overnight R_{CN}^{OV} and intraday R_{CN}^{IN} returns using Equation (5), we find that the positive overnight return transmission from the United States to China is almost twice as strong on average as the daily transmission in the same direction, i.e., 0.43 for $\alpha_{US} = 0.1$ to $\alpha_{CN} = 0.1$, 0.46 for $\alpha_{US} = 0.5$ to $\alpha_{CN} = 0.5$, and 0.40 for $\alpha_{US} = 0.9$ to $\alpha_{CN} = 0.9$ (all significant at the 5% level). In contrast, interestingly, most of the intraday return spillovers from the United States to China are negative and negligible, which is possibly a correction for the overreaction of the positive overnight return spillovers. Similar results can be documented for the spillovers of wheat, corn, and sugar from the United States to China, in which the magnitude of the overnight return transmission is more than twice the size of the daily return spillovers (highlighted in bold), and the intraday return transmissions are negative and insignificant.

Table VI summarizes the results for 1-day-ahead directional predictability from China to the United States in the same structure as Table V. In terms of soybean futures, the transmission from Chinese daily returns $R_{CN,t}^{D}$ to the U.S. intraday returns $R_{US,t}^{IN}$ is more significant and positive than via the overnight returns $R_{US,t}^{OV}$ for the three quantiles under consideration. Mixed results are observed for wheat and corn, where the spillovers via overnight returns

TABLE VI
Cross-Quantilogram of the First Lag, the Chinese Daily Return Spillovers via U.S. Daily and Decomposed Returns

	Daily R_{US}^{D}			*Overnight* R_{US}^{OV}			*Intraday* R_{US}^{IN}		
		95% CI			*95% CI*			*95% CI*	
α_{CN} *to* α_{US}	*CQ*	*LB*	*UB*	*CQ*	*LB*	*UB*	*CQ*	*LB*	*UB*
					Soybeans				
0.1 to 0.1	0.1533*	−0.0476	0.0436	0.0941*	−0.0377	0.0468	**0.1315***	−0.0436	0.0467
0.5 to 0.5	0.1487*	−0.0320	0.0337	0.0954*	−0.0376	0.0315	**0.1285***	−0.0359	0.0303
0.9 to 0.9	0.1439*	−0.0458	0.0441	0.1128*	−0.0405	0.0405	**0.1159***	−0.0436	0.0410
					Wheat				
0.1 to 0.1	0.0751*	−0.0478	0.0478	**0.0757***	−0.0474	0.0486	0.0621*	−0.0430	0.0472
0.5 to 0.5	0.0816*	−0.0447	0.0353	0.0275	−0.0400	0.0345	**0.0643***	−0.0384	0.0439
0.9 to 0.9	0.0414	−0.0388	0.0523	0.0588*	−0.0422	0.0542	**0.0414**	−0.0558	0.0448
					Corn				
0.1 to 0.1	0.0701*	−0.0532	0.0437	**0.0701***	−0.0502	0.0474	0.0523*	−0.0448	0.0443
0.5 to 0.5	0.1111*	−0.0360	0.0408	0.0512*	−0.0424	0.0424	**0.0935***	−0.0376	0.0400
0.9 to 0.9	0.0751*	−0.0493	0.0488	0.0523*	−0.0399	0.0493	**0.0751***	−0.0537	0.0355
					Sugar				
0.1 to 0.1	0.1050*	−0.0527	0.0684	**0.1458***	−0.0636	0.0618	0.0650*	−0.0570	0.0562
0.5 to 0.5	0.0871*	−0.0484	0.0464	**0.0943***	−0.0443	0.0453	0.0665*	−0.0412	0.0474
0.9 to 0.9	0.0764*	−0.0558	0.0530	**0.0936***	−0.0557	0.0598	0.0308	−0.0440	0.0586

Note. Table summarizes the results of cross-quantilogram from the Chinese daily return to the U.S. daily, overnight and intraday returns with the first lag for soybean, wheat, corn, and sugar futures in the same quantiles. It measures the significance of the 1 day return spillovers from China to the United States. R_{US}^{D} is the daily return of the U.S. market, which is further decomposed to overnight R_{US}^{OV} and intraday R_{US}^{IN} returns in the United States. α_{CN} to α_{US} represents the quantile selected from the Chinese market to the U.S. market. CQ represents the statistics of the cross-quantilogram for the first lag. 95% CI is the bootstrapped confidence interval for no predictability at a significance level of 5%. Statistics marked by an asterisk are significant at 5% significance level. Results printed in bold show the most significant decomposed return spillovers for each quantile from China to the United States.

dominate the spillovers via intraday returns for low quantiles in both countries. In contrast, the transmission through intraday returns is more critical in the median and upper quantiles. For sugar futures, the overnight transmission plays a more substantial role than the intraday transmission regardless of the quantile selected in both countries, which is similar to the decomposed pattern emerging from the United States to China (Table V) but at a much lower magnitude, i.e., 0.15 (China to the United States) vs. 0.34 (United States to China), 0.09 vs. 0.45, and 0.09 vs. 0.37 when the returns are low, median, and high, respectively. In general, the decomposition shows a very different picture of the transmission from China to the United States: in many cases, the overnight spillovers no longer dominate and the intraday spillovers are more pronounced.

To conclude, the decomposed transmission pattern from the United States to China, is consistent for all commodities: the positive spillovers via overnight returns are the main source for daily transmission, with a magnitude more than twice as large as that of the daily spillovers. The spillovers via intraday returns, however, are negative and insignificant for all commodities. From China to the United States, the decomposed return transmission varies across commodities and quantiles: rather than offsetting in the case of return transmission

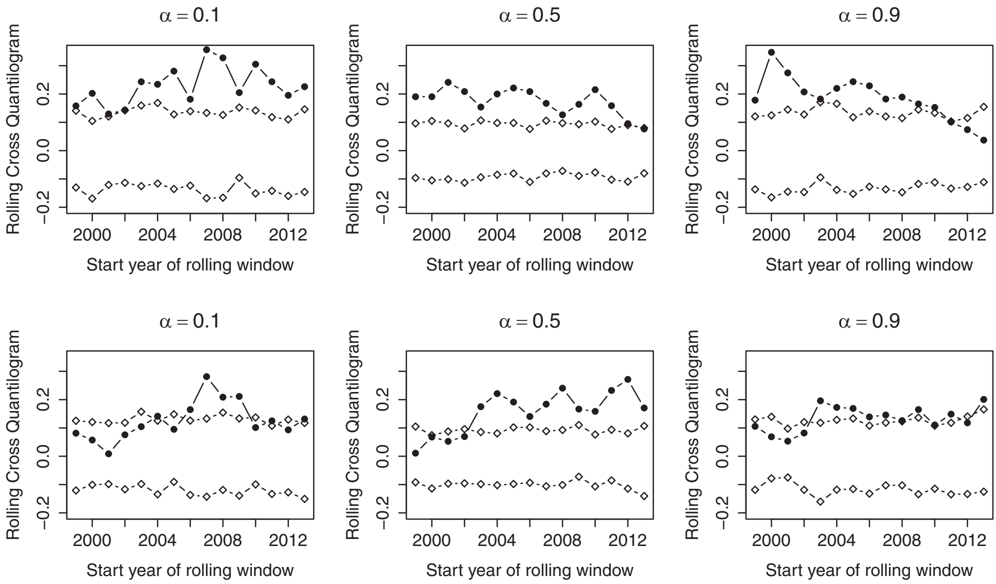


FIGURE 8

Rolling Daily Return Spillovers for Soybean Futures

Note. Top panel exhibits the 1 day ahead rolling spillovers from the United States to China at low ($\alpha = 0.1$), median ($\alpha = 0.5$), and high ($\alpha = 0.9$) quantiles from the left to the right. Bottom panel presents rolling spillovers from China to the United States, respectively. Starting year of the rolling window is marked on the horizontal axis. Black dots are the rolling cross-quantilogram for 1 day spillovers, hollow squares are 95% bootstrapped confidence intervals for no predictability based on 1,000 bootstrapped replicates.

from the United States to China, both the overnight and intraday return spillovers are significant in explaining the daily return spillovers, resulting in a stronger daily return transmission from China to the United States.

5.4. Rolling Daily Return Spillovers

In light of the dynamic nature of the agricultural futures markets from 2000 to 2014 (Figure 2), in this subsection, we present a rolling cross-quantilogram for each of the four commodities. The rolling analysis uncovers possible structural changes in the time series against major market events and provides a robustness check of the results obtained from the entire sample. For each time series, data of the first two years from the starting year are selected to compute the cross-quantilogram. Then, we roll over to the start of the second year covering another 2 years, until data from 2013 to 2014, as the latest subsample, are used[12].

Figures 8–11 present the rolling quantilogram results of the first lag for four commodities[13]. The top panel of each figure displays the 1-day-ahead spillover from the United States to China at three different quantiles. The bottom panel presents corresponding spillovers

[12]The results from 3- and 4-year rolling windows are conducted as robustness checks and provide similar dynamics as the 2-year rolling window. The results are not reported here to save space, but available upon request.

[13]In line with the daily and decomposed results of the entire sample, the bilateral rolling spillovers are strongest for the same quantiles and are short-lived (1 day). The results from cross-quantiles with longer lags are not reported to save space.

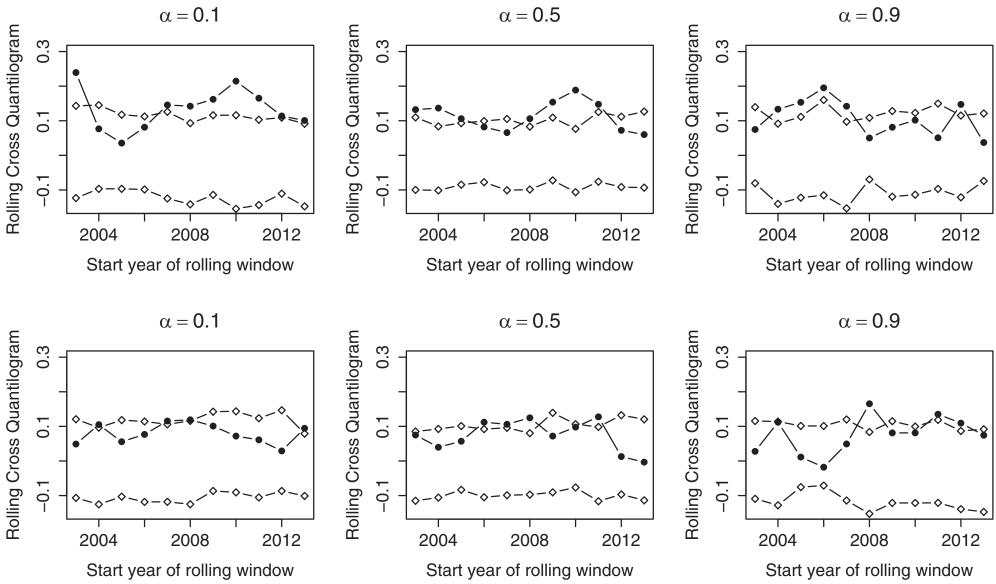


FIGURE 9

Rolling Daily Return Spillovers for Wheat Futures

Note. Top panel exhibits the 1 day ahead rolling spillovers from the United States to China at low ($\alpha = 0.1$), median ($\alpha = 0.5$), and high ($\alpha = 0.9$) quantiles from the left to the right. Bottom panel presents rolling spillovers from China to the United States, respectively. Starting year of the rolling window is marked on the horizontal axis. Black dots are the rolling cross-quantilogram for 1 day spillovers, hollow squares are 95% bootstrapped confidence intervals for no predictability based on 1,000 bootstrapped replicates.

from China to the United States. Each dot in the figure is generated using the rolling method described above, and the starting year of the rolling window is marked on the horizontal axis. The black dots are the rolling cross-quantilogram for 1-day spillovers, the hollow squares are the 95% bootstrapped confidence intervals for no predictability.

Overall, the spillover effect is relatively stronger during the Global Financial Crisis (GFC) at the lower quantiles. In accordance with the results from the entire sample, the rolling spillovers are in general more significant from the United States to China than the other way round. For the soybean and sugar markets, the directional predictability is consistently significant from the United States to China rolling throughout the entire sample period, whereas the spillover from China to the United States is weaker and mainly occurs during the GFC. While some significant spillovers are detected in the wheat and corn markets during the crisis period, these spillovers are generally weaker.

5.5. Further Discussion

On a daily basis, a stronger positive return spillover from the United States to China than from China to the United States is identified, particularly for soybeans and sugar. This trend is probably due to the considerable consumption and import level for both commodities in China. Additionally, the United States is the world's largest soybean exporter to China. Its pricing power on the global agricultural futures has been documented by numerous studies. The fact that the 1-day positive predictability is lower for wheat and corn is likely to be an

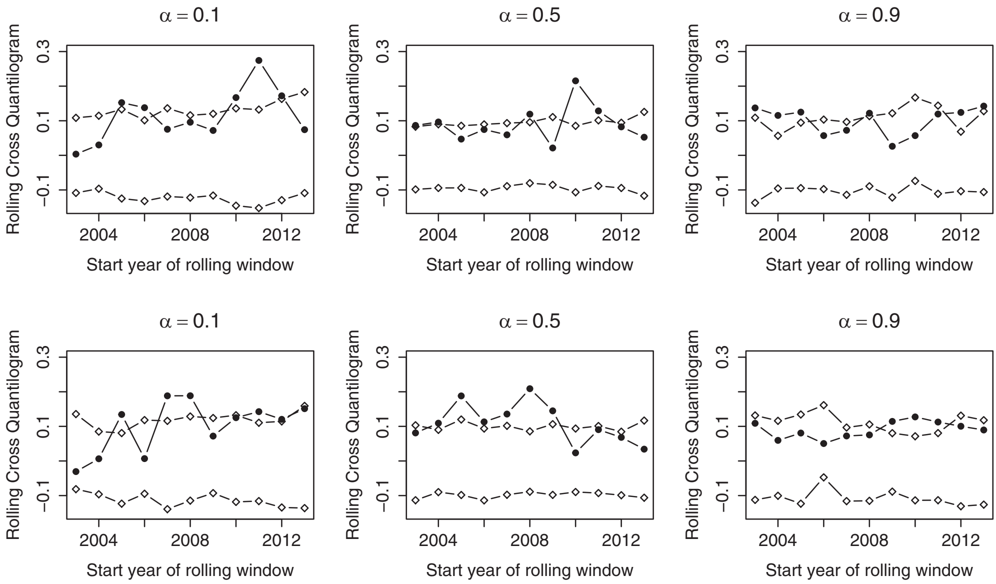


FIGURE 10

Rolling Daily Return Spillovers for Corn Futures

Note. Top panel exhibits the 1 day ahead rolling spillovers from the United States to China at low ($\alpha = 0.1$), median ($\alpha = 0.5$), and high ($\alpha = 0.9$) quantiles from the left to the right. Bottom panel presents rolling spillovers from China to the United States, respectively. Starting year of the rolling window is marked on the horizontal axis. Black dots are the rolling cross-quantilogram for 1 day spillovers, hollow squares are 95% bootstrapped confidence intervals for no predictability based on 1,000 bootstrapped replicates.

outcome of heavy regulations imposed by the Chinese government. In addition, because of the health problems that genetically modified food can potentially cause, in 2012 and 2013, China returned 1252000 tons of corn with the unapproved MIR162 modified gene to the United States. This action might have reduced the price control of the United States on China in the corn market. In terms of international trade, factors that can strengthen the predictability of the U.S. market for the Chinese market involve the use of the U.S. dollar as a global settlement currency as well as monetary policy and trade regulations in both countries. The significant return transmission pattern from China to the United States for soybeans reflects the increasing importance of the Chinese market.

The CBOT and ICE in the United States can be accessed by a wide range of market participants, over 70% of whom are institutional investors potentially reacting more rationally than individual investors. This can explain our findings of less significant daily return spillovers to overnight and intraday returns from China to the United States. In contrast, as a part of an emerging economy, the Chinese futures market is less transparent. Chinese investors, of whom 90% are individuals, probably attach greater weight to information from the U.S. futures market than the other way around, resulting in a more notable positive return spillover via the overnight return component. Moreover, the slightly negative and insignificant intraday return transmission on the next trading day can be regarded as a correction of the overreaction from overnight periods, suggesting that local Chinese investors adjust their strategies more frequently compared to participants in the U.S. futures markets.

From an investment perspective, the analysis of return spillovers on different quantiles provides indications about the sources of return predictability. The positive and significant

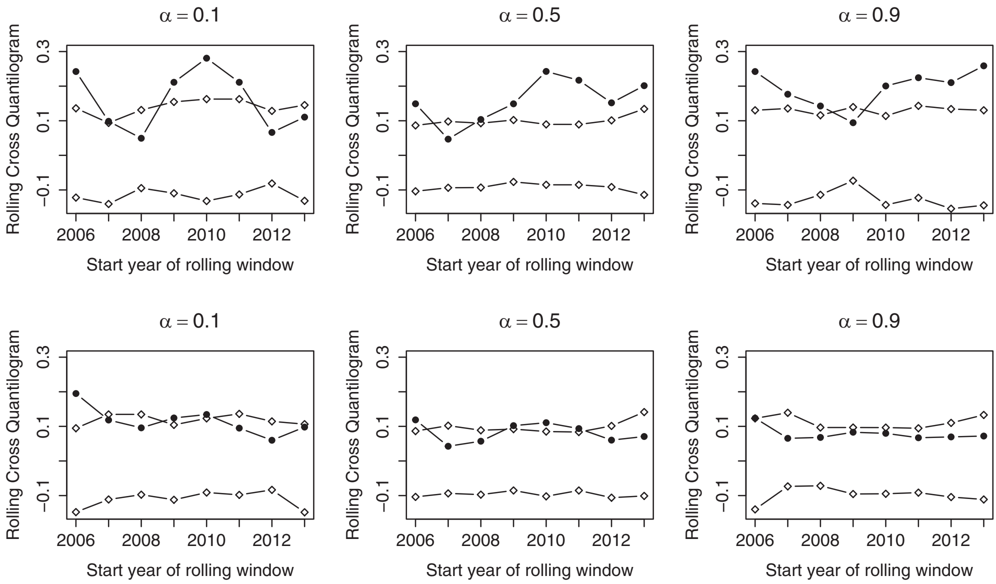


FIGURE 11
Rolling Daily Return Spillovers for Sugar Futures

Note. Top panel exhibits the 1 day ahead rolling spillovers from the United States to China at low ($\alpha = 0.1$), median ($\alpha = 0.5$), and high ($\alpha = 0.9$) quantiles from the left to the right. Bottom panel presents rolling spillovers from China to the United States, respectively. Starting year of the rolling window is marked on the horizontal axis. Black dots are the rolling cross-quantilogram for 1 day spillovers, hollow squares are 95% bootstrapped confidence intervals for no predictability based on 1,000 bootstrapped replicates.

daily return spillovers from the United States to Chinese agricultural futures, especially in soybeans and sugar, suggest that the return on U.S. commodity futures on trading day t can be seen as an indicator for the movement of the return from the Chinese commodities futures on trading day $t + 1$, and the overnight return spillover is the main source of the daily transmission. In addition, the predictive power of the Chinese return series is very limited. This provides further confirmation that U.S. markets are a predictor of other financial markets (Goh et al., 2013; Rapach et al., 2013; Zhang and Li, 2014). The stronger bilateral spillovers through lower quantiles during the GFC period provide evidence of asymmetric spillovers under extreme events. The stronger directional predictability in the quantiles of the U.S. market to the Chinese market for lower tail of the sample distribution indicates that Chinese agricultural commodity markets are likely to face contagion risk from the U.S. market.

6. CONCLUSION

The existing literature mostly addresses the contemporaneous effects, determinants, and spillovers in the volatility of agricultural commodities futures across countries. This paper applies the cross-quantilogram and portmanteau test of Han et al. (2014) with critical values generated with stationary bootstrapping to study the spillovers and directional predictability of the returns between Chinese and U.S. futures markets for soybeans, wheat, corn, and sugar. In regard to the bi-directional daily return spillovers between the United States and

China, a significant and short-lived (1 day) positive dependence is documented in both the extreme and median quantiles. The spillovers are much stronger from the United States to China than in the opposite direction for all commodities. Moreover, the lead–lag impact is most pronounced for soybean futures bi-directionally, and the transmission is most likely to occur in the same quantiles, meaning that when the return in one country is low (moderate/high), the return on the next day in the other country will also most likely to be low (moderate/high). In terms of the auto-quantilogram in return series for both countries, barely any dependence can be extracted from U.S. market returns. The slightly negative return autocorrelations in the Chinese futures market are almost negligible.

Decomposing the short-lived (1 day) return transmissions reveals contrasting patterns. The positive overnight spillovers from the United States to China consistently play a dominant role and offset the negative and insignificant intraday return spillovers. In contrast, the structure of the decomposed return transmissions from China to the United States varies across commodities. The rolling cross-quantilogram shows the dynamics of the transmission patterns over the period of 2000–2014. Despite the difference in patterns across different quantiles and commodities, the rolling results confirm the stronger spillovers from the United States to China especially for soybeans. The fact that the spillovers are strongest during the GFC, particularly for the lower quantiles for all commodities, demonstrates the sensitivity of the transmission to extreme events, as well as the importance of downside risk management.

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