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Dynamics of volatility transmission between the U.S. and the Chinese agricultural futures markets

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ABSTRACT
The U.S. and China are two of the biggest players in the world agricultural market. The literature documents that volatility in the U.S. agricultural futures market spills over significantly to that of China. This article provides further insights into the spillovers from China to the U.S. as well as the time horizon and dynamics of the bidirectional spillovers through the application of a multivariate extension of the heterogeneous autoregressive model, in relation to four commodities – soybean, wheat, corn and sugar. The results confirm the existence of significant spillovers from the U.S. to China for four commodities, which are primarily generated by the shorter-term volatility components in the U.S., and provide evidence for the increasing pricing power of the Chinese market. The findings are robust against various specifications and have important investment and policy implications.

KEYWORDS
HAR model; volatility spillovers; agricultural commodities futures; U.S.; China

JEL CLASSIFICATION
C13; C32; G13

I. Introduction

The study of the volatility transmission dynamics between markets is one that is important and much needed for a number of reasons. First, the transmission of fluctuations of prices between markets can be a complex process (Arouri, Lahiani, and Nguyen 2011) that affects expectations of market participants. This is why insights into the changes in volatility transmission will assist in building accurate asset pricing and forecasting models. Second, the volatility transmission dynamics contains important information regarding market integration and changing market conditions (Bubák, Kočenda, and Žikeš 2011; Nazlioglu, Erdem, and Soytas 2013). Therefore, it is necessary to undertake a more systematic study of the volatility transmission process. Third, volatility transmission varying over time implies dynamic correlations which have large implications for diversification purposes and portfolio allocation (Maheu and McCurdy 2004). In the case of agricultural markets, volatility in food prices can have significant impact on the food security of the poorer members of *the* population (Naylor and Falcon 2010; Sanders and Irwin 2011; Ivanic, Martin, and Zaman 2012). Hence, understanding the changes in volatility transmission between markets would be of great merit to scholars, policymakers and investors.

The U.S. and China are two of the world's biggest trading partners and players in relation to agricultural commodities. The U.S. agricultural futures market is the world's most active while the Chinese market is the world's fastest growing, hence, the interaction between these two markets is of great importance as this would have impact on other markets (Christofoletti, Silva, and Mattos 2012; Han, Liang, and Tang 2013; Hernandez, Ibarra, and Trupkin 2014). The existing literature documents significant interaction between these two markets with volatility in the U.S. market spilling over to the Chinese futures market. However, there is a lack of studies that systematically investigate the dynamics and mechanics of the volatility transmission process between these two markets. Our study addresses this important knowledge gap.

This study contributes to the empirical literature in several important aspects. First, to investigate the dynamics of the volatility transmission between the U.S. and Chinese agricultural futures markets in relation to the major commodities – corn, soybean, wheat and sugar – we apply the multivariate heterogeneous autoregressive (HAR, thereafter) model which enables us to

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analyse the volatility transmission process between the two markets over various time horizons. This model has more desirable properties compared to other techniques, which are discussed in the methodology section of the article. Second, our work provides a more elaborate understanding of the dynamics of the volatility transmission process based on evidence from the agricultural futures markets of two of the world's largest agricultural market players. For each commodity, using the multivariate HAR model with USD/CNY exchange rate, WTI, GSCI Index and GSCI Agriculture Index as control variables, we examine the transmission of volatility on a daily, weekly and monthly basis across different time periods – before, during and after the global financial crisis (GFC). Third, the results show significant volatility spillovers from the U.S. to China for all four commodities, with the dynamics of spillover differing among these commodities. It is most pronounced in relation to soybean as this occurs on a daily, weekly and monthly basis for the full sample period. For wheat and corn, volatility spillovers are observed on the daily and weekly basis. The subsample results demonstrate that the magnitude of volatility spillovers is stronger from China to the U.S. for corn and sugar than from the U.S. to China. Our analysis provides an empirical complement to the volatility spillover literature with evidence of the increasing importance of the Chinese market and the global market integration. Last, our study is useful from both the investment and policy perspectives. For instance, investors can utilize the significant spillovers between the U.S. and China in soybean market to design a trading strategy based on volatility signals. The government, especially in China, can also make use of the significant transmission, to intervene in the market when necessary in order to stabilize the local price volatility.

The remainder of this study is organized as follows. Section II reviews the literature on volatility spillovers among agricultural commodity markets. Section III introduces the agricultural commodities and futures market in both countries. Sections IV and V introduce the methodology and the data, followed by the presentation of the empirical results in Section VI. Section VII concludes the article.

II. Literature review

In the area of volatility transmission among agricultural commodity markets, earlier papers include Spriggs, Kaylen and Bessler (1982) who study the wheat prices between the U.S. and Canada with Granger Causality tests and do not find any significant price leadership role between the U.S. and Canada. Yang, Zhang and Leatham (2003) estimate cross-country relations for wheat futures between the U.S., Canada and the European Union with a vector autoregression (VAR) system. In terms of volatility transmission, their results show no distinctive leadership role in international wheat markets, with all three markets exhibiting features of price leadership to some extent. Hernandez, Ibarra and Trupkin (2014) explore the dynamics across major exchanges of corn, wheat and soybean in the U.S., Europe and Asia with a multivariate generalized autoregressive conditional heteroscedasticity (MGARCH) approach. Their findings suggest that the agricultural markets are highly interrelated, and there are both local and cross-boundary volatility dependence among most of the exchanges. In particular, Chicago plays a major role regarding to spillover effects over other markets. Zhao and Goodwin (2011) apply a VAR model with Fourier seasonal components and BEKK–GARCH models to the U.S. corn and soybean markets and find deviating results: The VAR model-based analysis indicates that volatility spillovers exist from the corn market to the soybean market, but not vice versa. Results from the BEKK model show that volatility spillovers exist between the two markets.

With the application of GARCH-in-mean VAR models, Beckmann and Czudaj (2014) analyse the volatility spillovers of the U.S. corn, cotton and wheat futures markets. Our study differs from their study mainly in two aspects. First, Beckmann and Czudaj (2014) apply GARCH-in-mean VAR models to analyse daily return volatilities. The impulse responses provide spillovers for longer horizons conditional on what has happened for the previous lag term. The HAR model used in this article takes weekly (midterm) and monthly (long-term) volatilities as dependent variables and includes the whole period and not partial responses to an impulse. Second, Beckmann and Czudaj (2014) analyse the U.S. corn–cotton–wheat in bivariate settings across commodities while we examine spillovers for the same commodities across markets that brings further insights regarding global market integration.

In relation to the volatility spillovers between the U.S. and China, the literature applies exclusively MGARCH, VAR, vector error correction model (VECM), Granger Causality, Wavelet or impulse response functions and has primarily focused on commodities such as soybean, wheat, corn, sugar and cotton. In general, most of the studies uncover the leading role of the U.S. market with regard to the Chinese market but very limited attention was given to the pricing power of the Chinese market. Table 1 catalogues the findings from the literature based on the type of agricultural commodity. Except Ge, Wang and Ahn (2010) who utilize futures prices at a weekly frequency, all of the remaining studies use daily closing prices from both the U.S. and Chinese agricultural futures. Consistent results can be found for soybean, sugar and cotton – the U.S. appears to have a dominant role in explaining the course of volatility in the Chinese market (Liu and An 2011; Liu 2009a; Fung, Leung, and Xu 2003; Shi and He 2013; Liu 2009b; Zhang and Tong 2012; Kong and Li 2008; Ge, Wang, and Ahn 2010), whereas the results for wheat and corn are divergent (Liu 2009a; Fung, Leung, and Xu 2003; Hua and Chen 2007; Christofoletti, Silva, and Mattos 2012; Shi and He 2013). Recently, three studies found significant bidirectional volatility transmission between the U.S. and China for soybean, wheat and corn (Yang and Liu 2013; Han, Liang, and Tang 2013; Hernandez, Ibarra, and Trupkin 2014).

To conclude, the literature demonstrates significant volatility spillovers from the U.S. to the Chinese agricultural futures market. Although some of the studies use data with length of more than a decade, none of them has considered the dynamic changes of the volatility transmission from both the U.S. to China and China to the U.S. Our work is primarily motivated by the diverging findings in the literature as well as the lack of studies that employ a methodology that can assess the observed spillover effects at different time horizons. We also split the data into subsamples to reveal the dynamics of the transmission pattern.

III. Market background

Agricultural commodities markets

This section provides an overview of the fundamentals for soybean, wheat, corn and sugar commodities in the U.S. and China, based on annual statistics from 2000 to 2014 from the National Bureau of Statistics of China and the USDA, to give the reader an understanding of the degree to which the two markets are connected and how the connection varies over time.

The first two rows in Table 2 give the world ranking of the U.S. and Chinese annual consumption levels of the four representative commodities

Table 1. Summary of the literature – spillovers between the U.S. and China.

Authors	Data	Models	Spillover direction
Soybean			
Liu and An (2011)	January 2004–December 2009	MGARCH	U.S. to China
Liu (2009a)	September 2004–January 2009	VAR, VECM, IR	U.S. to China
Fung, Leung and Xu (2003)	September 1995–March 2001	MGARCH	U.S. to China
Shi and He (2013)	July 2006–December 2011	MGARCH	U.S. to China
Liu (2009b)	March 2004–March 2007	MGARCH, GC	U.S. to China
Yang and Liu (2013)	January 2011–December 2012	Wavelet, VAR, MGARCH	Bidirection
Han, Liang and Tang (2013)	March 2002–September 2011	SVAR, VECM, IR	Bidirection
Hernandez, Ibarra and Trupkin (2014)	2004–2009	MGARCH	Bidirection
Wheat			
Liu (2009b)	March 2004–March 2007	MGARCH, GC	U.S. to China
Hernandez, Ibarra and Trupkin (2014)	2004–2009	MGARCH	Bidirection
Fung, Leung and Xu (2003)	1996–2002	MGARCH	No-spillover
Hua and Chen (2007)	1996–2002	ECM, GC	No-spillover
Corn			
Christofoletti, Silva and Mattos (2012)	2002–2011	ECM	U.S. to China
Hernandez, Ibarra and Trupkin (2014)	2004–2009	MGARCH	bidirection
Shi and He (2013)	2006–2011	MGARCH	no-spillover
Sugar			
Zhang and Tong (2012)	January 2007–June 2011	GC	U.S. to China
Cotton			
Kong and Li (2008)	June 2006–September 2008	VECM, GC	U.S. to China
Ge, Wang and Ahn (2010)	December 2004–December 2008	MGARCH, GC	U.S. to China

IR: Impulse response function. GC: Granger Causality.

Table 2. Fundamentals of agricultrual commodities between the U.S. and China.

	Soybean	Wheat	Corn	Sugar
CN consumption[a]	1st	1st	2nd	2nd
U.S. consumption[b]	2nd	4th	1st	4th
CN import/CN consumption	77.63%	2.27%	2.05%	16.35%
CN production/CN consumption	23.89%	96.66%	112.38%	89.49%
U.S. export/CN import	42.68%	36.22%	57.90%	0.0086%
U.S. export/CN production	138.68%	0.84%	1.42%	0.0016%
U.S. export[c]	1st	1st	1st	13th

Source: Bric database.
The reported figures are averages for 2004–2014.
[a]The world ranking of China in terms of the averaged annual consumption.
[b]The world ranking of the U.S. in terms of the averaged annual consumption.
[c]The world ranking of the U.S. as an exporter to China. CN is short for China.

over the past 10 years. Clearly, both countries were among the top four consumers in the world for all four commodities. China was the world's largest consumer of soybean. Only 23.89% of this consumption was supplied locally while 77.63%[1] came from imports, with the U.S. making the biggest contribution (42.68%). China was the world's largest and second largest consumer, respectively, of wheat and corn during the period of 2004–2014. Unlike the soybean market, China was almost self-sufficient with regards to wheat and corn with imports accounting for only 2.27% and 2.05%, respectively, of its total consumption of these commodities. Of the total wheat and corn imports of China, 36.22% and 57.90%, respectively, were imported from the U.S., making the U.S. the largest exporter of both commodities to China. In relation to sugar, on average, in the past 10 years, 89.49% of China's consumption came from local production, and the U.S. ranked thirteenth globally as an exporter of sugar to China.

Figure 1 presents imports as a percentage of China's consumption and the percentage of Chinese imports

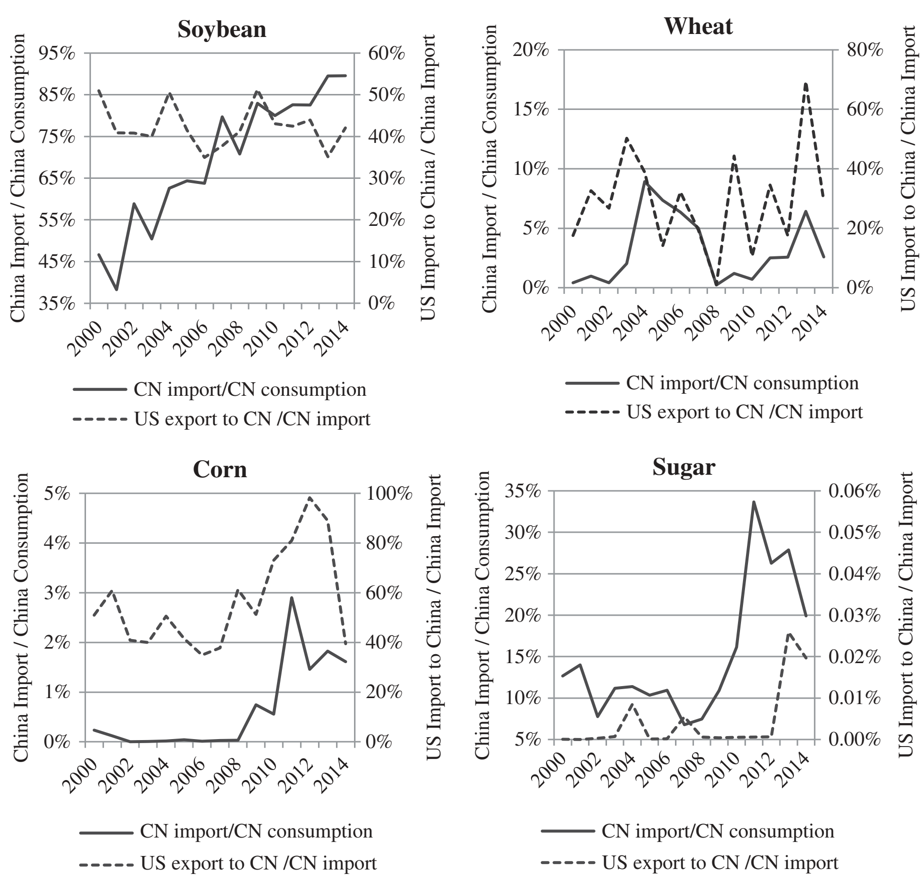

Figure 1. Import ratios in China, 2000–2014. Source: Bric database.

Notes: The figure is generated with annual data from 2000 to 2014. Solid lines graph the net import in China as a percentage of domestic consumption with the scale on the left-hand side. Dashed lines graph the percentage of Chinese import that is exported by the U.S., the scale is on the right-hand side.

[1]The given percentage figures for CN import/CN consumption and CN production/CN consumption do not add up to 1 as stock is considered.

that was accounted for by the U.S. from 2000 to 2014 for the four commodities. It is clear that there was a persistent increase in the proportion of consumption coming from imports over time with regards to soybean while the proportion of imports coming from the U.S. remained stable between 35% and 52% from 2000 to 2014. Both ratios, however, are more volatile for the wheat market, with the proportion of wheat imports increasing from 2004 to 2007 followed by a considerable reduction starting from 2008. In terms of the corn and sugar markets, there was an upsurge in the Chinese import amount relative to its consumption after 2008, and the percentage of imports from the U. S. remained high between 2010 and 2013 for corn, and since 2013 for sugar.

Agricultural futures markets

The U.S. futures market, that is, Chicago Board of Trade (CBOT) and Intercontinental Exchange (ICE), is globally well-established agricultural futures market and can be accessed by different types of participants, that is, professional, proprietary, domestic, foreign, institutional and individual (Talpsepp 2011). However, due to the restriction of the RMB as an international settlement currency and the potential interference that foreign investors might cause in the local market, the Chinese futures market, that is, Dalian Commodities Exchange (DCE) and Zhengzhou Commodities Exchange (ZCE), is more restricted to foreign participation and over 95% of the investors in the Chinese futures market are domestic. Most of the foreign market participants are institutional investors and fund managers who enter the Chinese futures market by going into partnership with local companies. Unlike 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 whereas the remaining 90% are predominantly individual investors, which may stimulate speculative and noisy trades (Wang 2012).

Figure 2 presents the course of the average monthly closing prices of the futures on soybean, wheat, corn and sugar in the U.S. and Chinese markets. Clearly, the price movements for soybean and sugar in both the U.S. (in grey) and Chinese (in black) markets are very similar, with price increases and declines occurring almost at the same time. The prices in the markets for corn and wheat, however, appear to be less correlated.

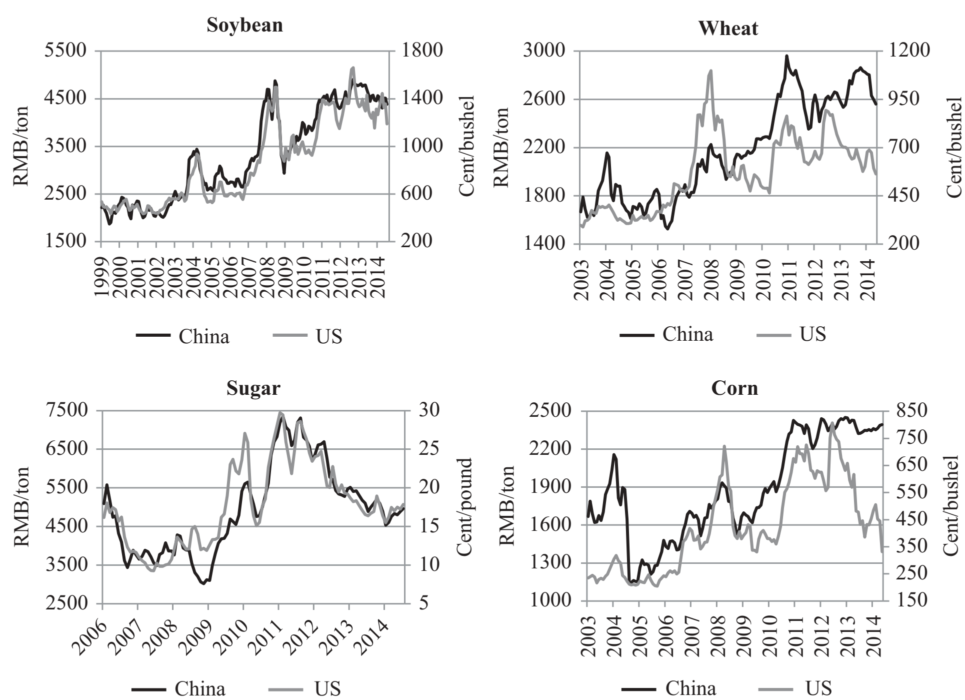

Figure 2. Monthly averaged closing prices for the U.S. and Chinese futures. Source: Bric database.

Notes: The closing prices are monthly averaged with the daily data, the sample size is up to July 2014. For each commodity, the monthly closing prices are presented with black line for the Chinese futures market, with the scale on the left-hand side and grey line for the U.S. futures market, with the scale on the right-hand side.

IV. Methodology

The long-memory feature of volatility is often modelled by fractionally integrated GARCH (FIGARCH) models of returns or autoregressive fractionally integrated moving average (ARFIMA) models of realized volatility. However, the fractional integrated models are non-trivial to estimate and not easily extendible to multivariate processes (Corsi 2009). To study the interrelations of volatility from different markets, we modify the HAR model of Corsi (2009), an autoregressive-type model for realized volatility components established over multiple time periods, that is, daily, weekly and monthly. The HAR model is more powerful than the methodologies employed so far in this domain as it not only sufficiently captures the short-, mid- and long-term features of the historical volatility components but can also be flexibly augmented with external variables. The HAR model has a good ability to capture the true long-memory properties of the volatility and remains intuitive and simpler than the FIGARCH models.

In the default univariate version of the HAR model, volatility is forecast by a linear function of the daily, weekly and monthly realized volatilities as follows:

$$v_{t+h} = c + \beta^{(d)} v_t^{(d)} + \beta^{(w)} v_t^{(w)} + \beta^{(m)} v_t^{(m)} + \epsilon_{t+h}, \tag{1}$$

where $v_t^{(d)}$, $v_t^{(w)}$ and $v_t^{(m)}$ are daily, weekly and monthly observed volatilities at time t. $v_t^{(w)}$ and $v_t^{(m)}$ are calculated as the normalized volatilities summed over the last 5 and 22 trading days, respectively:

$$v_t^{(w)} = \frac{1}{5}\sum_{i=1}^{5} v_{t-i} \tag{2}$$

and

$$v_t^{(m)} = \frac{1}{22}\sum_{i=1}^{22} v_{t-i}. \tag{3}$$

To assess the volatility spillovers of agricultural futures between the U.S. and China at three different time horizons, we employ six specifications of the HAR model with the logarithmic transformation[2] of the variance, as originally extended and applied by Bubák, Kočenda and Žikeš (2011) and Souček and Todorova (2013). In addition, we add USD/CNY exchange rate, WTI, S&P GSCI Index and S&P GSCI Agriculture Index as control variables.[3] The six specifications uncover the explanatory power of the realized daily, weekly and monthly volatilities from both China and the U.S. to the future daily, weekly or monthly volatility in each country i, $i = US$ or CN:

$$\begin{aligned} V_{i,t+1}^{(k)} = {} & c + \beta_{CN}^{(d)} v_{CN,t}^{(d)} + \beta_{CN}^{(w)} v_{CN,t}^{(w)} + \beta_{CN}^{(m)} v_{CN,t}^{(m)} + \beta_{US}^{(d)} v_{US,t}^{(d)} \\ & + \beta_{US}^{(w)} v_{US,t}^{(w)} + \beta_{US}^{(m)} v_{US,t}^{(m)} + \beta_{FX} R_{FX,t} + \beta_{WTI} R_{WTI,t} \\ & + \beta_{GSCI} R_{GSCI,t} + \beta_{GSCIA} R_{GSCIA,t} + \epsilon_{i,t+1}^{(k)}, \\ & k = d, w, m. \end{aligned} \tag{4}$$

The dependent variable $V_{i,t+1}^{(k)}$ is the 1-day-ahead daily, averaged weekly or averaged monthly volatility of country i, $i = US$ or CN.[4] The independent variables $v_{CN,t}^{(d)}$, $v_{CN,t}^{(w)}$ and $v_{CN,t}^{(m)}$ are the daily, weekly and monthly realized volatilities in China; $v_{US,t}^{(d)}$, $v_{US,t}^{(w)}$ and $v_{US,t}^{(m)}$ are the corresponding volatility components in the U.S.[5] $R_{FX,t}$, $R_{WTI,t}$, $R_{GSCI,t}$ and $R_{GSCIA,t}$ are the returns of the USD/CNY exchange rate, WTI, GCSI and GSCI Agriculture Index. In line with the existing literature, Equation (4) is fitted using a Newey–West correction of the standard errors.

[2]Two main advantages of employing the logarithmic variance rather than volatility itself are that (1) the distribution of the logarithmic variance is closer to a normal distribution and (2) no parametric restrictions are required to ensure the non-negativity of the variance.

[3]Consistent with the timeline of the default HAR model, the lagged term of the return series are used.

[4]The original specification of the HAR model includes daily, weekly and monthly historical volatilities based on the notion that different types of market participants cause and react differently to volatility. While it is suggested that longer-term volatility has a stronger impact on shorter-term volatility than the other way around, this does not necessarily mean that the relationship in the opposite direction is negligible. When the dependent variable is the weekly or monthly volatility, the historical daily volatility can be interpreted as a proxy for short-term shocks and thus has an important role, especially in turbulent financial market periods.

[5]Daily, weekly and monthly volatilities defined in this way is related on the one hand to some degree of aggregation and on the other hand, to a certain overlap as the weekly volatilities include the daily volatilities, and the monthly volatilities contain the daily and weekly ones. This cascade-like structure is the fundamental of the HAR model and is based on the economic notion of market participants with different planning horizons. If the daily volatility is excluded from the weekly volatility and in turn, the monthly volatilities are established in a way not to contain the immediately preceding weekly volatilities, this maybe seem consistent in a statistical sense but would aggravate the economic interpretation of the results. Moreover, the current parsimonious model specification has proven to be very successful in capturing the dynamics of volatility and it is likely that by changing it, potential longer-term effects will remain undetected as the regressions would include monthly volatilities with a lag of 1 week and thus of a much more limited informational content.

The HAR model used in the article does not take account of price spillovers. However, this issue is likely to concern daily horizon only because price spillovers between U.S. and Chinese futures markets for these assets in the recent years are documented to be of short-lived nature only and mainly due to the non-synchronicity of the U.S. and Chinese markets which trade in different time zones (Jiang et al. 2016). Price spillovers are shown to become statistically insignificant beyond the first lag which is in line with the market efficiency paradigm.

Initially, the HAR model was designed for modelling realized volatility with high-frequency intraday data. Daily range-based estimators are used in this study due to the unavailability of intraday data in particular for the Chinese agricultural market. Without intraday data, it is not possible to obtain realized volatility estimates. Alternative proxies of the daily volatility are daily squared returns or daily range-based estimators. Range-based estimators are motivated by the idea that the price range (high minus low) over a time interval may capture volatility better than the corresponding daily squared returns which are sampled at fixed intervals, and have largely proven to be more efficient estimators than close-to-close returns (Alizadeh, Brandt, and Diebold 2002; Vipul and Jacob 2007; Todorova and Husmann 2012, among others). As a result, we apply the model to three different range-based volatility proxies introduced by Parkinson (1980), Garman and Klass (1980) and Rogers and Satchell (1991) utilizing daily high, low, opening and closing prices. First, we calculate the daily volatility with the Parkinson (1980) estimator (PK) by considering the logs of the daily high (H_t) and daily low (L_t) prices:

$$\sigma^2_{PK,t} = \frac{(H_t - L_t)^2}{4\ln(2)}. \tag{5}$$

Garman and Klass (1980) (GK) adjusted the estimator of Parkinson (1980) by incorporating the log of opening (O_t) and closing prices (C_t):

$$\sigma^2_{GK,t} = 0.511(H_t - L_t)^2 - 0.019[(C_t - O_t)(H_t + L_t - 2O_t) - 2(H_t - O_t)(L_t - O_t)] - 0.383(C_t - O_t)^2. \tag{6}$$

Rogers and Satchell (1991) proposed an alternative (RS):

$$\sigma^2_{RS,t} = (H_t - C_t)(H_t - O_t) + (L_t - C_t)(L_t - O_t). \tag{7}$$

To better interpret the results, we report the statistics of the annualized volatility by multiplying the daily estimator by 260, which is the average number of trading days per year over the entire sample period. In the following, we establish daily, weekly and monthly volatilities based only on information from the opening market time, disregarding overnight jumps because the overnight returns are known to be very noisy. However, to check the robustness of our findings, we recalculated the transmission models by adding squared overnight returns to the daily variance estimates. The results are qualitatively and quantitatively similar to those reported here.

To assess the significance of the observed relations, we employ the modified Wald test (with Newey–West standard errors) to check whether the daily, weekly and monthly volatilities in one country jointly significantly influence the corresponding one-step-ahead volatility in the other country at three forecasting horizons.

The article utilizes prices of continuous futures contracts on soybean, wheat, corn and sugar traded in China and the U.S. The sample periods for the four commodities extend to 18 October 2016, with the starting date depending on the initial introduction of the corresponding futures contract. Inspired by Souček and Todorova (2013), this article first investigates the volatility spillovers for the full sample to obtain an overview of the market interactions. To discover the dynamics of transmission over time, the entire series for each commodity is split into three subsamples, that is, pre-crisis, crisis and post-crisis, based on the GFC.[6]

[6]To detect the structural breaks in volatilities of the four commodities, we performed 'F stats' and 'Empirical Fluctuation Processes' from Chow test and 'breakpoints' from Bai–Perron test (for both individual future GK volatility series and for the HAR regressions with control variables: lagged return of FX, WTI, GSCI INDEX and GSCI agriculture index). All three methods lead to deviating numbers of structural breaks for each commodity occurring at different times. To make the analysis more clearly arranged and the results comparable across commodities, we follow a frequently adopted approach in literature and opt for the same cut-off dates across commodities and markets (see Souček and Todorova 2013; Nazlioglu, Erdem, and Soytas 2013; Bubák, Kočenda, and Žikeš 2011; among others). This approach facilitates the comparison of the findings for the individual assets and interprets the spillover effects found in the entire sample against major market events and government interventions that occurred during different subperiods.

V. Data

The data employed in this study were obtained from Beijing Bric Agricultural Information Science Co., Ltd., with the daily data for the Chinese agricultural commodity futures market collected automatically and linked directly to ZCE and DCE. Given that the Chinese agricultural futures market is fairly new relative to the U.S. market and the four commodities were initially listed on the Chinese commodity exchange on different dates, we adjust the time interval of each commodity and choose the period for which data for both markets are available. Details about the sample periods can be found in Table 3.

When analysing volatility spillovers between markets in different time zones, special care needs to be taken in respect to non-synchronous trading. Figure 3 presents the asynchronous trading hours in the Chinese and the U.S. futures markets. After converting opening and closing times for both markets to the Greenwich Mean Time (GMT), there is no overlap in trading sessions between the two countries. On each trading day, the futures trading in China begins and ends first, followed by the opening of floor trading in the U.S. Given that this article focuses on the bidirectional spillovers between the U.S. and China, days of deviating activity also need to be considered. Taking Chinese volatility as the dependent variable, only days on which the Chinese market is open are considered. If, for example, the U.S. market was open on a Tuesday but the Chinese exchange was not, the equation for the Chinese volatility on the next day (Wednesday) omits Tuesday's U.S. volatility and instead utilizes Monday's U.S. volatility as the previous day's volatility. On Thursday, however, the U.S. volatility from Tuesday is included in the calculation of the weekly and monthly historical components. Same treatment is applied when the U.S. volatility is the dependent variable.

Table 4 reports the descriptive statistics for the annualized GK volatility[7] calculated employing Equation (6). Apparently, the U.S. futures market is more volatile than the Chinese market for all four commodities. Apart from soybean, whose annualized volatility for the U.S. market is 20.61%, which is almost twice as much as that for China (11.79%), the volatilities for wheat, corn and sugar futures in the U.S. are all more than twice the volatilities of the corresponding commodity futures in China. It is interesting to note that in China, the annualized volatility of 14.66% for sugar is the highest instead of soybean, one of the most actively traded commodities. The same conclusion can be drawn for the U.S. commodity futures. The autocorrelation of

Table 3. Sample description.

Futures	Sample period	Sample size
Soybean	15 March 2002–18 October 2016	3807
Wheat	29 April 2005–18 October 2016	2991
Corn	22 September 2004–18 October 2016	3148
Sugar	1 January 2006–18 October 2016	2811

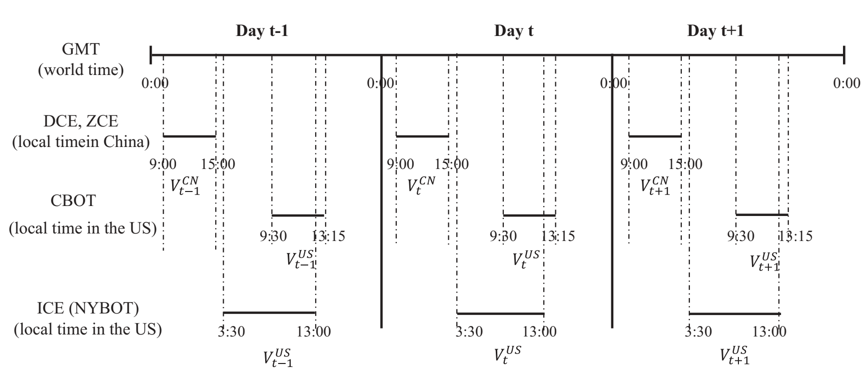

Figure 3. Asynchronous trading hours.

Notes: This figure illustrates asynchronous trading hours in China (DCE and ZCE) and the U.S. (CBOT and ICE). GMT is Greenwich Mean Time.

[7]PK employs only the prices of H_t and L_t. RS can be zero in the very few cases when $H_t = C_t$ and $L_t = O_t$ or when $H_t = O_t$ and $L_t = C_t$, which is clearly not the real volatility of day t. The correlation of PK, GK and RS demonstrates that GK is the volatility estimator with a correlation of more than 0.95 with both PK and RS for all commodities, whereas the correlation between PK and RS is below 0.85 for sugar and only slightly above 0.85 for soybean and wheat. As a result, in the following, we will present results based on GK volatility to save space, the use of the other measures is for robustness check (not tabulated).

Table 4. Descriptive statistics of the annualized GK volatility.

	China				The U.S.			
	Soybean	Wheat	Corn	Sugar	Soybean	Wheat	Corn	Sugar
Mean	0.1179	0.0872	0.0883	0.1449	0.2061	0.2672	0.2535	0.2785
SD	0.0055	0.0548	0.0577	0.0808	0.1108	0.1391	0.1334	0.1441
Skew	2.3617	2.1505	2.2073	2.3272	2.2479	2.8449	1.8718	1.8643
Kurt	15.8887	10.4499	11.3082	13.6040	11.2940	27.0665	9.7987	9.4743
Min	0.0000	0.0000	0.0110	0.0000	0.0000	0.0000	0.0196	0.0397
Max	1.0689	0.4584	0.5652	0.8999	1.1505	2.5670	1.5077	1.4486
Autocor (1)	0.4652	0.4257	0.5289	0.4182	0.4453	0.4326	0.4322	0.4581
Autocor (5)	0.3198	0.3258	0.3903	0.3289	0.3687	0.3428	0.3549	0.3584
Autocor (10)	0.3193	0.2555	0.3236	0.2652	0.3608	0.3325	0.3188	0.3114
Autocor (15)	0.2777	0.2515	0.2769	0.2575	0.3441	0.2710	0.3110	0.2992
Autocor (20)	0.2659	0.2127	0.2551	0.2333	0.3101	0.2671	0.2736	0.2953
CN versus the U.S.	0.3000	0.1970	0.1486	0.2177				
Corr	(0.0000)	(0.0000)	(0.0000)	(0.0000)				

The table shows the descriptive statistics of the annualized GK volatility calculated using Equation (6). Autocor $(\cdot)$ reports the autocorrelation for GK estimator of lags 1, 5, 10, 15 and 20. CN versus the U.S. Corr reports the Pearson correlation between the corresponding Chinese and the U.S. assets, with p-values given in parentheses.

the GK estimator presents a gradual decay pattern for all futures, with the twentieth lag still remaining significant. In general, the slow decay pattern is more persistent in the U.S. market especially after lag five. The Pearson correlation in the last two rows in Table 4 exhibits a significant correlation between the Chinese and the U.S. markets for all types of commodities.

Figure 4 depicts the volatility of the U.S. (black line) and Chinese (grey line) futures as estimated by the annualized GK estimator. It is clear that for the four commodities, the U.S. not only has more volatile futures markets but also exhibits greater volatility clustering than does China.

VI. Results

This section reports the HAR results of bidirectional volatility spillovers for the entire sample period. Following the notion that the GFC may cause structural breaks in the course of the volatility of any commodity that cannot be captured by the

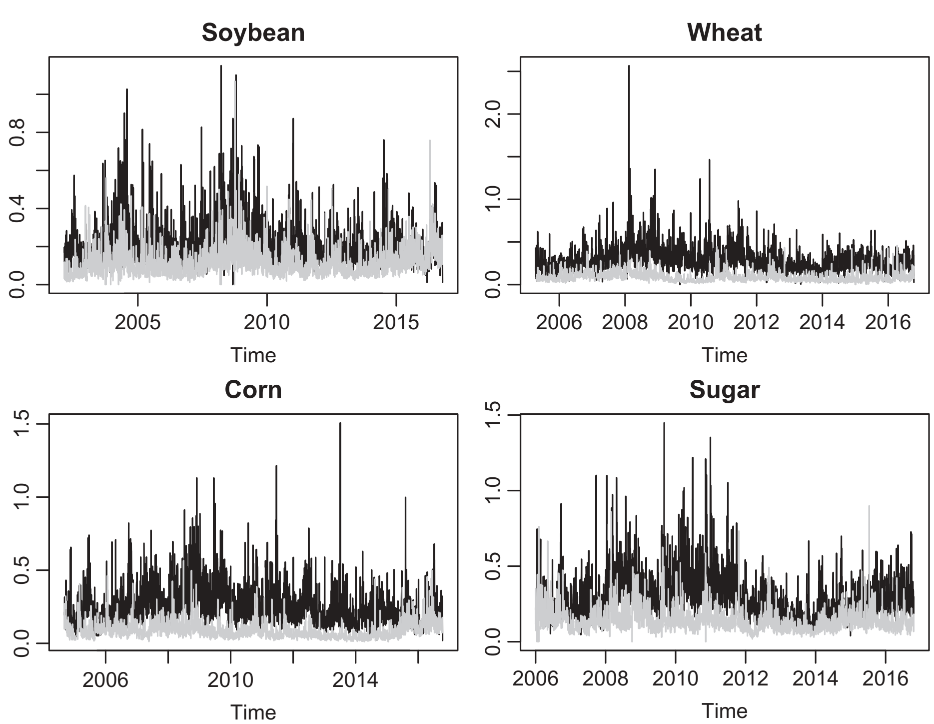

Figure 4. Volatility of U.S. and Chinese agricultural futures.

Notes: The figure depicts the volatility of the U.S. (black line) and Chinese (grey line) futures as estimated by the annualized GK estimator.

traditional HAR model as applied to the entire data set, three subsamples covering the pre-crisis (start date – 31 May 2008), crisis (01 June 2008–31 December 2011) and post-crisis (01 January 2012–18 October 2016)[8] periods are also assessed to examine how the parameters evolve over time.

Volatility spillover from the U.S. to China

Entire sample

Table 5 displays the regression results for soybean, wheat, corn and sugar with the entire sample fitting the GK volatility estimator in Equation (4).[9] In accordance with the hypothesis for soybean futures market, the impact of the volatility from the U.S. to China appears to be consistently and jointly significant regardless of the forecasting horizon. The Wald test statistics confirm a pronounced transmission, which is mainly through the daily and weekly realized volatility of the U.S. This behaviour is probably a result of China's satisfying almost one half of its soybean consumption utilizing the U.S. imports over the decade under consideration; subsequently, its price closely followed the movements of the U.S. market. For the control variables, the GSCI Index significantly influences the volatility transmission on the monthly basis.

For the wheat market, a significant positive volatility transmission from the U.S. to China can be detected on the daily and weekly basis, with the Wald test significant at a 10% level. In the corn market, the results demonstrate that the volatility components from the U.S. market jointly influence the Chinese daily and weekly volatilities at the 5% level, and the spillover from the daily U.S. volatility is particularly significant. Regarding the market for

Table 5. Estimation results for spillovers U.S. to China (whole sample).

Dep Var	Int	$\beta_{CN}^{(d)}$	$\beta_{CN}^{(w)}$	$\beta_{CN}^{(m)}$	$\beta_{US}^{(d)}$	$\beta_{US}^{(w)}$	$\beta_{US}^{(m)}$	β_{FX}	β_{WTI}	β_{GSCI}	β_{GSCIA}	Adj R^2	Wald
Soybean: 1 January 2000–18 October 2016													
$V_{CN,t+1}^{(d)}$	0.001	0.158	0.220	0.378	0.016	0.055	−0.001	0.195	0.000	−0.035	0.006	0.281	19.300
	(0.002)	(0.000)	(0.000)	(0.000)	(0.243)	(0.069)	(0.981)	(0.212)	(0.987)	(0.183)	(0.667)		(0.000)
$V_{CN,t+1}^{(w)}$	0.000	0.094	0.808	0.044	0.013	0.003	−0.001	0.044	−0.002	−0.002	−0.001	0.901	25.000
	(0.007)	(0.000)	(0.000)	(0.002)	(0.000)	(0.709)	(0.935)	(0.294)	(0.626)	(0.737)	(0.800)		(0.000)
$V_{CN,t+1}^{(m)}$	0.000	0.006	0.031	0.955	0.000	0.008	−0.005	−0.003	0.001	−0.003	0.001	0.989	20.100
	(0.230)	(0.000)	(0.000)	(0.000)	(0.685)	(0.000)	(0.021)	(0.771)	(0.503)	(0.065)	(0.449)		(0.000)
Wheat: 29 April 2005–18 October 2016													
$V_{CN,t+1}^{(d)}$	0.001	0.176	0.328	0.305	0.013	0.016	−0.010	−0.230	−0.006	−0.019	−0.005	0.309	8.000
	(0.005)	(0.000)	(0.000)	(0.000)	(0.153)	(0.376)	(0.613)	(0.047)	(0.654)	(0.393)	(0.695)		(0.046)
$V_{CN,t+1}^{(w)}$	0.000	0.095	0.836	0.029	0.003	0.005	−0.004	−0.041	0.001	−0.007	−0.002	0.913	6.600
	(0.019)	(0.000)	(0.000)	(0.037)	(0.266)	(0.270)	(0.448)	(0.182)	(0.828)	(0.214)	(0.538)		(0.087)
$V_{CN,t+1}^{(m)}$	0.000	0.009	0.034	0.952	0.000	0.002	−0.001	−0.017	−0.001	0.000	0.000	0.989	5.700
	(0.773)	(0.000)	(0.000)	(0.000)	(0.478)	(0.196)	(0.437)	(0.046)	(0.460)	(0.854)	(0.588)		(0.130)
Corn: 22 September 2004–18 October 2016													
$V_{CN,t+1}^{(d)}$	0.001	0.231	0.385	0.213	0.016	0.027	−0.028	−0.192	0.006	−0.033	−0.015	0.376	11.300
	(0.002)	(0.000)	(0.000)	(0.000)	(0.069)	(0.173)	(0.174)	(0.078)	(0.597)	(0.106)	(0.171)		(0.010)
$V_{CN,t+1}^{(w)}$	0.000	0.105	0.846	0.009	0.005	0.006	−0.007	−0.056	0.002	−0.010	−0.002	0.925	11.100
	(0.008)	(0.000)	(0.000)	(0.441)	(0.052)	(0.225)	(0.190)	(0.052)	(0.434)	(0.066)	(0.414)		(0.011)
$V_{CN,t+1}^{(m)}$	0.000	0.010	0.045	0.941	0.000	0.001	−0.001	−0.026	0.000	−0.001	−0.001	0.992	4.000
	(0.805)	(0.000)	(0.000)	(0.000)	(0.477)	(0.382)	(0.652)	(0.001)	(0.607)	(0.303)	(0.069)		(0.260)
Sugar: 1 January 2006–18 October 2016													
$V_{CN,t+1}^{(d)}$	0.001	0.141	0.334	0.321	−0.025	0.044	0.009	0.015	0.001	−0.026	−0.016	0.298	7.100
	(0.000)	(0.000)	(0.000)	(0.000)	(0.073)	(0.107)	(0.740)	(0.935)	(0.977)	(0.443)	(0.359)		(0.069)
$V_{CN,t+1}^{(w)}$	0.000	0.082	0.838	0.036	−0.001	−0.002	0.009	0.012	−0.002	0.000	−0.007	0.907	2.800
	(0.001)	(0.000)	(0.000)	(0.012)	(0.806)	(0.824)	(0.212)	(0.806)	(0.729)	(0.978)	(0.116)		(0.420)
$V_{CN,t+1}^{(m)}$	0.000	0.008	0.043	0.946	−0.001	0.006	−0.004	−0.002	0.001	−0.002	−0.001	0.991	10.100
	(0.266)	(0.000)	(0.000)	(0.000)	(0.253)	(0.002)	(0.022)	(0.870)	(0.510)	(0.399)	(0.230)		(0.017)

The table shows regression results obtained using Equation (4). For each of four commodities, one-step-ahead daily, averaged weekly and averaged monthly volatilities in the Chinese market are used as the dependent variables. *p*-values based on Newey–West standard errors are given in parentheses. The Wald test statistics and *p*-values given in the last column are based on the null hypothesis that the daily, weekly and monthly volatilities of the corresponding the U.S. market jointly have no significant influence on the futures volatility in the Chinese futures market.

[8]Subsamples are divided based on the course of the Chinese market volatility, where a significant jump was observed in June 2008 followed by a gradual decline starting in January 2012.

[9]The results with PK and RS volatility estimators are similar and are not reported here to save space.

sugar, volatility spillovers from the U.S. to China can be found on the daily and monthly basis. Regarding the control variables, explanatory power is uncovered with the GSCI Index and the GSCI Agriculture Index for the U.S. to Chinese volatility spillover in the corn market.

Subsample analysis

In this section, we discuss the results obtained for three subsamples, that is, pre-crisis, crisis and post-crisis, of each commodity and explain the results from the perspective of the fundamentals and local government interventions across different time intervals.

The subsample estimation results for soybean in Table 6 indicate a considerable volatility transmission from the U.S. to China through shorter-term volatilities in the U.S. for subsamples 1 and 2. However, the intensity of the volatility transmission from the U.S. to China diminished from January 2012. From a policy perspective, a potential explanation for the insignificant spillover from the U.S. to China in the post-GFC period might be the national government's implementation of a temporary purchasing and storage policy for soybeans in 2012 with the clear purpose of adjusting the local soybean price to lower the price volatility relative to the world soybean price volatility (SAG 2013). Explanatory power can be found in the GSCI Index and the GSCI Agriculture Index.

Table 7 presents the subsample results of the wheat market. It becomes clear that volatility spillovers emerged mainly from the daily and weekly U.S. volatilities in the pre-crisis and post-crisis periods. The Wald test does not provide evidence of a significant joint impact for the crisis period. The Chinese wheat market was relatively free from government intervention before the dramatic food price increase in 2008, leading to a sensitive and rapid reaction of the Chinese wheat market to the U.S. wheat market, which is in line with our findings in subsample 1. The government, however, started to strictly control wheat prices by charging a 25–30% export tax instead of an export tax refund beginning in 2008, which contributed to the local wheat supply and price stability. It is important to note that the dramatic reduction in Chinese wheat imports to its consumption from 2008 (Figure 2) could have weakened the link between the Chinese wheat price and wheat prices in the global integrated market, leading to a diminishing volatility transmission from the U.S. to China during the second subsample period.

Table 6. Subsample results for spillovers the U.S. to China for soybean.

Dep Var	Int	$\beta_{CN}^{(d)}$	$\beta_{CN}^{(w)}$	$\beta_{CN}^{(m)}$	$\beta_{US}^{(d)}$	$\beta_{US}^{(w)}$	$\beta_{US}^{(m)}$	β_{FX}	β_{WTI}	β_{GSCI}	β_{GSCIA}	Adj R^2	Wald
Subsample 1: 1 January 2000–31 May 2008													
$V_{CN,t+1}^{(d)}$	0.001	0.189	0.183	0.402	0.009	0.110	−0.059	0.143	0.004	0.000	0.085	0.268	13.100
	(0.123)	(0.000)	(0.006)	(0.000)	(0.633)	(0.010)	(0.215)	(0.598)	(0.873)	(0.996)	(0.003)		(0.004)
$V_{CN,t+1}^{(w)}$	0.000	0.099	0.804	0.045	0.009	0.023	−0.019	−0.016	−0.002	0.006	0.016	0.899	14.800
	(0.135)	(0.000)	(0.000)	(0.031)	(0.079)	(0.040)	(0.129)	(0.817)	(0.767)	(0.599)	(0.017)		(0.002)
$V_{CN,t+1}^{(m)}$	0.000	0.007	0.032	0.954	0.001	0.007	−0.007	−0.013	0.000	0.001	0.003	0.988	9.600
	(0.457)	(0.003)	(0.000)	(0.000)	(0.333)	(0.027)	(0.041)	(0.497)	(0.865)	(0.689)	(0.136)		(0.022)
Subsample 2: 1 June 2008–31 December 2011													
$V_{CN,t+1}^{(d)}$	0.001	0.165	0.210	0.214	0.016	0.036	0.117	0.454	−0.002	−0.054	−0.042	0.308	11.800
	(0.156)	(0.000)	(0.014)	(0.071)	(0.588)	(0.547)	(0.115)	(0.219)	(0.937)	(0.241)	(0.128)		(0.008)
$V_{CN,t+1}^{(w)}$	0.000	0.097	0.804	0.007	0.021	−0.017	0.033	0.069	−0.003	−0.001	−0.016	0.902	14.000
	(0.261)	(0.000)	(0.000)	(0.821)	(0.008)	(0.306)	(0.099)	(0.493)	(0.646)	(0.907)	(0.029)		(0.003)
$V_{CN,t+1}^{(m)}$	0.000	0.007	0.029	0.949	−0.002	0.011	−0.002	0.014	0.002	−0.009	0.000	0.990	10.900
	(0.785)	(0.024)	(0.000)	(0.000)	(0.458)	(0.009)	(0.638)	(0.591)	(0.197)	(0.009)	(0.869)		(0.012)
Subsample 3: 1 January 2012–18 October 2016													
$V_{CN,t+1}^{(d)}$	0.001	0.095	0.333	0.372	0.042	−0.030	−0.023	−0.042	0.012	−0.042	0.010	0.215	2.200
	(0.017)	(0.021)	(0.000)	(0.000)	(0.146)	(0.627)	(0.765)	(0.836)	(0.740)	(0.550)	(0.733)		(0.530)
$V_{CN,t+1}^{(w)}$	0.000	0.076	0.832	0.046	0.014	−0.008	−0.007	0.046	0.004	−0.011	0.008	0.884	3.600
	(0.047)	(0.000)	(0.000)	(0.050)	(0.068)	(0.628)	(0.712)	(0.381)	(0.672)	(0.565)	(0.299)		(0.310)
$V_{CN,t+1}^{(m)}$	0.000	0.003	0.035	0.954	0.001	0.004	−0.006	−0.013	−0.002	0.001	0.002	0.988	2.800
	(0.238)	(0.249)	(0.000)	(0.000)	(0.539)	(0.285)	(0.276)	(0.336)	(0.556)	(0.794)	(0.341)		(0.420)

The table shows regression results obtained using Equation (4). For each subsample, one-step-ahead daily, averaged weekly and averaged monthly volatilities in the Chinese market are used as the dependent variables. *p*-values based on Newey–West standard errors are given in parentheses. The Wald test statistics and *p*-values given in the last column are based on the null hypothesis that the daily, weekly and monthly volatilities of the corresponding the U.S. market jointly have no significant influence on the futures volatility in the Chinese futures market.

Table 7. Subsample results for spillovers the U.S. to China for wheat.

Dep Var	Int	$\beta_{CN}^{(d)}$	$\beta_{CN}^{(w)}$	$\beta_{CN}^{(m)}$	$\beta_{US}^{(d)}$	$\beta_{US}^{(w)}$	$\beta_{US}^{(m)}$	β_{FX}	β_{WTI}	β_{GSCI}	β_{GSCIA}	Adj R^2	Wald
Subsample 1: 29 April 2005–31 May 2008													
$V_{CN,t+1}^{(d)}$	0.001	0.215	0.256	0.163	0.021	0.032	0.040	−0.163	0.034	−0.069	0.025	0.295	17.100
	(0.084)	(0.000)	(0.003)	(0.130)	(0.165)	(0.288)	(0.313)	(0.451)	(0.304)	(0.140)	(0.265)		(0.001)
$V_{CN,t+1}^{(w)}$	0.000	0.100	0.834	−0.005	0.004	0.011	0.002	−0.045	0.016	−0.026	0.005	0.912	10.900
	(0.107)	(0.000)	(0.000)	(0.869)	(0.368)	(0.156)	(0.875)	(0.420)	(0.055)	(0.028)	(0.369)		(0.012)
$V_{CN,t+1}^{(m)}$	0.000	0.014	0.026	0.948	−0.001	0.004	0.002	−0.002	0.002	−0.004	0.001	0.988	13.100
	(0.623)	(0.000)	(0.000)	(0.000)	(0.522)	(0.045)	(0.431)	(0.874)	(0.445)	(0.259)	(0.354)		(0.005)
Subsample 2: 1 June 2008–31 December 2011													
$V_{CN,t+1}^{(d)}$	0.001	0.132	0.456	0.249	−0.005	−0.004	0.012	−0.388	−0.019	0.018	−0.038	0.372	0.340
	(0.156)	(0.002)	(0.000)	(0.002)	(0.707)	(0.884)	(0.675)	(0.094)	(0.238)	(0.538)	(0.034)		(0.950)
$V_{CN,t+1}^{(w)}$	0.000	0.090	0.853	0.021	−0.003	−0.001	0.004	−0.065	−0.004	0.002	−0.008	0.926	1.300
	(0.164)	(0.000)	(0.000)	(0.318)	(0.376)	(0.874)	(0.630)	(0.299)	(0.377)	(0.752)	(0.079)		(0.730)
$V_{CN,t+1}^{(m)}$	0.000	0.004	0.042	0.950	0.001	−0.001	−0.001	−0.031	−0.001	0.002	−0.002	0.992	0.700
	(0.335)	(0.233)	(0.000)	(0.000)	(0.551)	(0.712)	(0.745)	(0.066)	(0.239)	(0.471)	(0.101)		(0.870)
Subsample 3: 1 January 2012–18 October 2016													
$V_{CN,t+1}^{(d)}$	0.001	0.167	0.216	0.075	0.041	0.026	0.016	−0.119	0.030	−0.105	0.033	0.117	11.500
	(0.015)	(0.000)	(0.009)	(0.536)	(0.053)	(0.543)	(0.752)	(0.487)	(0.362)	(0.091)	(0.181)		(0.001)
$V_{CN,t+1}^{(w)}$	0.000	0.090	0.809	−0.021	0.016	0.008	−0.004	−0.013	0.008	−0.024	0.005	0.838	17.900
	(0.055)	(0.000)	(0.000)	(0.522)	(0.004)	(0.487)	(0.781)	(0.768)	(0.359)	(0.144)	(0.465)		(0.000)
$V_{CN,t+1}^{(m)}$	0.000	0.008	0.032	0.938	0.003	0.002	0.002	−0.015	0.001	−0.004	0.001	0.970	10.800
	(0.811)	(0.010)	(0.000)	(0.000)	(0.102)	(0.522)	(0.596)	(0.230)	(0.730)	(0.350)	(0.585)		(0.013)

Same as Table 6.

Contrary to the statistics for soybean and wheat, where the volatility transmission pattern was pronounced in the pre-GFC period, the transmission pattern as a whole is particularly significant in the corn market in the last subsample, when the impact emerged from all the U.S. volatilities (Table 8). This was probably due to the considerable increase in corn imports relative to its consumption after 2010 as well as the fact that the U.S. is the world's largest corn exporter to China, contributing more than 70% of China's corn imports during this period.

The results from the transmission models for the sugar market in Table 9 suggest that spillovers occur in the cases of Chinese daily and weekly volatilities in

Table 8. Subsample results for spillovers the U.S. to China for corn.

Dep Var	Int	$\beta_{CN}^{(d)}$	$\beta_{CN}^{(w)}$	$\beta_{CN}^{(m)}$	$\beta_{US}^{(d)}$	$\beta_{US}^{(w)}$	$\beta_{US}^{(m)}$	β_{FX}	β_{WTI}	β_{GSCI}	β_{GSCIA}	Adj R^2	Wald
Subsample 1: 22 September 2004–31 May 2008													
$V_{CN,t+1}^{(d)}$	0.001	0.241	0.415	0.083	0.030	0.000	−0.008	−0.284	−0.007	−0.032	0.005	0.304	4.200
	(0.014)	(0.000)	(0.000)	(0.286)	(0.098)	(1.000)	(0.851)	(0.194)	(0.821)	(0.466)	(0.791)		(0.240)
$V_{CN,t+1}^{(w)}$	0.000	0.107	0.856	−0.025	0.008	0.003	−0.007	−0.089	−0.003	−0.004	−0.002	0.910	4.000
	(0.015)	(0.000)	(0.000)	(0.235)	(0.081)	(0.805)	(0.514)	(0.127)	(0.723)	(0.749)	(0.741)		(0.260)
$V_{CN,t+1}^{(m)}$	0.000	0.010	0.055	0.932	0.001	0.000	0.002	−0.023	−0.001	0.000	−0.001	0.988	2.800
	(0.373)	(0.002)	(0.000)	(0.000)	(0.492)	(0.999)	(0.588)	(0.151)	(0.781)	(0.991)	(0.622)		(0.420)
Subsample 2: 1 June 2008–31 December 2011													
$V_{CN,t+1}^{(d)}$	0.001	0.238	0.371	0.121	0.001	0.017	0.024	−0.281	0.002	−0.012	−0.028	0.304	3.200
	(0.161)	(0.000)	(0.000)	(0.156)	(0.949)	(0.593)	(0.515)	(0.251)	(0.915)	(0.690)	(0.118)		(0.360)
$V_{CN,t+1}^{(w)}$	0.000	0.109	0.840	−0.009	0.001	−0.002	0.011	−0.066	0.003	−0.010	−0.004	0.908	2.300
	(0.276)	(0.000)	(0.000)	(0.695)	(0.738)	(0.798)	(0.275)	(0.319)	(0.520)	(0.222)	(0.367)		(0.500)
$V_{CN,t+1}^{(m)}$	0.000	0.011	0.037	0.948	0.000	0.001	−0.001	−0.035	0.001	−0.002	−0.001	0.989	0.440
	(0.695)	(0.000)	(0.000)	(0.000)	(0.944)	(0.559)	(0.755)	(0.042)	(0.489)	(0.381)	(0.269)		(0.930)
Subsample 3: 1 January 2012–18 October 2016													
$V_{CN,t+1}^{(d)}$	0.000	0.191	0.382	0.355	0.029	0.067	−0.094	−0.119	0.030	−0.078	−0.019	0.441	15.600
	(0.426)	(0.000)	(0.000)	(0.000)	(0.045)	(0.035)	(0.009)	(0.380)	(0.225)	(0.097)	(0.317)		(0.001)
$V_{CN,t+1}^{(w)}$	0.000	0.093	0.845	0.043	0.008	0.023	−0.030	−0.038	0.005	−0.014	0.002	0.937	21.400
	(0.356)	(0.000)	(0.000)	(0.030)	(0.039)	(0.006)	(0.001)	(0.283)	(0.396)	(0.252)	(0.726)		(0.000)
$V_{CN,t+1}^{(m)}$	0.000	0.009	0.045	0.947	0.001	0.002	−0.002	−0.025	0.001	−0.003	−0.002	0.994	4.900
	(0.274)	(0.000)	(0.000)	(0.000)	(0.345)	(0.274)	(0.495)	(0.005)	(0.532)	(0.273)	(0.188)		(0.180)

Same as Table 6.

Table 9. Subsample results for spillovers the U.S. to China for sugar.

Dep Var	Int	$\beta_{CN}^{(d)}$	$\beta_{CN}^{(w)}$	$\beta_{CN}^{(m)}$	$\beta_{US}^{(d)}$	$\beta_{US}^{(w)}$	$\beta_{US}^{(m)}$	β_{FX}	β_{WTI}	β_{GSCI}	β_{GSCIA}	Adj R^2	Wald
Subsample 1: 1 January 2006–31 May 2008													
$V_{CN,t+1}^{(d)}$	0.002	0.206	0.225	0.335	−0.052	−0.009	0.102	0.515	0.049	−0.074	0.005	0.261	5.100
	(0.053)	(0.000)	(0.022)	(0.002)	(0.090)	(0.890)	(0.143)	(0.264)	(0.417)	(0.416)	(0.895)		(0.160)
$V_{CN,t+1}^{(w)}$	0.000	0.091	0.826	0.030	0.005	−0.034	0.037	0.151	−0.001	−0.001	−0.008	0.889	4.100
	(0.093)	(0.000)	(0.000)	(0.322)	(0.554)	(0.064)	(0.059)	(0.241)	(0.959)	(0.980)	(0.452)		(0.250)
$V_{CN,t+1}^{(m)}$	0.000	0.006	0.046	0.943	−0.003	0.008	−0.003	0.024	0.004	−0.004	−0.001	0.990	3.400
	(0.697)	(0.084)	(0.000)	(0.000)	(0.189)	(0.091)	(0.505)	(0.461)	(0.354)	(0.523)	(0.796)		(0.330)
Subsample 2: 1 June 2008–31 December 2011													
$V_{CN,t+1}^{(d)}$	0.003	0.186	0.363	0.222	−0.016	0.041	−0.035	−0.115	−0.002	−0.027	−0.028	0.267	1.300
	(0.003)	(0.000)	(0.000)	(0.011)	(0.415)	(0.296)	(0.460)	(0.771)	(0.951)	(0.573)	(0.324)		(0.730)
$V_{CN,t+1}^{(w)}$	0.001	0.098	0.843	0.013	−0.003	0.002	−0.002	−0.092	−0.003	0.000	−0.005	0.906	0.430
	(0.016)	(0.000)	(0.000)	(0.567)	(0.570)	(0.874)	(0.901)	(0.368)	(0.607)	(0.999)	(0.475)		(0.930)
$V_{CN,t+1}^{(m)}$	0.000	0.012	0.041	0.944	0.000	0.005	−0.005	−0.005	0.001	−0.003	−0.001	0.990	4.000
	(0.423)	(0.000)	(0.000)	(0.000)	(0.833)	(0.074)	(0.109)	(0.865)	(0.461)	(0.325)	(0.596)		(0.260)
Subsample 3: 1 January 2012–18 October 2016													
$V_{CN,t+1}^{(d)}$	0.001	−0.009	0.317	0.512	−0.020	0.139	−0.079	0.051	−0.019	0.014	−0.011	0.239	8.300
	(0.132)	(0.816)	(0.000)	(0.000)	(0.435)	(0.008)	(0.197)	(0.799)	(0.616)	(0.848)	(0.691)		(0.039)
$V_{CN,t+1}^{(w)}$	0.000	0.046	0.818	0.095	−0.004	0.032	−0.017	0.042	0.002	−0.003	−0.009	0.883	6.700
	(0.235)	(0.000)	(0.000)	(0.000)	(0.563)	(0.021)	(0.279)	(0.425)	(0.805)	(0.888)	(0.247)		(0.081)
$V_{CN,t+1}^{(m)}$	0.000	0.003	0.036	0.956	−0.001	0.008	−0.005	−0.005	−0.002	0.004	−0.003	0.989	5.300
	(0.634)	(0.173)	(0.000)	(0.000)	(0.438)	(0.027)	(0.229)	(0.725)	(0.356)	(0.456)	(0.186)		(0.150)

Same as Table 6.

subsample 3. The result may be explained by the upsurge in imports of sugar to China especially after 2011.

For the subsample analysis in general, the GSCI Agriculture Index has the strongest influence to the volatility transmission from the U.S. to China, followed by the USD/CNY exchange rate.

Volatility spillover from China to the U.S

The results from the whole sample and subsample analysis of the spillovers emerging from China to the U.S. are reported in Tables 10–14. Compared to the volatility transmission from the U.S. to China, the spillovers from China to the U.S. are stronger for wheat and sugar for the whole sample. The volatility spillovers are mainly driven by the weekly and monthly historical components at all forecasting horizons.

The subsample analysis reveals that, for soybean futures, the magnitude of Chinese volatility transmission to the U.S. decreases with time. For wheat futures, the bidirectional transmissions are both insignificant in subsample 2. The volatility spillovers in the corn market increases from the U.S. to China while the impact from China to the U.S. is significant only during the crisis. For sugar futures, the impact from the U.S. to China is significant in subsample 3 whereas the transmission from China to the U.S. is significant during the crisis. These relationships suggest that despite being regulated locally, the Chinese futures market has become more integrated to the world market, especially for soybean and sugar for which China is the world's largest importer. Our results provide further evidence to the literature that the U.S. holds the pricing power for the global agricultural futures, and show that the Chinese market has become more important globally.[10] The results from the control variables show again the importance of the GSCI Agriculture Index and the USD/CNY exchange rate, whereas the impact from WTI and the GSCI Index to the China to the U.S. volatility spillover is limited.

Implications of the empirical findings

From an investment perspective, this article provides insights for the design of a trading strategy using volatility as a signal. Given that significant spillovers between the U.S. and China have been found at three different time horizons, that is, on a daily, weekly and monthly basis, a potentially profitable trading strategy can be developed that uses the

[10]Given that the Chinese market opens 13 and 12 hours ahead of the CBOT and NYBOT in the summer and 14 and 13 hours ahead during winter, respectively, we also account for the time difference of the U.S. volatility by lagging the volatility from the Chinese market by 1 day. The results after making these adjustments do not lead to different conclusions and are not reported to save space.

Table 10. Estimation results for spillovers China to the U.S. (whole sample).

Dep Var	Int	$\beta_{CN}^{(d)}$	$\beta_{CN}^{(w)}$	$\beta_{CN}^{(m)}$	$\beta_{US}^{(d)}$	$\beta_{US}^{(w)}$	$\beta_{US}^{(m)}$	β_{FX}	β_{WTI}	β_{GSCI}	β_{GSCIA}	Adj R^2	Wald
Soybean: 1 January 2000–18 October 2016													
$V_{US,t+1}^{(d)}$	0.001	0.034	0.179	−0.075	0.141	0.144	0.529	0.368	−0.006	0.016	−0.032	0.318	18.700
	(0.000)	(0.331)	(0.011)	(0.370)	(0.000)	(0.003)	(0.000)	(0.134)	(0.818)	(0.703)	(0.155)		(0.000)
$V_{US,t+1}^{(w)}$	0.000	0.009	0.045	−0.029	0.091	0.801	0.072	0.038	0.000	0.003	−0.003	0.912	15.900
	(0.002)	(0.299)	(0.013)	(0.191)	(0.000)	(0.000)	(0.000)	(0.553)	(0.990)	(0.785)	(0.602)		(0.001)
$V_{US,t+1}^{(m)}$	0.000	0.001	0.008	−0.002	0.006	0.028	0.958	0.004	0.001	−0.002	−0.001	0.992	9.300
	(0.056)	(0.621)	(0.081)	(0.751)	(0.000)	(0.000)	(0.000)	(0.804)	(0.580)	(0.561)	(0.459)		(0.025)
Wheat: 29 April 2005–18 October 2016													
$V_{US,t+1}^{(d)}$	0.002	0.112	0.166	−0.078	0.159	0.314	0.365	0.010	0.037	−0.085	0.136	0.315	11.600
	(0.017)	(0.096)	(0.230)	(0.611)	(0.000)	(0.000)	(0.000)	(0.977)	(0.335)	(0.196)	(0.006)		(0.009)
$V_{US,t+1}^{(w)}$	0.000	0.013	0.045	−0.009	0.089	0.833	0.042	−0.115	0.001	−0.003	0.026	0.911	7.500
	(0.056)	(0.477)	(0.208)	(0.819)	(0.000)	(0.000)	(0.004)	(0.192)	(0.899)	(0.878)	(0.022)		(0.057)
$V_{US,t+1}^{(m)}$	0.000	0.000	0.025	−0.016	0.007	0.043	0.946	0.004	0.002	−0.006	0.008	0.991	12.100
	(0.665)	(0.942)	(0.006)	(0.111)	(0.000)	(0.000)	(0.000)	(0.869)	(0.462)	(0.143)	(0.005)		(0.007)
Corn: 22 September 2004–18 October 2016													
$V_{US,t+1}^{(d)}$	0.002	0.004	0.276	−0.270	0.139	0.190	0.542	0.314	−0.023	0.012	−0.026	0.310	9.800
	(0.000)	(0.950)	(0.012)	(0.015)	(0.000)	(0.000)	(0.000)	(0.266)	(0.467)	(0.828)	(0.351)		(0.020)
$V_{US,t+1}^{(w)}$	0.000	0.002	0.052	−0.053	0.083	0.808	0.081	0.024	−0.010	0.009	−0.004	0.910	5.500
	(0.001)	(0.881)	(0.068)	(0.040)	(0.000)	(0.000)	(0.000)	(0.740)	(0.224)	(0.537)	(0.588)		(0.140)
$V_{US,t+1}^{(m)}$	0.000	−0.001	0.011	−0.010	0.006	0.034	0.955	−0.010	0.000	−0.001	0.000	0.991	2.800
	(0.096)	(0.896)	(0.152)	(0.220)	(0.000)	(0.000)	(0.000)	(0.597)	(0.935)	(0.748)	(0.880)		(0.420)
Sugar: 1 January 2006–18 October 2016													
$V_{US,t+1}^{(d)}$	0.001	−0.042	0.338	−0.158	0.133	0.326	0.408	−0.308	0.009	−0.023	−0.013	0.371	19.800
	(0.027)	(0.349)	(0.000)	(0.107)	(0.000)	(0.000)	(0.000)	(0.344)	(0.811)	(0.723)	(0.681)		(0.000)
$V_{US,t+1}^{(w)}$	0.000	−0.016	0.093	−0.050	0.090	0.826	0.055	−0.110	0.009	−0.020	0.002	0.928	19.700
	(0.034)	(0.142)	(0.000)	(0.035)	(0.000)	(0.000)	(0.000)	(0.177)	(0.334)	(0.213)	(0.798)		(0.000)
$V_{US,t+1}^{(m)}$	0.000	−0.001	0.012	−0.001	0.008	0.036	0.953	−0.024	0.002	−0.003	0.002	0.993	8.700
	(0.783)	(0.702)	(0.065)	(0.897)	(0.000)	(0.000)	(0.000)	(0.276)	(0.463)	(0.445)	(0.467)		(0.033)

The table shows regression results obtained using Equation (4). For each of four commodities, one-step-ahead daily, averaged weekly and averaged monthly volatilities in the U.S. market are used as the dependent variables. *p*-values based on Newey–West standard errors are given in parentheses. The Wald test statistics and *p*-values given in the last column are based on the null hypothesis that the daily, weekly and monthly volatilities of the corresponding Chinese market jointly have no significant influence on the futures volatility in the U.S. futures market.

Table 11. Subsample results for spillovers China to the U.S. for soybean.

Dep Var	Int	$\beta_{CN}^{(d)}$	$\beta_{CN}^{(w)}$	$\beta_{CN}^{(m)}$	$\beta_{US}^{(d)}$	$\beta_{US}^{(w)}$	$\beta_{US}^{(m)}$	β_{FX}	β_{WTI}	β_{GSCI}	β_{GSCIA}	Adj R^2	Wald
Subsample 1: 1 January 2000–31 May 2008													
$V_{US,t+1}^{(d)}$	0.002	0.044	0.070	0.072	0.185	−0.052	0.623	0.512	−0.029	0.059	−0.065	0.237	5.100
	(0.004)	(0.473)	(0.556)	(0.616)	(0.000)	(0.498)	(0.000)	(0.297)	(0.544)	(0.415)	(0.141)		(0.160)
$V_{US,t+1}^{(w)}$	0.000	0.011	0.012	0.009	0.097	0.769	0.089	−0.009	−0.006	0.016	−0.011	0.883	2.500
	(0.028)	(0.499)	(0.705)	(0.813)	(0.000)	(0.000)	(0.000)	(0.947)	(0.639)	(0.396)	(0.278)		(0.470)
$V_{US,t+1}^{(m)}$	0.000	0.004	0.015	−0.006	0.010	0.010	0.966	0.007	0.002	−0.001	−0.002	0.989	11.900
	(0.029)	(0.299)	(0.067)	(0.547)	(0.000)	(0.069)	(0.000)	(0.843)	(0.622)	(0.864)	(0.522)		(0.008)
Subsample 2: 1 June 2008–31 December 2011													
$V_{US,t+1}^{(d)}$	0.002	0.043	0.373	−0.168	0.048	0.354	0.356	0.717	0.028	−0.038	−0.013	0.386	19.400
	(0.019)	(0.488)	(0.003)	(0.333)	(0.262)	(0.000)	(0.001)	(0.172)	(0.465)	(0.582)	(0.746)		(0.000)
$V_{US,t+1}^{(w)}$	0.000	0.013	0.100	−0.060	0.071	0.832	0.045	−0.027	0.011	−0.015	0.002	0.929	20.100
	(0.046)	(0.404)	(0.002)	(0.186)	(0.000)	(0.000)	(0.111)	(0.840)	(0.277)	(0.397)	(0.824)		(0.000)
$V_{US,t+1}^{(m)}$	0.000	−0.001	0.006	0.007	−0.002	0.046	0.946	0.013	0.003	−0.006	0.001	0.93	2.600
	(0.481)	(0.886)	(0.473)	(0.559)	(0.471)	(0.000)	(0.000)	(0.730)	(0.338)	(0.218)	(0.818)		(0.460)
Subsample 3: 1 January 2012–18 October 2016													
$V_{US,t+1}^{(d)}$	0.002	0.027	−0.058	0.025	0.147	0.197	0.439	0.155	−0.004	−0.035	0.000	0.156	0.310
	(0.004)	(0.641)	(0.626)	(0.843)	(0.000)	(0.027)	(0.000)	(0.589)	(0.935)	(0.716)	(0.999)		(0.960)
$V_{US,t+1}^{(w)}$	0.000	0.004	−0.002	−0.003	0.100	0.810	0.046	0.117	−0.001	−0.010	0.004	0.861	0.076
	(0.028)	(0.794)	(0.941)	(0.938)	(0.000)	(0.000)	(0.096)	(0.117)	(0.910)	(0.682)	(0.673)		(0.990)
$V_{US,t+1}^{(m)}$	0.000	0.002	−0.005	0.002	0.007	0.039	0.952	−0.001	−0.002	0.000	−0.001	0.982	0.430
	(0.713)	(0.681)	(0.538)	(0.797)	(0.014)	(0.000)	(0.000)	(0.976)	(0.634)	(0.970)	(0.747)		(0.930)

The table shows regression results obtained using Equation (4). For each subsample, one-step-ahead daily, averaged weekly and averaged monthly volatilities in the U.S. market are used as the dependent variables. *p*-values based on Newey–West standard errors are given in parentheses. The Wald test statistics and *p*-values given in the last column are based on the null hypothesis that the daily, weekly and monthly volatilities of the corresponding Chinese market jointly have no significant influence on the futures volatility in the U.S. futures market.

Table 12. Subsample results for spillovers China to the U.S. for wheat.

Dep Var	Int	$\beta_{CN}^{(d)}$	$\beta_{CN}^{(w)}$	$\beta_{CN}^{(m)}$	$\beta_{US}^{(d)}$	$\beta_{US}^{(w)}$	$\beta_{US}^{(m)}$	β_{FX}	β_{WTI}	β_{GSCI}	β_{GSCIA}	Adj R^2	Wald
						Subsample 1: 29 April 2005–31 May 2008							
$V_{US,t+1}^{(d)}$	0.002	0.102	0.468	−0.098	0.200	0.286	0.185	0.242	0.045	−0.075	0.279	0.284	10.00
	(0.070)	(0.433)	(0.071)	(0.760)	(0.000)	(0.002)	(0.113)	(0.708)	(0.649)	(0.587)	(0.000)		(0.018)
$V_{US,t+1}^{(w)}$	0.001	0.017	0.091	−0.012	0.094	0.832	0.004	−0.275	−0.006	0.012	0.050	0.899	5.100
	(0.132)	(0.622)	(0.196)	(0.891)	(0.000)	(0.000)	(0.893)	(0.117)	(0.836)	(0.741)	(0.007)		(0.160)
$V_{US,t+1}^{(m)}$	0.000	0.002	0.054	−0.040	0.006	0.046	0.935	0.020	0.001	−0.007	0.020	0.990	17.900
	(0.161)	(0.779)	(0.001)	(0.044)	(0.051)	(0.000)	(0.000)	(0.617)	(0.837)	(0.436)	(0.000)		(0.000)
						Subsample 2: 1 June 2008–31 December 2011							
$V_{US,t+1}^{(d)}$	0.004	0.068	0.261	−0.107	0.122	0.353	0.290	−1.222	0.074	−0.054	0.015	0.186	3.800
	(0.025)	(0.659)	(0.349)	(0.708)	(0.006)	(0.000)	(0.006)	(0.136)	(0.210)	(0.622)	(0.821)		(0.290)
$V_{US,t+1}^{(w)}$	0.001	−0.017	0.093	−0.022	0.080	0.838	0.028	−0.359	0.010	0.003	0.004	0.872	3.400
	(0.056)	(0.670)	(0.188)	(0.765)	(0.000)	(0.000)	(0.296)	(0.086)	(0.528)	(0.915)	(0.824)		(0.330)
$V_{US,t+1}^{(m)}$	0.000	−0.001	0.018	−0.009	0.007	0.043	0.947	−0.053	0.002	0.000	0.000	0.984	1.800
	((0.852)	(0.946)	(0.338)	(0.654)	(0.030)	(0.000)	(0.000)	(0.344)	(0.590)	(0.960)	(0.934)		(0.620)
						Subsample 3: 1 January 2012–18 October 2016							
$V_{US,t+1}^{(d)}$	0.002	0.181	−0.148	0.311	0.125	0.295	0.307	0.576	−0.018	−0.105	0.166	0.226	7.400
	(0.063)	(0.028)	(0.377)	(0.211)	(0.004)	(0.001)	(0.004)	(0.100)	(0.774)	(0.383)	(0.001)		(0.059)
$V_{US,t+1}^{(w)}$	0.000	0.036	−0.028	0.079	0.094	0.825	0.023	0.129	0.001	−0.031	0.033	0.881	5.300
	(0.204)	(0.094)	(0.518)	(0.220)	(0.000)	(0.000)	(0.401)	(0.157)	(0.939)	(0.314)	(0.010)		(0.150)
$V_{US,t+1}^{(m)}$	0.000	0.000	0.011	0.006	0.005	0.037	0.948	0.028	0.005	−0.018	0.010	0.983	2.500
	(0.745)	(0.935)	(0.357)	(0.733)	(0.115)	(0.000)	(0.000)	(0.286)	(0.298)	(0.044)	(0.004)		(0.480)

Same as Table 11.

Table 13. Subsample results for spillovers China to the U.S. for corn.

Dep Var	Int	$\beta_{CN}^{(d)}$	$\beta_{CN}^{(w)}$	$\beta_{CN}^{(m)}$	$\beta_{US}^{(d)}$	$\beta_{US}^{(w)}$	$\beta_{US}^{(m)}$	β_{FX}	β_{WTI}	β_{GSCI}	β_{GSCIA}	Adj R^2	Wald
						Subsample 1: 22 September 2004–31 May 2008							
$V_{US,t+1}^{(d)}$	0.003	0.017	0.264	−0.405	0.126	0.180	0.584	0.338	−0.130	0.131	−0.013	0.277	5.600
	(0.024)	(0.863)	(0.126)	(0.021)	(0.003)	(0.049)	(0.000)	(0.502)	(0.070)	(0.199)	(0.788)		(0.130)
$V_{US,t+1}^{(w)}$	0.000	0.025	0.028	−0.082	0.081	0.806	0.094	−0.018	−0.038	0.036	−0.004	0.899	4.300
	(0.095)	(0.340)	(0.531)	(0.071)	(0.000)	(0.000)	(0.000)	(0.890)	(0.045)	(0.175)	(0.745)		(0.230)
$V_{US,t+1}^{(m)}$	0.000	0.001	0.021	−0.028	0.004	0.028	0.966	−0.001	−0.003	−0.001	0.001	0.989	5.900
	(0.219)	(0.918)	(0.088)	(0.025)	(0.214)	(0.000)	(0.000)	(0.974)	(0.496)	(0.887)	(0.669)		(0.120)
						Subsample 2: 1 June 2008–31 December 2011							
$V_{US,t+1}^{(d)}$	0.003	−0.012	0.383	−0.038	0.121	0.261	0.352	−0.380	0.032	−0.045	−0.069	0.224	8.600
	(0.005)	(0.914)	(0.033)	(0.874)	(0.003)	(0.004)	(0.001)	(0.569)	(0.518)	(0.608)	(0.173)		(0.036)
$V_{US,t+1}^{(w)}$	0.001	−0.026	0.116	−0.014	0.075	0.819	0.044	−0.138	0.004	0.001	−0.017	0.88	8.300
	(0.010)	(0.367)	(0.023)	(0.814)	(0.000)	(0.000)	(0.090)	(0.413)	(0.775)	(0.969)	(0.175)		(0.040)
$V_{US,t+1}^{(m)}$	0.000	0.000	0.001	0.016	0.006	0.044	0.941	−0.062	0.002	−0.002	−0.003	0.987	1.900
	(0.341)	(0.974)	(0.939)	(0.352)	(0.048)	(0.000)	(0.000)	(0.188)	(0.548)	(0.771)	(0.363)		(0.600)
						Subsample 3: 1 January 2012–18 October 2016							
$V_{US,t+1}^{(d)}$	0.004	0.046	0.052	−0.233	0.164	0.032	0.573	0.776	−0.097	0.138	0.021	0.170	2.100
	(0.000)	(0.664)	(0.794)	(0.256)	(0.000)	(0.719)	(0.000)	(0.035)	(0.128)	(0.257)	(0.678)		(0.550)
$V_{US,t+1}^{(w)}$	0.001	0.026	−0.033	−0.020	0.094	0.775	0.085	0.157	−0.025	0.028	0.011	0.856	2.000
	(0.004)	(0.353)	(0.530)	(0.708)	(0.000)	(0.000)	(0.001)	(0.105)	(0.132)	(0.387)	(0.397)		(0.580)
$V_{US,t+1}^{(m)}$	0.000	−0.001	0.011	−0.019	0.008	0.023	0.961	0.021	−0.006	0.010	0.000	0.983	1.900
	(0.035)	(0.881)	(0.422)	(0.196)	(0.005)	(0.000)	(0.000)	(0.424)	(0.185)	(0.264)	(0.921)		(0.590)

Same as Table 11.

latest daily, averaged weekly and averaged monthly volatilities in one country as the trigger to trade on the volatility in the other country. Our finding of increasing significance in the volatility transmission from China to the U.S. over time provides an indication of the increasing importance of the Chinese market and global integration of markets. To better understand the volatility movements in their own country, investors in the U.S. and China can make use of the volatility information in each other's country. Given that the spillovers are more pronounced from the U.S. to China, for soybean and wheat, and from China to the U.S., for soybean, corn and sugar, during the period of the GFC, this may give guidance to investors in terms of formulating risk management strategies.

Table 14. Subsample results for spillovers China to the U.S. for sugar.

Dep Var	Int	$\beta_{CN}^{(d)}$	$\beta_{CN}^{(w)}$	$\beta_{CN}^{(m)}$	$\beta_{US}^{(d)}$	$\beta_{US}^{(w)}$	$\beta_{US}^{(m)}$	β_{FX}	β_{WTI}	β_{GSCI}	β_{GSCIA}	Adj R^2	Wald
Subsample 1: 1 January 2006–31 May 2008													
$V_{US,t+1}^{(d)}$	0.002	−0.041	0.213	−0.080	0.198	0.236	0.414	0.615	0.015	−0.098	0.091	0.261	2.100
	(0.202)	(0.639)	(0.223)	(0.679)	(0.000)	(0.041)	(0.001)	(0.453)	(0.887)	(0.545)	(0.199)		(0.560)
$V_{US,t+1}^{(w)}$	0.000	−0.025	0.082	−0.037	0.104	0.812	0.052	0.111	0.014	−0.026	0.010	0.889	4.400
	(0.274)	(0.233)	(0.050)	(0.421)	(0.000)	(0.000)	(0.077)	(0.573)	(0.580)	(0.500)	(0.548)		(0.220)
$V_{US,t+1}^{(m)}$	0.000	−0.002	0.001	0.004	0.010	0.039	0.951	−0.006	0.000	−0.008	0.007	0.990	0.320
	(0.894)	(0.680)	(0.946)	(0.740)	(0.003)	(0.000)	(0.000)	(0.911)	(0.987)	(0.453)	(0.124)		(0.960)
Subsample 2: 1 June 2008–31 December 2011													
$V_{US,t+1}^{(d)}$	0.005	−0.052	0.513	−0.223	0.104	0.326	0.249	−1.297	−0.009	0.057	−0.106	0.267	14.900
	(0.003)	(0.541)	(0.002)	(0.214)	(0.016)	(0.000)	(0.012)	(0.105)	(0.869)	(0.580)	(0.078)		(0.002)
$V_{US,t+1}^{(w)}$	0.001	−0.005	0.124	−0.073	0.087	0.825	0.018	−0.481	0.014	−0.025	−0.008	0.906	13.500
	(0.009)	(0.799)	(0.003)	(0.066)	(0.000)	(0.000)	(0.460)	(0.017)	(0.327)	(0.341)	(0.602)		(0.004)
$V_{US,t+1}^{(m)}$	0.000	−0.002	0.022	−0.002	0.006	0.032	0.953	−0.102	0.001	0.001	−0.002	0.989	9.700
	(0.874)	(0.802)	(0.055)	(0.901)	(0.044)	(0.000)	(0.000)	(0.071)	(0.728)	(0.927)	(0.626)		(0.021)
Subsample 3: 1 January 2012–18 October 2016													
$V_{US,t+1}^{(d)}$	0.002	−0.035	−0.002	0.114	0.067	0.436	0.325	−0.045	0.042	−0.083	0.045	0.239	1.200
	(0.012)	(0.543)	(0.989)	(0.441)	(0.092)	(0.000)	(0.000)	(0.883)	(0.442)	(0.422)	(0.293)		(0.760)
$V_{US,t+1}^{(w)}$	0.000	−0.022	−0.006	0.034	0.066	0.849	0.054	0.016	−0.007	0.007	0.011	0.883	3.200
	(0.035)	(0.141)	(0.871)	(0.378)	(0.000)	(0.000)	(0.027)	(0.843)	(0.630)	(0.782)	(0.322)		(0.360)
$V_{US,t+1}^{(m)}$	0.000	0.000	0.003	0.002	0.006	0.041	0.947	0.008	0.003	−0.005	0.002	0.989	0.620
	(0.365)	(0.939)	(0.752)	(0.840)	(0.032)	(0.000)	(0.000)	(0.720)	(0.403)	(0.460)	(0.492)		(0.890)

Same as Table 11.

Furthermore, it is well recognized that high and increasing food prices pose significant policy challenges, particularly in countries such as China, where the share of food in household expenditures is relatively high (FAO 2012). The high volatility of food prices and the associated uncertainty may impede the production and investment decisions of food producers, leading to inefficient resource allocation in agriculture and most importantly, severe food security issues (Naylor and Falcon 2010). This article provides information on the historical patterns of the volatility spillovers between the U.S. and China, which could be useful for local Chinese governments in formulating policies to contain price hikes and volatilities in the agricultural market. For example, the consistently significant spillover from the U.S. to the Chinese soybean market suggests that when the volatility in the U.S. soybean market is high, it is likely that the volatility in the Chinese market will also increase. Hence, an increasing volatility in the U.S. market may provide a signal to the Chinese Government to start considering interventions such as temporary purchasing and storage for the purpose of stabilizing the price of soybean.

VII. Conclusion

Applying a modified HAR model, this article extends the literature by providing detailed insights into the time horizon and dynamics of the volatility spillovers between the U.S. and China for agricultural futures on soybean, wheat, corn and sugar. We find significant volatility transmission from the U.S. to China in relation to all four commodities. The volatility spillover is most pronounced in regards to soybean, where it occurs on a daily, weekly and monthly basis for the entire sample, due to the large export amount from the U.S. to China. For wheat, corn and sugar, a significant volatility spillover can be found on the daily and weekly basis. Regarding the spillover from China to the U.S., the results from the whole sample show stronger transmission for the soybean and sugar market than from the U.S. to China.

By splitting the data into pre-crisis, crisis and post-crisis periods, this study provides an explanation of the volatility dynamics from the perspective of fundamentals and government interventions. The results show significant spillovers from the U.S. to China before and during the GFC for soybean. For wheat, the volatility spillover is significant for all forecast horizons before and post the turmoil. The transmission pattern as a whole is particularly significant in the Chinese corn market in the most recent subsample which could be due to the dramatic increase in the China's imports from the U.S. in 2012 and 2013. For the local sugar market in China, we find a significant explanatory power of the U.S. volatility in the daily and weekly volatility models after the financial downturn.

Importantly, this study uncovers the increasing pricing power of the Chinese futures market, which has not been often discussed in the literature yet. The volatility transmission from China to the U.S. is stronger than from the U.S. to China for soybean and sugar. For wheat and corn, although the spillover is weaker than from the U.S. to China, significant spillovers can be found at pre- and post-GFC periods for wheat, and during-GFC period for corn through shorter forecast horizons. These findings further confirm that the Chinese agricultural futures market is becoming increasingly integrated with the world market, and bring valuable implications from the investment and policy aspects.

Disclosure statement

No potential conflict of interest was reported by the authors.

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