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Information Flows Between the US and China's Agricultural Commodity Futures Markets—Based on VAR–BEKK–Skew-t Model

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ABSTRACT: The information flow in the volatility and the skewness of returns are two factors closely influences the hedging risks for cross-border transactions. This article adopts a VAR–BEKK–MGARCH model with multivariate skew-t error terms to investigate the mean and volatility spillovers, while accounting for the potential skewness. The model is applied to real returns of corn, wheat, and soybeans futures in United States and China. The empirical results indicate the major role of United States in information transmission, and the increasing volatility spillovers of China to United States in highly marketized commodities and after trading structure changes. The analysis of skewness provides evidences for market inefficiency and implication on the investment decision and trading strategies.

KEY WORDS: agricultural commodity futures, information flows, multivariate skew-t distribution, VAR–BEKK–MGARCH model, volatility spillover

Introduction

Background

Recent frequent upheavals and severe fluctuations in global agricultural markets, especially in the food prices, have called attention to the information flows across borders. There are mainly three channels of information flows. The most intuitive one is between commodity markets. For instance, during the food crisis in 2007 and 2008, with the increase in agricultural commodity prices in the United States, food prices in China, especially the prices of corn and wheat, also suffered from severe escalation. The second channel lies between the spot markets and the futures markets, and evidences show that the former's prices are generally discovered by the latter's, as discussed in Yang and Leatham (1999) and Easwaran and Ramasundaram (2008). The third channel connects international futures markets. Although China currently restricts the futures market to domestic investors, the government plans to gradually open it up to the oversea investors. Johansson (2010) provides a comprehensive analysis on the integration of China's financial market with the major regional and global markets. As part of the financial markets, China's commodity futures market is expected to be cointegrated with major international futures markets as well. In this regard, examining the cross-market information flows of agricultural commodity futures has become an important issue for both the researchers and the policy makers. Market practitioners (hedge funds and portfolio managers, multinational corporations, etc.) may also benefit from the study of information flow patterns in agricultural commodity futures markets, when making decisions about asset allocations and international investments.

Despite the leading role of US futures market in terms of information flow (Hernandez, Ibarra, and Trupkin 2014; Fung, Leung, and Xu 2001), Fung, Liu, and Tse (2010) argued that the US futures markets are not necessarily more efficient and may be affected by the factors of emerging markets and speculators' ability to obtain relevant information. In fact, earlier than that, Henriques (2008) and Ruggiero (2008) linked the extraordinary price hikes and volatility in the commodity markets during

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2006 and 2008 with the rampant speculation and arbitrage trading activities in derivative markets, especially in the emerging markets such as China and India. Fung et al. (2013) compared 16 commodity futures contracts in China with their foreign counterparts and found that China's futures markets are information efficient, particularly the returns of day-time trading session are less likely to be led by foreign markets than the over-night returns. Tu, Song, and Zhang (2013) discussed the increasingly important role of China's futures market of transmitting information in the world financial markets from the point of asset allocation.

This article attempts to explore further of the information transmission patterns and efficiency between the Chinese and US futures markets, with focus on three agricultural commodities, i.e., corn, wheat, and soybeans, which occupy important positions in the international trade. China is both one of the largest producers and importers of the three commodities. United States ranks first in China's agricultural imports, between 2005 and 2015. While China's total agricultural imports from United States increased 286% over this period, the percentage changes are 64,351%, 104%, and 368%, respectively, for corn, wheat, and soybeans.

Nevertheless, the trade patterns of these three commodities are somewhat different. China was a net exporter of corn before 2010. However, with the decline in domestic production and the rapidly increasing demand for aquaculture and corn processing, China's corn imports have exceeded the exports since 2010. It is until then United States has become the main country for China's corn imports.

Soybeans own the highest degree of marketization of all agricultural commodities in China. There are two types of soybeans futures traded in China's market. The No. 1 Soybeans futures, whose delivery goods are China's nongenetically modified (non-GMO) soybeans, was one of the earliest commodity futures traded in China. The No. 2 Soybeans futures, whose delivery goods are the imported GMO soybeans, was launched in 2004, as a complement to the No. 1 Soybeans. Despite the imported (mostly GMO) soybeans accounting for 80% of total soybeans traded in China, the trading volume of No. 2 Soybeans futures is less than 1% of that of No. 1 Soybeans futures.

The picture is different for wheat. Although China's demand for wheat largely exceeds its production, it imports relatively much lower quantity of wheat from the United States compared to its imports of soybeans and corn. Fung, Leung, and Xu (2003) pointed out that a series of protective policies, including restrictive import policy, tends to immunize the China's wheat prices from the world market fluctuations.

Clearly, the degree of integration of futures markets varies with different commodities, which may be subject to specific government regulations on the commodities and market policies. Consequently, these three agricultural commodity futures are expected to demonstrate very different cross-border information flow patterns.

This study contributes to the literature by looking at market dependence between United States and China in a multivariate framework, while accounting for the higher moment of the futures returns, in the hope of providing multiple perspectives of risks for the investors and traders when making investment decision and implementing trading strategy.

Review on Parametric Information Flow Models

The information flows of the futures markets lie in two aspects: (1) mean (return) spillover or price linkage and (2) volatility spillover.

Proposed in Sims (1980), the vector autoregression (VAR) model is one of the most popular parametric methods to capture the dynamic relationship in the first moment of multiple markets. Toda and Yamamoto (1995) developed Granger causality test based on VAR models, and the test is used to reveal the relationship between agricultural commodity and the oil price by Nazlioglu (2011) and Nazlioglu and Soytas (2011). Malliaris and Urrutia (1996) use the vector error correction (VEC) model of Davidson et al. (1978), which is an extension of VAR models, to disclose the linkages between agricultural commodity futures in the US market.

Typically, multivariate-GARCH models are used in studying the linkages between the volatilities and co-volatilities of several markets or assets. Constant conditional correlation, dynamic conditional correlation (DCC) of Engle (2002) and BEKK[1] of Engle and Kroner (1995) are three most popular matrix operations of MGARCH model. The BEKK–MGARCH has an advantage in measuring the volatility spillover effects of time series, while the DCC–MGARCH merely evaluates the correlation of conditional variances. With increasing interest in fully exploring and depicting the cross-markets information flows patterns in both the mean and the volatility of financial returns, the MGARCH-type models are combined with various mean functions. For instance, Fung, Leung, and Xu (2003) use the AR model with bivariate GARCH to characterize the information flows between the US and China's futures markets. Sehgal, Berlia, and Ahmad (2013) use the VEC model with BEKK–MGARCH and DCC–MGARCH, respectively, to analyze the volatility spillover and the conditional volatility correlation of crude oil in international commodity markets. Similarly, Yang, Zhang, and Leatham (2003) apply a VAR–BEKK–MGARCH model to the wheat futures returns in the US, Canadian, and European markets, and Hernandez, Ibarra, and Trupkin (2014) provide details of using vector moving average with the abovementioned three MGARCH models to analyze the agricultural commodity futures markets.

Skewness of Financial Returns

However, all of the abovementioned information transmission studies have only considered symmetric conditional distribution for the innovations, e.g., the Student t in Hernandez, Ibarra, and Trupkin (2014) and the normal in other articles, ignoring the obvious evidence (Singleton and Wingender 1986 and Jondeau and Rockinger 2003 to name a few) of skewness demonstrated in most financial return time series. Reviews of similar evidence in the futures market are provided in Eastman and Lucey (2008) and Christie-David and Chaudhry (2001).

In the literature of commodity futures pricing, the futures return skewness reflects the commodity risk factors, e.g., the supply and demand shocks (Brennan 1958; Kaldor 1939; Working 1949) or the hedging pressure (Cootner 1960; Hirshleifer 1988; Keynes 1930). More recently, Fernandez-Perez et al. (2018) provides evidence in their working article that skewness matters because of homogeneous preferences of investors, especially in the futures market which is dominated by speculators and hedgers. Indeed, the investigation of Patton (2004) shows that nonincreasing absolute risk averse investors have a preference for positively skewed portfolios. Knowledge of skewness is probably more important when studying an emerging market like China. Bae et al. (2006) suggested that the stock returns in emerging markets are more positively skewed than those in developed markets, as a consequence of poor corporate governance and poor information disclosure. Thus, skewness can be also viewed as an instrument to evaluate market efficiency.

The increasing interest in the return skewness is also due to the concern of the limited ability of the second moment as a usual measure of risk of an asset, as it does not distinguish between the number of the returns above and below the mean. Interestingly, significant impact of conditional skewness on the estimated conditional volatility is revealed in Harvey and Siddique (1999). Their results suggest less persistent conditional volatility and disappeared leverage effect after conditional skewness is included in the modeling framework. Tomek and Peterson (2001) also made a strong argument that correct description of the higher moments of underlying return distribution plays a more important role in determining the risk premia in futures markets than the form of conditional volatility models.

Meanwhile, abundant academic studies combine asymmetric return distributions with univariate GARCH type models for the dynamics in the financial time series. Just to name a few, Peters (2001) and Kercheval and Liu (2011) use a skew-t of Hansen (1994) as the error distribution, combined with GARCH volatility to model the stock returns; Lee and Pai (2010) consider volatility prediction in the context of a skew-generalized error distribution (GED) conditional return distribution; Gerlach, Lu, and Huang (2013) develop an asymmetric Laplace distribution as the conditional return distribution.

This article proposes a VAR–BEKK–MGARCH model with skew-t innovations, to estimate the mean and variance spillovers of the same commodity across different markets. By assuming a skew-t conditional distribution, the model is more general and flexible by taking the potential asymmetric properties and higher moments in the returns into account. In this sense, with improved accuracy in parameter estimation, the model is expected to explain the cross-border information flow patterns more clearly than the existing literature.

The rest of the article is structured as follows. The first section describes the VAR–BEKK–MGARCH model with the skew-t distributed innovations. The next section presents the data with brief details of data processing. The following section presents and discusses the empirical results. The final section concludes.

Model Specification and Methodology

This section specifies the model used in the empirical section from two aspects, i.e., (1) VAR for the (potentially skewed) mean (return) spillover or price linkage and (2) MGARCH for the volatility spillover. Note that we deliberately exclude the possible leverage effect in the conditional volatility, following the finding of Harvey and Siddique (1999) that the effect of asymmetry in conditional volatility is overwhelmed by that of asymmetry in the conditional return distribution. The best orders of the VAR–BEKK–MGARCH model are determined based on the Akaike information criterion (AIC).

We propose a VAR(1)–BEKK(1,1)-skt model as follows:

$$\boldsymbol{r_t} = \boldsymbol{\mu} + \Phi^T \boldsymbol{r}_{t-1} + \varepsilon_t, \tag{1}$$

$$\varepsilon_t \sim \text{Skew } T(0, H_t, v, \gamma), \tag{2}$$

$$H_t = C^T C + A^T \varepsilon_{t-1} \varepsilon_{t-1}^T A + B^T H_{t-1} B, \tag{3}$$

The mean return follows an VAR(1) model in (1), where $\boldsymbol{r}_t = [r_{1t}, r_{2t}, \ldots, r_{nt}]^T \in \mathbb{R}^n$ is a concatenated vector containing n observations at time t; $\boldsymbol{\mu} = [\mu_{1t}, \mu_{2t}, \ldots, \mu_{nt}]^T \in \mathbb{R}^n$ is the constant vector, which represents the constant iteration shift.

$$\Phi^T = \begin{bmatrix} \phi_{11} & \phi_{12} & \cdots & \phi_{1n} \\ \phi_{21} & \phi_{22} & \cdots & \phi_{2n} \\ \vdots & \cdots & \cdots & \vdots \\ \phi_{n1} & \phi_{n2} & \cdots & \phi_{nn} \end{bmatrix}^T \tag{4}$$

is the autoregressive matrix, where the off-diagonal element ϕ_{ij}, $i \neq j$ of Φ represents the mean spillover of return series i to series j, and the diagonal element ϕ_{ii} represents the first-order autocorrelation in the return series i at time t.

Equation (2) defines the concatenated vector of innovations of the VAR(1) model $\varepsilon_t = [\varepsilon_{1,t}, \varepsilon_{2,t}, \ldots, \varepsilon_{n,t}]^T$, which is assumed to follow a skew-t distribution in Aas and Haff (2006). Although a few latest works (Orskaug 2009; Fioruci, Ehlers, and Andrade Filho 2014) proposed the MGARCH model with multivariate skew-t distributed innovations, their work is quite different from us in the following ways: first, their work is based on DCC–MGARCH model and is unable to reveal the directions of volatility spillovers among multiple return series; second, to accommodate the DCC model, they employed the skew-t distribution of Azzalini and Capitanio (2003), which is different in form from the one employed in this article; last but not least, they did not discuss the implication of the skewness to the market practitioners and policy makers, which is one of the major interests in this article. The VAR–BEKK–MGARCH is also different from the multivariate VAR–GARCH proposed by Ling and McAleer (2003) in that the latter does not allow the nesting of ARCH and GARCH model and assumes non-time-varying conditional correlations.

Aas and Haff (2006) defines that a n-dimensional random vector $X \in \mathbb{R}^n$ follows a skew-t distribution with the scalar degree of freedom (d.o.f.) v, the vector of skewness parameters $\gamma = [\gamma_1, \gamma_2, \ldots, \gamma_n]^T$, the mean vector η (for ε_t, $\eta = 0$), and the covariance matrix Ω denoted as $X \sim \text{Skew}\, T(x|\eta, \Omega, v, \gamma)$, if its probability density function is

$$f(x; \boldsymbol{\eta}, \Omega, v, \gamma) = c \frac{K_{(v+n/2)}\left(\sqrt{(v+\rho(x))(\gamma^T\Omega^{-1}\gamma)}\right) e^{(x-\eta)^T\Omega^{-1}\gamma}}{\left(\sqrt{(v+\rho(x))(\gamma^T\Omega^{-1}\gamma)}\right)^{-(v+n/2)} (1+(\rho(x)/v))^{(v+n/2)}}, \tag{5}$$

where

$$\rho(x) = (x-\boldsymbol{\eta})^T\Omega^{-1}(x-\boldsymbol{\eta}); \quad c = \frac{2^{1-(v+n/2)}}{\Gamma(v/2)(\pi v)^{n/2}|\Omega|^{1/2}},$$

and K_λ denotes a modified Bessel function of the second kind with index λ,

$$K_\lambda(x) = \frac{1}{2}\int_0^\infty y^{\lambda-1} e^{-(x/2)(y+y^{-1})} \mathrm{d}y, \quad x > 0.$$

In particular, $\gamma_i > 0$ (<0) indicates that the ith return series is positively (negatively) skewed, while $\gamma_i = 0$, the skew-t is reduced to the Student t distribution. The conditional variance–covariance matrix exists when $v > 2$.

Equation (3) defines BEKK–MGARCH(1,1) term with the parameter matrices C, A and B in the following forms:

$$C = \begin{bmatrix} c_{11} & c_{12} & \cdots & c_{1n} \\ 0 & c_{22} & \cdots & c_{2n} \\ \vdots & \cdots & \cdots & \vdots \\ 0 & 0 & \cdots & c_{nn} \end{bmatrix}, \quad A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \cdots & \cdots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{bmatrix}, \quad B = \begin{bmatrix} b_{11} & b_{12} & \cdots & b_{1n} \\ b_{21} & b_{22} & \cdots & b_{2n} \\ \vdots & \cdots & \cdots & \vdots \\ b_{n1} & b_{n2} & \cdots & b_{nn} \end{bmatrix}. \tag{6}$$

$C \in \mathbb{R}^{n \times n}$ is an upper triangular matrix, the ARCH parameter matrix $A \in \mathbb{R}^{n \times n}$ indicates the relationship between the historical innovations and the conditional volatility at time t. GARCH parameter matrix $B \in \mathbb{R}^{n \times n}$ indicates persistence of conditional volatility, i.e., the relationship between the conditional volatility and its first order lag. To ensure the stationarity of BEKK model, all eigenvalues of $A* + B*$ are less than one in modulus (for more details, refer to Boussama, Fuchs, and Stelzer (2011)), given duplication matrix D_n and its generalized inverse D_n^+

$$A* = D_n^+(A \otimes A)D_n$$

$$B* = D_n^+(B \otimes B)D_n$$

This condition is enforced during estimation.

With respect to information flow, the off-diagonal elements a_{ij} and b_{ij}, $i \neq j$ represent the impacts of the lagged innovation and lagged conditional volatility, respectively, of return series i, to the conditional volatility of return series j.

Denote $\boldsymbol{u} = \text{vec}\{\boldsymbol{\mu}, \Phi, \tilde{C}, \tilde{A}, \tilde{B}, v, \gamma\}$ the vectorization of the parameters in (1)–(3), the log-likelihood function of the corresponding is

$$l(\boldsymbol{r}_1, \boldsymbol{r}_2, \ldots, \boldsymbol{r}_T, u) = \log\left(\prod_{t=3}^{T} \mathrm{Skew\,T}(\varepsilon_t|0, H_t, v, \gamma)\right) = \sum_{t=3}^{T} \log(\mathrm{Skew\,T}(\varepsilon_t|0, H_t, v, \gamma)) \qquad (7)$$

This article uses the BFGS quasi-Newton method with a cubic line search procedure to numerically solve the maximum optimization problem for these almost strictly concave quadratic functions, as seen in Shanno (1970), Fletcher (1970), Goldfarb (1970), and Shanno (1970). By this means, all the parameters are estimated simultaneously.

Data

We examine the daily commodity futures prices of corn, wheat, and soybeans in Chicago Board of Trade in the United States, wheat in Zhengzhou Commodity Exchange in China, and corn, No. 1 Soybeans and No. 2 Soybeans in Dailian Commodity Exchange in China from January 2005 to December 2014. To construct continuous time series, this article follows the international practice as seen in Booth, Martikainen, and Tse (1997), Geoffrey Booth, Brockman, and Tse (1998), and Xu and Fung (2005), chooses the daily closing price of the nearest-to-deliver contracts on matching trading days of the US and China's markets, and discards those unmatching ones when either market is closed. The data are obtained from the website of Bloomberg and the Wind Financial Terminal. The model is applied to the stationary return series of the futures, following the convention. The return series are defined as

$$r_t = 100 \times \ln\left(\frac{p_t}{p_{t-1}}\right) = 100 \times (\ln p_t - \ln p_{t-1}), \qquad (8)$$

where p_t is the daily closing price at day t. Thus, there is 2367 observations for each commodity future.

Table 1 reports their descriptive statistics. The average returns of all futures are close to zero, which is consistent with the common assumption that the mean of return series is approximately zero. The sample skewness statistics of all series are significantly different from zero. In particular, for the futures of same underlying commodity, the sample skewness of Chinese market is more positively skewed than that of the US market, which is similar to the finding of Bae et al. (2006) for the stock returns in the emerging market. In addition, there exists significant amount of excess kurtosis (ranging between 6.54 and 45.97) in all the returns series. The non-normality of the return series is further confirmed by the rejection results of the Jarque–Bera normality test.

Empirical Research

This section presents and interprets the estimation results of the skew-t, VAR, and the BEKK–MGARCH parameters separately. To reveal the information transmission patterns, we focus the discussion on the off-diagonal elements for the VAR parameter matrix Φ in (4) and BEKK parameter matrix A and B in (6) with emphasis on the latter and do not elaborate on the diagonal elements. After including the skewness in the model framework, the VAR–BEKK–MGARCH is expected to shed a brighter light on the cross-border information flow patterns in the mean and volatility.

In order to take the structural change point in Sino–US corn trade in 2010 into account, we divide the corn futures returns series into two subsamples, i.e., from January 2005 to December 2009 and from January 2010 to December 2014. Chow (1960) test validates the significance of this break-point for the corn futures with the corresponding p-value 1.95×10^{-7}, while no significant structural breaks are detected for the wheat and soybeans futures.

Table 1. Summary statistics for three agricultural commodity futures price returns.

	Corn		Wheat		Soybeans		
	US	CH	US	CH	US	CH1	CH2
Mean	0.024	0.031	0.020	0.098	0.023	0.022	0.010
Median	0.000	0.000	–0.052	0.000	0.107	0.034	0.000
Maximum	10.884	8.654	25.805	202.815	20.321	6.497	6.647
Minimum	–39.861	–5.750	–22.569	–132.796	–23.411	–10.983	–15.896
Std. dev.	2.182	0.781	2.307	8.898	1.837	1.218	1.305
Skewness	–2.538*	1.033*	0.206*	4.527*	–1.130*	–0.427*	–1.056*
Kurtosis	45.971	16.157	11.343	150.976	20.632	6.540	12.458
Jarque–Bera	201517*	23109*	24743*	275279*	117324*	3959*	15424*

Sources: Bloomberg and Wind Financial Terminal.
Notes: CH1 denotes No. 1 Soybeans in China; CH2 denotes No. 2 Soybeans in China.
*Indicates the statistics are significant at 1% level.

Skewness of the Futures Returns

This section analyzes the skewness features (hereafter, the terminology "skewness" is referred to the skewness of conditional return distribution) of three agricultural commodity futures returns in the US and China's markets.

Harvey and Siddique (1999, 2000) and Ait-Sahalia and Brandt (2001) point out the importance of including skewness in the investment decision-making. They argue that, given everything else constant, risk-averse investors should prefer portfolios that are right-skewed (more and larger pay-offs, fewer and smaller losses) to those that left-skewed. The implications of knowledge of return skewness are threefold. First, it could allow more accurate pricing on the options on the futures contracts; second, it could aid market participants to design better trading strategies; last but not least, it could provide useful information on market efficiency.

The estimates of the skew-t parameters as well as the skewness are presented in Table 2. Clearly that the d.o.f. v for all futures return series is significant and smaller than 4, implying that the conditional kurtosis of all return series is infinite. Here, the return series across different markets are assumed to be distributed with identical d.o.f., which lies in the nature of this type of skew-t setting. Assuming that each return series has different d.o.f. may improve the flexibility of the model and can be achieved by scale mixture models under the Bayesian framework, as seen in Lin, Lee, and Yen (2007) and Lee and McLachlan (2013), among many others. However in practice, we find that the difference in the d.o.f.s for the same underlying commodity is minimal, so this article stays with the original skew-t setting with identical d.o.f.

It is noticeable that the skew-t shape parameter γ_i is significant at 1%, 5%, and 10% significance levels, respectively, for the US soybeans futures, China's corn futures between 2005 and 2009, and the US wheat futures and China's No. 1 Soybeans futures. All the other return series have insignificant skewness. Equivalently, at 5% level, all the significant skewness parameters are either significantly negative or significantly positive.

Although the US soybeans futures has similar slightly positive average returns but a smaller sample standard deviation over the whole sample period compared to the other two futures in United States, as shown in Table 1, its significant negative skewness parameter reveals more risk associated with higher possibility of considerably large loss, aside from the dynamics in conditional volatility. This is exactly the case where the second moment is not enough to depict the risk. Similarly, White, Kim, and Manganelli (2008) spotted dangerous situation when particularly large negative return occurred in low volatility period by estimating conditional skewness with multi-dynamic quantile model.

Table 2. Skew-t parameters estimation results for three agricultural commodity futures price returns.

	Corn (2005–2009)		Corn (2010–2014)		Wheat		Soybeans		
	US	CH	US	CH	US	CH	US	CH1	CH2
	(i = 1)	(i = 2)	(i = 1)	(i = 2)	(i = 1)	(i = 2)	(i = 1)	(i = 2)	(i = 3)
γ_i	0.003	0.020**	–0.002	0.004	0.029*	0.006	–0.033***	0.011*	0.005
	(0.022)	(0.010)	(0.020)	(0.006)	(0.017)	(0.008)	(0.011)	(0.006)	(0.006)
v	3.892 * * *		3.710 * * *		3.596 * * *		3.664 * * *		
	(0.357)		(0.344)		(0.251)		(0.204)		
$\widehat{SK}$	0.0448	**0.2759**	–0.0409	0.0715	**0.5651**	0.1210	**–0.6020**	**0.1984**	0.092

Notes: ***, **,* indicate that the values are significant at 1%, 5%, and 10% levels, respectively. CH1 denotes No. 1 Soybeans in China; CH2 denotes No. 2 Soybeans in China. Values in parentheses () indicate the standard errors of the estimate. $\widehat{SK}$ is the estimated conditional skewness under skew-t. The significant conditional skewness are in bold.

The skewness parameter of China's corn futures is significantly positive during 2005–2009 and become insignificant after China opened up its corn market to United States. The implication could be that, before the structural change in 2010, there existed speculation opportunity with extremely high payoffs in China's corn futures market, probably due to less efficient governance and imbalance between the increasing demand and limited domestic production; by opening the market and increasing trading with international markets, the market efficiency for China's corn futures was largely improved. China's corn futures may also be subsequently less attractive for arbitrage trading and speculation since then. In this sense, China's No. 1 Soybeans futures has positive conditional skewness and could remain attractive for risk averse investors.

With respect to the market efficiency in the United States, the significantly right skewed conditional return distribution of US wheat futures indicates that even in a developed market like United States, there could exist certain assets or commodity futures that are not traded efficiently. The estimated conditional skewness of US wheat futures is even more positive than that of China's corn futures before 2010 and that of China's No. 1 Soybeans futures—traders could explore speculation and arbitrage opportunities, and investors could expect even higher payoffs by including US wheat futures in their asset portfolio.

While the skew-t specification effectively distinguish the different shapes of conditional return distributions for the United States and China, of the corn futures in 2005–2009, the wheat futures and the soybeans futures, the insignificant shape parameters for the corn futures returns in both US and Chinese market during 2010 and 2014, implies that the skew-t can be reduced to a Student's *t* distribution. However, it is still necessary to employ a skew-t error distribution instead of a Student's *t* when analyzing the information flow patterns because of two reasons. First, it is not reasonable to assume the futures returns of two different markets identically distributed; the slightly different shape parameters of skew-t model allows the return distributions vary for each market to a small extent, while small changes in the d.o.f. parameters could incur large change in the shape of distribution, as noticed by Jondeau and Rockinger (2003). Second, Levy (1969) suggests that higher moments should be added in the modeling framework even if they add little information about the shape of the distribution in portfolio analysis. After all, the estimation of the skew-t model is not inevitably more costly than a Student's *t* model.

We did also attempt with the normal and the Student *t* error distribution[2] and report the log-likelihood and the AIC of the models in Table 3. The model with skew-t error terms has the largest log-likelihood values and the smallest AIC for all three commodities. Clearly, the skew-t model does not necessarily have higher estimation cost but actually fits the data best. Besides allowing for asymmetric tails, the skew-t also provides more flexibility in the d.o.f. While the estimated d.o.f.s of skew-t model ranges from 3.596 to 3.892, those of Student's *t* model vary in a much narrower range of [3.510, 3.583]. The estimated d.o.f.s of Student's *t* model are smaller than those of skew-t model, as the Student *t* model has to stretch out in order to capture the asymmetric extreme tails in the return distribution, which is effectively captured by the shape parameters in the skew-t model. These evidence further justify our choice of the skew-t as the conditional return distribution.

Table 3. Log-Likelihood and AIC of VAR–BEKK–MGARCH models with different innovation distributions.

	Normal distribution		*T* distribution		Skew-t distribution	
	Log-likelihood	AIC	Log-likelihood	AIC	Log-likelihood	AIC
Corn (2005–2009)	−1950.09	3934.19	−1937.50	3911.01	−1934.85	3909.69
Corn (2010–2014)	−1566.65	3167.29	−1197.71	2431.43	−1193.11	2426.21
Wheat	−5402.33	10838.67	−3538.36	7112.73	−3503.41	7046.82
Soybeans	−5597.83	11267.67	−4306.87	8687.74	−4288.48	8656.97

Table 4. Estimation results of VAR for three agricultural commodity futures returns.

	Corn (2005–2009)		Corn (2010–2014)		Wheat		Soybeans		
	US	CH	US	CH	US	CH	US	CH1	CH2
	(i = 1)	(i = 2)	(i = 1)	(i = 2)	(i = 1)	(i = 2)	(i = 1)	(i = 2)	(i = 3)
ϕ_{1i}	0.032	**0.028**	0.008	**0.058**	–0.007	**0.042**	**–0.068**	**0.177**	**0.157**
	(0.033)	(0.010)	(0.027)	(0.009)	(0.021)	(0.006)	(0.022)	(0.016)	(0.015)
ϕ_{2i}	–0.104	**–0.122**	0.000	**–0.126**	–0.027	**–0.069**	0.009	**–0.167**	0.039
	(0.062)	(0.027)	(0.096)	(0.032)	(0.056)	(0.016)	(0.036)	(0.020)	(0.024)
ϕ_{3i}	–	–	–	–	–	–	–0.003	–0.026	**–0.177**
							(0.036)	(0.016)	(0.024)
μ_i	0.027	–0.026	0.006	0.000	–0.056	–0.007	**0.090**	–0.010	0.001
	(0.040)	(0.014)	(0.038)	(0.009)	(0.029)	(0.012)	(0.019)	(0.010)	(0.010)

Notes: Boldface indicates that the values are significant at 5% level. CH1 denotes No. 1 Soybeans in China; CH2 denotes No. 2 Soybeans in China. Values in parentheses () indicate the standard errors of the estimate.

Mean Spillover Effects

The estimation results for the VAR(1) model in (1) and specifically the autoregressive matrix Φ defined in (4) are shown in Table 4. Note that in Granger causality analysis, the off-diagonal elements $\phi_{ij}, \quad i \neq j$ in Φ indicate the Granger causality of each pair of return series. For all return groups, significant ϕ_{1i} ($\phi_{12} = 0.28$, $\phi_{12} = 0.058$, $\phi_{12} = 0.042$, $\phi_{12} = 0.177$, and $\phi_{13} = 0.157$ for Corn 05–09, Corn 10–14, Wheat, and Soybeans, respectively) and insignificant ϕ_{i1} $(i = 2.3)$ suggest significant unilateral information flow in the returns from the US market to China's market.

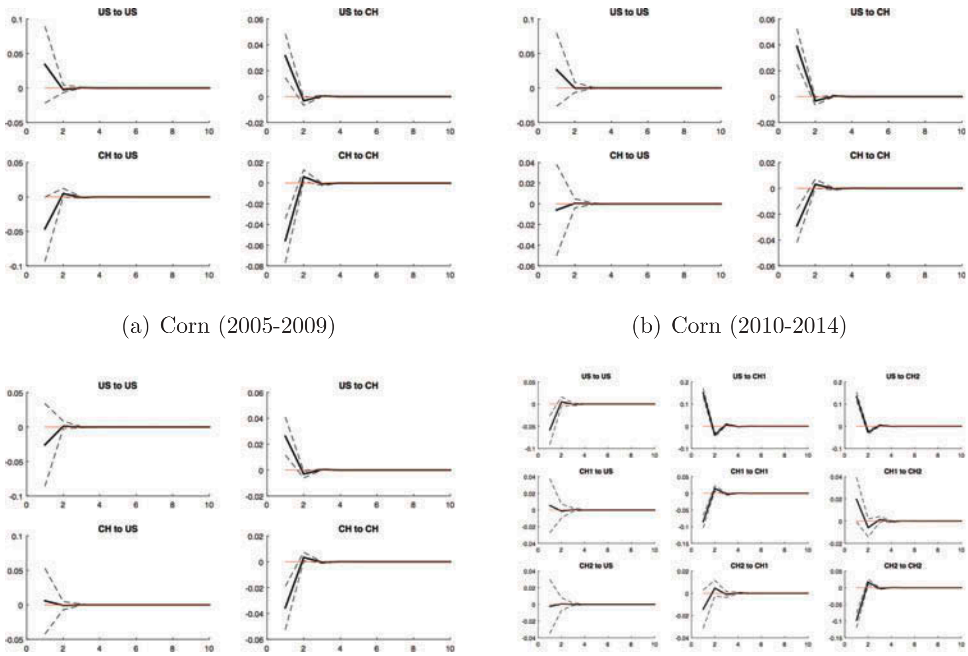
Granger causality test results in Table 5 confirm that there is no feedback effect in mean from China's market to the US market. It is unable to reject the null hypothesis that the returns in China's market do not granger-cause the returns in the US market for any commodity futures, at 5% significance level.

Figure 1 contains the impulse response function with 95% confidence intervals (CIs) (based on asymptotic theory), which further confirms the Granger causality test results. All impact shows a short memory processes. The response of China's market to the US market has much greater magnitude compared with the response of the US market to China's market. To be noted that subject to the definition of CI, the CIs for the insignificant parameters may contain zero. For example, in plot (a), corn US to US, while the response is positive, the CI is negative at the beginning, because $\phi_{11} = 0.032$ is insignificant.

Table 5. Test results for Granger causality in mean.

	Null hypothesis	*p* Value		Null hypothesis	*p* Value
Corn	US does not Granger-cause CH	**0.0030**		US does not Granger-cause CH1	**0.0000**
(2005–2009)	CH does not Granger-cause US	0.0954		CH1 does not Granger-cause US	0.8088
Corn	US does not Granger-cause CH	**0.0000**	Soybeans	US does not Granger-cause CH2	**0.0000**
(2010–2014)	CH does not Granger-cause US	0.9991		CH2 does not Granger-cause US	0.9323
Wheat	US does not Granger-cause CH	**0.0000**		CH1 does not Granger-cause CH2	0.1091
	CH does not Granger-cause US	0.6305		CH2 does not Granger-cause CH1	0.0970

Notes: Boldface indicates that the null hypotheses are rejected at 5% level. CH1 denotes No. 1 Soybeans in China; CH2 denotes No. 2 Soybeans in China.



(a) Corn (2005-2009) (b) Corn (2010-2014)

(c) Wheat (d) Soybeans

Figure 1. Impulse response function analysis for three agricultural commodity futures returns.
***Notes*: Dash lines are the 95% confidence intervals. CH1 denotes No. 1 Soybeans in China; CH2 denotes No. 2 Soybeans in China.**

In summary, the information transmission patterns in the returns (prices) are quite consistent among the three futures—the US market has an overwhelming unilateral impact to China's markets, which is consistent with the existing literature.

Volatility Spillover Effects

Table 6 contains the estimation results of the BEKK–MGARCH model in (3). Table 7 contains the Wald test results on the joint significance of a set of BEKK–MGARCH parameters. For example, $H_0 : A = B = 0$ tests the joint significance of all parameters in matrix A and B, indicating whether the BEKK–MGARCH model is an effective form to capture either the long-term or the short-term dynamics in the conditional volatility. For all series vectors, this null can not be rejected; thus, BEKK–MGARCH is indeed an effective volatility form. Meanwhile, $H_0 : a_{ij} = b_{ij} = 0,\ i{\neq}j$ tests the joint significance of all off-diagonal elements in A and B, indicating existence of either long-term or short-term volatility spillover effect in any direction. The null again can not be rejected for any series vectors; thus, overall volatility information transmission exists in all three futures between United States and China. The rest of the hypotheses tests for the spillover effect of specific direction (i to j, $i{\neq}j$) in the volatility.

For the corn futures during 2005 and 2009, none of a_{12}, a_{21}, b_{12} and b_{21} is significant at 5% significance level in Table 6. Moreover, according to Table 7, neither the null hypothesis of no volatility spillovers from the US market to China's market ($a_{12} = b_{12} = 0$) nor the null hypothesis of no volatility spillovers from China's market to the US market ($a_{21} = b_{21} = 0$) can be rejected. It needs to be pointed out that the rejection of the null $H_0 : a_{ij} = b_{ij} = 0,\quad i{\neq}j$ for the corn futures 2005–2009 is probably due to the weakly significant (at 10% significance level) b_{21}. Nevertheless, it is

Table 6. BEKK–MGARCH parameters estimation results for three agricultural commodity futures price returns.

	Corn (2005–2009)		Corn (2010–2014)		Wheat		Soybeans		
	US	CH	US	CH	US	CH	US	CH1	CH2
	(i = 1)	(i = 2)	(i = 1)	(i = 2)	(i = 1)	(i = 2)	(i = 1)	(i = 2)	(i = 3)
c_{1i}	0.075	**–0.087**	**0.409**	0.037	**0.133**	0.004	**0.088**	0.020	0.016
	(0.046)	(0.031)	(0.146)	(0.020)	(0.021)	(0.003)	(0.012)	(0.010)	(0.011)
c_{2i}		–0.004		0.000		–0.007		–0.018	**0.043**
		(0.024)		(0.000)		(0.004)		(0.012)	(0.014)
c_{3i}	–	–	–	–	–	–			0.000
									(0.003)
a_{1i}	**0.181**	0.023	**0.113**	**0.065**	**0.208**	0.007	0.020	**0.041**	**0.026**
	(0.032)	(0.017)	(0.049)	(0.016)	(0.020)	(0.004)	(0.030)	(0.009)	(0.012)
a_{2i}	0.075	**0.207**	–0.231	**0.243**	–0.036	**0.072**	–0.016	**0.155**	–0.092
	(0.071)	(0.039)	(0.156)	(0.072)	(0.038)	(0.006)	(0.039)	(0.020)	(0.060)
a_{3i}	–	–	–	–	–	–	–0.024	–0.014	**–0.282**
							(0.027)	(0.027)	(0.052)
b_{1i}	**0.972**	0.017	–0.386	**0.201**	**0.947**	**–0.005**	**0.964**	**–0.031**	**–0.024**
	(0.027)	(0.061)	(0.232)	(0.021)	(0.009)	(0.002)	(0.010)	(0.012)	(0.010)
b_{2i}	–0.956	**–0.891**	**–2.251**	–0.382	0.035	**0.992**	**0.081**	**0.977**	0.069
	(0.500)	(0.060)	(0.555)	(0.225)	(0.019)	(0.002)	(0.035)	(0.011)	(0.045)
b_{3i}	–	–	–	–	–	–	0.026	0.007	**0.901**
							(0.019)	(0.014)	(0.041)

Notes: Boldface indicates that the values are significant at 5% level. CH1 denotes No. 1 Soybeans in China; CH2 denotes No. 2 Soybeans in China. Values in parentheses indicate the standard errors of the estimate.

Table 7. Wald test statistics for VAR–BEKK–MGARCH models for three agricultural commodity futures price returns.

Null hypothesis	Corn (2005–2009)	Corn (2010–2014)	Wheat	Soybeans
H_0: $A = B = 0$	**28956**	**1425**	**2293333**	**575435**
H_0: $a_{ij} = b_{ij} = 0$, for $i \neq j$	**49.5117**	**164.5382**	**9.6643**	**46.7749**
H_0: $a_{12} = b_{12} = 0$	1.7648	**90.4411**	**8.8165**	**31.578**
H_0: $a_{21} = b_{21} = 0$	3.8401	**21.1872**	3.7393	**9.1513**
H_0: $a_{13} = b_{13} = 0$	–	–	–	**11.3509**
H_0: $a_{31} = b_{31} = 0$	–	–	–	1.8166
H_0: $a_{23} = b_{23} = 0$	–	–	–	2.4215
H_0: $a_{32} = b_{32} = 0$	–	–	–	0.2644

Notes: Boldface indicates that the null hypotheses are rejected at 5% level.

still safe to conclude the lack of volatility spillovers effects, short term or long term, in the corn futures between the two markets during this period.

The story is different after the changes in the China's trade policy and the Sino–US trade patterns of the corn in 2010. Though a_{21} is insignificant, significant a_{12} indicates a unidirectional short-term shock transmitting from the US market to the China's market, at 5% level. Meanwhile, b_{12} and b_{21} are both significant, indicating the transmitted persistence in the conditional volatility from both directions. In addition, Table 7 confirms the existence of bidirectional volatility spillover effect between the two markets. Compared with the results of the period 2005–2009, there are obviously increased volatility information flows between the two markets after 2010. It suggests that the change in trade might affect the pattern of cross-border information flows, especially those associated with risks, between markets.

As for the wheat futures, considering the off-diagonal elements in A and B, b_{21} is the only significant coefficient at 5% level. It implies that the volatility information transmission between the two markets is relatively limited—there is merely long-term influence of conditional volatility from the US market to China's market. It is confirmed by the Wald test in Table 7 that it rejects the hypotheses of no volatility spillovers from the US market to China' market ($a_{12} = b_{12} = 0$) but cannot reject the hypothesis of no volatility spillovers from China's market to the US market ($a_{21} = b_{21} = 0$), showing the existence of minor volatility spillover effect from the US market to China' market.

Last but not least, the story of the soybeans is more complex. According to Table 6, significant a_{12} and a_{13} indicate the existence of short-term volatility spillover effects from the United States to the two soybeans commodity futures in China. Significant b_{12} and b_{21} suggest that there exist bidirectional long-term spillovers between the US soybeans futures and China's No. 1 Soybeans futures; meanwhile, b_{13} is significant and b_{31} is not, indicating a significant and unidirectional long-term volatility information transmission from the US soybeans futures to China's No. 2 Soybeans futures. Furthermore, the Wald test results in Table 7 confirm the above information flow patterns. It is noteworthy that Wald test also confirms that there is no volatility spillover between No. 1 Soybeans futures and No. 2 Soybeans futures in China ($a_{23} = b_{23} = 0$ and $a_{32} = b_{32} = 0$).

There are three other popular spillover tests on the conditional volatility in the literature. Cheung and Ng (1996) proposed a χ^2 test based on residual cross correlation function (CCF) on the causality in variance between two time series. Later, Hong (2001) extended this test by employing various weight functions. Table 8 records the results of Cheung and Ng (1996) test with $\pm$ 10 lags, as well as that of Hong (2001) with quadratic-spectral kernel function. The null hypothesis of no causality in variance is rejected for all six pairs of return series by the test of Cheung and Ng (1996), while all pairs except that of China's No. 1 and No. 2 soybeans are rejected by the test of Hong (2001). Obviously, these two similar tests disagree on the insignificance of the volatility spillover between these two soybean futures. Both tests capture the weak connection in variance for the corn futures 2005–2009. The residual CCF does not distinguish the dynamics in the second moment from those in the higher moments and is likely to exaggerate the conditional covariance. The volatility impulse response function (VIRF) based on Wald test, proposed by Hafner and Herwartz (2006), is often used to analyze the impact of one-time event on the conditional covariance. The result of this method varies largely with the choice of initial states and the effect is nonlinear. Therefore, VIRF is not quite applicable in addressing the focus in this article.

Table 8. Test results for Granger causality in variance.

		p Value	
	Null hypothesis	**Cheung and Ng (1996)**	**Hong (2001)**
Corn (2005–2009)	No granger-causality between US and CH	0.0000	0.0000
Corn (2010–2014)	No granger-causality between US and CH	0.0169	0.0011
Wheat	No granger-causality between US and CH	0.0003	0.0000
Soybeans	No granger-causality between US and CH1	0.0000	0.0324
	No granger-causality between US and CH2	0.0000	0.0006
	No granger-causality between CH1 and CH2	0.0000	**0.6283**

Notes: Boldface indicates the null hypotheses are rejected at 5% level. CH1 denotes No. 1 Soybeans in China; CH2 denotes No. 2 Soybeans in China.

In summary, the volatility spillover effects between the two markets are relatively weaker for the corn futures before 2010 and the wheat futures than that for the soybean futures. Evidence shows increasing information flow related to the volatility of the corn futures from both directions between the two countries after China opened up its corn commodity market to the Unites States in 2010. As the commodity has highest degree of marketization in China, the soybeans futures of the two countries demonstrate influential information transmission with respect to the volatility.

Combined with the analysis of VAR parameters, although the results confirms the dominant role of the US market in information flows in the returns, the significant cross-border volatility spillover effects, especially that from China to United States, reveal a much stronger relation between the two agricultural commodity futures markets. The extent of this dependence may not be disclosed by merely studying the price linkage. As both the volatility and skewness represent the asset's risks, after including the skewness, a better understanding of the volatility information flow patterns between the two markets may assist the investors to better manage both the domestic and international market risks.

Conclusion

As one of the largest importers and exporters of major agricultural commodities, does the corresponding futures market in China truly reflect its power in price discovery and information flows? In particular, if there exist bidirectional information flows between China's market and the developed markets, say the United States, what is the channel that China's market transmits information as an emerging market? This article attempted to address the above questions by investigating the dynamics and the relationships of the futures returns and their volatility of three major agricultural commodities between the US and China's markets via the proposed VAR–BEKK–Skew-t model, which distinguishes the risks of the second and the third moments.

The results confirm the leading role of the US futures market in terms of the mean and volatility information transmission. Interesting, evidences show that China's futures market has increased volatility spillovers to the US market, especially in highly marketized commodities, such as the corn and the soybeans. As the Sino–US corn trade increases dramatically, stronger spillover effect from China to US market is seen after 2010. The disappeared positive conditional return skewness also confirms the improved market efficiency brought by the increase in information flow. On the contrary, with the underlying commodity under strict government regulation in China, wheat futures in the two markets has the minimum information flows. Although the soybeans futures in China is highly market oriented, the trading mechanism of No. 2 Soybeans futures, after 10 years of its launch, is considerably less effective then that of the No. 1 Soybeans futures. Consequently, the tremendous discrepancy in the trading volumes of No. 2 Soybeans futures and the underlying commodity has impaired the futures function as a hedging vehicle for international risks. The situation may be improved if Chinese government could take measures to alleviate the trading restriction on the imported GMO soybeans. All the above evidences confirm a closer tie between the US and China's markets and that information flows need to work through trade conduction mechanism. Though China's market still lacks the pricing power of agricultural commodities in the international market, it should not be overlooked as it plays a critical role in transmitting the information associated with risks in the futures markets.

Besides the information transmission patterns, the analysis of skewness features also shed a light on the investment decision and the trading strategy for the investors and traders. The absolute risk-adverse investors, who are interested in including agricultural commodity futures in their portfolios, could consider investing in the futures with positively skewed returns, such as the US wheat futures and China's No. 1 soybeans futures, while avoid holding the US soybeans futures for too long period. When the investors trade the options based on these agricultural commodity futures, negative risk premia should be taken into account for the futures with positively skewed returns. The traders of the commodity of US soybeans could increase their hedging power by holding futures with more large positive payoffs, like China's No. 1 soybeans futures or US wheat futures, to hedge the possible large unexpected loss in the US soybeans. The speculators and arbitrage traders are more likely to make a profit in these two positively skewed futures as well.

Future work could consider devising time varying mechanism and correlation in higher moments and apply the approach to risk forecasting, such as value-at-risk and expected shortfall.

Notes

1. The early version of the model was proposed by Baba, Engle, Kraft, and Kroner; this model employs a convenient parameterization for estimation and for analysis of simultaneous equation systems.
2. Detailed results are not presented in the article due to limited space but can be requested from the authors.

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