Does More Trading Lead to Better Market Linkage? Evidence from the Commodity Futures Markets

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In this study, we use eight pairs of commodity futures data to investigate the impact of the recently launched nighttime trading session by Chinese futures exchanges. We conduct a thorough empirical analysis on the cross-market information transmission mechanisms between China and the U.S. We apply various econometric analyses including the co-integration analysis, the forecast error variance decomposition analysis, and the volatility spillover analysis with a bivariate GARCH model. Findings in this study indicate that, after the launching of nighttime-trading hours in China, the price discovery function of the Chinese futures market is noticeably improved, and that the Chinese market began to dominate the U.S. market in the bidirectional volatility spillover process. Thus, the introduction of the nighttime-trading hours appears to be an effective step toward China's long-term goal of establishing pricing power in key commodities on the global financial market.

Keywords: Chinese futures market, market linkage, nighttime trading.

1. Introduction

This paper investigates the effectiveness of the recently launched nighttime trading sessions on futures exchanges in China. We pay particular attention to the price linkages between the Chinese and US commodity futures market that is a global market leader and the implications behind the policy change allowing extended trading hours. Although the futures market started much later in China than in developed markets, it has been growing rapidly over the past couple of decades and drawn wide attention among investors around the world. In terms of the trading volume, many commodity futures in China are now among the most heavily traded contracts in global derivatives markets. China has three commodity futures exchanges and one financial futures exchange: the Shanghai Futures Exchange (SHFE), the Dalian Commodity Exchange (DCE), the Zhengzhou Commodity Exchange (ZCE), and the China Financial Futures Exchange (CFFEX). The futures market in China is dominated by

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various commodity futures in terms of trading volume and is characterized by frequent product innovations.

As one of the world's largest consumers of raw materials, China is trying to expand the influence of its domestic market on commodity futures prices through the development of its futures market. For a long time, the Chinese futures market was accessible only during daytime trading hours. The lack of trading opportunities during nighttime hours impeded the timely information transmission from active markets overseas to futures prices on the domestic Chinese market. To further improve the Chinese futures markets ability to compete globally and eventually establish the ability to set prices in key futures commodities, nighttime trading was launched by leading futures exchanges in China in 2013, beginning in July with the SHFE for gold and silver futures. Shortly afterward, the DCE and ZCE followed suit. By the end of 2015, 28 commodity futures in China had launched nighttime trading sessions.

The microstructure literature implies that information is revealed in security prices with trades (e.g., Copeland and Galai, 1983; Easley and O'Hara, 1987; Glosten and Milgrom, 1985; Hasbrouck, 1988, 1991; Kyle, 1985). For example, Garbade and Silber (1983) examine the price discovery function of the futures markets to confirm the leading role of futures markets over cash markets in terms of the incorporation of new information into prices. In addition, some empirical studies discuss the price discovery realized outside the trading periods in equity markets (Barclay and Hendershott, 2008; Cao, Ghysels and Hatheway, 2000). The implementation of nighttime trading sessions for commodity futures in China enables domestic traders to better manage their risk through prompt trading after new information is released in other markets while it is nighttime in China. The basic functions of the futures market – providing price discovery and hedging for domestic traders – are expected to be enhanced.

Prior studies have investigated the features of trading activities in futures markets and how those activities interact with pricing dynamics in the market (e.g., Bessembinder and Seguin, 1992, 1993; Chan, Fung and Leung, 2004; Fung, Mai and Zhao, 2016; Fung and Patterson, 1999; Fung and Patterson, 2001; Kao and Fung, 2012; Pliska and Shalen, 1991). Other streams in the literature explore cross-market analysis, which investigates linkage between futures and spot markets or the transmission of information across futures markets in different geographic locations (e.g., Eun and Shim, 1989; Fung, Leung and Xu, 2001; Ghosh, Saidi and Johnson, 1999; Xu and Fung, 2005; Kao, Ho and Fung, 2015). Despite the rising importance of Chinese commodity futures in the world derivatives market, few studies have thoroughly investigated the mechanisms of the Chinese futures market and its linkage with other markets. Fung, Tse, Yau and Zhao (2013) empirically investigate the efficiency of the Chinese commodity futures market. A recent paper by Fung, Mai and Zhao (2016) finds that, after nighttime trading was launched in China, the interaction between volatility and trading activity conform better to patterns observed in developed markets and show improved price efficiency in the Chinese futures market.

Many Chinese metal and agricultural futures are heavily traded and already rank at the top among peers globally, with support from the Chinese government to become globally competitive. Commodity futures traded on Chinese exchanges have distinctive characteristics and appear to serve various policy purposes. Some of these futures, such as iron ore, copper, and soybean meal, have shown increasing influence on commodity prices in the global market, while others, for instance, cotton and soybean futures, focus more on the local market by providing domestic traders with the basic functions of futures—price discovery and hedging.

Driven by strong domestic demand, China is the top consumer of many commodities. As widely reported in the media, China is the world's leading importer of iron ore, and its trading volume of iron ore futures is far above that of its peers in other global markets. Unlike iron ore futures in other markets, which are based on steel index prices and use cash settlement, Chinese iron ore futures use physical delivery as the settlement method to better reflect market forces. The high liquidity of Chinese iron ore futures attracts many investors and cash market traders. In addition to iron ore, China is also known for its heavy consumption of other commodities, such as copper and soybean meal. Futures contracts on such commodities in China are expected to become more internationalized and to play a more important role in the global market. The launching of nighttime trading allows more timely absorption of information from other active markets overseas, and thus better cross-market price linkage is expected. This change should therefore enable the Chinese futures market to have a greater impact on the global market and, in the long run, gain the power to set prices.

The price of several futures contracts in China, such as soybean and cotton, is affected by domestic government policies to a higher degree than elsewhere. The cross-market price linkage between China and the United States should show the underlying forces affecting futures prices. In the past, cotton futures prices in China, for example, deviated substantially from international prices because prices in China were driven by government policies more than by market forces. In 2014, China gradually moved from direct price support (through the cotton reserve policy) to a target price mechanism, which emphasizes the role of market forces in determining the cotton price (MacDonald, Gale and Hansen, 2015). Since then, many large consumers of cotton in China, such as textile manufacturers, have turned to the futures market for hedging tools against risks from the market-determined cash price. Correspondingly, the trading volume of cotton in China increased markedly from 2013 to 2014, and the price discovery function of cotton futures was thus utilized much more effectively than before. The pricing mechanism for Chinese soybean futures experienced similar changes as market forces began to play a key role. Many enterprises in industries related to soybeans began to actively participate in the futures market for hedging purposes. For these commodities in China, opening the futures market at night could reduce the price deviation between domestic and international markets and thus help establish a domestic price center that truly reflects aggregate demand and supply to facilitate hedging and price discovery.

This study examines the changes in dynamics of and information flows between China and the United States, the largest futures markets in the world, following the launching of the nighttime trading session in China. We focus on the cross-market information transmission mechanism between the commodities that are traded simultaneously in the Chinese and US futures markets. Our paper contributes to the literature in the following aspects. First, examining the impact of the recent policy change on cross-market linkage between these two countries sheds light on the evolution of the Chinese futures market and its role in the global financial market. Second, our sample consists of eight pairs of commodity futures traded in both the United States and China. After the implementation of the nighttime trading hours, some of the Chinese futures are found to have greater impact on the global market, while others are not, reflecting that the sample commodity futures serve different policy purposes in China. Third, we conduct a co-integration analysis to analyze the price discovery process and estimate volatility spillover with bivariate GARCH models to show price linkage across markets. The combination of the two modeling techniques, each capturing different perspectives on the data, can produce a more complete picture of the fundamental market dynamics.

The main findings are summarized as follows. First of all, there is solid bidirectional long-run feedback in futures prices between the Chinese and US futures markets during the full sample period. Second, during both the pre- and post-nighttime trading subsample periods, the US market plays a leading role in price discovery for the commodities studied. Most importantly, we observe several interesting patterns in the Chinese market following the policy change. Two commodities in China—soybean meal and iron ore futures—appear to be global leaders in the making. Copper, gold, and soybean oil futures in China have become more active global competitors since nighttime trading was launched. In contrast, Chinese silver, soybean, and cotton futures are being established as domestic centers. Third, since the introduction of nighttime trading, more volatility spillover is found from the Chinese market to the US market than the other way around.

The new trading policy allowing extended trading hours has been shown to be an effective step in strengthening China's status in the cross-market information transmission mechanism and improving the market's price discovery function, both of which are consistent with policy makers' long-term goal of establishing price-setting power in key commodities in the global market. The empirical results in this study provide practitioners interested in the Chinese futures markets with important information and offer other emerging markets possible strategies for developing their derivatives markets.

The remainder of the paper proceeds as follows. We describe research methodology and the data in Sections 2 and 3, respectively. We present the empirical results in Section 4. Section 5 discusses and summarizes the main findings.

2. Econometric Methodology

In this section, we describe the econometric methods we employ to investigate price and return dynamics and volatility spillover effect across the Chinese and US commodity futures markets. Our empirical framework is the standard vector autoregression (VAR) model. Let $y_t = \{y_{1,t}, y_{2,t}\}$ denote a (2×1) vector that includes Chinese and US futures contract prices (measured in logarithms) for a commodity, respectively. Assuming the existence of co-integration between the two nonstationary prices due to the law of one price or no arbitrage, the data-generating process of y_t can be written as a standard vector error correction model (VECM) with k lags:

$$\Delta y_t = \alpha\beta' y_{t-1} + \sum_{l=1}^{k} \Gamma_l \Delta y_{t-1} + \mu + \varepsilon_t \quad (t = 1, 2, \cdots, T), \tag{1}$$

where Δ is the difference operator ($\Delta y_t = y_t - y_{t-1}$), α and β are both $(2 \times r)$ matrices of parameters ($r < 2$) with β describing r long-run equilibriums among the two endogenous price variables, Γ_l is a (2×2) matrix of coefficients describing short-run dynamics, and μ is a (2×1) vector of constants, and finally, ε_t is a (2×1) zero-mean vector with a potentially time-varying variance covariance matrix H_t, which is positive definite. Therefore, the VECM (1) can be used to study both short-run dynamics and the long-run relationship in the commodity futures markets.

Market prices in China and the United States are nonsynchronous since, on any given calendar day (t), the US market opens and closes after the Chinese market. To account for this timing difference, we replace lags of Chinese market prices $y_{1,t-1}, y_{1,t-2}, \ldots, y_{1,t-k}$, in the second equation of model 1 with US prices with $y_{1,t}, y_{1,t-1}, \ldots, y_{1,t-k+1}$. Correspondingly, the co-integrating vector $(\beta_1 y_{1,t-1} - \beta_2 y_{2,t-1})$ also becomes $(\beta_1 y_{1,t} - \beta_2 y_{2,t-1})$ in the equation. Due to this change, we no longer estimate and conduct co-integration test in model 1 using Johansen's (1991) full information maximum likelihood procedure. Instead, we impose the theoretical restriction that the two prices do not deviate from each other for too long and follow the law of one price (except for transaction costs). Put another way, we assume the co-integration rank is one and the co-integrating vector is known after normalization $\beta = \{1, -1\}$.[1]

For the purpose of innovations accounting, we compute the popular forecast error variance decomposition (FEVD) based on model 1 to better estimate short-run dynamic

[1] Empirically, we find that both error correction terms $(y_{1,t-1} - y_{2,t-1})$ and $(y_{1,t} - y_{2,t-1})$ are stationary processes, which provides indirect evidence in support of the restriction we impose on model 1.

linkages of prices and returns across the markets.[1] Note that the existence of strong contemporaneous correlations among securities market innovations often casts doubt on the traditional orthogonalized FEVD based on the recursive Choleski factorization of VAR innovations. The reason is that the Choleski factorization depends on the order of variables in the VAR system. However, the use of Choleski factorization is appropriate for the non-overlapping data we use here. This is because, as pointed out earlier, the Chinese market opens and closes before the US market, underlying shocks from market 1 (the Chinese market) can cause same-day changes in market 2 (the US market) while shocks from the US market can affect the China market only in the following day. This provides a natural order for the two price series in the bivariate VAR.

Further exploiting rich information embedded in the co-integration model, we also study volatility spillover between the two markets. In estimating co-integration model 1 and conducting FEVD, we have followed the practice and assumed that the variance and covariance matrix H_t of the error term ε_t remains constant during some prespecified period. However, one of the stylized facts about security returns is that they feature significant time-varying (conditional) variance (volatility) and covariance. To study the volatility spillover across the markets, we adopt a sequential procedure and explicitly model the heteroscedasticity in the error term ε_t, which is estimated from the first-stage VECM model 1. Specifically, we model ε_t as following a bivariate GARCH(1,1) process whose second moments are specified as the popular BEKK model proposed by Engle and Kroner (1995) (BEKK):

$$H_t = CC' + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B, \tag{2}$$

where parameter matrices C, A, and B capture the constant part of the variance, the ARCH, and the GARCH effects, respectively.[2] In particular, matrix A has the following form:

$$A = \begin{bmatrix} a_{CC} & a_{UC} \\ a_{CU} & a_{UU} \end{bmatrix}, \tag{3}$$

where, in general, $a_{CU} \neq a_{UC}$. An obvious advantage of the BEKK model over other specifications is that each term is positive semidefinite by construction, which is important because optimization may run into a negative definite matrix and cause convergence issues in small samples. The cost is that, with all the parameters entering

[1] As FEVD is a standard tool and well known, we omit the computation details here.

[2] We do not consider other more complicated multivariate GARCH specifications since the size of the post-nighttime-trading sample period is small.

the model through quadratic forms, they are not globally identified. That is, changing the signs of all elements of C, B, or A will have no effect on the likelihood function.

This model specification suggests that the ARCH component of the conditional variance for the Chinese market (market 1) is the sum of three terms (i.e., $a_{CC}^2\varepsilon_{C,t-1}^2 + 2a_{CC}a_{CU}\varepsilon_{C,t-1}\varepsilon_{U,t-1} + a_{CU}^2\varepsilon_{U,t-1}^2$). Therefore, the spillover effect of volatility originating in the US market on Chinese market volatility is captured by the latter two terms. Nevertheless, since the effect reflected in the middle cross-product term is difficult to isolate, in the empirical section we focus only on the direct effect, namely, coefficient a_{CU}^2. Similarly, we use a_{UC}^2 to measure the spillover effect of Chinese market volatility on the US market.

Given a sample of T observations, the parameters of the two-factor GARCH-BEKK Equations (2)–(3) are estimated by maximizing the conditional log-likelihood function:

$$L = \sum_{t=1}^{T} l_t(\theta) = \sum_{t=1}^{T}\left(-\frac{1}{2}n\log(2\pi) - \frac{1}{2}\log|H_t| - \frac{1}{2}\varepsilon_t' H_t^{-1}\varepsilon_t\right), \tag{4}$$

where $n = 2$ is the dimension of the bivariate GARCH model, and θ denotes the vector of all the parameters to be estimated, including $H0$, the initial values of the variance and covariance, which we treat as unknown parameters.

To measure how the extended nighttime trading session affects the price information role played by the Chinese market, we include a dummy variable in both the mean equation (1) and conditional variance equation (2). The dummy variable takes the value of 0 for sample observations before the introduction of nighttime trading and 1 for observations thereafter. We allow the dummy variable to interact with all right-hand-side variables. So, all coefficients are allowed to vary across the two subsample periods. For example, the estimate of the adjustment vector in model 1 for the second subsample period would be $(\alpha + \lambda)$, where α is the vector of adjustment effect estimates for the default case (the pre-nighttime-trading period) and λ is the coefficient vector associated with the interaction term of the dummy variable and the error correction term. Similarly, the coefficient matrix A of the ARCH component in the second subsample period would be computed as follows:

$$(A+\Lambda) = \begin{bmatrix} a_{CC}+\lambda_{CC} & a_{UC}+\lambda_{UC} \\ a_{CU}+\lambda_{CU} & a_{UU}+\lambda_{UU} \end{bmatrix}, \tag{5}$$

where A measures the spillover effect in the pre-nighttime-trading sample period and Λ is the coefficient matrix associated with the interaction terms of the dummy variable and the quadratic error terms $\varepsilon_{t-1}\varepsilon'_{t-1}$ in BEKK model 2.

3. Data

Despite its rapid development and growing importance among global financial markets, the futures market in China was accessible only during daytime trading hours until 2013, when the Shanghai Futures Exchange introduced nighttime trading for its gold and silver futures. Numerous commodity futures at major futures exchanges in China have now adopted nighttime trading hours in addition to daytime trading, so futures traders in China can trade on new information released from markets overseas sooner than before. By the end of 2015, nighttime trading sessions had been implemented in China for 28 commodity futures, including gold, silver, copper cathode, aluminum, zinc, lead, steel rebar, natural rubber, bitumen, hot rolled coils, nickels, and tin futures on the SHFE; RBD palm olein, metallurgical coke, no. 1 soybeans, no. 2 soybeans, soybean meal, crude soybean oil, coking coal, and iron ore futures on the DCE; white sugar, pure terephthalic acid (PTA), no. 1 cotton, rapeseed meal, methanol, rapeseed oil, flat glass, and thermal coal futures on the ZCE.

In this study, we collect daily futures settlement prices from the Commodity Systems Inc. (CSI) database. Eight of the commodity futures traded in China could be matched up with comparable futures contracts traded on US exchanges and are thus included in our sample. Selected commodity futures contracts include copper, gold, silver, soybeans, soybean meal, soybean oil, iron ore, and cotton. The sample period is from the earliest available date in the CSI database to February 2016. Since the sample includes eight pairs of price series from two different markets, China and the United States, we construct standardized price quotation units so that the prices of the Chinese futures and US futures are comparable. In particular, we convert price quotations for Chinese futures to those of US futures using foreign exchange rate data retrieved from FRED, Federal Reserve Bank of St. Louis. We generate continuous futures price time series by rolling over to the next nearby contract when its open interest is larger.

Table 1 summarizes information on the sample. All the Chinese futures price quotations are transformed to the same quotation units used on the US market. The last two columns present the launch date and hours of nighttime trading sessions in China. In a later analysis, we divide the full sample data into subsamples: “Before nighttime trading,” which includes futures data prior to the launching of nighttime trading in China, and “After nighttime trading,” which refers to the time period after the launching of nighttime trading.

Table 2 presents descriptive statistics of futures returns for the full sample, the “before nighttime trading” subsample, and the “after nighttime trading” subsample. The statistics for each commodity futures are presented in separate panels. The futures return (R_t) is constructed as the log difference of daily settlement prices (i.e., $R_t = \log(P_t) - \log(P_{t-1})$).

Table 1. Summary of Sample Futures

China market		U.S. market		Price quote	Sample start	Sample end	Nighttime trading in China	
Contract (symbol)	Exchange	Contract (Symbol)	Exchange				Launching	Hours
Copper cathode (CU)	SHFE	Copper (HG)	COMEX	cents/lbs.	12/11/2003	2/29/2016	12/20/2013	21:00-1:00
Gold (AU)	SHFE	Gold (GC)	COMEX	USD/troy ounce	1/17/2008	2/29/2016	7/5/2013	21:00-2:30
Silver (AG)	SHFE	Silver (SI)	COMEX	cents/troy ounce	12/31/2012	2/29/2016	7/5/2013	21:00-2:30
No. 1 soybeans (A)	DCE	Soybean (S)	CBOT	cents/ bushel	12/11/2003	2/29/2016	12/26/2014	21:00-23:30
Soybean meal (M)	DCE	Soybean meal (ZM)	CBOT	USD/short ton	12/11/2003	2/29/2016	12/26/2014	21:00-23:30
Crude soybean oil (Y)	DCE	Soybean oil (ZL)	CBOT	cents/lbs.	5/19/2008	2/29/2016	12/26/2014	21:00-23:30
Iron ore (I)	DCE	Iron ore (TIO)	NYMEX	USD/ton	10/18/2013	2/29/2016	12/26/2014	21:00-23:30
Cotton No. 1 (CF)	ZCE	Cotton No. 2 (CT)	ICE Futures US	cents/lbs.	6/1/2004	2/29/2016	12/12/2014	21:00-23:30

Note: The price quotes of the Chinese futures are standardized to be consistent with US futures.

Table 2. Summary Statistics

	Full sample		Before nighttime trading		After nighttime trading	
	US	China	US	China	US	China
Panel A. Copper						
Mean	0.00031	0.00049	0.00055	0.00072	-0.00080	-0.00060
Std.	0.0194	0.0151	0.0206	0.0160	0.0126	0.0096
Skewness	–0.184***	–0.243***	–0.210***	–0.254***	0.005	–0.450***
Kurtosis	3.635***	1.759***	3.246***	1.381***	1.833***	3.569***
Panel B. Gold						
Mean	0.00011	0.00010	0.00017	0.00019	–0.00004	–0.00009
Std.	0.0129	0.0118	0.0140	0.0133	0.0102	0.0082
Skewness	–0.252***	–0.397***	–0.372***	–0.472***	0.392***	0.330***
Kurtosis	5.228***	4.406***	5.121***	3.660***	1.862***	2.249***
Panel C. Silver						
Mean	–0.00104	–0.00097	–0.00394	–0.00426	–0.00048	–0.00037
Std.	0.0180	0.0133	0.0212	0.0197	0.0173	0.0117
Skewness	–0.415***	–0.712***	–1.701***	–1.085***	0.076	–0.026
Kurtosis	4.681***	5.803***	8.310***	4.353***	2.628***	2.761***
Panel D. Soybean						
Mean	0.00016	0.00010	0.00025	0.00023	–0.00066	–0.00116
Std.	0.0161	0.0102	0.0165	0.0104	0.0119	0.0077
Skewness	–0.215***	–0.314***	–0.228***	–0.347***	–0.034	0.103
Kurtosis	1.994***	3.519***	1.819***	3.465***	4.610***	2.542***
Panel E. Soybean meal						
Mean	0.00036	0.00023	0.00049	0.00035	–0.00083	–0.00086
Std.	0.0181	0.0120	0.0185	0.0123	0.0134	0.0088

	Full sample		Before nighttime trading		After nighttime trading	
	US	China	US	China	US	China
Skewness	–0.142***	–0.190***	–0.165***	–0.215***	0.223	0.154
Kurtosis	1.718***	1.912***	1.604***	1.845***	2.540***	1.001***
Panel F. Soybean oil						
Mean	–0.00056	–0.00042	–0.00059	–0.00047	–0.00041	–0.00016
Std.	0.0153	0.0118	0.0156	0.0123	0.0140	0.0087
Skewness	0.055	–0.542***	0.056	–0.568***	0.059	0.111
Kurtosis	2.292***	3.001***	2.529***	2.858***	0.007	0.977***
Panel G. Iron ore						
Mean	–0.00122	–0.00126	–0.00110	–0.00214	–0.00135	–0.00034
Std.	0.0143	0.0139	0.0087	0.0118	0.0183	0.0158
Skewness	0.299***	–0.185*	0.299**	–0.371**	0.271*	–0.177
Kurtosis	5.367***	1.586***	10.907***	1.632***	2.602***	1.157***
Panel H. Cotton						
Mean	–0.00028	–0.00017	–0.00029	–0.00008	–0.00022	–0.00099
Std.	0.0172	0.0091	0.0178	0.0094	0.0116	0.0062
Skewness	–0.111**	–0.223***	–0.123**	–0.224***	0.311**	–0.642***
Kurtosis	1.298***	7.786***	1.144***	7.569***	1.827***	2.317***

Note: ***, ** and * are significant at the 1%, 5% and 10% level, respectively.

All eight Chinese futures exhibit significant negative skewness and excess kurtosis for the subsample before nighttime trading, while five of these futures (i.e., silver, soybean, soybean meal, soybean oil, and iron ore) no longer demonstrate negative skewness in the subsample after nighttime trading. Thus, sample futures on the Chinese market exhibit improved normality in the distribution of returns after the change in trading hours. Similarly, negative skewness in the copper, silver, soybean, and soybean meal futures in the US market is observed only in the subsample before nighttime trading. Overall, the summary statistics for the returns of sample futures indicate that the distribution of Chinese futures returns become more symmetric after nighttime trading hours are launched, showing that more balanced information is reflected in the prices on the market. As both the Chinese and US futures markets appear to suffer more from downside risk (i.e., negative skewness) in returns for the subsample before nighttime trading, the inclusion of data during the 2008 financial crisis in the pre-nighttime trading sample period may also play a role in the pattern observed.

Many Chinese commodity futures are now playing an important role in the world market. For example, in 2015, soybean meal, soybean oil, cotton, and soybean futures on Chinese exchanges ranked first, fifth, sixteenth, and eighteenth, respectively, among the world's most heavily traded agricultural futures.[1] Table 3 presents the annual trading volume of the sample futures from both markets from 2013 to 2015. As futures in the Chinese and US markets are traded in different contract sizes, we convert

[1] Will Acworth, "2015 Annual Survey: Global Derivatives Volume", March 15, 2016, retrieved from http://marketvoicemag.org/?q=content/2015-annual-survey-global-derivatives-volume/.

Chinese futures' trading volume to an equivalent value that is directly comparable to US futures. Thus, the trading volume of Chinese futures as shown in the table is in its standardized form. For the most recent year, 2015, we observe that the Chinese copper, soybean meal, soybean oil, and iron ore futures were traded more actively than their US counterparts, while heavier trading of gold, soybeans, and cotton futures is found in the US market. For silver futures, trading volume in both markets is relatively close, following a drop in the Chinese market from the previous year. The increasing popularity of iron ore futures trading in recent years has drawn wide attention in the market. The trading volume of Chinese iron ore futures increased by 170% in 2015 from 2014.

Table 3. Annual Trading Volume (2013–2015)

Futures	2015		2014		2013	
	China	US	China	US	China	US
Copper	38941772	16986055	31089686	14591200	28349586	17127383
Gold	8139657	41847338	7672895	40518804	6458376	47294551
Silver	13964957	13454406	18662290	13696961	16707685	14475593
Soybeans	1382225	54095051	1998466	49169361	807802	46721081
Soybean meal	31911548	24315276	22596135	20637382	29250659	20237181
Soybean oil	33989458	28897275	23546308	23769391	35396891	23805912
Iron ore	51914417	136158	19271826	24988	437843	22302
Cotton	4985199	6726586	7006692	5787883	1642898	6155024

Sources: China Futures Association website (http://www.cfachina.org/); CME Group website (http://www.cmegroup.com/); ICE Futures U.S. website (https://www.theice.com/futures-us).

Notes: The values shown in the table are number of contracts traded during the year. As futures contracts in China and the United States are traded in different sizes, all the Chinese futures trading volume data shown in the table are the equivalent US trading volume based on the contract size of US futures. After the standardization, volume data from different markets are directly comparable.

We first test the order of integration of the futures (log) prices on both the Chinese and US markets for the eight commodities using the popular augmented Dickey-Fuller test. The null hypothesis is that the price contains a unit root. The results are summarized in Table 4. We consider two testing models, one allowing for a linear time trend in addition to a drift and the other allowing a drift only. When the model includes a drift term only, the null hypothesis cannot be rejected for all eight commodity prices at the conventional 5% significance level. The results in the last column show that we also fail to reject the null hypothesis for all but one variable when both a drift and a linear trend are included in the model. The exception is futures prices for silver, for which we reject the unit-root hypothesis at the 5% level. Nevertheless, we again fail to reject the null at the less conservative 1% level. Overall, we conclude that all prices are level nonstationary. We then proceed to test for the nonstationarity of the first differences of the prices. The unit-root hypothesis can now be rejected for all first-differenced prices in both markets. These results combine to suggest that the commodity futures prices in both markets can be characterized as $I(1)$ variables.[1]

Table 4. Results of ADF Unit Root Tests

	With an intercept		With an intercept & trend	
	Lag order	ADF	Lag order	ADF
Copper				
US	1	-2.651	1	-1.823
China	1	-2.580	1	-1.706
Gold				
US	0	-1.633	0	-1.380
China	1	-1.555	1	-1.286
Silver				
US	0	-2.406	0	-3.685*
China	1	-2.576	1	-3.615*
Soybean				
US	0	-1.640	0	-1.607
China	1	-1.393	1	-1.137
Soybean meal				
US	0	-1.849	0	-2.199
China	1	-1.754	1	-1.521
Soybean oil				
US	0	-1.719	0	-1.758
China	1	-1.374	1	-1.467
Iron ore				
US	0	-1.210	0	-1.558
China	1	-1.173	1	-2.706
Cotton				
US	0	-1.650	0	-1.484
China	1	-1.002	1	0.189

Notes: This table reports augmented Dickey Fuller (ADF) test results. The number of lagged terms included in the tests is determined by BIC. The null hypothesis is that the series contains a unit root. * null hypothesis is rejected at the 5% level.

4. Empirical Results

4.1. Estimation of the Co-Integration Model

As the initial step in estimating a VAR model, we determine the autoregressive

[1] We also conduct an ADF test for nonstationarity allowing one structural break in the data using a procedure proposed by Carrion-i-Silvestre, Kim and Perron (2009). We fail to reject the unit-root hypothesis for all but three price series at the 5% significance level (silver in the United States and silver and iron ore in China).

lag order k in the model by minimizing the popular Schwarz's Bayesian information criterion (BIC), assuming a maximum of ten lags. The optimal lag orders are 3, 6, 2, 1, 1, 2, 1, and 1 for copper, gold, silver, soybean, soybean meal, soybean oil, iron ore, and cotton, respectively (the lag orders of the underlying VARs in levels would be 4, 7, 3, 2, 2, 3, 2, and 2). Table 5 reports the parameter estimation results of co-integration model (1), imposing the restriction $\beta = \{1, -1\}$ on the co-integration space. To save space, the short-run dynamics are not reported. Columns 1–4 report the constants (μ_1 and μ_2) and the estimates of the adjustment coefficients α_1 and α_2, for the full sample period. The corresponding results for the first and the second subsamples are presented in columns 5–8 and 9–12, respectively.

Table 5. The Key Parameter Estimates of the Vector Error Correction Models

Full sample				Before nighttime trading				After nighttime trading			
μ_1	α_1	μ_2	α_2	μ_1	α_1	μ_2	α_2	μ_1	α_1	μ_2	α_2
Panel A. Copper (k = 3)											
0.008***	–0.052***	–0.009***	0.062***	0.008***	–0.055***	–0.010***	0.070***	0.004*	–0.026**	–0.004	0.022
(5.897)	(–5.838)	(–4.015)	(4.098)	(5.638)	(–5.494)	(–3.977)	(4.118)	(1.871)	(–1.976)	(–1.114)	(0.876)
Panel B. Gold (k = 6)											
0.001***	–0.107***	–0.001	0.095***	0.001***	–0.128***	–0.000	0.081*	0.001*	–0.065**	–0.002**	0.157***
(3.248)	(–4.963)	(–1.481)	(2.763)	(2.827)	(–4.641)	(–0.712)	(1.868)	(1.840)	(–2.505)	(–2.466)	(2.841)
Panel C. Silver (k = 2)											
0.001	–0.022*	–0.003**	0.041**	0.013**	–0.371***	–0.022**	0.484**	0.002**	–0.028**	–0.002	0.027
(1.273)	(–1.931)	(–2.340)	(2.044)	(2.598)	(–3.284)	(–2.553)	(2.503)	(2.327)	(–2.554)	(–1.471)	(1.309)
Panel D. Soybean (k = 1)											
0.002**	–0.004**	–0.003*	0.007**	0.001	–0.003	–0.004**	0.011***	0.001	–0.003	–0.008	0.011
(2.182)	(–2.291)	(–1.928)	(2.174)	(1.598)	(–1.499)	(–2.408)	(2.669)	(0.296)	(–0.495)	(–1.203)	(1.095)
Panel E. Soybean meal (k = 1)											
0.002**	–0.006**	–0.003**	0.013***	0.002**	–0.007**	–0.003**	0.012**	0.008**	–0.046**	–0.011*	0.052
(2.258)	(–2.476)	(–2.355)	(2.695)	(2.351)	(–2.508)	(–2.056)	(2.439)	(2.223)	(–2.518)	(–1.652)	(1.593)
Panel F. Soybean oil (k = 2)											
0.001	–0.003	–0.008***	0.034***	0.000	–0.003	–0.009***	0.036***	0.002	–0.007	–0.009*	0.033
(0.374)	(–0.528)	(–3.816)	(3.837)	(0.273)	(–0.410)	(–3.598)	(3.635)	(0.558)	(–0.624)	(–1.657)	(1.621)
Panel G. Iron ore (k = 1)											
0.001	–0.017	–0.007***	0.036**	0.003	–0.037	–0.013***	0.096***	0.010*	–0.054*	–0.013**	0.062**
(0.626)	(–1.219)	(–2.765)	(2.312)	(0.768)	(–1.403)	(–3.139)	(3.143)	(1.817)	(–1.954)	(–2.283)	(2.100)
Panel H. Cotton (k = 1)											
–0.000	0.000	–0.005***	0.011***	0.000	–0.000	–0.005***	0.011***	–0.004	0.008	–0.007**	0.020**
(–0.216)	(0.187)	(–3.222)	(3.432)	(0.328)	(–0.264)	(–3.058)	(3.264)	(–1.606)	(1.289)	(–2.493)	(2.383)

Notes: This table reports the parameter estimates of the VECM model (1) for the eight commodity futures prices in both U.S. and Chinese markets. The co-integrating vector is known $\beta = \{1, -1\}$. k is the number of the lag order. Short-run dynamics Γs are not shown to save space. The values in parentheses are White heteroscedasticity-consistent t-statistics. *, ** and *** are significant at the 10%, 5% and 1% level, respectively.

Focusing on the parameters for the Chinese market (μ_1 and α_1), there is a positive drift in the returns on seven commodities, of which four are statistically significant.

The adjustment coefficient α_1, measuring how rapidly the Chinese market responds to mispricing (namely, the error correction term $(y_{1,t-1} - y_{2,t-1})$), is negative in all eight cases. This result is as expected, since when the lag price in the Chinese market is higher than that in the US market (the error correction term is positive), we expect a decrease in the current Chinese commodity price (hence, negative returns) to revert to the equilibrium price. α_1 is also statistically significant for copper, gold, soybean, and soybean meal at the 5% level and for silver at the marginal 10% level.

Comparing the magnitude of adjustment in the before- and after-nighttime-trading samples, we find that α_1 is smaller for copper, gold, and silver following the introduction of nighttime trading. In contrast, α_1 becomes larger for soybean meal and iron ore. Note that a coefficient may be statistically significant in the full sample and yet imprecisely estimated in either subsample (e.g., α_1 for soybean). This is likely because the sample size is smaller in the subsample periods. Noticeably, α_2, the speed with which the US market responds to mispricing $(y_{1,t} - y_{2,t-1})$, is significant at the 10% level for all eight commodities (in fact, it is significant at the 5% or better level for seven commodities) before nighttime trading was introduced in China. The adjustment is significant for three commodities (gold, iron ore, and cotton) only in the more recent sample period. The response is also stronger for gold and cotton.

In summary, according to the full sample estimation results, five out of the eight Chinese futures (i.e., copper, gold, silver, soybean, and soybean meal) and all eight US futures have significant error correction terms, implying that, in the bivariate system, more futures respond to mispricing in the US market than in the Chinese market in terms of statistical significance. These results indicate bidirectional adjustment to deviations in futures prices for most sample futures, yet the Chinese market dominates the US market in soybean oil, iron ore, and cotton futures. The relatively leading role taken by Chinese soybean oil and iron ore futures in the long-run feedback relationship is consistent with China's large trading volume in these commodities. The cotton price in China is relatively more policy driven, and the insignificant adjustment coefficient of this commodity is also as expected. From the subsample analysis, we find changes in the relative strengths of the cross-market price error correction after the launching of nighttime trading in China. On both markets, the copper and silver futures seem to become less responsive to price discrepancies. However, the gold and cotton futures in the United States, as well as soybean meal and iron ore futures in China, adjust more quickly to mispricing in the post-nighttime trading subsample.

The VECM analysis indicates close price linkage in the long term between the Chinese and US futures markets. The introduction of nighttime trading in China has brought noticeable changes to the relative responsiveness of each market to price discrepancies. The changes vary across commodities.

4.2. Innovations Accounting by FEVD

To illustrate the economic significance and the short-run dynamic pattern in information transmission between the two futures markets, we use FEVD—the percentage of price variations in the Chinese and US market at time $t+h$ that are due to shocks to the market itself at time t.[1] The decomposition is based on the VECM model parameters estimated above, and the largest h considered is 10 (days). Not surprisingly, at the longer horizon (h = 10), the cross-market impact is generally more intense.

Table 6 reports the results of variance decomposition at the three-day and ten-day horizons for simplicity.[2] Because each VAR system has only two prices, the variance decomposition of the Chinese (or US) market attributable to shocks to the Chinese and the US markets sum to 100%. Here, we focus on comparing the decompositions from the two subsamples. The results based on the full sample, where no dummy variable is included in model 1, are not reported because of space considerations.

Table 6 indicates several patterns arising from the variance decomposition analysis. The US market is a global leader in price discovery for commodity futures. For all the sample futures, the forecast error variance in the US market is mainly due to its own market shocks (i.e., more than 80%). After nighttime trading was launched in China, the impact of domestic market shocks on six out of the eight US futures has increased, while the forecast error variance of soybean meal and iron ore futures are affected more by cross-market information.

Table 6. Forecast Error Variance Decompositions

Horizon	China market		US market	
	Before nighttime trading	After nighttime trading	Before nighttime trading	After nighttime trading
		Panel A. Copper (k = 3)		
3	70.668	55.100	88.226	93.028
10	60.057	42.621	77.629	86.328
		Panel B. Gold (k = 6)		
3	52.724	41.054	86.975	92.115
10	31.415	29.810	80.497	81.813
		Panel C. Silver (k = 2)		
3	57.580	63.722	80.725	91.783
10	44.465	52.882	67.125	87.244
		Panel D. Soybean (k = 1)		
3	88.998	92.993	93.984	98.107

[1] One can also conduct an impulse response analysis to summarize the dynamics of price changes. Here we use variance decomposition because the sizes of shocks to the prices are likely to change over the sample period and variance decompositions inherently account for the varying shock size when dynamics from different subsamples are compared.

[2] We compute 90% confidence intervals for the point estimates of the decomposition by the bootstrap method. For ease of presentation, they are not shown in the table.

Horizon	China market		US market	
	Before nighttime trading	After nighttime trading	Before nighttime trading	After nighttime trading
10	85.751	90.596	90.850	96.417
		Panel E. Soybean Meal (k = 1)		
3	87.476	86.405	96.940	95.509
10	82.954	73.644	94.978	90.502
		Panel F. Soybean Oil (k = 2)		
3	81.884	72.864	86.427	97.653
10	78.459	67.595	75.530	94.793
		Panel G. Iron Ore (k = 1)		
3	98.322	92.165	82.870	79.606
10	95.854	83.584	57.626	68.420
		Panel H. Cotton (k = 1)		
3	93.271	94.306	95.835	98.941
10	91.336	94.982	93.011	97.069

Notes: The forecast error variance decomposition is conducted based on the vector error correction model (1) with one known co-integrating vector $\beta = \{1, -1\}$ (parameter estimates are reported in Table 3). Table entries are the decompositions (in percentage) of price variations in a market which are due to shocks to the market itself at the 3- and 10-day horizons. Bootstrap confidence intervals are not reported for ease of presentation.

Shocks to Chinese markets also play a dominant role in affecting the variations in futures prices. Several patterns are noted. First, the Chinese soybean meal and iron ore futures are global leaders in the making because they illustrate that China is the world's top consumer and has become affected less by domestic market shocks and more by shocks from the US market (i.e., the impact of shocks from China fell from 87.5% to 86.4% for soybean meal and from 98.3% to 92.2% for iron ore). At the same time, these Chinese futures affect the US market in a more effective way during the post-nighttime-trading subsample, as domestic market shocks lessened for both corresponding US futures. Their trading volume of these two commodities has been consistently higher than counterparts in the United States and increased from 2013 to 2015 (Table 3). In particular, the trading volume of Chinese iron ore futures has increased at a stunning rate, and in recent years it has dominated US futures (in terms of the number of contracts traded in 2015, trading volume for iron ore totaled 51914417 in China and 136158 in the United States).[1] Similarly, Chinese soybean meal futures are the world's most heavily traded agricultural futures, and the new nighttime trading policy has reinforced their popularity as well as global impact. The ramification is that these commodities are trying to become global price leaders as they allow more US information flow into the domestic market and exert a greater effect on the US market with this rapidly increasing trading volume.

[1] The trading volume for Chinese futures is converted into an equivalent value in US terms based on contract-size differences between the two markets. For instance, 51914417 is a transformed Chinese futures trading volume, which is directly comparable to US futures.

Second, Chinese copper, gold, and soybean oil futures are being developed into global competitors. In the post-nighttime-trading subsample, their price variations become less dependent on domestic market shocks (i.e., from 70.7% to 55.1% for copper, 52.7% to 41.1% for gold, and 81.9% to 72.9% for soybean oil), while corresponding US futures have increased dependence on their domestic market. The changes indicate that these Chinese commodities are embracing more information from the US market and, at the same time, trying to maintain their important role in the domestic market, given the large proportion of price variation explained by domestic market shocks (i.e., the impact of shocks from the Chinese market range from 41.1% for gold to 72.9% for soybean oil during the post-nighttime-trading subsample at the three-day horizon). Table 3 also shows that in recent years Chinese copper and gold futures have been traded more intensively. Although the volume is still relatively small compared with futures in the United States, trading in Chinese gold futures has been gradually catching up. Soybean oil futures, after dropping from 2013 to 2014, quickly picked up in 2015, when trading volume in both surpassed the level in the United States. Thus, this group of Chinese futures, either through their continuous increases in trading (i.e., copper and gold) or a quick recovery from previous downturns (i.e., soybean oil), is becoming more powerful players and competitors in the global commodity futures market.

Third, the remaining three Chinese commodities—soybeans, cotton, and silver—are becoming domestic centers for price discovery. In China, the price of agricultural commodities, such as soybeans and cotton, had been subject to heavy government regulations. Futures prices for these commodities deviated from those on the international market. The shift from direct price supports to a target price mechanism starting in 2014 gradually restored the hedging and price discovery functions of futures markets. As shown in Table 6, the price variations in these futures exhibit increased exposure to domestic market shocks (i.e., from 57.6% to 63.7% for silver, 89% to 93% for soybeans, and 93.3% to 94.3% for cotton). Thus, these commodities in China are ignoring turbulence on the global market and becoming more independent. Also, the shocks of these Chinese futures have a smaller impact on the US market in the post-nighttime-trading subsample (i.e., corresponding US futures are more affected by shocks from the US market itself), so their focus is the Chinese domestic market. These findings are consistent with China's transition stage, in which market forces are now replacing government policies in determining the price of these commodities. From 2013 to 2014, trading volume in Chinese cotton and soybean futures significantly increased. A slide occurred the following year, when regulatory measures were imposed to curb excessive speculation in the futures market. Soybeans and cotton, which are heavily affected by government policies while silver also appears to be affected by domestic forces in China. The trading of silver experienced a worldwide contraction in 2015. The decrease in trading volume on the SHFE is more than 25%, while the decrease in silver trading in the US market that year was around 2%. In addition to its safe haven feature, which is similar to the gold, silver is also used in the industry and thus is more sensitive to changes in industrial demand and market fundamentals.

Put together, the findings from the variance decomposition analysis show that the launching of nighttime trading in China has effectively affected the price discovery in both the Chinese and US futures markets, and that the outcomes vary across commodities.[1] Clearly, the new trading policy serves these commodities in different ways. The majority of Chinese commodities are striving to be more integrated into and exerting more impact on the global market, and a few commodities (i.e., silver, soybean, and cotton) in China are focusing more on the domestic market.

4.3. Volatility Spillover

In this subsection, we present the results on volatility spillover between the Chinese market and the US market, which are estimated from the GARCH-BEKK model (2) with a nighttime-trading dummy variable interacting with all right-hand-side predictive variables. Table 7 reports the two parameter estimates of our central interests, a_{UC} and a_{CU}, along with their robust standard errors by the quasi maximum likelihood method as briefly discussed in section 2. The left-hand panel shows the estimates for the sample observations before nighttime trading sessions were introduced. The volatility transmission from the Chinese market to the US market (a_{UC}) is statistically highly significant for six commodities. It is zero in the market for copper and insignificant for silver. The results in column 2 (a_{CU}) show that volatility in the Chinese market is affected by lagged volatility in the US market for six commodities at the 5% significance level and for one commodity (soybean oil) at the 10% level, although these effects are in general smaller in magnitude than the volatility spillover effects from the Chinese market to the US market. The evidence in Panel G suggests that volatility in the US iron ore market does not spill over to the Chinese market, further indicating the leading role of the Chinese iron ore futures market.

Table 7. Volatility Spillover

Before nighttime trading		After nighttime trading		Log likelihood
a_{UC}	a_{CU}	$(a_{UC} + \lambda_{UC})$	$(a_{UC} + \lambda_{CU})$	
Panel A. Copper				
0.002	0.051^{***}	0.140^{**}	0.092^{***}	17090.00
(0.121)	(7.211)	(2.319)	(3.630)	

[1] As a robustness check, we conduct the Granger-causality test between Chinese and US futures based on VECM model 1. The test result shows bidirectional causality for all the eight sample futures at conventional significance level, both before and after the nighttime trading. Thus, the evidence supports strong short-term cross-market interactions between China and the United States.

Before nighttime trading		After nighttime trading		Log likelihood
a_{UC}	a_{CU}	$(a_{UC}+\lambda_{UC})$	$(a_{UC}+\lambda_{CU})$	
Panel B. Gold				
0.307***	0.065***	0.308***	0.029	13026.21
(12.167)	(5.786)	(8.531)	(0.653)	
Panel C. Silver				
0.145	0.128**	0.351***	0.183***	4580.30
(0.795)	(2.094)	(8.706)	(17.635)	
Panel D. Soybean				
0.194***	0.143***	0.223**	0.150***	17272.05
(25.738)	(14.900)	(2.067)	(2.990)	
Panel E. Soybean meal				
0.301***	0.038***	0.466***	0.015	16334.64
(27.147)	(12.001)	(7.901)	(0.601)	
Panel F. Soybean oil				
0.160***	0.022*	0.280**	0.060**	11355.96
(9.529)	(1.917)	(2.255)	(1.987)	
Panel G. Iron ore				
0.259***	0.045	0.120***	0.032	3033.38
(4.060)	(0.411)	(3.768)	(1.407)	
Panel H. Cotton				
0.698***	0.126***	0.536***	0.030	16500.41
(14.790)	(17.220)	(2.730)	(0.103)	

Notes: The square of a_{UC} is the estimate of the pre-night-trading spillover effect of lagged volatility (squared residuals) of the Chinese markets on the volatility of US markets. Similarly, a_{CU} measures the effect of lagged volatility of the US market on the volatility of the Chinese market. $a^2_{2,UC}$ and $a^2_{2,CU}$ measure the corresponding post-night-trading spillover effect. They are the parameters in the bivariate GARCH-BEKK model for the residuals estimated from the earlier-stage vector error correction model (1). Values in parentheses are maximum likelihood estimates of *t*-statistics.

Focusing on the middle panel of Table 7, we find that the introduction of nighttime trading sessions overall has strengthened the volatility transmission from the Chinese market to the US market (a_{UC}). Specifically, the spillover effect turns statistically significant for copper and silver. Quantitatively, the effect becomes larger in the most recent period for copper, silver, and all three soybean-related commodities and remains largely the same for gold. The estimate decreases from 0.26 to 0.12 for iron ore (Panel G) and from 0.70 to 0.54 for cotton (Panel H). The additional trading hours have had more mixed results on the volatility transmission from the US market to the Chinese market (a_{CU}). The spillover effect remains statistically significant and becomes larger in magnitude for copper, silver, soybean, and soybean oil. In contrast, the effect turns insignificant from the first to the second sample period for the other three commodities, gold, soybean meal, and cotton. It remains insignificant in both periods for iron ore.

Findings from the volatility spillover analysis provide important evidence of the effectiveness of the new trading policy in China. First, linkage between the Chinese and US futures markets became stronger after the implementation of nighttime trading hours. In particular, five of the Chinese future (i.e., copper, silver, soybean, soybean meal, and soybean oil) and four of the US futures (i.e., copper, silver, soybean, and soybean oil) have increased the cross-market level of information transmission, while the Chinese market appears to be more integrated with the global futures market during the post-nighttime-trading subsample. Second, we find stronger bidirectional volatility spillover for copper, silver, soybean, and soybean oil futures. For these commodities, therefore, volatility in the Chinese (or US) market is more sensitive to innovations from the US (or Chinese) market with nighttime trading hours in China. Third, for gold, soybean meal, iron ore, and cotton futures, the Chinese market is now taking a leading role in the information transmission process, as significant volatility spillover is found from China to the United States, but not the other way around.

In short, the launching of nighttime trading in China is followed by closer linkage between the Chinese and US markets in price volatility. The role of the Chinese market in the cross-market information transmission mechanism is also effectively reinforced with extended trading hours at night, such that innovations from the Chinese market appear to have stronger influence on the volatility of the US market than before.

5. Conclusions

In this study, we use daily data on commodity futures on the Chinese and US exchanges to investigate the changes in the information transmission mechanism between these two important futures markets after nighttime trading was launched in China. Although started much later than its counterparts in developed markets, futures trading in China experienced rapid expansion and development during the past couple of decades. A series of regulatory changes have been implemented to improve the price discovery function and thus the overall efficiency of the futures market in China, among which the introduction of nighttime trading in 2013 is a significant step in achieving these goals. We investigate the effect of the additional nighttime trading hours on the cross-market information flows between Chinese and US futures markets. In particular, we test for influence on the price discovery process and volatility spillover between the two markets.

Our sample consists of eight commodity futures simultaneously traded in both China and the United States, with four metal futures (i.e., copper, gold, silver, and iron ore) and four agricultural futures (i.e., soybean, soybean meal, soybean oil, and cotton) from each market. The full sample spans from the earliest available date in the CSI database to the end of February 2016. Based on the date that nighttime trading sessions were implemented for the eight Chinese futures, two subsamples, before nighttime trading and after nighttime trading, are constructed to explore cross-market information flows during the pre- and post-nighttime-trading periods.

Chinese and US markets are found to be closely related during the full sample period as their futures prices adjust actively to mispricing. In particular, the Chinese market dominates the US market in soybean oil, iron ore, and cotton futures. The introduction of nighttime trading has brought changes in both the significance and adjustment speed in the error correction process between these two markets. The variance decomposition analysis indicates that the US market has the leading role in price discovery both before and after nighttime trading was introduced. The Chinese market, based on the changes in the effect of domestic market shocks as well as its influence on the US market, has shown three development trends: as domestic center (i.e., silver and soybean), global competitor (i.e., copper, gold, and soybean oil), and global leader (i.e., soybean meal, iron ore). Significant volatility spillover is found in both directions, indicating bidirectional information transmission between these two markets. There is evidence of closer cross-market linkage and stronger volatility spillover from the Chinese market to the US market in the post-nighttime-trading period.

In conclusion, our empirical tests detect close linkage between China and the United States in both futures prices and price volatility. Specifically, the launching of nighttime trading hours for Chinese futures markets brought significant changes to the price discovery process in these markets, and it has a profound impact on the cross-market information transmission mechanism. While the changes in the relative strength of long-term price causality vary across commodities, the Chinese market is now taking a leading role in the volatility spillover process. Therefore, the recent policy change in China has effectively enhanced information flow and enabled better linkage between the Chinese and US markets. It has proved to be a solid step in further internationalizing the Chinese futures market and strengthening China's price-setting power in key commodities on the global market.

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