Market Quality and the Connectedness of Steel Rebar and Other Industrial Metal Futures in China

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Abstract

We examine the market quality of China's steel rebar futures, along with three other important industrial metal futures. Steel rebar futures are the most active metal futures contracts in China. Our analyses show that while steel rebar and copper futures are comparable in terms of informational efficiency, they are more informationally efficient than iron ore and aluminum futures, with low bid-ask spread, volatility persistence, pricing error variance, and probability of informed trading. We find a bidirectional connection between iron ore and steel rebar futures. Furthermore, we show that these metal futures are weakly related to the Chinese stock market.

JEL classification: G10, G15, G19

Keywords: Market Microstructure, Market quality, Chinese commodity futures

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1. INTRODUCTION

Although steel is the world's second-most-traded commodity after crude oil, futures contracts for steel had not been popular until the past decade. This is because large steel producers could previously negotiate long-term pricing arrangements with their customers (Morrison, 2011). However, since the 2000s, prices for iron ore, the main raw materials for steel production, have been much more volatile as economic growth has greatly fluctuated.

The Shanghai Futures Exchange (SHFE) introduced steel rebar futures in April 2009. Since then, Shanghai steel rebar futures contracts (ticker symbol SRB) have been actively traded by domestic and international market participants, although strict regulations still dampen growth. The increasing exposure of international manufacturing companies to Chinese steel prices has increased their interest. Sanderson (2015) reports that daily trading volume of metal futures contracts on the SHFE exceeded that on the New York Mercantile Exchange (NYME) and the London Metal Exchange (LME) combined. According to an annual survey by the Futures Industry Association (FIA) conducted in 2017, the steel rebar futures contract traded on the SHFE is the most actively traded metal futures contract in the world. As with other commodity futures traded in China, most of the activities come from speculative trading by retail investors, which leads to greater market uncertainty compared to trading by institutional investors.

In this paper, we examine the market quality of steel rebar (or, for simplicity, steel) futures along with other important industrial metal futures, iron ore, aluminum, and copper, during the period November 2013–March 2018. Using intraday transaction data, we compare the bid-ask spreads, pricing error, volatility sensitivity and persistence, and the probability of informed trading (PIN) of the above four metal futures. The bid-ask spread offers a simple measure of transaction costs. Hasbrouck's (1993) pricing error measures the informational efficiency of prices, i.e. the deviation of the observed price to the efficient price. A lower variance in pricing error implies greater pricing efficiency and higher market quality. The sensitivity and persistence of volatility calculated using a GARCH model measure the degree of information shocks into the market and how quickly information is incorporated into prices, respectively. In this case, a high sensitivity of variance suggests that information shocks tend to have a large immediate impact whereas a high persistence of variance suggests that information is incorporated into prices gradually over time. Finally, the Easley et al.'s (1996) PIN provides evidence on information-based trading for the above industrial metal futures.

Our findings suggest that the four futures returns are significantly correlated, specifically iron and steel (0.75 based on daily returns) and copper and aluminum (0.44). We observe that steel futures make up a greater proportion of the large transactions (transaction larger than 500 contracts) than other futures, indicating the likely involvement of institutional investors. The bid-ask spread, pricing error variance, and volatility persistence of steel futures are lower than those for iron ore and aluminum futures, but higher than those for copper futures. Steel futures also have the lowest PIN. These results point toward the steel market being more informationally efficient than iron ore and aluminum futures.

We further examine the relation between Chinese commodities and stock markets using Diebold and Yilmaz's (2014) measure of connectedness. This approach estimates the share of forecast error variation in a market due to shocks initiated by itself (or idiosyncratic shocks) and other markets. We find strong pairwise connectedness between iron ore and steel futures, with iron ore being the largest contributor to variance. These results indicate that iron is the most useful and popular metal in various industrial activities. We also show that the Chinese stock market is fragmented from the commodities markets, with less than 10% of its variance of shocks derived from commodities and vice-versa.

The remainder of this paper proceeds as follows. Section 2 presents the data sources and summary statistics. Section 3 discusses the empirical findings based on different measures of market quality. Section 4 examines the connectedness between the commodities futures markets and the Chinese stock market. Section 5 concludes.

2. DATA AND SUMMARY STATISTICS

We focus on four major metals commodities futures: iron ore (ticker symbol DCIO), aluminum (SAF), copper (SCF), and steel rebar (SRB). Iron ore futures are traded on the Dalian Futures Exchange, and the other futures are traded on the SHFE. We list the specifications of these futures in Table 1. Because iron ore futures only started trading in late October 2013, we select the sample period for our study from November 1, 2013, to March 31, 2018. Trading in these futures occurs between 9:00 and 11:30 am and between 1:30 and 3:00 pm China Standard Time. The size of the iron ore futures contract is 100 metric tons, for aluminum and copper futures contracts is 5 tons, for steel contracts is 10 tons. These futures have twelve maturities per year. On each trading day, multiple maturities are traded with different levels of activity. We focus on nearby contracts, as they are the most liquid, and each contract is rolled over to the second-nearby contract when the volume of the second-nearby contract exceeds the volume of the front-end contract.

INSERT TABLE 1 HERE

We obtain transaction-level data for prices, volume, bid-ask quotes, and bid-ask depths from Thomson Reuters Tick History, maintained by the Securities Industry Research Centre of the Asia-Pacific. These data contain all activities observed at the top of the limit order book, which includes transactions and revisions in bid and ask prices and depths, time-stamped to the nearest millisecond. We treat multiple trades executed at the exact same time as one trade, as they typically reflect a trade initiated by one market participant but executed against the limit orders of multiple market participants. In such cases, we use the value-weighted average price and aggregate the traded volume. Trades are divided into buyer- and seller-initiated trades on the basis of the prevailing quotes prior to the trade. A trade is classified as buyer- (seller-) initiated if it is above (below) the midpoint of these quotes (midquote). Trades at the midquote are considered undetermined.

Table 2 presents summary statistics for the futures contracts in our sample. It reports the daily number of trades, and the dollar trading volume. The average daily number of trades is highest for steel futures at 20,600 trades per day, followed by iron ore, copper, and aluminum with 12,300, 9,100, and 4,800 trades, respectively. In terms of the dollar trading volume, it is highest for steel (7,800 million RMB) and copper (7,300 million RMB), followed by aluminum (1,200 million RMB) and iron ore (500 million RMB).[1] Hence, based on the dollar trading volume, steel and copper are the most liquid futures contracts. We further split trades into three groups of different trading sizes (number of contracts per trade). The first group consists of trades with 100 or fewer contracts. The majority of trades fall into this group, especially for aluminum and copper, for which close to 98% of trades are for 100 or fewer contracts. The second group is for trades with 100 to 500 contracts: 18% of the trades in steel futures fall into this group, followed by iron ore at 8%. The third group is for trades with more than 500 contracts. They are relatively common for steel and iron ore, but extremely rare for aluminum and copper.

[1]Figure A.1 in the Appendix shows the average daily trading volume (in million RMB) by year. Over the sample period from 2013 to 2018, steel and copper have been the most actively traded metal futures in China.

INSERT TABLE 2 HERE

Panel B in Table 2 reports the summary statistics of daily futures (log) returns. All futures returns are insignificantly negative. Iron ore is the most volatile, as indicated by the standard deviation, followed by steel, while aluminum and copper have much lower volatility than steel and iron ore. Because of the unstable price of iron ore, prices for all products across the steel industry have become volatile. Steel producers increasingly use iron ore and steel futures for hedging.

In the US and the UK, commodity futures trading is dominated by institutional investors, particularly hedge funds and large producers and consumers. In contrast, investors in China's commodities market are mostly retail investors and financial speculators (Liu, Tse, and Zhang, 2018). Retail frenzies in commodity trading may have been caused by liquidity trapped in China by decades of booming growth, capital controls, and limited investment alternatives. Chinese funds have drawn attention on global commodities markets. Financialization and speculation in Chinese commodities will also increase correlations among different commodities in China.

Our empirical analysis consists of two sections. First, we assess the market quality of commodity futures using various metrics, such as bid-ask spreads, pricing error, volatility sensitivity and persistence, and the probability of informed trading. Second, we assess the relations among the four commodities to determine which of them is the leader in price formation and whether these commodities are related to the local stock market.

3. MEASURES FOR MARKET QUALITY

3.1. Bid-Ask Spreads and Pricing Error

We first assess the cost of trading by computing the bid-ask spread daily over the sample period and compare the mean of these spreads across the four commodities. We report these results in Panel A in Table 3. Column 1 shows the quoted spread, measured as the difference between ask and bid prices, divided by the quote midpoint. As shown in the table, iron ore has the widest spread of around 12.9 basis points (bps). Aluminum and steel are next, with a quoted spread of around 4.0 bps and 3.8 bps, respectively. Copper has the narrowest spread, around 2.4 bps. These figures suggest that cost of trading is the lowest for copper futures and the highest for iron ore, consistent with the statistics in Table 1. Specifically, futures that are more frequently traded tend to have narrower spreads.

INSERT TABLE 3 HERE

Column 2 shows the effective spread, measured as twice the absolute value of the difference between the trade price and the midpoint, i.e.,

$$Espreadt = 2|p_t - m_t|/m_t \tag{1}$$

where p_t and m_t are the transaction prices and midquote at trade t, respectively. We estimate the spread each day using transaction data and average the results. The results based on the effective spread as shown in column 2 are consistent with the earlier finding. Specifically, we find that copper futures have the narrowest spread, followed by steel, aluminum, and iron ore. The test of equality in mean (last row) suggests that the spreads among these commodities are not equal.

Although the bid-ask spread is often used to compare market quality, the spread reflects the liquidity provider's profit only when orders at each extreme of the spread are filled. Because market imperfections cause the market price to deviate from the efficient price, a narrow spread does not necessarily mean that the market price is close to the efficient price. Therefore, another measure of market quality is needed to measure whether an asset can be traded easily at a price near the efficient price approximated by the midquote.

We use the Hasbrouck (1993) model to measure market quality. Hasbrouck models the trading price as a random-walk component that represents the true price of an asset and a transient component or pricing error that represents market imperfections. The higher the variance in the pricing error, the lower the market quality and vice versa. Hasbrouck (1993) decomposes an asset's price, p_t , into a random-walk component, q_t, and a pricing error, s_t.

$$p_t = q_t + s_t \tag{2}$$

$$q_t = q_{t-1} + w_t \tag{3}$$

where w_t is the serially uncorrelated innovation that captures all public information. The pricing error represents the deviation from the efficient price. Better market quality is indicated by a lower variance in the pricing error.

Hasbrouck (1993) estimates market quality from the following vector-autoregressive (VAR) model:

$$\begin{aligned} \Delta p_t &= a_1 \Delta p_{t-1} + a_2 \Delta p_{t-2} + \cdots + b_1 \Delta x_{t-1} + b_2 \Delta x_{t-2} + \cdots + e_{1t} \\ x_t &= c_1 \Delta p_{t-1} + c_2 \Delta p_{t-2} + \cdots + d_1 \Delta x_{t-1} + d_2 \Delta x_{t-2} + \cdots + e_{2t}, \end{aligned} \tag{4}$$

where $\Delta p_t = \log(p_t/p_{t-1})$ is the consecutive price change between trade t and $t-1$, x_t is a trade indicator variable (x_t = 1 for buy orders; x_t = -1 for sell orders), and e_{1t} and e_{2t} are random disturbances. Following Hasbrouck (1993), we use five lags to estimate this VAR.

Variance in pricing error also describes the market depth because trading prices fluctuate and deviate from the efficient price more often in a market with little depth.

Panel B in Table 3 reports the results for the pricing error standard deviations. It reports the daily mean, median, and standard deviation of pricing error for the four commodities. We find that the average daily standard deviation in the pricing error (10^{-3}) is the highest for iron ore futures (0.16), followed by aluminum (0.093), steel (0.073), and copper (0.064). The difference in mean is statistically significant ($p < 0.001$). Results are similar when we compare the medians. These results suggest that copper and steel futures are the most informationally efficient, given that trades are executed at prices closest to the efficient price. This finding also confirms the spread results in Panel A, which show that trading cost is the lowest for copper and steel futures.

3.2. Volatility Sensitivity and Persistence

Introduced by Engle (1982) and Bollerslev (1986), the autoregressive conditional heteroscedasticity (ARCH) and generalized ARCH (GARCH) models are often used to measure time-variation in volatility of financial returns. The extent to which the current variance is affected by lagged innovations to the return series and lagged variance in a GARCH model is described as the asset's sensitivity and persistence level, respectively. Following Kavajecz and Odders-White (2001), we compare sensitivity and persistence levels in variance to draw conclusions regarding the flow of information and how quickly it is incorporated into prices.

We adopt the commonly used GARCH(1,1) model, which has the desirable features of interpretability and good fit for high-frequency data. The following equations are jointly estimated using maximum likelihood:

$$\sigma_t^2 = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \alpha_2\sigma_{t-1}^2, \tag{5}$$

$$\sigma_t^2 = \alpha_0 + (\alpha_1 + \alpha_2)\sigma_{t-1}^2 + \alpha_1(\varepsilon_{t-1}^2 - \sigma_{t-1}^2). \tag{6}$$

As explained in Campbell, Lo, and MacKinlay (1997) and Kavajecz and Odders-White (2001), α_1 measures the sensitivity of variance to the most recent shock, indicating the overall flow of information shocks into the market, and a high (low) sensitivity of variance suggests that information shocks tend to have a large (small) immediate impact. Correspondingly, $(\alpha_1 + \alpha_2)$ measures the persistence of information shocks in the variance, indicating how quickly information is incorporated into prices. A high (low) persistence of variance suggests that information is gradually (quickly) incorporated into prices (Tse and Zabotina, 2004).

Table 4 shows the results for volatility sensitivity (Panel A) and volatility persistence (Panel B). Focusing first on Panel A, we observe that volatility sensitivity is the highest for copper (α_1 = 0.095), followed by steel (α_1 = 0.081), aluminum (α_1 = 0.063), and iron ore (α_1 = 0.055). The difference in both the mean and the median is statistically significant. These results suggest that information shocks have a larger immediate impact on copper and steel futures, i.e., trades are more informative. Panel B reports the results for volatility persistence. The persistence level ($\alpha_1 + \alpha_2$) is the highest for iron ore futures (0.917), and the lowest for copper futures (0.732). These results indicate that information is incorporated into prices in the former more gradually than in the latter. Overall, Table 5 suggests that copper and steel futures offer better quality than aluminum and iron ore in terms of incorporating information shocks into prices while, at the same time, reducing the time it takes for volatility to dissipate.

INSERT TABLE 4 HERE

3.3. Probability of Informed Trading

Our next analysis is to determine the probability of information-based trading in commodities. Market microstructure theory shows that informed trading reduces liquidity. Liquidity providers have to deal with the adverse selection problem caused by informed traders who hide among uninformed traders. As such, higher PIN is often associated with higher transaction costs and lower liquidity. Following Barclay and Hendershott (2003) and others, we use the PIN trading model of Easley et al. (1996, 1997) to measure informed trading. The model uses available information on buy and sell transactions to estimate the probability of informed trades.

If informed trades follow a Poisson process with arrival rate μ, and uninformed trades also follow a Poisson process but with arrival rate ε, we can estimate the probability of informed trading using the maximum-likelihood method as follows:

$$\mathrm{L}\big((\mathrm{B},\mathrm{S})\big|\alpha,\delta,\mu,\varepsilon\big) = (1-\alpha)e^{-\varepsilon T}\frac{(\varepsilon T)^{B}}{B!}e^{-\varepsilon T}\frac{(\varepsilon T)^{S}}{S!} + \alpha\delta e^{-\varepsilon T}\frac{(\varepsilon T)^{B}}{B!}e^{-(\mu+\varepsilon)T}\frac{\big((\mu+\varepsilon)T\big)^{S}}{S!}$$
$$+\alpha(1-\delta)e^{-\varepsilon T}\frac{(\varepsilon T)^{S}}{S!}e^{-(\mu+\varepsilon)T} \qquad (7)$$

where B and S are the total number of buy and sell trades on a given day.

The trade process depends on four parameters: (1) the probability of an information event, α; (2) the probability that new information is bad news, δ; (3) the arrival of uninformed traders, ε; and (4) the arrival rate of informed traders, μ. We estimate the parameters of the trade process for each commodity in our sample by maximizing the likelihood function conditional on the trade data. The probability parameters α and δ are restricted to (0, 1) using logit transformation, whereas ε and μ are restricted to (0, ∞) by a logarithmic transformation. Standard errors for the parameter estimates are calculated using the delta method. Given these parameters, the PIN is then estimated as:

$$\text{PIN} = \frac{\alpha\mu}{2\varepsilon+\alpha\mu}. \quad (8)$$

Table 5 presents the means of the estimated parameters. We first consider the estimates of the information event parameter, α. The mean α is the highest for the most active commodity steel (α = 0.53) and iron ore (α = 0.47), and declines for less active commodities and aluminum (α = 0.38) and copper (α = 0.28). The second information parameter in our model is δ, which reflects the probability of bad news arrival. Our results suggest that, except for aluminum, the probability of bad news entering the market is more than 50%. We explore this further by comparing the number of days with positive returns to total trading days. Except for aluminum, with 50.4% of days with positive returns, the remaining futures have less days with positive returns: iron ore (48.3%), copper (48.2%), and steel (48.9%). Hence, our estimates provide confirmation of the sensibility of our model.

The last row shows the probability of information-based trading, calculated based on interactions among various parameters characterizing the trade process. The results reveal that PIN is the lowest for steel (0.070), followed by copper (0.073), iron ore (0.15), and aluminum (0.21). Thus, steel and copper have, on average, lower probabilities of informed trading than iron ore and aluminum. Overall, the results for market quality are consistent: Copper and steel futures seem to be more price efficient and have better market quality than aluminum and iron ore futures.

INSERT TABLE 5 HERE

4. CONNECTEDNESS AMONG COMMODITIES AND THE LOCAL STOCK MARKET

We further assess the temporal relation among Chinese commodities futures and stock markets. To this end, we employ Diebold and Yilmaz's (2014) measure of connectedness. This approach to connectedness is based on assessing shares of forecast error variation in a variable (assets, firms, etc.) due to shocks arising elsewhere. The underlying idea is related to the econometric notion of a variance decomposition, in which the forecast error variance of a variable i is decomposed into parts attributed to the various variables in the system (see, e.g. Booth et al., 1997). This connectedness measure was recently used in Andrada-Félix et al. (2018) to examine the interconnection between five implied volatility indices, and in Corbet et al. (2018) to explore the relations between cryptocurrencies and other financial assets. Of particular interest in this paper, we investigate the causal relations between the stock market and commodities in China.

Consider a covariance stationary N-variable VAR(p):

$$x_t = \Theta(L)u_t \tag{9}$$

where x_t is the vector of assets' returns, $\Theta(L) = \Theta_0 + \Theta_1 L + \Theta_2 L^2 + \cdots$, and $E(u_t, u_t') = I$. The moving-average coefficients Θ are key to understanding the dynamics in the system. Following Diebold and Yilmaz (2014), we rely on variance decompositions, which help explain the forecast error variances of an asset into parts attributable to shocks from the system.

Diebold and Yilmaz (2014) propose a connectedness table, such as Table 6, to understand the various connectedness measures and their relationships. Its main upper-left $N \times N$ block, which contains the variance decompositions, is called the "variance decomposition matrix" and is denoted by D^H, where H is the number of period-ahead forecasts.[2] The off-diagonal entries of D^H are the parts of the N forecast-error variance decompositions of

[2]Certain considerations in certain contexts may help guide selection of the connectedness horizon, H. For example, $H = 10$ is often used to be consistent with the 10-day value at risk (VaR) requirement under the Basel accord.

relevance from a connectedness perspective. In particular, the gross pairwise directional connectedness from j to i is denoted by d_{ij}^{H}.

INSERT TABLE 6 HERE

The connectedness table also includes the rightmost column which contains the row sums, the bottom row which contains the column sums, and the bottom-right cell which contains the grand average, in all cases for $i \neq j$. Hence, the off-diagonal-entry-row sums in the connectedness table indicate the share of forecast-error variance of variable i from shocks in other variables. In particular, total directional connectedness from others to i is defined as

$$C_{i\leftarrow\bullet}^{H} = \sum_{\substack{j=1 \\ j\neq i}}^{N} d_{ij}^{H}, \tag{10}$$

whereas the column sum indicates total directional connectedness from j to others and is defined as

$$C_{\bullet\leftarrow \mathrm{j}}^{H} = \sum_{\substack{i=1 \\ j\neq i}}^{N} d_{ji}^{H}. \tag{11}$$

We can also define net total directional connectedness as

$$C_{i}^{H} = C_{\bullet\leftarrow i}^{H} - C_{i\leftarrow\bullet}^{H}. \tag{12}$$

Finally, the grand total of the off-diagonal entries in D^{H}(equivalently, the average of the FROM column or TO row) measures total connectedness:

$$C^{H} = \frac{1}{N}\sum_{\substack{i,j=1 \\ j\neq i}}^{N} d_{ij}^{H}. \tag{13}$$

The generalized VAR framework of Koop, Pesaran, and Potter (1996) and Pesaran and Shin (1998) is used to produce the variance decomposition. We can then write the H-step generalized variance decomposition (GVD) matrix as $D^{gH} = \left[d_{ij}^{gH}\right]$, where

$$d_{ij}^{gH} = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' \Theta_h \Sigma e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' \Theta_h \Sigma \Theta_h' e_i\right)}. \tag{14}$$

In this case, e_i is a vector with ith element unity and zeros elsewhere, Θ_h is the coefficient matrix in the infinite moving-average representation from VAR, Σ is the covariance matrix of the shock vector in the non-orthogonalized-VAR, σ_{jj} being its jth diagonal element. In this GVD framework, the lack of orthogonality means that the rows of d_{ij}^{gH} do not have sum unity. In order to obtain a generalized connectedness index such that $\widetilde{D}^g = \left[\tilde{d}_{ij}^g\right]$, the following normalization is necessary: $\tilde{d}_{ij}^g = \frac{d_{ij}^g}{\sum_{j=1}^N d_{ij}^g}$, in which, by construction, $\sum_{j=1}^N \tilde{d}_{ij}^g = 1$ and $\sum_{i,j=1}^N \tilde{d}_{ij}^g = N$. The matrix $\widetilde{D}^g = \left[\tilde{d}_{ij}^g\right]$ permits us to define similar concepts as before for the orthogonal case, that is, total directional connectedness, net total directional connectedness, and total connectedness.

Table 7 reports the correlation matrix among commodities and Chinese Stock Index (CSI300) futures. The correlations are high among commodities, particularly between iron ore and steel, which have a correlation coefficient of 0.75. Because iron ore is the main raw material in steel production, movements in steel prices should be closely related to iron prices. All the other pairs are also significantly correlated, e.g., a coefficient of 0.44 between copper and aluminum. Intuitively, these correlations could shed light on connections between these assets, which are assessed next.

INSERT TABLE 7 HERE

In Table 8, we report the full-sample connectedness table. All results are based on VAR of order 1 and 10-day-ahead GVD. As mentioned previously, the off-diagonal cells measure the connectedness between asset returns, i.e., the ijth entry of the upper-left 5×5 market submatrix indicates the contribution to the forecast-error variance of market i's return from market j. Hence, the off-diagonal column (labeled TO) and the row sums (labeled FROM) give the total directional connectedness to all others from i and from all others to i, respectively. The bottom-right cell is the total connectedness, which is calculated as the sum of the non-diagonal elements of the connectedness matrix, divided by number of assets.

INSERT TABLE 8 HERE

As can be seen, the diagonal cells are the largest individual values in the table, ranging from 39.1% (steel) to 91.2% (CSI300). The highest observed pairwise connectedness is between iron ore and steel: from iron ore to steel at 45.9% and from steel to iron ore at 30.7%. The Chinese stock market seems fragmented from the commodities futures market, as shown by CSI300's low contribution (4.5%) and the low receivership of variance (8.8%).

On a daily basis, total connectedness is 42.4%, indicating that 57.6% of the variation is due to idiosyncratic shocks. Regarding to the net contribution (TO minus FROM), iron ore is the largest contributor to variance at 40.1% while others, such as aluminum, copper, steel, and CSI300, are receivers of shocks (-15.3%, -20.1%, -0.3%, and -4.4%, respectively). These results indicate that iron is the most useful and popular industrial metal. Price movements of iron ore have a significant impact on those of other metals.

The results also show that the stock market is fragmented from the commodities markets: Each of the four commodities contributes less than 2% of the variance of the shocks from the stock market, and vice versa. These results are consistent with Liu et al. (2018). They show that the VaR risk derived from one market does not spill over to the other. The authors suggest that the Chinese stock and commodities futures markets are driven by different risk factors because of excessive speculation in commodities, different investment factors, and government regulations on commodity and equity trading.

5. CONCLUSIONS

Since the Shanghai Futures Exchange introduced steel rebar futures in April 2009, these contracts have been actively traded by domestic and international market players. Examining the market quality of this most active metal futures contract and the relations with other metals futures and the stock market in China is important for investors and policy makers worldwide.

We use transaction data to examine the market quality of steel futures traded on the SHFE, along with three other important industrial metal futures, iron ore, aluminum, and copper, in China during the sample period November 2013–March 2018. Steel futures make up a larger proportion of large transactions than other contracts. The overall results show that steel and copper futures are more informationally efficient than iron ore and aluminum futures, with a narrow bid-ask spread and low volatility persistence, pricing error variance, and PIN.

Examining daily connectedness between commodities and stock markets, we find that iron ore is the largest contributor to price variance in other commodities, and a significant bidirectional connection exists between iron ore and steel futures. These results indicate that iron ore is not only the major raw material in steel but also the most widely used industrial metal. Price movements of other commodities are influenced by those of iron ore. We also show that the Chinese stock market has a weak relation with the commodities futures. The connectedness measure between the stock market and each of the four commodities is less than 2%, suggesting that the Chinese stock and commodities futures markets are driven by different economic and investment factors.

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APPENDIX

Figure A.1. Futures trading volume

This figure plots the average daily trading volume (in millions Yuan) for iron ore, aluminum, copper, and steel rebar futures over the sample period from 2013 to 2018.

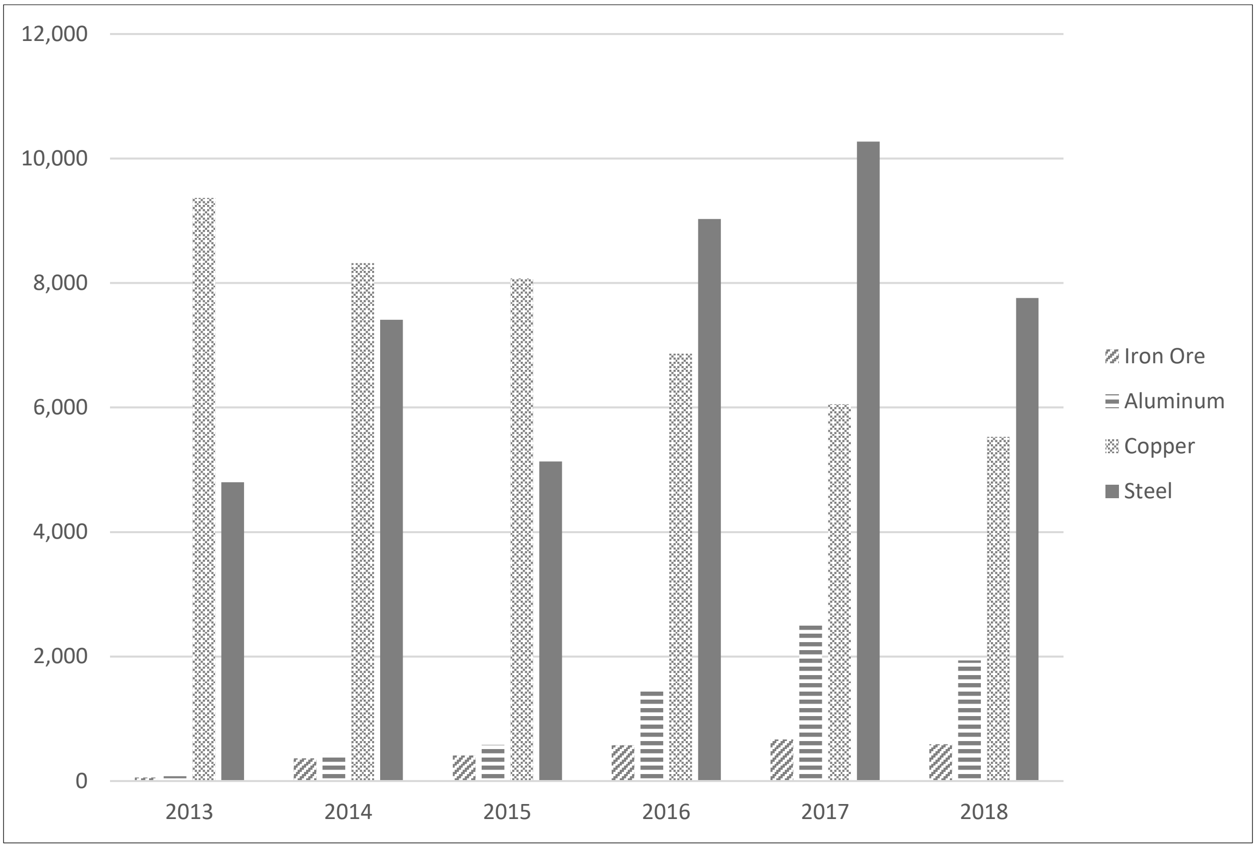

Table 1. Chinese commodity futures contracts

This table lists the futures contracts used in our study. It includes the futures symbol, exchange venue, period of data availability, and contract size (in tons/contract).

Commodity	Symbol	Exchange Venue	First full month of data availability	Contract Size
Iron Ore	DCIO	Dalian Commodity Exchange	Nov-13	100 metric tons
Aluminum	SAF	Shanghai Futures Exchange (SHFE)	Jan-04	5 tons
Copper	SCF	Shanghai Futures Exchange (SHFE)	Jan-04	5 tons
Steel Rebar	SRB	Shanghai Futures Exchange (SHFE)	Apr-09	10 tons

Table 2. Summary Daily Statistics

Panel A reports the trading activity for the various futures contracts. It shows the daily number of trades, dollar trading volume (in Yuan), and the proportion of trades by size (number of contracts). Panel B reports daily returns statistics for various commodity futures. It reports the mean, standard deviation, skewness, kurtosis and the maximum and minimum returns over the sample period.

Panel A: Daily Trading Volume

Commodity	Number of Trades (thousands)	Trading Volume (millions RMB)	Transaction by Size (number of contracts)		
			≤ 100	$100 < x \leq 500$	> 500
Iron Ore	12.30	492	88.03%	8.37%	3.41%
Aluminum	4.76	1,240	97.63%	2.34%	0.03%
Copper	9.13	7,309	97.50%	2.47%	0.03%
Steel Rebar	20.64	7,826	74.83%	18.06%	6.93%

Panel B: Daily Return Statistics

Daily Return	Iron Ore	Aluminum	Copper	Steel Rebar
Mean	-0.07%	0.00%	0.00%	-0.01%
SD	2.47%	1.02%	1.17%	1.81%
Skew	-0.38	0.48	0.11	-0.16
Kurtosis	4.84	5.03	5.27	4.02
Maximum	12.49%	5.52%	7.79%	7.83%
Minimum	-16.21%	-6.21%	-6.18%	-10.27%
Observations	1076	1076	1076	1076

Table 3. Bid-ask spreads and Pricing error standard deviation

This table provides bid-ask spreads (Panel A) and pricing error standard deviation (Panel B) for four Chinese commodities in the sample. The percentage quoted spread, *%QSpread*, is measured as the difference between ask and bid prices, divided by the quote midpoint, while the percentage effective spread, *%ESpread*, is measured as two times the absolute difference between transaction price and the midpoint, divided by the quote midpoint. For the pricing error, we report the mean, median, and standard deviation (10^{-3}). The bottom row presents the p-values for the test of equality in mean and median.

	Panel A: Bid-ask spread		Panel B: Pricing error		
Commodity	*%QSpread*	*%ESpread*	Mean	Median	St. dev.
Iron Ore	0.129%	0.129%	0.160	0.154	0.035
Aluminum	0.040%	0.039%	0.093	0.091	0.019
Copper	0.024%	0.023%	0.064	0.060	0.016
Steel Rebar	0.038%	0.038%	0.073	0.068	0.026
Test of equality p-value	<0.001	<0.001	<0.001	<0.001	

Table 4. Volatility sensitivity and persistence

This table reports the degree of volatility sensitivity (Panel A) and volatility persistence (Panel B) for the four Chinese commodity futures in the sample. The figures reported are the mean, median and standard deviation of the volatility measures. The bottom row presents the p-values for the test of equality in mean and median.

	Mean	Median	St. dev.
Panel A: Volatility Sensitivity (α_1)			
Iron Ore	0.055	0.056	0.017
Aluminum	0.063	0.062	0.017
Copper	0.095	0.090	0.032
Steel Rebar	0.081	0.077	0.025
p-value	<0.001	<0.001	
Panel B: Volatility Persistence ($\alpha_1 + \alpha_2$)			
Iron Ore	0.917	0.922	0.043
Aluminum	0.897	0.901	0.039
Copper	0.732	0.757	0.132
Steel Rebar	0.797	0.801	0.086
p-value	<0.001	<0.001	

Table 5. Probability of informed trading

This table reports the parameter estimates for the model of probability of informed trading over the sample period from November 2013 to March 2018. The parameter α is the probability of an information event, δ is the probability that new information is bad news, ε is the arrival rate of uninformed traders, and μ is the arrival rate of informed traders. PIN is measured as $\alpha\mu/\,(\alpha\mu + 2\varepsilon)$ and reflects the probability of information-based trade. Figures in parentheses are the t-statistics. *** denotes statistical significance at the 1% level.

	Panel A: Iron Ore		Panel B: Aluminum		Panel C: Copper		Panel D: Steel Rebar	
	coefficient	*t*-stat	coefficient	*t*-stat	coefficient	*t*-stat	coefficient	*t*-stat
α	0.47***	(38.48)	0.38***	(29.61)	0.28***	(19.02)	0.53***	(39.87)
δ	0.63***	(28.95)	0.44***	(17.37)	0.62***	(21.53)	0.56***	(26.02)
ε	519.3***	(64.28)	188.5***	(38.80)	420.5***	(102.59)	959.1***	(183.98)
μ	392.2***	(67.07)	255.8***	(36.60)	234.4***	(28.17)	273.2***	(90.23)
PIN	0.15		0.21		0.073		0.070	

Table 6. Connectedness table schematic

This table presents the schematic for the connectedness results among assets. The rightmost column contains the row sums (total directional connectedness FROM others), the bottom row contains the column sums (total directional connectedness TO others), and the bottom-right cell contains the grand average (the overall connectedness).

	x_1	x_2	x_N	Connectedness FROM others
x_1	d_{11}^H	d_{12}^H	d_{13}^H	$\Sigma_{j=1}^N d_{1j}^H, j \neq 1$
x_2	d_{21}^H	d_{22}^H	d_{23}^H	$\Sigma_{j=1}^N d_{2j}^H, j \neq 2$
x_N	d_{N1}^H	d_{N2}^H	d_{N3}^H	$\Sigma_{j=1}^N d_{Nj}^H, j \neq N$
Connectedness TO others	$\Sigma_{i=1}^N d_{i1}^H$, $i \neq 1$	$\Sigma_{i=1}^N d_{i2}^H$, $i \neq 2$	$\Sigma_{i=1}^N d_{iN}^H$, $i \neq N$	**Total Connectedness =** $\frac{1}{N}\Sigma_{i,j=1}^N d_{iN}^H, i \neq N$

Table 7. Correlation among commodities and local stock market returns

This table presents the correlation matrix of the returns among commodities futures and the CSI300 stock index futures (ticker symbol CIF). Daily returns data are from November 2013 to March 2018. *** indicates significance at the 1% level.

	Iron Ore	Aluminum	Copper	Steel Bar	CSI300
Iron Ore	1				
Aluminum	0.27***	1			
Copper	0.42***	0.44***	1		
Steel Rebar	0.75***	0.27***	0.42***	1	
CSI300	0.12***	0.13***	0.18***	0.12***	1

Table 8. Connectedness among commodities and local stock market

This table reports the connectedness results among the commodities and domestic equity index. Variance decomposition is derived from a VAR model estimated over the sample period November 1, 2013 to March 31, 2018, using daily returns data. Number of lag is one based on the SIC, and the predictive horizon is 10 days. Column 1 represents variable i, and the top row represents variable j. Hence, the ij-th entry of the upper-left 5×5 submatrix gives the ij-th pairwise directional connectedness; i.e., the percentage of 10-day-ahead forecast error variance of variable i due to shocks from variable j. The right-most (FROM) column gives total directional connectedness from all others to variable i. The second to last (TO) row gives total directional connectedness to all others from j. The last (NET) row gives the difference in total directional connectedness between TO and FROM. The bottom-right cell (in boldface) is total connectedness (mean "FROM" connectedness, or equivalently, mean "TO" connectedness).

	Iron Ore	Aluminum	Copper	Steel Rebar	CSI 300	Directional **FROM** others
Iron Ore	54.7%	4.0%	9.8%	30.7%	0.7%	45.3%
Aluminum	12.3%	61.6%	15.2%	9.6%	1.3%	38.4%
Copper	25.3%	13.1%	41.3%	18.6%	1.7%	58.7%
Steel Rebar	45.9%	4.2%	10.1%	39.1%	0.8%	60.9%
CSI300	1.8%	1.8%	3.5%	1.7%	91.2%	8.8%
Directional **TO** others	85.4%	23.1%	38.6%	60.6%	4.5%	**42.4%**
NET contribution (TO – FROM)	40.1%	-15.3%	-20.1%	-0.3%	-4.4%	