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Night Trading with Futures in China: The Case of Aluminum and Copper

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Abstract

We use high-frequency data to examine the effects of introducing a night trading session at the Shanghai Futures Exchange (SHFE) for Copper and Aluminum in 2013. For Copper, the realized volatility of the regular session is endogenously determined and the night session is driven by the immediately preceding volatility of the London Metal Exchange (LME). In contrast, the Chinese Aluminum futures market is more resistant to exogenous factors and shows a pronounced long memory structure. We find no indications that the SHFE draws volume from LME by means of simultaneous trading. The existing break between daytime and night sessions has significant informational content and should be separated when jump components are extracted from realized volatility.

Keywords: SHFE; Futures Markets; Aluminum; Copper; High-frequency data; Night trading.

JEL classification: C2; C22; G15; Q02;

1. Introduction and Literature Review

This paper is the first to address thoroughly the role of the newly introduced night trading sessions (NTS) for Chinese commodity futures markets. These markets are unique in that the large majority of the participants are individual or retail investors rather than institutions, and direct participation by foreign individual investors in the Chinese futures market is restricted.¹ To boost its role in global commodity trading, China is undertaking a number of measures, such as allowing international participants to trade in a range of commodity futures (currently crude oil, iron ore and PTA) and waiving income tax for foreign investors (Bloomberg, 2018). In addition, to offer market participants more flexible choices of hedging and the opportunity to react to news from international markets immediately upon their arrival, Chinese futures exchanges introduced NTS. Starting with Gold and Silver in July 2013, night trading was launched for most commodity futures

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¹Refer to Zhao (2015) for the history of Chinese futures markets and to Fan & Zhang (2018) for a detailed overview of institutional settings, regulations and trading rules and the investor structure of China's commodity futures markets..

contracts in China enabling trades for an additional 2.5 to 5.5 hours (varying across commodities) at night.

This work focuses on China’s Copper and Aluminum futures markets. China is a significant player in the global markets for non-ferrous metals with derivatives trading on the SHFE and China’s real activity being significantly related to base metals’ prices (Wang & Wang, 2017). Global primary Aluminum production increased by 5.8 percent in 2017, with a 10 percent increase in China and stable production in North America and Europe (Aluminum, 2018). The Aluminum market is exposed to continued political uncertainty, such as those related to US tariffs on Aluminum imports, with the US market becoming gradually closed to Chinese exporters, and stringent environmental regulations leading to closures of Aluminum operators. On the other hand, global demand for primary and recycled Aluminum is driven by the trend toward lightweight construction in the automotive industry. With Copper used widely in power and construction, the Copper market is experiencing volatility because of the escalating trade tension with the US, which adds to the fears of a slowdown in the world’s largest importer of Copper. After reaching a four-year high of almost USD 3,500 per ton in early June 2018, Copper fell sharply—by about USD 1,000 per ton—in the next month (FT, 2018). These recent developments emphasize the need to understand the volatility dynamics of these assets and the relationship of the Chinese futures to international commodity markets.

When the two-hour lunch break that occurs during regular daily trading is taken into account, a regular trading day of the SHFE during business hours comprises 3.5 hours. Adding four hours of trading at night more than doubles the active trading hours, which is likely to induce significant changes in the futures markets. Based on an extensive dataset of intraday price records, we investigate the course of realized volatility and trading volumes over the recent years to shed light on the relationship between China’s Copper and Aluminum markets and the LME, which is the established venue for industrial metals trading.²

The literature has indicated continuing improvement in the efficiency of China’s relatively young metals market (e.g., Xin et al., 2006) and its growing global importance. A number of studies have specifically addressed the relationship between Chinese and international non-ferrous metal markets. Li & Zhang (2008) concluded that, in the period between November 1993 and June 2006, the SHFE’s and the LME’s Copper futures prices had a long-run relationship, with the influence of the LME on the SHFE being more pronounced than the other way round. Fung et al. (2010) examined the information flow and market efficiency between the US and Chinese Aluminum and Copper futures

²The COMEX issues futures contracts on Copper and Aluminum, but while the COMEX’s Copper futures have notable trading volumes, the trading in Aluminum futures has been thin, so there are too few high-frequency price records to warrant a reliable estimate of daily realized volatility. For this reason, the present study focuses on the LME as an international metal-prices benchmark.

markets over the period from 1999 to 2009 and found that the two futures prices were co-integrated. Using data from 2005 to 2011, Li & Zhang (2013) concluded that the price impact of the SHFE's Copper futures on the LME's Copper futures has been increasing since 2007, while the reverse effect has been decreasing. Rutledge et al. (2013) investigated the price links and information transitions between the Copper markets of the COMEX, the LME and the SHFE between June 2006 and May 2011 and saw significant bidirectional Granger causality across the three markets. Yin & Han (2013) found bidirectional but asymmetric lead/lag relationships and volatility spillovers between the LME and the SHFE, as well as between the NYMEX and the SHFE, with the stronger effect from the two developed markets to the two immature markets in the time series from January 2004 to April 2012. Hou et al. (2015) used data from November 2000 to January 2012 to show the increasingly prominent role of the SHFE in the price-formation process and the cross-volatility spillover effects in the Copper market since 2008. Looking at the period between August 2007 and April 2016, Kang et al. (2018) documented that London's nonferrous futures market generally leads Shanghai's market, especially in the medium-run.

Most of the aforementioned studies were based on closing prices that were sampled at a daily frequency or less and did not account for the differing times when the individual markets are open. Moreover, as their data samples span periods before the night trading was launched in China, the links between the Chinese and international markets have not been assessed against the backdrop of the newly extended trading hours. Breaking close-to-close returns of futures on Copper, soybeans and rubber into overnight and open-to-close returns in the context of Value-at-Risk (VaR) and expected shortfall estimations, Liu & Yunbi (2014) showed that the information that accumulates during non-trading hours contributes substantially to overall risks, with non-trading VaR weights exceeding 40 percent in these markets. In particular, the information that accumulates during non-trading hours appears to be more important than the information that accumulates during trading hours. Using time-stamped bid and ask prices and trade prices for the three-month Copper futures contracts traded on the COMEX, the LME and the SHFE from July 2005 to December 2005, Lien & Yang (2009) documented a significant unidirectional volatility spillover from the LME to the SHFE. Using daily data of sixteen commodity futures up to October 2011, Fung et al. (2013) suggested that China's commodity futures markets are likely to be driven by local market dynamics that occur during the daytime, as foreign markets' trading sessions' returns have a significant impact on China's overnight (close-to-open) returns, but China's commodity futures contracts' daytime (open-to-close) returns are not led by foreign daytime returns. These studies make clear that, before the introduction of night trading, overnight and daily dynamics differed to a considerable extent, and overnight information from international markets that arrives while the Chinese futures exchanges are closed causes a large part of the

overall metal market’s volatility.

To the best of our knowledge, only a few studies have addressed the effect of Chinese futures markets’ overnight trading.³ Fung et al. (2016) used daily prices and trading activity data from Chinese commodity futures to document that the returns have become more symmetric and that interactions between trading activity and volatility have conformed better to the observed patterns in developed markets. Using daily closing and opening prices, Du (2018) ran VAR models to predict commodity returns and volatility and established the presence of a leading effect of overnight returns to daytime trading returns. Jin et al. (2018) and Xu & Zhang (2019) used intraday data to investigate the price discovery and market quality of Chinese gold markets and provided evidence of the importance of NTS in this regard.

We contribute to the research on global futures markets in three primary ways. First, we use an extensive set of high-frequency data to obtain the precise realized volatility of futures and match volatility and trading volume to individual trading sessions in the SHFE and the LME. Industrial metals are known to exhibit low seasonal variation in supply and demand, so there is no need to account for seasonal effects in the raw data. As explained below, we also use three-month futures contracts from both exchanges, so the results are not affected by issues that may arise for contracts that are nearing maturity. Second, we analyze the regular session and the night trading session at the SHFE and find that the dynamics of the realized volatility differ in both sessions. With the additional NTS, the break between the regular SHFE session and the NTS—labeled the *evening break*—is shown to have significant informational content, so we demonstrate that failing to treat the evening break separately for jump estimation purposes may introduce a jump bias. Third, we find that the realized volatility of LME futures is a major driver of the realized volatility of Copper in the NTS. In contrast, Aluminum trading volume has surged in recent years, and realized volatility seems to be driven mainly by local factors, with the LME volatility playing only a negligible role.

The remainder of this paper is organized as follows. The methodology and intraday separation of returns are outlined in Section 2. Data and preliminary analyses are presented in Section 3. Section 4 discusses the estimation results and Section 5 summarizes the main findings and concludes this article.

³A line of literature has used intraday data for volatility forecasting of the SHFE’s industrial metal futures with heterogeneous autoregressive (HAR) models (e.g. Zhu et al., 2017, Zhang et al., 2018, Gong & Lin, 2018). These studies did not address the introduction of NTS.

2. Methodology

2.1. Intraday returns and separation of the night trading session

The empirical analysis uses intraday data and starts with a comprehensive overview of return and trading dynamics before and after the launch of NTS. The trading hours at the LME and the SHFE, including the NTS, are visualized in Figure 1.

Intraday returns $r_{j,t}$ on day t are defined as the log difference of two consecutive prices,

$$r_{t,j} = \log P_{t,j} - \log P_{t,j-1}, \text{ for } j = 2, \dots, M, \quad (1)$$

where M denotes the number of intraday prices and $t = 1, \dots, N$. Here, we use prices sampled at five-minute frequencies, which is discussed further in Sec. 3. Analogously, an open-to-close return over a particular trading session is defined as the log difference of the closing and opening prices of this trading session.

This return describes only the price changes during active trading hours.⁴ The closing price of the last trading session of trading day $t - 1$, and the opening price of the current day t yield the overnight return r_t^{ON} , defined as

$$r_t^{\text{ON}} = \log P_{t,\text{open}} - \log P_{t-1,\text{close}}. \quad (2)$$

Before the introduction of night trading, the close-to-close return r_t^{cc} is calculated for $t = 2, \dots, N$ as

$$r_t^{\text{cc}} = \log P_{t,\text{close}} - \log P_{t-1,\text{close}}. \quad (3)$$

Using the SHFE's additional NTS beginning on December 20, 2013, which runs from 13:00 GMT to 17:00 GMT (21:00 to 1:00 CST), we undertake a further decomposition of the returns. Ignoring the gap between the end of the regular session at 7:00 GMT (15:00 CST) and the beginning of the NTS at 13:00 GMT (21:00 CST) would lead to including an implicit jump in the intraday returns, which may yield positively biased jump components and lead to spurious inferences in statistical analyses. Therefore, similar to an overnight return, we define an SHFE-specific evening break return, r_t^{EB} , which is calculated as

$$r_t^{\text{EB}} = \log P_{t,\text{open}}^{\text{nts}} - \log P_{t,\text{close}}^{\text{reg}}, \quad (4)$$

where $P_{t,\text{open}}^{\text{nts}}$ is the opening price of the NTS starting at 13:00 GMT (21:00 CST), and $P_{t,\text{close}}^{\text{reg}}$ is the closing price of the regular session, ending at 7:00 GMT (15:00 GMT). Consequently, we obtain two returns covering the open market sessions, $r_t^{(1)}$ and $r_t^{(2)}$, for

⁴The SHFE has a lunch break between 11:30 and 13:30 CST that is strictly observed, so the daily trading session comprises four hours of active trading: from 09:00 to 11:30 and from 13:30 to 15:00 China Standard Time (CST). Since the lunch break is not subject of this study, we define the regular daily trading session from 09:00 to 15:00 CST, disregarding this suspension of trading.

the regular day-time session and the NTS, respectively. In the notation of Eq. (1), we then obtain

$$r_t^{(1)} = \sum_{j=1}^K r_{t,j} = \log P_{t,\text{close}}^{\text{reg}} - \log P_{t,\text{open}}^{\text{reg}}, \quad \text{and} \quad r_t^{(2)} = \sum_{j=K+1}^M r_{t,j} = \log P_{t,\text{close}}^{\text{nts}} - \log P_{t,\text{open}}^{\text{nts}}, \quad (5)$$

where K is the last index of intraday returns within the regular trading hours. It holds that $K \leq M$, as the NTS is occasionally not carried out, such as when the following day is a bank holiday. Therefore, the daily close-to-close return is comprised of four components,

$$r_t^{\text{cc}} = r_t^{\text{ON}} + r_t^{(1)} + r_t^{\text{EB}} + r_t^{(2)}, \quad (6)$$

which are analyzed separately below.

Analogously, the daily trading volume v_t is also decomposed into the trading volume during the regular session, $v_t^{(1)}$, and the trading volume during the NTS, $v_t^{(2)}$, which yields the total daily volume $v_t = v_t^{(1)} + v_t^{(2)}$.

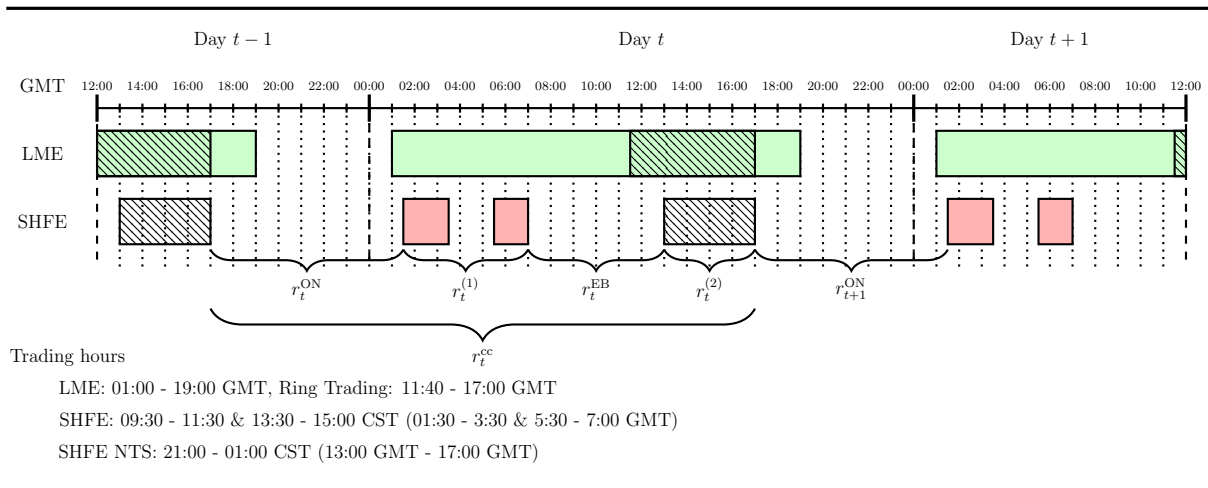


Figure 1: Trading hours of LME and SHFE on weekdays, including the night trading session (since December 20, 2013) in GMT.

2.2. Realized volatility

The daily realized volatility on day t , denoted RV_t , is widely estimated in literature as the sum of squared intraday returns.⁵ Like Eq. (5), we calculate the realized volatility for the regular and NTS separately:

$$RV_t^{(1)} = \sum_{j=1}^K r_{t,j}^2 \quad \text{and} \quad RV_t^{(2)} = \sum_{j=K+1}^M r_{t,j}^2.$$

⁵Similar to the majority of related studies, the terms 'variance' and 'volatility' are used interchangeably throughout the text.

For non-trading periods, the corresponding squared returns, $(r_t^{\text{ON}})^2$ and $(r_t^{\text{EB}})^2$ are used as proxies of the volatility.⁶ As in Todorova et al. (2014), Todorova (2015), Zhu et al. (2017), we decompose the daily realized volatility into intraday volatility during actively traded hours and overnight or trading break volatilities which are proxied by squared returns. Summing the individual components over a 24h hour period yields the 24h realized volatility,

$$RV_t^{(24)} = (r_t^{\text{ON}})^2 + RV_t^{(1)} + (r_t^{\text{EB}})^2 + RV_t^{(2)}. \quad (7)$$

2.3. Heterogeneous Autoregressive Models

To model the realized volatility of the regular session, $RV_t^{(1)}$, the NTS, $RV_t^{(2)}$, and the 24-hour volatility, RV_t^{24} , we begin with a simplistic heterogeneous autoregressive (HAR) model version for each component given in Eq. (8.1), (9.1), and (10.1) below. This HAR specification follows the standard definition of Corsi (2009) and puts the realized volatility over a future period $t + 1$ in relation to the asset's average realized volatility on the last day, the last week, and the last month, respectively, with an unpredictable error term ε_t . Weekly and monthly components are daily averages of realized volatility over the corresponding periods of five or twenty-two trading days. The HAR model effectively depicts short and long memory in realized volatilities and is popular in the recent literature.⁷ The HAR model has been shown to capture volatility transmission across various markets in the context of LME industrial metals (Todorova et al., 2014).

For the regular session, the simple HAR is estimated for the periods before and after the introduction of the NTS,⁸ so, we obtain two sets of estimates for Eq. (8.1),

$$RV_{t+1}^{(1)} = \beta_0 + \beta_1 RV_t^{(1)} + \beta_2 RV_{t-5,t}^{(1)} + \beta_3 RV_{t-22,t}^{(1)} + \varepsilon_t. \quad (8.1)$$

To determine what influence the previous day has on the regular session's volatility, we include the evening break as well as the realized volatility of the immediately preceding NTS,

$$RV_{t+1}^{(1)} = \beta_0 + \beta_1 RV_t^{(1)} + \beta_2 RV_{t-5,t}^{(1)} + \beta_3 RV_{t-22,t}^{(1)} + \beta_4 RV_t^{(2)} + \beta_5 (r_t^{\text{EB}})^2 + \varepsilon_t. \quad (8.2)$$

Next, we replace the evening break and the NTS's volatility with the previous days'

⁶The lunch break is not separately accounted for, and the price change during this halt in trading is treated as a regular intraday return.

⁷The standard HAR is augmented and modified to account for different stylized facts, such as jumps (e.g. Barndorff-Nielsen, 2004, Andersen et al., 2007), separation in continuous and non-continuous RV components (e.g. Patton & Sheppard, 2015), realized semi-variances (e.g. Patton & Sheppard, 2015), among many others, and has also been applied successfully to the Chinese industrial metal futures markets (e.g. Zhang et al., 2018, Gong & Lin, 2018). A broad overview of HAR specifications can be found in, for example Sévi (2014).

⁸For reasons of parsimony, we do not include $(r_t^{\text{ON}})^2$ in these HAR variants as estimates are insignificant before and after the introduction of NTS. These results are available on request.

realized volatility on the LME, RV_t^{LME} to determine the influence of the LME on the regular SHFE session,

$$RV_{t+1}^{(1)} = \beta_0 + \beta_1 RV_t^{(1)} + \beta_2 RV_{t-5,t}^{(1)} + \beta_3 RV_{t-22,t}^{(1)} + \beta_4 RV_t^{\text{LME}} + \varepsilon_t. \quad (8.3)$$

For the NTS, we again begin with the simple HAR to identify internal dependencies and long memory,

$$RV_{t+1}^{(2)} = \beta_0 + \beta_1 RV_t^{(2)} + \beta_2 RV_{t-5,t}^{(2)} + \beta_3 RV_{t-22,t}^{(2)} + \varepsilon_t. \quad (9.1)$$

This simple HAR is then augmented with the regular session's realized volatility and that of the same day's evening break,⁹

$$RV_{t+1}^{(2)} = \beta_0 + \beta_1 RV_t^{(2)} + \beta_2 RV_{t-5,t}^{(2)} + \beta_3 RV_{t-22,t}^{(2)} + \beta_4 RV_{t+1}^{(1)} + \beta_5 (r_{t+1}^{\text{EB}})^2 + \varepsilon_t. \quad (9.2)$$

As we did with the regular session, we replace the evening break with the realized volatility of the LME during that break only¹⁰ to directly measure the impact of the LME on the evening break's volatility at SHFE:

$$RV_{t+1}^{(2)} = \beta_0 + \beta_1 RV_t^{(2)} + \beta_2 RV_{t-5,t}^{(2)} + \beta_3 RV_{t-22,t}^{(2)} + \beta_4 RV_{t+1}^{(1)} + \beta_5 RV_{t+1}^{\text{LME-EB}} + \varepsilon_t. \quad (9.3)$$

For the daily realized volatility $RV^{(24)}$, we carry out a standard HAR for the period before and after the introduction of the NTS,

$$RV_{t+1}^{(24)} = \beta_0 + \beta_1 RV_t^{(24)} + \beta_2 RV_{t-5,t}^{(24)} + \beta_3 RV_{t-22,t}^{(24)} + \varepsilon_t. \quad (10.1)$$

This HAR is augmented with the LME's daily realized volatility to account for the LME's possible influence on the daily realized volatility, including all breaks,

$$RV_{t+1}^{(24)} = \beta_0 + \beta_1 RV_t^{(24)} + \beta_2 RV_{t-5,t}^{(24)} + \beta_3 RV_{t-22,t}^{(24)} + \beta_4 RV_t^{24,\text{LME}} + \varepsilon_t. \quad (10.2)$$

All models are estimated with White's adjusted heteroscedasticity-consistent least-squares regression (White, 1980).

2.4. Detection and estimation of intraday jumps

While keeping the realized volatility models as simple as possible, we address jumps separately. We show that ignoring the evening break introduces a positive jump bias. We calculate jumps with the bi-power variation (BPV) as introduced by Barndorff-Nielsen

⁹While this approach makes forecasting for the next day unfeasible, we seek to explain the volatility behaviour of the NTS.

¹⁰To that end, the LME's RV is calculated for the time slot from 07:00 to 13:00 GMT.

(2004),

$$BPV_t = \mu_1^{-2} \left(\frac{M}{M-1} \right) \sum_{j=1}^{M-1} |r_{t,j}| |r_{t,j+1}|.$$

We follow the jump detection approach of Huang & Tauchen (2005) and calculate the jump component $J_{t,\alpha}$ as

$$J_{t,\alpha} = I_{\{Z_t > \Phi_\alpha\}} (RV_t - BPV_t) \quad (11)$$

with

$$Z_t = \sqrt{M} \frac{1 - BPV_t \cdot RV_t^{-1}}{\sqrt{(\mu_1^{-4} + 2\mu_1^{-2} - 5) \max(1, TQ_t \cdot BPV_t^{-2})}}$$

and $\mu_1 = \mathbb{E}(Z) = \sqrt{2/\pi}$. The tri-power quarticity TQ_t is defined as

$$TQ_t = M \mu_{4/3}^{-3} \sum_{j=1}^{M-2} |r_{t,j}|^{4/3} |r_{t,j+1}|^{4/3} |r_{t,j+2}|^{4/3},$$

where $\mu_p = 2^{p/2} \cdot \Gamma(1/2 \cdot (p+1)) \cdot \Gamma(1/2)$. If $\alpha = 0.5$, Eq. (11) is equivalent to the jump detection in Barndorff-Nielsen (2004).¹¹

As the previously defined jump measure is not robust to very small or very high jumps or jump-like intraday returns (e.g. a non-separated evening break), Andersen et al. (2012) proposed *median RV* measures. We use the following definition as an additional robustness check for jumps estimation,

$$MedRV_t = \frac{\pi}{6 - 4\sqrt{3} + \pi} \frac{M}{M-2} \sum_{j=2}^{M-1} \text{med}(|r_{t,j-1}|, |r_{t,j}|, |r_{t,j+1}|)^2,$$

then

$$J_{t,\alpha}^{MedRV} = I_{\{Z_t^{MedRV} > \Phi_\alpha\}} (RV_t - MedRV_t),$$

with

$$Z_t^{MedRV} = \sqrt{M} \frac{1 - MedRV_t \cdot RV_t^{-1}}{\sqrt{0.96 \max\{1, MedRQ_t \cdot MedRV_t^{-2}\}}},$$

$$MedRQ_t = \frac{3\pi}{9\pi + 72 - 52\sqrt{3}} \frac{M}{M-2} \sum_{j=2}^{M-1} \text{med}(|r_{t,j-1}|, |r_{t,j}|, |r_{t,j+1}|)^4.$$

We report $J_{t,\alpha}$ and $J_{t,\alpha}^{MedRV}$ for $\alpha = 0.99$ with and without separating the evening break to demonstrate the importance of a separate break that is similar to an overnight period.

¹¹Setting $\alpha = 0.5$ implies $Z_t > 0$ which is the case when $RV_t > BPV_t$.

3. Data

We obtain five-minute futures price data¹² and volumes for the SHFE's and the LME's futures contracts on Copper and Aluminum from the Thomson Reuters Tick History database at the Securities Industries Research Centre of the Asia Pacific (Sirca). In the case of the Chinese futures, we roll the futures contracts to the next most liquid month when the daily trading volume of the current contract is exceeded. As a result, we usually use intraday data from three-month futures contracts, which are very liquid (e.g. Zhang 2018). As the LME trades three-month futures contracts on Aluminum and Copper, the exchange's most frequently traded contracts, every day, this study uses the LME's three-month contracts.

Our sample period spans January 4, 2010, to May 21, 2018, yielding $N=2,035$ observation days. The sample period is split on December 20, 2013, the day the SHFE introduced the NTS for futures contracts of Copper and Aluminum, along with other commodities. Prior to the NTS, we record approximately $\bar{M} = 48$ five-minute price observations per day for the SHFE, and with the NTS, this number increases to $\bar{M} = 95$ intraday data records. The additional NTS is suspended if the following day is a holiday, while the regular session is traded. The number of observations for Aluminum is only insignificantly different. A detailed overview of daily and intraday observations is given in Table 1. The SHFE's prices for Copper and Aluminum are given in RMB/ton, and the contract size is set at five tons.¹³ The LME's prices are denominated in USD/ton, and the contract size is set at twenty-five tons.¹⁴

Table 1 approximately here.

Figure 2 plots the daily closing prices for Copper and Aluminum futures. As a general observation, prices declined between 2011 and 2016 and increased again from 2016 to mid-2017. Aluminum in particular showed severe losses in late 2017 and the beginning of 2018, which can be directly linked to the tense relationship between China and the US because of the US's imposed and announced tariffs on imports of steel and base metals from China (and the rest of the world, for that matter).

Descriptive statistics on the intraday returns defined in Eq. (6) and visualized in Figure 1 are given in Table 2 for Copper and in Table 3 for Aluminum. As their development in our sample period is a key element of the analysis of the NTS, a detailed breakdown follows in the next section.

We process the raw data of SHFE volumes. The SHFE trading volume data on futures contracts are double-side counted, recording volume for the long and corresponding short transaction separately and summing both in the five-minute data provided. We account

¹²We use the open and close prices of five-minute price intervals.

¹³Additional details on contract specifications can be found in Fan & Zhang (2018).

¹⁴To avoid additional volatility emerging from foreign exchange markets, we do not incorporate the effects of foreign exchange rates into our calculations of returns on the LME.

for this reporting when we compare the SHFE’s and the LME’s volume data.



Figure 2: Prices of Copper and Aluminum futures contracts from January 4, 2010 to May 21, 2018

Table 2 and 3 approximately here.

4. Results: What has changed with the introduction of the night trading session?

This section discusses our analysis of the impact of introducing an additional trading period at the SHFE. First, we focus on intraday returns and their decomposition to determine how the SHFE’s futures markets changed with the integration of a trading session that is synchronized with the LME’s and the COMEX’s main trading hours, in addition to the regular session. Second, we address the development of trading volumes to explore the importance of this new trading session in particular and the maturing of the SHFE in general. Finally, we study the realized volatilities of the separate trading sessions and their interconnectedness to explain whether Chinese metal futures’ volatility is driven by endogenous or exogenous factors. We finish with a note on jump estimation.

4.1. Intra-day return decomposition: on overnight and evening breaks

We follow the return decomposition introduced in Eq. (6) and compare descriptive statistics of the components which are presented in Table 2 for Copper and Table 3 for Aluminum.¹⁵ Box plots for these returns are visualized in Figure 3 and Figure A.7 for Copper and Aluminum, respectively. Our subsamples are labeled T_1 for the period from January 4, 2010 to December 19, 2013 and T_2 for the period after the introduction of the NTS running from December 20, 2013 to May 21, 2018.

¹⁵Since the focus of this study is on Chinese industrial metal futures markets, no corresponding descriptive statistics are reported for the LME returns and realized volatilities for the sake of brevity. These statistics are available on request.

We begin with the overnight return r_t^{ON} , defined in Eq. (2), which refers to the return between the closing price of the last traded five-minute block of the previous day and the opening price of the current day.¹⁶ In T_1 , the overnight return has the highest spread of outliers, ranging from -6.73 percent to 6.42 percent in the case of Copper. This range indicates that there are comparatively large overnight jumps and exogenous price shocks during the time that the SHFE is not open for trading. After the introduction of the NTS, these previously volatile overnight returns became virtually non-existent in T_2 . There are several possible explanations for the vanishing of $r_{T_2}^{\text{ON}}$, the most likely of which is that the LME is closed during those hours as well (Figure 1). These negligible overnight returns also indicate that the Chinese markets are not influenced to a significant extent by regular arrivals of news from other sources.

If there are no longer news effects or jumps during the SHFE's overnight period, does news arrive exclusively during traded hours? The evening break period provides clear evidence that such is still not the case, as we find that returns from the evening break, $r_{T_2}^{\text{EB}}$ are significantly different from zero. Furthermore, these returns are much more distinctive than the overnight returns in $r_{T_2}^{\text{EB}}$ are much more distinctive than the overnight returns in T_2 , as the mean and median are highly negative and are abnormal compared to those of T_1 or T_2 returns of the overnight, regular, or close-to-close periods. Therefore, there are pronounced news arrivals and jump effects between the regular session and the night session; the previously significant overnight price movements are simply transferred to the evening break after the regular session and before the NTS. A possible explanation for this is the ring trading session at the LME, which starts almost two hours before the NTS at the SHFE begins.

In this section, we identified several noteworthy effects of the introduction of NTS. First, classical overnight returns at the SHFE vanish almost completely, and the NTS of the previous day dictates the opening price of the current day, absent exogenous disturbances like news or contagion effects from other markets. Second, extreme movements during trading sessions are reduced in magnitude and numbers, perhaps because of a more evenly distributed trading time, where the NTS is synchronized with the LME's major trading hours. Third, the evening break has relatively large returns and now acts as the most important overnight period in terms of linking trading periods at the SHFE when other markets are actively trading. The magnitude of this evening break's returns underscores the necessity to treat it separately, as the literature is doing with overnight returns for major developed markets because returns during trading and non-trading market times have different dynamics (e.g., Andersen et al., 2011; Bertram, 2004; Todorova & Soucek, 2014).

¹⁶With the NTS, the overnight return is that between the NTS's closing price and the regular session's opening price, even though the NTS ends at 1:00 a.m. local time.

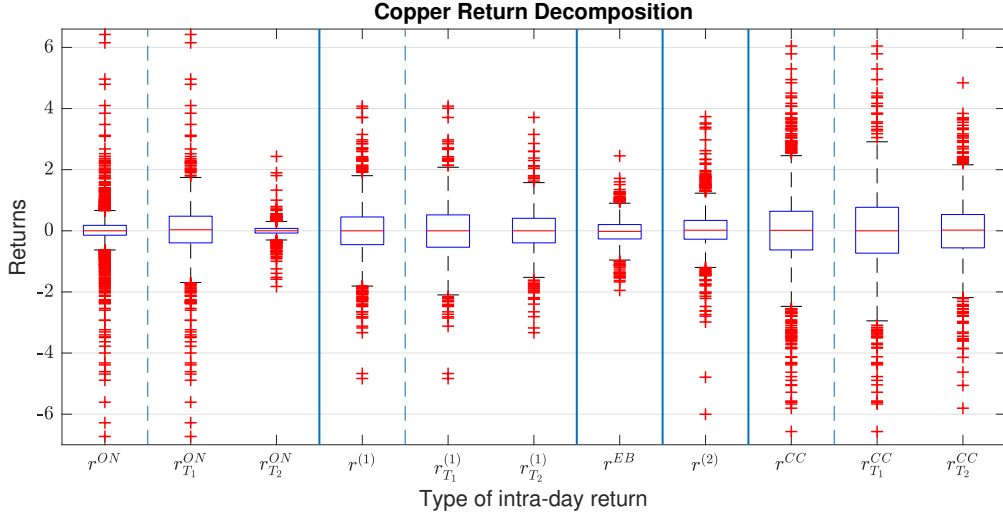


Figure 3: Box plots of different intraday components for Copper following the decomposition in Eq. (6). Different disjoint periods are denoted by T_1 and T_2 which refer to the observations before (January 4, 2010 to December 19, 2013) and after (December 19, 2013 to May 21, 2018) the introduction of the NTS, respectively; yielding $n_1 = |T_1| = 959$ and $n_2 = |T_2| = 1076$ observations. The full sample of $n = 2035$ observations is plotted for r^{ON} , $r^{(1)}$, and r^{CC} . For r^{EB} and $r^{(2)}$, which are defined for T_2 only, we omit the index.

4.2. Trading volumes: Has the SHFE become more attractive for traders with the introduction of the night trading session?

Copper volumes of the most liquid (3-month) futures contracts are plotted in Figure 4. With the introduction of the NTS, the plot distinguishes among total volume ($v_{T_2}^{total}$), the volume in the regular session ($v^{(1)}$), and the volume in the NTS ($v^{(2)}$). How the originally reported volume evolves throughout our sample has several notable features.

First, sudden jumps in volume before the introduction of the NTS are present but are relatively infrequent, and if volume increases suddenly, it remains elevated for some time, suggesting some persistence. With the NTS, these volume spikes appear more frequently but are more short-lived, spanning only a few trading days. Second, the volume of the NTS was low compared to the regular session in the first year after being introduced to the SHFE. From 2015 on, the regular session's and the NTS's volumes are similar such that, if an abnormally high trading volume is observed in the regular session, the NTS also shows abnormally high trading volumes.

Unreported in this paper in detail is that the regular session's and NTS's volumes are almost perfectly correlated on daily resolution. This phenomenon reinforces that the appearance of sudden, short-lived volume spikes in the regular session is mirrored in the night session, yielding very high total daily volumes. The spikes often occur at intervals of around twenty-two and forty-four trading days, so they are connected to roll-over effects. Overall, the trading volume after introducing the NTS appears to be much more volatile than before, and the NTS may be seen as a contributing factor to these higher deviations in volume.

We focus on the SHFE's and the LME's daily volumes to compare the development

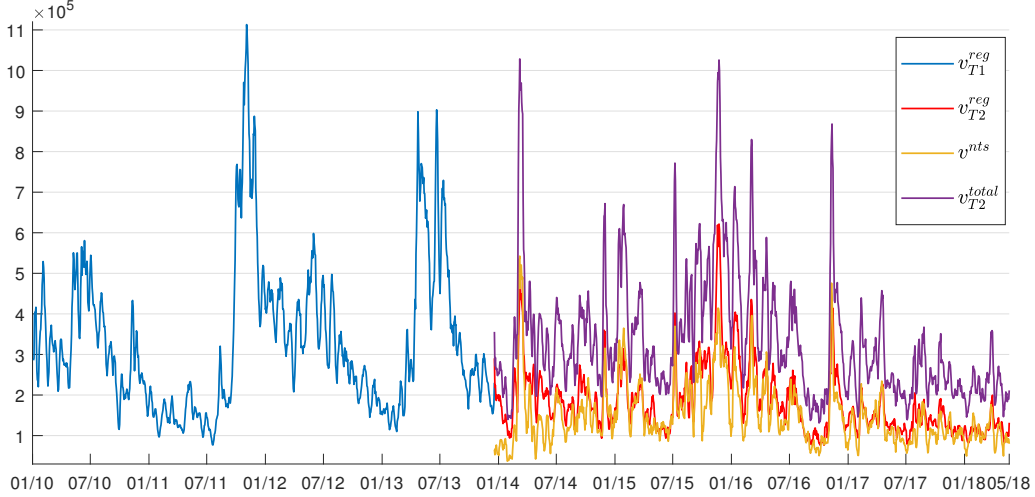


Figure 4: Volume of Copper SHFE futures decomposed to the respective components and smoothed by an MA(5). Different disjoint periods denoted by T_1 and T_2 are identical to the previous figures.

of traded volumes in global Copper futures markets, We adjust the trading volume for the differing contract sizes (SHFE’s 5 tons vs LME’s 25 tons per contract), as well as the SHFE’s double-side count in terms of long and short positions in 3-month futures contracts, yielding the comparable volume measures that are plotted in Figure A.8. We find no indications that the introduction of the NTS attracted investors who would otherwise trade at the LME, as volumes at the LME did not decrease; on the contrary, there was a slightly upward trend in trading volume at the LME. If we observe spikes in the LME’s daily volumes, they are also observed during the SHFE’s NTS. The SHFE’s volumes are much more volatile, underscoring the speculative nature of Chinese investors. Adding to the speculative character of the SHFE, we also observe a significant difference in trade size, defined as volume per trade, between the regular session and the NTS. Albeit of similar overall trading volume, the volume per trade is between 20 and 25 percent smaller during the NTS than it is during the regular session.

The volume per trade over each session on daily resolution, which is visualized in Figure 5, suggests that retail investors are more active in the NTS and that, given the correlated trading volume, some positions are opened in the regular session and closed later in the NTS. This finding is in line with the documented speculative activity, most of which is conducted through high-frequency transactions (e.g., Liao et al., 2016, Wellenreuther & Voelzke, 2019). Furthermore, the volume per trade decreases sharply throughout the NTS, which is plotted for thirty-minute blocks of the NTS in Figure 5. Trade sizes are lowest in the later hours, and trade values average around USD 80,000-120,000, too low to be considered purely institutional trades that are present in each thirty-minute block, as indicated by large outliers. Volume per trade is negatively correlated with Copper prices, which is further indication for the significant involvement of small investors that is of a primarily speculative nature. Unreported in detail here, the open interest in the

SHFE-specific counting underlines this conjecture by featuring highly volatile day-to-day changes.

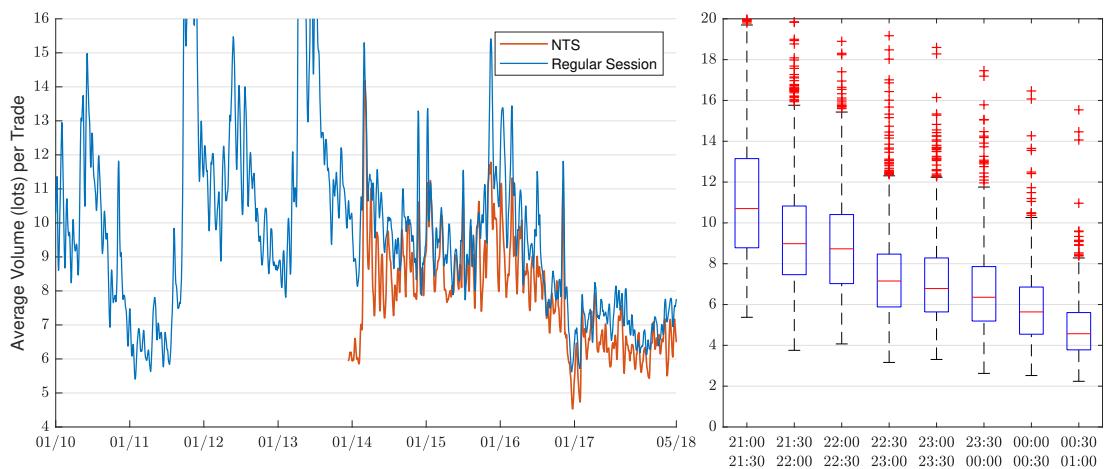


Figure 5: *Left*: Volume per trade, averaged for each session and in number of lots (one lot translates to 5 tons), for Copper futures contracts during the regular session (blue) and the night trading session (orange). *Right*: Quartiles of volume per trade (in lots) for 30-minute blocks of the NTS.

Trading volumes for Aluminum are plotted in Figure 9 with an identical decomposition. In this case, the daily trading volume is differs from that of Copper. Between 2012 and 2013, volumes were low, and contracts were only thinly traded. In Q4 2015, trading of Aluminum futures picked up with significant jumps in volume. From this point of time on, trading volumes exhibited a magnitude comparable to that of Copper futures. In Q4 2015, the market underwent a major change. Since the SHFE reflects domestic speculative activity far more it does than international industrial hedging, the surge in trading volumes was largely driven by retail investors in China seeking trading opportunities because of the government’s interventions in the Chinese stock markets (e.g., Home, 2018).

Overall, we observe a change in the distribution of daily trading volumes. While total trading volumes remain comparable between pre-NTS periods and NTS periods, the volume of the regular session is more than halved, so it appears that trading volume simply migrates from the regular session to the NTS; we find no evidence that trading volume is pulled from the LME to the SHFE. In addition, it appears that the increased trading volume reflects mostly domestic speculative activity rather than international industrial hedging, so the increased variability in the SHFE’s trading activity might be due to Chinese speculators becoming more active with an additional, synchronized trading session that allows them to trade immediately on news arrivals during the night. Finally, Aluminum markets are in transition, and trading volume increased in late 2015, which was not linked to the introduction of the NTS.

4.3. Realized volatilities: What drives the separated trading sessions?

Descriptive statistics of the realized volatility measures are given in Table 2 and Table 3 for Copper and Aluminum, respectively. For Copper, we find that the 24h realized volatility, as the sum of all intraday components, decreased after the NTS was introduced. The regular session's realized volatility declined by almost 40 percent on average and in relative terms. Similar to the returns of the NTS and the evening break period, we find that RV_t^{ON} is small, while RV_t^{EB} is significantly larger. The NTS's average realized volatilities are similar to those of the regular session, but their maximum, standard deviation, skewness, and kurtosis indicate a much broader dispersion with more extreme values than those of the regular session. The NTS is characterized by higher intraday movements than those of the regular session, suggesting that the daytime trading session's and the NTS's volatility behavior differs and may have differing drivers.

Moving to the HAR model estimations with Eq. (8.1)-(10.2), we detect several changes with the introduction of the NTS. The estimation results, adjusted R^2 , and error measures for Copper are given in Table 4. We focus first on the realized volatility of the regular trading session, $RV_t^{(1)}$. Comparing the estimates of the basic HAR of Eq. (8.1) of the period before and after the introduction of the NTS reveals that the medium to long memory, measured by β_2 and β_3 , decreases in significance. In the second period, the previous day's realized variance becomes much more important, with a significant load of $\beta_1 = 0.3600$, while the parameters of the weekly and monthly realized variance decrease. Augmenting the base HAR with the evening break and the realized volatility of the NTS of the previous day shows the long memory decreasing farther, driven largely by the previous NTS's realized volatility. We also note that the R^2 increases significantly when the NTS is included. The previous day's evening break is not significant. If we replace the previously augmented factors with the LME's realized daily volatility, we observe similar effects regarding the long memory and the goodness-of-fit, although they are slightly lower. The only significant components are the LME factor and the regular session's weekly realized volatility.

Second, the basic HAR using only daily, weekly, and monthly historical volatilities in Eq. (9.1) is a poor fit for the realized volatility of the NTS formalized in $RV_t^{(2)}$ in terms of the regression's explanatory power. Considering that the NTS follows the regular session on the same day, we control for intraday movements that may affect the realized volatility on a larger scale. We use the regular session's volatility of the same day ($RV_{t+1}^{(1)}$), as well as the same day's evening break to cover this news arrival in Eq. (9.2) and find that NTS-specific regressors (daily, weekly, and monthly $RV^{(2)}$) are no longer significant. However, the evening break and the regular session of the same day are highly significant, suggesting that there is less variance memory in the NTS, as neither short-, medium-, nor long-term memory is present in the NTS. The impact of news during the evening break appears to be the most pronounced driver of $RV^{(2)}$. To find the source of this impact, we replace the

evening break with the LME’s realized variance during these break hours only, denoted $RV_{t+1}^{\text{LME-EB}}$, in Eq. (9.3). The goodness of fit increases from 0.1825 in the base model to 0.4028 in the current modification. The LME’s volatility factor has an exceptionally high load of $\beta_5 = 0.7984$ and is significant, as is the regular session’s RV , indicating that the NTS is driven primarily by this exogenous, short-term variance in the LME, which is observed during the immediately preceding non-traded hours. As this data is of the same day, forecasting model Eq. (9.3) is no longer as straightforward as other specifications, and we find no indication that the realized variance of the NTS of the previous day or any other horizon plays a role.

Finally, we compare the findings for the sum of all daily realized variance components in $RV_t^{(24)}$ in Eq. (10.1) which includes the high overnight return RV_t^{ON} before introduction of the NTS, as described in Sec. 4.1. The basic HAR achieves a poor fit in the pre-NTS period, but the fit changes for the second period, perhaps because of the reduced impact of unexpected jumps in the overnight return that have moved to the evening break, and the subsequent trading reaction to these jumps in the NTS. We find a strong immediate reaction to the previous day’s daily realized variance and declining significance for longer horizons, a finding that remains when we augment the daily volatility with the LME’s daily realized variance of the previous day in Eq. (10.2), where this factor is not significant.

Table 4 approximately here.

The estimation figures for Aluminum futures, given in Table 5 show that the results for the regular session are comparable to those for Copper. The realized variance from the immediately preceding NTS has a significant impact on the regular session. In contrast to Copper, historical weekly and monthly volatilities are significant for Aluminum. Replacing the NTS with the LME’s volatility decreases the fit and does not result in the LME having a significant impact. The realized volatility of the regular session of the same day appears to be the strongest driver of the immediately following NTS. In contrast, neither the evening break nor the realized volatility estimate for the corresponding LME contract has a significant impact. The same holds for the 24-hour realized variance $RV_t^{(24)}$ (Eq. 10.1).

These results corroborate the findings regarding the increased trading volume in the SHFE’s Aluminum futures. The Aluminum futures market in China seems to have become a popular venue for speculative activities, so the market volatility in the NTS or over a 24-hour period is driven mostly by the own volatility dynamics, with less improvement in explanatory power when the LME’s realized volatility is included in the regressions.

Table 5 approximately here.

Overall, we find that the behavior of realized volatility differs before and after the introduction of the NTS, so there are grounds for labeling this event a change point in volatility behavior. For Copper, the regular session becomes more predictable based on its own short-term history and the realized variance of the previous NTS. The newly introduced NTS is driven primarily by intraday factors: the regular session’s realized

variance, the subsequent break in the same day, and most important, the LME’s realized variance during that break. This evidence indicates that there is a strong spillover effect from the LME to the SHFE’s NTS Copper markets. The once-important overnight period shrinks from 18.5 hours to 8.5 hours of no trading activity and is replaced by the evening break, with the LME as the main contributor of news impact on the SHFE. It appears that the regular session is an isolated session for Chinese investors and hedgers, with some degree of medium-range memory, while the NTS is driven primarily by the LME and short-term movements. For Aluminum, we find no evidence that the LME spills over to the SHFE, as Aluminum futures seem to be affected mainly by local news and less by the volatility coming from the LME.

4.4. On the severity of ignoring paused trading and the evening break

Extant research has usually separated the overnight break from intraday price movements for the purposes of volatility estimation and forecasting. Our findings and discussion suggest that the NTS should be separated in cases that are specific to the SHFE, as its dynamics are more significant than the overnight period. As we identified the differences in volatility behavior beginning in late December 2013 with basic HAR models, we do not use more sophisticated HAR-specifications that include jumps. However, we briefly demonstrate the impact on jump components of not treating the NTS as a separate period. In particular, the models affected are HAR-CJ (Andersen et al., 2007), LHAR-CJ (Corsi & Renò, 2012), or HAR- Δ J (Patton & Sheppard, 2015), which split the realized variance into a continuous component and a jump component or include jump measures in the HAR framework. In what follows, we calculate this jump component according to the definition of Eq. (11) for the case of no separation ($J_{t,\alpha}^{no-sep}$) and separately for the regular session and the NTS (as the daily sum of intraday jumps $J_{t,\alpha}^{reg} + J_{t,\alpha}^{NTS}$). We repeat these calculations for the *MedRV* measure of Andersen et al. (2012). The results are visualized in Figure 6 for both types of measures for Copper futures.

Figure 6 makes clear that neglecting to separate the evening break yields more pronounced jump components and indicates jumps during trading hours where there are none. Of course, some jumps remain during the regular session’s and the NTS’s trading hours, but these are less regular than without separation. This effect holds for both measures, but it becomes more obvious when the *MedRV* measure is used, as it is more robust to very small and very high jumps. With the separation, far fewer jumps are detected, so ignoring the evening break as such introduces a positive jump bias. Subsequently, models that cover jumps separately (e.g. the HAR-CJ) are likely to yield more significant (in both magnitude and statistical significance) jump components, which might lead to spurious conclusions based on non-existent jumps.

These findings have several practical implications. Risk management that is based on forecasts of realized volatilities is affected if the two trading sessions are not separated.

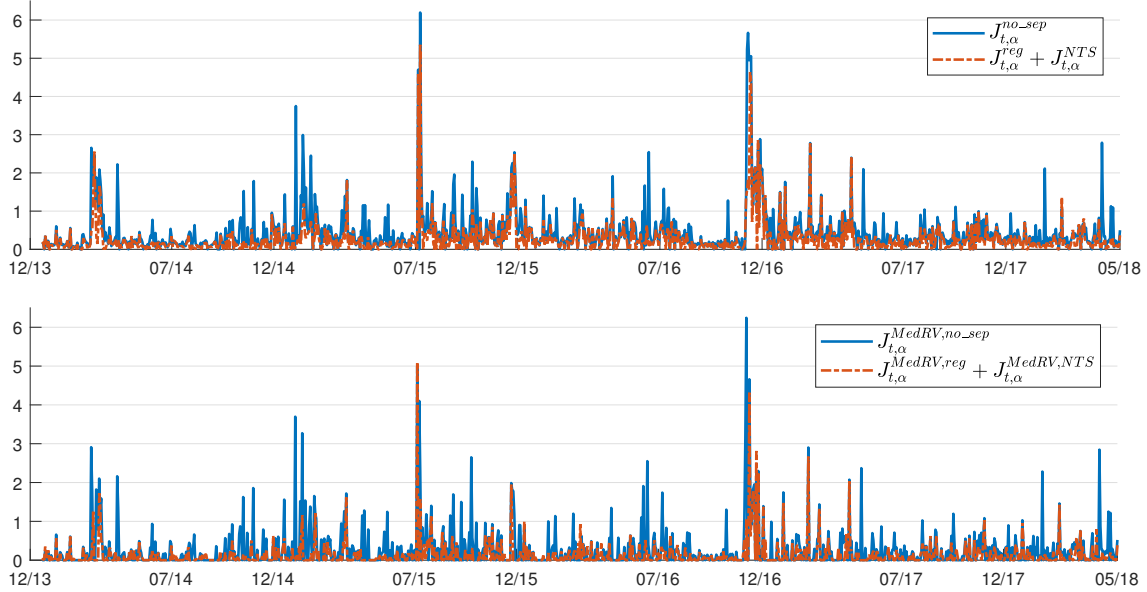


Figure 6: *Top*: Jump components without separating the evening break ($J_{t,\alpha}$, blue) and as sum of the jump components of the regular session ($J_{t,\alpha}^{reg}$) and the NTS ($J_{t,\alpha}^{NTS}$) with separation of the evening break (red). *Bottom*: Analogous plot with a jump detection based on the median RV ($MedRV$) approach of Andersen et al. (2012).

Forecasting volatility of intraday prices in the presence of jumps is a particular difficulty (Corsi & Renò, 2012, Degiannakis & Filis, 2017), especially over longer time horizons. Having a positive jump bias and subsequently an increased volatility premium might also affect the pricing of derivatives themselves.

The results for Aluminum futures prices are qualitatively the same in terms of biased jump detection if the evening break is not separated. For the sake of brevity, detailed results are not presented here but are available on request.

5. Conclusion

We focus on the introduction of an additional trading session at SHFE and its effects on trading volume and intraday price movements of Copper and Aluminum futures as well as its role in global markets. For Copper, volatility behavior changes are prominently in the end of 2013 and the NTS introduction causes a structural break. Previously of large magnitude, the overnight return vanishes and is replaced by an evening break, that has a strong impact on the volatility during the NTS. The synchronous trading with LME during the NTS reduces overnight jumps and news arrive either during the evening break or the NTS itself. The evening break is a significant factor for intraday movements and needs to be separated otherwise a jump bias is introduced. This is of high importance for research as modeling intraday data of futures markets becomes more and more popular.

Copper volatilities are largely affected by the LME, mainly in the NTS. On the other hand, the regular session depicts a short and medium-term memory and is driven by en-

ogenous elements. The LME seems to have only negligible impact on the regular session while it is an important exogenous driver for the NTS. There is no additional trading volume detected after the introduction of the NTS; the volume is simply split between regular session and the NTS. The LME on the other hand shows some increasing volume. Hence, there is no evidence that SHFE is pulling volume from the LME. Furthermore, the trading volume at SHFE is more volatile after the introduction of NTS, indicating that there might be a larger share of speculative investors exploiting the longer trading times. An indication for this is the fact that volumes of the NTS mirror those of the previous regular session which suggests that some positions are opened during the regular session and closed during the NTS. During the NTS, volume per trade is 20-25% smaller than in the regular session which underlines increased small investor activity in the late session.

In contrast, the Chinese Aluminum futures market seems to be more resistant against exogenous factors and show a pronounced long memory structure. The LME has no significant impact on either the NTS or the daily realized variance. Aluminum futures markets are in a transition with volume picking up significantly since late 2015.

Our findings also indicate that LME is the main driver of the evening break dynamics in the Chinese markets which could be exploited in a more encompassing HAR specifications. Future research could address jump models that incorporate the evening break in more detail.

In this study we only focus on Copper and Aluminum futures prices. However, those are not the only futures contracts that are traded in a separate night trading session at SHFE. Gold, Silver, Zinc, and since end of 2014 also Rebar Steel, Rubber, and Hot Rolled Coils amongst others are traded at night. Hence, all data on these futures are prone to a intraday gap between trading session. With this paper, we are the first to provide clear evidence that this gap needs to be handled accordingly, otherwise models based on realized volatilities such as HAR are compromised. Handling of this gap and the impact of the LME on the NTS and the evening break pose a challenge for future research.

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Tables

Panel A: Copper			
	Full Sample	Period 1 (T_1)	Period 2 (T_2)
Dates	01/04/2010 – 05/21/2018	01/04/2010 – 12/19/2013	12/20/2013 – 05/21/2018
n_{total}	148 554	46 298	102 256
\bar{M}	73.0	48.3	95.0
N	2 035	959	1 076
Panel B: Aluminum			
	Full Sample	Period 1	Period 2
n_{total}	144 976	44 263	100 713
\bar{M}	71.2	46.2	93.6
N	2 035	959	1 076

Table 1: Number of total intraday (n_{total}) and average daily intraday (\bar{M}) observations as well as number of observation days (N) for Copper and Aluminum for the full sample and the split sample analysis at the SHFE.

Descriptive Statistics									
Panel A: Period 1 (observations 1:959), January 4, 2010 – December 19, 2013									
	r_t^{ON}	$r_t^{(1)}$	r_t^{cc}	RV_t^{ON}	$RV_t^{(1)}$	RV_t^{EB}	$RV_t^{(2)}$	$v_t^{(1)}$	$v_t^{(2)}$
Mean	-0.0090	-0.0082	-0.0169	1.1553	0.8444	0.2014	0.5231	183.804	155.801
Median	0.0352	0.0000	0.0000	0.2025	0.5232	0.0591	0.3163	155.516	130.706
Minimum	-6.7285	-4.8326	-6.5687	0.0000	0.0000	0.0000	0.0250	55.156	28.692
Maximum	6.4241	4.0792	6.0452	45.2732	17.1618	6.0125	20.2038	782.738	1.069.344
Std	1.0754	0.9510	1.4411	3.7657	1.1063	0.4261	0.8550	98.921	98.220
Skewness	-0.5688	-0.0547	-0.2642	7.2699	6.0243	5.4148	13.1826	1.95	2.65
Kurtosis	11.5958	5.2567	5.7531	66.6639	64.5528	49.1622	277.5415	8.52	16.02

Panel B: Period 2 (observations 960:2035), December 20, 2013–May 21, 2018											
	r_t^{ON}	$r_t^{(1)}$	r_t^{EB}	$r_t^{(2)}$	r_t^{cc}	RV_t^{ON}	$RV_t^{(1)}$	RV_t^{EB}	$RV_t^{(2)}$	$v_t^{(1)}$	$v_t^{(2)}$
Mean	-0.0027	-0.0004	-0.0329	0.0365	0.0009	0.0562	0.5423	0.2014	0.5231	183.804	155.801
Median	0.0000	0.0000	-0.0285	0.0277	0.0222	0.0056	0.3543	0.0591	0.3163	155.516	130.706
Minimum	-1.8213	-3.3329	-1.9488	-6.0029	-5.8043	0.0000	0.0000	0.0000	0.0250	55.156	28.692
Maximum	2.4340	3.7082	2.4520	3.7365	4.8427	5.9242	7.7656	6.0125	20.2038	782.738	1.069.344
Std	0.2372	0.7187	0.4478	0.7514	1.1287	0.3013	0.6809	0.4261	0.8550	98.921	98.220
Skewness	0.6255	-0.0045	0.0724	-0.3301	-0.1614	12.2817	5.1958	5.4148	13.1826	1.95	2.65
Kurtosis	29.7467	5.5730	5.5185	11.4755	5.6771	187.4359	41.0244	49.1622	277.5415	8.52	16.02

Table 2: Descriptive statistics of Copper intraday returns and realized volatilities for the periods without night trading session (Panel A, January 4, 2010 – December 19, 2013) and with daily decomposition after introduction of the night trading session (Panel B, December 20, 2013–May 21, 2018).

Descriptive Statistics										
Panel A: Period 1 (observations 1:959), January 4, 2010 – December 19, 2013										
	r_t^{ON}	$r_t^{(1)}$	r_t^{cc}	RV_t^{ON}	$RV_t^{(1)}$	$v_t^{(1)}$		RV_t^{EB}	$RV_t^{(2)}$	$v_t^{(2)}$
Mean	-0.0075	-0.0148	-0.0208	0.3675	0.3916	42.669		0.1106	0.4925	75.924
Median	0.0000	-0.0302	0.0000	0.0490	0.1420	16.908		0.0325	0.2878	58.086
Minimum	-4.3816	-3.1188	-5.3581	0.0000	0.0192	2.792		0.0000	0.0275	1.380
Maximum	3.8477	4.4715	4.2512	19.1986	24.9698	566.944		22.7307	20.5252	702.358
Std	0.6065	0.6111	0.8087	1.4741	1.0731	66.471		0.7274	0.8734	153.163
Skewness	-1.5017	0.2116	-0.7206	8.9521	14.3045	3.66		29.3801	13.2770	2.30
Kurtosis	17.0061	11.3700	10.9002	97.6131	297.7872	20.40		910.9367	277.8134	12.40
Panel B: Period 2 (observations 960:2035), December 20, 2013–May 21, 2018										
	r_t^{ON}	$r_t^{(1)}$	r_t^{cc}	RV_t^{ON}	$RV_t^{(1)}$	$v_t^{(1)}$		RV_t^{EB}	$RV_t^{(2)}$	$v_t^{(2)}$
Mean	0.0133	-0.0464	0.0090	0.0398	0.5394	103.940		0.1106	0.4925	75.924
Median	0.0000	-0.0417	0.0000	0.0014	0.3471	91.244		0.0325	0.2878	58.086
Minimum	-2.4925	-3.4987	-3.0267	0.0000	0.0302	3.740		0.0000	0.0275	1.380
Maximum	2.0138	4.2007	4.2506	6.2123	6.2627	554.948		22.7307	20.5252	702.358
Std	0.1990	0.7563	0.5993	1.0122	0.6013	86.727		0.7274	0.8734	153.163
Skewness	-2.5146	0.1875	-2.5504	15.2876	3.4728	1.31		29.3801	13.2770	2.30
Kurtosis	58.2443	6.2441	7.8320	269.6948	22.6142	5.38		910.9367	277.8134	12.40

Table 3: Descriptive statistics of Aluminum intraday returns and realized volatilities for the periods without night trading session (Panel A, January 4, 2010 – December 19, 2013) and with daily decomposition after introduction of the night trading session (Panel B, December 20, 2013–May 21, 2018).

	$RV_t^{(1)}$				$RV_t^{(2)}$			$RV_t^{(24)}$		
	Eq. (8.1)	Eq. (8.1)	Eq. (8.2)	Eq. (8.3)	Eq. (9.1)	Eq. (9.2)	Eq. (9.3)	Eq. (10.1)	Eq. (10.1)	Eq. (10.2)
	T_1	T_2	T_2	T_2	T_1	T_2	T_2	T_1	T_2	T_2
β_0	0.1458 (0.0431)	0.1377 (0.0304)	0.0854 (0.0307)	0.0070 (0.0378)	0.1676 (0.0335)	0.0438 (0.0404)	-0.1565 (0.0392)	0.5812 (0.1616)	0.3162 (0.0663)	0.2359 (0.1035)
β_1	0.2280 (0.0697)	0.3600 (0.0988)	0.1806 (0.0954)	0.0901 (0.1004)	0.2668 (0.1582)	0.0734 (0.1089)	0.0391 (0.0339)	0.0112 (0.0749)	0.5323 (0.1421)	0.3489 (0.1246)
β_2	0.4011 (0.1270)	0.3675 (0.1166)	0.2855 (0.0912)	0.2914 (0.1032)	0.2223 (0.0855)	0.0446 (0.0744)	0.0214 (0.0577)	0.4026 (0.2343)	0.1345 (0.0791)	0.0993 (0.0873)
β_3	0.1868 (0.1200)	0.0220 (0.0867)	0.0366 (0.0720)	0.0193 (0.0743)	0.1873 (0.1188)	0.1248 (0.1255)	0.1065 (0.0692)	0.2796 (0.1943)	0.0946 (0.0807)	0.0838 (0.0847)
β_4			0.3273 (0.0529)	0.2095 (0.0460)		0.5210 (0.1784)	0.3315 (0.0432)			0.2492 (0.1701)
β_5			0.0912 (0.0778)			0.3065 (0.0766)	0.7984 (0.0568)			
R^2	0.3354	0.3658	0.4943	0.4572	0.1825	0.3102	0.4028	0.1259	0.4074	0.4191
RMSE	0.8728	0.5495	0.4906	0.5083	0.7759	0.7128	0.6632	3.8473	1.1845	1.1727
MAE	0.4086	0.2766	0.2591	0.2648	0.3053	0.2867	0.3121	1.5863	0.6316	0.6256

Table 4: Parameter estimation results and robust standard errors in parenthesis of Copper futures for the HAR specifications defined in Eq. (8.1) - (10.2). β_1 , β_2 , and β_3 denote the dependent variable's own previous day's, week's and month's components, respectively. In model (8.2), β_4 and β_5 denote the immediately preceding night trading session and evening break, respectively. In model (8.3), β_4 denotes the immediately preceding realized volatility of the LME copper futures contract. In (9.2), β_4 and β_5 denote the day-time trading session and evening break on day t , respectively. In (9.3), β_4 and β_5 denote the immediately preceding day-time trading session at SHFE and the realized volatility at LME during the evening break on day $t + 1$, respectively. In Eq. (10.2), β_4 denotes the LME realized volatility on day t . The estimates are obtained with a White adjusted heteroskedastic consistent least-squares regression with robust standard errors given in parenthesis.

	$RV_t^{(1)}$				$RV_t^{(2)}$			$RV_t^{(24)}$		
	Eq. (8.1)	Eq. (8.1)	Eq. (8.2)	Eq. (8.3)	Eq. (9.1)	Eq. (9.2)	Eq. (9.3)	Eq. (10.1)	Eq. (10.1)	Eq. (10.2)
	T_1	T_2	T_2	T_2	T_1	T_2	T_2	T_1	T_2	T_2
β_0	0.0801 (0.0174)	0.0727 (0.0225)	0.0734 (0.0198)	0.0652 (0.0267)	0.1291 (0.0382)	0.0446 (0.0337)	0.0367 (0.0398)	0.2200 (0.0493)	0.2444 (0.0616)	0.2527 (0.1522)
β_1	0.3636 (0.1277)	0.2544 (0.0768)	0.1533 (0.0740)	0.2516 (0.0768)	0.1978 (0.1002)	0.0966 (0.0883)	0.0961 (0.0375)	0.1563 (0.0952)	0.1835 (0.1071)	0.1872 (0.1167)
β_2	0.2223 (0.1024)	0.3994 (0.0993)	0.3092 (0.0873)	0.3989 (0.0991)	0.2100 (0.1306)	0.0857 (0.1182)	0.0870 (0.0683)	0.2415 (0.1200)	0.3539 (0.1277)	0.3560 (0.1221)
β_3	0.1576 (0.0806)	0.2141 (0.0714)	0.1915 (0.0663)	0.2158 (0.0712)	0.3273 (0.0800)	0.1815 (0.0805)	0.1842 (0.0799)	0.2517 (0.1323)	0.2579 (0.0685)	0.2554 (0.0596)
β_4			0.2406 (0.0160)	0.0049 (0.0086)		0.4705 (0.0916)	0.4690 (0.0575)			-0.0072 (0.1257)
β_5			-0.0039 (0.0056)			0.0620 (0.0369)	0.0211 (0.0214)			
R^2	0.2990	0.4242	0.5252	0.4244	0.1791	0.2324	0.2305	0.1277	0.2675	0.2675
RMSE	0.5624	0.4415	0.4009	0.4414	0.7942	0.7680	0.7689	1.5704	1.3083	1.3083
MAE	0.2205	0.2551	0.2371	0.2552	0.2825	0.2641	0.2642	0.5858	0.5621	0.5615

Table 5: Parameter estimation results and robust standard errors in parenthesis of Aluminum futures for the HAR specifications defined in Eq. (8.1) - (10.2). β_1 , β_2 , and β_3 denote the dependent variable's own previous day's, week's and month's components, respectively. In model (8.2), β_4 and β_5 denote the immediately preceding night trading session and evening break, respectively. In model (8.3), β_4 denotes the immediately preceding realized volatility of the LME aluminum futures contract. In (9.2), β_4 and β_5 denote the day-time trading session and evening break on day t , respectively. In (9.3), β_4 and β_5 denote the immediately preceding day-time trading session at SHFE and the realized volatility at LME during the evening break on day $t + 1$, respectively. In Eq. (10.2), β_4 denotes the LME realized volatility on day t . The estimates are obtained with a White adjusted heteroskedastic consistent least-squares regression with robust standard errors given in parenthesis.

Appendix A. Appendix: Additional Figures

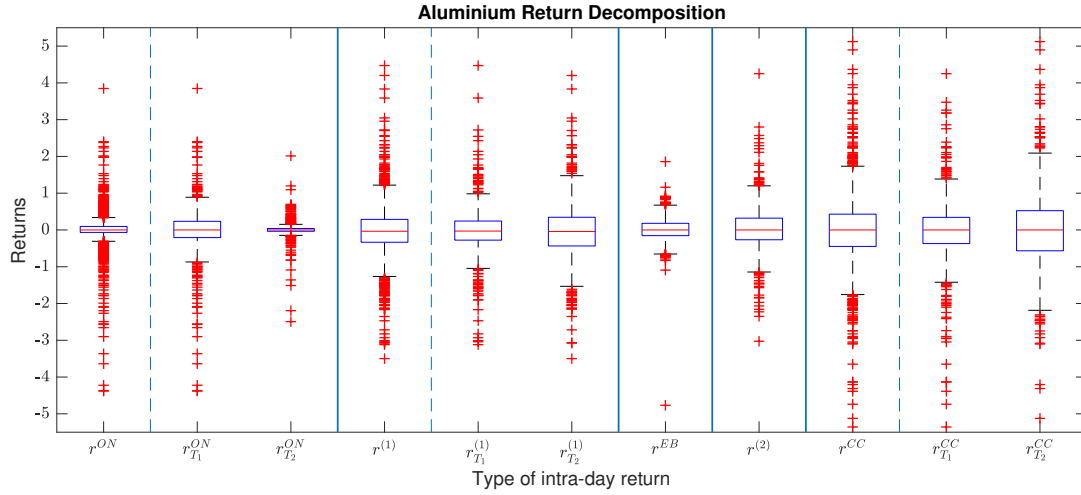


Figure A.7: Box plots of different intraday components for Aluminum following the decomposition in Eq. (6). Different disjoint periods are denoted by T_1 and T_2 which refer to the observations before (January 4, 2010 to December 19, 2013) and after (December 19, 2013 to May 21, 2018) the introduction of the night trading session, respectively; yielding $n_1 = |T_1| = 959$ and $n_2 = |T_2| = 1076$ observations. The full sample of $n = 2035$ observations is plotted for r^{ON} , $r^{(1)}$, and r^{CC} . For r^{EB} and $r^{(2)}$, which only exist in T_2 , we omit the index.

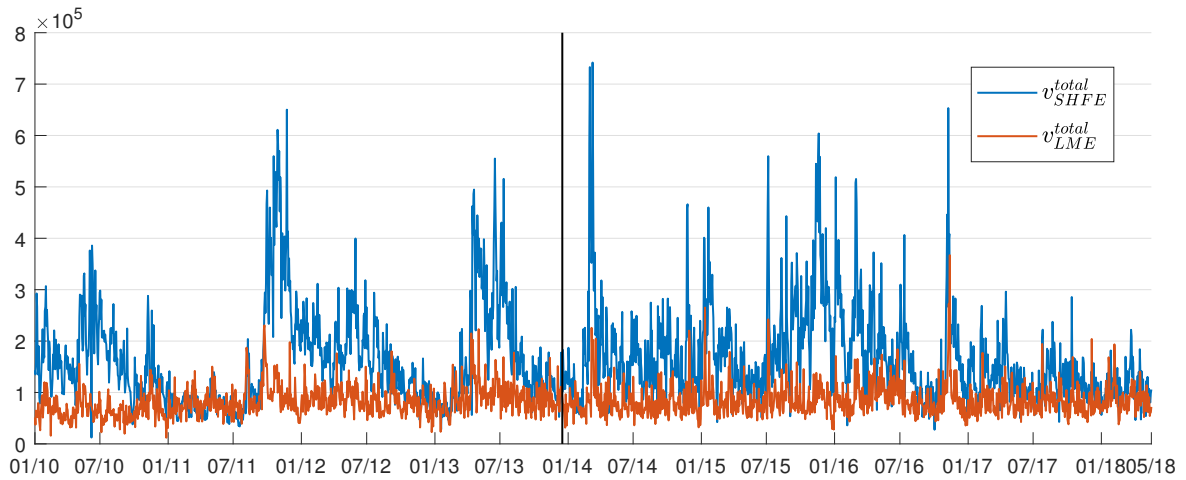


Figure A.8: Volumes (unsmoothed) of SHFE 3M Copper futures and LME 3M futures adjusted for SHFE's double-side counting and LME's fivefold contract size. The introduction of the night trading session is marked with a vertical line.

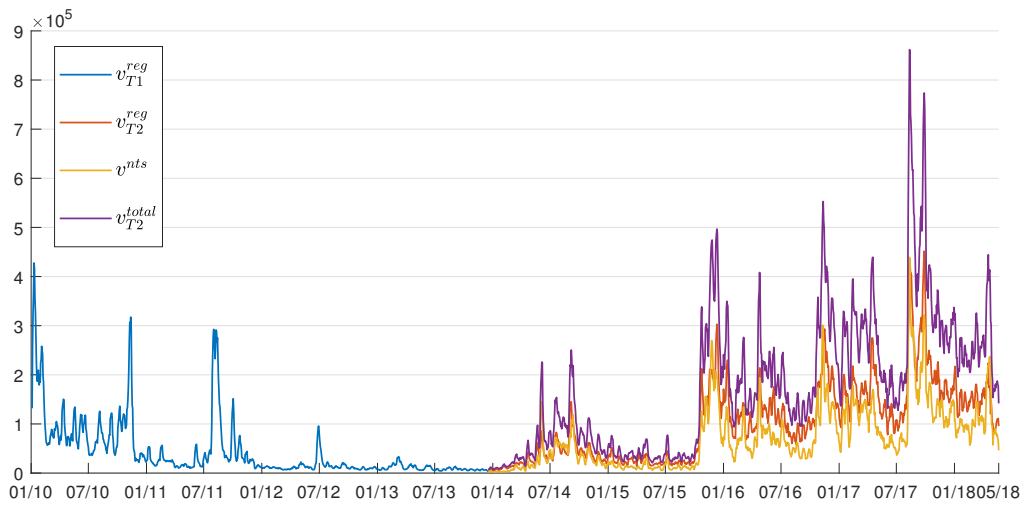


Figure A.9: Volume of Aluminum decomposed to the respective components and smoothed by an MA(5). Different disjoint periods denoted by T_1 and T_2 are identical to the previous figures.