Night trading momentum and determinants of predictability: Evidence from Chinese metal futures market

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Abstract

In this paper, we analyze the impact of the launch of night trading, a unique trading mechanism in China, on intraday momentum in four Chinese metal futures markets, namely gold, silver, aluminum, and copper. Based on high-frequency (1-minute) data, we find that before the launch of night trading, the first half-hour return in the daytime has a positive predictability for half-hour returns later in the same day in the four markets, but not necessarily the last half-hour return as often found in the stock market. After the launch of night trading, the predictive ability of the first half-hour return in the daytime disappears, whereas the first half-hour return at the night trading becomes the new efficient predictor. As a possible explanation for the change of intraday predictive patterns, we refer to the immediate reaction of domestic investors to international news released in the evening. We further provide evidence that the magnitude of the intraday predictability varies with levels of realized volatility, trading volume, and illiquidity. Additional analysis shows that the profits generated by a market timing strategy based on our findings exceed those of the always-long benchmark strategy.

Keywords: Intraday momentum; Chinese metal futures; Night trading; High-frequency data; Market timing strategy

JEL Classification: G12, G13, G15

1. Introduction

Momentum is a well-known anomaly in financial markets and constitutes the base of momentous trading strategy across various assets (Asness et al., 2013). It reflects the tendency of relative wining (losing) assets to continue to win (lose). The momentum literature falls into two main categories, cross-sectional and time-series. Cross-sectional momentum examines whether assets that have outperformed their peers in the past will also outperform their peers in the future (Jegadeesh & Titman 1993). Time-series momentum focuses on whether an asset's future return can be positively predicted based on its own past return (Moskowitz *et al.* 2012). Most forms of momentum are studied at low frequency data covering monthly, weekly, or daily frequencies. With the development of technology and availability of high-frequency data, intraday trading has grown in popularity, which has led scholars to use high-frequency data to study financial markets and momentum. Notably, Gao et al. (2018) employ high-frequency S&P 500 ETF data to extend the time-series momentum to the intraday level, and document an intraday momentum pattern in the US stock market: the last half-hour return can be significantly predicted by the first half-hour return within the same day. Since then, the literature on intraday momentum extends to several other markets, including Chinese stocks(e.g., Chu *et al.* 2019; Zhang *et al.* 2019; Li *et al.* 2020), and to various assets such as foreign exchange rates (e.g., Elaut *et al.* 2018), US crude oil (e.g., Wen *et al.* 2021b), and commodities(e.g., Xu *et al.* 2020).

However, the intraday momentum literature remains understudied in the Chinese metal futures markets. These markets have a unique trading mechanism, being the night trading session launch after 2013, which constitutes our main motivation. Extended trading hours brought by the night trading session have some impacts the first half-hour return. On the one hand, the first half hour may contain different information after the launch of night trading, since the non-trading hours before the market open have changed. On the other hand, Miwa (2019) documents that the extended trading hours can change the price behavior after the market open. Given the importance of the first half-hour return in the intraday momentum, these impacts on the first half-hour return may cause the intraday momentum in Chinese metal futures markets exhibits different patterns after the launch of night trading.

Before July 2013, futures in China were only traded during the daytime from 9:00 a.m. to 3:00 p.m., Beijing time.[1] After July 2013, Chinese futures exchanges have begun to introduce night trading sessions, in order to enable domestic investors to timely digest international market information and reduce overnight risk. The night trading session in China allows trading for more 2 to 5.5 hours at night.[2] The additional trading sessions widely cover active trading hours of the major international metal futures exchanges, for example, COMEX and LME. As a result, the trading behavior of traders has largely changed as reflected by the shape of the intraday volume. For example, intraday trading volume, previously being L-shaped, has become W-shaped with the introduction of night trading. Specially, the trading volume at night is much higher than that in the daytime. Given the importance of the shape of the intraday trading volume for intraday momentum (see, Gao *et al.* 2018), some important questions arise: Did the launch of night trading alter intraday momentum? If the intraday momentum was altered, why did this momentum change? Is the intraday predictor useful to build profitable strategies? We seek to answer these questions in the current paper.

Our focus is on China's four metal futures: gold, silver, aluminum, and copper. China is the second largest economy in the world, and its economy is significantly influenced by these metals' prices (Wang & Wang 2019; Gao *et al.* 2020). On the one hand, gold and silver are good representatives of precious metals and play a crucial role in the global financial system. They are often seen as a safe haven or hedge against stock market declines, economic uncertainty, and inflation (Aye *et al.* 2016; Beckmann *et al.* 2018; Chen & Wang 2019). On the other hand, aluminum and copper are good representatives of industrial metals. They are widely used in a variety of industries, including power, transportation and construction and their futures markets are vital for metal producers, retailers, consumers, and the entire country (Ma

[1] The daytime trading is separated into two sessions: the morning session (from 9:00 a.m. to 11:30 a.m., Beijing time) and the afternoon session (from 1:30 p.m. to 3:00 p.m., Beijing time). Furthermore, there is a 15-minute break (from 10:15 a.m. to 10:30 p.m., Beijing time) in the morning.

[2] The night trading starts from 9:00 p.m. for all types of commodity futures, but the end time varies cross commodities. The night trading of a certain trading day takes place in the night of the previous trading day. That is to say, the night trading of Monday takes place in the night of last Friday, the night trading of Tuesday takes place in the night of Monday and so on (Zhang *et al.* 2020).

& Xiong 2021). Having these reasons in mind, we extend the growing intraday momentum literature to these four Chinese metal futures and consider the impact of night trading.

There are several notable findings provided by our empirical analysis. First, intraday momentum patterns are found to be different under different trading mechanisms in Chinese metal futures markets. Before the launch of night trading, the first half-hour return in the daytime is the efficient predictor in each market. However, the intraday predictive patterns are not the same across the four metal markets. Specifically, which half-hour returns can be positively predicted seem to market-dependent. After the launch of night trading, there are two kinds of first half-hour return: the first half-hour return in the day trading session and the first half-hour return in the night trading session (Zhang *et al.* 2020). In this regard, we find that the forecasting ability of the first half-hour return in the day session disappeared, while the first half-hour return at night became effective predictors. The intraday momentum patterns remain different across the four markets. This finding sharply contrasts with previous researches on other markets such as stocks, in which the first half-hour return is useful to predict the last half-hour return on the same trading day. It highlights the unique features of the Chinese metals markets. Notably, this finding is confirmed by out-of-sample (OOS) analysis.

Second, we investigate the impacts of volatility, trading volume, and illiquidity on intraday predictability. For volatility and illiquidity, their impacts are consistent before and after the launch of night trading. The empirical results show that higher volatility and illiquidity are associated with stronger intraday momentum in the four futures markets. For trading volume, it exhibits different impacts on intraday predictability under different trading mechanisms. Specifically, before the launch of night trading, some intraday predictive patterns are stronger on high trading volume days, and others are stronger on low volume days. However, after the launch of night trading, most intraday predictive patterns are stronger on high volume days.

We provide several theoretical explanations on the intraday momentum. First, we argue that the intraday momentum can be caused by investors' infrequent trading behavior. Infrequent traders who absorb a liquidity shock through holding a sub-optimal position will rebalance their portfolio in the next active period, resulting in another liquidity shock with the same direction (Bogousslavsky 2016). Second, another explanation is based on late-informed investors. Late-informed investors receive and process information later than early-informed investors and both of them trade in the same direction (Cushing & Madhavan 2000), which leads to a positive correlation of returns between the two periods. Third, investors' overconfidence can explain the momentum effect, as argued by Chan *et al.* (1996); Barberis *et al.* (1998); Daniel *et al.* (1998) and Daniel *et al.* (2001) . For example, overconfident investors tend to ignore and underreact to the news, which is against their beliefs. Fourth, intraday momentum can also be driven by hedging demand. To hedge gamma exposure, traders need to sell securities when prices fall and buy when prices rise, thereby causing momentum (Baltussen *et al.* 2021). In addition, for China's futures markets, there is an additional specific question: why have the intraday momentum patterns changed? We provide a possible explanation related to international news and risks. Previous literature documents that Chinese futures markets are significantly influenced by international markets (Liu & An 2011; Cai *et al.* 2020). After the launch of night trading, domestic investors incline to immediately adjust to news and risk from global markets in the evening, rather than waiting for the daytime. Thus, the first half hour of night trading becomes more informative and predictive than the first half hour of day trading.

Finally, we assess the economic value of intraday momentum by employing the efficient predictor as a trading signal for the market timing strategy. We find that the market timing strategy outperforms the benchmark always-long strategy, since it can generate a larger return, a larger sharp ratio, and a larger success rate. This finding is valid across all the four metal futures markets, conforming the change of intraday momentum patterns in these markets and providing intraday traders important practical implications.

This paper makes important contributions in several aspects. First, we find evidence of a new intraday momentum pattern in Chinese metal futures markets. Specifically, returns in other half hours, not necessarily the last half hour, can be predicted by the return in the first half hour. This is very different from previous studies on other markets, which only found evidence on the predictability of the last half-hour return (e.g., Gao *et al.* 2018; Jin *et al.* 2019; Baltussen *et al.* 2021). Our finding underlines the unique characteristics of Chinese futures market, which, to the best of our knowledge, is new to the academic literature. Second, this paper contributes to the literature on the trading strategies in commodity futures markets. For example, Miffre and Rallis (2007) and Szakmary *et al.* (2010) investigate whether momentum or trend-following strategies can earn excess profits using data of commodity futures. The trading strategies of these studies are based on monthly data. However, our trading strategy is based on high-frequency trading data, which is useful to day and high-frequency traders. Third, our paper adds to studies that concentrate on the impact of night trading sessions. The introduction of night trading has made a large impact on China's futures markets, but the related literature is quite limited and most of previous studies focus on volatility and market quality (e.g., Jiang *et al.* 2020; Klein & Todorova 2021). Instead, we investigate the effect of night trading sessions from a new perspective of intraday return predictability, giving in-depth insight to policymakers and high-frequency traders.

The rest of the paper is organized as follows. Section 2 presents a review of related literature. Section 3 describes the data used for analysis. Section 4 presents the major results of empirical analysis and offers several explanations. Section 5 estimates the economic significance of the intraday momentum. Section 6 concludes.

2. Related literature

In this section, we present three streams of literature that are closely related to our current study on the impacts of the launch of night trading on intraday momentum patterns in Chinese metal futures markets.

The first strand of literature considers intraday momentum using high-frequency information. In this regard, time-series momentum is a popular research field (see, e.g., Moskowitz *et al.* 2012; Asness *et al.* 2013; Neely *et al.* 2014; Zhou *et al.* 2020). Gao *et al.* (2018) first extend this kind of momentum to intraday level and document the power of the first half-hour return to forecast the last half-hour return. Since then, a growing body of literature explores intraday momentum in a variety of markets. For example, Chu *et al.* (2019), Zhang *et al.* (2019), and Li *et al.* (2020) provide robust evidence that intraday momentum also exists in China’s stock market. Similarly, Li *et al.* (2021) analyze intraday momentum in an international context and test several hypotheses to explain the source of intraday momentum. Xu *et al.* (2020) observe different intraday momentum patterns in three commodity ETFs: crude oil, gold and silver. Wen *et al.* (2021a) show no evidence of intraday momentum in China’s crude oil futures market. In line with these researches, we extend the intraday momentum to China's metal futures market which is characterized by a unique trading mechanism.

The second strand of literature concerns extending trading hours, which has been increasingly analyzed in several markets. Some studies document the benefits of extending trading hours. For example, Fan and Lai (2006) find that after the extension of 1.5 trading hours in Taiwan stock market, intraday volume and volatility patterns do not change much, but the bid-ask spread declines. Cheng *et al.* (2004), Hua *et al.* (2016), Sohn and Zhang (2017) and Wang *et al.* (2018) find that both in Hong Kong and China, extended trading time facilitate price discovery. Others find that the extension of trading time is not always beneficial. Miwa (2019) examines two stock futures in Japan which have been continuously and asynchronously extended, and report that the overreaction phenomenon becomes worse when the extended trading hours are longer. In general, the above studies mainly focus on equity futures markets and investigate extensions to original trading sessions. As a nice complement to these studies, this paper investigates the impact of extending hours in Chinese commodity futures markets which introduced a new, separate night trading session.

The third strand of literature is related to night trading, which has been widely studied in U.S. financial markets. For example, Barclay and Hendershott (2003) study 250 NASDAQ stocks and find that the night trading, especially the pre-open trading, generates significant price discovery, although the trading volume during night is much lower. Giannetti *et al.* (2006) show that extreme price movements in stock markets at night are likely to do with mispricing and often accompanied by reversals. Dungey *et al.* (2009) use data on equity futures contracts to investigate the role of night trading in absorbing news releases. They find that the price impact is statistically lower in pre-open than in post-close period. Comparatively, the literature on night trading in China is understudied and the few related studies mostly focus on volatility and market quality (see, e.g., Jiang *et al.* 2020; Klein & Todorova 2021; Yao *et al.* (2021)). In contrast, we examine the role of night trading in China from the perspective of return predictability.

As Gao *et al.* (2018) documented, due to the digestion of new information and the avoidance of overnight risk, the trading volume in the first and last half hour is significantly higher, which is proved by the U-shaped trading volume pattern. Given this feature of the US stock market, they document an intraday momentum pattern: the first half-hour return positively predicts the last half-hour return. Before the launch of night trading, Chinese metal futures markets show similar characteristics to the US stock market. In particular, the trading volume in the first half hour is also much higher than that in other periods. However, there are still some unique trading features in Chinese metal futures markets. For example, the intraday volume shows L-shaped rather than U-shaped in Chinese metal futures markets before the launch of night trading, which means that there is no significant difference between the volume in the last half hour and other half hours. Comparing the intraday volume patterns of Chinese metal futures markets and US stock market, and considering the analysis of Gao, we believe that the first half-hour return of the Chinese metal futures markets is still a predictor before the launch of night trading, but the intraday momentum may show different patterns from the US stock market. Therefore, we posit the following:

Hypothesis 1. Given the L-shaped pattern of intraday volume, with the high trading volume for the first half hour, the intraday momentum exists in the Chinese metal futures markets before the launch of night trading, but the intraday predictive patterns differ from that in US stock market.

After the launch of night trading, the intraday volume pattern of Chinese metal futures markets becomes W-shaped, with two peaks occurring in the first half hour at night and the first half hour in the morning. Similar to that before the launch of night trading, the high volume during these two periods is the result of digestion and reflection of news released before market opening. Different news released at different time leads to the two first half hours contain different kinds of information. As a result, after the launch of night trading, the first half-hour return at night and the first half-hour return in the morning may present different forecasting power. In addition, the trading volume in the first half hour at night is higher than that in the first half hour in the morning. So, we infer that the first half-hour return contains more useful predictive information than the first half hour in the morning. We propose the following:

Hypothesis 2. After the launch of night trading, the intraday momentum patterns in Chinese metal futures markets have changed. And the predictive ability of the first half-hour return at night is stronger than that of the first half-hour return in the morning.

3. Data

3.1. Chinese metal futures

We use 1-minute frequency price data to calculate the half-hour returns for Chinese metal futures markets. To meet our requirement, we download the dataset from JoinQuant[3], which is a professional quantitative trading platform provided by a private Chinese company. Since these futures were launched at different times, the sample periods vary. Specifically, gold data spans from January 10, 2008 to October 20, 2021; silver data spans from May 11, 2012 to October 20, 2021; aluminum and copper data span from January 2, 2008 to October 20, 2021[4].

3.2. Trading mechanism of Chinese metal futures markets

The trading periods for these Chinese metal futures are noteworthy. The Shanghai Futures Exchange (SHFE) introduced night trading for the metal futures at different times, specifically on July 5th, 2013 for gold and silver, and on December 20th, 2013 for aluminum and copper. Before the introduction of night trading, the trading time for these metal futures was from 9:00 a.m. to 3:00 p.m. with a 15-minute break (10:15 a.m. – 10:30 a.m.) in the morning and a 2-hour lunch break (11:30 a.m. – 1:30 p.m.).[5] After the introduction of night trading, daytime trading hours for all futures remain unchanged, but night trading hours vary across commodity futures. Specifically, night trading for gold and silver starts at 9:00 p.m. on the previous day and ends at 2:30 a.m. on the next day, while night trading for copper and aluminum lasts from 9:00 p.m. to 1:00 a.m.[6] The additional trading hours at night has many useful aspects. First, it helps strengthening the price-setting power of major commodities on the global financial market. Second, it supports Chinese and foreign investors on the Chinese commodity markets to better manage their daily risk and react more quickly to the arrival of information from international

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[3] For more information, please visit https://www.joinquant.com/.

[4] In the early days of the COVID-19 outbreak, the Shanghai Futures Exchange suspended night trading for several months (from February 3rd, 2020 to May 6th, 2020). Thus, we remove this interval form our data sample.

[5] Notably, here we use Beijing Time, which is 12 hours ahead of Eastern Standard Time (EST) in Summer Time and 13 hours ahead of EST in Winter Time.

[6] According to the trading rules adopted by SHFE, the night trading session starting at 9:00 p.m. on day t-1 belongs to trading day t.

markets through rapid trading. Third, it should lead to more participation, more investor and trader competition, and thus higher market efficiency.

3.3. Construction of intraday returns

To examine the intraday predictability, we compute the half-hour returns as the difference of logarithmic prices. The formula for calculating half-hour returns in the daytime is as follows:

$$r_{i,t}^{day} = \log(p_{i,t}^{day}) - \log(p_{i-1,t}^{day}),\ i = 1, 2, 3, ..., 8, \tag{1}$$

where $p_{i,t}^{day}$ denotes the price at the i th half hour on day t, and $p_{i-1,t}^{day}$ denotes the price at the previous half hour. Generally, the day trading session starts from 9:00 a.m. to 3:00 p.m. with two breaks, so there are 8 half-hour intervals for each daytime trading session. Note that $p_{0,t}$ is the closing price of the previous trading session. Specifically, before the launch of night trading session, $p_{0,t}^{day}$ represents the price at market close on day $t-1$ (i.e. 3:00 p.m.), while after the launch of night trading, $p_{0,t}^{day}$ represents the closing price of the night session on day t (i.e. 2:30 a.m. for gold and silver, 1:00 a.m. for aluminum and copper). Thus, the first half-hour return contains information released after the market close.

The half-hour returns at night can be obtained similarly:

$$r_{i,t}^{night} = \log(p_{i,t}^{night}) - \log(p_{i-1,t}^{night}),\ i = 1, 2, 3, ..., n, \tag{2}$$

where $p_{i,t}^{night}$ denotes the i th half-hour price of the night session of trading day t. $p_{0,t}^{night}$ is the price at 3:00 p.m. on trading day $t-1$. Notably, the night trading sessions vary across different metals, that is, for gold and silver it starts from 9 p.m. to 2:30 a.m., and for copper and aluminum is lasts from 9 p.m. to 1:00 a.m.. So n is different for different metals. Specifically, n equals to 11 for gold and silver, and 8 for aluminum and copper.

Descriptive statistics for half-hour returns of the Chinese metal futures before and after the launch of night trading are shown in Table 1 and Table 2, respectively. As shown in Table 1, before the launch of night trading, the mean values of half-hour returns are mostly around zero and the first half-hour returns have the highest standard deviation. Table 2 shows that after the launch of night trading, the mean values of half-hour returns are also around zero for all futures. However, the standard deviations of returns in the first half hour of night and daytime trading sessions are significantly higher than those in other periods. Given these characteristics, the first half-hour returns seem to contain more important information than other half-hour returns.

[Insert Table 1 about here]

[Insert Table 2 about here]

4. Intraday return predictability before and after the launch of night trading

4.1. In-sample (IS) analysis

In this section, we examine the intraday return forecasting patterns before and after the launch of night trading sessions in China's metal futures markets. The great impacts of the launch of night trading have been documented from the perspective of market quality and volatility predictability. For example, Jiang *et al.* (2020) find that the launch of night trading has improved market quality, and has made Chinese futures price more connected to international price. Yao *et al.* (2021) showed that night trading can significantly improve predictive performance of Chinese gold futures' volatility. However, the impacts of night trading on return forecasting are understudied. Therefore, it is worthwhile to explore whether the launch of night trading has changed the intraday momentum patterns. Moreover, previous studies on intraday momentum are mostly limited to the predictability of the last half-hour returns. We extend this predictive analysis to all half-hour returns throughout the trading day. Specifically, we investigate whether later half-hour returns can be positively predicted by their counterparts near the market open on the same day, for the four China's metal futures, gold, silver, aluminum and copper. The reason why we use the first half-hour return as the predictor is that the first half hour is the most active trading period. News released during the closing hours may lead to the first half hour contain more useful information.

We first examine the intraday momentum before the introduction of night trading, using the following regression:

$$r_{i,t}^{day} = \alpha + \beta_1 r_{1,t}^{day} + \epsilon_{i,t},\ t = 1, 2, ..., T;\ i = 2, 3, ..., 8, \qquad (3)$$

where $r_{i,t}^{day}$ is the i th half-hour returns on day t.

Table 3 reports the results. In all the four China's metal futures markets, the first half-hour return exhibits the ability to significantly and positively predict other half-hour returns, and the intraday predictive patterns vary across the futures markets. The first half-hour return ($r_{1,t}^{day}$) positively predicts the 6th half-hour returns ($r_{6,t}^{day}$) for gold, silver and aluminum, with a t-statistic of 4.396, 1.704 and 5.1, respectively. For copper, the first half-hour return ($r_{1,t}^{day}$) exhibits positively predictive ability for the fifth ($r_{5,t}^{day}$), sixth ($r_{6,t}^{day}$), seventh ($r_{7,t}^{day}$) and last ($r_{8,t}^{day}$) half-hour returns at the significance level of 10%, 10%, 5%, and 1% respectively. In addition, some significant negative values of β_1 are shown in the table, indicating that there is a reversal phenomenon in China's metal futures markets[7]. Overall, the intraday momentum exists in Chinese metal futures markets before the launch of night trading sessions. Various intraday momentum patterns highlight the intrinsic differences across the metal futures markets.

[Insert Table 3 about here]

After the launch of night trading sessions, there are two first half-hour returns: the first half-hour return of night session, and the first half-hour return of day session. The night trading takes place before the daytime trading for a given trading day. Therefore, it is relevant to understand which first half-hour return has stronger forecasting power. To answer this question, we conduct the in-sample analysis. The predictive model for the first half-hour return of day session is the same as equation (2). However, the predictive model for the first half-hour return of night session is given by:

$$\begin{aligned} r_{i,t}^{night} &= \alpha + \beta_1 r_{1,t}^{night} + \epsilon_{i,t},\ t = 1,2,...,T;\ i = 2,3,...n, \\ r_{i,t}^{day} &= \alpha + \beta_1 r_{1,t}^{night} + \epsilon_{i,t},\ t = 1,2,...,T;\ i = 1,2,...8, \end{aligned} \tag{4}$$

where $r_{i,t}^{night}$ denote the i th half-hour return at night, and $r_{i,t}^{day}$ denote the i th half-hour return in the daytime on trading day t. n equals to 11 for gold and silver, and 8 for aluminum and copper.

In Table 4, we report the predictive ability of the first half-hour return of day session after the launch of night trading. The result indicates that there is no significant positive relation

[7] However, this phenomenon is not universal in these futures markets and is not the focus of the current study.

between the first half-hour return of day session and its subsequent counterparts. This finding is inconsistent with previous literature on intraday momentum. Those literature all document the predictive ability of the first half-hour return near the market open in the morning (e.g., Gao *et al.* 2018; Li *et al.* 2021; Wen *et al.* 2021b). Hence, trading strategies adopted in other markets are useless here. High-frequency traders in Chinese metal futures markets should look for new trading strategies.

[Insert Table 4 about here]

Regarding the night session, Table 5 and Table 6 show the results for the first half-hour return. Intraday momentum can be identified in all four futures markets, and the four markets still have different intraday predictive patterns. Specifically, for gold, the first half-hour return at night ($r_{1,t}^{night}$) exhibits significant and positive predictive power for the first half-hour return in the daytime ($r_{1,t}^{day}$), with a t-statistic of 3.0 and an R^2 of 0.56%. For silver, the first half-hour return at night ($r_{1,t}^{night}$) positively forecasts the tenth half-hour return at night ($r_{10,t}^{night}$) and the first ($r_{1,t}^{day}$), fifth ($r_{5,t}^{day}$), sixth ($r_{6,t}^{day}$) and last ($r_{8,t}^{day}$) half-hour returns of day session, statistically significant at the level of 10%, 1%, 5%, 1% and 10%, respectively. For aluminum, there is a significant and positive correlation between the first half-hour return at night ($r_{1,t}^{night}$) and the last two half-hour returns ($r_{7,t}^{day}$ and $r_{8,t}^{day}$). Their coefficients are both significant at the 1% level. For copper, the coefficients for the last two half-hour returns ($r_{7,t}^{day}$ and $r_{8,t}^{day}$) are also significantly positive, with a t-statistic of 2.896 for the penult ($r_{7,t}^{day}$) and a t-statistic of 1.898 for the last ($r_{8,t}^{day}$).These results indicate that if the first half-hour return at night is positive (negative), then some other half-hour returns later on the same trading day are to be positive (negative). This finding provides new insights for high-frequency traders in Chinese metal futures markets. Furthermore, related literature documents that the overnight news matters for the predictability (e.g., Gao *et al.* 2018; Wen *et al.* 2021b). Comparing the forecasting power of the first half hour returns before and after the launch of night trading, we suggest that the intraday predictability in Chinese metal futures markets is mainly attributable to news released before the open time of night trading sessions (9:00 p.m.). We discuss more economic explanations about the change of intraday momentum patterns in section 5. Moreover, the reversal effects still exist in several markets, possibly due to investor overreaction to the arrival of information. In short, after the launch of night trading, the intraday momentum patterns have changed a lot. The first half-hour return of day session lost its positively predictive power, while the first half-hour return of night session become efficient in forecasting subsequent returns.

[Insert Table 5 about here]

[Insert Table 6 about here]

In summary, the intraday momentum exists in China's metal futures markets, but the predictive patterns are different under different trading mechanisms. It is noteworthy that the in-sample R^2 values yielded in all efficient intraday predictive patterns here are much higher than those shown in other studies using low-frequency predictors (e.g., Rapach *et al.* 2010).

4.2. Out-of-sample (OOS) analysis

Up to this point, the IS predictability of the first half-hour return has been evaluated. However, Welch and Goyal (2008) document that the IS predictability may largely vanish when regressions are estimated out of sample. Notably, OOS predictability is more useful because financial practitioners invest for future. Therefore, we examine the OOS predictive ability of the first half-hour return via two statistics in this section. While doing so, we only concentrate on the OOS performance of the intraday momentum patterns which is found significant in the IS analysis.

The first statistic used to assess the OOS performance is OOS R-square (i.e., R_{OS}^2), which measures how much the mean squared prediction error (MSPE) of the forecasting model is reduced compared to the historical average model. To generate the OOS R-square (i.e., R_{OS}^2), we separate the entire sample into two parts. One contains the first m observations for the initial IS regression, and the other contains the rest q observations for OOS forecast. Then, we conduct a recursive expanding window approach, regressing equation (2) or equation (3) by adding 1 more observation at a time. For example, if equation (2) is used, the first OOS forecast (i.e.

$\hat{r}^{day}_{i,m+1}$) is given by:

$$\hat{r}^{day}_{i,m+1} = \hat{\alpha}_m + \hat{\beta}_{1,m} r^{day}_{1,m+1}, \tag{5}$$

where $r^{day}_{1,m+1}$ is the actually realized first half-hour return on day m+1, and $\hat{\alpha}_m$ and $\hat{\beta}_{1,m}$ are the OLS estimates of parameters using the first m observations. Another OOS forecast is computed as:

$$\hat{r}^{day}_{i,m+2} = \hat{\alpha}_{m+1} + \hat{\beta}_{1,m+1} r^{day}_{1,m+2}, \tag{6}$$

where $\hat{r}^{day}_{i,m+2}$ and $r^{day}_{1,m+2}$ represent the predicted i th half-hour return and the actually realized first half-hour return on trading day m+2, respectively, and $\hat{\alpha}_{m+1}$ and $\hat{\beta}_{1,m+1}$ are generated based on the first m+1 observations. Furthermore, we calculate the OOS R-square (i.e., R^2_{OS}) as follows:

$$R^2_{os} = 1 - \frac{\sum_{t=m+1}^{T} \left(r^{day}_{i,t} - \hat{r}^{day}_{i,t} \right)^2}{\sum_{t=m+1}^{T} \left(r^{day}_{i,t} - \overline{r}^{day}_{i,t} \right)^2}, \tag{7}$$

where $r^{day}_{i,t}$ is the realized return of i th half hour on trading day t, and $\hat{r}^{day}_{i,t}$ and $\overline{r}^{day}_{i,t}$ are the estimated values using our predictive model and historical mean, respectively, of i th half-hour return. T is the length of the entire sample period, and m is the number of observations used for the first regression. Here, we use m = 200. In a similar way, we can also compute the OOS R-square (i.e., R^2_{OS}) for equation (3). If R^2_{OS} >0, then the predictive model outperforms the historical mean.

The second statistic is the Clark and West (2007) MSPE-adjusted. We employ this statistic to test the null hypothesis (H_0) that the MSPE of the predictive model of interest is equal to or larger than the MSPE of historical mean model (i.e., $R^2_{OS} \leq 0$) against the alternative hypothesis (H_1) that the MSPE of the predictive model of interest is less than the MSPE of historical mean (i.e. $R^2_{OS} \geq 0$). To compute this statistic, we first define a time series f_t as:

$$f_t = \left(r_{i,t} - \overline{r}_{i,t}\right)^2 - \left(r_{i,t} - \hat{r}_{i,t}\right)^2 + \left(\overline{r}_{i,t} - \hat{r}_{i,t}\right)^2. \tag{8}$$

Next, we regress f_t on a constant. The Clark and West (2007) MSPE-adjusted equals to the t-statistic of the constant, and p-value is obtained by the one-sided (upper-tail) test.

We report the two OOS statistics together with the average coefficients of recursively regressions before and after the launch of night trading, in Table 7 and Table 8, respectively. In each table, the OOS values for gold, silver, aluminum and copper are shown in panel A, B, C and D, respectively. Both tables show that the average β_1 are positive for all intraday momentum patterns and most of them are significant. Before the launch of night trading, the R_{OS}^2 for all intraday momentum patterns is positive. As for the Clark and West (2007) MSPE-adjusted, the null hypothesis (i.e., $R_{OS}^2 \leq 0$) is rejected in most intraday momentum patterns, except the cases when r_5^{day} and r_7^{day} are predicted in the copper market. After the launch of night trading, most intraday momentum patterns also exhibit positive R_{OS}^2 and significant MSPE-adjusted, with only three exceptional cases. Two of them appear in the silver market when r_{10}^{night} and r_8^{day} are predicted. The other is that r_1^{night} predict r_8^{day} in copper market. Overall, most intraday momentum patterns found in the IS analysis continue to perform well in the OOS analysis. Thus, our main finding in the previous section that the predictive patterns are different under different trading mechanisms is confirmed by the OOS analysis.

[Insert Table 7 about here]

[Insert Table 8 about here]

4.3. The impacts of volatility, volume, and illiquidity

Previous studies argue that volatility, volume, and illiquidity play an important role in intraday momentum in stock markets (e.g., Gao *et al.* 2018). Specifically, they indicate that predictability appears stronger on days of high volatility, high volume, and high illiquidity. Motivated by this finding form the existing literature, we try to investigate the impacts of volatility, trading volume, and illiquidity on intraday momentum in Chinese metal futures markets and compare their role before and after the launch of night trading.

First, to explore the role of realized volatility in intraday momentum, we divide the trading days into two subgroups, based on the first half-hour volatility. The realized volatility is calculated by adding up the squares of 1-minute returns in the first half hour. Then, we analysis the intraday momentum for each subgroup. The results before the introduction of night trading are reported in the third and fourth columns of Table 9. The same columns of Table 10 report the results after the introduction of night trading. Measured by the significance of β_1 and the value of R^2, the predictive ability of the first half-hour return is stronger in the high-volatility subgroup across all the four futures markets, no matter before or after the introduction of night trading. For example, in the gold market, before the launch of night trading, the slope of the predictor for high-volatility subgroup is 0.0308 with a t-statistic of 3.693 and an R^2 of 2.48%, whereas its counterpart for the low-volatility subgroup is 0.0795 with a t-statistic of 2.987 and an R^2 of 1.58%. After the launch of night trading, the slope of the predictor for the high-volatility subset is significant at 1% level with an R^2 of 0.78%, whereas the slope for the low-volatility subgroup is significant at 5% level with an R^2 of 0.47%. This result is consistent with the findings of previous studies, which suggest that the price persistence increases with the market uncertainty (e.g., Zhang 2006; Gao *et al.* 2018; Wen *et al.* 2021b).

Second, we investigate the influence of trading volume on intraday momentum. Since trading volume tends to increase with time, we separate the trading day into two parts for each year, according to the trading volume in the first half hour. After combining each part across all years, we obtain two subsets. We then compare the predictive power of the first half-hour return in each subset. The results before the introduction of night trading are reported in the fifth and sixth columns of Table 9. We find that the impact of trading volume on intraday momentum in Chinese metal futures markets varies across markets before the introduction of night trading. For gold, the intraday momentum is stronger in high volume subset because both the t-statistic of the slope and R^2 are larger. For silver, as shown in panel B, the slope of the first half-hour return become insignificant in both subsets. For aluminum, the predictability, measured by the t-statistic of the slop and the R^2, is a decreasing function of trading volume. For copper, the predictability for the 6th half-hour return is larger in the high-volume subset, but the predictability for the last half-hour return is larger in the low volume subset. Moving to the results after the introduction of night trading, the fifth and sixth columns of Table 10 show that the high-volume subset mostly produces a higher significance level of β_1 and a larger value of R^2, with the only exceptional case when the 5th half-hour return in the day is predicted in the silver market. In general, after the launch of night trading, the trading volume shows a positive impact on intraday return predictability for most futures, which is significantly different from that before the launch of night trading.

Third, to explore whether illiquidity impacts intraday momentum, we split the trading days into two subgroups according to their illiquidity. Following Amihud (2002), we calculate the illiquidity measure for each day as the ratio of the daily absolute return to the dollar volume on that day. Then, we run the predictive regression in each subset separately. The results before and after the introduction of night trading are reported in the last two columns of Table 9 and Table 10, respectively. For each futures market in the both tables, the t-statistic of the predictor slope and the value of R^2 are larger in the high illiquidity subgroup. Note that the coefficient of $r_{1,t}^{day}$ even become negative in the low illiquidity subgroup for some intraday momentum patterns. Overall, the intraday momentum is stronger for days lacking liquidity, irrespective of whether it is before or after the launch of night trading. This seems intuitive since the forecasting ability is harder to exploit away when the market is less liquid.

[Insert Table 9 about here]

[Insert Table 10 about here]

4.4. Economic explanations

In the previous section, we have confirmed that intraday momentum exists in Chinese futures markets, and the patterns of intraday predictability are different under different trading mechanisms. These phenomena raise two questions: What drive the intraday momentum? Why have the intraday predictive patterns changed after the launch of night trading? To answer them, we provide the below discussion.

For the first question, we provide four explanations by referring to related studies (Gao *et al.* 2018; Baltussen *et al.* 2021; Li *et al.* 2021). First, the intraday momentum can be driven by infrequent portfolio rebalancing. Bogousslavsky (2016) proposes a theoretical model in which part of traders trade only infrequently. Infrequent traders take an excess position after absorbing a liquidity shock. They tend to rebalance their portfolio in the next active trading period, which result in another liquidity with the same direction. In the intraday context, infrequent traders have the intention to delay their portfolio rebalancing to later active trading periods instead of trading immediately after the market open, which brings about the positive correlation. Second, the intraday momentum can be explained by the presence of late-informed investors. For the news released overnight, some investors can take actions immediately in the first half hour after the market open. However, other investors may react slowly since they either do not receive the news instantly (Baker & Wurgler 2006) or cannot process the news quickly (Cohen & Frazzini 2008; Huang *et al.* 2015). Intuitively, the late-informed traders trade in the same direction with the early-informed traders, which generates a positive correlation between returns in two half-hour intervals. Third, another possible explanation is based on the investor overconfidence which has been documented theoretically and empirically (e.g., Chan *et al.* 1996; Barberis *et al.* 1998; Daniel *et al.* 1998 and Daniel *et al.* 2001). Based on investor overconfidence and biased self-attribution, Daniel *et al.* (1998) develop a theory implying that overconfident investors tend to underreact to public information since they overestimate their ability to generate information. For example, consider a day with good news released publicly overnight. Overconfident investors incline to ignore and underreact to the news if their private information is bad, which leads to the price persistence. The fourth explanation relates to hedging demand. Gamma measures the acceleration of the derivative price when the price of the underlying security changes. Market makers of products, such as leveraged ETFs and options, usually net short these products if they have gamma exposure. Therefore, to guarantee the delta neutrality of their positions, they must trade in the same direction of price movements. In other words, they have to buy the security when the price rises and sell it when the price falls. This hedging activity tends to increase market volatility and thereby leads to intraday momentum.

Before answering the second question, it is worthwhile to explore the volume patterns of these futures markets. Panel A of Figure 1 plots the half-hour average trading volume before the launch of night trading. Unlike the U-shaped pattern found in the stock markets (e.g., Gao *et al.* 2018; Zhang *et al.* 2019), we instead notice an L-shaped volume pattern for the four metal futures markets. The trading volume peaks in the first 30 minutes and then drops sharply. Note that the volume of third half hour is much lower than other periods. This results from the 15-min trading break (from 10:15 a.m. to 10:30 a.m.). Panel B of Figure 1 plots the trading volume patterns after the launch of night trading. It shows a W-shape for all futures, which is significantly different from before the launch of the night trading. Now the highest trading volume occurs during the first half hour at night instead of the first half hour in the morning, suggesting that the first half hour at night may be more informative. This is consistent with the previous finding that the first half-hour return at night has become the efficient predictor after the launch of night trading.

[Insert Figure 1 about here]

So what is the potential reason for the change of intraday momentum patterns? Liu and An (2011) and Cai *et al.* (2020) document that China's futures markets are largely influenced by the international markets. LME and COMEX are the major metal futures exchanges in the world and their most active trading hours occur in the evening of Beijing time. Before the introduction of night trading, domestic investors cannot trade for the news from the international markets until the domestic markets open at 9:00a.m., Beijing time. After the launch of night trading, the additional trading session widely covers active trading hours of the major international metal futures exchanges. Then, for the international news, investors can react at night instead of waiting for the day. This makes the first half-hour return at night to contain more useful information and to have stronger predictive power than the first half-hour return in the daytime, which has led for the change of intraday predictive patterns.

5. Economic value of intraday momentum: A market timing strategy

In this section, we construct a market timing strategy to estimate the economic value of the intraday momentum in each market. According to this strategy, the trading sign depends on the sign of the efficient intraday predictor, which is the first half-hour return in the daytime before the launch of night trading, and becomes the first half-hour return at night after the launch of night trading. Specifically, if the efficient intraday predictor is positive, we take a long position for the positively predicted trading periods. Conversely, if it is negative, we take a short position. The return realized on trading day t equals to the sum of returns that are obtained by this strategy in all positively predicted periods on the same day. We compare the market timing strategy with the always-long benchmark strategy. The always-long strategy means that we always take a long position for all positively predicted periods.

Table 11 shows the results of the two strategies. For each trading strategy, we report the typical summary statistics, such as average annualized return, t-statistics, standard deviation, Sharpe ratio, skewness, and kurtosis. We also report the success rate that is computed as the percentage of trading days with nonnegative returns. From Table 11, we find that compared to the always-long benchmark strategy, our market timing strategy achieves higher average annualized return, higher sharp ratio, and higher success rate across all four markets, regardless whether it is before or after the launch of night trading. Taking the gold market after the launch of night trading as an example, we notice that the following: the average annualized return of the market timing strategy is 6.77% which is much higher than that of the benchmark strategy, with the value of 1.00%; the Sharpe ratios of the market timing strategy is 21.25, almost 7 times the 3.13 reported for the benchmark strategy; and the success return of the market timing strategy and the benchmark are 53% and 49%, with the former slightly higher than the latter. Figure 3 reports the log cumulative wealth obtained by an investor who begins with 1 yuan and reinvests all the profits according to the two strategies. We can see that the log cumulative return based on the market timing strategy presents a more stable and substantial growth than the benchmark strategy in each market, irrespective of whether it is before or after the launch of night trading. In summary, the above evidence suggests that the intraday momentum in Chinese metal futures markets can generate positive economic value from the perspective of a market timing strategy.

[Insert Table 11 about here]

[Insert Figure 2 about here]

6. Conclusion

This paper provides first empirical evidence on the existence of intraday momentum in Chinese metal (gold, silver, aluminum, and copper) futures markets, and notably it demonstrates that the launch of night trading, a special trading mechanism in Chinese futures markets, has changed the intraday momentum patterns. Before the launch of night trading, the first half-hour return in the day had the ability to positively predict later half-hour returns, but which half-hour returns can be positively predicted depended on the metal markets. After the launch of night trading, the predictive ability of the first half-hour return in the day disappeared, while the first half-hour return at night becomes the efficient predictor, and the positively predicted trading periods still vary across the metal markets. This intraday return predictability is statistically significant for both in-sample and out-of-sample analysis. Further analysis indicates that the intraday predictability is stronger on trading days with higher volatility and higher illiquidity, both before and after the launch of night trading. As for the relation between trading volume and intraday momentum, it is mixed before the launch of night trading, but after the launch of night trading, it becomes positive. To capture the implications of the intraday momentum, we show that the market timing strategy, based on the intraday momentum, can generate more sizeable and stable economic values than the always-long benchmark strategy. Theoretically, we argue that the intraday momentum can be caused by infrequent portfolio rebalancing, the presence of late-informed investors, the investor overconfidence, and the hedging demand for short gamma exposure. As for a possible explanation on why the intraday momentum patterns changed after the launch of night trading, we argue that investors can react to the international news immediately at night, which leads to the first half hour of the night trading session contains more useful information.

Our findings provide some useful and insightful implications for high-frequency investors in Chinese metal futures markets. Given the significantly positive economic gains, investors should focus on the first half hour at night, especially for days of high volatility, high trading volume, and high illiquidity. However, investors should not to utilize the information during the first half hour in the day because of its lack of predictive ability. Furthermore, they should not treat the four markets homogenously when it comes to intraday predictability and trading strategies. Our current research leads to a few open issues. First, given that the Shanghai Futures Exchange suspended night trading for several months in the early days of the COVID-19 outbreak, it would be interesting to investigate how the COVID-19 outbreak impacts the intraday momentum. Second, our findings are based on data from Chinese metal futures markets. Thus, it is relevant to examine whether the findings hold in other commodity futures markets such as crude oil. Third, the relation between intraday predictability and monthly predictability is also a fruitful topic, which can be the subject of futures research.

References

Amihud, Y., 2002. Illiquidity and stock returns: cross-section and time-series effects. Journal of Financial Markets 5, 31-56

Asness, C.S., Moskowitz, T.J., Pedersen, L.H., 2013. Value and Momentum Everywhere. Journal of Finance 68, 929-985

Aye, G.C., Chang, T., Gupta, R., 2016. Is gold an inflation-hedge? Evidence from an interrupted Markov-switching cointegration model. Resources Policy 48, 77-84

Baker, M., Wurgler, J., 2006. Investor sentiment and the cross-section of stock returns. Journal of Finance 61, 1645-1680

Baltussen, G., Da, Z., Lammers, S., Martens, M., 2021. Hedging demand and market intraday momentum. Journal of Financial Economics 142, 377-403

Barberis, N., Shleifer, A., Vishny, R., 1998. A model of investor sentiment. Journal of Financial Economics 49, 307-343

Barclay, M.J., Hendershott, T., 2003. Price Discovery and Trading After Hours. Review of Financial Studies 16, 1041-1073

Beckmann, J., Berger, T., Czudaj, R., 2018. Gold price dynamics and the role of uncertainty. Quantitative Finance 19, 663-681

Bogousslavsky, V., 2016. Infrequent Rebalancing, Return Autocorrelation, and Seasonality. The Journal of Finance 71, 2967-3006

Cai, H., Ahmed, S., Jiang, Y., Liu, X., 2020. The impact of US macroeconomic news announcements on Chinese commodity futures. Quantitative Finance 20, 1927-1966

Chan, L.K., Jegadeesh, N., Lakonishok, J., 1996. Momentum strategies. The Journal of Finance 51, 1681-1713

Chen, K., Wang, M., 2019. Is gold a hedge and safe haven for stock market? Applied Economics Letters 26, 1080-1086

Cheng, L.T.W., Jiang, L., Ng, R.W.Y., 2004. Information content of extended trading for index futures. Journal of Futures Markets 24, 861-886

Chu, X., Gu, Z., Zhou, H., 2019. Intraday momentum and reversal in Chinese stock market. Finance Research Letters 30, 83-88

Clark, T.E., West, K.D., 2007. Approximately normal tests for equal predictive accuracy in nested models. Journal of Econometrics 138, 291-311

Cohen, L., Frazzini, A., 2008. Economic links and predictable returns. Journal of Finance 63,

1977-2011
Cushing, D., Madhavan, A., 2000. Stock returns and trading at the close. Journal of Financial Markets 3, 45-67
Daniel, K., Hirshleifer, D., Subrahmanyam, A., 1998. Investor Psychology and Security Market under-and Overreactions. Journal of Finance, 1839-1885
Daniel, K.D., Hirshleifer, D., Subrahmanyam, A., 2001. Overconfidence, arbitrage, and equilibrium asset pricing. Journal of Finance 56, 921-965
Dungey, M., Fakhrutdinova, L., Goodhart, C., 2009. After-hours trading in equity futures markets. Journal of Futures Markets 29, 114-136
Elaut, G., Frömmel, M., Lampaert, K., 2018. Intraday momentum in FX markets: Disentangling informed trading from liquidity provision. Journal of Financial Markets 37, 35-51
Fan, Y.-J., Lai, H.-N., 2006. The intraday effect and the extension of trading hours for Taiwanese securities. International Review of Financial Analysis 15, 328-347
Gao, L., Han, Y., Zhengzi Li, S., Zhou, G., 2018. Market intraday momentum. Journal of Financial Economics 129, 394-414
Gao, R., Zhao, Y., Zhang, B., 2020. The spillover effects of economic policy uncertainty on the oil, gold, and stock markets: Evidence from China. International Journal of Finance & Economics 26, 2134-2141
Giannetti, A., Larson, S.J., Lee, C.I., Madura, J., 2006. Price movements, information, and liquidity in the night trading market. Financial Review 41, 119-137
Hua, R., Liu, Q., Tse, Y., 2016. Extended trading in Chinese index markets: Informed or uninformed? Pacific-Basin Finance Journal 36, 112-122
Huang, D.S., Jiang, F.W., Tu, J., Zhou, G.F., 2015. Investor Sentiment Aligned: A Powerful Predictor of Stock Returns. Review of Financial Studies 28, 791-837
Jegadeesh, N., Titman, S., 1993. Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. The Journal of Finance 48, 65-91
Jiang, Y., Kellard, N., Liu, X., 2020. Night trading and market quality: Evidence from Chinese and US precious metal futures markets. Journal of Futures Markets 40, 1486-1507
Jin, M., Kearney, F., Li, Y., Yang, Y.C., 2019. Intraday time-series momentum: Evidence from China. Journal of Futures Markets 40, 632-650
Klein, T., Todorova, N., 2021. Night trading with futures in China: The case of Aluminum and Copper. Resources Policy 73
Li, Y., Shen, D., Wang, P., Zhang, W., 2020. Does intraday time-series momentum exist in Chinese stock index futures market? Finance Research Letters 35
Li, Z., Sakkas, A., Urquhart, A., 2021. Intraday time series momentum: Global evidence and links to market characteristics. Journal of Financial Markets
Liu, Q., An, Y., 2011. Information transmission in informationally linked markets: Evidence from US and Chinese commodity futures markets. Journal of International Money and Finance 30, 778-795
Ma, R.R., Xiong, T., 2021. Price explosiveness in nonferrous metal futures markets. Economic Modelling 94, 75-90
Miffre, J., Rallis, G., 2007. Momentum strategies in commodity futures markets. Journal of Banking & Finance 31, 1863-1886

Miwa, K., 2019. Trading hours extension and intraday price behavior. International Review of Economics & Finance 64, 572-585
Moskowitz, T.J., Ooi, Y.H., Pedersen, L.H., 2012. Time series momentum. Journal of Financial Economics 104, 228-250
Neely, C.J., Rapach, D.E., Tu, J., Zhou, G.F., 2014. Forecasting the Equity Risk Premium: The Role of Technical Indicators. Management Science 60, 1772-1791
Newey, W.K., West, K.D., 1987. A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. Econometrica 55, 703-708
Rapach, D.E., Strauss, J.K., Zhou, G.F., 2010. Out-of-Sample Equity Premium Prediction: Combination Forecasts and Links to the Real Economy. Review of Financial Studies 23, 821-862
Sohn, S., Zhang, X., 2017. Could the Extended Trading of CSI 300 Index Futures Facilitate Its Role of Price Discovery? Journal of Futures Markets 37, 717-740
Szakmary, A.C., Shen, Q., Sharma, S.C., 2010. Trend-following trading strategies in commodity futures: A re-examination. Journal of Banking & Finance 34, 409-426
Wang, J., Chen, S.W., Wang, B.T., 2018. Predicting opening spot prices using extended futures trading. Journal of Forecasting 38, 155-174
Wang, T., Wang, C., 2019. The spillover effects of China's industrial growth on price changes of base metal. Resources Policy 61, 375-384
Welch, I., Goyal, A., 2008. A Comprehensive Look at The Empirical Performance of Equity Premium Prediction. Review of Financial Studies 21, 1455-1508
Wen, D., Wang, Y., Zhang, Y., 2021a. Intraday return predictability in China's crude oil futures market: New evidence from a unique trading mechanism. Economic Modelling 96, 209-219
Wen, Z., Gong, X., Ma, D., Xu, Y., 2021b. Intraday momentum and return predictability: Evidence from the crude oil market. Economic Modelling 95, 374-384
Xu, Y., Bouri, E., Saeed, T., Wen, Z., 2020. Intraday return predictability: Evidence from commodity ETFs and their related volatility indices. Resources Policy 69
Yao, X., Hui, X., Kang, K., 2021. Can night trading sessions improve forecasting performance of gold futures' volatility in China? Journal of Forecasting 40, 849-860
Zhang, W., Wang, P., Li, Y., 2020. Intraday momentum in Chinese commodity futures markets. Research in International Business and Finance 54
Zhang, X.F., 2006. Information Uncertainty and Stock Returns. Journal of Finance 61, 105-136
Zhang, Y., Ma, F., Zhu, B., 2019. Intraday momentum and stock return predictability: Evidence from China. Economic Modelling 76, 319-329
Zhou, G., D. S., Li, J.Y., Wang, L.Y., Zhou, G.F., 2020. Time series momentum: Is it there? Journal of Financial Economics 135, 774-794

Table 1. Descriptive summary statistics: Before the launch of night trading

Variable	Obs	Mean	Std.Dev.	Min	Max	Skewness	Kurtosis	ADF-test
Panel A: Gold								
r_1^{day}	1329	-0.02%	1.25%	-8.33%	6.84%	-0.50	5.54	-11.05***

r_2^{day}	1329	0.00%	0.17%	-2.30%	0.99%	-2.25	34.63	-11.09^{***}
r_3^{day}	1329	0.00%	0.11%	-0.89%	0.90%	0.13	14.65	-11.31^{***}
r_4^{day}	1329	0.01%	0.16%	-1.39%	1.17%	0.14	14.69	-10.69^{***}
r_5^{day}	1329	0.00%	0.13%	-1.03%	1.38%	0.05	18.71	-10.84^{***}
r_6^{day}	1329	0.01%	0.29%	-2.31%	2.64%	-0.19	15.38	-11.76^{***}
r_7^{day}	1329	0.00%	0.16%	-1.65%	1.58%	0.09	17.11	-10.15^{***}
r_8^{day}	1329	0.01%	0.20%	-1.66%	2.14%	0.75	15.80	-13.13^{***}
Panel B: Silver								
r_1^{day}	277	-0.14%	1.61%	-9.45%	5.82%	-0.63	5.55	-6.20^{***}
r_2^{day}	277	0.01%	0.25%	-1.32%	1.17%	0.01	5.40	-6.27^{***}
r_3^{day}	277	0.01%	0.16%	-0.72%	1.08%	1.01	9.12	-6.47^{***}
r_4^{day}	277	0.00%	0.25%	-1.40%	1.73%	0.58	12.86	-6.53^{***}
r_5^{day}	277	-0.02%	0.22%	-1.58%	0.98%	-1.20	11.82	-6.86^{***}
r_6^{day}	277	-0.01%	0.36%	-1.55%	1.83%	0.12	4.85	-6.00^{***}
r_7^{day}	277	-0.02%	0.22%	-1.07%	0.85%	-0.70	4.28	-6.98^{***}
r_8^{day}	277	0.03%	0.27%	-0.88%	0.84%	-0.07	0.97	-8.13^{***}
Panel C: Aluminum								
r_1^{day}	1448	0.00%	0.85%	-6.05%	4.85%	-1.07	9.27	-8.91^{***}
r_2^{day}	1448	0.00%	0.26%	-2.52%	1.67%	-1.22	21.57	-11.24^{***}
r_3^{day}	1448	-0.01%	0.19%	-2.89%	1.57%	-3.28	53.96	-10.36^{***}
r_4^{day}	1448	0.00%	0.25%	-2.50%	2.77%	0.30	25.25	-10.38^{***}
r_5^{day}	1448	-0.01%	0.20%	-1.67%	1.15%	-0.42	9.67	-11.41^{***}
r_6^{day}	1448	0.00%	0.35%	-3.27%	2.45%	-0.28	16.11	-12.02^{***}
r_7^{day}	1448	0.00%	0.21%	-1.45%	1.77%	0.24	15.94	-9.83^{***}
r_8^{day}	1448	0.01%	0.27%	-1.92%	2.77%	1.12	17.61	-11.51^{***}
Panel D: Copper								
r_1^{day}	1448	0.00%	1.43%	-6.20%	5.73%	-0.50	3.05	-9.13^{***}
r_2^{day}	1448	0.00%	0.34%	-1.73%	3.17%	0.85	9.96	-11.96^{***}
r_3^{day}	1448	0.00%	0.25%	-1.95%	2.04%	-0.27	14.68	-11.51^{***}
r_4^{day}	1448	-0.03%	0.32%	-1.67%	2.06%	-0.02	5.19	-11.51^{***}
r_5^{day}	1448	0.00%	0.33%	-1.90%	2.91%	0.32	9.69	-11.97^{***}

r_6^{day}	1448	-0.01%	0.47%	-3.77%	3.72%	-0.30	10.92	-12.00^{***}
r_7^{day}	1448	0.01%	0.29%	-1.49%	2.00%	0.38	5.62	-12.17^{***}
r_8^{day}	1448	0.02%	0.35%	-2.05%	1.71%	0.14	3.42	-11.12^{***}

Notes: This table reports the descriptive statistics of return series for four Chinese metal futures: gold, silver, aluminum, and copper, before the launch of night trading. r_i^{day} represents the i th half-hour return during the day trading session. We also report the result of the Augmented Dickey-Fuller test with the significance levels of 10%, 5%, and 1% denoted by *, **, and ***, respectively.

Table 2. Descriptive summary statistics: After the launch of night trading

Variable	Obs	Mean	Std.Dev.	Min	Max	Skewness	Kurtosis	ADF-test
Panel A: Gold								

r_1^{night}	1900	0.00%	0.45%	-3.15%	2.90%	-0.05	5.08	-11.50***
r_2^{night}	1900	-0.01%	0.22%	-2.74%	1.40%	-1.34	20.30	-11.50***
r_3^{night}	1900	0.00%	0.18%	-1.59%	1.03%	-0.56	8.10	-12.30***
r_4^{night}	1900	-0.01%	0.18%	-1.42%	1.03%	-1.02	10.12	-11.73***
r_5^{night}	1900	0.01%	0.15%	-0.91%	1.22%	0.27	6.90	-11.34***
r_6^{night}	1900	0.00%	0.13%	-1.44%	0.69%	-1.25	14.08	-12.41***
r_7^{night}	1900	0.00%	0.11%	-0.83%	0.93%	0.32	8.59	-13.12***
r_8^{night}	1900	0.00%	0.11%	-0.88%	1.30%	0.83	21.00	-12.86***
r_9^{night}	1900	0.00%	0.11%	-0.84%	1.17%	0.22	14.44	-12.25***
r_{10}^{night}	1900	0.00%	0.11%	-0.88%	1.26%	1.55	25.24	-12.28***
r_{11}^{night}	1900	0.00%	0.14%	-1.21%	1.50%	0.30	19.12	-12.61***
r_1^{day}	1956	0.01%	0.41%	-4.21%	5.69%	1.61	36.87	-10.92***
r_2^{day}	1956	0.01%	0.12%	-0.78%	1.08%	0.36	9.37	-13.16***
r_3^{day}	1956	0.00%	0.08%	-0.75%	1.11%	2.10	34.84	-14.76***
r_4^{day}	1956	0.01%	0.11%	-1.07%	1.49%	0.65	22.64	-12.10***
r_5^{day}	1956	0.00%	0.10%	-1.62%	1.17%	-1.14	48.58	-12.77***
r_6^{day}	1956	0.01%	0.17%	-1.43%	1.23%	-0.60	9.40	-11.93***
r_7^{day}	1956	-0.01%	0.12%	-0.94%	0.59%	-0.91	8.27	-13.58***
r_8^{day}	1956	0.00%	0.13%	-1.00%	1.02%	-0.41	9.96	-12.73***
Panel B: Silver								
r_1^{night}	1900	0.04%	0.74%	-5.00%	3.62%	-0.29	5.56	-11.53***
r_2^{night}	1900	-0.01%	0.37%	-3.97%	2.75%	-0.71	17.18	-11.85***
r_3^{night}	1900	-0.01%	0.31%	-3.93%	1.71%	-2.03	30.35	-12.21***
r_4^{night}	1900	0.00%	0.31%	-1.94%	2.63%	-0.11	13.91	-11.43***
r_5^{night}	1900	0.02%	0.23%	-1.44%	1.62%	0.47	7.68	-11.68***
r_6^{night}	1900	0.00%	0.21%	-1.79%	1.17%	-1.50	14.33	-12.46***
r_7^{night}	1900	0.00%	0.19%	-1.46%	1.44%	-0.43	13.14	-12.81***
r_8^{night}	1900	0.00%	0.19%	-3.24%	1.68%	-2.98	57.75	-13.09***
r_9^{night}	1900	0.00%	0.21%	-3.01%	2.31%	-1.54	58.27	-11.01***
r_{10}^{night}	1900	0.00%	0.16%	-2.14%	2.45%	0.81	46.89	-11.83***
r_{11}^{night}	1900	0.00%	0.21%	-2.30%	2.05%	-0.26	21.88	-11.93***

r_1^{day}	1956	-0.02%	0.70%	-17.03%	5.50%	-7.00	185.27	-12.30***
r_2^{day}	1956	0.00%	0.23%	-2.77%	1.39%	-0.65	16.01	-12.56***
r_3^{day}	1956	0.00%	0.14%	-1.11%	1.55%	0.93	18.58	-13.95***
r_4^{day}	1956	0.00%	0.23%	-2.60%	2.39%	0.14	25.88	-11.68***
r_5^{day}	1956	0.00%	0.20%	-4.02%	2.05%	-2.82	89.30	-12.89***
r_6^{day}	1956	0.00%	0.36%	-2.68%	2.80%	-0.19	11.59	-12.24***
r_7^{day}	1956	-0.01%	0.23%	-2.44%	1.56%	-0.64	13.76	-12.73***
r_8^{day}	1956	0.01%	0.24%	-2.17%	2.98%	0.54	22.25	-12.25***
Panel C: Aluminum								
r_1^{night}	1789	0.04%	0.49%	-4.00%	4.48%	0.51	11.36	-11.16***
r_2^{night}	1789	0.00%	0.25%	-2.37%	1.59%	-0.79	12.95	-11.14***
r_3^{night}	1789	0.00%	0.23%	-1.67%	1.84%	0.07	11.26	-11.29***
r_4^{night}	1789	0.00%	0.22%	-2.24%	1.59%	-1.29	16.12	-11.18***
r_5^{night}	1789	0.01%	0.20%	-1.06%	1.89%	1.18	11.75	-11.72***
r_6^{night}	1789	0.00%	0.16%	-1.55%	0.93%	-0.84	11.39	-13.24***
r_7^{night}	1789	-0.01%	0.14%	-2.13%	0.80%	-2.64	38.08	-12.13***
r_8^{night}	1789	0.00%	0.14%	-1.16%	0.80%	-0.36	6.56	-10.92***
r_1^{day}	1843	0.01%	0.44%	-8.03%	3.52%	-3.22	66.80	-11.55***
r_2^{day}	1843	-0.02%	0.26%	-1.73%	1.28%	-0.53	6.79	-12.64***
r_3^{day}	1843	-0.02%	0.18%	-1.74%	1.29%	-0.77	10.23	-10.34***
r_4^{day}	1843	0.00%	0.24%	-2.49%	1.46%	-0.78	11.65	-10.51***
r_5^{day}	1843	0.00%	0.23%	-1.87%	1.39%	-0.32	7.64	-9.90***
r_6^{day}	1843	0.01%	0.28%	-1.74%	2.20%	0.05	5.45	-11.37***
r_7^{day}	1843	-0.01%	0.22%	-1.59%	1.52%	-0.16	7.74	-11.93***
r_8^{day}	1843	0.00%	0.25%	-1.30%	2.01%	0.88	8.70	-11.00***
Panel D: Copper								
r_1^{night}	1789	0.00%	0.55%	-3.28%	5.05%	0.36	6.62	-11.56***
r_2^{night}	1789	0.00%	0.26%	-2.60%	1.40%	-0.67	9.09	-11.56***
r_3^{night}	1789	0.00%	0.24%	-1.42%	1.38%	-0.33	4.98	-12.65***
r_4^{night}	1789	0.01%	0.25%	-2.68%	1.59%	-0.78	11.12	-11.25***
r_5^{night}	1789	0.01%	0.23%	-1.77%	1.62%	0.15	7.97	-11.43***

r_6^{night}	1789	0.00%	0.20%	-1.57%	1.30%	-0.10	8.99	-11.51***
r_7^{night}	1789	0.00%	0.16%	-1.40%	1.17%	-0.65	13.17	-12.50***
r_8^{night}	1789	0.01%	0.16%	-0.99%	2.06%	1.32	18.94	-10.61***
r_1^{day}	1843	0.02%	0.48%	-6.30%	3.05%	-2.37	33.48	-12.14***
r_2^{day}	1843	-0.01%	0.22%	-1.54%	1.56%	0.62	7.79	-12.74***
r_3^{day}	1843	0.00%	0.15%	-1.64%	1.67%	1.01	22.03	-11.72***
r_4^{day}	1843	0.00%	0.20%	-1.86%	1.31%	-0.30	10.41	-12.48***
r_5^{day}	1843	0.01%	0.21%	-1.88%	2.54%	-0.03	20.17	-12.54***
r_6^{day}	1843	0.00%	0.29%	-2.26%	1.74%	-0.16	6.35	-12.22***
r_7^{day}	1843	0.00%	0.21%	-1.10%	1.36%	0.15	3.92	-11.68***
r_8^{day}	1843	-0.01%	0.23%	-1.17%	1.07%	-0.19	2.52	-11.97***

Notes: This table reports the descriptive statistics of return series for four Chinese metal futures: gold, silver, aluminum, and copper, after the launch of night trading. r_i^{night} represents the i th half-hour return during the night trading session. r_i^{day} represents the i th half-hour return during the day trading session. We also report the result of the Augmented Dickey-Fuller test with the significance levels of 10%, 5%, and 1% denoted by*, **, and***, respectively.

Table 3. In-sample predictability performance before the launch of night trading: Using the first half-hour return in the day as the predictor

	r_2^{day}	r_3^{day}	r_4^{day}	r_5^{day}	r_6^{day}	r_7^{day}	r_8^{day}

Panel A: Gold							
Intercept	1E-05	3E-06	1E-04	2E-05	1E-04	2E-05	1E-04*
	(0.119)	(0.120)	(1.428)	(0.685)	(1.596)	(0.449)	(1.694)
r_1^{day}	-0.0087***	-0.0067**	-0.006	0.0022	**0.0322*** **	-0.0078	0.0118
	(-2.618)	(-2.126)	(-1.457)	(0.523)	**(4.396)**	(-0.946)	(1.565)
Obs.	1,329	1,329	1,329	1,329	1,329	1,329	1,329
R^2(%)	0.42	0.61	0.23	0.05	2.00	0.35	0.52
Panel B: Silver							
Intercept	2E-04	1E-04	-2E-05	-2E-04	-1E-04	-2E-04*	3E-04**
	(1.152)	(0.725)	(-0.168)	(-1.228)	(-0.469)	(-1.775)	(2.137)
r_1^{day}	0.0082	-0.0038	-0.0058	0.017	**0.0219* **	-0.0024	-0.0031
	(0.562)	(-0.582)	(-0.523)	(1.506)	**(1.704)**	(-0.370)	(-0.448)
Obs.	277	277	277	277	277	277	277
R^2(%)	0.28	0.14	0.14	1.56	0.98	0.03	0.03
Panel C: Aluminum							
Intercept	-5E-05	-1E-04	-3E-05	-1E-04	1E-05	-4E-05	1E-04
	(-0.718)	(-1.377)	(-0.364)	(-1.600)	(0.173)	(-0.661)	(0.930)
r_1^{day}	-0.0559***	-0.0067	-0.0386***	0.0041	**0.0673*** **	0.0146	0.0301
	(-4.303)	(-0.723)	(-3.345)	(0.343)	**(5.100)**	(1.115)	(1.542)
Obs.	1,448	1,448	1,448	1,448	1,448	1,448	1,448
R^2(%)	3.44	0.09	1.73	0.03	2.62	0.36	0.92
Panel D: Copper							
Intercept	5E-05	-3E-05	-3E-04***	-1E-05	-1E-04	1E-04*	2E-04**
	(0.493)	(-0.427)	(-2.994)	(-0.156)	(-0.642)	(1.647)	(2.385)
r_1^{day}	-0.015	0.0051	-0.0160***	**0.0112* **	**0.0233* **	**0.0121** **	**0.0216*** **
	(-1.490)	(0.910)	(-2.891)	**(1.695)**	**(1.813)**	**(1.988)**	**(3.018)**
Obs.	1,448	1,448	1,448	1,448	1,448	1,448	1,448
R^2(%)	0.39	0.09	0.52	0.23	0.50	0.36	0.80

Notes: This table reports the in-sample regression results for four metal futures: gold, silver, aluminum and copper, before the launch of night trading. In this regression, we regress the first half-hour return during day trading hours against subsequent half-hour returns of the same day. We report the Newey and West (1987) t-statistics in the parentheses. *, **, and *** denote the significance level at 10%, 5%, and 1%, respectively.

Table 4. In-sample predictability performance after the launch of night trading: Using the first half-hour return in the daytime as the predictor

	r_2^{day}	r_3^{day}	r_4^{day}	r_5^{day}	r_6^{day}	r_7^{day}	r_8^{day}

Panel A: Gold							
Intercept	1E-04***	5E-05***	1E-04**	-1E-05	1E-04**	-1E-04**	-1E-05
	(3.852)	(2.873)	(2.086)	(-0.419)	(2.283)	(-2.180)	(-0.462)
r_1^{day}	-0.0061	0.0031	-0.0098	-0.001	0.0025	-0.0139*	-0.0078
	(-0.540)	(0.538)	(-1.128)	(-0.083)	(0.163)	(-1.937)	(-0.996)
Obs.	1,956	1,956	1,956	1,956	1,956	1,956	1,956
R^2(%)	0.04	0.02	0.12	0.00	0.00	0.22	0.06
Panel B: Silver							
Intercept	0	-1E-05	2E-06	-1E-05	1E-04	-1E-04*	1E-04
	(0.005)	(-0.207)	(0.042)	(-0.296)	(0.616)	(-1.715)	(1.520)
r_1^{day}	-0.0081	0.01	0.0015	-0.0078	-0.0031	-0.0116	-0.0156
	(-0.898)	(1.304)	(0.188)	(-0.500)	(-0.166)	(-1.303)	(-1.299)
Obs.	1,956	1,956	1,956	1,956	1,956	1,956	1,956
R^2(%)	0.06	0.25	0.00	0.07	0.00	0.13	0.20
Panel C: Aluminum							
Intercept	-2E-04***	-2E-04***	4E-05	1E-05	1E-04	-1E-04	5E-05
	(-3.107)	(-3.644)	(0.637)	(0.186)	(1.441)	(-1.081)	(0.776)
r_1^{day}	-0.0374	-0.0173	0.0225	-0.0205	0.0092	-0.0097	0.0192
	(-1.634)	(-1.282)	(1.351)	(-1.227)	(0.442)	(-0.736)	(0.933)
Obs.	1,843	1,843	1,843	1,843	1,843	1,843	1,843
R^2(%)	0.40	0.19	0.18	0.16	0.02	0.04	0.12
Panel D: Copper							
Intercept	-1E-04***	4E-05	-1E-05	1E-04	2E-05	3E-05	-1E-04**
	(-2.864)	(1.147)	(-0.233)	(1.469)	(0.4066)	(0.595)	(-2.323)
r_1^{day}	-0.0287*	0.0132	0.0008	-0.0118	-0.014	-0.0035	0.0025
	(-1.804)	(1.157)	(0.059)	(-0.978)	(-0.846)	(-0.378)	(0.202)
Obs.	1,843	1,843	1,843	1,843	1,843	1,843	1,843
R^2(%)	0.38	0.17	0.00	0.07	0.05	0.01	0.00

Notes: This table reports the in-sample predictability performance after the launch of night trading for four metal futures: gold, silver, aluminum and copper. In this table, we use the first half-hour return in the daytime as the predictor. We regress the predictor against subsequent half-hour returns of the same day. We report the Newey and West (1987) t-statistics in the parentheses. *, **, and *** denote the significance level at 10%, 5%, and 1%, respectively.

Table 5. In-sample predictability performance of the night session after the launch of night trading: Using the first half-hour return at night as the predictor

	r_2^{night}	r_3^{night}	r_4^{night}	r_5^{night}	r_6^{night}	r_7^{night}	r_8^{night}	r_9^{night}	r_{10}^{night}	r_{11}^{night}
Panel A: Gold										
Intercept	-1E-04	-3E-05	-1E-04*	1E-04***	-1E-05	1E-06	-2E-05	1E-05	2E-05	-2E-06
	(-1.388)	(-0.650)	(-1.900)	(2.665)	(-0.255)	(0.021)	(-0.688)	(0.588)	(0.697)	(-0.051)
r_1^{day}	-0.0067	-0.0052	-0.0005	-0.0001	-0.0214***	0.0035	0.0034	0.0121	0.0039	0.0039
	(-0.488)	(-0.448)	(-0.037)	(-0.012)	(-2.583)	(0.480)	(0.378)	(1.422)	(0.424)	(0.485)
Obs.	1,900	1,900	1,900	1,900	1,900	1,900	1,900	1,900	1,900	1,900
R^2(%)	0.02	0.02	0.00	0.00	0.55	0.02	0.02	0.23	0.03	0.02
Panel B: Silver										
Intercept	-1E-04	-1E-04	-2E-06	2E-04***	-3E-05	-4E-05	-2E-05	-4E-05	1E-05	-4E-05
	(-1.207)	(-0.858)	(-0.031)	(3.946)	(-0.714)	(-0.965)	(-0.540)	(-0.880)	(0.220)	(-0.869)
r_1^{day}	-0.0223*	-0.0135	-0.0326**	-0.006	-0.0174**	-0.002	0.0135	0.0127	**0.0194***	0.0109
	(-1.692)	(-0.896)	(-2.2340)	(-0.686)	(-1.973)	(-0.211)	(1.357)	(0.897)	**(1.862)**	(1.237)
Obs.	1,900	1,900	1,900	1,900	1,900	1,900	1,900	1,900	1,900	1,900
R^2(%)	0.20	0.10	0.61	0.04	0.39	0.01	0.26	0.20	0.77	0.15
Panel C: Aluminum										
Intercept	1E-04	4E-06	3E-05	1E-04**	-2E-05	-1E-04**	-2E-05			
	(0.955)	(0.070)	(0.545)	(2.172)	(-0.570)	(-2.187)	(-0.497)			
r_1^{day}	-0.0345	-0.0238	-0.0423	0.0113	-0.0122	-0.0280**	0.0083			
	(-1.304)	(-1.087)	(-1.443)	(0.682)	(-0.979)	(-2.176)	(0.810)			

Obs.	1,789	1,789	1,789	1,789	1,789	1,789	1,789
R^2(%)	0.47	0.27	0.88	0.08	0.14	0.99	0.08
Panel D: Copper							
Intercept	-4E-05	-3E-05	1E-04*	1E-04*	-1E-05	-2E-05	1E-04
	(-0.686)	(-0.609)	(1.874)	(1.857)	(-0.151)	(-0.438)	(1.520)
r_1^{day}	-0.0164	0.0148	0.0034	-0.0093	-0.0078	-0.0091	-5E-05
	(-1.023)	(0.840)	(0.173)	(-0.793)	(-0.734)	(-0.829)	(-0.004)
Obs.	1,789	1,789	1,789	1,789	1,789	1,789	1,789
R^2(%)	0.12	0.12	0.01	0.05	0.05	0.10	0.00

Notes: This table reports the in-sample predictability performance of the night session after the launch of night trading for four metal futures: gold, silver, aluminum and copper. In this table, we use the first half-hour return at night as the predictor. We regress the predictor against subsequent half-hour returns of the night session on the same trading day. We report the Newey and West (1987) t-statistics in the parentheses. *, **, and *** denote the significance level at 10%, 5%, and 1%, respectively.

Table 6. In-sample predictability performance of the day session after the launch of night trading: Using the first half-hour return at night as the predictor

	r_1^{day}	r_2^{day}	r_3^{day}	r_4^{day}	r_5^{day}	r_6^{day}	r_7^{day}	r_8^{day}
Panel A: Gold								
Intercept	4E-05	1E-04***	5E-05***	4E-05*	-1E-05	1E-04**	-1E-04**	-1E-05
	(0.553)	(3.755)	(2.946)	(1.688)	(-0.348)	(1.998)	(-2.122)	(-0.473)
r_1^{day}	**0.0530*** **	0.0022	-0.0013	0.0013	0.0077	0.0076	-0.007	0.0088
	(3.000)	(0.262)	(-0.284)	(0.193)	(1.467)	(0.813)	(-1.002)	(1.086)
Obs.	1,900	1,900	1,900	1,900	1,900	1,900	1,900	1,900
R^2(%)	0.56	0.01	0.01	0.00	0.11	0.04	0.07	0.10
Panel B: Silver								
Intercept	-1E-04	4E-06	1E-06	-2E-05	-1E-05	2E-05	-1E-04*	1E-04
	(-1.025)	(0.080)	(0.049)	(-0.402)	(-0.264)	(0.256)	(-1.718)	(1.622)
r_1^{day}	**0.0657*** **	-0.0082	-0.0039	0.0096	**0.0176** **	**0.0360*** **	0.0036	**0.0243* **
	(3.745)	(-0.760)	(-0.586)	(1.134)	**(2.204)**	**(2.877)**	(0.384)	**(1.839)**
Obs.	1,900	1,900	1,900	1,900	1,900	1,900	1,900	1,900
R^2(%)	0.90	0.07	0.04	0.10	0.40	0.54	0.01	0.53
Panel C: Aluminum								
Intercept	1E-04	-2E-04***	-2E-04***	1E-04	1E-05	1E-04	-1E-04	3E-05
	(0.890)	(-3.008)	(-3.031)	(0.760)	(0.170)	(1.217)	(-1.377)	(0.472)
r_1^{day}	0.026	0.0253	-0.0364**	0.0142	0.0127	0.0146	**0.0365*** **	**0.0756*** **
	(0.870)	(1.303)	(-2.444)	(0.675)	(0.866)	(0.739)	**(2.619)**	**(4.678)**

Obs.	1,789	1,789	1,789	1,789	1,789	1,789	1,789	1,789
R^2(%)	0.12	0.23	1.03	0.09	0.08	0.06	0.69	2.27
Panel D: Copper								
Intercept	2E-04**	-1E-04**	1E-04	-1E-05	1E-04	1E-05	3E-05	-1E-04**
	(2.288)	(-2.499)	(1.337)	(-0.201)	(1.533)	(0.212)	(0.623)	(-2.039)
r_1^{day}	0.0077	0.0136	0.0155	-0.0031	0.0126	-0.0023	**0.0325*** **	**0.0247***
	(0.363)	(1.087)	(1.374)	(-0.280)	(1.179)	(-0.163)	**(2.896)**	**(1.898)**
Obs.	1,789	1,789	1,789	1,789	1,789	1,789	1,789	1,789
R^2(%)	0.01	0.12	0.31	0.01	0.11	0.00	0.75	0.35

Notes: This table reports the in-sample predictability performance of the day session after the launch of night trading for four metal futures: gold, silver, aluminum and copper. In this table, we use the first half-hour return at night as the predictor. We regress the predictor against subsequent half-hour returns of the day session on the same trading day. We report the Newey and West (1987) t-statistics in the parentheses. *, **, and *** denote the significance level at 10%, 5%, and 1%, respectively.

Table 7. Out-of-sample predictability performance: before the launch of night trading

	Averaged Intercept	Ave. β_i	R^2_{OS} (%)	MSPE-adj.
Panel A: Gold				
r_6^{day}	1.37E-04	0.04^{***}	1.75	3.65^{***}
Panel B: Silver				
r_6^{day}	-5.16E-05	0.02	0.78	1.60^{*}
Panel C: Aluminum				
r_6^{day}	7.48E-05	0.07^{***}	1.34	2.62^{***}
Panel D: Copper				
r_5^{day}	2.03E-05	0.01	0.10	1.01
r_6^{day}	-5.08E-05	0.01	0.30	1.80^{**}
r_7^{day}	1.28E-04	0.01^{*}	0.07	1.07
r_8^{day}	1.88E-04	0.02^{***}	0.57	2.41^{***}

Notes: This table shows the result of out-of-sample analysis before the launch of night trading. We use the first 200 observations for the first regression, and recursively regress the predictive model by adding 1 observation at a time. We report the coefficients averaged from all individual regressions. Their significance levels are generated by the average Newey and West (1987) t-statistics (unreported). We also present the R^2_{OS} and Clark and West (2007) MSPE-adjusted. Newey and West (1987) corrections are applied in calculating the Clark and West (2007) MSPE-adjusted. *, **, and *** denote the significance level at 10%, 5%, and 1%, respectively.

Table 8. Out-of-sample predictability performance: after the launch of night trading

	Averaged Intercept	Ave. β_i	R^2_{OS} (%)	MSPE-adj.
Panel A: Gold				
r_1^{day}	-6.72E-05	0.05**	0.24	1.87**
Panel B: Silver				
r_{10}^{night}	1.49E-05	0.02***	-0.30	1.05
r_1^{day}	-4.35E-04**	0.04*	0.76	2.46***
r_5^{day}	-5.37E-05	0.02**	0.22	1.66**
r_6^{day}	1.56E-04	0.05*	0.28	2.34***
r_8^{day}	1.47E-04	0.02*	0.14	0.96
Panel C: Aluminum				
r_7^{day}	-4.68E-05	0.03*	0.32	1.78**
r_8^{day}	6.39E-05	0.06***	1.94	3.64***
Panel D: Copper				
r_7^{day}	3.77E-05	0.03***	0.52	2.12**
r_8^{day}	-6.27E-06	0.03*	-0.89	-0.05

Notes: This table shows the result of out-of-sample analysis after the launch of night trading. We use the first 200 observations for the first regression, and recursively regress the predictive model by adding 1 observation at a time. We report the coefficients averaged from all individual regressions. Their significance levels are generated by the average Newey and West (1987) t-statistics (unreported). We also present the R^2_{OS} and Clark and West (2007) MSPE-adjusted. Newey and West (1987) corrections are applied in calculating the Clark and West (2007) MSPE-adjusted. *, **, and *** denote the significance level at 10%, 5%, and 1%, respectively.

Table 9. Impact of volatility, volume, and illiquidity on intraday momentum: Before the launch of night trading.

		Volatility		Trading volume		Illiquidity	
		High	Low	High	Low	High	Low
Panel A: Gold							
r_6^{day}	Intercept	2E-04**	-3E-05	2E-04	1E-04	2E-04**	-1E-05
		(1.990)	(-0.360)	(1.459)	(0.800)	(2.265)	(-0.061)
	β_1	0.0308***	0.0795***	0.0378***	0.0198**	0.0443***	-0.0291
		(3.693)	(2.987)	(3.725)	(2.125)	(5.416)	(-1.066)
	R^2 (%)	2.48	1.58	2.47	0.99	5.15	0.69
Panel B: Silver							
r_6^{day}	Intercept	2E-04	-4E-04	1E-04	-4E-04	-4E-04	2E-04
		(0.706)	(-1.411)	(0.374)	(-1.448)	(-1.294)	(0.753)
	β_1	0.0228*	0.0472	0.0260	0.0122	0.0242*	-0.0067
		(1.850)	(1.075)	(1.496)	(0.713)	(1.947)	(-0.231)
	R^2 (%)	1.71	0.56	1.30	0.36	2.07	0.02
Panel C: Aluminum							
r_6^{day}	Intercept	2E-04	-1E-04**	1E-04	-5E-05	-1E-04	1E-04
		(1.048)	(-1.996)	(0.485)	(-0.623)	(-1.149)	(0.736)
	β_1	0.0662***	0.0921***	0.0600***	0.1046***	0.0993***	0.0315
		(3.591)	(3.745)	(2.963)	(4.216)	(18.478)	(1.237)
	R^2 (%)	2.78	1.62	2.27	4.43	9.83	0.39
Panel D: Copper							
r_6^{day}	Intercept	-3E-05	-1E-04	-1E-04	-1E-05	1E-04	-1E-04
		(-0.135)	(-0.936)	(-0.750)	(-0.109)	(0.487)	(-1.020)
	β_1	0.0237*	0.0192	0.0120	0.0478***	0.0384**	-0.0653***
		(1.746)	(0.702)	(0.600)	(3.558)	(2.505)	(-2.645)
	R^2 (%)	0.63	0.09	0.12	2.40	1.81	1.51
r_8^{day}	Intercept	3E-04**	4E-05	3E-04***	1E-05	3E-04**	2E-04
		(2.471)	(0.402)	(2.915)	(0.103)	(2.315)	(1.423)

β_1	0.0209***	0.0368**	0.0264***	0.0110	0.0338***	-0.0511***
	(2.789)	(1.994)	(3.089)	(1.080)	(4.426)	(-3.053)
R^2 (%)	1.04	0.41	1.26	0.19	2.90	1.47

Notes: This table shows the predictive performance of intraday momentum patterns under different levels of volatility, trading volume, and illiquidity, before the launch of night trading. The volatility is calculated based on 1-minute returns during the first half hour in the day. We split the entire sample into a high subset and a low subset according to their volatility. The volume is the total trading volume of the first half hour in the day. We sort all the trading days into a high group and a low group year by year, and combine each group across all years to generate two trading volume subsets. The Amihud (2002) illiquidity measure is defined as the ratio of the daily absolute return to the dollar volume on that day. This measure is also used to sort the data sample into two subsets. We then conduct the predictive regression in each subset for all efficient intraday momentum patterns. The Newey and West (1987) t-statistics are in the parentheses. *, **, and *** denote the significance level at 10%, 5%, and 1%, respectively.

Table 10. Impact of volatility, volume, and illiquidity on intraday momentum: After the launch of night trading.

		Volatility		Trading volume		Illiquidity	
		high	low	high	low	high	low
Panel A: Gold							
r_1^{day}	Intercept	1E-04	2E-05	1E-04	2E-05	1E-04	2E-05
		(0.564)	(0.255)	(0.546)	(0.234)	(0.563)	(0.292)
	β_1	0.0477***	0.1274**	0.0576***	0.0350	0.0841***	-0.0313
		(2.597)	(2.351)	(2.794)	(1.045)	(3.681)	(-0.953)
	R^2 (%)	0.78	0.47	0.88	0.12	1.51	0.17
Panel B: Silver							
r_1^{day}	Intercept	-2E-05	-2E-04*	-2E-04	-1E-05	2E-04	-4E-04***
		(-0.090)	(-1.856)	(-1.267)	(-0.040)	(0.960)	(-3.021)
	β_1	0.0682***	0.0104	0.0656***	0.0686	0.1199***	-0.0341
		(3.721)	(0.160)	(3.808)	(1.464)	(4.680)	(-1.084)
	R^2 (%)	1.42	0.00	1.24	0.40	3.15	0.23
r_5^{day}	Intercept	-1E-04	3E-05	-1E-04	1E-04	4E-05	-5E-05
		(-0.812)	(0.741)	(-1.603)	(1.556)	(0.660)	(-0.656)
	β_1	0.0180**	0.0125	0.0145	0.0352**	0.0309**	-0.0075
		(2.107)	(0.723)	(1.414)	(2.303)	(2.449)	(-0.698)
	R^2 (%)	0.51	0.05	0.34	0.75	1.77	0.05
r_6^{day}	Intercept	-4E-05	1E-04	-4E-05	1E-04	-1E-04	2E-04
		(-0.268)	(0.869)	(-0.244)	(0.816)	(-0.607)	(1.548)
	β_1	0.0345**	0.0678*	0.0403***	0.0150	0.0722***	-0.0353
		(2.509)	(1.832)	(2.988)	(0.571)	(4.111)	(-1.258)
	R^2 (%)	0.62	0.43	0.88	0.04	2.52	0.41
Panel C: Aluminum							
r_7^{day}	Intercept	-1E-04	-2E-05	-1E-04*	1E-05	-1E-04	-2E-05
		(-1.177)	(-0.462)	(-1.713)	(0.137)	(-1.353)	(-0.327)
	β_1	0.0398***	0.0118	0.0403***	0.0218	0.0630***	0.0028

		(2.635)	(0.445)	(2.673)	(0.900)	(3.152)	(0.129)
	R^2 (%)	1.02	0.03	1.06	0.12	2.34	0.00
r_8^{day}	Intercept	1E-04	1E-05	1E-04	-1E-05	1E-04	-1E-04
		(0.506)	(0.089)	(0.748)	(-0.180)	(1.480)	(-0.936)
	β_1	0.0787***	0.0447	0.0840***	0.0337	0.0927***	0.0580**
		(4.152)	(1.245)	(4.555)	(1.490)	(4.498)	(1.967)
	R^2 (%)	3.03	0.29	3.72	0.20	3.38	1.35
Panel D: Copper							
r_7^{day}	Intercept	-2E-05	1E-04	-2E-05	1E-04	1E-04	-1E-05
		(-0.203)	(1.359)	(-0.280)	(1.238)	(1.036)	(-0.207)
	β_1	0.0331***	0.0261	0.0322***	0.0336	0.0497***	-0.0030
		(2.677)	(1.019)	(2.598)	(1.561)	(3.868)	(-0.156)
	R^2 (%)	1.11	0.13	1.05	0.29	1.97	0.01

Notes: This table shows the predictive performance of intraday momentum patterns under different levels of volatility, trading volume, and illiquidity, after the launch of night trading. The volatility is calculated based on 1-minute returns during the first half hour at night. We split the entire sample into a high subset and a low subset according to their volatility. The volume is the total trading volume of the first half hour at night. We sort all the trading days into a high group and a low group year by year, and combine each group across all years to generate two trading volume subsets. The Amihud (2002) illiquidity measure is defined as the ratio of the daily absolute return to the dollar volume on that day. This measure is also used to sort the data sample into two subsets. We then conduct the predictive regression in each subset for all efficient intraday momentum patterns. The Newey and West (1987) t-statistics are in the parentheses.*, **, and *** denote the significance level at 10%, 5%, and 1%, respectively.

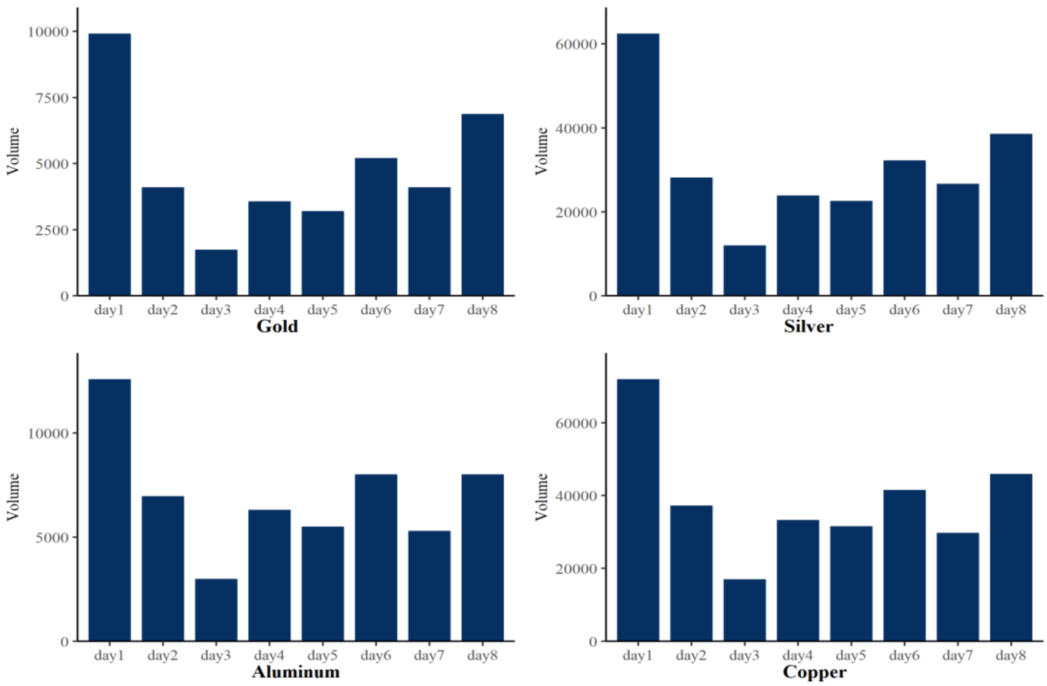
Table 11. Market timing strategy

Futures	Trading strategy	Ave.Ret. (%)	T_stat.	Std.Dev.	Sharpe ratio	Skewness	Kurtosis	Success rate
Panel A: Before the launch of night trading								
Gold	Market timing	11.51	5.97	0.28	40.95	1.96	15.10	0.55
	Always long	2.59	1.33	0.28	9.09	-0.17	15.60	0.51
Silver	Market timing	11.36	2.14	0.35	32.10	0.73	4.61	0.53
	Always long	-3.28	-0.61	0.36	-9.20	0.12	4.85	0.47
Aluminum	Market timing	10.30	4.46	0.35	29.31	0.24	16.43	0.52
	Always long	0.33	0.14	0.35	0.95	-0.28	16.10	0.44
Copper	Market timing	13.84	3.64	0.58	23.94	-0.25	6.18	0.54
	Always long	2.54	0.67	0.58	4.37	0.02	5.98	0.52
Panel B: After the launch of night trading								
Gold	Market timing	6.77	3.71	0.32	21.25	0.40	7.70	0.54
	Always long	1.00	0.55	0.32	3.13	0.65	7.70	0.50
Silver	Market timing	10.20	2.68	0.66	15.36	0.70	9.53	0.52
	Always long	-1.77	-0.46	0.67	-2.66	0.71	9.66	0.48
Aluminum	Market timing	6.79	3.40	0.34	20.07	0.67	7.12	0.57
	Always long	0.32	0.16	0.34	0.95	0.30	7.23	0.53
Copper	Market timing	2.99	2.42	0.21	14.32	0.23	3.88	0.56
	Always long	0.73	0.59	0.21	3.49	0.16	3.91	0.51

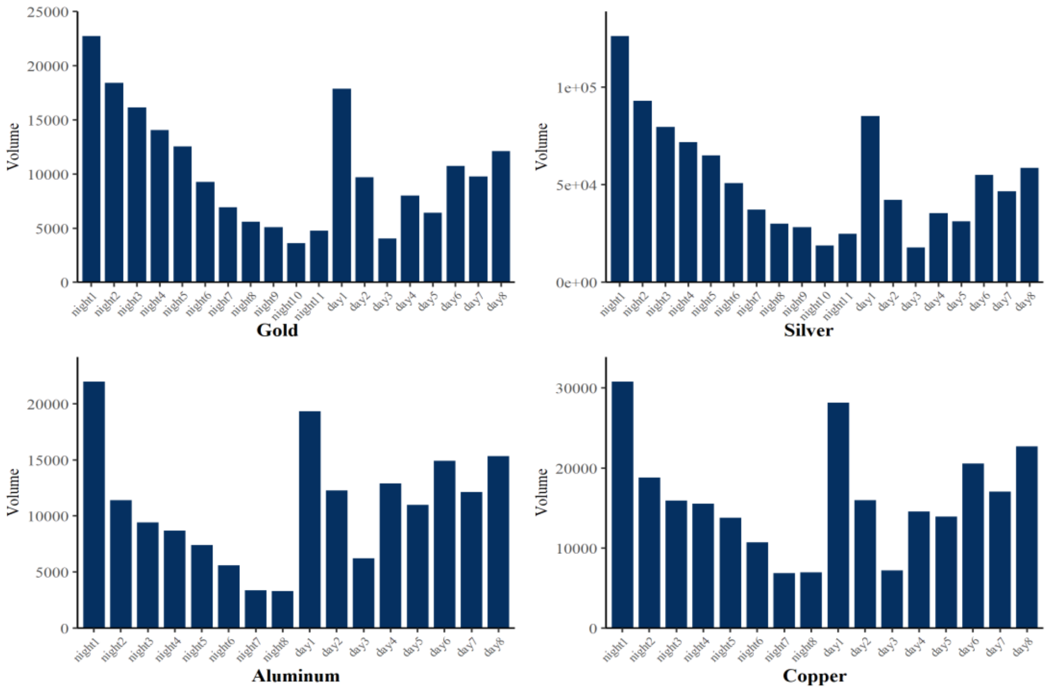
Notes: This table presents the economic value of the market timing strategy, before and after the launch of night trading. This timing strategy takes a long position during the predicted periods if the predictor is positive and a short position if the predictor is negative. The always-long benchmark strategy always takes a long position during the predicted periods regardless of the sign of the predictor. In this table, we report the average annualized return, Newey and West (1987) robust t-statistics, standard deviation, Sharpe ratio, skewness, kurtosis, and success rate.

Figure 1. Average half-hour trading volume patterns

Panel A. Before the launch of night trading



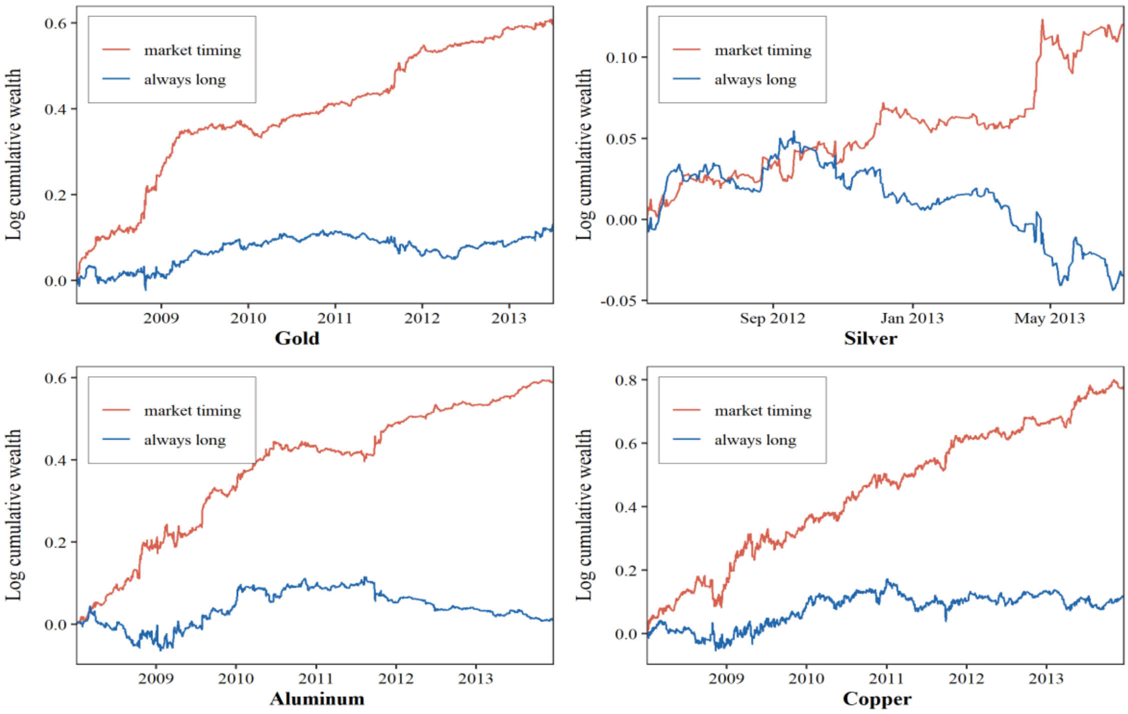
Panel B. After the launch of night trading



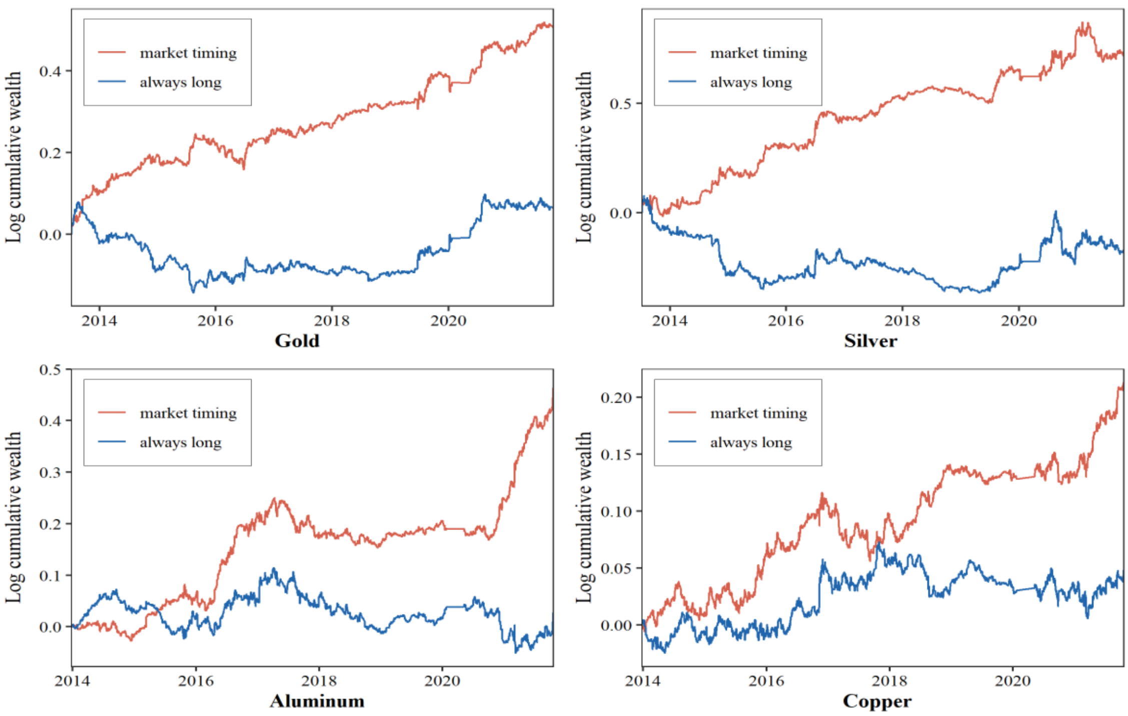
Notes: Before the launch of night trading, there are 8 half-hour intervals, labeled from day1 to day8 during the day trading session (from 9:00 a.m. to 3:00 p.m.). After the launch of night trading, for gold and silver, the night trading session is from 9:00 p.m. to 2:30 a.m., labelled from night1 to night11. For aluminum and copper, it is from 9:00 a.m. to 1:00 a.m., labelled from night1 to night8.

Figure 2. Log cumulative wealth

Panel A. Before the launch of night trading



Panel B. After the launch of night trading



Notes: Log cumulative wealth based on the perspective of market timing, before and after the launch of night trading. We assume the investor start with $1 and reinvest all proceed.