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Night trading and market quality: Evidence from Chinese and US precious metal futures markets

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Abstract

Given a dominant exchange, how should other exchanges set their trading hours? We examine the introduction of a night session by the Shanghai Futures Exchange, allowing trading concurrently with daytime trading at the Commodity Exchange in the United States. After developing hypotheses, results for gold and silver show: trading activity has increased; liquidity in Shanghai has risen and prices are less volatile at market opening; the price discovery share of Chinese gold futures has fallen but this is not a sign of weakening market quality; and volatility spillovers increase bidirectionally. Longer trading hours have decreased market segmentation and increased information flow.

K E Y W O R D S

information flow, intraday data, price discovery, trading hours, volatility spillovers

JEL CLASSIFICATION G13; G14

1 | INTRODUCTION

The concept of dominant and satellite markets was first proposed by Garbade and Silber (1979) who analyze the short-run price behavior of an identical asset traded in two different markets. Since then, numerous studies have investigated price discovery in informationally linked markets (see H. Chen, Choi, & Hong, 2013; Gonzalo & Granger, 1995; Hasbrouck, 1995; Rapach, Strauss, & Zhou, 2013; Ye, 2014). In global futures trading, it has been found that preeminent exchanges take the lead in price discovery for certain commodities (see Covrig, Ding, & Low, 2004; Gong & Zheng, 2016; Han, Liang, & Tang, 2013; Jiang, Su, Todorova, & Roca, 2016; Liu & An, 2011; Yin & Han, 2013). Given this, how should newer entrants behave, particularly when setting trading hours? Clearly, there may be liquidity shortages if a market is open for long periods during which demand for trading is scarce. On the other hand, a shorter trading period may attract enough volume but gives rise to more time when the market is closed. New information impounded in the price of the preeminent exchange might not be reflected in the price of the entrant for several hours, leading to price jumps and unnecessary volatility when the entrant market opens.

To investigate the question of optimal trading hours for newer entrant markets, we examine the introduction of night trading by the Shanghai Futures Exchange (SHFE) for gold and silver futures¹ on July 5, 2013. Before this period,

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¹As additional motivation note that the price behavior of international commodity futures markets, including precious metals, has been shown to be useful in predicting business cycles (see Kang & Kwon, 2017) and stock market returns (see Alvesy & Szymanowska, 2019) in many countries.

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trading took place during daylight hours in Shanghai between 9:00 a.m.–11:30 a.m. and 1:30 p.m.–3:00 p.m. From July 2013, an additional session was added which runs from 9:00 p.m. to 2:30 a.m. the following day (see Jin, Li, Wang, & Yang, 2018), more than doubling the amount of time available for trading during a 'trading' day. The SHFE view was, "The purpose of night trading is to help prices [on the Shanghai exchange] better connect with global prices, and to help achieve our goal of internationalizing our contracts" (Li, 2013). So did this actually happen? And, in particular, what happened to important measures of market quality, such as volume, liquidity, price discovery, and volatility, as a result of this new policy?

Although the SHFE is the second largest gold futures exchange worldwide by volume traded (Jin et al., 2018; Reuters, 2017), the Commodity Exchange (COMEX) in New York, where gold futures first started trading in 1974, is larger. Indeed, recent work suggests that the COMEX gold futures play the leading role globally in price setting and discovery (Fung, Tse, Yau, & Zhao, 2013; Hauptfleisch, Putnins, & Lucey, 2016; X. Xu & Fung, 2005). By opening at 9:00 p.m. in China, which is 9:00 a.m. Eastern Standard Time (EST) in New York, the SHFE trading for gold and silver futures now overlaps with the active trading period in the United States given that the COMEX opens at 8:20 a.m. EST.

To examine the effect of this overlap, our paper develops several testable hypotheses which we subsequently empirically test using both daily and intraday data from Chinese and US futures markets. Specifically, we posit that post the introduction of night trading at the SHFE, in Chinese markets (a) volume will be higher at night; (b) liquidity will rise; (c) perhaps counterintuitively, price discovery measures will fall; and (d) volatility spillovers will increase bidirectionally but particularly from the United States to China.

Employing a sample period from January 2008 to April 2016, our empirical tests validate our hypotheses to a large extent but also reveal some unexpected findings. First, trading activity, as measured by volume, turnover, and open interest, for both China and the United States is higher after the introduction of night trading. Moreover, after the introduction and in China at least, such activity is higher during the night trading session than the daylight alternative. This provides a prima facie case that Chinese futures traders value the night trading session and that, consequently, market quality indicators are likely to have improved.

Second, using three popular measures, namely, Roll's spread, the Amihud illiquidity measure, and the proportion of zero returns, we examine liquidity dynamics before and after the introduction of night trading. The Roll and Amihud measures, specifically, indicate that typically liquidity has improved at the SHFE as hypothesized postintroduction and suggest that market quality has increased. On average, traders can make transactions more easily and with less price effects than before July 2013. In particular, comparing the first daylight trading hour in China pre- and postnight trading, Roll, Amihud and realized volatility measures are lower for the postnight trading subsample. The opening of the Chinese night trading session, crucially overlapping with the COMEX daylight trading period, enables the SHFE markets to capture relevant price information from the United States in real time. As a consequence, this ensures a less volatile market when Shanghai opens the following morning.

Third, recent literature suggests that price discovery is more likely to occur in the SHFE gold futures market relative to the Shanghai Gold Exchange (SGE)² physical market and that, within both markets, price discovery is more prevalent during night trading sessions (Jin et al., 2018). Here we extend such work by examining the price discovery function of the SHFE gold and silver futures relative to the preeminent US futures exchange. Strikingly, employing established measures, such as the component share (CS) of Gonzalo and Granger (1995), the information share (IS) of Hasbrouck (1995), and the modified information share (MIS) of Lien and Shrestha (2009), we show that for gold, price discovery share actually *falls* relative to the United States after the introduction of night trading. However, we posit this is not a sign of weakening market quality but the contrary. Before July 2013, Chinese and US markets were more segmented, as the SHFE was closed during the active daylight trading period in the United States. However, night trading in China now allows greater information transmission between the two markets over a much longer, contemporaneous trading period. This lessening of market segmentation implies that the preeminent market's share of price discovery will rise and this is observed empirically.³

Finally, to further investigate the changing interdependence between the two exchanges we implement the volatility spillover index proposed by Diebold and Yilmaz (2012). As hypothesized, directional (and total) spillovers grow following the introduction of night trading but particularly from the United States to China for both commodities. Moreover, while volatility spillovers increase most starkly from the United States to China during night trading, they

²Other work examining market quality at the SGE includes C. Xu and Zhang (2019).

³Interestingly, price discovery measures for Chinese silver futures rise after the introduction of night trading, albeit from a very low base. This we ascribe to the SHFE silver futures market being particularly new, opening as it did in June 2012, only a year before night trading was introduced. US silver futures still dominate in terms of price discovery in postnight trading.

also increase during the day and from China to the United States. It would appear likely that declining market segmentation, coupled with the importance of China as an importer and trader of commodities, has substantially enhanced the interdependence of the two countries.

The contribution of our paper, as well as its novelty, lies in its investigation of market quality given an extension of trading hours, when an entrant exchange aims to better connect with international prices set by an established and dominant player. We show that the policy of extending trading hours into the night at the SHFE has increased its market quality, and helped it better integrate with the global market. Hence, our comprehensive empirical evidence supports the new policy and is relevant to regulators, traders, and portfolio managers alike. Our findings are of particular use to policymakers in other futures exchanges when setting trading hours.

The remainder of the paper is divided into six sections. Section 2 considers the extant literature and theoretical underpinnings of our work, while Section 3 outlines the methodology. In Section 4, we provide some institutional details and summarize the data, while Section 5 presents the empirical results. Finally, Section 6 offers the related discussion and conclusion.

2 | LITERATURE AND THEORETICAL UNDERPINNINGS

Assuming a preeminent exchange (such as the COMEX) that takes the lead in price setting, what might happen to indicators of market quality, including trading volume, liquidity, price discovery, and volatility, if a newer exchange (such as the SHFE) extends its trading hours?

2.1 | Volume and liquidity

Although volume is often found to be positively associated with both returns and volatility in financial markets (Karpov, 1986, 1987), the determinants of volume, particularly for newer exchanges, are less explored. Earlier work, such as Pennings and Leuthold (1999), shows that hedging effectiveness is a significantly positive factor in the trading volume of commodity futures markets. Of course, classic measures of hedging effectiveness, such as Ederington (1979), are a function of basis risk:

$$e = 1 - \frac{\operatorname{Var}(R)}{\operatorname{Var}(U)} = \frac{\sigma_{\mathrm{fs}}^2}{\sigma_{\mathrm{f}}^2 \sigma_{\mathrm{s}}^2} = \rho_{\mathrm{fs}}^2, \tag{1}$$

where *R* denotes the return on a hedged position, *U* the return on the unhedged position, and ρ_{fs} , σ_s^2 , σ_s^2 , and σ_{fs} represent the correlation coefficient, variances, and covariance, respectively, of futures and spot price changes. In our context, given the COMEX is the leading market for price discovery globally, hedgers and other market participants in China will desire the correlation coefficient between the COMEX and the SHFE futures to be as close to unity as possible. The opening of the Chinese night trading session, overlapping with the COMEX daytime trading period, should enable the SHFE markets to more quickly reflect relevant price information from the United States, leading to a higher correlation coefficient between the returns of the two markets and, consequently, a higher volume of trading in Shanghai.

Hypothesis 1a. After the introduction of night trading, trading volume will be higher in Chinese markets, particularly at night.

Of course, trading volume is often taken as a rudimentary measure of liquidity (see, e.g., Darolles, Fol, & Mero, 2015; Domowitz & Wang, 1994; Gallant, Rossi, & Tauchen, 1992; Zhang & Ding, 2018). While both volume and liquidity in precious metals markets can be affected by a number of factors (see, e.g., Smales & Lucey, 2019),⁴ given liquidity's association with volume and as a corollary of Hypothesis 1a, we can state:

Hypothesis 1b. After the introduction of night trading, liquidity will rise in Chinese markets.

⁴Smales and Lucey (2019) show that the effect of monetary policy announcements on the liquidity of gold and silver instruments (i.e., physical, futures, and exchange-traded funds [ETFs]) is partially determined by current investor sentiment.

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In related work, Iwatsubo, Watkins, and Xu (2018) examine platinum and gold futures traded in Tokyo and their counterparts in New York. They note that during the evening trading session in Tokyo, which partially overlaps with day trading in New York, more informed traders place their orders relative to the day trading session in Tokyo. This provides prima facie support for Hypotheses 1a and 1b and may clearly have implications for price discovery.

2.2 | Price discovery

In an efficient market, price reflects all relevant information and therefore represents the fundamental value of a security⁵ (Fama, 1970). Recent work examining gold spot and futures markets in China has suggested a relatively high level of efficiency (Jin et al., 2018). Other literature that examines precious metals markets outside the United States, including Kumar and Pandey (2013), has found inefficiencies particularly in thin markets.⁶ A related concept, price discovery embodies how quickly and accurately new information is included in the price and can be inhibited by regulations, high transaction costs, and uninformed traders (Lien & Shrestha, 2009). As noted in Section 1, recent work assessing Chinese precious metals has suggested that price discovery occurs in the futures market (Jin et al., 2018).⁷

By definition, the preeminent, or dominant as termed in Garbade and Silber (2003), exchange takes the lead in price discovery (Fung, Liu, & Tse, 2010, 2013; Han et al., 2013; Liu & An, 2011). However, if a newer market is closed daily during the more active trading sessions of the preeminent market as was the case with the SHFE and the COMEX before July 2013, IS measures used in the literature will potentially indicate that neither market is dominant.

As an example, consider the CS measure of Gonzalo and Granger (1995). They decompose the vector of nonstationary price series Y_t (where Y_t is an $n \times 1$ vector of unit-root series and it is assumed there are n - 1 cointegrating vectors) into a permanent component (or common factor) f_t and a transitory (stationary) component \tilde{Y}_t . The series Y_t can therefore be written as

$$Y_t = Af_t + \tilde{Y}_t. \tag{2}$$

Under a linearity condition, the permanent component f_t can be written as follows:

$$f_t = \Gamma Y_t, \tag{3}$$

where Γ , the permanent component coefficient vector, is $1 \times n$. The identification of the common factor is achieved by imposing that the error correction term does not Granger-cause the common factor in the long run. According to Gonzalo and Granger (1995), the permanent component represents the fundamental or efficient price in this decomposition method.

As each of the original nonstationary series potentially contributes to the permanent component in Equation (3), one can use Γ_i , the *i*th component of the coefficient vector Γ , to measure the contribution of market price *i* to the price discovery process. Harris, McInish, and Wood (2002) suggest the use of elements in Γ as measures of price discovery after the normalization so that the sum of the elements is equal to 1. For clarity, given two markets, if $\Gamma_1 = 1$ and $\Gamma_2 = 0$, then market 1 entirely dominates the price discovery process while market 2 is redundant.

Consider now two markets (i.e., a preeminent market 1 and a newer entrant market 2) and two periods (i.e., a period 1 where the active trading sessions do not overlap and subsequently, a period 2 where this market segmentation is removed and trading takes place simultaneously in the active trading sessions of both markets). Define Γ_{ij} as the contribution of price *i* during period *j* to the price discovery process. In period 1, given reduced trading in the

⁵Aside from a potential risk premium. See Snaith, Kellard, and Ahmad (2018) for further discussion.

⁶Using a variance ratio approach, Iwatsubo et al. (2018) show that Japanese metals markets are on average less efficient than analogous markets in New York. Interestingly, the earlier work on Indian commodity markets, including gold, found futures markets were efficient (Sahoo & Kumar, 2009). ⁷Similar results are shown in other markets, such as India in the case of gold, sliver, and copper markets (Behera, 2016).



preeminent market, there is little instantaneous information transmission to the newer entrant and neither market dominates:

Hypothesis 2a. $\Gamma_{11} \approx \Gamma_{21} \approx 0.5$.

In period 2, however, the active trading sessions overlap. This gives rise to a greater information transmission from the preeminent market to the newer entrant thus the price discovery share of the former market increases, while the latter falls:

Hypothesis 2b. $\Gamma_{12} \gg \Gamma_{22}$.

In the context of the COMEX and the SHFE, before the introduction of night trading in China, Hypothesis 2a suggests neither exchange is likely to dominate. Conversely, when night trading is introduced, Hypothesis 2b indicates that the price discovery share of the US exchange will increase, while the measure for the Chinese market will fall.

2.3 | Volatility spillovers

Although the extant literature has not investigated volatility spillovers in the presence of a change in trading hours, Iwatsubo et al. (2018) show that precious metals traded in Japan and the United States have analogous intraday volatility patterns.⁸ Moreover, Liu and An (2011) investigate price discovery and volatility spillover among US (i.e., the New York Mercantile Exchange [NYMEX], the Chicago Board of Trade [CBOT], and Chicago Mercantile Exchange [CME] Globex) and Chinese exchanges (i.e., the SHFE and the Dalian Commodity Exchange) for copper and soybeans futures. They show that there is a bidirectional relationship in terms of price and volatility spillovers between US and Chinese markets, and the effect is stronger from the US to Chinese markets. Hernandez, Ibarra, and Trupkin (2014) examine the level of interdependence and volatility transmission in global agricultural futures markets. They find that Chicago plays a major role in terms of spillover effects over the other markets, particularly for corn and wheat. China and Japan also show important cross-volatility spillovers for soybeans. Similarly, Q. Chen and Weng (2018) examine volatility spillovers between the two countries in corn, soybeans, and wheat futures, documenting bidirectional effects for corn and soybeans. Interestingly, the magnitude of the bidirectional spillovers in corn futures increases after regulation in 2010 that opened the Chinese market to overseas market participants.

Perhaps the closest study to ours in terms of spillovers is Lucey, Larkin, and O'Connor (2014). Employing a gold prices data set at a daily frequency from January 2008 to October 2013, they show that the SHFE is relatively detached from other international markets, including the COMEX. However, given cross-country information flows drive volatility spillovers (Liu & An, 2011), and that the introduction of night trading in China allows for greater information transmission, we posit that spillovers between the two countries will increase. As the United States is the price setting market, the spillovers are likely to be larger from the United States to China.

Hypothesis 3. After the introduction of night trading, volatility spillovers will increase bidirectionally but particularly from the United States to China.

3 | METHODOLOGY

In this section, we outline the liquidity measures that we adopt to gauge the liquidity of gold and silver futures in the two markets, and the IS measures widely used in the literature for estimating price discovery. Finally, the directional spillover measure of Diebold and Yilmaz (2012) is introduced.

⁸Of course, volatility itself in precious metals markets can be affected by several factors (see, e.g., Batten, Ciner, & Lucy, 2010; Elder, Miao, & Ramchander, 2012). In other related work on volatility, recent empirical research on Indian commodity futures (Kumar, 2018), including precious metals (i.e., gold and silver) and industrial metals (i.e., aluminum, copper, and zinc), suggests that the volatility of the net convenience yield does not respond in line with predictions of the theory of storage.

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3.1 | Liquidity measures

The first measure is the effective spread (ES) of Roll (1984), later modified by Goyenko, Holden, and Trzcinka (2009). The second measure is the proportion of zero returns of Lesmond, Odgen, and Trzcinka (1999), and the third is the Amihud (2002) illiquidity estimator. These measures perform well at capturing different aspects of asset liquidity (Goyenko et al., 2009).

3.1.1 | Effective Roll's spread

Roll (1984) estimates asset liquidity using a simple serial covariance spread model of transaction price changes. The model has led to a burgeoning research area in the market microstructure literature with many modifications and extensions (see, e.g., Chang & Chang, 1993; George, Kaul, & Nimalendran, 1991). The ES defined as follows:

$$ES = 2\sqrt{-Cov(\Delta P_t, \Delta P_{t-1})},$$
(4)

where P_t denotes the closing price on day *t* (or other time interval of interest), Δ the change operator, and Cov the serial covariance between changes in prices. When the sample serial covariance is positive, the ES is undefined. In this paper, we follow Goyenko et al. (2009) and adopt a modified version of the Roll (1984) spread so that a numerical value is always obtained as follows:

$$\operatorname{Roll} = \begin{cases} 2\sqrt{-\operatorname{Cov}(\Delta P_{t}, \Delta P_{t-1})} & \text{if } \operatorname{Cov}(\Delta P_{t}, \Delta P_{t-1}) < 0, \\ 0 & \text{otherwise.} \end{cases}$$
(5)

The lower the ES, the higher the liquidity of the asset.

3.1.2 | Proportion of zero returns

The proportion of zero returns proposed by Lesmond et al. (1999) is particularly useful and effective in studying liquidity for emerging markets (see, e.g., Bekaert, Harvey, & Lundblad, 2007; Lesmond, 2005). This measure is based on the transaction cost perspective, that is, if the value of an information signal is insufficient to outweigh the cost associated with trading, market participants will choose not to trade, resulting in a zero return. The measure is easy to calculate since it only requires the time series of transaction data. It is specified as follows:

$$Zeros = (\# \text{ of intraday time intervals with zero returns})/N,$$
(6)

where *N* is the total number of time intervals in a trading day (n = 1, 2, ..., N). Intuitively, the lower the proportion of zero returns, the better the liquidity of the asset.

3.1.3 | The illiquidity measure of Amihud (2002)

The illiquidity measure of Amihud (2002) is another widely used estimator (Amihud, Mendelson, & Pedersen, 2012; Baker & Stein, 2004). It is a price impact measure that captures the price response associated with one unit currency of trading volume. Hence, the lower the measure, the higher the asset liquidity. It is defined by the following ratio:

$$Amihud = Average(\frac{|r_n|}{Volume_n}),$$
(7)

where r_n is the asset logarithmic return over the *n*th time interval and Volume_n the trading volume (in terms of RMB in our case) over the same time interval.

3.2 | Price discovery measures

To determine the relative contribution of the Chinese and US markets in the price discovery of gold and silver futures, we consider three commonly used measures of IS, namely, the CS of Gonzalo and Granger (1995), the IS of Hasbrouck (1995), and the MIS of Lien and Shrestha (2009). The IS presents the percentage subset of a market's information that is impounded into prices by different markets trading the same underlying security. All three IS measures are based on the estimation of a vector error correction model (VECM):

$$\Delta Y_t = \alpha \beta' Y_{t-1} + \sum_{j=1}^k A_j \Delta Y_{t-j} + \varepsilon_t, \tag{8}$$

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where Y_t is an $n \times 1$ vector of unit-root series where it is assumed that there are n - 1 cointegrating vectors, β and α are $n \times (n - 1)$ matrices of rank (n - 1), and denote (n - 1) cointegrating vectors and adjustment coefficients, respectively. The covariance matrix of the error term is given by $E[\varepsilon_t \varepsilon'_t] = \Omega$.

Following Stock and Watson (1988), the above equation can be transformed into the following vector moving average (VMA) representation (Hasbrouck, 1995):

$$\Delta Y_t = \Psi(L)\varepsilon_t,\tag{9}$$

and its integrated form

$$Y_t = \Psi(l) \sum_{s=1}^{l} \varepsilon_s + \Psi^*(L)\varepsilon_t, \tag{10}$$

where $\Psi(L)$ and $\Psi^*(L)$ are the matrix polynomials of the lag operator *L*. The impact matrix, $\Psi(l)$, is the sum of moving average coefficients, and $\Psi(l)\varepsilon_t$ is defined as the common trend component among prices or long-run impact of an innovation on each of the prices. It is thus the main focus of the analysis. Finally, $\Psi^*(L)\varepsilon_t$ is the transitory portion.

In this paper, we consider the Chinese and US precious metal futures markets so n = 2 in Equation (8). The VECM is hence specified as follows:

$$\Delta p_{1,t} = \alpha_1 (p_{1,t-1} - p_{2,t-1}) + \sum_{i=1}^L \xi_i \Delta p_{1,t-i} + \sum_{j=1}^L \delta_j \Delta p_{2,t-j} + \varepsilon_{1,t}, \tag{11}$$

$$\Delta p_{2,t} = \alpha_2 (p_{1,t-1} - p_{2,t-1}) + \sum_{k=1}^{L} \varphi_k \Delta p_{1,t-k} + \sum_{m=1}^{L} \phi_m \Delta p_{2,t-m} + \varepsilon_{2,t}, \tag{12}$$

where $\Delta p_{i,t}$ (*i* = 1, 2) is the change in the logarithmic price ($p_{i,t}$) at time interval *t* of the futures contracts traded in market *i* (Shanghai or New York) at time *t*, and *L* is the lag length.

3.2.1 Component share of Gonzalo and Granger (1995)

Gonzalo and Granger (1995) propose an alternative decomposition to that of Stock and Watson (1988). As we noted in Section 2.2, they decompose the vector of nonstationary series Y_t into a permanent component (or common factor) f_t and a transitory (stationary) component \tilde{Y}_t , where one can use Γ_i from Equation (3) to assess the share of market *i* to price discovery. Gonzalo and Granger (1995) show that $\Gamma = \alpha_{\perp}$, where α_{\perp} is a column vector orthogonal to the adjustment coefficient matrix α in Equation (8), that is, $\alpha_{\perp}^T \alpha = 0$.

When n = 2, $\Gamma = (\gamma_1, \gamma_2)'$, and $\alpha = (\alpha_1, \alpha_2)'$, the normalized Γ must satisfy the orthogonality condition $\gamma_1 \alpha_1 + \gamma_2 \alpha_2 = 0$ (i.e., $\alpha_{\perp} = (\gamma_1, \gamma_2)'$) and $\gamma_1 + \gamma_2 = 1$. This leads to the following CS measure of price discovery:

$$CS_1 = \gamma_1 = \frac{\alpha_2}{\alpha_2 - \alpha_1}, \quad CS_2 = \gamma_2 = \frac{\alpha_1}{\alpha_1 - \alpha_2}.$$
(13)

3.2.2 | Information share of Hasbrouck (1995)

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Hasbrouck (1995) states that the rows of $\Psi(l)$ in Equation (10) are identical. Let $\psi = (\psi_1, \psi_2, ..., \psi_n)$ represent the identical row of $\Psi(l)$. The increment $\psi \varepsilon_t$ is the component of the price change, presumably due to new information, that is permanently impounded into the price. A market's relative contribution to price discovery is defined as the proportion of the variance of the common efficient equilibrium price that can be attributed to this particular market. Denote $\psi \Omega \psi'$ as the variance of the common efficient equilibrium price, the IS of market *j* can be expressed as follows:

$$\mathrm{IS}_{j} = \frac{([\psi F]_{j})^{2}}{\psi \Omega \psi'},\tag{14}$$

where *F* is the Cholesky factorization of the estimated VECM variance–covariance matrix Ω and $[\psi F]_j$ the *j*th element of row vector ψF . For *j* = 1, 2, by construction IS₁ + IS₂ = 1. Price discovery occurs predominantly in the market for which the IS exceeds the value of 0.5. In our case, Ω is defined as follows:

$$\Omega = \begin{pmatrix} \sigma_1^2 & \rho \sigma_1 \sigma_2 \\ \rho \sigma_1 \sigma_2 & \sigma_2^2 \end{pmatrix}$$
(15)

and its Cholesky factorization is $\Omega = FF'$, where

$$F = \begin{pmatrix} f_{11} & 0\\ f_{12} & f_{22} \end{pmatrix} = \begin{pmatrix} \sigma_1 & 0\\ \rho \sigma_2 & \sigma_2 (1 - \rho^2)^{1/2} \end{pmatrix}.$$
 (16)

We obtain the IS of Hasbrouck (1995) as follows:

$$IS_{1} = \frac{(\gamma_{1}f_{11} + \gamma_{2}f_{12})^{2}}{(\gamma_{1}f_{11} + \gamma_{2}f_{12})^{2} + (\gamma_{2}f_{22})^{2}}, \quad IS_{2} = \frac{(\gamma_{2}f_{22})^{2}}{(\gamma_{1}f_{11} + \gamma_{2}f_{12})^{2} + (\gamma_{2}f_{22})^{2}}, \quad (17)$$

where γ_1 and γ_2 are defined in Equation (13).

Unlike the CS measure of Gonzalo and Granger (1995), which assumes that the contribution of each market to price discovery is only related to the size of the market's error correction coefficient, the Hasbrouck (1995) IS method incorporates both the error-correction coefficients as well as the innovation covariances. Because the IS is affected by the order of the price series in the Cholesky factorization, we compute the upper and lower bounds of IS for each potential ordering and take the average as in Baillie, Booth, Tse, and Zabotina (2002).

3.2.3 | Modified information share of Lien and Shrestha (2009)

The final measure we adopt is the MIS of Lien and Shrestha (2009). It extends the IS measure of Hasbrouck (1995) by factoring not directly on the innovation matrix but on the innovation correlation matrix hence avoiding the ordering issue in the Cholesky factorization. Let Φ denote the innovation correlation matrix; Λ is the diagonal matrix with diagonal elements being the eigenvalues of the correlation matrix Φ , where the corresponding eigenvetors are given by the columns of matrix *G*; and *V* is a diagonal matrix containing the innovation standard deviations on the diagonal; that is, $V = \text{diag}(\sqrt{\Omega_{11}}, \sqrt{\Omega_{22}}, ..., \sqrt{\Omega_{nn}})$. This leads to the following factor structure for innovations:

$$\varepsilon_t = F^* z_t^*,\tag{18}$$

where z_t^* is the transformed innovation with zero mean and identity covariance matrix, $F^* = [G\Lambda^{-1} G^T V^{-1}]^{-1}$. Note that $\Omega = F^*(F^*)'$. Thus the MIS is given by

$$MIS_{j} = \frac{([F^{*}\psi]_{j})^{2}}{\psi\Omega\psi'}.$$
(19)

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Under this new factor structure, the resulting ISs are independent of ordering. The interpretation of the MIS is similar to that of the IS measure of Hasbrouck (1995), that is, price discovery is dominated by the market whose MIS exceeds 0.5. When n = 2, we have the following equations:

$$G = \begin{bmatrix} \frac{1}{\sqrt{2}} & -\frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \end{bmatrix},$$
 (20)

$$\Lambda = \begin{bmatrix} (1+\rho) & 0\\ 0 & (1-\rho) \end{bmatrix},\tag{21}$$

$$F^* = \begin{bmatrix} 0.5(\sqrt{1+\rho} + \sqrt{1-\rho})\sigma_1 & 0.5(\sqrt{1+\rho} - \sqrt{1-\rho})\sigma_1 \\ 0.5(\sqrt{1+\rho} - \sqrt{1-\rho})\sigma_2 & 0.5(\sqrt{1+\rho} + \sqrt{1-\rho})\sigma_2 \end{bmatrix}.$$
 (22)

3.3 | Volatility spillover

We use the Diebold and Yilmaz (2012) volatility spillover measure which is based on forecast error variance decompositions from the relevant vector autoregression (VAR). The measure extends the Diebold and Yilmaz (2009) method that relies on Cholesky factor identification whose variance decompositions depend on the variable ordering. The Diebold and Yilmaz (2012) method is not only invariant to ordering but also provides directional spillovers. It is based on the estimation of a covariance stationary *N*-variable VAR(p) as follows:

$$x_t = \sum_{i=1}^p \Phi_i x_{t-i} + \varepsilon_t, \tag{23}$$

where $\varepsilon \sim (0, \Sigma)$ is a vector of independently and identically distributed disturbances. The moving average representation of the VAR is given by the following equation:

$$x_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i},\tag{24}$$

where A_i s are $N \times N$ coefficient matrices and obey the recursion $A_i = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + \dots + \Phi_p A_{i-p}$, with A_0 being an $N \times N$ identity matrix and with $A_i = 0$ for i < 0.

The variance decomposition allows us to allocate the forecast error variances of each variable to parts which are attributable to the various system shocks. Diebold and Yilmaz (2012) use the generalized VAR framework of Koop, Pesaran, and Potter (1996; KPPS), which instead of attempting to orthogonalize shocks in variance decomposition, allows correlated shocks but accounts for them appropriately using the historically observed distribution of errors. By construction, the sum of the contributions to the variance of forecast errors (the row sum of the elements of the variance decomposition) is not necessarily equal to one. The spillovers are thus defined as the fractions of the *H*-step-ahead error variances in forecasting x_i that are due to shocks to x_i , for i, j = 1, 2, ..., N, $i \neq j$.

Denoting the KPPS *H*-step-ahead forecast error variance decompositions by $\theta_{ij}^{g}(H)$, for H = 1, 2, ..., we have the following equation:

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e'_{i} A_{h} \sum e_{j} \right)^{2}}{\sum_{h=0}^{H-1} \left(e'_{i} A_{h} \sum A'_{h} e_{i} \right)^{2}},$$
(25)

where Σ is the variance matrix for the error vector ε , σ_{ii} the standard deviation of the error term for the *j*th equation, and e_i the selection vector, with 1 as the *i*th element and 0 otherwise. Diebold and Yilmaz (2012) normalize each entry of the variance decomposition matrix by the row sum as follows:

$$\tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{i=1}^{N} \theta_{ij}^{g}(H)}$$
(26)

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so that $\sum_{j=1}^{N} \tilde{\theta}_{ij}^{g}(H) = 1$ and $\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H) = N$. With the above variance decomposition, Diebold and Yilmaz (2012) construct the *total volatility* spillover index which measures the contribution of spillover of volatility shocks across all markets/assets under scrutiny as follows:

$$S^{g}(H) = \frac{\sum_{i,j=1,i\neq j}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H)} \cdot 100 = \frac{\sum_{i,j=1,i\neq j}^{N} \tilde{\theta}_{ij}^{g}(H)}{N} \cdot 100.$$
(27)

Meanwhile, the *directional* spillover is also developed using the normalized elements of the generalized variance decomposition matrix as the generalized impulse responses and variance decompositions are invariant to the ordering of variables. They quantify the directional volatility spillover received by market *i* from all other markets *j* as follows:

$$S_{i}^{g}(H) = \frac{\sum_{j=1, j\neq i}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}^{g}(H)} \cdot 100 = \frac{\sum_{j=1, j\neq i}^{N} \tilde{\theta}_{ij}^{g}(H)}{N} \cdot 100.$$
(28)

Similarly, the directional volatility spillover transmitted by market *i* to all other markets *j* is as follows:

$$S_{i}^{g}(H) = \frac{\sum_{j=1, j\neq i}^{N} \tilde{\theta}_{ji}^{g}(H)}{\sum_{i, j=1}^{N} \tilde{\theta}_{ji}^{g}(H)} \cdot 100 = \frac{\sum_{j=1, j\neq i}^{N} \tilde{\theta}_{ji}^{g}(H)}{N} \cdot 100.$$
(29)

The set of directional spillovers can be regarded as providing a decomposition of the total spillover to those coming from (or going to) a particular source.

As for the volatility measure, we adopt the widely used Parkinson (1980) method to estimate 15-min range-based interval variance using high and low prices within the interval. For market *i* during time interval *n*, the variance is as follows:

$$\sigma_{i,n}^2 = 0.361 \left[\ln \left(P_{i,n}^{\max} \right) - \ln \left(P_{i,n}^{\min} \right) \right]^2, \tag{30}$$

where $P_{i,n}^{\max}(P_{i,n}^{\min})$ is the high (low) price in market *i* during time interval *n*. We therefore substitute x_t with σ in Equation (23) to conduct the volatility spillover analysis.

INSTITUTIONAL DETAILS AND DATA 4

Institutional details 4.1

Futures markets are relatively new phenomena in China but their recent growth and influence mirrors that of the economy as a whole.⁹ The SHFE was incorporated in December 1999¹⁰ and is currently the tenth largest derivative exchange globally by volume with 1.2 billion contracts traded in 2018.¹¹ Although trading in 1999 commenced with

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⁹Peck (2008) provides an excellent summary of the development of Chinese futures markets in the 1990s and early 2000s.

¹⁰Effectively this was a consolidation of three exchanges: the Shanghai Metals Exchange, the Shanghai Cereals and Oil Exchange, and the Shanghai Commodity Exchange.

¹¹See the Futures Industry Association for more detailed rankings.

copper, aluminum, and natural rubber, presently the SHFE has 12 metal futures products (including gold and silver), six energy and chemical products and two options products (i.e., copper and natural rubber).

The gold futures market at the SHFE opened in January 2008, while the silver futures market opened in June 2012. As we commented earlier, for our purposes it is important to note that, before July 5, 2013, trading occurred in Shanghai precious metals only between 9:00 a.m.-11:30 a.m. and 1:30 p.m.-3:00 p.m. However, from July 5, 2013, a night trading session was added, running from 9:00 p.m. to 2:30 a.m. the following day.

Each gold contract represents a kilogram weight and the minimum price fluctuation is 0.02 Yuan/g. The last trading day is the 15th of each month¹² and delivery takes place on any of the five working days after the last trading day. Contracts are available for delivery over the next 3 consecutive months and then consecutive even months, within the next 13 months. The minimum trade margin is 4% of the contract. By contrast, each silver contract represents a 15-kg weight and the minimum price fluctuation is 1 Yuan/kg. Contracts are available for delivery over the next 12 consecutive months, while margining, last trading day and delivery details are the same as gold.

4.2 | Data

Data for the SHFE gold and silver futures are obtained from the China Stock Market and Accounting Research (CSMAR) database and include open, high, low, and close prices, volume, and open interest for contracts at 5-min intervals for all delivery months. The US futures data are obtained from the TickData LLC, which contain tick-by-tick prices and volumes of gold and silver futures traded on the COMEX in New York. We construct 15-min series from the original data set for our empirical analysis. The sample starts from January 10, 2008 for gold and June 1, 2012 for silver, and both series end on April 29, 2016.

For gold and silver futures in China and gold futures in the United States, the June and December contracts are usually the most frequently traded. Therefore, we use June and December contracts to construct continuous time series of prices. Specifically, each year we switch contract on June 1 and December 1, the first day of the delivery month for June and December contracts.¹³ For US silver futures, however, the active contracts are those maturing in March, May, July, September, and December. Therefore, we construct a continuous time series for US silver futures using the prices of these contracts, switching on the first day of the delivery month of each contract. The US futures prices are converted¹⁴ to RMB prices/unit, that is, RMB/g for gold futures and RMB/kg for silver futures. We match the Chinese and US price series according to the Chinese trading time in Shanghai.

We split the whole sample into two subsamples on July 5, 2013, the starting date for night trading in China. The subsamples before and after this date are called the *pre-* and *postnight* trading period, respectively. We further separate day trading (from 9:00 a.m. to 3:00 p.m.) from night trading (from 9:00 p.m. to 2:30 a.m.) for the latter subsample. Table 1 tabulates descriptive statistics for 15-min return series for these subsamples.

We notice that all return series exhibit approximately zero mean and excess kurtosis hence the normality of return distributions is clearly rejected. The average of trading volume, turnover, and open interest for both contracts in the two markets are also reported and we observe important differences in these statistics between the pre- and postnight trading periods.¹⁵ First, for both countries, trading is much more active during the postnight trading period and provides support for Hypothesis 1a discussed in Section 2.1. For example, as shown in Panel A, the average 15-min trading volume for Chinese gold futures is 5,162 contracts, whereas before the onset of night trading period is more than twice the prenight trading period. Interestingly, a similar pattern is also observed in the United States. The average trading volume of gold futures after and before Chinese night trading is 1,063 and 259, respectively; and the average turnover postnight is 809,487 thousands RMB, more than three times higher than before night trading. The results for silver futures of the two markets are in line with those of the gold futures.

Second, when we split the postnight trading in China into day and night trading, we observe that the average volume, turnover, and open interest during night trading hours are higher than during the day. For example, the average trading

¹⁵We do not have open interest data for the United States.

¹²Unless this day is a public holiday, in which case the last trading day is the first working day after the holiday.

¹³For example, from December 1, 2009 to May 31, 2010, we use prices for June 2010 delivery, and from June 1 to November 30, 2010, we use prices for December 2010 delivery.

¹⁴We employ the daily exchange rate obtained from Wind Co. Ltd. Hence, for intraday prices, we use the same rate within a day.



TABLE 1	Descriptive statistics of	Chinese and US gold and silver futures returns at 15-min inter	vals

	Mean	SD	Kurt	Skew	Count	Average volume	Average turnover	Average open interest
Panel A: Chinese gold a	nd sliver futures							
Gold futures								
2008.1.10-2013.7.4	6.03E – 06	0.0034	100.72	-1.64	21,533	1,881	594,347	52,166
2013.7.5-2016.4.29								
All trading	-4.70E - 07	0.0015	82.27	1.59	26,345	5,162	1,290,784	178,374
Day trading	7.12E – 06	0.0014	191.50	3.90	11,405	4,216	1,051,813	177,392
Night trading	-6.30E - 06	0.0016	30.12	0.38	14,940	5,881	1,472,357	179,121
Silver futures								
2012.6.1-2013.7.4	-0.0001	0.0041	116.01	-3.36	4,471	10,161	886,688	141,638
2013.7.5-2016.4.29								
All trading	-6.0E - 06	0.0021	93.84	1.92	27,912	33,743	2,007,238	464,043
Day trading	-2.3E - 05	0.0021	180.23	4.29	12,053	28,425	1,703,079	454,218
Night trading	7.02E - 06	0.0021	33.27	0.23	15,859	37,782	2,238,242	471,305
Panel B: US gold and sli	ver futures							
Gold futures								
2008.1.10-2013.7.4	1.63E – 05	0.0010	20.09	-0.39	21,381	259	238,392	
2013.7.5-2016.4.29								
All trading	3.30E - 06	0.0016	110.87	1.87	26,345	1,063	809,487	
China day trading	1.98E - 05	0.0016	255.85	4.22	11,405	515	370,656	
China night trading	-9.30E - 06	0.0017	26.02	0.42	14,940	1,480	1,144,282	
Silver futures								
2012.6.1-2013.7.4	-9.40E - 05	0.0041	116.14	-3.37	4,437	192	16,783,002	
2013.7.5-2016.4.29								
All trading	-5.00E - 06	0.0025	89.78	1.51	27,521	602	33,148,727	
China day trading	-1.30E - 05	0.0023	238.17	5.39	11,887	243	13,695,518	
China night trading	8.49E – 07	0.0027	33.21	-0.17	15,634	874	47,939,585	

Note: This table reports the descriptive statistics of the Chinese and US gold and silver futures returns at 15-min intervals. For gold, both Chinese and US data series are for June and December deliveries. For silver, the Chinese data are for June and December deliveries, whereas the US data are for March, May, July, September, and December deliveries, switching on the first day of the delivery month. Trading time is matched between the two markets. We report the statistics for all trading, day trading, and night trading from July 2013 when night trading sessions are introduced. The average turnover is in thousands RMB. We do not have data for US open interest.

volume is 4,216 and 28,425 contracts, respectively, for gold and sliver futures during the day, and this increases to 5,881 and 37,782, respectively, during the night. Overall, the descriptive statistics paint a clear picture that since the introduction of night trading, the Chinese precious metal market has become more active, especially during the night.

As we have intraday data, during some of our later empirical work we wish to examine measures of market quality during various parts of a trading day. Given the session trading times and 15-min data frequency, we group our 15-min data in blocks of time where we try to evenly balance the number of observations in each block. Hence, in the morning and evening sessions we have four observations regularly for each interval; for example, one block of observations is 22:00, 22:15, 22:30, and 22:45 giving a time block between 22:00 and 22.45. The subsequent block of observations is 23.00, 23:15, 23:30, and 23:45. In this way we have time block 22:00–22:45, followed by time block 23:00–23:45, and no data are omitted given our 15-min data structure.

The approach above leads to night blocks of 21:00–21:45, 22:00–22:45, 23:00–23:45, 0:00–0:45, and 1:00–1:45, all with the same number of observations. Given trading finishes at 2:30 a.m., our last night block contains one fewer observation (i.e., 2:00, 2:15, and 2:30) and hence is written 2:00-2:30. Similarly, morning blocks are 9:00-9:45, 10:00-10:45, and 11:00–11:30; the last block containing one fewer observation as morning trading finishes at 11.30 a.m. Lastly, given the afternoon trading session is from 13:30 to 15:00, we decided to break this into two blocks: 13:30-14.15 and 14.30-15.00.

 TABLE 2
 Daily liquidity measures of the Chinese gold and silver futures returns at 15-min intervals

	Gold futures			Silver futures				
	Roll	Zeros	Amihud	Roll	Zeros	Amihud		
2008.1.10-2013.7	.4 Prenight trading		2012.6.1-2013.7	.4				
Mean	0.9441	0.0612	0.6670	1.2806	0.1237	0.0062		
SD	1.4770	0.1038	2.8612	1.6425	0.0975	0.0190		
Median	0.4949	0.0588	0.0310	0.6480	0.1176	0.0013		
Min	0.9441	0.0612	0.6670	0.0000	0.0588	0.0000		
Max	18.842	0.9375	38.557	11.778	0.9412	0.2040		
2013.7.5–2016.4.29 All postnight trading								
Mean	0.6008***	0.1728***	0.0720***	0.8608***	0.1786***	0.0010***		
SD	0.6991	0.0977	0.2296	1.1053	0.0976	0.0043		
Median	0.4606	0.1724	0.0228	0.6577	0.1750	0.0026		
Min	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000		
Max	5.4747	1.0000	3.6572	15.484	1.0000	0.0606		
2013.7.5-2016.4.2	29 Postnight, day tra	ding						
Mean	0.5784	0.2252	0.0137	0.8772	0.2171	0.0020		
SD	0.7297	0.0833	0.0275	1.2193	0.0884	0.0031		
Median	0.4674	0.2353	0.0067	0.6752	0.1765	0.0012		
Min	0.0000	0.0588	0.0021	0.0000	0.0588	0.0002		
Max	7.3785	0.5294	0.3584	20.236	0.9412	0.0027		
2013.7.5-2016.4.2	29 Postnight, night ti	ading						
Mean	0.7512	0.1328	0.1069	1.0396	0.1496	0.0016		
SD	0.8277	0.1148	0.3060	1.2306	0.1164	0.0067		
Median	0.5596	0.0909	0.0331	0.7547	0.1304	0.0035		
Min	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000		
Max	6.1314	1.0000	4.2538	10.271	1.0000	0.0992		

Note: This table reports daily descriptive statistics of three liquidity measures for gold and silver futures obtained from 15-min intervals. Roll refers to the effective spread of Roll (1984); Zeros are the proportion of 15-min zero returns during a trading day; and Amihud is the illiquidity measure of Amihud (2002). We report the statistics for all trading, day trading, and night trading from July 2013 when night trading sessions are introduced. ***A difference-in-means test between the prenight, and the all postnight trading measures are significant at the 1% level.

5 | EMPIRICAL ANALYSIS

5.1 | Liquidity

To gain a better understanding of precious metal futures markets, we construct three popular liquidity measures as described in Section 3.1 to gauge liquidity dynamics before and after the introduction of night trading. Table 2 shows descriptive statistics of daily liquidity measures which are calculated from 15-min intervals for Chinese gold and silver futures returns.¹⁶

For all liquidity measures, typically the lower the values, the better the liquidity. Table 2 shows higher Roll and Amihud illiquidity measures for the prenight trading period compared with the postnight period, for both gold and silver futures, and lends strong support to Hypothesis 1b. For instance, the mean Roll's spread is 0.94 for gold futures before July 2013, and 0.60 overall afterwards—a difference that is significant at the 1% level. This indicates that the night trading policy has pushed up the overall liquidity of the precious metal futures markets.

Interestingly, the proportion of zero returns increases after night trading is introduced for both contracts (e.g., 12–17% for silver), at first glance indicating less frequent trading. However, the amount of trading time has more than

¹⁶Summary statistics of equivalent measures for the US market are not reported to save space. They are available upon request from the authors.

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TABLE 3	Liquidity measures	for intraday time	blocks of Chinese g	old and silver futures returns
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Interval	Roll		Zeros (%)	Amihud		Volume		Realized v	olatility
Gold futures										
21:00-21:45	2.0355		0.77		0.4873		9,144		0.0646	
22:00-22:45	1.1576		1.09		0.0125		9,120		0.0449	
23:00-23:45	1.0540		1.26		0.0141		7,073		0.0411	
0:00-0:45	0.7355		2.29		0.0347		4,284		0.0362	
1:00-1:45	0.7741		2.54		0.0383		2,634		0.0342	
2:00-2:30	0.8864		1.87		0.0576		2,452		0.0329	
9:00-9:45	2.0061	2.1460	3.41	0.89	0.0241	0.8202	5,425	3,127	0.0496	0.0851
10:00-10:45	0.5144	0.	3.86	2.91	0.0105	0.6073	2,761	1,088	0.0328	0.0358
11:00-11:30	0.7470	0.1288	1.29	0.73	0.0111	0.5179	3,026	1,241	0.0301	0.0284
13:30-14:15	0.7349	1.1785	0.77	0.78	0.0082	0.6405	4,875	1,891	0.0321	0.0419
14:30-15:00	0.8466	1.2512	0.85	0.89	0.0071	0.5976	5,355	1,969	0.0302	0.0380
Silver futures										
21:00-21:45	2.9746		7.07		0.0071		63,719		0.0729	
22:00-22:45	1.6212		12.46		0.0002		55,498		0.0500	
23:00-23:45	1.3150		14.49		0.0002		42,706		0.0458	
0:00-0:45	1.0068		18.26		0.0004		26,843		0.03971	
1:00-1:45	0.9095		18.80		0.0007		16,935		0.0374	
2:00-2:30	1.1150		19.03		0.0012		15,390		0.0353	
9:00-9:45	2.7729	3.3414	30.18	5.23	0.0003	0.0234	34,781	13,698	0.0581	0.0974
10:00-10:45	0.8588	0.9670	35.23	31.46	0.0002	0.0005	17,831	6,837	0.0408	0.0448
11:00-11:30	1.3570	1.4090	15.09	7.35	0.0002	0.0005	20,580	7,627	0.0389	0.0406
13:30-14:15	1.2495	1.8130	8.25	6.64	0.0001	0.0006	35,366	10,520	0.0410	0.0506
14:30-15:00	1.2932	1.5891	9.07	7.02	0.0001	0.0005	36,857	12,034	0.0378	0.0474

Note: This table reports the average liquidity measures for gold and silver futures, over a specific time block, obtained from 15-min intervals using three liquidity measures. Roll refers to the effective spread of Roll (1984); Zeros are the proportion of 15-min zero returns during a trading day (in percent); and Amihud is the illiquidity measure of Amihud (2002). Volume refers to the number of contracts during the interval. Columns with (without) night trading hours contain results after (before) the introduction of night trading session on July 5, 2013.

doubled and so one would expect an increase in the percentage of zero returns even if the *frequency* of trading time stays the same. When we separate day and night trading hours for the period after July 2013, we find that both the Roll's spread and the Amihud illiquidity measure are generally larger during the night, suggesting lower liquidity.¹⁷ On the contrary the proportion of zero returns is lower during night trading hours, suggesting a more even spread of trades and highlighting that there are likely to be large intraday differences in liquidity both within and between contracts. We investigate this next.

Liquidity can be driven by short periods of intense trading hence in Table 3 we provide our liquidity measures, trading volume, and realized volatility over specific time blocks to better understand how night trading impacts intraday variation in trading activities.

We report the average of liquidity measures, the number of contracts traded, and realized volatility aggregated from 15-min intervals. The realized volatility is calculated by summing 5-min squared returns (see Andersen, Bollerslev, Diebold, & Labys, 2001; Koopman, Jungbacker, & Hol, 2005). We notice a number of interesting findings. First, comparing the first time block (9:00–9:45) in the pre- and postnight trading, the Roll's spread, the Amihud illiquidity measure, and realized volatility are higher for the prenight trading subsample. This indicates that the introduction of the night trading session, which overlaps with the US daytime trading period, enables the Chinese market to absorb relevant price information from the United States contemporaneously, leading to a more stable market when Shanghai opens the following morning. By contrast, when there is no night trading,

information accumulated overnight floods the market as soon as it opens, leading to a more volatile and less liquid market on the subsequent day.

Second, in terms of the Roll's spread, the Amihud illiquidity measure, and realized volatility, the first time blocks exhibit the largest values for both day and night trading sessions, that is, 9:00–9:45 for day trading, and 21:00–21:45 for night trading. The same pattern can be observed for the prenight trading period in that these measures are the highest between 9:00 and 9:45. For example, the Roll's spread is 2.04 and 2.01, respectively, between 21:00–21:45 and 9:00–9:45 for gold futures in the second subsample period and these are by far the highest during their corresponding night and day trading hours. The results imply that, in the first trading hour or so, the market is affected by information accumulated during nontrading hours, causing higher price variation and less liquid trading. As information is gradually digested and incorporated into prices, the market becomes more liquid and less volatile.

Third, the proportion of zero returns exhibits the highest values during the second block of the daytime trading, that is, 10:00–10:45, showing the least frequent trading activities. For instance, there are 2.91% and 3.86% zero returns for gold futures during 10:00–10:45 interval for pre- and postnight trading period, respectively. The phenomenon is in line with the trading regulation on commodity futures by the SHFE that there is trading suspension during 10:15–10:30. Considering zero returns for the postnight trading period, the first block in the morning session shows the highest value during the day, if we omit the second block which includes the 15-min break in trading, while this is not observed for the first time block of the night session. Indeed, the first block of night trading exhibits the lowest percentage of zero returns. By contrast, the Roll and Amihud measures show the lowest liquidity in the first block for both sessions. The combination of low zero returns and high Roll and Amihud measures would suggest frequent trading with high price impact; a foreseeable occurrence in the first block of night trading when new information from the United States is being assessed.

Finally, regarding trading volume, the highest values of the day typically take place when the market opens. For example, in our postnight period, the volume for 21:00–21:45 and 9:00–9:45 are 9,144 and 5,425, respectively, for gold futures. Comparing the first trading hour during day and night sessions, trading volume in the night session is about 68% higher than that of the day session, indicating that investors are more active when they can trade alongside an active US market. The number of contracts then declines gradually and reaches its lowest level between 2:00 and 2:30 during the early morning when night trading closes. As for the morning and afternoon sessions, trading begins with a high volume and declines before rebounding in the afternoon. This phenomenon occurs both before and post the introduction of night trading. In addition, the volume is the lowest for 10:00–10:45 in the morning session, resulting from the trading break during 10:15–10:30. Results for silver futures are consistent with the above pattern for gold futures.

We also report the liquidity measures for intraday time blocks (using Chinese time) of US gold and silver futures in Table 4.

Interestingly, the US market exhibits patterns that are similar to the Chinese market in terms of liquidity and volatility. For example, the first time block (using Chinese time) shows the lowest liquidity in terms of Roll's spread and the Amihud illiquidity measure and the highest volatility, regardless of whether it is during day or night trading in China, or pre- or postnight trading, for gold or silver futures. However, the US market trades via an electronic platform and it is unlikely that higher illiquidity is caused by an aggregation of information since it trades almost continuously. Furthermore, we find that US zero returns are at their highest when the Chinese market breaks in the morning (10:00–10:45) for both gold and sliver futures, a result again consistent with that of the Chinese market. Taken as a whole, these results suggest that the US market is to some extent affected by trading activities in China, and in particular, the recent introduction of night trading in China. We investigate this further below.

5.2 | Price discovery

The price discovery measures described in Section 3.2 are such that the price series included in vector Y_t are unit root processes with the number of cointegrating vectors equal to the number of price series minus one. Hence in our case, it requires gold and silver futures prices in China and the United States to be nonstationary processes and with a single cointegrating relationship. Table 5 shows the Augmented Dickey–Fuller (ADF) test for unit root analysis.

We test the full sample, and separately before and after night trading. For the postnight trading subsample, we report results for day and night trading hours separately. The null hypothesis that the price series has a unit root is not rejected for Chinese and the US gold and silver futures for any sample periods. However, all the first-difference series are shown to be stationary, indicating price series are all I(1) processes.

|--|

Interval	Roll		Zeros ((%)	Amihud		Volume		Realized	volatility
Gold futures										
21:00-21:45	1.8481		0.62		6.1519		2000.0		0.0662	
22:00-22:45	1.4194		0.68		2.5392		2216.6		0.0487	
23:00-23:45	1.2504		0.66		2.7703		1503.0		0.0449	
0:00-0:45	0.8348		1.58		2.9332		999.6		0.0392	
1:00-1:45	0.8898		1.46		3.0916		921.9		0.0371	
2:00-2:30	1.0165		1.47		2.7763		761.5		0.0328	
9:00-9:45	1.4279	0.9023	1.39	4.55	8.0675	5.7180	487.9	275.1	0.0520	0.0385
10:00-10:45	0.5885	0.6760	2.62	5.40	3.7277	4.2386	354.3	208.1	0.0307	0.0325
11:00-11:30	0.5793	0.1151	1.96	3.35	3.5908	3.9011	314.0	180.9	0.0257	0.0239
13:45-14:15	0.6874	0.8954	0.90	4.25	7.5539	5.0887	545.0	255.3	0.0360	0.0312
14:30-15:00	0.7126	0.9446	1.43	3.44	3.0339	4.6862	626.2	358.3	0.0263	0.0341
Silver futures										
21:00-21:45	3.3057		0.53		0.0444		1,155		0.0833	
22:00-22:45	2.2766		0.77		0.0232		1,160		0.0613	
23:00-23:45	1.9785		0.97		0.0188		1,005		0.0578	
0:00-0:45	1.5159		1.62		0.0230		682.3		0.0502	
1:00-1:45	1.4525		1.52		0.0355		599.5		0.0478	
2:00-2:30	1.4661		1.56		0.0214		498.8		0.0408	
9:00-9:45	2.2749	2.8950	0.99	1.04	0.1146	0.1258	306.2	259.9	0.0635	0.1006
10:00-10:45	1.0890	1.2146	1.57	2.16	0.0685	0.0302	168.7	150.1	0.0425	0.0444
11:00-11:30	1.1425	1.1601	1.42	1.35	0.0677	0.0299	151.8	118.7	0.0374	0.0381
13:30-14:15	1.1928	1.6071	0.54	0.97	0.0439	0.0366	272.8	196.1	0.0446	0.0531
14:30-15:00	1.2606	1.5007	0.77	1.17	0.0471	0.0281	290.0	225.9	0.0372	0.0435

TABLE 4 Liquidity measures for intraday time blocks (using Chinese time) of US gold and silver futures returns

Note: This table reports the average liquidity measures for US gold and silver futures, over a specific time block, obtained from 15-min intervals using three liquidity measures, at the corresponding Chinese time.

Moving on, Table 6 summarizes the Johansen trace test statistics.

Results show that the null hypothesis of no cointegration between Chinese and the US gold and silver futures price series is rejected for all cases, mostly at the 1% significance level. However, the null hypothesis that the two series have at most 1 cointegrating relationship is not rejected across any sample period. These results provide evidence confirming that prices of Chinese and US gold and silver futures share one common stochastic trend, and that they meet the requirements of the IS analysis.

In Table 7 Panel A, we report the IS measures for the relative contribution of the Chinese and US markets to the price discovery of gold and silver prices.

Panel A summarizes our three IS measures for the full sample, two subsamples, and day and night trading in China. Interestingly, results indicate that before night trading is introduced, the IS for Chinese gold futures is around 0.5, suggesting that China and the United States contribute almost equally to price discovery. For instance, the CS, IS, and MIS are 0.51, 0.5, and 0.5, respectively, for gold futures before night trading, providing evidence for Hypothesis 2a. Given the active trading period does not overlap, there is little instantaneous information transmission between the two markets and no market dominates.

After night trading is introduced, the IS of Chinese gold futures drops, and the US market takes the leading role in the price discovery process. For example, the Chinese IS for all trading hours after the introduction of night trading is 0.32, 0.35, and 0.33, respectively, supporting Hypothesis 2b. Similar results can be found for the CS and MIS. For silver futures, the US market takes the lead in price discovery regardless of the sample period as the contribution of the Chinese market is consistently <0.5.¹⁸

¹⁸Given silver futures have only traded at the SHFE since May 2012, this result suggests the market is potentially too immature before the introduction of night trading to have developed much pricing power relative to New York.

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TABLE 5 The Augmented Dickey–Fuller test results

	Chinese series		US series	
	Price	First difference	Price	First difference
Gold futures				
2008.01-2016.04	-1.76	-224.63***	-1.99	-221.97***
2008.01-2013.07	-1.20	-150.41***	-1.38	-141.91***
2013.07-2016.04				
All trading	-1.94	-166.59***	-2.24	-167.87***
Day trading	-2.05	-106.77***	-2.33	-106.83***
Night trading	-1.97	-124.74***	-2.22	-125.05***
Silver futures				
2012.6-2016.4	-1.82	-174.89***	-1.89	-175.36***
2012.6-2013.7.4	0.56	-64.60***	0.37	65.05***
2013.7.5-2016.4				
All trading	-1.62	-166.78***	-1.61	-165.78***
Day trading	-1.69	-106.37***	-1.61	-105.41***
Night trading	-1.62	-125.09***	-1.53	-123.50***

Note: This table reports the Augmented Dickey–Fuller test with the null hypothesis that the price series is a unit root process. The third and last columns show the results for the first difference of price series.

***Statistical significance at the 1% level.

Comparing the day and night trading hours for gold futures, the US market makes a larger contribution during Chinese night trading than during day trading. In other words, night trading in China leads to a greater role of the US market in price discovery. For silver futures, however, although the United States is still the major contributor to price discovery, the role of the Chinese market is greater for night trading than during the day. This is captured by the IS, CS, and MIS measures being 0.36, 0.40, and 0.24, respectively, during the night, but only 0.28, 0.20, and 0.06, respectively, during the day.

In Panel B, we break the IS measures down and report time block values throughout the day allowing us to analyze time variation in the price discovery process. Consistent with the aggregate statistics in Panel A, over the prenight trading period, the contributions of Chinese and US gold futures are quite similar. To be clear, from 9:00 a.m. to 3:00 p.m., the IS of Chinese gold futures typically ranges between 0.46 and 0.52 across the three measures. The only exception occurs during the last half hour of the morning session between 11:00 a.m. and 11:30 a.m.; the CS is particularly low at 0.10 and the MIS is also much lower at 0.32. This may be potentially caused by sample bias in this slot given fewer observations. For silver futures, the US market generally contributes more to price discovery with the exception being the first trading hour during which the Chinese market takes the lead.

	Gold futures			Silver future	s
	None	At most 1		None	At most 1
2008.01-2016.04	84.56***	3.48	2012.6-2016.4	15.76**	1.41
2008.01-2013.07	154.49***	1.51	2012.6-2013.7	29.80***	1.57
2013.07-2016.04					
All trading	28.97***	4.66		32.20*	2.89
Day trading	28.56***	4.93		25.53***	3.13
Night trading	28.19***	4.69		32.20***	2.89

TABLE 6 Trace statistics of Johansen cointegration test

Note: This table reports the trace statistics of Johansen cointegration test for the Chinese and US gold and sliver futures prices. Columns titled *None* are the results for the null hypothesis of no cointegrating relationship between two variables; and *At most 1* refers to the null hypothesis that two variables have at most 1 cointegrating relationship. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Gold futures				Silver fu	Silver futures			
	CS	IS	MIS		CS	IS	MIS		
Panel A: Subperiod analysis									
2008.1-2016.4	0.40	0.46	0.43	2012.6-2016.4	0.31	0.42	0.31		
2008.1-2013.6	0.51	0.50	0.50	2012.6-2013.6	0.03	0.33	0.06		
2013.7-2016.4									
All trading	0.25	0.32	0.26		0.29	0.27	0.04		
Day trading	0.29	0.35	0.30		0.20	0.28	0.06		
Night trading	0.20	0.33	0.26		0.31	0.36	0.24		
Panel B: Intraday time blocks									
2008.01-2013.6				2012.6-2013.6					
9:00-9:45	0.50	0.50	0.49		0.65	0.52	0.55		
10:00-10:45	0.52	0.50	0.50		0.17	0.46	0.38		
11:00-11:30	0.10	0.42	0.32		0.15	0.45	0.35		
13:30-14:15	0.53	0.50	0.51		0.19	0.46	0.39		
14:30-15:00	0.46	0.49	0.48		0.19	0.46	0.38		
2013.7-2016.4									
21:00-21:45	0.17	0.34	0.26		0.32	0.30	0.06		
22:00-22:45	0.25	0.36	0.30		0.33	0.29	0.05		
23:00-23:45	0.29	0.38	0.32		0.33	0.36	0.06		
00:00-00:45	0.33	0.39	0.35		0.33	0.32	0.08		
1:00-1:45	0.35	0.40	0.36		0.27	0.32	0.12		
2:00-2:30	0.35	0.41	0.37		0.30	0.32	0.10		
9:00-9:45	0.25	0.33	0.27		0.34	0.29	0.05		
10:00-10:45	0.17	0.35	0.26		0.37	0.33	0.05		
11:00-11:30	0.21	0.36	0.28		0.37	0.43	0.06		
13:30-14:15	0.28	0.39	0.33		0.39	0.44	0.04		
14:30-15:00	0.24	0.38	0.31		0.37	0.33	0.05		

Note: This table reports three information share measures: the component share (CS) of Gonzalo and Granger (1995), the information share (IS) of Hasbrouck (1995), and the modified information share (MIS) of Lien and Shrestha (2009) for the Chinese gold and silver futures contracts.

For the rest of the trading hours before the introduction of night trading, US silver is the major contributor and the dynamics of price discovery are relatively stable.

Continuing to focus on Panel B of Table 7, during the postnight trading subsample, the IS for both Chinese markets is typically lower, except the CS for silver, compared with the prenight subsample, reinforcing the view that parallel trading in the United States and China has meant that the US market has become more informationally dominant over the Chinese market. Finally, unlike liquidity, the price discovery dynamics do not exhibit a clear time-varying pattern for different time blocks.

5.3 | Volatility spillovers

We analyze volatility spillovers to further understand the variation in interdependence between the two countries. Specifically, we implement the volatility spillover index proposed by Diebold and Yilmaz (2012) and report the total and directional spillovers between the two markets on an annual basis in Table 8.

The total spillover index measures the contribution of spillovers of volatility shocks of the two markets to the total forecast error variance in Equation (23). The directional spillover measures the contribution to the forecast error variance of market i coming from innovations to market j. The results are based on VARs of order 2 and generalized variance decompositions of 10-step-ahead volatility forecast errors.

TABLE 8 Total and directional volatility spillover

	Day trading			Night trading			
	$US \!\rightarrow \! China$	$China {\rightarrow} US$	Total spillover	$\mathbf{US} \mathop{\rightarrow} \mathbf{China}$	$\mathbf{China} \rightarrow \mathbf{US}$	Total spillover	
Gold futures							
2008	0.88	3.19	4.06				
2009	0.35	1.65	2.00				
2010	0.45	2.37	2.81				
2011	1.19	3.46	4.65				
2012	0.21	0.30	0.51				
2013 1st half	11.94	2.90	14.84				
2013 2nd half	15.28	6.08	21.36	20.66	6.25	26.91	
2014	17.41	8.47	25.88	18.35	7.20	25.54	
2015	21.60	12.35	33.95	18.54	7.63	26.17	
2016.01-2016.04	15.40	5.60	20.99	22.64	6.23	28.87	
Silver futures							
2012	13.05	6.70	19.76				
2013 1st half	14.04	3.80	17.83				
2013 2nd half	22.71	9.38	32.09	22.23	6.07	28.30	
2014	20.03	10.06	30.09	25.33	8.77	34.10	
2015	17.64	9.33	26.98	22.93	6.97	29.90	
2016.01-2016.04	19.15	10.83	30.30	24.54	9.01	33.55	

Note: This table reports the Diebold and Yilmaz (2012) spillover index. Total spillover denotes the contribution of volatility spillover from two markets. Directional spillover measures contribution of market *i* to the forecast error variance which comes from innovations to market *j*. $US \rightarrow China$ denotes directional volatility spillover from the United States to China, and *China* \rightarrow *US* denotes directional volatility spillover from China to the United States. Numbers are in percent.

We observe several interesting results for gold futures. The directional spillover (in percentage terms) from the United States to China is less than from China to the United States in the prenight trading period. For example, for 2008 and 2009, the directional spillover from the United States to China is 0.88 and 0.35, respectively, and from China to the United States is 3.19 and 1.65, respectively. The total spillover for that period is generally under 5%. This is not surprising given that the Chinese daytime corresponds to the US nighttime when trading in the latter market is relatively thin.

From 2013 onwards, the volatility spillover from the United States to the Chinese market increases substantially. The directional spillovers from the second half of 2013 to 2016 are 15.28, 17.41, 21.60, and 15.40, respectively, for daytime trading hours. These are considerably higher than before 2013. Moreover, during the night, the spillovers from the United States to China are more than twice as high as that from China to the United States. For example, the directional spillovers from China to the United States are 8.47 and 12.35 for 2014 and 2015, respectively, for the day, and 17.41 and 21.60, respectively, from the United States to China. Additionally, the total spillover between the two markets is significantly higher for the postnight trading period compared with the prior period, indicating that interdependence of the two markets increases massively when trading in China overlaps with the active trading period in the United States.

After the second half of 2013, directional spillovers from China to the United States are generally higher than those before 2013, but the increase is much larger for the spillovers from the United States to the Chinese market, providing evidence for Hypothesis 3. For the postnight trading period, note also that spillovers from the United States to China are in most cases higher during night trading than during day trading. For example, the volatility contribution from the United States to China is 20.66, 18.35, and 22.64 for night trading hours in the second half of 2013, 2014, and 2016, respectively. The corresponding values for day trading hours are lower, at 15.28, 17.41, and 15.40, respectively.

For silver futures, the results are generally in line with those of the gold futures. First, the spillovers are generally higher in both directions after the night trading policy is introduced. Second, the spillover from the United States to China is generally higher than that in the opposite direction after the second half of 2013. Third, the total spillover is higher for the postnight trading period. Fourth, during the night trading hours, both directional spillover from the

United States to China and total spillover are more pronounced than during day trading hours. Note finally that comparing the results for silver and gold futures for the prenight trading period, both the directional spillover from the United States to China and the total spillover are significantly larger for silver than for gold (e.g., 13.05 and 0.21, respectively, for silver and gold for the directional spillover from the United States to China in 2012). This indicates possible differences between the two types of precious futures markets.

In summary, by analyzing the volume, liquidity, price discovery, and volatility spillovers of Chinese precious metal futures markets, we find that, first, after the introduction of night trading, the trading intensity is substantially increased for both China and the US markets and trading during the Chinese nighttime is more active than during the daytime. Second, in general the Chinese market is more liquid since the introduction of the night trading policy as captured by the Roll's spread and the Amihud illiquidity measure. Third, night trading eases the illiquidity and high volatility of the opening time block and enhances the role played by the US market in price discovery. It also strengthens the volatility interdependence of the two markets. Said differently, the US market exhibits more impact on Chinese market volatility during the Chinese night trading than during the day trading.

6 | CONCLUSION

In this paper, we examine how extended trading hours, introduced via a night trading session, have impacted the Chinese precious metal futures market at the SHFE. Understanding such impacts, if any, is vital for traders and policymakers alike. This is especially the case given the SHFE gold and silver futures are the first two commodity products that provide night trading sessions in China. Hence, a better understanding of the influence of this new policy may have significant implications for other commodity futures.

Adopting a comprehensive approach, we consider a range of market quality measures, such as trading activity, liquidity, price discovery, and volatility spillovers; the latter two, in particular, are analyzed relative to commodities traded at the US-based exchange (COMEX), which is generally considered the preeminent market for price discovery. Given the Chinese night trading session overlaps with the active COMEX daytime trading period, we posit that increased information flows, particularly from the United States to China, will result in improved market quality.

Employing daily and intraday data from before and after the introduction of night trading in July 2013, we find that the new policy significantly improves the volume and liquidity of gold and silver futures in China. In particular, the improvement in liquidity as captured by Roll's spread and the Amihud illiquidity measure suggests decreased transactions costs and less price impact. For example, using Roll's measure of the ES suggests a reduction by approximately a third of such trading costs when one compares the pre- and postnight trading periods. It would appear that Chinese investors take the advantage of the overlapping trading period with the US market by trading more actively during the night session. Additionally, since information from the US market is rapidly absorbed by the SHFE market during the night session, the price volatility for the opening period of daytime trading in China is largely reduced. Before the introduction of night trading, opening period excessive price volatility was a significant issue whereby accumulated overnight information flooded the market upon commencement of the morning session. The reduced price volatility in the opening period of daytime trading translates into less risk for the trader. Indeed, for both gold and silver, the risk (represented by realized volatility) is approximately 40% lower.

Post July 2013, empirical results also show a leading role in price discovery for the US market, particularly during the Chinese night session and this likely benefits the efficiency of the SHFE pricing process. Finally, the volatility interdependence of the two countries has deepened, especially for directional spillovers from the United States to China. This provides further support that the new policy has led to decreased market segmentation, increased relevant information flow, and that Chinese futures prices are more connected to international prices. Other futures markets in China and Asia can legitimately consider introducing similar sessions.

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DATA AVAILABILITY STATEMENT

The data employed in this study are available from the China Stock Market and Accounting Research (CSMAR) database, TickData LLC, and Wind Co. Ltd. Restrictions apply to the availability of these databases, which can be

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acquired with fee. The data that support the findings of this study are available from the corresponding author upon reasonable request.

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