Are Tightened Trading Rules Always Bad? Evidence from the Chinese Index Futures Market

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Abstract

This paper investigates the impact of tightened trading rules on the market efficiency and the price discovery function of Chinese stock index futures in 2015. In contrast with severe criticism of these changes, we fail to find empirical evidence that market efficiency and price discovery deteriorated after these rule changes. Using variance ratio and spectral shape tests, we find that the Chinese index futures market became even more efficient after the tightened rules came into effect. Furthermore, by employing Schwarz and Szakmary (1994) and Hasbrouck (1995) price discovery measures, we find that the price discovery function, to some extent, became better. This is consistent with Stein (2009), who finds that regulations on leverage can be helpful in a bad market state, and Zhu (2014), who finds that price discovery can be improved with reduced liquidity. It also suggests that the new rules may effectively regulate the manipulation behaviour of the Chinese stock index futures market, and then positively affect its market efficiency and price discovery function.

JEL classification: G13; G14; G15

Keywords: Tightened trading rules; index futures; market efficiency; price discovery; manipulation.

1 Introduction

Between July and September 2015, a series of tightened trading policies were executed in the Chinese stock index futures market, one of the largest index futures markets in the world.[1] The purpose of changing trading rules is aimed at reducing leverage and building a high barrier for speculators to trade. In this paper, we analyze the impact of these trading rule changes on the market efficiency and price discovery of the Chinese index futures market.

An index futures market provides an effective way to hedge, arbitrage, speculate and manipulate. The functions of an index futures market have been a prevailing topic in both the academic and industry domains since the 1980s. Kawaller et al. (1987), Stoll and Whaley (1990), Kim et al. (1999), Tse (1999), and Booth et al. (1999) find that index futures play a crucial role in price discovery and volatility spillover effects in the United States and Germany. So and Tse (2004) show that the futures market contains the most information compared with the spot market in Hong Kong. Roope and Zurbruegg (2002) find that the Singapore futures market influences the Taiwan stock market. There is consistent international evidence that the index futures market is important for the effective transmission of information on financial markets.

The evidence in the Chinese index futures market is not conclusive, however. Yang et al. (2012) document that the cash market is found to play a more dominant role in the price discovery process just after the introduction of index futures, while Hou and Li (2013) show that the CSI 300 index futures market dominated in the price discovery process about one year after its inception and that new information is disseminated more rapidly in the stock index futures market than the stock market.

The key advantage of stock index futures is its loosen trading rules, including low transaction costs and high leverage, which makes them attractive to informed traders (Berkman et al., 2005). Chan (1992) demonstrates that low transaction costs and high leverage contribute to the lead-lag

[1] The daily volume of CSI 300 index futures (trading code: IF) in July 2015 averaged 1.7 million contracts, while it was only 1.5 million contracts for S&P 500 index futures traded on the Chicago Mercantile Exchange (CME) during the same period. However, after these tightened trading rules took effect, the daily volume of IF shrank sharply, more than 99 percent after September.

relationship between the index futures market and the spot market. Longin (1999) also suggests that the margin level is inversely proportional to the attractiveness of index futures to investors. In this aspect, a loose trading rule with smaller transaction costs tends to provide an environment closer to a perfect market, and thus is important for an efficient market.

Low transaction costs and high leverage not only make hedging and arbitraging using index futures easier, but also reduce the costs of insider trading and market manipulation. Hedging and arbitraging behaviours are important to improve market efficiency and price discovery, while excessive insider trading and market manipulation damage them and might cause a crash under a bad market state. As a result, there exists an optimal trading rule level to balance the positive and negative effects. This level depends on the distribution of participants and the market state. If the index futures market is dominated by hedgers and arbitragers and the market is in a normal state, the trading rule is set at a loose level to let the positive effect function. On the other hand, if there exists excessive market manipulation and the market is in a bad market state, the trading rule should be tightened to control for the negative effect. Stein (2009) provides good theoretical support for this argument, showing that capital regulation on an increasing margin rate may be helpful to prevent a crash in a bad market state.

In this paper, we provide the first comprehensive analysis of the impact of tightened trading rules on the market efficiency and price discovery function of the Chinese index futures market in 2015. Besides the relatively long-established CSI (China Security Index) 300 index futures (IF), we take into consideration the other two nascent index futures, namely, the CSI 500 (IC) and the SSE (Shanghai Security Exchange) 50 (IH) index futures. We examine the impact of the tightened trading rules on the market efficiency of the Chinese stock index and index futures market. We apply the variance ratio (VR) test with the truncation lag levels selected by using Choi (1999), and the spectral shape test proposed by Durlauf (1991). The results show that there was no deterioration effect on market efficiency in both markets after the new trading rules became effective. We fail to find the evidence that the new trading rules negatively affected the market efficiency in both markets. More interestingly, the market efficiency of Chinese stock index futures became even slightly better under the new rules. This is consistent with Stein (2009) about the usefulness of regulation in a bad market state.

We run a vector error correction model (VECM) on the three stock index and index futures and do several tests, separately. We first examine the long-run and short-run Granger causality effect between the stock index and index futures. The results continue to show that there is no significant change of Granger causality between the two markets. The Granger causality effect from index futures to the stock index continues to be stronger than the effect from the stock index to index futures before and after the rule changes. Using VECM, we calculate the Schwarz and Szakmary (1994) and Hasbrouck (1995) price discovery measures of Chinese stock index futures. The results strongly indicate that the price discovery function of the Chinese index futures market improves after the trading rule changes in September 2015. We then run the multivariate GARCH model on the residuals of VECM to investigate the volatility spillover between the two markets. We follow Engle and Kroner (1995) to use the BEKK model to model the conditional variance. Similar to the Granger causality test results, our findings show that the volatility spillover effect continues to exist under the new rules. The volatility spillover effect from index futures to the stock index also continues to be stronger than that from the stock index to index futures.

We fail to find empirical evidence that the market efficiency and price discovery function of the Chinese stock index futures deteriorate after the tightened rule changes. The results are robust across the three index futures. This is in contrast with the severe criticism against them. The tightened trading rules exercised in 2015 were regarded by the financial industry as a destructive behaviour against the newly established Chinese stock index futures market. For example, on September 9, 2015, Bloomberg commented that China had killed the world's biggest stock index futures market. Bloomberg stated that the daily volume of the futures had been decimated by 99 percent from the peak in June, since authorities increased the margin rate, tightened position limits, and started a police investigation into bearish wagers. The Financial Times also pointed out that the new rules had made life more difficult for speculators and hedgers due to the illiquidity problem. [2] These comments focused on the impact of the trading rule changes on market trading. In this paper, we address this question from another aspect, by focusing on the impact on market efficiency and price discovery.

This paper contributes to the literature in several ways. We are the first to provide empirical evidence of the impact of the tightened rule changes in the Chinese index futures market in 2015. Our results provide empirical support of the usefulness of rule tightening under certain circumstances, as shown in Stein (2009).

More interestingly, while the rule changes negatively affect the liquidity of the index futures market, they have had no impact on the market efficiency and price discovery function. Our analysis contributes to literature about the relationship between liquidity and price discovery. For example, Kwan (1996) and Chakravarty et al. (2004) show that price discovery is positively related to liquidity in the corporate bond and options market, respectively. However, Hotchkiss and Ronen (2002) find that corporate bond returns cannot be predicted by past stock returns, although the corporate bond market is much less liquid. Barclay and Hendershott (2003) show that it is possible to generate significant price discovery with very little, but very informative trading. Zhu (2014) shows that price discovery can be improved with reduced liquidity. Our results provide empirical results consistent with Barclay and Hendershott (2003) and Zhu (2014).

This paper is organized as follows. Section 2 provides the historical background of the newly established Chinese stock index futures market, and the details of the tightened trading rules exercised between July and September 2015. Section 3 presents the empirical methodology used to analyze the data. Section 4 presents the empirical results. Finally, Section 5 concludes the paper.

2 Background

On September 8, 2006, the China Financial Futures Exchange (CFFEX) was established in Shanghai, with the aim of promoting the development of a Chinese financial derivatives market.

[2] http://www.bloomberg.com/news/articles/2015-09-08/china-just-killed-the-world-s-biggest-stock-index-futures-market and https://next.ft.com/content/8d09afa2-6737-11e5-a57f-21b88f7d973f

In early 2008, CFFEX launched its first contract, the CSI 300 index futures (IF). IF contracts were officially listed at CFFEX on April 16, 2010. This began a new era in the Chinese financial market, with investors being able to protect themselves with short positions on index futures to hedge downside risks without selling stocks. Five years later, on April 16, 2015, the two other index futures–CSI 500 (IC) and SSE 50 (IH) index futures–were also listed at CFFEX. There are three Chinese stock index futures traded at CFFEX.

Table 1 explains the contract specifications of the three Chinese stock index futures traded on CFFEX. The underlying indices of the IF, IC and IH contracts are the CSI 300, CSI 500 and SSE 50 indexes, respectively. As the first equity index introduced by the Shanghai and Shenzhen stock exchanges together, the CSI 300 reflects the price performance and fluctuation of the China A share market. It is a free-float, weighted index that consists of 300 A-share stocks listed on the Shanghai or Shenzhen Stock Exchanges. The index had a base level of 1000 on December 31, 2004. The CSI 500 aims to comprehensively reflect the price fluctuation and performance of the small-cap companies in the Shanghai and Shenzhen securities markets. The selection criteria of the CSI 500 is as follows. First, the stocks in the index universe (excluding the stocks either in the CSI 300 or the top-ranked 300 in the Shanghai and Shenzhen stock markets according to the daily average total market capitalization of the past recent year) are ranked by the daily average trading value during the past recent year (in the case of a new issue, during the time since it was listed) in descending order. The bottom-ranked 20% of stocks are first deleted. The rest of the stocks are then ranked by the daily average total market capitalization of the most recent year in descending order. The stocks that rank in the top 500 are selected as CSI 500 constituents. The SSE 50 index selects the 50 largest stocks of good liquidity and representativeness from the Shanghai security market. Its objective is to reflect the whole picture of those good-quality large enterprises that are the most influential ones in the Shanghai Security Exchange.

By December 31, 2015, the component stocks of the CSI 300 and the CSI 500 accounted for nearly 70% and 20% of the total market value in both the Shanghai and Shenzhen Stock Exchanges, respectively, while the SSE 50 constituent stocks constituted over 50% of the market value in the

Shanghai Stock Exchange. The trading of the three index futures meets the hedging demands of different stocks, and provides an efficient tool of risk management in the Chinese financial market.

[Insert Table 1]

Unfortunately, the Chinese stock market underwent a turbulent period shortly after IC and IH were listed on CFFEX in April 2015. The Shanghai Composite Index reached its peak at 5178.34 on June 12, 2015, and plummeted over 30% to 3373.54 on July 9, 2015, and over 44% to 2850.71 on August 26, 2015. In order to effectively regulate market manipulation and stabilize the Chinese financial market, CFFEX introduced several tightened trading rules for the Chinese stock index futures between July and September 2015.

Table 2 lists the main trading rule changes introduced by CFFEX between July and September 2015. The trading of Chinese index futures is tightened in three ways. Firstly, the margin rate requirement dramatically increased, especially for non-hedging accounts. Before July 2015, the margin rate to trade the Chinese stock index futures was only 10%. However, it became 40% for the non-hedging account and 20% for the hedging account after September 7, 2015. Secondly, the maximum trading volume of each index futures contract was limited. After September 7, 2015, the maximum daily total trading volume in each index futures contract by a non-hedging account is 10 contracts. Lastly, the transaction costs of index futures also increased. After September 7, 2015, the transaction fee of closing an index futures contract increased to 23 bps of the trading amount.

[Insert Table 2]

3 Empirical methodology

In this section, we explain the main methods used in our empirical analysis. They include a market efficiency test, a Granger causality test, a price discovery measure, and a volatility spillover test.

3.1 Market efficiency

We first use a variance ratio test. Variance ratio tests have been used widely in market efficiency tests (Lo and MacKinlay, 1988). The motivation behind this test is that the variance of the increments of a random walk process is linear in the sampling interval. For example, if asset prices follow a random walk process, the variance of weekly returns will be five times as large as the variance of daily returns. In particular, the null hypothesis is H_0: Δp_t is serially uncorrelated, where p_t is the natural logarithmic price. The variance ratio for price series p_t with truncation point l is defined as

$$VR(l) = \frac{Var(p_t - p_{t-l})}{lVar(p_t - p_{t-1})}. \quad (1)$$

When $\{\Delta p_t\}$ is serially uncorrelated, that is, when the price series is a random walk process, $VR(l)$ is equal to one at all lag truncation points l.

The variance ratio (VR) statistics is defined as

$$\hat{VR}(l) = 1 + 2\sum_{i=1}^{T-1} k(i/l)\hat{\rho}(i), \hat{\rho}(i) = \sum_{i=1}^{T-i} \Delta p_t \Delta p_{t+i} / \sum_{i=1}^{T} \Delta p_t^2, \quad (2)$$

$$k(x) = \frac{25}{12\pi^2 x^2}\left[\frac{\sin(6\pi x/5)}{6\pi x/5 - \cos(6\pi x/5)}\right].$$

The asymptotic distribution of the test is

$$VR = \sqrt{T/l}[\hat{VR}(l) - 1]/\sqrt{2} \xrightarrow{d} N(0,1) \;\; as \;\; T \to \infty, l \to \infty, T/l \to \infty, \quad (3)$$

where $\xrightarrow{d}$ denotes the convergence in distribution. In practice, a truncation point l has to be selected to run the variance ratio test. Following Andrews and Monahan (1992), Choi (1999) proposes a way to choose the best truncation point, which is data-dependent. In this paper, we follow Choi (1999) and choose the optimal truncation lag to calculate the VR statistics.

When $l \to \infty$ as $T \to \infty$, the VR statistic is asymptotically equivalent to

$$VR(l) = \frac{\pi}{2}\sqrt{T/p}[\hat{f}(0) - \frac{1}{2\pi}], \tag{4}$$

where $\hat{f}(0)$ is a kernel-based normalized spectral density estimator at frequency zero with the Bartlett kernel $K(z) = (1-|z|)1(|z| \leq 1)$, where $1(|z| \leq 1)$ is an indicator function that equals one if the random variable z is between $[-1,1]$ and zero otherwise.

As variance ratio tests focus on the zero frequency in isolation and may have the problem of test inconsistency, Durlauf (1991) proposes the spectral shape tests designed to overcome the problem by searching over all frequencies of the spectral density. The spectral shape tests are

$$AD_T = \int_0^1 U_T^s(q)^2/[q(1-q)]dq, \tag{5}$$

$$CVM_T = \int_0^1 U_T^s(q)^2 dq, \tag{6}$$

where

$$U_T^s(q) = \sqrt{2}T^{1/2}\left[\frac{2\pi}{T}\sum_{s=1}^{[Tq/2]} I\left(\frac{2\pi s}{T}\right) - \frac{q}{2}\sum_{t=2}^{T}\Delta p_t^2/T\right] / \left[\sum_{t=2}^{T}\Delta p_t^2/T\right], \tag{7}$$

$$I(\lambda) = (2\pi T)^{-1}|\sum_{t=0}^{T-1}\Delta p_t exp(-i\lambda t)|^2.$$

Shorack and Wellner (1987) list the asymptotic behaviour of spectral shape tests, including the Anderson-Darling (AD_T) statistic and the Cramer-von Mises (CVM_T) statistic. They show the 10%, 5%, and 1% asymptotic critical values of AD_T and CVM_T are separately (1.93, 2.49, 3.85) and (0.35, 0.46, 0.74). We also use these two tests in our analysis.

3.2 Granger causality test

In order to do the Granger causality test, we run the vector error correction model (VECM) to the logarithms of stock index (s_t) and index futures (f_t) first. We select the optimal lag order of VECM using Schwarz's Bayesian Information Criterion (SIC). The VECM could be written as follows:

$$\Delta s_t = b_{s,0} + \gamma_s ect_{t-1} + \sum_{i=1}^{n} b_{ss,i}\Delta s_{t-i} + \sum_{i=1}^{n} b_{fs,i}\Delta f_{t-i} + e_{s,t}, \tag{8}$$

$$\Delta f_t = b_{f,0} + \gamma_f ect_{t-1} + \sum_{i=1}^{n} b_{sf,i}\Delta s_{t-i} + \sum_{i=1}^{n} b_{ff,i}\Delta f_{t-i} + e_{f,t}, \tag{9}$$

where $b_{s,0}$ and $b_{f,0}$ are the constant term, $ect_t = f_t - a_0 - a_1 s_t - a_2 m_t$ represents the error correction term (Zhong et al., 2004), and m_t is the time to maturity of index futures. $e_{j,t}(j = s, f)$ are serially uncorrelated innovations with a mean of zero and a covariance matrix with diagonal elements σ_1^2 and σ_2^2 and off-diagonal elements $\rho\sigma_1\sigma_2$.

In the VECM, the coefficient of γ measures the response to the deviation from the long-run equilibrium effect, ect_{t-1}, while the coefficients b_{ss}, b_{sf}, b_{fs} and b_{ff} measure the response to the short-run change. [3]

We run two types of tests to examine the long- and short-run Granger causality separately. The type 1 test is to test the short-run Granger causality from futures to spot (spot to futures) by testing $b_{fs,i} = 0$ $(b_{sf,i} = 0)$ for all $i = 1, ..., n$. The type 2 test is to test the long-run Granger causality from futures to spot (spot to futures) by testing $\gamma_s = 0$ $(\gamma_f = 0)$. If either null hypothesis is rejected, then we can infer that the futures (spot) market Granger causes the spot (futures) market.

A no-arbitrage index futures pricing model implies $a_1 = 1$ in the ect term. To make no-arbitrage pricing framework work effectively, a large position on the index futures market should be allowed with low costs. These two conditions are not satisfied after tightened traing rules were executed in the Chinese index futures market, which suggests no-arbitrage pricing framework on longer works. Therefore, we do not impose $a_1 = 1$ in the VECM, but let the data determine their long-run equilibrium relationship. In other words, we are not interested in whether no-arbitrage index

[3] As Zhong et al. (2004) point out, there are two opposing effects determining the relative change of spots and futures. For instance, if there exists disequilibrium that the index future price is relatively higher than the spot price, it will lead to a potential negative change of the futures price or a positive change of the spot index as the arbitrage force can correct the mispricing by selling futures and buying stocks to obtain riskless profits. However, the index is not a tradable asset but the weighted average of individual stocks. If there exists a momentum effect, some constituting stocks may decline even more when the index is already lower than the corresponding futures, which contributes to an even larger deviation of futures compared with the index. As a result, the coefficients of the error correction terms (γ) in the above VECM can be negative or positive.

pricing model holds in the Chinese index futures market, but the information flow between the Chinese stock and the Chinese index futures market. As a robustness check, we also run the tests under the condition of $a_1 = 1$ and obtain similar results.

3.3 Price discovery measure

We employ the two price discovery measures suggested by Hasbrouck (1995) and Schwarz and Szakmary (1994) to assess the price discovery function of index futures. Based on VECM, we estimate Hasbrouck measure as follows:

$$H_s(u) = \frac{(-\gamma_f \sigma_1 + \gamma_s \rho \sigma_2)^2}{(-\gamma_f \sigma_1 + \gamma_s \rho \sigma_2)^2 + (\gamma_s \sigma_2 \sqrt{1-\rho^2})^2}, \tag{10}$$

$$H_f(l) = \frac{(\gamma_s \sigma_2 \sqrt{1-\rho^2})^2}{(-\gamma_f \sigma_1 + \gamma_s \rho \sigma_2)^2 + (\gamma_s \sigma_2 \sqrt{1-\rho^2})^2}, \tag{11}$$

where u indicates the upper bound and l indicates the lower bound. Reversing the order in the vector of the price series gives the upper bound $H_f(u)$ and the lower bound $H_s(l)$. The average of these two bounds is the Hasbrouck measure of price discovery.

The Schwarz-Szakmary measure for spot and futures are calculated with the corresponding coefficients in equation (8) and equation (9):

$$S_s = \frac{|\gamma_f|}{\gamma_s + |\gamma_f|}, S_f = \frac{\gamma_s}{\gamma_s + |\gamma_f|}. \tag{12}$$

In essence, we can get $S_s = 1 - S_f$.

The Hasbrouck measure evaluates each market's contribution to the variance of the innovations to the common factor, while the Schwarz-Szakmary measure considers the components of the common factor and the error correction process, which is closely related to other popular measures like that of Gonzalo and Granger (1995). In our paper, we focus on the price discovery ability of the futures market, which means we analyze S_f and the average of the Hasbrouck upper bounds and lower bounds in the futures market ($H_f(u)$ and $H_f(l)$).

3.4 Volatility spillover test

With consideration of volatility spillover effects between two markets, we apply a bivariate GARCH model based on VECM. Compared with a univariate GARCH model, a bivariate GARCH model has the advantage of applying information in both markets' history and testing the volatility spillover effect. In this paper, we utilize the BEKK model. An important characteristic of this model is that it allows the interaction of variances and covariances between stock and stock futures market without too much complexity in parameter estimation. This model also guarantees the positive semi-definite property of a conditional variance-covariance matrix in the computation process, which is a necessary condition to ensure the estimated variances are well defined.

We first run the VECMs to stock index futures and their underlying stock indexes and obtain the residuals. Define the variance-covariance matrix of the residuals conditional on the information set I_{t-1} as:

$$var(e_{s,t}, e_{f,t}|I_{t-1}) = H_t = \begin{bmatrix} h_{ss,t} & h_{fs,t} \\ h_{sf,t} & h_{ff,t}. \end{bmatrix} \tag{13}$$

The BEKK model for the multivariate GARCH(1,1) model can be expressed as follow:

$$H_t = C^{'}C + A^{'}(e_{t-1}e^{'}_{t-1})A + B^{'}H_{t-1}B \tag{14}$$

where C (lower triangular), A and B are $n \times n$ matrices.

In bivariate case:

$$\begin{bmatrix} h_{ss,t} & h_{fs,t} \\ h_{sf,t} & h_{ff,t} \end{bmatrix} = \begin{bmatrix} c_{11} & c_{12} \\ c_{21} & c_{22} \end{bmatrix}^{'} \begin{bmatrix} c_{11} & c_{12} \\ c_{21} & c_{22} \end{bmatrix} + \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}^{'} \begin{bmatrix} e^2_{s,t-1} & e_{s,t-1}e_{f,t-1} \\ e_{f,t-1}e_{s,t-1} & e^2_{f,t-1} \end{bmatrix} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} + \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}^{'} \begin{bmatrix} h_{ss,t-1} & h_{fs,t-1} \\ h_{sf,t-1} & h_{ff,t-1} \end{bmatrix} \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}, \tag{15}$$

where $h_{ss,t}$ and $h_{ff,t}$ are the conditional variances of spot and futures market, and $h_{sf,t}$ and $h_{fs,t}$

are the conditional covariance between the two markets. Similarly, the c_{ij} are elements in the 2×2 constant matrix C, and the a_{ij} in matrix A gauges the ARCH effect, while the b_{ij} in matrix B measures the GARCH effect. In particular, $a_{1,2}^2$ and $b_{1,2}^2$ measure the volatility spillover from stock index futures to stock index, while $a_{2,1}^2$ and $b_{2,1}^2$ measure the volatility spillover from stock index to index futures.

4 Data and empirical analysis

4.1 Data

We download the high-frequency data from *Wind*®, the leading provider of financial data, information and services in mainland China. The data period is from April 16, 2015 to December 31, 2015. We choose April 16, 2015 as the sample starting date to cover the two newly listed index futures, IC and IH. We stop the data at December 31, 2015 to make sure we have about the same data period before and after the trading rule changes between July and September 2015. We mainly use five-minute price data in the analysis. To eliminate the effect of expiration, we use the data of current month contracts (00) until one week before their expiration.

Table 3 reports the summary statistics of the stock indexes and its index futures using five-minute interval data. The trading volume (in 100 million RMBs) of the stock index is the average trading volume of its constituent stocks in five minutes. The trading volume (in 100 million RMBs) of the stock index futures is measured by the average five-minute trading volume of the current month contract. All the mean returns are close to zero. The CSI 500 index and IC00 returns have the largest standard deviation, since they represent small-capitalization stocks, which are more volatile. The trading is dominated by IF00. IF futures have a relatively longer history, so their liquidity is better and institutional investors would prefer to trade them. The sample distributions of stock index returns are skewed left, while those of index futures returns are skewed right, and both are leptokurtic. The ARCH-LM test result suggests that there exists significant heteroscedasticity for all six return series.

[Insert Table 3]

Table 4 reports the results of the stationarity (Panel A) and the co-integration test (Panel B). We employ three tests, including the Augmented-Dickey-Fuller (ADF) test, the Phillips-Perron (PP) test and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test. The null hypothesis of the ADF and PP tests is that the time series has a unit root, while the null hypothesis of the KPSS test is that the time series is stationary. The results strongly suggest that all the price series are non-stationary and all the return series are stationary.

We run two co-integration tests between the index futures and their underlying stock indexes. Firstly, we test whether there exists a co-integration relationship between these two series ($r = 0$). We report two different test statistics, including Eigenvalues statistics and Trace statistics. Both statistics strongly reject the null hypothesis of no co-integration between the stock index and its index futures. We then test whether these exists one co-integration vector between the stock index and its index futures ($r \leq 1$). Both the Eigenvalues statistics and the Trace statistics fail to reject the null hypothesis. These results suggest that we are able to run the VECM model with one co-integration vector to examine the relationship between the stock indexes and their index futures.

[Insert Table 4 here]

We now turn to empirical analysis. We first run the market efficiency test to examine how quickly each market reflects its own historical information. We then do the cross-market analysis, testing how the information in one market affects the other. We consider three periods. Period A uses the whole sample period data to provide a picture of overall results. Period B uses the data before the trading rule changes[4], that is, from April 16, 2015 to July 8, 2015. Period C uses the data after the trading rule changes from September 7, 2015 to December 31, 2015. We exclude the data between July 9, 2015 and September 2, 2015[5] to control for the impact of trading rule

[4] As we can see in Table 2, compared with the trading volume limit, which can be easily avoided by trading in different accounts, it is more vital for speculation by increasing the margin rate for non-hedging accounts; thus we choose July 8, 2015 as the real prelude of the tightened trading policy.

[5] September 7 is the next trading day after September 2, 2015.

instability. We use the difference between the results of Periods B and C to assess the impact of the trading rule changes on the Chinese index futures market.

4.2 Market efficiency

Table 5 reports the results of the market efficiency test. We run two tests, including a variance ratio (VR) tests and a spectral shape tests (AD_T and CVM_t). The left, middle and right columns report the results of the Period A (whole), Period B (before) and Period C (after), respectively. We report the results of 5-, 20- and 60-minute returns in the upper, middle and bottom panels. We have several interesting findings. Stock index futures tend to be more efficient than the stock index. For example, the variance ratio (VR) statistics of IF00 using five-minute returns during the whole sample period is -2.94 and significant at the 1% level, while the VR statistics of its underlying index, CSI 300, is higher, with a value of -5.09. The VR statistics of IC00 using 5-minute returns is not significant during the whole sample period, while its underlying index, CSI 500, is significant at the 1% level. The results suggest that overall the index futures market reflects the historical information more efficiently than the stock market in China. The results of the spectral shape test are similar to those of the VR test.

Next we compare the market efficiency before and after the trading rule changes. Surprisingly, we fail to find evidence that the tightened trading rule deteriorated the market efficiency of either the stock index or the index futures. There is limited change in the VR, AD_T and CVM_T statistics for the stock indexes after the trading in their index futures was tightened between July and September 2015. Moreover, all the test statistics become less significant for the three index futures after the trading rule changes. Before the rule changes, the VR statistics of IF00, IC00 and IH00 using five-minute returns are -3.17, -2.73 and -3.05, respectively. All of them are significant at the 1% level. They dramatically decline to 0.38, 0.09 and -1.43, separately, after the rule changes. None of them is significant at the 5% level. The results suggest that the new trading rule in effect improves the market efficiency of Chinese stock index futures. The results using 20- and 60-minute returns are weaker but there exists similar pattern.

Our empirical finding that the efficiency of the Chinese stock index market improves after the trading rule changes is consistent with Stein (2009). Loose trading rules might be important for an efficient market under a normal state; Stein (2009) shows that the regulations on leverage can prevent a crash in a bad state. Another possible reason for this improvement is that the new trading rules effectively squeeze out market manipulation using index futures by non-hedging investors. This is an interesting question for further investigation.[6]

[Insert Table 5]

4.3 Cross-market analysis

The market efficiency test evaluates how quickly one market reflects its own historical information. It does not tell how the information in one market affects another market. We next run a cross-market analysis examining the information impact between the stock index and index futures. We first test the Granger causality between the stock index and index futures. We then examine the volatility spillover between these two markets. Finally, we assess the price discovery contribution by the index futures.

4.3.1 Granger causality test

Table 6 reports the results of Granger causality between the Chinese stock market and the stock index futures market. We first run VECM models (Eq. (8) and (9)) to the natural logarithmic price series of futures (f_t) and spot (s_t). The type 1 test is to test the short-run Granger causality from futures to spot (spot to futures) by testing $b_{fs,i} = 0$ ($b_{sf,i} = 0$) for all $i = 1, ..., n$. The type 2 test is to test the long-run Granger causality from futures to spot (spot to futures) by testing $\gamma_s = 0$ ($\gamma_f = 0$).

[6] Chinese government made a statement on August 4, 2016 that China formally charged three people of Yishidun company for manipulating the stock index futures market. The official Xinhua news agency said Yishidun started with just 3.6 million RMB ($540 thousand) in funds, but reaped gains of more than 2 billion RMB ($300 million). Refer to http://www.bangkokpost.com/news/asia/1052841/china-charges-three-for-stock-futures-manipulation.

The upper panel reports the results for the whole period. All type 1 tests of $b_{fs,i} = 0, \forall i$ and type 2 tests of $\gamma_s = 0$ are significant at least at the 5% level, suggesting that the index futures Granger causes the stock index both in the short and long run. On the other hand, there is less significant evidence that the stock index Granger causes index futures. Only the short-run Granger causality from stock index to index futures for IC00 and IH00 is significant at the 5% level. None of the long-run Granger causality tests from the stock index to index futures is significant. The results suggest that the information spillover from index futures to the stock index is more significant that the information spillover in the other direction during the whole sample period. The Chinese index futures tend to lead their underlying stock indexes.

The middle and bottom panels report the results of before and after the trading rule changes. The Granger causality test results during these two sub-periods are close to each other, and also similar to the results during the whole sample period. The tightened trading rule changes during July and September 2015 seem to have little impact on the Granger causality effect from index futures to their underlying stock indexes. Index futures continue to play a more significant role in the information transmission between the futures and spot market.

[Insert Table 6]

4.3.2 Price discovery

Table 7 reports the results of the price discovery analysis for the three Chinese stock index futures. We run VECM models to calculate both the Hasbrouck (1995) measure and Schwarz and Szakmary (1994) measure. The middle panel collects the results of the mean of the upper bound and the lower bound with the Hasbrouck measure for index futures, while the right panel reports the Schwarz-Szakmary measure for index futures.

The results of the whole sample period show that the price discovery contribution by index futures is higher than that by their underlying stock indexes. For example, the Hasbrouck measures of IF00, IC00 and IH00 are 63.69%, 78.67% and 57.77%, respectively. This suggests that the Hasbrouck measures of the CSI 300, CSI 500 and SSE 50 are 36.31%, 21.33% and 42.23%, respectively. The index futures market plays a more important role in the price discovery between index futures market and the stock market. The results using the Schwarz-Szakmary measure are similar. This is consistent with the empirical findings of other countries or regions (Kawaller et al., 1987; Roope and Zurbruegg, 2002; So and Tse, 2004).

Next, we turn to the comparison before and after the new trading rules become effective. We find strong evidence that the price discovery contribution by index futures becomes higher after the trading rule changes. The Hasbrouck measures of the three index futures (IF00, IC00 and IH00) are 62.49%, 87.41% and 49.18%, respectively, before the trading rule change, and 70.08%, 74.45% and 58.17%, respectively, after. Similarly, the Schwarz-Szakmary measures of IF00, IC00 and IH00 are 87.49%, 85.19% and 43.93%, respectively, before the rule changes, and 95.60%, 92.14% and 69.12%, respectively, after. Five of the six measures increase except the Hasbrouck measure of IC00. The index futures market plays a more important role in the price discovery after the new trading rules are put into place. This result is consistent with the findings of the market efficiency test.

The price discovery function of Chinese index futures improves after the new rules. This is in contrast with the rules' impact on market activity. The trading of the Chinese index futures market declined more than 99% after September 2015. The results together support the finding of Zhou (2014) in that price discovery could be improved with reduced liquidity.

[Insert Table 7]

4.3.3 Volatility spillover

Table 8 reports the results of volatility spillover between the Chinese stock index and index futures. We use a two-stage approach similar to So and Tse (2004) and Tse (1999). $a^2_{1,2}$ and $b^2_{1,2}$ measure the volatility spillover from stock index futures to stock index, while $a^2_{2,1}$ and $b^2_{2,1}$ measure the volatility spillover from stock index to index futures. The left, middle and right columns report the results of Period A (whole), Period B (before) and Period C (after) respectively.

The results of the whole sample period suggest that there exists bi-directional volatility spillover between index futures and their underlying indexes. Most of $a_{1,2}$, $b_{1,2}$, $a_{2,1}$, and $b_{2,1}$ are significant. There exists higher volatility spillover from index futures to their underlying stock indexes. Most value of $a_{1,2}^2$ and $b_{1,2}^2$ are greater than $a_{2,1}^2$ and $b_{2,1}^2$, respectively. The results during the two sub-periods (Period B and C) do not change much. Similar to the Granger causality test, there is no evidence that the new trading rules affect the volatility spillover from the index futures market to the underlying stock market.

[Insert Table 8]

4.4 Market efficiency with no arbitrage restriction

Zhong et al. (2004) test two restrictions of the estimated co-integration vector $ect_t = f_t - a_0 - a_1 s_t - a_2 m_t$ implied by a no-arbitrage index futures pricing model. One is $a_1 = 1$, and the other is $a_0 = 0$ and $a_1 = 1$ jointly. Kuruppuarachchi et al. (2016) show that a_0 is not zero if the variables are time-varying. We only test $a_1 = 1$ to account for the impact of time-varying variables.

Panel A of Table 9 reports the test statistics. The results strongly reject the null hypothesis of $a_1 = 1$, suggesting that the no-arbitrage relationship between the stock index and index futures does not exist. This finding is similar to Zhong et al. (2004) using Mexican data. This suggests that on emerging markets, the trading mechanism still needs to be improved to make no arbitrage work between the stock index and index futures. In other words, there exist arbitrage opportunities of index futures in these markets.

The results are robust across three periods. The test statistics of IF, IC and IH change from 383.5, 327.4 and 638.5 to 1679.8, 199.9 and 733.2, respectively. The no-arbitrage relationship of IF and IH deteriorates after the tightened trading rules, while that of IC becomes better. The impact of the tightened trading rules is strongest for long-established IF contracts.

Panel B of Table 9 reports the price discovery measures of index futures under the constraint of $a_1 = 1$, while Panel C of Table 9 reports the results of the Granger causality test. Similar to the results without constraint, the index futures market plays an important role in price discovery. There is no evidence that price discovery of index futures weakens after the tightened trading rule changes. For example, the Hasbrouck measures of IF, IC and IH during the whole period are 51.60%, 71.83% and 46.62%, respectively. They are 65.20%, 88.68% and 47.01%, respectively, before the rule changes, and 60.22%, 72.17% and 48.96% , respectively, after the rule changes.

There are stronger Granger causality effects from index futures to the stock index than from the stock index to index futures. The Granger causality relationship between the stock index and index futures does not change much before and after the tightened trading rule changes.

[Insert Table 9]

5 Conclusion

Index futures play an important role in transmitting information among financial markets. How to effectively regulate the index futures market is of great interest to both academics and policy makers. Using high-frequency Chinese index futures data in 2015, this paper investigates the impact of tightened trading rules on the market efficiency and price discovery of Chinese index futures.

The key finding of this paper is we fail to find evidence that tightened trading rules negatively affected the market efficiency and price discovery of the three Chinese index futures. The market efficiency test suggests that the Chinese index futures market became slightly more efficient after the rule changes. The price discovery analysis also implies that the price discovery function of the Chinese index futures market improved with the new rule changes. These findings provide empirical support for Stein (2009), and document the importance of tightening rules under a bad market state.

The different impacts that the new trading rules had on market liquidity and price discovery provide insight into the relationship between market liquidity and price discovery. The findings in this paper support Zhu (2014), in that they show price discovery can be improved with reduced liquidity.

Besides the prevention of a crash under a bad state, the other possible reason for the improved market efficiency and price discovery is that the tightened rules effectively squeeze out insider trading and market manipulation by non-hedging investors. The trading in the Chinese index futures market became more information relevant after the participation of insider traders and market manipulators was reduced, which further improved its market efficiency and price discovery function. We would be able to address this question if we had access to the account information of the Chinese index futures market; this is something for future investigation.

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Table 1. Contract specifications of the three Chinese stock index futures
This table explains the contract specifications of the three Chinese stock index futures (IF, IC and IH) traded on the Chinese Financial Futures Exchange (CFFEX). They include underlying index, contract number, tick size, date of listing, contract months, trading hours, price limit per day, last trading day, delivery day and settlement method.

Trading Code	IF	IC	IH
Underlying Index	CSI 300 Index	CSI 500 Smallcap Index	SSE 50 Index
Contract multiplier	CNY 300	CNY 200	CNY 300
Tick size	0.2 point	0.2 point	0.2 point
Date of listing	April 16, 2010	April 16, 2015	April 16, 2015
Contract months	Current month (00), next month (01), next two calendar quarters (02 and 03)		
Trading hours	Before January 1 2016, 9:15 am to 11:30 am, and 1:00 pm to 3:15 pm; After January 1 2016, 9:30 am to 11:30 am, and 1:00 pm to 3:00 pm		
Limit up/down	$+/-$ 10 percent of settlement price on the previous trading day		
Last trading day	The third Friday of the contract month; Postponed to next trading day if it is a holiday		
Delivery day	The same as the last trading day		
Settlement method	Cash settlement		

Table 2. Trading policy changes of the Chinese stock index futures market in 2015

This table lists the important trading rule changes of the Chinese stock index futures market in 2015.

Date	Change details
July 6, 2015	The maximum daily long or short trading volume in each IC contract is 1200 contracts
July 8, 2015	The margin rate of shorting IC futures contracts by a non-hedging account increases from 10% to 20%
July 9, 2015	The margin rate of shorting IC futures contracts by a non-hedging account increases from 20% to 30%
August 3, 2015	The transaction fee increases to 0.23 bps of the trading amount, while the declaration fee is 1RMB per order
August 26, 2015	The maximum daily total trading volume in each index futures contract by a non-hedging account is 600 contracts
August 26, 2015	The transaction fee of closing index futures contracts increases to 1.15 bps of the trading amount
August 26, 2015	The margin rate to trade IF and IH futures contract by a non-hedging account increases from 10% to 12%
August 26, 2015	The margin rate to long IC futures contract by a non-hedging account increases from 10% to 12%
August 27, 2015	The margin rate to trade IF and IH futures contract by a non-hedging account increases from 12% to 15%
August 27, 2015	The maring rate to long IC futures contract by a non-hedging account increases from 12% to 15%
August 28, 2015	The margin rate to trade IF and IH futures contract by a non-hedging account increases from 15% to 20%
August 28, 2015	The margin rate to long IC futures contract by a non-hedging account increases from 15% to 20%
August 31, 2015	The margin rate to trade IF and IH futures contract by a non-hedging account increases from 20% to 30%
August 31, 2015	The margin rate to long IC futures contract by a non-hedging account increases from 20% to 30%
September 7, 2015	The maximum daily total trading volume in each index futures contract by a non-hedging account is 10 contracts
September 7, 2015	The transaction fee of closing index futures contract increases to 23 bps of the trading amount
September 7, 2015	The margin rate to trade all stock index futures contract by a non-hedging account increases from 30% to 40%
September 7, 2015	The margin rate to trade all stock index futures contract by a hedging account increases from 10% to 20%

Table 3. Statistical summary of the Chinese stock index and index futures returns

This table shows the statistical summary of the Chinese stock index and index futures returns in five minutes. The trading volume (in 100 million RMBs) of the stock index is the average trading volume of its constituent stocks in five minutes. The trading volume (in 100 million RMBs) of stock index futures is measured by the average five-minute trading volume of the current month contract. The ARCH-LM(12) is the Lagrange multiplier test for ARCH with 12 lag-levels. [a], [b], [c] denote significance at the 1%, 5% and 10% level separately. The sample period is from April 16, 2015 to December 31, 2015.

Trading code	mean	SD (%)	Volume	Open Interest	Skewness	Kurtosis	ARCH-LM(12)
CSI 300	$-1.88e-05$	0.397	8.24	–	-1.05	35.53	142.55[a]
CSI 500	$3.00e-08$	0.448	4.64	–	-1.41	25.27	164.55[a]
SSE 50	$-2.86e-05$	0.384	2.80	–	-0.70	46.19	231.97[a]
IF00	$-2.09e-05$	0.463	20.96	68041	0.10	18.73	681.52[a]
IC00	$-2.35e-06$	0.585	3.53	15562	0.42	22.78	244.43[a]
IH00	$-3.05e-05$	0.435	2.81	24081	0.54	23.92	476.28[a]

Table 4. Unit root and co-integration tests of the Chinese stock index spot and futures market

This table shows the unit root and co-integration tests of the Chinese index spot and futures. In Panel A, ADF test refers to the Augmented-Dickey-Fuller test, PP test to the Phillips-Perron test, and KPSS test to the Kwiatkowski-Phillips-Schmidt-Shin test. Panel B reports the result of co-integration with Eigenvalues and Trace tests. The null hypothesis of the ADF and PP test is that the time series has a unit root, while the null hypothesis of the KPSS test is that the time series is stationary. [a], [b], [c] denote significance at the 1%, 5% and 10% level separately.

Panel A. Unit root tests

	ADF test		PP test		KPSS test	
	Intercept	Intercept and trend	Intercept	Intercept & trend	Intercept	Intercept and trend
CSI 300 price	−1.25	−1.66	−1.27	−1.27	42.61[a]	9.47[a]
CSI 500 price	−1.25	−1.65	−1.37	−1.42	27.34[a]	6.35[a]
SSE 50 price	−1.37	−1.64	−1.34	−1.34	46.58[a]	11.27[a]
IF00 price	−1.38	−1.73	−1.36	−1.32	41.55[a]	9.98[a]
IC00 price	−1.54	−1.93	−1.54	−1.51	27.83[a]	6.77[a]
IH00 price	−1.46	−1.65	−1.44	−1.40	45.47[a]	11.64[a]
	None	Intercept	None	Intercept	Intercept	
CSI 300 return	−68.65[a]	−68.65[a]	−98.29[a]	−98.27[a]	0.1093	–
CSI 500 return	−67.26[a]	−67.26[a]	−97.54[a]	−97.68[a]	0.1360	–
SSE 50 return	−68.59[a]	−68.58[a]	−98.93[a]	−98.94[a]	0.1040	–
IF00 return	−67.97[a]	−67.97[a]	−95.00[a]	−95.18[a]	0.1025	–
IC00 return	−67.23[a]	−67.24[a]	−93.38[a]	−93.43[a]	0.1024	–
IH00 return	−68.91[a]	−68.91[a]	−96.63[a]	−96.91[a]	0.1115	–

Panel B. Cointegration Tests

	Null hypothesis	Eigenvalues statistics	95% Critical Value	Trace statistics	95% Critical Value
CSI 300 vs IF00	$r \leq 1$	1.78	8.18	1.78	8.18
	$r = 0$	52.47[a]	14.90	54.25[a]	17.95
CSI 500 vs IC00	$r \leq 1$	2.41	8.18	2.16	8.18
	$r = 0$	70.49[a]	14.90	72.89[a]	17.95
SSE 50 vs IH00	$r \leq 1$	2.03	8.18	2.03	8.18
	$r = 0$	51.51[a]	14.90	53.54[a]	17.95

Table 5. Market efficiency test

This table summarize the results of the market efficiency test of the Chinese stock market and the stock index futures market. We report the results of the variance ratio test (VR) and spectral shape test (AD_T and CVM_T) for 5-, 20- and 60-minute returns, respectively. We follow Choi (1999) to select the optimal truncation lag to calculate the VR statistics. We follow Durlauf (1991) to calculate two spectral shape test statistics, AD_T and CVM_T. AD_T is the Anderson-Darling (AD_T) statistic, while CVM_T is the Cramer-von Mises statistic. The whole period is from April 16, 2015 to December 31, 2015. The period before the rules implementation is from April 16 , 2015 to July 8, 2015, while the period after the implementation of new trading rules is from September 7, 2015 to December 31, 2015. ^{a}, ^{b}, ^{c} denote significance at the 1%, 5% and 10% level separately.

Index	VR	AD_T	CVM_T	VR	AD_T	CVM_T	VR	AD_T	CVM_T
	Period A (whole)			Period B (before)			Period C (after)		
5-minute return									
CSI 300	-5.09^a	18.29^a	3.63^a	-4.62^a	17.17^a	3.57^a	-3.18^a	11.41^a	1.80^a
CSI 500	-3.49^a	13.86^a	2.89^a	-3.18^a	12.59^a	2.81^a	-4.42^a	21.91^a	3.92^a
SSE 50	-5.22^a	21.34^a	4.22^a	-4.89^a	22.13^a	4.46^a	-0.73	3.53^b	0.48^b
IF00	-2.94^a	5.03^a	0.97^a	-3.17^a	6.21^a	1.25^a	0.38	2.79^b	0.47^b
IC00	-0.71	2.43^c	0.40^c	-2.73^a	5.27^a	1.03^a	0.09	1.94^c	0.33
IH00	-4.22^a	10.89^a	2.11^a	-3.05^a	5.96^a	1.13^b	-1.43^c	3.94^a	0.59^b
20-minute return									
CSI 300	0.92	0.83	0.17	-0.23	0.95	0.14	-0.99	1.89	0.40^c
CSI 500	3.23^a	8.31^a	1.73^a	-2.38^a	4.39^a	0.89^a	-0.65	1.40	0.26
SSE 50	0.05	1.20	0.19	-2.25^a	4.59^a	0.79^a	-0.29	0.74	0.13
IF00	1.19	1.96^c	0.42^c	0.00	1.25	0.16	-0.23	0.50	0.08
IC00	2.29^a	3.30^b	0.73^b	0.61	0.62	0.12	0.39	0.56	0.09
IH00	0.08	1.63	0.24	-1.34^c	3.27^b	0.53^b	-0.98	1.42	0.31
60-minute return									
CSI 300	-1.32^c	2.44^c	0.57^b	-1.33^c	1.88	0.43^c	0.61	0.55	0.11
CSI 500	0.05	1.19	0.18	0.57	1.47	0.23	1.02	1.49	0.29
SSE 50	-2.04^a	8.32^a	1.73^a	-2.32^a	6.61^a	1.43^a	-0.05	0.55	0.08
IF00	-1.64^b	2.26^c	0.53^b	-1.57^c	2.67^b	0.59^b	0.47	0.48	0.10
IC00	-1.52^c	2.10^c	0.46^b	-0.08	0.62	0.11	0.38	0.49	0.09
IH00	-1.97^b	5.68^a	1.13^a	-2.44^a	5.58^a	1.19^b	-0.01	0.55	0.06

Table 6. Short-run and long-run Granger causality test

This table reports the results of Granger causality between the Chinese stock market and stock index futures market. We report the results of Period A (whole period, from April 16, 2015 to December 31, 2015), and two subperiods of Period B (before the rules implementation, from April 16, 2015 to July 8, 2015) and Period C (after the rules implementation, from September 7, 2015 to December 31, 2015). We run the following VECM to the natural logarithmic price series of futures (f_t) and spots (s_t).

$$\Delta s_t = b_{s,0} + \gamma_s ect_{t-1} + \sum_{i=1}^{n} b_{ss,i}\Delta s_{t-i} + \sum_{i=1}^{n} b_{fs,i}\Delta f_{t-i} + e_{s,t},$$
$$\Delta f_t = b_{f,0} + \gamma_f ect_{t-1} + \sum_{i=1}^{n} b_{sf,i}\Delta s_{t-i} + \sum_{i=1}^{n} b_{ff,i}\Delta f_{t-i} + e_{f,t}.$$

The type 1 test is to test the short-run Granger causality from the futures to spots (the spots to futures) by testing $b_{fs,i} = 0$ ($b_{sf,i} = 0$) for all $i = 1, ..., n$. The type 2 test is to test the long-run Granger causality from the futures to spots (the spots to futures) by testing $\gamma_s = 0$ ($\gamma_f = 0$). [a], [b],[c] denote significance at the 1%, 5% and 10% level, separately.

Period	Spot or futures	Type 1 test Null hypothesis ($\chi^2(5)$)	Statistics	Type 2 test Null hypothesis ($\chi^2(1)$)	Statistics
Period A	CSI 300	$b_{fs,i} = 0, \forall i$	229.28[a]	$\gamma_s = 0$	14.24[a]
	IF00	$b_{sf,i} = 0, \forall i$	5.89	$\gamma_f = 0$	0.81
	CSI 500	$b_{fs,i} = 0, \forall i$	441.54[a]	$\gamma_s = 0$	38.15[a]
	IC00	$b_{sf,i} = 0, \forall i$	12.69[b]	$\gamma_f = 0$	0.89
(Whole)	SSE 50	$b_{fs,i} = 0, \forall i$	138.07[a]	$\gamma_s = 0$	8.46[b]
	IH00	$b_{sf,i} = 0, \forall i$	17.48[b]	$\gamma_f = 0$	1.30
Period B	CSI 300	$b_{fs,i} = 0, \forall i$	103.82[a]	$\gamma_s = 0$	5.52[b]
	IF00	$b_{sf,i} = 0, \forall i$	10.76[c]	$\gamma_f = 0$	0.09
	CSI 500	$b_{fs,i} = 0, \forall i$	198.04[a]	$\gamma_s = 0$	15.83[a]
	IC00	$b_{sf,i} = 0, \forall i$	19.37[a]	$\gamma_f = 0$	0.31
(Before)	SSE 50	$b_{fs,i} = 0, \forall i$	101.22[a]	$\gamma_s = 0$	1.81
	IH00	$b_{sf,i} = 0, \forall i$	16.49[a]	$\gamma_f = 0$	2.53
Period C	CSI 300	$b_{fs,i} = 0, \forall i$	103.81[a]	$\gamma_s = 0$	10.38[a]
	IF00	$b_{sf,i} = 0, \forall i$	21.77[a]	$\gamma_f = 0$	0.01
	CSI 500	$b_{fs,i} = 0, \forall i$	138.48[a]	$\gamma_s = 0$	23.61[a]
	IC00	$b_{sf,i} = 0, \forall i$	10.13[c]	$\gamma_f = 0$	0.11
(After)	SSE 50	$b_{fs,i} = 0, \forall i$	25.21[a]	$\gamma_s = 0$	4.11[b]
	IH00	$b_{sf,i} = 0, \forall i$	83.66[a]	$\gamma_f = 0$	0.70

Table 7. Price discovery measures of the Chinese stock index futures market

This table reports the results of the price discovery analysis for the three Chinese stock index futures. We run VECM models to calculate both the Hasbrouck (1995) measure and the Schwarz and Szakmary (1994) measure. Period A (whole period) is from April 16, 2015 to December 31, 2015. Period B (before) is from April 16, 2015 to July 8, 2015, while Period C (after) is September 7, 2015 to December 31, 2015. The middle panel collects the results of the mean of upper bound and lower bound with the Hasbrouck measure for index futures, while the right panel reports the Schwarz-Szakmary measure for index futures.

Index	Trading code	Hasbrouck measure			Schwarz-Szakmary measure		
		Period A(%) (Whole)	Period B(%) (Before)	Period C(%) (After)	Period A(%) (Whole)	Period B(%) (Before)	Period C(%) (After)
CSI 300	IF00	63.69	62.49	70.08	78.08	87.49	95.60
CSI 500	IC00	78.67	87.41	74.45	97.19	85.19	92.14
SSE 50	IH00	57.77	49.18	58.17	68.87	43.93	69.12

Table 8. Volatility spillover between the Chinese stock index and index futures

This table reports the results of volatility spillover between the Chinese stock index and index futures. We run BEKK-GARCH(1,1) model to the residuals of VECM model. $a_{1,2}^2$ and $b_{1,2}^2$ measure the volatility spillover from the stock index futures to stock index, while $a_{2,1}^2$ and $b_{2,1}^2$ measure the volatility spillover from the stock index to index futures. Period A (whole period) is from April 16, 2015 to December 31, 2015 and Period B (before) is from April 16, 2015 to July 8, 2015, while Period C (after) is September 7, 2015 to December 31, 2015. ^{a}, ^{b}, ^{c} denote significance at the 1%, 5% and 10% level separately.

CSI 300 vs IF00	Period B (before)		Period B (before)		Period C (after)	
	$H_t = CC^{'} + A(e_{t-1}e_{t-1}^{'})A^{'} + BH_{t-1}B^{'}$					
C	$c_{1,1}$	$c_{1,2}$	$c_{1,1}$	$c_{1,2}$	$c_{1,1}$	$c_{1,2}$
	$2.86e-03^{a}$	$4.11e-03^{a}$	$1.01e-03^{a}$	$1.39e-03^{a}$	$-2.12e-03^{a}$	$-2.17e-03^{a}$
	$c_{2,1}$	$c_{2,2}$	$c_{2,1}$	$c_{2,2}$	$c_{2,1}$	$c_{2,2}$
	0.00	$-8.58e-05^{a}$	0.00	$1.81e-03^{a}$	0.00	$1.67e-03^{a}$
A	$a_{1,1}$	$a_{1,2}$	$a_{1,1}$	$a_{1,2}$	$a_{1,1}$	$a_{1,2}$
	1.06^{a}	1.44^{a}	-0.257^{a}	-0.739^{a}	0.273^{a}	0.380^{a}
	$a_{2,1}$	$a_{2,2}$	$a_{2,1}$	$a_{2,2}$	$a_{2,1}$	$a_{2,2}$
	-0.985^{a}	-1.09^{a}	0.541^{a}	1.34^{a}	-0.276^{a}	-0.333^{a}
B	$b_{1,1}$	$b_{1,2}$	$b_{1,1}$	$b_{1,2}$	$b_{1,1}$	$b_{1,2}$
	-0.537^{a}	0.454^{a}	1.36^{a}	0.966^{a}	-0.537^{a}	-0.257^{a}
	$b_{2,1}$	$b_{2,2}$	$b_{2,1}$	$b_{2,2}$	$b_{2,1}$	$b_{2,2}$
	$2.00e-02$	-0.516^{a}	-1.03^{a}	-0.524^{a}	$6.56e-02^{c}$	0.197^{a}
CSI 500 vs IC00	Period A (whole)		Period B (before)		Period C (after)	
C	$c_{1,1}$	$c_{1,2}$	$c_{1,1}$	$c_{1,2}$	$c_{1,1}$	$c_{1,2}$
	$2.31e-03^{a}$	$2.82e-03^{a}$	$4.95e-04^{a}$	$-1.23e-03^{a}$	$-3.35e-03^{a}$	$-3.15e-03^{a}$
	$c_{2,1}$	$c_{2,2}$	$c_{2,1}$	$c_{2,2}$	$c_{2,1}$	$c_{2,2}$
	0.00	$-3.84e-03^{a}$	0.00	$2.70e-04^{a}$	0.00	$-2.46e-03^{a}$
A	$a_{1,1}$	$a_{1,2}$	$a_{1,1}$	$a_{1,2}$	$a_{1,1}$	$a_{1,2}$
	0.716^{a}	0.686^{a}	$-4.54e-02^{c}$	-0.326^{a}	-0.271^{a}	$-4.22e-02$
	$a_{2,1}$	$a_{2,2}$	$a_{2,1}$	$a_{2,2}$	$a_{2,1}$	$a_{2,2}$
	-0.330^{a}	-0.672^{a}	-0.163^{a}	0.515^{a}	$2.79e-02$	$-6.75e-02^{c}$
B	$b_{1,1}$	$b_{1,2}$	$b_{1,1}$	$b_{1,2}$	$b_{1,1}$	$b_{1,2}$
	0.737^{a}	0.572^{a}	$9.48e-02^{a}$	1.09^{a}	0.132^{a}	0.458^{a}
	$b_{2,1}$	$b_{2,2}$	$b_{2,1}$	$b_{2,2}$	$b_{2,1}$	$b_{2,2}$
	-0.053^{b}	-0.126^{a}	-0.744^{a}	-1.14^{a}	$3.17e-02$	$-5.34e-02$
SSE 50 vs IH00	Period A (whole)		Period B (before)		Period C (after)	
C	$c_{1,1}$	$c_{1,2}$	$c_{1,1}$	$c_{1,2}$	$c_{1,1}$	$c_{1,2}$
	$-3.31e-03^{a}$	$-2.60e-03^{a}$	$4.93e-03^{a}$	$4.67e-03^{a}$	$2.51e-03^{a}$	$1.43e-03^{a}$
	$c_{2,1}$	$c_{2,2}$	$c_{2,1}$	$c_{2,2}$	$c_{2,1}$	$c_{2,2}$
	0.00	$4.92e-04^{a}$	0.00	$1.81e-03^{a}$	0.00	$2.84e-04^{a}$
A	$a_{1,1}$	$a_{1,2}$	$a_{1,1}$	$a_{1,2}$	$a_{1,1}$	$a_{1,2}$
	$-1.78e-03$	0.831^{a}	-0.112	0.973^{a}	0.931^{a}	0.821^{a}
	$a_{2,1}$	$a_{2,2}$	$a_{2,1}$	$a_{2,2}$	$a_{2,1}$	$a_{2,2}$
	0.398^{a}	-0.229^{a}	-0.126^{c}	0.102^{c}	-0.917^{a}	-0.860^{a}
B	$b_{1,1}$	$b_{1,2}$	$b_{1,1}$	$b_{1,2}$	$b_{1,1}$	$b_{1,2}$
	$-2.23e-02$	-0.724^{a}	$1.94e-03$	$-5.50e-03$	-0.394^{a}	-0.960^{a}
	$b_{2,1}$	$b_{2,2}$	$b_{2,1}$	$b_{2,2}$	$b_{2,1}$	$b_{2,2}$
	-0.51^{a}	$2.44e-02$	$-1.71e-02$	$-6.04e-04$	0.260^{a}	0.495^{a}

Table 9. Price discovery and Granger causality under the no-arbitrage constraint

This table reports the results of price discovery and Granger causality under no-arbitrage constraint. Panel A reports the test statistics of no-arbitrage relationship between the stock index and index futures. The nulll hypothesis is $a_1 = 1$ in the error correction term $ect_t = f_t - a_0 - a_1 s_t - a_2 m_t$. Panel B and Panel C report the price discover measure and Granger causality test results under no-arbitrage constraint of $a_1 = 1$, respectively. Assuming $ect_t = f_t - a_0 - s_t - a_2 m_t$, we run the following VECM to the natural logarithmic price series of futures (f_t) and spot prices (s_t),

$$\Delta s_t = b_{s,0} + \gamma_s ect_{t-1} + \sum_{i=1}^{n} b_{ss,i} \Delta s_{t-i} + \sum_{i=1}^{n} b_{fs,i} \Delta f_{t-i} + e_{s,t},$$
$$\Delta f_t = b_{f,0} + \gamma_f ect_{t-1} + \sum_{i=1}^{n} b_{sf,i} \Delta s_{t-i} + \sum_{i=1}^{n} b_{ff,i} \Delta f_{t-i} + e_{f,t}.$$

Short-run Granger causality is to test $b_{fs,i} = 0$ ($b_{sf,i} = 0$) for all $i = 1, ..., n$, while long-run Granger causality is to test $\gamma_s = 0$ ($\gamma_f = 0$). ^{a}, ^{b},^{c} denote significance at the 1%, 5% and 10% level separately.

Panel A. No arbitrage relationship test

Test	Futures	Period A (whole)	Period B (before)	Period C (after)
$a_1 = 1$	IF	8226.5^a	383.5^a	1679.8^a
	IC	3192.6^a	327.4^a	199.9^a
	IH	7066.3^a	638.5^a	733.2^a

Panel B. Price discovery measure under no arbitrage constraint

Measure	Futures	Period A (%) (whole)	Period B (%) (before)	Period C (%) (after)
Hasbrouck (%)	IF	51.60	65.20	60.22
	IC	71.83	88.68	72.17
	IH	46.62	47.01	48.96
Schwarz-Szakmary (%)	IF	49.49	97.46	72.31
	IC	79.03	80.31	99.40
	IH	38.05	35.57	45.26

Panel C. Granger causality test under no arbitrage constraint

	Short-run Granger causality test			Long-run Granger causality test		
	Period A (whole)	Period B (before)	Period C (after)	Period A (whole)	Period B (before)	Period C (after)
CSI 300	225.53^a	103.21^a	102.08^a	3.29^c	4.94^b	4.39^b
IF00	5.93	11.21^c	22.10^a	2.49	0.00	0.51
CSI 500	438.18^a	196.93^a	138.34^a	21.46^a	13.92^a	20.79^a
IC00	12.52^b	19.51^a	10.14^c	0.86	0.55	0.00
SSE 50	134.78^a	99.89^a	24.33^a	1.45	0.78	1.56
IH00	17.58^a	17.43^a	83.94^a	3.18^c	2.21	1.95

Figure 1. Price and basis of the Chinese stock index futures
This graph plots the price and basis of the three Chinese stock index futures, IF00, IC00 and IH00. The underlying indexes of IF, IC and IH contracts are CSI 300 index, CSI 500 index, and SSE 50 index, respecctively. 00 means the current month contract.