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# Are tightened trading rules always bad? Evidence from the Chinese index futures market

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This paper investigates the impact of tightened trading rules on the market efficiency and price discovery function of the Chinese stock index futures in 2015. The market efficiency and price discovery of the Chinese stock index futures do not deteriorate after these rule changes. Using variance ratio and spectral shape tests, we find that the Chinese index futures market becomes even more efficient after the tightened rules came into effect. Furthermore, by employing Schwarz and Szakmary [*J. Futures Markets*, 1994, **14**(2), 147–167] and Hasbrouck [*J. Finance*, 1995, **50**(4), 1175–1199] price discovery measures, we find that the price discovery function, to some extent, becomes better. This finding is consistent with Stein [*J. Finance*, 2009, **64**(4), 1517–1548], who documents that regulations on leverage can be helpful in a bad market state, and Zhu [*Rev. Financ. Stud.*, 2014, **27**(3), 747–789.], 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 during a bad market state, and then positively affect its market efficiency and price discovery function.

*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. The purpose of changing trading rules is aimed at reducing leverage and building a high barrier to trade for speculators. In this paper, we analyse 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 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 plays 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 when 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 an effective transmission of information on the financial market.

The evidence on the Chinese index futures market is not conclusive, however. Yang *et al.* (2012) document that the cash market plays a more dominant role in the price discovery process just after the introduction of index futures. On the other hand, Hou and Li (2013) show that the CSI 300 index futures market dominated 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 in the stock market.

The critical advantage of stock index futures is its looser trading rules, including low transaction cost and high leverage, which makes them attractive to informed traders (Berkman *et al.* 2005). Chan (1992) demonstrates that low transaction cost and high leverage contribute to the lead–lag relationship between the index futures market and the spot market. Longin (1999) also suggests that margin level is inversely proportional to the attractiveness of index futures to investors. In this aspect, a loose trading rule with smaller transaction cost tends to provide an environment closer to a perfect market, and this is important for an efficient market.

Low transaction cost and high leverage not only makes hedging and arbitraging using index futures easier but also reduces the cost of insider trading and market manipulation. Hedging and arbitraging behaviours are essential to improve market efficiency and price discovery, while excessive insider

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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 arbitrageurs and the market is in a normal state, the trading rule is set at a lenient level to let the positive effects 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 adverse effect. Stein (2009) provides an excellent 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 functions 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 new 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. We apply the variance ratio (VR) test with the truncation lag levels selected using Choi (1999), and the spectral shape test proposed by Durlauf (1991). Results show that there is no deterioration effect on the market efficiency in both markets after the new trading rules became effective. We do not find evidence that the new trading rules negatively affect the market efficiency in both markets. More interestingly, the market efficiency of Chinese stock index futures even becomes slightly better under the new rules. This finding is consistent with Stein (2009) concerning the usefulness of regulation in a bad market state.

We run a vector error correction model (VECM) on the three stock indexes and index futures and do several tests, separately. We first examine long-run and short-run Granger causality effects between stock index and index futures. 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 stock index continues to be stronger than the impact from stock index to index futures both before and after the rule changes. Using VECM, we calculate the (Schwarz and Szakmary 1994) and the (Hasbrouck 1995) price discovery measures of Chinese stock index futures. Results indicate that the price discovery function of the Chinese index futures market improves after the trading rule changes in September 2015. We then run a bivariate DCC GARCH model on the residuals of VECM and calculate realized correlation using high-frequency data to investigate the volatility spillover between the two markets. Similar to the Granger causality test results, our findings show that the volatility effect continues to exist under the new rules. We finally run several robustness tests, and the primary empirical results hold.

The market efficiency and price discovery functions of the Chinese stock index futures do not deteriorate after the tightened rule changes. Results are robust across the three index futures. This finding is in contrast with the severe criticism against them. The financial industry regarded the tightened trading rules exercised in 2015 as destructive behaviour against the newly established Chinese stock index futures market. For example, on 9 September 2015, Bloomberg commented that China had killed the world's biggest stock index futures market. Bloomberg stated that the daily volume of the Chinese index futures market had been decimated by 99 per cent from the peak in June, since authorities increased 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.† 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 effect on market efficiency and price discovery.

Market efficiency and price discovery are essential questions for both policy-makers and portfolio management. Study of the impact of regulatory policy on market efficiency and the price discovery function provides an objective assessment of one policy's effectiveness. An effective policy is one that can improve the market efficiency and price discovery roles of one financial market. For investment, they tell the importance of historical price information. One market is more efficient means historical information is less critical to predicting its future price change, while a high price discovery function suggests its historical information is vital to other markets. By addressing these two questions on the Chinese index futures market, investors can understand whether or how to use the past knowledge of Chinese index futures, and whether they are affected by the rule changes.

This paper contributes to the literature in several ways. First, although there exists a large number of comments on the tightened rules, there has been limited academic research that aims to provide an assessment using high-frequency data. In a recent work, Han and Liang (2017) analyse the impact of Chinese index futures trading restrictions and show that Chinese stock market quality deteriorates after the limits are introduced. Different from Han and Liang (2017), this paper fills in a gap in the literature by providing the first empirical evidence of the impact of the tightened rule changes on the market efficiency and the price discovery function of the Chinese index futures market.

Second, most of the comments on the tightened rules are negative. These claims are primarily based on the negative impact of the rule changes on market trading and liquidity. In this paper, we address a more fundamental research question about the effect of the rule changes on market efficiency and price discovery. We do not find any evidence of negative impact by these rule changes. In contrast, the market efficiency and the price discovery function of Chinese index futures slightly improves after the rule changes. These novel findings help provide a broader assessment of the effectiveness of Chinese index futures market regulation in 2015. Our results provide empirical support for the usefulness of rule tightening under certain circumstances, as shown in Stein (2009).

Third, 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

†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.

bond and options market, respectively. Hong *et al*. (2012) find that past stock returns could predict corporate bond returns. 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 findings 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 analyse the data. Section 4 presents the empirical results. Section 5 runs several robustness checks. Finally, Section 6 concludes the paper.

## 2. Background and hypothesis

On 8 September 2006, the China Financial Futures Exchange (CFFEX) was established in Shanghai, with the aim of promoting the development of a Chinese financial derivatives market. In early 2008, CFFEX launched its first contract, the CSI 300 index futures (IF). IF contracts were officially listed at CFFEX on 16 April 2010. After this, it 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 16 April 2015, two other index futures—CSI 500 (IC) and SSE 50 (IH) index futures—were also listed at CFFEX.

Table 1 explains the contract specifications of the three Chinese stock index futures traded on CFFEX. The underlying indexes of the IF, IC, and IH contracts are the CSI 300, CSI 500 and SSE 50 index, respectively. As the first equity index introduced by Shanghai and Shenzhen Stock Exchange together, the CSI 300 reflects the price performance and fluctuation of Chinese A-share market. It is a free-float, weighted index that consists of 300 A-share stocks listed on the Shanghai or Shenzhen Stock Exchange. The index had a base level of 1000 on 31 December 2004. The CSI 500 aims to comprehensively reflect the price fluctuation and performance of the small-cap companies in the Shanghai and Shenzhen security market. 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 market according to the daily average total market capitalization of the past recent year) are ranked by the daily average trading value during the past 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 Stock Exchange.

By 31 December 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 Exchange, respectively, while the SSE 50 constituent stocks constituted over 50% of the market value in the Shanghai Stock Exchange. Trading of the three index futures meets the hedging demands of different stocks and provides an efficient tool for risk management in the Chinese financial market.

Unfortunately, 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 12 June 2015, and plummeted over 30% to 3373.54 on 9 July 2015, and over 44% to 2850.71 on 26 August 2015. 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 the Chinese index futures was tightened in three ways. First, margin rate requirement dramatically increased, especially for non-hedging accounts. Before July 2015, the margin rate to trade Chinese stock index futures was only 10%. However, it became 40% for the non-hedging account and 20% for the hedging account after 7 September 2015. Second, the maximum trading volume of each index futures contract was limited. After 7 September 2015, the maximum daily total trading volume in each index futures contract by a non-hedging account is ten contracts. Third, the transaction cost of trading index futures also increased. After 7 September 2015, the transaction fee of closing an index futures contract rose to 23 bps of the trading amount.

These tightened rules had a dramatic impact on the trading of Chinese index futures market. The high margin requirement was aimed at cutting leverage and made stock index futures much harder to speculate. The cost of hedging rose substantially. Some investors also moved to offshore, for example, turned toward A50 futures in Singapore that uses Chinese stock index as the underlying asset.

The IF contract was the most frequently traded index futures contract in the world before the rule changes. Its daily average trading volume in July 2015 was 1.7 million contracts, which is larger than 1.5 million contracts of the S&P 500 index futures traded on Chicago Mercantile Exchange (CME). After the tightened rules took effect, trading of Chinese index futures market shrank by 99%. It was commented that 'China's stock index futures market, once the world's most vibrant, has been decimated in recent weeks by new regulations designed to discourage bearish speculators blamed for a stock market rout.'†

It is clear that these tightened rules significantly affect the trading of Chinese index futures market. Nevertheless, how the change of trading is relevant to the market efficiency and price discovery change of Chinese index futures market is an open question that has not been addressed in the literature. We have two alternative hypothesis for this issue. One is that market efficiency and price discovery function of Chinese

†http://www.bloomberg.com/news/articles/2015-09-08/china-just-killed-the-world-s-biggest-stock-index-futures-market.

Table 1. Contract specifications of the three Chinese stock index futures.

| 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 | 16 April 2010 | 16 April 2015 | 16 April 2015 |
| Contract months | Current month (00), next month (01), next two calendar quarters (02 and 03) | | |
| Trading hours | Before 1 January 2016, 9:15 am to 11:30 am, and 1:00 pm to 3:15 pm; After 1 January 2016, 9:30 am to 11:30 am, and 1:00 pm to 3:00 pm | | |
| Limit up/down | $+/-$ 10 per cent 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 | | |

Note: This table explains the contract specifications of the three Chinese stock index futures (IF, IC and IH) traded on the CFFEX. Information includes 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.

index futures market worsen after the rule changes due to their severe negative impact on trading and market liquidity. The alternative hypothesis is that market efficiency and price discovery function of Chinese index futures market do not change much or even slightly improve if the negative impact on trading is compensated by the positive effect on squeezing insider trading and market manipulation and stabilizing market to prevent a market crash.

## 3. Empirical methodology

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

### 3.1. Pricing efficiency

For a futures market, one of the most important questions is the pricing efficiency, i.e. whether futures prices are unbiased estimator of future spot prices. The pricing efficiency of futures largely depends on the existence of no-arbitrage relationship. If no-arbitrage relationship does not work in Chinese index futures market, then futures prices will be inefficient as the estimator of future spot prices. Under the null hypothesis of no-arbitrage relationship, futures prices are unbiased estimator of future spot prices under risk-neutral measure (Hull 2012),

$$F_t = E^Q(S_{t+m}) = S_t e^{(r-q)m_t}, \tag{1}$$

where $F_t$ and $S_t$ are the futures and spot price at time $t$, respectively. $Q$ means risk-neutral measure, $r$ is the risk-free rate, $q$ is the dividend yield and $m_t$ is the time to maturity of the index futures. Take the logarithms on both sides, we have the following result:

$$f_t = s_t + (r-q) \times m_t, \tag{2}$$

where $f_t$ and $s_t$ are the logarithms of index futures and stock index, respectively. This suggests that there exists an co-integration relationship between $f_t$ and $s_t$ with $a_1 = 1$ in the error correction term, $ect_t$

$$ect_t = f_t - a_0 - a_1 s_t - a_2 m_t. \tag{3}$$

We test the pricing efficiency of Chinese index futures market by testing $a_1 = 1$.† Following Baillie and Bollerslev (1989), Barnhart and Szakmary (1991), Bessler and Covey (1991), Chowdhury (1991), we use the two-step procedure of Engle and Granger (1987) to test the co-integration relationship between $f_t$ and $s_t$ and the restriction of $a_1 = 1$.

### 3.2. Market efficiency

We first use the 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 $H_0$: $\Delta p_t$ 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:

$$VR(l) = \frac{Var(p_t - p_{t-l})}{l Var(p_t - p_{t-1})}. \tag{4}$$

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

The variance ratio (VR) statistics is defined as:

$$\begin{aligned} \hat{VR}(l) &= 1 + 2\sum_{i=1}^{T-1} k(i/l)\hat{\rho}(i), \\ \hat{\rho}(i) &= \sum_{i=1}^{T-i} \Delta p_t \Delta p_{t+i} / \sum_{i=1}^{T} \Delta p_t^2, \\ k(x) &= \frac{25}{12\pi^2 x^2}\left[\frac{\sin(6\pi x/5)}{6\pi x/5 - \cos(6\pi x/5)}\right]. \end{aligned} \tag{5}$$

†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.* (2018) 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.

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

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

Note: This table lists the critical trading rule changes of the Chinese stock index futures market between July and September 2015.

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

| 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] |

Notes: This table shows the statistical summary of Chinese stock index and index futures returns in five minutes. The trading volume (in 100 million RMB) of a stock index is the average trading volume of its constituent stocks in five minutes. The trading volume (in 100 million RMB) of 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 16 April 2015 to 31 December 2015.

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

| | ADF test | | PP test | | KPSS test | |
|---|---|---|---|---|---|---|
| Panel A. Unit root tests | | | | | | |
| Intercept | Intercept & 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 | None | Intercept |
| CSI 300 return | −68.65[a] | −68.65[a] | −98.29[a] | −98.27[a] | 0.1093 | 0.1039 |
| CSI 500 return | −67.26[a] | −67.26[a] | −97.54[a] | −97.68[a] | 0.1360 | 0.1384 |
| SSE 50 return | −68.59[a] | −68.58[a] | −98.93[a] | −98.94[a] | 0.1040 | 0.0765 |
| IF00 return | −67.97[a] | −67.97[a] | −95.00[a] | −95.18[a] | 0.1025 | 0.0895 |
| IC00 return | −67.23[a] | −67.24[a] | −93.38[a] | −93.43[a] | 0.1024 | 0.1046 |
| IH00 return | −68.91[a] | −68.91[a] | −96.63[a] | −96.91[a] | 0.1115 | 0.0681 |
| Panel B. Co-integration 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 | |

Notes: This table shows the unit root and co-integration tests of Chinese stock indexes and index 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 KPSS 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.

The asymptotic distribution of the test statistic is:

$$VR = \sqrt{T/l}[\hat{VR}(l) - 1]/\sqrt{2} \xrightarrow{d} N(0,1) \ \text{as} \ \times T \to \infty, l \to \infty, T/l \to \infty, \tag{6}$$

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

$$VR(l) = \frac{\pi}{2}\sqrt{T/p}[\hat{f}(0) - \frac{1}{2\pi}], \tag{7}$$

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 the variance ratio test focuses 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:

$$AD_T = \int_0^1 U_T^s(q)^2/[q(1-q)]\mathrm{d}q, \tag{8}$$

$$CVM_T = \int_0^1 U_T^s(q)^2\mathrm{d}q, \tag{9}$$

where

$$U_T^s(q) = \sqrt{2}T^{1/2}\left[\frac{2\pi}{T}\sum_{s=1}^{[Tq/2]} I\left(\frac{2\pi s}{T}\right) - \frac{q}{2}\sum_{t=2}^{T}\Delta p_t^2/T\right]\Bigg/ \times\left[\sum_{t=2}^{T}\Delta p_t^2/T\right], \quad (10)$$

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

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

### 3.3. *Granger causality test*

In order to do the Granger causality test, we run a vector error correction model (VECM) to the logarithms of stock index ($s_t$) or 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:

$$\Delta s_t = b_{s,0} + \gamma_s ect_{t-1} + \sum_{i=1}^{n} b_{ss,i}\Delta s_{t-i} + \sum_{i=1}^{n} b_{fs,i}\Delta f_{t-i} + e_{s,t}, \quad (11)$$

$$\Delta f_t = b_{f,0} + \gamma_f ect_{t-1} + \sum_{i=1}^{n} b_{sf,i}\Delta s_{t-i} + \sum_{i=1}^{n} b_{ff,i}\Delta f_{t-i} + e_{f,t}, \quad (12)$$

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 $\sigma_1^2$ and $\sigma_2^2$ and off-diagonal elements $\rho\sigma_1\sigma_2$.

In the VECM, the coefficient of $\gamma$ 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.†

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 $i = 1, \dots, n$. 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 on the index futures market, a large position should be allowed with low costs. These two conditions are not satisfied after tightened trading rules took effect in the Chinese index futures market, which suggests no-arbitrage pricing framework no 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 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.‡

### 3.4. *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:

$$H_s(u) = \frac{(-\gamma_f\sigma_1 + \gamma_s\rho\sigma_2)^2}{(-\gamma_f\sigma_1 + \gamma_s\rho\sigma_2)^2 + (\gamma_s\sigma_2\sqrt{1-\rho^2})^2}, \quad (13)$$

$$H_f(l) = \frac{(\gamma_s\sigma_2\sqrt{1-\rho^2})^2}{(-\gamma_f\sigma_1 + \gamma_s\rho\sigma_2)^2 + (\gamma_s\sigma_2\sqrt{1-\rho^2})^2}, \quad (14)$$

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 equations (11) and (12):

$$S_s = \frac{|\gamma_f|}{\gamma_s + |\gamma_f|},\ S_f = \frac{\gamma_s}{\gamma_s + |\gamma_f|}. \quad (15)$$

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 element 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 analyse $S_f$ and the average of the Hasbrouck upper bounds and lower bounds of the futures market ($H_f(u)$ and $H_f(l)$).

†As Zhong *et al.* (2004) point out, two opposing effects are determining the relative change of spot and futures. For instance, if there exists disequilibrium that the index futures 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 ($\gamma$) in the above VECM can be negative or positive.

‡The results are reported in Section 5.1.

### 3.5. *Volatility effect*

With consideration of volatility effect between the two markets, we employ two approaches. First, we apply a bivariate DCC GARCH model based on VECM. We first run the VECMs of equations (11) and (12) and obtain the residuals $[e_{s,t} \quad e_{f,t}]'$. Define the variance–covariance matrix of the residuals conditional on the information set $I_{t-1}$ as:

$$var([e_{s,t} \quad e_{f,t}]'|I_{t-1}) = H_t = D_t R_t D_t. \tag{16}$$

$D_t$ is a $2 \times 2$ diagonal matrix of time varying standard deviation of univariate GARCH process. $R_t$ is the conditional correlation matrix of standardized disturbance $\epsilon_t$, where $\epsilon_t = D_t^{-1}[e_{s,t} \quad e_{f,t}]' \sim N(0, R_t)$.

$$R_t = \begin{bmatrix} 1 & q_{12,t} \\ q_{21,t} & 1 \end{bmatrix} \tag{17}$$

To guarantee that both $H_t$ are positive definite and all elements of $R_t$ are no more than one, $R_t$ are decomposed into

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1}. \tag{18}$$

$Q_t$ is a positive definite matrix defining the structure of the dynamics and follows:

$$Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha\epsilon_{t-1}\epsilon'_{t-1} + \beta Q_{t-1}, \tag{19}$$

where $\bar{Q}$ is the unconditional covariance of the standardized disturbances $\epsilon_t$. $Q_t^{*-1} = diag(Q)^{-1}$. $\alpha$ and $\beta$ are scalars that determine the time varying dynamics of conditional correlation.†

Second, we calculate the realized correlation between the three Chinese index futures and their underlying indexes using high-frequency data. we follow Andersen *et al.* (2003), Barndorff-Nielsen and Shephard (2004) and Corsi (2009) to calculate the realized variances of Chinese stock indexes and their futures, and the realized covariance between them. The daily realized variances of the stock indexes and their index futures are calculated by:

$$RV_{jt} = \sum_{h=1}^{M} r_{j,h,t}^2, \; j = s, f, \tag{20}$$

where $RV_{jt}$ are the realized variance of stock index ($j = s$) or index futures ($j = f$) in day $t$, $r_{j,h,t}$ is the $h$th interval return in day $t$, and $M$ is the total number of intervals in day $t$. In our empirical analysis, we use five-minute interval return and $M = 48$.

The realized covariance is calculated by:

$$RCOV_{sf,t} = \sum_{h=1}^{M} r_{s,h,t} r_{f,h,t}, \tag{21}$$

and the realized correlation between $s$ and $f$ in day $t$ is calculated by:

$$RCORR_{sf,t} = \frac{RCOV_{sf,t}}{\sqrt{RV_{st} RV_{ft}}}. \tag{22}$$

†Please refer to Engle (2002) about how to estimate the DCC GARCH model.

## 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. Data period is from 16 April 2015 to 31 December 2015. We choose 16 April 2015, as the sample starting date to cover the two newly listed index futures, IC and IH. We stop the data on 31 December 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 contract (00) until one week before their expiration.

Table 3 reports the summary statistics of the stock indexes and their index futures using five-minute interval data. The trading volume (in 100 million RMB) of the stock index is the average trading volume of its constituent stocks in five minutes. The trading volume (in 100 million RMB) 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. IF00 dominates the trading of Chinese index futures market. IF futures have a relatively long 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 with 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.

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 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. 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. First, 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 exist 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 can run the VECM model with one co-integration vector to examine the relationship between the stock indexes and their index futures.

We now turn to empirical analysis. We first run the market efficiency test to examine how quickly each market reflects its 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

Table 5. No-arbitrage relationship test.

| Test | Futures | Period A (whole) | Period B (before) | Period C (after) |
|---|---|---|---|---|
| $a_1 = 1$ | IF | $8226.5^{a}$ | $459.09^{a}$ | $1679.8^{a}$ |
| | IC | $3192.6^{a}$ | $406.53^{a}$ | $199.9^{a}$ |
| | IH | $7066.3^{a}$ | $641.42^{a}$ | $733.2^{a}$ |

Notes: This table reports the test statistics of no-arbitrage relationship between Chinese stock indexes and their index futures. The null hypothesis is $a_1 = 1$ in the error correction term $ect_t = f_t - a_0 - a_1 s_t - a_2 m_t$. We follow the two-step procedure of Engle and Granger (1987) to test the co-integration relationship between $f_t$ and $s_t$ with the restriction of $a_1 = 1$. $^{a}$, $^{b}$, $^{c}$ denote significance at the 1, 5 and 10% level separately.

Table 6. Market efficiency test. This table summarizes the results of the market efficiency test of Chinese stock indexes and their index futures.

| 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 | $-5.09^{a}$ | $18.29^{a}$ | $3.63^{a}$ | $-3.83^{a}$ | $18.03^{a}$ | $3.91^{a}$ | $-3.18^{a}$ | $11.41^{a}$ | $1.80^{a}$ |
| CSI 500 | $-3.49^{a}$ | $13.86^{a}$ | $2.89^{a}$ | $-2.81^{a}$ | $16.59^{a}$ | $3.64^{a}$ | $-4.42^{a}$ | $21.91^{a}$ | $3.92^{a}$ |
| SSE 50 | $-5.22^{a}$ | $21.34^{a}$ | $4.22^{a}$ | $-3.96^{a}$ | $17.83^{a}$ | $3.76^{a}$ | $-0.73$ | $3.53^{b}$ | $0.48^{b}$ |
| IF00 | $-2.94^{a}$ | $5.03^{a}$ | $0.97^{a}$ | $-3.38^{a}$ | $8.45^{a}$ | $1.79^{a}$ | $0.38$ | $2.79^{b}$ | $0.47^{b}$ |
| IH00 | $-4.22^{a}$ | $10.89^{a}$ | $2.11^{a}$ | $-3.09^{a}$ | $7.16^{a}$ | $1.48^{a}$ | $-1.43^{c}$ | $3.94^{a}$ | $0.59^{b}$ |
| | | | | | 20-minute return | | | | |
| CSI 300 | 0.92 | 0.83 | 0.17 | 0.11 | 0.29 | 0.05 | $-0.99$ | 1.89 | $0.40^{c}$ |
| CSI 500 | $3.23^{a}$ | $8.31^{a}$ | $1.73^{a}$ | $3.06^{a}$ | $5.77^{a}$ | $1.15^{a}$ | $-0.65$ | 1.40 | 0.26 |
| SSE 50 | 0.05 | 1.20 | 0.19 | $-0.27$ | 1.41 | 0.22 | $-0.29$ | 0.74 | 0.13 |
| IF00 | 1.19 | $1.96^{c}$ | $0.42^{c}$ | $-0.19$ | 1.32 | 0.21 | $-0.23$ | 0.50 | 0.08 |
| IC00 | $2.29^{a}$ | $3.30^{b}$ | $0.73^{b}$ | 0.87 | 0.80 | 0.17 | 0.39 | 0.56 | 0.09 |
| IH00 | 0.08 | 1.63 | 0.24 | $-1.43^{c}$ | $3.46^{b}$ | $0.59^{b}$ | $-0.98$ | 1.42 | 0.31 |
| | | | | | 60-minute return | | | | |
| CSI 300 | $-1.32^{c}$ | $2.44^{c}$ | $0.57^{b}$ | $-0.65$ | 1.56 | 0.30 | 0.61 | 0.55 | 0.11 |
| CSI 500 | 0.05 | 1.19 | 0.18 | 0.38 | 1.37 | 0.21 | 1.02 | 1.49 | 0.29 |
| SSE 50 | $-2.04^{a}$ | $8.32^{a}$ | $1.73^{a}$ | $-1.65^{b}$ | $2.92^{b}$ | $0.62^{b}$ | $-0.05$ | 0.55 | 0.08 |
| IF00 | $-1.64^{b}$ | $2.26^{c}$ | $0.53^{b}$ | $-1.48^{c}$ | $2.53^{b}$ | $0.53^{b}$ | 0.47 | 0.48 | 0.10 |
| IC00 | $-1.52^{c}$ | $2.10^{c}$ | $0.46^{b}$ | $-0.13$ | 0.98 | 0.19 | 0.38 | 0.49 | 0.09 |
| IH00 | $-1.97^{b}$ | $5.68^{a}$ | $1.13^{a}$ | $-2.29^{b}$ | $4.53^{a}$ | $0.97^{a}$ | $-0.01$ | 0.55 | 0.06 |

Notes: We report the results of the variance ratio test (VR) and the 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 16 April 2015 to 31 December 2015. The period before the rule implementation is from 16 April 2015 to 5 July 2015, while the period after the implementation of new trading rules is from 7 September 2015 to 31 December 2015. $^{a}$, $^{b}$, $^{c}$ denote significance at the 1, 5 and 10% level separately.

data before the trading rule changes according to Table 2, that is, from 16 April 2015 to 5 July 2015. Period C uses the data after the trading rule changes from 7 September 2015 to 2031 December 2015. We exclude the data between 6 July 2015 and 6 September 2015 to control for the impact of trading rule instability. We use the difference between the results of Periods B and C to assess the effect of the trading rule changes on the Chinese index futures market.

### 4.2. *Price efficiency*

Table 5 reports the results of test statistics of $a_1 = 1$ in the co-integration between the Chinese stock indexes and their futures. Results strongly reject the null hypothesis of $a_1 = 1$, suggesting that no-arbitrage relationship between the Chinese stock index and the Chinese index futures does not exist. This finding is similar to Zhong *et al*. (2004) using Mexican data. This finding suggests that on emerging markets, the trading mechanism still needs to be improved to make the no-arbitrage relationship between stock index and index futures work. In other words, there exist arbitrage opportunities of index futures in these markets.

Results are robust across three periods. The test statistics of IF, IC and IH change from 459.09, 406.53 and 641.42 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 the strongest for the long-established IF contract.

### 4.3. *Market efficiency*

Table 6 reports the results of the market efficiency test. We run two tests, including the variance ratio (VR) and spectral shape test ($AD_T$ and $CVM_t$). The left, middle and right columns report the results of 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

Table 7. Short-run and long-run Granger causality test.

| Period | Spot or futures | Type 1 test Null hypothesis ($\chi^2(5)$) | Statistics | Type 2 test Null hypothesis ($\chi^2(1)$) | Statistics |
|---|---|---|---|---|---|
| | CSI 300 | $b_{fs,i} = 0, \forall i$ | 229.28[a] | $\gamma_s = 0$ | 14.24[a] |
| Period 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 |
| | CSI 300 | $b_{fs,i} = 0, \forall i$ | 110.36[a] | $\gamma_s = 0$ | 7.07[b] |
| Period B | IF00 | $b_{sf,i} = 0, \forall i$ | 13.78[b] | $\gamma_f = 0$ | 0.01 |
| | CSI 500 | $b_{fs,i} = 0, \forall i$ | 248.31[a] | $\gamma_s = 0$ | 24.14[a] |
| | IC00 | $b_{sf,i} = 0, \forall i$ | 15.97[a] | $\gamma_f = 0$ | 2.07 |
| (Before) | SSE 50 | $b_{fs,i} = 0, \forall i$ | 93.45[a] | $\gamma_s = 0$ | 0.2 |
| | IH00 | $b_{sf,i} = 0, \forall i$ | 20.85[a] | $\gamma_f = 0$ | 4.73[a] |
| | CSI 300 | $b_{fs,i} = 0, \forall i$ | 103.81[a] | $\gamma_s = 0$ | 10.38[a] |
| Period C | 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 |

Notes: This table reports the results of Granger causality between Chinese stock indexes and their index futures. We report the results of Period A (whole period, from 16 April 2015 to 31 December 2015), and two subperiods of Period B (before the rule implementation, from 16 April 2015 to 5 July 2015) and Period C (after the rule implementation, from 7 September 2015 to 31 December 2015). We run the following VECM to the natural logarithmic price series of futures ($f_t$) and spot ($s_t$). $\Delta s_t = b_{s,0} + \gamma_s ect_{t-1} + \sum_{i=1}^{n} b_{ss,i}\Delta s_{t-i} + \sum_{i=1}^{n} b_{fs,i}\Delta f_{t-i} + e_{s,t}$, $\Delta f_t = b_{f,0} + \gamma_f ect_{t-1} + \sum_{i=1}^{n} b_{sf,i}\Delta s_{t-i} + \sum_{i=1}^{n} b_{ff,i}\Delta f_{t-i} + e_{f,t}$. The type 1 test is to test the short-run Granger causality from futures to spot (spot to futures) by testing $b_{fs,i} = 0$ ($b_{sf,i} = 0$) for all $i = 1, \ldots, n$. The type 2 test is to test the long-run Granger causality from futures to spot (spot to futures) by testing $\gamma_s = 0$ ($\gamma_f = 0$). [a], [b],[c] denote significance at the 1, 5 and 10% level separately.

Table 8. Price discovery measures of Chinese index futures market.

| Index | Trading code | Hasbrouck measure Period A(%) (Whole) | Period B(%) (Before) | Period C(%) (After) | Schwarz-Szakmary measure Period A(%) (Whole) | Period B(%) (Before) | Period C(%) (After) |
|---|---|---|---|---|---|---|---|
| CSI 300 | IF00 | 58.58 | 64.71 | 70.59 | 64.78 | 93.29 | 93.67 |
| CSI 500 | IC00 | 74.81 | 87.66 | 74.99 | 85.84 | 79.96 | 90.20 |
| SSE 50 | IH00 | 52.11 | 49.76 | 57.77 | 52.78 | 43.06 | 67.91 |

Notes: 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 16 April 2015 to 31 December 2015. Period B (before) is from 16 April 2015 to 5 July 2015, while Period C (after) is 7 September 2015 to 31 December 2015. The middle panel collects the results of the mean of upper bound and lower bound of the Hasbrouck measure for index futures, while the right panel reports the Schwarz-Szakmary measure for index futures.

Table 9. Estimation result of DCC GARCH model.

| Parameter | CSI300 vs. IF00 | CSI500 vs. IC00 | SSE50 vs. IH00 |
|---|---|---|---|
| $\alpha$ | 0.0065 | 0.0031 | 0.0061 |
| $\beta$ | 0.77[c] | 0.99[a] | 0.92[a] |

Notes: This table reports the estimation result of bivariate DCC GARCH model based on VECM. We first run the VECMs to the three Chinese index futures and their underlying stock indexes and obtain the residuals $[e_{s,t} \quad e_{f,t}]'$. We define the variance–covariance matrix of the residuals conditional on the information set $I_{t-1}$ as $var([e_{s,t} \quad e_{f,t}]'|I_{t-1}) = H_t = D_t R_t D_t$, where $D_t$ is a $2 \times 2$ diagonal matrix of time varying standard deviation of univariate GARCH process. $R_t$ is the conditional correlation matrix and follows $R_t = Q_t^{*-1} Q_t Q_t^{*-1}$. $Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha \epsilon_{t-1}\epsilon_{t-1}' + \beta Q_{t-1}$, where $\bar{Q}$ is the unconditional covariance of the standardized disturbances $\epsilon_t$. $Q_t^{*-1} = diag(Q)^{-1}$. $\alpha$ and $\beta$ are scalars that determine the time varying dynamics of conditional correlation.

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. Results suggest that overall the index futures market reflects 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. These findings are consistent with (Hou and Li 2013).

Table 10. Price discovery and Granger causality under no-arbitrage constraint.

| Measure | Futures | Period A (%) (whole) | Period B (%) (before) | Period C (%) (after) | | |
|---|---|---|---|---|---|---|
| Panel A. Price discovery measure under no arbitrage constraint | | | | | | |
| | IF | 46.34 | 61.85 | 62.03 | | |
| Hasbrouck (%) | IC | 67.19 | 87.63 | 72.87 | | |
| | IH | 40.65 | 44.78 | 47.68 | | |
| | IF | 38.21 | 96.29 | 77.31 | | |
| Schwarz-Szakmary (%) | IC | 69.65 | 79.96 | 98.07 | | |
| | IH | 20.90 | 43.06 | 41.82 | | |
| Panel B. 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$^{a}$ | 110.36$^{a}$ | 7.07$^{a}$ | 4.94$^{b}$ | 4.39$^{b}$ |
| IF00 | 5.93 | 11.21$^{c}$ | 13.78$^{b}$ | 0.01 | 0.00 | 0.51 |
| CSI 500 | 438.18$^{a}$ | 196.93$^{a}$ | 248.31$^{a}$ | 24.14$^{a}$ | 13.92$^{a}$ | 20.79$^{a}$ |
| IC00 | 12.52$^{b}$ | 19.51$^{a}$ | 15.97$^{c}$ | 2.07 | 0.55 | 0.00 |
| SSE 50 | 134.78$^{a}$ | 99.89$^{a}$ | 93.45$^{a}$ | 0.2 | 0.78 | 1.56 |
| IH00 | 17.58$^{a}$ | 17.43$^{a}$ | 20.85$^{a}$ | 4.73$^{b}$ | 2.21 | 1.95 |

Notes: This table reports the results of price discovery and Granger causality under no-arbitrage constraint. Panel A and Panel B report the price discovery measure and Granger causality test results under the 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 $i = 1, \ldots, n$, 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.

Next, we compare the market efficiency before and after the trading rule changes. Surprisingly, the tightened trading rules do not affect 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 −3.38, −1.76 and −3.09, respectively. All of them are significant at least at the 5% 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. 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 than those of 5-minute returns, but the patterns are similar.

The findings in Table 6 are different from Han and Liang (2017) that document a negative impact of the index futures trading restriction on Chinese stock market in 2015. They support the hypothesis stated earlier that tightened rules might be useful when there exists excessive market manipulation and the market is close to a crash state.

The change of market efficiency before and after the rule implementation has important implication for investment. None of the three index futures is weakly efficient in period B. This suggests that historical information is helpful to predict future index futures price change before the rule changes. However, past information becomes less important after the rule changes. Investors will not be able to gain from using historical information as much as before. It is of their better interest to adjust their investment strategy by depending less on the historical information of index futures prices.

Our empirical finding that the efficiency of the Chinese stock index market improves after the trading rule changes are consistent with Stein (2009). Loose trading rules might be necessary 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. How these new rules affect the Chinese index futures trading is an interesting question for further investigation.†

### *4.4. 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 the index futures. We first test the Granger causality between the three Chinese stock indexes and their index futures. We then assess the price discovery contribution by the three index futures. Finally, we examine the volatility effect between these two markets.

**4.4.1. Granger causality test.** Table 7 reports the results of Granger causality between the three Chinese index futures and

†For example, the Chinese government made a statement on 4 August 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. In robustness test, we address this question by summarizing the total number of case releases by Chinese Securities Regulatory Commission (CSRC).

Table 11. Market efficiency test: A robustness check.

| | Rank-based VR test | | | Automatic portmanteau test | | |
|---|---|---|---|---|---|---|
| | Period A (Whole) | Period B (Before) | Period C (After) | Period A (Whole) | Period B (Before) | Period C (After) |
| CSI300 | 8.01[a] | 7.62[a] | 5.25[a] | 11.24[a] | 10.69[a] | 9.54[a] |
| CSI500 | 8.15[a] | 6.53[a] | 6.83[a] | 8.51[a] | 6.45[a] | 56.38[a] |
| SSE50 | 7.13[a] | 7.21[a] | 2.99[a] | 8.88[a] | 10.87[a] | 1.24 |
| IF00 | 5.15[a] | 4.66[a] | 4.47[a] | 2.05 | 3.04[c] | 0.09 |
| IC00 | 3.08[a] | 1.48 | 1.47 | 0.52 | 1.31 | 0.04 |
| IH00 | 6.19[a] | 4.81[a] | 4.01[a] | 4.56[b] | 2.89[c] | 1.03 |

Notes: This table reports the results of market efficiency test using the rank-based variance ratio test proposed by Wright (2000), and the automatic portmanteau test of autocorrelation proposed by Escanciano and Lobato (2009). We use 5-minute returns in the analysis. The whole period is from 16 April 2015 to 31 December 2015. The period before the rule implementation is from 16 April 2015 to 5 July 2015, while the period after the enforcement of new trading rules is from 7 September 2015 to 31 December 2015. [a], [b], [c] denote significance at the 1, 5 and 10% level separately.

Table 12. Market conditions before and after the rule implementation.

| | | Period B | Period C | Difference | $t$-stat |
|---|---|---|---|---|---|
| CSI300 | Return (%) | −0.28 | 0.13 | 0.41 | 0.90 |
| | Realized variance | 0.22 | 0.08 | −0.14 | −3.81 |
| CSI500 | Return(%) | −0.14 | 0.28 | 0.42 | 0.77 |
| | Realized variance | 0.26 | 0.12 | −0.14 | −3.00 |
| SSE50 | Return(%) | −0.38 | 0.10 | 0.48 | 1.12 |
| | Realized variance | 0.20 | 0.07 | −0.13 | −3.96 |
| Closed-end fund discount rate (%) | | 3.66 | 5.60 | 1.94 | 8.47 |

Notes: This table reports the mean daily return and realized variance of three Chinese stock indexes before (Period B) and after (Period C) the rule implementation. Daily realized variance is calculated from high-frequency data of five-minute interval return following Corsi (2009). The last row reports the results of the closed-end fund discount rate in two periods. The last two columns report the difference between these measures in two periods with their $t$ statistics.

their underlying indexes. We first run VECM models (equations (11) and (12)) 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 $i = 1, \ldots, n$. The type-2 test is to test the long-run Granger causality from futures to spot (spot to futures) by testing $\gamma_s = 0$ ($\gamma_f = 0$).

The upper panel of Table 7 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 Chinese index futures Granger causes Chinese stock index in both the short- and long-run. On the other hand, there is less significant evidence that Chinese stock index Granger causes Chinese 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 stock index to index futures is significant. Results suggest that the information spillover from index futures to stock index is more significant than the information spillover in the other direction during the whole sample period. The Chinese index futures tend to lead their underlying stock indexes. These findings are also consistent with those in Hou and Li (2013).

The middle and bottom panels report the results 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 have little impact on the Granger causality effect from Chinese index futures to their underlying stock indexes. Index futures continue to play a more significant role in the information transmission between futures and spot market.

**4.4.2. Price discovery.** Table 8 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 reports 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.

Results of the whole sample period show that the price discovery contribution by index futures is higher than that of their underlying stock indexes. For example, the Hasbrouck measures of IF00, IC00, and IH00 are 58.58, 74.81 and 52.11%, respectively. This suggests that the Hasbrouck measures of the CSI 300, CSI 500 and SSE 50 are 41.42, 25.19 and 47.89%, 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. The price discovery contribution of index futures becomes slightly higher after the trading rule changes. The Hasbrouck measures of the three index futures (IF00, IC00 and IH00) are 64.71, 87.66 and 49.76%, respectively, before the trading rule change, and 70.59, 74.99 and

Table 13. Market efficiency and market condition.

| | CSI300 | CSI500 | SSE50 | IF00 | IC00 | IH00 |
|---|---|---|---|---|---|---|
| Intercept | 0.5503[a] | 0.5928[a] | 0.5319[a] | 0.5358[a] | 0.5950[a] | 0.5290[a] |
| $dummy_t$ | 0.0109 | 0.0002 | 0.0187 | 0.0189 | 0.0461 | 0.0277 |
| $r_t$ | 0.3101 | 0.2579 | 0.2379 | 0.2122 | −0.5566 | 0.3494 |
| $RV_t$ | 18.01 | 9.486 | 19.36 | 11.19 | 12.40 | 17.38 |
| $Sent_t$ | 0.0766 | 0.4204 | −0.0072 | −0.0953 | 1.40 | 0.0652 |
| Adjusted $R^2$ | −0.0204 | −0.0246 | −0.0179 | −0.0173 | −0.0066 | −0.0093 |

Notes: This table reports the regression result of daily market inefficiency measure on market condition variables. The daily market inefficiency measure is calculated by the absolute difference between variance ratio measure and 1, $VR_t = |\frac{Var(10)}{2Var(5)} - 1|_t$, where $Var(10)$ and $Var(5)$ are the variance of 10-minute and 5-minute return, respectively. Market condition variables include daily return ($r_t$), daily realized variance ($RV_t$) and daily sentiment measure ($Sent_t$). Daily realized variance is calculated from high-frequency data of five-minute interval return following Corsi (2009). Sentiment is measured by close-end fund discount rate. We introduce a dummy variable to test whether there is a significant change of market efficiency controlling for the impact of market condition. The regression model is $VR_t = Intercept + \beta_0 dummy_t + \beta_1 r_t + \beta_2 RV_t + \beta_3 Sent_t + \epsilon_t$,where $dummy_t = 1$ in period B and zero otherwise. [a], [b], [c] denote significance at the 1, 5 and 10% level separately.

Table 14. Case release of CSRC.

| Time period | Total | Inside trading only | Market manipulation only | Inside trading & market manipulation | Others |
|---|---|---|---|---|---|
| January 2014∼June 2014 | 10 | 3 | 1 | 0 | 6 |
| July 2014 ∼December 2014 | 1 | 1 | 0 | 0 | 0 |
| January 2015∼June 2015 | 1 | 0 | 0 | 0 | 1 |
| July 2015 ∼December 2015 | 20 | 1 | 7 | 4 | 8 |
| January 2016∼June 2016 | 6 | 0 | 1 | 2 | 3 |
| July 2016 ∼December 2016 | 4 | 0 | 1 | 0 | 3 |
| January 2017∼June 2017 | 4 | 0 | 0 | 2 | 2 |

Notes: This table summarizes the number of case releases by CSRC from January 2014 to June 2017. For every six months during the same period, we report the number of all case releases, case releases of inside trading only, case releases of market manipulation only, case releases of both inside trading and market manipulation, and others.

57.77%, sequentially, after. Similarly, the Schwarz-Szakmary measures of IF00, IC00 and IH00 are 93.29, 79.96 and 43.06%, respectively, before the rule changes, and 93.67, 90.20 and 67.91%, respectively, after. Five of the six measures increase and all the measures in Period C are higher than 50%, which means 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 and supports our hypothesis about the importance of tightened regulation under particular conditions.

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

Results in tables 7 and 8 show that the Chinese index futures price contains more information about the interaction between Chinese index future market and Chinese stock market. Such informational role becomes slightly more important after the rule changes. Economically, these findings suggest that Chinese index futures market provides useful information for investors of Chinese stock market to time the market. This economic significance continues to exist, or become slightly stronger after the rule changes.

**4.4.3. Volatility effect.** Table 9 reports the estimation result of bivariate DCC GARCH model based on VECM. We first run the VECMs to stock index futures and their underlying stock indexes and obtain the residuals. These residuals are then used in the DCC GARCH model specified in section 3 (equations (16)–(19)). None of $\alpha$ is significant, while all $\beta$s are significant at at least the 10% level. Results suggest a significant dynamic conditional correlation relationship between the three Chinese stock indexes and their futures (see Figure 1).

Figure 2 plots the time series of the dynamic conditional correlation. The dynamic conditional correlation fluctuates more frequently between July 2015 and September 2015, which reflects the impact of the rule uncertainty. On the other hand, the dynamic conditional correlation pattern in period B and C is close to each other. There is no significant change of dynamic conditional correlation after the rule implementation.

Figure 3 plots the time series of the realized correlation between the three Chinese stock index futures and their underlying stock indexes. Realized correlation fluctuates more between July 2015 and September 2015, and share a similar pattern in period B and period C. These findings are consistent with those of bivariate DCC GARCH model. To summarize, the tightened trading rules have no significant impact on the dynamic correlation between the three Chinese stock indexes and their index futures.

## 5. Robustness test

### *5.1. Market efficiency with no arbitrage restriction*

Panel A of Table 10 reports the price discovery measures of the three Chinese index futures under the constraint of $a_1 = 1$ in

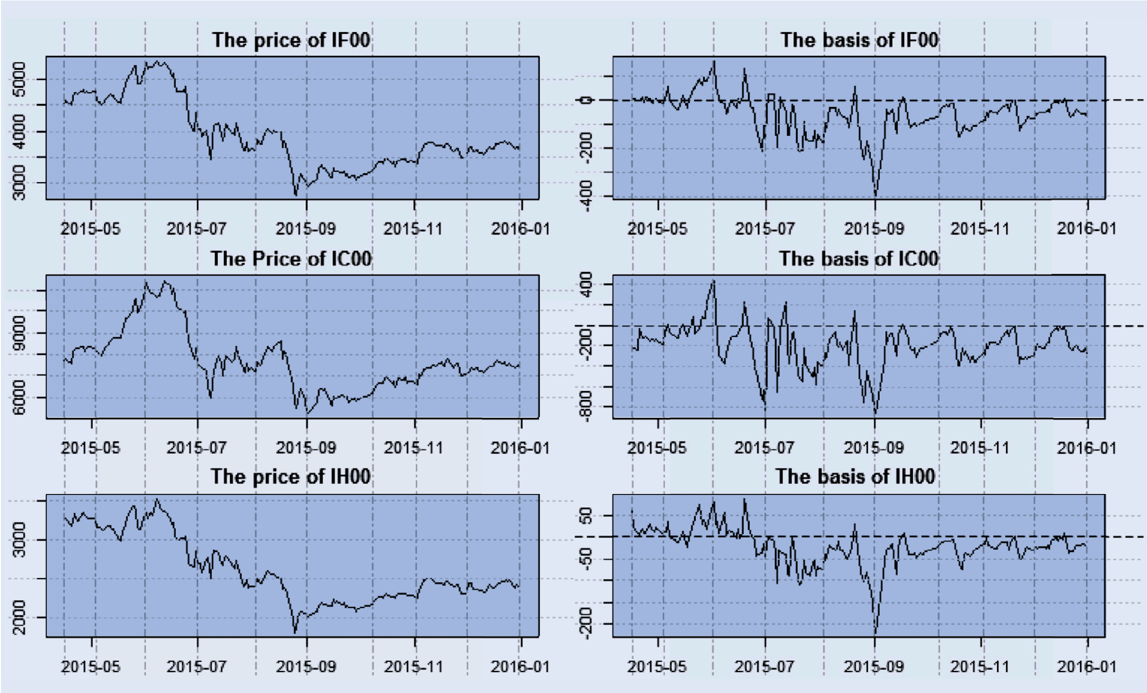


Figure 1. Price and basis of the Chinese stock index futures. This graph plots the price and the basis of the three Chinese stock index futures, IF00, IC00 and IH00. The underlying indexes of IF, IC, and IH contracts are CSI 300 index, CSI 500 index and SSE 50 index, respectively. 00 means the current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

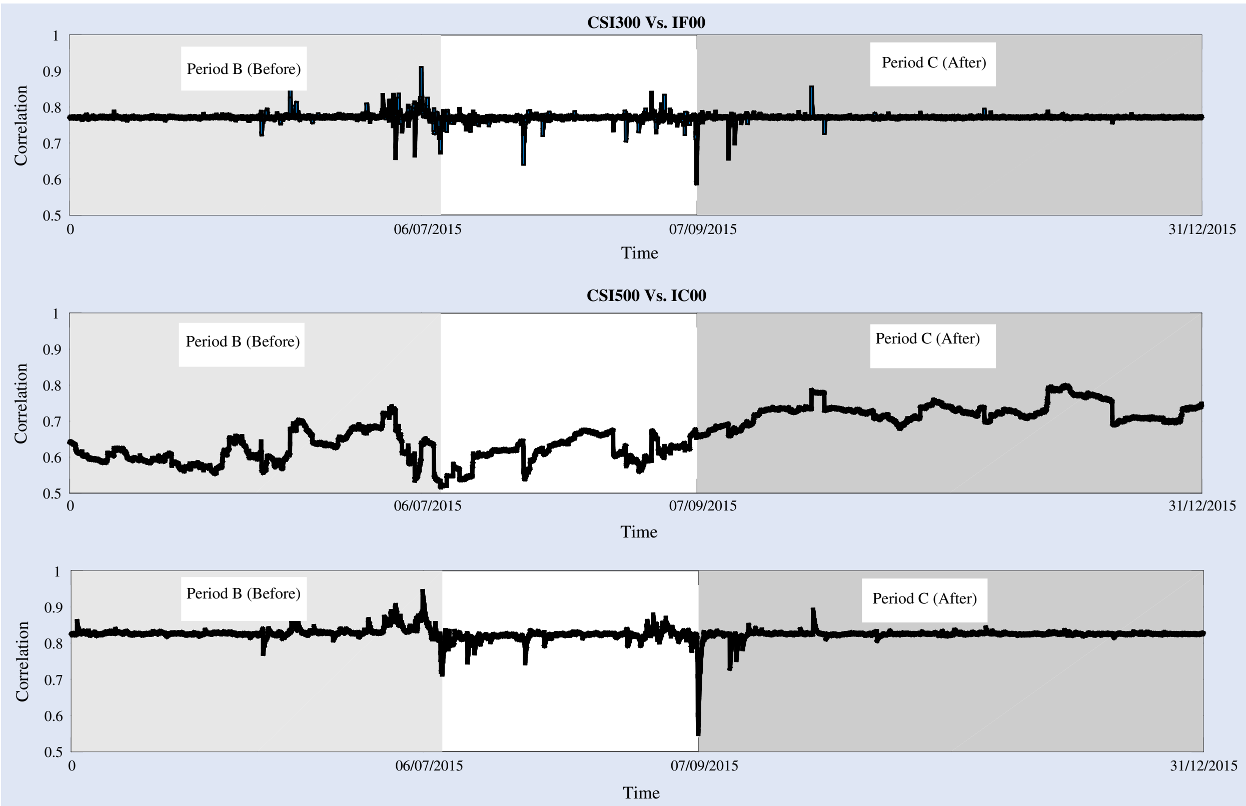


Figure 2. Dynamic conditional correlation. This graph plots the dynamic conditional correlation between the three Chinese stock index futures and their underlying stock indexes between 16 April 2015 and 31 December 2015. Period B (before) is from 16 April 2015 to 5 July 2015, while Period C (after) is 7 September 2015 to 31 December 2015.

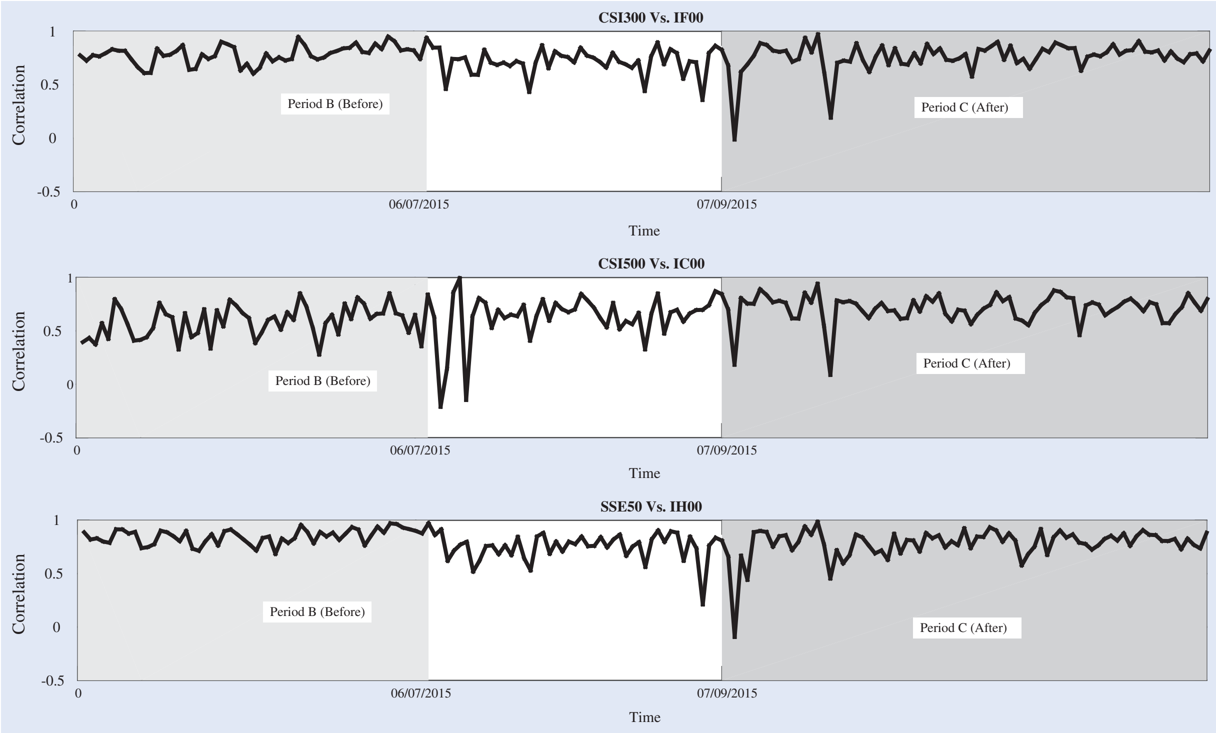


Figure 3. Daily realized correlation. This graph plots the daily realized correlation between three Chinese stock index futures and their underlying stock indexes between 16 April 2015 and 31 December 2015. Period B (before) is from 16 April 2015 to 5 July 2015, while Period C (after) is 7 September 2015 to 31 December 2015.

equation (13), while Panel B of Table 10 reports the results of the Granger causality test. Similar to the results without constraint, index futures plays a vital role in price discovery. The price discovery of index futures does not become weaker after the tightened trading rule changes since four of six measures in Period C are larger than 50%. For example, the Hasbrouck measures of IF, IC and IH during the whole period are 46.34, 67.19 and 40.65%, respectively. They are 61.85, 87.63 and 44.78%, respectively, before the rule changes, and 62.03, 72.87 and 47.68%, respectively, after the rule changes.

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

### 5.2. *Market efficiency using other tests*

We use the variance ratio and the spectral shape method to test the market efficiency of Chinese stock indexes and their futures in our primary analysis. The variance ratio test was proposed by Lo and MacKinlay (1988), while the spectral shape test was introduced by Durlauf (1991). These two methods are a little bit old-fashioned. To examine whether our results of market efficiency are robust to the choice of testing methods, we use the methods developed more recently and re-run our test. We use the rank-based variance ratio test proposed by Wright (2000), and the automatic portmanteau test of autocorrelation proposed by Escanciano and Lobato (2009) in our robustness check.

Table 11 reports the results. Results suggest that market efficiency of Chinese stock indexes and index futures does not deteriorate after the tightened trading rules. Most of the rank-based VR test statistics are slightly smaller in Period C than in Period B, which implies that market becomes slightly more efficient in Period C. For example, the rank-based VR test statistics of CSI300, CSI500, SSE50, IF00, IC00, and IH00 are 7.62, 6.53, 7.21, 4.66, 1.48 and 4.81, respectively in Period B, while they are 5.25, 6.83, 2.99, 4.47, 1.47 and 4.01, respectively in Period C. Results of the automatic portmanteau test are similar. These results suggest that the impact of the tightened trading rules on the market efficiency of Chinese stock indexes and index futures is slightly positive, and robust to the market efficiency test method used.

### 5.3. *Market efficiency and market condition*

Besides the tightened trading rules, the market condition might also affect market efficiency. For example, market efficiency could be influenced by market state (bull or bear market) or investment sentiment. We follow two steps to address this concern. In the first step, we investigate whether there exists a significant difference of market condition before and after the rule implementation. We use daily return and daily realized variance to measure the market state, and closed-end fund discount rate to measure the market sentiment.†

Table 12 reports the results. The stock return difference between period B and period C is not significant. The $t$-stats

†Closed-end fund discount rate is used by Baker and Wurgler (2006) to construct their investment sentiment measure.

of the return difference of CSI300, CSI500 and SSE50 are 0.90, 0.77 and 1.12, respectively. None of them is significant. Nevertheless, the daily realized variances of the Chinese stock indexes are significantly higher in period B than in period C. For example, the mean daily realized variance of CSI300 is 0.22 in period B and 0.08 in period C.† Their difference is −0.14 with a $t$-stat of −3.81. Results of CSI500 and SSE50 are similar. There exists significant change of market volatility before and after the rule implementation.

The last row of Table 12 reports the result of closed-end fund discount rate. The mean discount rate is 3.66% in period B and 5.60% in period C. Their difference is 1.94% with a $t$-stat of 8.47. The closed-end fund discount rate is significantly higher in period C, suggesting that investors are more pessimistic after the rule implementation.

In the second step, we run a time series regression of daily market inefficiency measure on market condition variables, including return ($r_t$), realized variance ($RV_t$) and sentiment ($Sent_t$) measured by closed-end fund discount rate,

$$VR_t = \text{Intercept} + \beta_0 dummy_t + \beta_1 r_t + \beta_2 RV_t + \beta_3 Sent_t + \epsilon_t, \quad (23)$$

where $VR_t$ is the daily market inefficiency measure. We follow Saffi and Sigurdsson (2010) to calculate $VR_t$ by the absolute difference between variance ratio measure and 1, $VR_t = |\frac{Var(10)}{2Var(5)} - 1|_t$, where $Var(10)$ and $Var(5)$ are the variance of 10-minute and 5-minute return, respectively. $dummy_t$ is the dummy variable with $dummy_t = 1$ if it is in period B and zero otherwise. We are interested in whether the coefficient of $dummy_t$ is significant to measure the impact of the tightened rules on market efficiency after controlling for market conditions.

Table 13 reports the regression results. Although there exists significance change of realized variance and sentiment after the rule implementation indicated in Table 12, none of them has a significant relationship with the daily market inefficiency measure. None of the dummy variables is significant. The regression results suggest that there does not exist significant change of market efficiency in period C compared to period B after market conditions are controlled.

All the dummy variables $dummy_t$ are insignificantly positive. These show weak evidence to support that the market inefficiency measures are smaller in period C than in period B. This is consistent with our earlier finding that market efficiency slightly improves after the rule changes.

Another possible reason for market efficiency change is market matureness. Among the three Chinese index futures, IF was listed on 16 April 2010, and is the most prime contract. It has been traded for around five years when we use its data in the analysis. If the matureness of the index futures is one possible reason for the change of market efficiency and price discovery, we should be able to observe a different pattern between the IF and the other two index futures. Nevertheless, empirical results do not show this pattern. This suggests that market matureness does not drive the change of market efficiency and price discovery function of Chinese index futures around the tightened rule implementation.

†The realized variances are annualized.

### 5.4. *Market efficiency and regulation*

There are two possible channels through which the tightened rules improve the market efficiency of Chinese stock index futures market. The first channel is that the tightened regulations squeeze out insider trading and market manipulation. We do not have access to the tick-by-tick transaction data of Chinese stock market and stock index futures market and fail to provide a direct evidence. We indirectly address this question. We collect the case release announcement of CSRC from January 2014 to June 2017.‡ For every six months during the sample period, we summarize the number of all case releases, case releases of inside trading only, case releases of market manipulation only, case releases of both inside trading and market manipulation, and others. A significant increase in insider trading or market manipulation case release around July 2015 is used as indirect evidence to support our argument, and show that CSRC is aiming to strengthen its law enforcement.

Table 14 reports the summary statistics. The total number of case releases during July 2015 and December 2015 is 20 and much higher than that in other periods. Among the 20 case releases, 12 (1 + 7 + 4) cases are relevant to insider trading or market manipulation, which is also much larger than other periods. There is clear evidence that CSRC tried to strengthen its law enforcement to reduce insider trading and market manipulation during July 2015 and December 2015. The tightened trading rules are possibly used as another way to squeeze out insider trading and market manipulation.

The second channel is that the tightened rules also keep noise traders from the market. Hwang and Li (2017) show that noise traders are more susceptible to behaviour bias, and generate higher pricing errors in the distress stocks that make their prices less efficient. Since there is a relatively high capital requirement to trade Chinese index futures,§ Chinese index futures market is less subject to the impact of noise trading by retail investors. The improvement through the second channel is thus limited. It is of great interest to quantitatively identify the contribution of each channel to the change of market efficiency. This question will be for future research.

## 6. Conclusion

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

Our empirical results show that the tightened trading rules implemented in 2015 do not have a negative impact on the market efficiency and the price discovery of the three Chinese index futures. Market efficiency tests suggest that Chinese index futures market becomes slightly more efficient after the rule changes. Price discovery analysis also implies that the price discovery function of the Chinese index futures market

‡http://www.csrc.gov.cn/pub/newsite/jcj/aqfb/.

§For example, the initial capital required to open a trading account of Chinese stock index futures is 500 000 RMB.

improves 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 have 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), which shows 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. Trading in the Chinese index futures market becomes more information relevant after the participation of insider traders and market manipulators is reduced, which further improves 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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## Disclosure statement

No potential conflict of interest was reported by the authors.

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