Role of Index Futures on China's Stock Markets: Evidence from Price Discovery and Volatility Spillover

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Abstract

The introduction of stock index futures in China in 2010 marked an important development in the country's financial markets. It was however not without controversy as regulators blamed the futures market for its role in the stock market crash in 2015. This paper examines the intraday price discovery and volatility spillover relationship between the CSI 300 equity index and index futures in China. Results from the study, covering the period 2010-2015, reveal that index futures plays a dominant role in contributing towards price discovery, with an average yearly information share of about 67%. The price leadership of the futures market, although found to be strong, is diminished in the presence of stringent regulatory trading curbs that were put in place as a response to the crisis. Furthermore, investigation into volatility spillover documents significant return and volatility shocks transmitted from the stock market to the futures market. The evidence, which contradicts regulatory claims, is explained in the context of the unique institutional trading structure in China.

Keywords: Index Futures; China's Stock Market; Information Sharing; Volatility Spillover

1 Introduction

The introduction of stock index futures in China in April 2010 was hailed as one of the landmark developments in Chinese financial markets. The dominant view prevailing at that time among investors and regulators was that index futures would play a stabilizing force in China's financial markets.[1] However, these views came under harsh scrutiny when the Chinese stock market crashed in June 2015, an event that erased nearly $2 trillion of market capitalization. In an apparent volte-face, the China Securities Regulatory Commission (CSRC) blamed the stock market collapse on "malicious short-selling" by speculators in the futures market and described index futures as "weapons of mass destruction".[2] In an attempt to stem the steep decline in stock prices and restore confidence in the market, CSRC quickly intervened with several restrictive measures in the futures market. The measures included increasing trading curbs, raising margin requirements for non-hedging purposes, imposing higher transaction fees, placing limits on same-day trading,[3] and suspending trading in various company shares that accounted for nearly 40% of market capitalization. In addition, CSRC announced a high profile investigation into the trading activities of the top 50 traders in the equity index futures, and introduced a string of state-led bailout measures of the stock market.

The tumultuous market events in 2015, combined with the unique institutional trading structure in China, provide motivation for investigating several issues related to the price

[1] Several public comments by regulators support this view. On December 5, 2014, Xiao Gang, chairman of the China Securities Regulatory Commission (CSRC) remarked, "Stock index futures are sophisticated risk management tools for improving the stock market operation mechanism, providing hedging instruments, improving the investment product market system and promoting stable development of great significance." In a different comment Huo Ruirong, Executive Vice President of the Shanghai Futures Exchange (SHFE) and Executive Director of Shanghai Institute of Futures and Derivatives (SIFD) indicated that the "innovative development of the futures market not only involves the futures market itself but also is of great significance to improving the financial market system, promoting the real economy's development, facilitating the internationalization, and strengthening the price influence."

[2] The "malicious short selling" in the futures market was defined by CSRC spokesman Deng Ge as "cross-market or cross-maturity manipulation."

[3] Among the harshest new rules included the definition of "abnormal trading" to positions over 10 contracts on a single index future. Fees for settling positions were also raised 100-fold, from 0.023‰ to 2.3‰, while margin requirements on futures contracts were also increased considerably.

discovery function of financial markets. Specifically, this paper examines the effect of the market crisis and corresponding regulatory interventions on price discovery and volatility relationships between the CSI 300 stock and futures indexes. The analysis will also shed light on regulatory claims that futures trading resulted in destabilizing the spot market. The study contributes to the literature in at least three important ways.

First, as described earlier, the information rich environment in 2015 in China motivates us to examine the contribution of futures trading to the efficiency of the underlying stock market in terms of price discovery. In general, researchers attribute the informational advantage of the futures market to its greater leverage, lower transaction costs, and ability to short-sell, among other factors. However, the stability of this relationship is subject to interpretation in the presence of severe market shocks and regulatory events. Previous studies in this area do not provide adequate guidance to our analysis since most futures markets examined in the literature are relatively homogenous in terms of their investor and trading structure, and the resulting evidence is primarily drawn from mature markets. In contrast to developed markets, trading in China's stock markets are dominated by individual (retail) investors (Ng and Wu, 2007), who are believed to be not as well informed when compared with their institutional counterparts.[4] Studies such as by Seasholes and Wu (2007) and Dhar and Zhu (2006) suggest that individual investors are less informed and therefore more susceptible to sentiment swings and behavioral biases than their institutional counterparts. Under these conditions, we posit that the stock market in China may carry only a diminutive role in the price discovery process.

Second, unlike other large financial markets, China tightly controls its stock exchanges through a variety of measures such as trading restrictions, regulatory curbs, high barriers for foreign investor to enter the market, constrained access to credit, among other factors. If

[4] According to Reuters about 85% of trades on the Chinese stock market are retail investors with increasing dependence on leverage. Not surprisingly, as noted by Credit Suisse, the market is also shown to have one of the highest turnover ratios. It has also been documented that less than 7% of urban Chinese have money invested in the stock market, with a large group of investors possessing an education level of middle school or below (see China Household Finance Survey).

investors in China view index futures as a vehicle to circumvent onerous trading restrictions in the stock market such as same-day trading and short-sale ban, then the futures market arguably should assert greater leadership in price discovery.

Third, the recent stock market crisis and the alleged role of the futures market in causing the crisis provide an interesting window to examine the price discovery function in Chinese financial markets. In response to the stock market crash in June 2015 the Chinese regulatory authority undertook a series of intervention measures and launched a formal investigation into the role played by the futures market in exacerbating the crisis. An analysis of specific interventions during this period will provide granular insights into the stability of the price leadership relationship between index futures and the stock market.[5]

To summarize, the presence of the differential institutional trading features in China combined with regulatory interventions in the immediate aftermath of the stock market crisis provide an interesting experimental setting to examine the price discovery role of financial markets. In line with this argument, our study also examines volatility linkages between the CSI 300 index futures and the corresponding equity index markets. Volatility linkages may arise from either common information that alter expectations, thereby affecting asset demand, or cross-market hedging that results in information spillovers. The findings here will help us evaluate regulatory claims that trading in futures market played a destabilizing role in the stock market.

The contributions of the study can also be framed in the context of theoretical predictions on the impact of trading costs and policy shocks on price discovery. Fleming et al. (1996) introduce the "trading cost" hypothesis which suggests that the cost of trading has an impact on the price leadership between futures and cash markets. Kim et al. (1999) test and confirm the "trading cost" hypothesis across various futures and cash indices. Additionally, Ito and Lin (2001) propose the "policy spillover" effect when policy changes such as increases in margin requirement transfer trading volume to closely linked markets. Hsieh (2004) examines

[5]We will provide a detailed discussion about the time line of regulatory interventions and their impact on information shares in Section 6.

the impact of market regulatory changes on the information leadership and finds that both lower transaction cost and higher trading volume are associated with greater price discovery and information transmission. In our study, the transaction fees for daily purchases and sales were raised 100-fold, from 0.023‰ to 2.3‰, along with a significant increase in margin requirements for futures trading from 10% to 40% of the contract value. In addition, the trading volume declined about 90% in the stock index futures transaction after the CFFEX imposed position limits for all investors deemed to engage in "abnormal trading." Therefore, according to the "trading cost" hypothesis and the "policy spillover" effect, we expect that the significant increase of overall trading costs and dramatic decrease of trading volume will lead to weaker price leadership of the futures market in the presence of stringent regulatory trading curbs during the crisis.

It is also important to highlight how our study differs from previous research of the Chinese stock market. We believe that our study offers the most comprehensive investigation of price discovery and volatility transmission effects in the Chinese stock market. In contrast to earlier studies that use relatively low frequency (daily or 5 minutes frequency) (c.f. Judge and Reancharoen 2014; Xie and Huang 2014) and short examination windows surrounding the introduction of equity futures in China in 2010 (c.f. Yang et al. 2012), our analysis benefits from a longer sample period that spans April 2010 through December 2015. Importantly, none of the earlier studies examine the crisis period in 2015. Our study employs intraday data measured at 5-second intervals thus providing an added level of granularity as well as robustness to the analysis. The start of the sample period coincides with the launch of the CSI 300 stock index futures, and our sample period captures the overall evolution of the market as evinced by its steep rise and dramatic decline.

Our results are summarized as follows. The information sharing model indicates that the CSI 300 index futures plays a dominant role in the price discovery process over the sample period. Notably, the price leadership of the futures market, although still strong, is found to be greatly attenuated after the Chinese government imposed regulatory constraints in 2015 that increased margin requirements, transaction fees and position limits. Our results also provide evidence of an asymmetry in the relationship between the CSI 300 stock and futures indexes, with significant return and volatility shocks transmitted from the stock market to the futures market. The evidence, which contradicts regulatory claims, is explained in the context of the unique investor trading structure in China, one that is characterized by a large institutional and well-educated retail investors' presence in the futures market. Our conclusions remain robust to alternative price discovery metrics and to the choice of different roll-over dates in constructing the futures price series.

The remainder of the paper is organized as follows. Section 2 provides a brief overview of the literature and draws comparison with our study. Section 3 provides background information on the institutional characteristics and trading environment of the Chinese equity market. The data and methodology are explained in Section 4. The results are discussed in Section 5. This is followed by a discussion of robustness tests in Section 6. Section 7 concludes the paper.

2 Literature Review

One of the basic axioms of efficient financial markets is that asset prices incorporate consensus views of market participants and make rapid price adjustments to reflect changing information. This axiom is often tested on assets asset that trade in related markets and by observing which market bears the primary responsibility of making price adjustments. In the case of stock index, the majority of empirical evidence points to the leading role of futures markets in the price discovery process.[6] The influential role of futures markets is attributed to their higher leverage, greater liquidity, lower transaction costs, and additional flexibility of short-selling.[7] However, it is possible that the direction of lead-lag patterns between the

[6] See for example, Kawaller et al. (1987), Stoll and Whaley (1990); So and Tse (2004).

[7] Spot market transactions may require more initial up-front capital and may take longer to implement (c.f. Silvapulle and Moosa, 1999; Bekiros and Diks, 2008). On the other hand, futures transactions can be implemented much more quickly and with little initial outlay. Under these circumstances both speculators

futures and underlying stock market is predicated on how various market participants filter information relevant to their own stock or futures position (see Kawaller et al., 1987). Chan et al. (1991), for instance, finds equity index futures to be relatively more sensitive to aggregate macro-based information when compared with firm-specific information. Under these conditions, information about individual stocks is transferred to the whole index, and this may cause futures prices to lag corresponding changes in index prices. Mukherjee and Mishra (2006) argue that, at least in developed markets, the trend towards lower transaction costs and easier access to information has led to the gradual weakening of the leading role of futures markets.

In examining price discovery of the CSI 300 index futures, Feng et al. (2010) study lead-lag relationships between the Hong Kong Hang Seng index futures and the CSI 300 index futures, and find that the former "Granger-causes" the CSI 300 index futures. On the other hand, Hua and Liu (2010) show a bidirectional relationship between these two markets. Other studies, such as Yang et al. (2012) focus on the market response to the introduction of equity index futures and find price leadership of the CSI 300 index futures to be relatively weak. More recently, Wang et al. (2017) examine the lead-lag dependence between the CSI 300 index spot and futures markets from 2010 to 2014 and confirm price discovery in the Chinese futures market. Importantly, all these studies predate the onset of the financial crisis in 2015 and fail to account for the influence of restrictive regulatory actions on the stability of price discovery relationship. Furthermore, the results are not explained in the context of the unique trading environment in China.

There is also a rich stream of literature examining volatility linkages between stock index and futures markets. Studies such as by Arshanapalli and Doukas (1994), Antoniou et al. (2005), Kavussanos et al. (2008) and Dawson and Staikouras (2009) document that futures volatility spills over to the underlying equity market, a finding that is attributed to the higher leverage provided by futures market. On the other hand, index futures have been shown to

and hedgers will react to new information by preferring futures rather than spot transactions.

lend stability to the market because futures trading improves price discovery, contributes to market efficiency and market depth, and provides a financial tool for investors to hedge against the risk of lower prices (see, for example, Kyle, 1985 and Stoll and Whaley, 1988). Investors may also feel less pressure to sell stocks they hold since selling index futures is usually cheaper than unloading a large block of shares that could put downward pressure on prices (see Turnovsky, 1983). Danthine (1978) argues that the better-informed investor in futures market have an advantage over stock market investors, allowing information to transfer from futures market to the stock market. Finally, studies also document bidirectional volatility transmissions between the futures market and the underlying stock market (e.g. Koutmos and Tucker,1996; So and Tse, 2004).

In the case of Chinese financial markets, Xie and Huang (2014) use daily data, for the period 2005 to 2012, to examine the impact of the introduction of the CSI 300 index futures on equity market volatility. They run separate GARCH models on the stock index and compare whether the parameters are different between the two periods surrounding the futures launch date. The authors document that the CSI 300 index futures trading does not reduce stock market volatility. Other studies have examined volatility spillover effects between the two markets with results suggesting feedback effects (Yang, et al., 2012), as well as unidirectional relationship with futures market dampening stock market volatility (Chen et al., 2013; Bohl et al., 2014). A notable downside of prior studies is their reliance on relatively short sample periods, lasting only a few months, and examining a period that does not fully take into account the broader evolution of the equity index and futures market. For instance, Yang et al. (2012) use 5-minute frequency data for a short 3-month period starting April 2010; whereas, Yang and Wan (2010) employ daily data ranging from January 2009 to August 2010.

3 Institutional Structure and Trading Environment

China's capital markets have grown rapidly since the establishment of the Shanghai and Shenzhen stock exchanges in 1990 and 1991, respectively. By early 2015, the two exchanges collectively became the second largest stock market in the world behind the U.S. stock market, and the world's largest emerging market.[8] The two stock exchanges simultaneously trade two different classes of shares, denoted as A and B shares. A-shares are quoted in Chinese Remnibi and traded only by domestic investors; whereas, B-shares sold only to foreign investors until February 2001, are open to both foreign and domestic investors. The B-shares are quoted in U.S. Dollars on the Shanghai stock exchange, or quoted in Hong Kong Dollars in the Shenzen Stock Exchange.

Several distinguishing elements are evident in the Chinese stock market. First, retail investors represent a large portion of the investment holdings and trading. At the end of 2012, retail investors' holding of the free-float market cap of A-shares was about 25%, compared to 18% by professional institutional investors. These investment holding features transfer to the trading structure as well with about 85% of the total trading volume accounted by retail investors. Furthermore, given the closed nature of the market, foreign shareholders account for only less than 2% of the Chinese shares.[9] Although China has eased some restrictions on capital flows and now allows a limited number of foreign investors to trade on the Shanghai and Shenzhen exchanges, these changes are, at best, still tenuous.[10]

[8]The combined market capitalization of the Shanghai and Shenzhen exchanges exceeded $10 trillion in May 2015, which is nearly twice the capitalization of the Tokyo stock exchange (as the 3^{rd} largest market), and second only to the $27 trillion combined capitalization of the NYSE and Nadaq markets in the US. The size of the Chinese stock index futures market, which was introduced only recently in 2010, is equally impressive. In May 2015, the Chinese stock index futures surpassed the S&P 500 index futures in terms of turnover and was ranked by the *World Federation of Exchanges* as the most active market for index futures in the world.

[9]According to CNBC,"China's stock market tends not to correlate with other world markets, and less than 2 percent of Chinese shares are owned by foreigners." http://www.cnbc.com/2015/07/09/three-charts-explaining-chinas-strange-stock-market.html

[10]China restricts foreign capital in its mainland exchanges. The Qualified Foreign Institutional Investors (QFII) are allowed to participate by special permission. More recently, the launch of the Shanghai-Hong Kong Stock Connect programme on November 17, 2014 further relaxes restrictions that historically split the Chinese stock market between shares targeted at local investors and those available to international investors, but the futures market is still off limits to international participants.

Second, the mainland Chinese stock market imposes several trading restrictions such as price-limit rules, margin trading, short-selling restrictions and T+1 trading constraints. Beginning December 1996, the price limit rule is triggered when any stock changes by more than 10% from its previous day's closing price. In addition, poor performing firms classified as "special treatment" (ST) by CSRC are subject to tighter price limits, limiting their daily price movements to 5% (c.f. Kim, Liu and Yang, 2013).

In March 2010, CSRC introduced the margin trading and short-selling (MTSS) program that enabled investors to borrow funds (stocks) and buy (short-sell) select A-share stocks. MTSS maintains a list of such stocks. However, for the majority of stocks that are not included on the MTSS program, they are subject to short-selling and arbitrage limitations. Finally, in an attempt to curb same-day trading, Chinese regulators instituted the "T+1" trading rule that prevents investors to profit from intraday gains by selling securities on the same day as they were bought.

The launch of the CSI 300 index on April 8, 2005 followed by the introduction of the CSI 300 futures index on April 16, 2010, which trades on the China Financial Futures Exchange (CFFEX)[11] in Shanghai marked an important development in the evolution of the Chinese financial market. The CSI 300 index is a free-float weighted index that comprises 300 of the largest and actively traded A-share stocks listed on the Shanghai and Shenzhen Stock Exchanges. It tracks approximately 2700 stocks listed on the two exchanges. It is one of the most widely followed stock index in China and is used by investors to develop and benchmark their investment portfolios. At the end of 2014, the market valuation of the CSI 300 index was about USD 4.5 trillion, representing a 16-fold increase in valuation since its inception. The index covers 10 different sectors of the Chinese economy and captures approximately 75% of the overall equity market capitalization in the country.

In highlighting the relevance of our paper, it is important to note that the CSI 300 stock futures is the first tradable index futures in the Chinese stock market. The futures mar-

[11] CFFEX is approved and governed by the State Council and CSRC.

ket allowed investors to circumvent some of the trading restrictions in the stock market. Furthermore, unlike the stock market, trading in the future market is dominated by domestic institutional investors and highly educated individuals.[12] Therefore, given the inherent trading advantages and investor characteristics, it is possible that the futures market would respond faster to the arrival of new information than the underlying equity market index, and play a leading role in the price discovery process. On the other hand, the presence of speculative trading in the futures market may exacerbate stock market volatility and vitiate the price discovery function of the index futures. Importantly, the stability of the price discovery and volatility spillover relationships may be subject to further modifications in light of the stock market crisis in 2015 and the regulatory curbs that were imposed in its immediate aftermath. Our paper will provide important insights that are germane to understanding these issues.

4 Data Description

Our study is based on data that includes intraday CSI 300 index prices and tick-by-tick transaction prices of the CSI 300 index futures. The sample period spans April 16, 2010 to December 31, 2015. The data is obtained from RESSET High Frequency Data System. It is compiled and calculated by the China Securities Index Company, Ltd..

At any given point, there are four CSI 300 index futures contracts, with different expiration days, traded simultaneously. The four expiration days correspond to the third Friday of the current month, the next month, and the subsequent two quarter-ending months. The futures contract is quoted in index points, and the contract size is the index point multiplied by RMB 300. The trading hours of the stock market is from 9:30 to 11:30 (morning session, Beijing Time) and from 13:00 to 15:00 (afternoon session, Beijing Time), Monday through Friday. Trading in the index futures begins 15 minutes before the morning session opens in

[12] According to Financial Times, "The individuals trading in Chinese futures are not generally the "Shanghai grannies" who crowd into equity brokerages.", May 6, 2016. https://www.ft.com/content/5094d2e8-1387-11e6-91da-096d89bd2173

the stock market, and ends 15 minutes after the close of the afternoon session. The stock and index futures markets are closed during the lunch hour between 11:30 to 13:00.

The CSI 300 index prices are compiled at 5-second intervals, while the futures data is compiled at the 1-second interval. For the purpose of empirical analysis the futures data are resampled at 5-second intervals in order to match a common data frequency for both time series. A continuous daily time series of index futures prices is constructed by using near term contracts and switching to the next term contracts when they are less than 10 days away from expiration.[13]

[Insert Figure 1 Here]

Figure 1 shows the daily movements of the two price series over the sample period. As shown in the figure, both the index and index futures prices track each other very closely. Furthermore, there appears to be three distinct phases in the price patterns over the sample period. First, the period between November 2010 and March 2014 is marked by a general decline in the stock market, with the stock index losing about 40% of its value during this time. This is followed by a short, but rapid, run-up in equity prices.During 2015 the stock index stacked up an impressive gain of 51% and reached its peak on June 12, 2015. Finally, the period between June 13, 2015 to December 31, 2015 witnessed steep declines in the market. From its peak, in a span of just 18 trading days the index lost nearly one-third of its value. In response to the crash, the Chinese government called into action several emergency measures in attempting to restore confidence in its financial markets. CSRC announced a series of restrictions to control the "inherent risks" of futures trading. The restrictions included increasing margin requirements, imposing position limits, and raising transaction fees in futures trading. The new policies were announced between August 3, 2015 and September 7, 2015. The initial measures seemed to stabilize the market, but only for a short while as prices fell sharply, by about 9%, on August 24, 2015.

[13] We also construct price series using 5 days and 15 days away from maturity. These alternative price series are used in robustness tests.

[Insert Table 1 Here]

Given the presence of various important market events in 2015, we test for the stability of the price dynamics and volatility spillover relationships by dividing the year into five sub-periods. They are as follows: Period A: 01/03/2015 to 04/30/2015; Period B: 05/01/2015 to 06/12/2015; Period C: 06/13/2015 to 07/08/2015; Period D: 07/09/2015 to 09/06/2015; and Period E: 09/07/2015 to 12/31/2015. The first period captures a dramatic rise of 30% in the market. During period B, the index was still in an uptrend, but at a much more moderate place. After dropping slightly from 4749 to 4553, the index continued going up and reached its peak of 5335, a rise of 17%. Periods A and B can be characterized as the two bullish time intervals in 2015. In period C, the index dropped nearly 31% in a span of 18 trading days to 3663. Finally, Period D captures the government announcements of regulatory restrictions in futures trading, while Period E takes into account the implementation of the changes.

Table 1 reports summary statistics for the stock index and futures daily return series for each year in the sample period (Panel A) and corresponding statistics for each of the five sub-periods in 2015 (Panel B). In general, the returns for both index futures and the index are very close to each other for all periods. It is interesting to observe that the index futures has higher maximum returns for all years, including all sub-periods in 2015. For instance, the maximum daily return of the index futures was about 7.08% in 2014; whereas, the maximum daily returns of the index was only about 4.61%. Similarly, the index futures exhibit lower minimum returns for all years, with the exception of 2012 and for the second sub-period B in 2015. Furthermore, with the exception of 2012, the standard deviations of the futures returns are higher than the stock index returns for all other years. Prior to 2015, the standard deviations are relatively close to each other; however, in 2015 the spread between the standard deviations of the futures and stock index returns is much larger than before. For instance, in sub-period D, the standard deviations of futures and stock index are 5.06% and 3.60%, respectively.

5 Methodology

The study employs the Hasbrouck (1995) information share (IS) analysis and a VAR-GARCH based model to examine price discovery and short-run volatility dynamics between the futures and stock index.

5.1 Information Share Analysis

Price discovery analysis is based on the econometrics of cointegrated vector autoregressions. Suppose we observe a price vector $P_t = [P_{1t}, P_{2t}]'$, where P_1 and P_2 are the time series of the "same" security at one or more market venues, which in our case refer to the CSI 300 index futures and CSI 300 index, respectively. In Hasbrouck (1995), the two price series are cointegrated on a daily basis, so their temporary divergence is accommodated by the cointegrating vector. The cointegration of prices implies that they may be represented in a vector error correction model (VECM) of order K.

$$\Delta P_t = \alpha\beta' P_{t-1} + \sum_{k=1}^{K} \varepsilon_K \Delta P_{t-k} + \varepsilon_t \quad , \tag{1}$$

where P_t is a vector of prices, α and β are the error correction vector and the co-integrating vector respectively, ε_K are matrices of autoregressive coefficients, and ε_t are error terms with constant variance Ω. This model can be represented by a vector moving average process:

$$P_t = \Psi(1) \sum_{v}^{t} \varepsilon_v + \Psi^*(L)\varepsilon_t \quad , \tag{2}$$

where $\Psi(1) = (1 + \Psi_1 + \Psi_2 + \cdots)$ and $\Psi^*(L)$ is a matrix polynomial in the lag operator (L). The first part on the right hand side of equation (2) measures the long-run impact of innovation on prices, i.e., the common factor component among the price series (Andersen and Bollerslev, 1998). The second part is transitory and measures the temporary influence on prices. Hasbrouck (1995) defines the information share (IS) for the i^{th} price series to be

$$IS_i = \frac{\psi_i^2 C_{ii}}{\psi \Omega \psi'} \quad , \tag{3}$$

where ψ is any identical row of $\Psi(1)$, C is the lower triangular Cholesky factorization of Ω . Upper and lower bounds of IS_i are calculated by applying different order of the Cholesky factorization. Baillie et al. (2002) find that the average IS from across all orderings is a reasonable estimate of that price series' contribution to price discovery.[14]

In order to reduce the number of parameters to estimate we follow Hasbrouck (2003) by constraining the set of coefficients to be constant or lie on a polynomial function of the lag. We estimate the IS model for each trading day containing approximately 2880 observations sampled at 5-second intervals. There are a total of 1385 trading days in our sample period.

5.2 Volatility Spillover Analysis

We use the VAR-GARCH model with BEKK specification to model volatility spillover between the underlying CSI300 index and index futures. In particular, we construct the following model:

$$\Delta P_t = \mu + \sum_{i=1}^{k-1} \Gamma_i \Delta P_{t-i} + \varepsilon_t, \qquad \varepsilon_t | \mathcal{F}_{t-1} \sim N(0, H_t) \quad , \tag{4}$$

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon_{t-1}^{'} A + B' H_{t-1} B \quad , \tag{5}$$

where $P_t = \begin{pmatrix} P_{1t} \\ P_{2t} \end{pmatrix}$, $\mu = \begin{pmatrix} \mu_1 \\ \mu_2 \end{pmatrix}$, $\Gamma_i = \begin{pmatrix} \Gamma_{11} & \Gamma_{12} \\ \Gamma_{21} & \Gamma_{22} \end{pmatrix}$, $\varepsilon_t = \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix}$, and $H_t = \begin{pmatrix} h_{11} & h_{12} \\ h_{21} & h_{22} \end{pmatrix}$. Ω_{t-1} represents the conditioning information set at time t-1, and H_t represents the conditional covariance matrix at time t. A , B , and C are matrices.

The information transmission through the volatility linkage is analyzed by estimating the

[14] The interested reader is referred to Hasbrouck (1995, 2003) and Baillie et al. (2002) for more details on the information share estimation procedure.

conditional covariance matrix H_t equation. There are several parameters to estimate in the conditional covariance matrix H_t in multivariate GARCH models (Engle and Kroner, 1995). Therefore, a bivariate GARCH (1, 1)-BEKK specification is adopted as follows:

$$\begin{aligned} H_t = & \begin{pmatrix} c_{11} & c_{12} \\ 0 & c_{22} \end{pmatrix}' \begin{pmatrix} c_{11} & c_{12} \\ 0 & c_{22} \end{pmatrix} \\ & + \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix}' \begin{pmatrix} \varepsilon_{1,t-1}^2 & \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{2,t-1}\varepsilon_{1,t-1} & \varepsilon_{2,t-1}^2 \end{pmatrix} \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix} \\ & + \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix}' \begin{pmatrix} h_{11,t-1} & h_{12,t-1} \\ h_{21,t-1} & h_{22,t-1} \end{pmatrix} \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix} . \end{aligned} \tag{6}$$

Equation (6) describes how information and volatility are temporally transmitted across the stock index and index futures markets. The impact of volatility across stock index and index futures, can be observed through the following four channels: past squared errors or deviations from the mean of $(\varepsilon_{1,t-1}^2, \varepsilon_{2,t-1}^2)$, past conditional volatility $(h_{11,t-1}, h_{22,t-1})$, indirectly through the covariance term $(h_{12,t-1})$ and cross-product of error term $(\varepsilon_{1,t-1}\varepsilon_{2,t-1})$. The impact of the residual term could be interpreted as the return innovation effect; the impact of cross-product error terms could be interpreted as the potential presence of bi-directional shock; the impact of the variance could be interpreted as an indication of volatility persistence (from its own lagged terms) and volatility spillover effect (from the cross-market lagged terms). According to Edy (2002), shocks in asset returns take effect directly through the residuals first, and then the impact of the lagged variance on the present variance would cause an effect which occurs in the variance equation again. In equation (6), the impact of "new information" from the second market (CSI 300 index) to the first market (CSI 300 index futures) is measured by coefficients a_{21}^2, while the corresponding impact from the first market to the second market is measured by coefficients a_{12}^2. The effect of past volatility in the second market on the conditional variance of the first market is measured by b_{21}^2, and the effect of past volatility in the first market on the conditional variance of the second market is measured by b_{12}^2. The equations are estimated simultaneously using maximum likelihood estimation. There are two advantages of this model. First, the conditional covariance matrix is guaranteed to be positive semi-definite with this specification. Second, the off-diagonal parameters in matrices A and B are used to explain the volatility spillover effect.

6 Empirical Results

6.1 Information Share

Tables 2 and 3 presents the IS results at the 5-second frequency level. It provides the means, medians and standard deviations across days for both the upper bound, lower bound and the average of upper and lower bounds in each sample period.

[Insert Table 2 Here]

The results indicate that index futures play a dominant role in price discovery. The IS (the average of the bounds) attributed to futures prices is above 67% for each year over the sample period. The standard deviation and the spreads between the upper bounds and lower bounds are relatively small, which support the reliability of the IS estimates. In observing the average yearly IS estimates of CSI 300 futures we notice that it is 78% in 2010, stays above 80% from 2012 to 2014, but drops significantly to 67% in 2015. Given the turbulent market events in 2015, Table 3 provides additional insights into the IS characteristics during this year. The results show that the average IS of the futures market is 78% at the start of 2015, but monotonically declines each consecutive period during the year before reaching a low of 53% by the end of the year.

Tables 4 provides results from t-tests that compare IS of the futures market in 2015 with prior years as well as across different time periods within the year.

[Insert Table 4 Here]

Table 4 indicates that the IS contribution of the index futures in 2015 (67%) is smaller and statistically different from the average IS over the 2010 to 2014 period (81%). There is also significant variation in IS of the futures market during 2015. With the exception of Period A, for all remaining periods in 2015, the IS attributed to the futures market is smaller and statistically significant when compared with prior years. Within 2015 the futures IS is not statistically different between Period C (market slump period) and Periods A and B, and furthermore, Period D shows no statistical difference from Periods A, B and C. However, there is a perceptible reduction of futures IS, statistically significant at the 1% level, during the last period of 2015 (Period E).

[Insert Figure 2 Here]

The dynamic changes in IS are illustrated in Figure 2, which plots the evolution of the monthly averages of IS for both futures and stock index. The plot shows that the IS of the futures index clearly dominate stock index across the sample period, with the exception of September 2015 where we find that the futures volume to drop precipitously (over 90%) on September 7, 2015. It also shows that the regulatory intervention by the government resulted in diminishing the IS of the futures market; however, even in the presence of the intervention, the futures market still leads the stock index in terms of price discovery.

In 2015, the CFFEX took a string of unprecedented regulatory interventions to restrict futures trading through margin requirements, transaction fees and position limits. The impact of specific regulatory actions on price discovery is examined by estimating IS of the futures market during a 30-day window surrounding each intervention. Table 5 provides a detailed timeline of important regulatory actions taken in 2015[15] and Table 6 provides corresponding IS estimates.

[Insert Tables 5 and 6 Here]

[15] All information about regulatory changes are obtained from the CFFEX website: http://www.cffex.com.cn/tzgg/jysgg

Ironically, right before the market crash in June 2015, the CFFEX significantly increased the position limit for the speculative traders from 600 contracts to 5000 contracts on April 10, 2015. In response, the futures IS increased significantly from 0.745 to 0.836. After the market crash, on August 3, 2015, margin requirements were increased from 0.015 ‰to 0.023 ‰. This resulted in decreasing the futures IS, but the change is not statistically significant. Finally, starting August 26, 2015 the CFFEX imposed a series of punitive measures, almost on a daily basis, to curb speculative activities in the index futures market. This lasted until September 7, 2015.

Specifically, margin requirements for futures trading was increased to 40% of the contract value.[16] The transaction fees for daily purchases and sales were raised 100-fold, from 0.023 ‰to 2.3 ‰. Finally, the CFFEX imposed position limits for all investors deemed to engage in "abnormal trading" – i.e., defined as anyone opening a position of more than 10 contracts on any single day – which immediately triggered a 90% decline in the stock index futures transaction. Results in Table 6 show that these series of actions between August 26, 2015 and September 7, 2015 resulted in a 41% decrease in futures IS from 0.721 to 0.423.[17]

6.2 Volatility Spillover

This section discusses the volatility spillover relationship between the CSI 300 index futures and the underlying stock index. We run a VAR(1)-BEKK-GARCH model for each trading day at the 5-second frequency across the entire sample period.

[Insert Table 7 Here]

Table 7 presents the estimates of average squared a_{21} (a_{12}) for each year (Panel A) as

[16] More specifically, the margin requirement was increased by 2%, 3% and 5% on the first three days, respectively, and then by 10% each trading day thereafter until it reached 40%.

[17] Note that the futures market was closed from August 29 to August 30 for weekend, and from September 02, 2015 to September 06, 2015 for a major military parade to commemorate the end of World War II and subsequent weekend, therefore we consider these consecutive regulation interventions as one major change during this very short period.

well as for the different sub-periods in 2015 (Panel B).[18] The results reveal the presence of significant volatility linkages between the CSI 300 index and index futures throughout the sample period. For instance, in 2010, a 1-unit shock in excess returns at time t–1 on the stock index increases the volatility in the futures markets by about 5.23% units at time t. In contrast, a 1-unit shock in excess returns at time t–1 on the futures increases the volatility in the stock index by only about 0.19% unit at time t. The t-tests confirm that the differences between a_{21} and a_{12} are statistically significant for each year in the sample period. Furthermore, the coefficient of importance, a_{21}, is significantly larger in magnitude than that of a_{12}. Overall, results indicate that return innovations from stock index have a relatively larger impact on conditional volatility in futures market, than the corresponding impact of the futures index on the stock market.

Figure 3 illustrates the monthly evolution of the two ARCH terms (a_{21} and a_{12}). Average a_{21} starts at 5.23% in 2010 and decreases to the minimum (2.00%) in the 2012, and then reverses to 6.00% in 2015. By comparison a_{12} achieves its maximum (1.42%) in 2013 and then drops to 0.33% in 2015, indicating that the interaction of information transmission through volatility between the two markets follows different temporal patterns. Consistent with results in Table 7, the monthly average a_{21} is generally greater than that of a_{12}.[19] Right after the launch of the CSI 300 index futures in April 2010, a_{21} increases dramatically and reaches its multi-year peak within the first 4 months, while a_{12} remains relatively stable for the next two years. These findings support Yang et al. (2012) who document that return shocks in futures market do not have a significant influence on the conditional volatility of the stock index. In contrast, it is the return shock of CSI 300 index that has an increasing influence on the conditional volatility of the futures. In addition, during our sample period, a_{21} is more volatile than a_{12}; whereas, a_{12} is relatively stable until July 2012, but then

[18] We run the model for each trading day at the 5-second frequency, and equals all the insignificant parameters (at 5% significant level) to zero and then take average by each year or each sup-period. We refer to the squared parameter in the following discussion.

[19] During all sample period, the average a_{21} falls below the average a_{12} for only eight times (August 2012, September 2012, October 2012, November 2012, October 2013, November 2013, February 2014 and July 2014).

exhibits greater volatility during the period August 2012 to April 2014. After July 2014, the influence of the returns shocks in futures on the conditional volatility of stock index is relatively weak.

[Insert Figure 3 Here]

Table 7 also reports the GARCH terms b_{12} and b_{21} as measures of the cross-market conditional volatility dynamics between the two markets. The non-zero average b_{12} and b_{21} indicates strong bidirectional volatility linkages between the two markets. For instance, in 2010, a 1-unit volatility increase in stock index at t–1 increases the conditional variance in futures by about 10.43% units in period t; while a 1-unit of volatility increase in futures at t–1 increases the conditional variance in stock index by only about 3.46% units in period t. The coefficient b_{21} is larger than b_{12} for most years;[20] whereas, the differences between the two GARCH terms are only statistically different for three out of the six years in the sample. In general, results document that the dominant volatility spillover effect is from the stock index to the futures market.

[Insert Figure 4 Here]

Figure 4, shows the monthly behavior of the GARCH parameters b_{12} and b_{21}. The graph confirms the relative importance of the conditional volatility of the stock index in influencing the volatility of futures returns. Beginning April 2010 to October 2011, b_{12} keeps increasing and reaches its peak (0.192) in October 2011. Similar to the results from return shocks, starting July 2014 there is a perceptible downward trend in b_{12}. The average b_{12} is 0.093 in July 2014 and falls to 0.009, a 90% decrease within a span of 13 months.

Overall, results suggest strong feedback effects, with volatility in the stock index dominating the relationship. The futures market is found to be more highly sensitive to information (both return shocks and past conditional volatility) emanating from the stock index. These

[20]With only two notable exceptions: b_{21} is 7.53%, smaller than b_{12} (8.85%) in 2012 and b_{21} (1.164%) is also smaller than b_{12} (1.957%) in sub-period C in 2015.

results, which corroborate previous findings, may be explained in the context of the unique institutional and market features in China. Due to high entry barriers, futures market investors are predominated by institutional investors, while the Chinese stock market is dominated by smaller retail investors. The former clientele are more capable of analyzing and interpreting new information, and therefore believed to contribute more towards information.

On the other hand, the predominance of individual retail investors in the underlying stock market can explain its somewhat weak response to information originating from the futures market. This can be seen by the relatively lower a_{12} compared to a_{21}, and b_{12} compared to b_{21}. It is also important to highlight that the weak influence of futures volatility is found to be even more subdued during 2015.

[Insert Tables 8 and 9 Here]

These findings are presented in Tables 8 and 9. The tables report the statistical tests of the mean differences in the relevant ARCH and GARCH terms for different sample periods. Several important results are evident from conducting a joint examination of the two tables. First, with the exception of the last period in 2015 (Period E), a_{21} is not found to be statistically different from each other. There is no evidence that the influence of return shocks from the stock index on the conditional volatility of futures changed or weakened during much of 2015. However, there is a significant increase in a_{21} during Period E (9.589% compare to an average of 4.265% for Periods A through D, and 3.328% for 2010 to 2014). The t-stats are both significant at the 1% level. The results highlight that only during period E, with the implementation of trading restrictions, did return shocks in the stock index heighten the conditional volatility in futures. Second, and equally important, for periods B to E in 2015, a_{12} is statistically significantly smaller than the period 2010 to 2014. In particular, the periods D and E show smallest a_{12} among all the periods. The evidence indicates that the impact of return shocks of futures prices on the volatility of spot market gets gradually weaker in 2015. Third, a somewhat similar pattern can be found for the GARCH terms (b_{12} and b_{21}). For 2015 as a whole, b_{21} is not significantly different from the previous years (10.140% vs. 11.217%). However, b_{12} is significantly smaller than the corresponding averages for 2010 to 2014 (2.808% vs 8.508%). Finally, in examining the market crisis period (Period C), both a_{12} and b_{12} decreases significantly when compared with previous years (2010-2014) as well as Periods A and B in 2015. In other words, the futures market did not seem to exacerbate the volatility in the stock index during this period. During Period D, both a_{12} and b_{12} decrease even further while both a_{21} and b_{21} remain largely unchanged, which suggests that the announcement of trading restrictions may have partly contributed to the diminishing influence of the futures market on the stock market. More broadly, the evidence from the volatility spillover analysis undercuts regulatory claims that the index futures played a destabilizing role in precipitating the crisis.

In concluding the empirical analysis, it is worth mentioning that due to the unique nature of the study our results are not directly comparable with prior examinations in this area. Having said this, however, our results generally support the accumulating evidence of price leadership by the futures market and the stabilizing influence of index futures on the stock market. Furthermore, comparisons of price discovery before and after the dramatic regulatory changes in China's market provide new evidence that regulatory policy shocks combined with an increase in trading costs and decline in trading volume resulted in a significant impact on price discovery and information transmission. The results are consistent with the "policy spillover" effect and "trading cost" hypothesis proposed in the literature (Fleming et al. 1996; Ito and Lin 2001).

7 Robustness Checks

In order to test the robustness of our conclusions we conduct several additional tests along two broad dimensions.[21] First, we re-estimate the IS and volatility spillover regression models using alternative futures price series, constructed from different roll-over dates. Specifically,

[21] In order to conserve space, these results are not provided, but can be obtained from the authors upon request.

we stitch together a continuous price series by using the near term contract and switching to the next front-month contract when it is less than 5 and 15 days away from expiration, respectively (instead of 10 days). Second, we employ a different price discovery metric, termed the information leadership share (ILS) proposed by Putnins (2013). Under specific assumptions, ILS provides a more robust measure of the contribution of a price series to impounding new information. One key assumption of ILS, however, is that the structural model has only one permanent and one transitory shock. In our study, given the presence of multiple changes in the stock market and trading environment during 2015, the results obtained from ILS must be interpreted with some caution.

Results from robustness tests generally corroborate our main conclusions. Using different roll-over procedures, we find that price discovery of the futures market decreased significantly in 2015 compared to previous years. An analysis of specific regulatory events indicates that futures ILS increased significantly after position limits were relaxed on April 10, 2015. However, in contrast to earlier findings, we find that restrictive regulations from August 26, 2015 to September 7, 2015 did not have a significant impact on the price leadership of the futures market. We propose that this confounding result might be an artifact of the limitations of ILS in the presence of multiple shocks in the structural model (see Putnins, 2017). Finally, in terms of volatility spillover, using alternative roll-over dates we are able to corroborate earlier evidence that establish information linkages between the CSI 300 index and index futures. Specifically, return innovations from stock index have a disproportionately larger impact on futures conditional volatility, and furthermore the dominant volatility spillover effect is from the stock index to the futures market. Overall, robustness results support our central findings related to the role of index futures on China's stock market.

8 Concluding Remarks

The introduction of stock index futures in China in April 2010 marked an important development in the country's financial markets. It signified a growing maturity of China's financial markets as well as confidence that futures markets would play a stabilizing role in the stock market. However, the stock market crash in 2015 led to intense government scrutiny that called into question the moderating influence and efficacy of the futures market. In particular, regulators blamed trading in the index futures to exacerbate stock market volatility and cause its precipitous decline. Given this backdrop, this paper formally investigates the intraday price discovery and volatility spillover relationships between the CSI 300 equity index and index futures in China.

The study measures the extent to which the futures market impounds new information about the "true" value of the underlying asset. We consider an expansive sample period, 2010 through 2015, to conduct our analysis and use the Hasbrouck Information Share and VAR-GARCH methodologies to examine the characteristics of price discovery and volatility dynamics, respectively. Results from the study indicate that the index futures market play a dominant role in the overall price discovery, with an average yearly information share of 67%. Using a detailed timeline of specific regulatory actions between April 2015 and September 2015 we show that the price discovery contribution of the futures market, while still strong, is found to be significantly diminished in the presence of stringent trading curbs that were put in place by the government as a response to the crisis. The findings are explained in the context of high trading barriers in the futures market as well as an investor clientele in the futures market that may be more adept in contributing towards price discovery.

Our investigation into volatility transmission document asymmetrical feedback effects between the CSI 300 stock and future indexes. There is evidence of bi-directional volatility linkages; however, it is the return and volatility shocks from the stock market that dominate the relationship. The presence of different types of investor clienteles in the stock versus futures markets offer a potential explanation to this result. In particular, we argue that the prevalence of more sophisticated institutional trades in the futures market may render this market to be more sensitive to new information arising from the stock market. On the other hand, the preponderance of individual small investors in the stock market may impair the market's ability to respond quickly to information shocks originating from the futures market. It is worth noting that the influence of both returns and volatility shocks from the futures market on the conditional variance in the stock market is even lower during the crisis period in 2015. Overall, our evidence undercuts Chinese regulatory claims that blame the index futures market for increased stock market volatility.

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Table 1: Summary Statistics of CSI 300 Stock Index and Futures Index Return Series

This table reports summary statistics of the daily return series of the CSI 300 Index (Index) and CSI Index Futures (Futures) for each year in the sample period and five sub-periods in 2015. The five sub-periods in 2015 are as follows: 01/03/2015-04/30/2015 (2015 A), 05/01/2015-06/12/2015 (2015 B), 06/13/2015-07/08/2015 (2015 C), 07/09/2015-09/06/2015 (2015 D), and 09/07/2015-12/31/2015 (2015 E), respectively. The return and standard deviation are reported in percentage.

Period	Max		Average		Min		Std. Dev.	
	Futures	Index	Futures	Index	Futures	Index	Futures	Index
Panel A: Year by Year								
2010	4.299	3.789	-0.030	-0.026	-6.732	-6.147	1.888	1.695
2011	3.739	3.655	-0.112	-0.109	-4.006	-3.793	1.264	1.298
2012	5.614	5.004	0.038	0.038	-2.779	-2.820	1.244	1.282
2013	6.387	4.635	-0.023	-0.024	-6.626	-6.289	1.416	1.399
2014	7.077	4.614	0.184	0.179	-4.926	-4.386	1.378	1.216
2015	10.211	6.697	0.060	0.053	-9.916	-8.791	3.207	2.483
Panel B: Sub-periods in 2015								
2015 A	4.685	4.461	0.388	0.395	-9.527	-7.707	2.024	1.736
2015 B	7.188	4.837	0.427	0.412	-6.556	-6.705	2.504	2.246
2015 C	9.524	6.697	-2.510	-2.111	-8.509	-7.879	5.127	4.024
2015 D	10.211	6.404	-0.233	-0.147	-9.916	-8.791	5.063	3.602
2015 E	7.391	4.981	0.295	0.147	-6.962	-5.385	2.438	1.826

Table 2: Yearly Information Share

This table reports results from the information share model that is estimated daily for each year across the sample period. The mean, median, and standard deviation of the upper and lower bounds are reported. The corresponding summary statistics of the average of the lower and upper bounds are also reported.

Period	Asset	Upper Bound			Lower Bound			Average of Bounds		
		Mean	Median	Std. Dev.	Mean	Median	StDev	Mean	Median	StDev
2010	Future	0.791	0.860	0.200	0.768	0.826	0.208	0.780	0.850	0.204
	Index	0.232	0.174	0.208	0.209	0.140	0.200	0.220	0.150	0.204
2011	Future	0.818	0.871	0.190	0.799	0.857	0.200	0.809	0.863	0.194
	Index	0.201	0.143	0.200	0.182	0.129	0.190	0.191	0.137	0.194
2012	Future	0.855	0.926	0.174	0.818	0.893	0.192	0.837	0.907	0.182
	Index	0.182	0.107	0.192	0.145	0.074	0.174	0.163	0.093	0.182
2013	Future	0.863	0.936	0.168	0.789	0.851	0.204	0.826	0.892	0.184
	Index	0.211	0.149	0.204	0.137	0.064	0.168	0.174	0.108	0.184
2014	Future	0.842	0.911	0.197	0.774	0.837	0.226	0.808	0.873	0.210
	Index	0.226	0.163	0.226	0.158	0.089	0.197	0.192	0.127	0.210
2015	Future	0.724	0.810	0.260	0.615	0.673	0.273	0.670	0.737	0.262
	Index	0.385	0.327	0.273	0.276	0.190	0.260	0.330	0.263	0.262

Table 3: Information Share of Index Futures for the Various Sub-periods in 2015

This table reports results of the information share model, estimated daily, for the five sub-periods in 2015. The five sub-periods are as follows: 01/03/2015-04/30/2015 (2015 A), 05/01/2015-06/12/2015 (2015 B), 06/13/2015-07/08/2015 (2015 C), 07/09/2015-09/06/2015 (2015 D), and 09/07/2015-12/31/2015 (2015 E), respectively. The mean, median, and standard deviation of the upper and lower bounds are reported. The corresponding summary statistics of the average of the lower and upper bounds are also reported.

Period	Asset	Upper Bound			Lower Bound			Average of Bound		
		Mean	Median	Std. Dev.	Mean	Median	StDev	Mean	Median	StDev
2015 A	Future	0.832	0.902	0.173	0.729	0.793	0.207	0.781	0.852	0.189
	Index	0.271	0.207	0.207	0.168	0.098	0.173	0.219	0.148	0.189
2015 B	Future	0.798	0.839	0.158	0.635	0.660	0.195	0.716	0.749	0.175
	Index	0.365	0.340	0.195	0.202	0.161	0.158	0.284	0.251	0.175
2015 C	Future	0.789	0.886	0.255	0.613	0.724	0.271	0.701	0.815	0.260
	Index	0.387	0.276	0.271	0.211	0.114	0.255	0.299	0.185	0.260
2015 D	Future	0.721	0.835	0.298	0.639	0.685	0.307	0.680	0.761	0.302
	Index	0.361	0.315	0.307	0.279	0.165	0.298	0.320	0.239	0.302
2015 E	Future	0.577	0.550	0.279	0.483	0.469	0.288	0.530	0.525	0.273
	Index	0.517	0.531	0.288	0.423	0.450	0.279	0.470	0.475	0.273

Table 4: Changes in Information Share of Index Futures across Different Periods

This table reports t-test results of the differences between means of the futures market information share (the average of bounds) for different periods. The five sub-periods in 2015 are as follows: 01/03/2015-04/30/2015 (2015 A), 05/01/2015-06/12/2015 (2015 B), 06/13/2015-07/08/2015 (2015 C), 07/09/2015-09/06/2015 (2015 D), and 09/07/2015-12/31/2015 (2015 E), respectively. The subscripts ***, **, *, indicate statistical significance at the 1%, 5%, and 10%, respectively.

Time Periods		Information Share			
Period 1	Period 2	Period 1	Period 2	Difference	T-stat
2015	2010-2014	0.670	0.814	-0.144	-8.115***
2015 A	2010-2014	0.781	0.814	-0.033	-1.480
2015 B	2010-2014	0.716	0.814	-0.098	-2.996***
2015 C	2010-2014	0.701	0.814	-0.113	-1.779*
2015 D	2010-2014	0.678	0.814	-0.136	-2.758***
2015 E	2010-2014	0.530	0.814	-0.284	-9.077***
2015 C	2015 A,B	0.701	0.763	-0.062	-0.943
2015 D	2015 A,B,C	0.678	0.755	-0.077	-1.474
2015 E	2015 A,B,C,D	0.530	0.736	-0.206	-5.804***

Table 5: Timeline of Regulatory Changes in 2015

Notes: This table reports the timeline of each regulatory intervention in 2015. The symbol “-” represents no change.

Date	Required margin for non-hedger	Required margin for hedger	Transaction fee	Position limit for speculative trader
Before April 10, 2015	10%	10%	0.015‰	600 contracts
April 10, 2015	-	-	-	5000 contracts
August 3, 2015	-	-	0.023‰	-
August 26, 2015	12%	-	0.115‰	-
August 27, 2015	15%	-	-	-
August 28, 2015	20%	-	-	-
August 31, 2015	30%	-	-	-
September 7, 2015	40%	20%	2.3‰	more than 10 contracts is “abnormal” trading

Table 6: Changes in Information Shares of Index Futures Surrounding Each Regulatory Action

This table reports t-test results of the differences between means of the futures market information share (the average of bounds) for each regulatory change spanning thirty trading days pre- and post- intervention date. The subscripts ***, **, *, indicate statistical significance at the 1%, 5%, and 10%, respectively.

Regulatory Changes	Before	After	Difference	T-stat
April 10, 2015	0.745	0.826	0.081	1.713^{*}
August 3, 2015	0.669	0.623	−0.046	−0.576
August 26, 2015 - September 7, 2015	0.721	0.423	−0.298	-4.317^{***}

Table 7: Volatility Spillover Effect

The table reports the average of the relevant ARCH and GARCH terms estimated daily using the VAR-GARCH-BEKK model. The yearly average of the coefficients for 2010-2015 and the average for the various sub-periods in 2015 are reported. The five sub-periods for 2015 are as follows: 01/03/2015-04/30/2015 (2015 A), 05/01/2015-06/12/2015 (2015 B), 06/13/2015-07/08/2015 (2015 C), 07/09/2015-09/06/2015 (2015 D), and 09/07/2015-12/31/2015 (2015 E), respectively. The parameters are reported as a percentage.

Year	a_{21}	a_{12}	Difference	T-Stat	b_{21}	b_{12}	Difference	T-Stat
Panel A: Year by Year								
2010	5.228	0.189	5.039	6.710***	10.428	3.463	6.965	2.728***
2011	4.557	0.624	3.933	6.506***	12.008	11.544	0.464	0.226
2012	1.996	0.997	0.999	3.353***	7.530	8.850	−1.319	−0.877
2013	2.447	1.421	1.026	3.112***	11.406	9.660	1.746	0.944
2014	3.002	1.317	1.685	4.172***	14.287	7.478	6.809	3.336***
2015	5.997	0.328	5.670	7.581***	10.140	2.808	7.332	2.348**
Panel B: Sub-periods in 2015								
2015 A	3.988	0.764	3.224	3.606***	3.713	3.705	0.008	0.008
2015 B	5.898	0.127	5.771	3.350***	3.056	2.974	0.083	0.057
2015 C	3.336	0.260	3.075	2.699**	1.164	1.957	−0.793	−0.994
2015 D	3.920	0.105	3.816	3.112***	10.581	0.787	9.794	1.893*
2015 E	9.598	0.100	9.497	5.123***	20.892	3.032	17.860	1.963*

Table 8: Mean Differences of Return Shocks

This table reports the t-test of differences between the relevant ARCH terms for different examination periods. The means of the parameters, a_{12}, and a_{21} are reported in percentage. The five sub-periods in 2015 are as follows: 01/03/2015-04/30/2015 (2015 A), 05/01/2015-06/12/2015 (2015 B), 06/13/2015-07/08/2015 (2015 C), 07/09/2015-09/06/2015 (2015 D), and 09/07/2015-12/31/2015 (2015 E), respectively. The subscripts ***, **, *, indicate statistical significance at the 1%, 5%, and 10%, respectively.

Period		a_{21}				a_{12}			
Period 1	Period 2	Period 1	Period 2	Difference	T-stat	Period 1	Period 2	Difference	T-stat
2015	2010-2014	5.997	3.328	2.669	3.442***	0.328	0.950	−0.622	−8.875***
2015 A	2010-2014	3.988	3.328	0.660	0.723	0.764	0.950	−0.186	−1.570
2015 B	2010-2014	5.898	3.328	2.570	1.481	0.127	0.950	−0.823	−13.016***
2015 C	2010-2014	3.336	3.328	0.008	0.007	0.260	0.950	−0.689	−7.832***
2015 D	2010-2014	3.920	3.328	0.592	0.476	0.105	0.950	−0.845	−11.285***
2015 E	2010-2014	9.598	3.328	6.270	3.361***	0.100	0.950	−0.850	−13.918***
2015 C	2015 A,B	3.336	4.529	−1.193	−0.857	0.260	0.583	−0.323	−3.103***
2015 D	2015 A,B,C	3.920	4.372	−0.452	−0.319	0.105	0.541	−0.437	−5.111***
2015 E	2015 A,B,C,D	9.598	4.265	5.333	2.731***	0.100	0.437	−0.337	−5.567***

Table 9: Mean Differences of Volatility Shocks

This table reports the t-test of differences between the relevant GARCH terms for different examination periods. The means of the parameters, b_{12}, and b_{21} are reported in percentage. The five sub-periods in 2015 are as follows: 01/03/2015-04/30/2015 (2015 A), 05/01/2015-06/12/2015 (2015 B), 06/13/2015-07/08/2015 (2015 C), 07/09/2015-09/06/2015 (2015 D), and 09/07/2015-12/31/2015 (2015 E), respectively. The subscripts ***, **, *, indicate statistical significance at the 1%, 5%, and 10%, respectively.

Period		b_{21}				b_{12}			
Period 1	Period 2	Period 1	Period 2	Difference	T-stat	Period 1	Period 2	Difference	T-stat
2015	2010-2014	10.140	11.217	−1.077	−0.334	2.808	8.508	−5.700	−13.286***
2015 A	2010-2014	3.713	11.217	−7.504	−6.000***	3.705	8.508	−4.803	−8.313***
2015 B	2010-2014	3.056	11.217	−8.161	−5.253***	2.974	8.508	−5.534	−8.072***
2015 C	2010-2014	1.164	11.217	−10.053	−10.050***	1.957	8.508	−6.551	−9.916***
2015 D	2010-2014	10.581	11.217	−0.636	−0.122	0.787	8.508	−7.721	−19.488***
2015 E	2010-2014	20.892	11.217	9.675	1.061	3.032	8.508	−5.476	−8.741***
2015 C	2015 A,B	1.164	3.527	−2.363	−2.473**	1.957	3.498	−1.541	−2.296**
2015 D	2015 A,B,C	10.581	3.217	7.363	1.412	0.787	3.296	−2.509	−6.596***
2015 E	2015 A,B,C,D	20.892	4.966	15.926	1.734*	3.032	2.700	0.332	0.567

Figure 1: Price Movements of the CSI 300 Equity Index and Index Futures

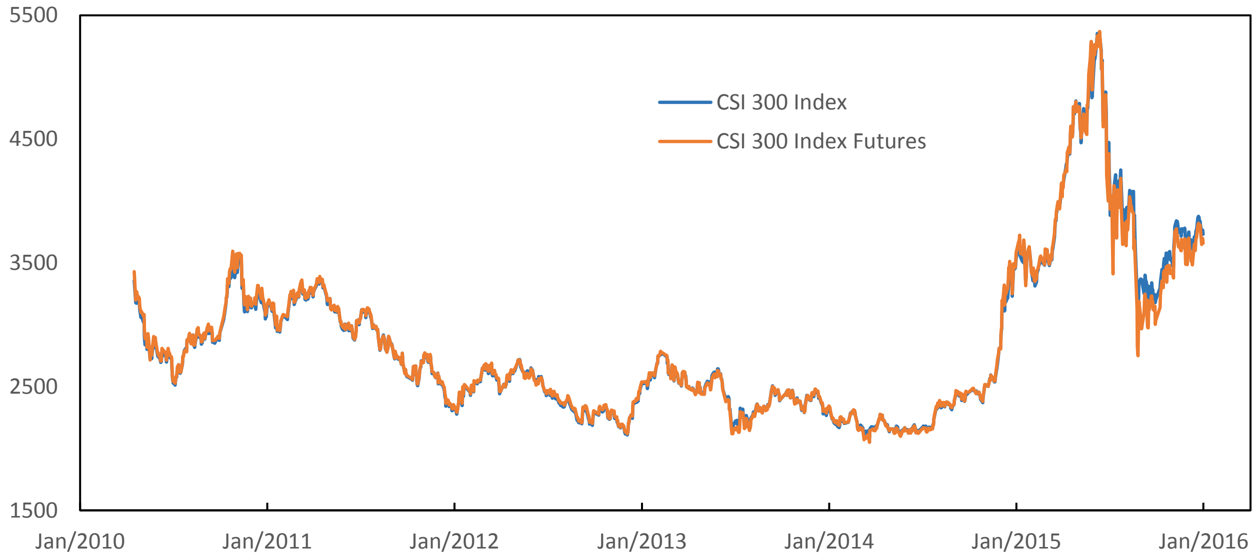

Figure 2: Monthly Average of the Information Share Contribution of the Futures Market

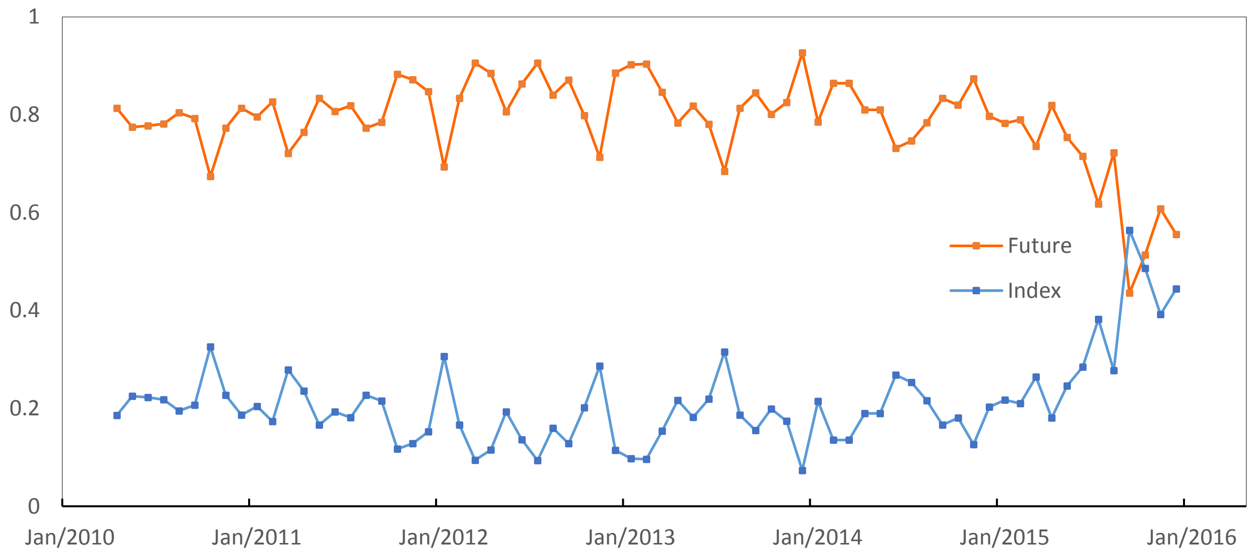

Figure 3: Monthly Average of the Impact of Return Shocks

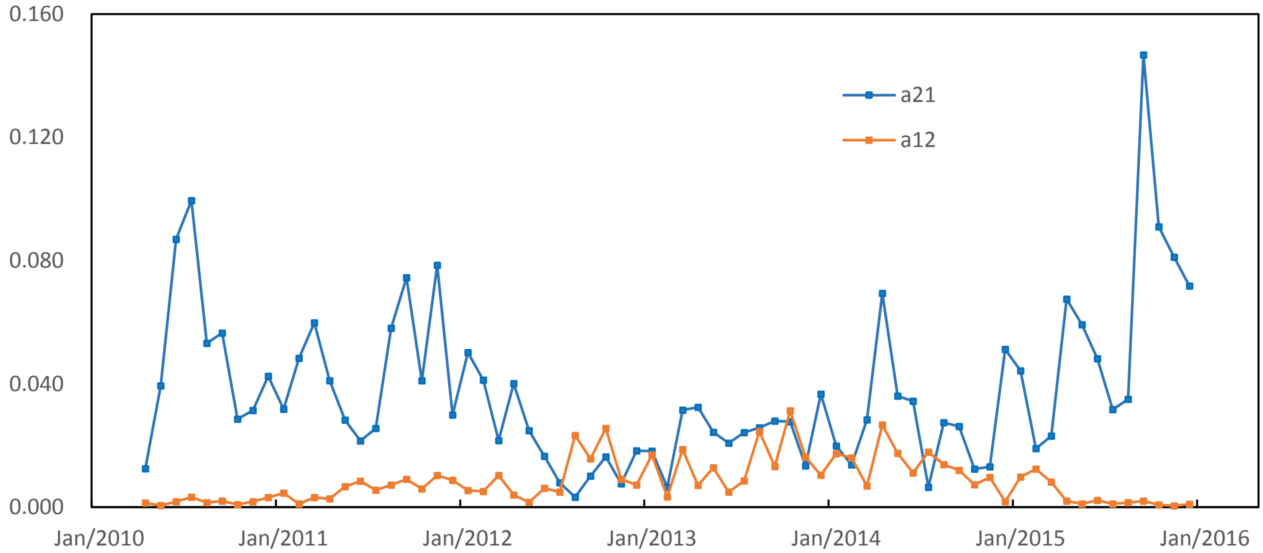

Figure 4: Monthly Average of the Impact of Volatility Shocks