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The Effect of Index Futures Trading on Volatility: Three Markets for Chinese Stocks.*

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Abstract

This paper examines whether the introduction of Chinese stock index futures had an impact on the volatility of the underlying spot market. To this end, we estimate several Generalized Auto-Regressive Conditional Heteroscedasticity (GARCH) models and compare our findings for mainland China with Chinese index futures traded in Singapore and Hong Kong. Our results indicate that Chinese index futures decrease spot market volatility in all three spot markets considered. In contrast, we do not obtain the same results for the companion index futures markets in Hong Kong and Singapore. China's stock market is relatively young and largely dominated by private retail investors. Nevertheless, our evidence is favorable to the stabilization hypothesis usually confirmed in mature markets.

JEL Classification: G10, G14, G15, G18

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1 Introduction

Since the introduction of index futures trading, extensive research has been devoted to the question whether index futures trading results in volatility spillovers between futures markets and their underlying spot markets. A vast part of the literature has upheld the so-called stabilization hypothesis which posits that futures markets reduce volatility of the underlying spot market. By contrast, others find that the introduction of futures markets increases stock market volatility. Unsurprisingly, this phenomenon is referred to as the destabilization hypothesis.

Many of the futures markets investigated in the literature are homogeneous in terms of their investor structure. Historically, the introduction of futures trading in developed financial markets coincided with the rise of institutional ownership in the early 1980s. Hence, futures markets typically investigated in the earlier literature are dominated by institutional investors. These institutions are presumed to be run by well-informed, rational investors as opposed to individual investors, who are viewed as uninformed or driven by sentiment or other behavioral biases (Lee et al., 1999; Cohen et al., 2002; Barber and Odean, 2008; Kaniel et al., 2008). Early empirical findings indicate evidence in favor of the stabilizing hypothesis for mature financial markets dominated by institutional investors. In contrast, papers focusing on developing derivatives markets typically dominated by individual investors report evidence in favor of the destabilizing hypothesis.

China's stock index futures provides a unique and interesting setting for research: it is a large market dominated by private investors as opposed to institutional investors. It is the first market in mainland China, where futures on Chinese stock indices can be bought. Previously, investors' only option was to trade Chinese stock index futures offshore in Singapore and Hong Kong. Accordingly, we compare our findings to developments in both the A50 and HSCEI sister markets. This makes an investigation of the introduction of a mainland market all the more interesting from the perspective of the stabilizing role of futures markets. Equally important is that, given their location, there may well be spillover effects between the three markets that are also considered in this study. To the extent that there are institutional characteristics which may lead to differences in market behavior it is of considerable interest to investigate these effects. This also represents another feature of our analysis which, as far as we are aware, has not before been considered in the extant literature.

On April 16, 2010, the Shanghai-based China Financial Futures Exchange (CFFEX) launched the country's first stock index futures on the CSI300 index. With 93.3 million futures contracts traded with a notional value of USD 12.1 trillion in 2012, the CSI300 index futures market is one of the largest in the world. At the same time, it is a tightly regulated market with high barriers to entry and an interesting investor structure: 98 percent of CSI300 index futures market participants are so-called retail investors; only up to 2 percent are (foreign) institutional investors. Given this unusual setting, it is of separate interest to investigate whether the introduction of the CSI300 index futures had an impact on the volatility of prices in the underlying spot market. As the CSI300 index futures market is a relatively young, yet impressively large market where typical institutional investors play a negligible role, we assume to find evidence in favor of the destabilizing hypothesis. However, investors in the CSI300 futures market face high monetary and regulatory barriers to entry. Therefore, their characteristics must certainly differ from what is commonly known in the financial literature. One may therefore question if our preliminary hypothesis is plausible.

To the best of our knowledge, the type of comparison undertaken in this paper has not yet been considered in the literature. To this end, we follow the existing literature and estimate different varieties of Generalized Auto-Regressive Conditional Heteroscedasticity (GARCH) models. Besides the widely used GARCH(1,1)-model, we also consider both GJR-GARCH and EGARCH variants.

The rest of the paper proceeds as follows: Section 2 outlines the history and institutional setting of the markets under consideration. SECTION 3 offers a brief literature review, SECTION 4 describes the data and methodology. SECTION 5 provides our empirical results while SECTION 6 concludes. Additional institutional information on Asian spot and derivatives markets is provided in the Appendix.

2 The Chinese Spot and Derivatives Market(s)

Since their introduction in 1990 and 1991, both stock exchanges in Shanghai and Shenzhen have grown to become two of the largest stock exchanges in Southeast-Asia. At the end of 2012, total market capitalization had reached USD 2,547 billion in Shanghai and USD 1,150 billion for the smaller Shenzhen stock exchange, rivaling the Tokyo stock exchange with a market capitalization of about USD 3,479 billion. By comparison, at the same time, the NYSE Euronext had a total market capitalization of USD 14,085 billion (World Federation of Exchanges, 2012).[1]

Initially, stock markets in Shanghai and Shenzhen were segmented into A and B shares which ensured discrimination according to ownership restrictions. Domestic citizens could only buy or sell A-shares, whereas foreign investors were only allowed to trade B-shares. This separation of ownership according to investor groups was abolished in two steps. First, in order to improve liquidity and market capitalization of B-shares, the Chinese Securities Regulatory Commission (CSRC) allowed domestic investors to enter the market in early 2001. Second, the CSRC liberalized the A-share market to encourage foreign investment in late 2002. However, market entrance is still restricted to Qualified Foreign Institutional Investors (QFIIs), foreign institutions that are allowed to participate in a special certification system.

The CSI300 is the first stock index to broadly reflect performance across both stock exchanges in mainland China. Created on April 8, 2005, it is compiled and published by the China Securities Index Company and consists of 300 large-capitalization and actively traded stocks listed in Shanghai (195 stocks) and Shenzhen (105 stocks). The CSRC gave its approval for the creation of financial futures in 2006, and the CFFEX was inaugurated in September that year. A month later, mock trading began on the CSI300 stock index contract and continued through to 2010. On April 16, 2010, the

[1]Unless noted otherwise, the information in this section relies on discussion with and material provided by Metzler Asset Management, Frankfurt, Germany, KPMG (2011), and Walter and Howie (2012).

CSI300 index futures market was finally launched.[2] It is interesting that the market was launched in the aftermath of the so-called global financial crisis (GFC) and shortly after Europe's own financial crisis erupted in May 2010.

The Chinese authorities designed markets with conservative specifications and high barriers to entry. The contract size is the index value of the CSI300 index futures multiplied by Chinese Yuan Renminbi (CNY) 300 (approximately USD 48). The relatively large multiplier of 300 tends to discourage participation of small investors in the market. Five futures contracts are traded simultaneously; their expiration dates fall over the next three consecutive months and the two nearest quarter-end months (which are March, June, September and December). The third Friday of each month is the settlement day and the settlement price is calculated as the arithmetic average of the CSI300 spot index during the last two trading hours of that day. A price limit of +/- 10 percent with respect to the settlement price of the last trading day ought to limit extensive price fluctuations. In addition, if changes in the daily futures price exceed 6 percent and last for more than a minute, bid/ask quotes are restricted to a range between +/- 6 percent for the following 10 minutes. This procedure is designed to stabilize the futures market under conditions of extremely high volatility.

Before opening a futures trading account, investors are required to deposit at least CNY 500,000 (approximately USD 81,000). The minimum trading account size is CNY one million. Initial margins are set at 12 percent; the tick size is 0.2 index points worth USD 8.8. A single futures trading account can have only 100 contracts, though the limit can be raised by approval of the CFFEX. Domestic mutual funds can only have a long futures position of up to 10 percent of its assets under management, and a short futures position of up to 20 percent of its stock holdings. Investors must have prior experience with commodities futures trading or mock trading of index futures.

[2] Information on CSI300 futures contract specifications is obtained from `http://www.cffex.com.cn/en_new/sspz/hs300zs/` as well as the authors' calculations based on data from Thomson Reuters Datastream.

Initially, foreign investors were excluded from the market. However, since May 4, 2011, QFIIs are allowed to participate. The same holds for equity funds, balanced funds and capital preservation funds. Overall, high market entry barriers as well as the large contract size of CSI300 index futures show that the product has been designed to offset speculators.

Prior to the introduction of CSI300 index futures, investors could already invest in two off-shore sister spot and index futures markets in Singapore and Hong Kong. The FTSE China A50 index is a real-time index comprising the 50 largest A-Share companies by market capitalization. Its base date is July 21, 2003 and its base value is 5000. The SGX FTSE China A50 index futures are offshore futures denominated in USD and first issued on September 5, 2006 by the Singapore exchange.[3] Facing the competition from mainland China, it made a series of substantial revisions to the futures contract specifications on August 23, 2010 at which point the contract size was reduced to USD 1 from USD 10 multiples of the futures price. With the index futures closing at 8,540 points on January 4, 2013, one futures contract cost USD 8,540. Following changes leading to extended trading hours, reduced entry barriers, smaller contract sizes, and lower margin requirements, A50 trading volume increased sharply.

The contract months are the two nearest consecutive months and March, June, September and December on a one-year cycle. The last trading day is the second last business day of the contract month. The final settlement price is the official closing price of the FTSE China A50 index rounded to the nearest two decimal places. There are price limits of 10 percent and 15 percent from the previous day's settlement price followed by a cooling off period of 10 minutes when the limit is reached. There are no price limits for the rest of the day nor for expiring contracts on their last trading day.

Although the A50 futures market's trading volume is only 9 percent of that of the CSI300 futures market, it has some advantages over the much larger futures market in

[3] Relevant information from `http://www.sgx.com/wps/portal/sgxweb/home/products/derivatives/equity/chinaa50` and own calculations.

Shanghai. First, the A50 index futures market has considerably lower entry barriers for investors. Its contract size is smaller and its initial margin is lower. Second, the A50 futures market opens 15 minutes earlier and closes 10 minutes later than the CSI300 futures market. In addition, there is no lunch break in the A50 futures market. Investors can therefore trade in the market longer and without mid-day interruptions. Third, the A50 futures market has an additional T+1 session that lasts until the next day. When the market has unexpected news during extended T and T+1 sessions, the only place where investors can trade is the A50 futures market. Fourth, the A50 futures contract is settled in USD, which is particularly convenient for international investors. Fifth, unlike in the pure order-driven CSI300 futures market, there are market makers for A50 futures, which ensures liquidity.

The Hang Seng China Enterprise Index (HSCEI) is a market capitalization-weighted stock index compiled and calculated by the Hang Seng Index Company. It has existed since August 8, 1994 and tracks the performance of 40 major H-shares, CNY-denominated shares issued by the People's Republic of China (PRC) issuers under PRC law but listed on the Hong Kong stock exchange. While the par value of its components is denominated in CNY, they are subscribed for and traded in Hong Kong dollar (HKD).

The respective HSCEI index futures were introduced on December 3, 2003 and are traded on the same exchange as the underlying index.[4] All contracts are traded in HKD at the size of 50 times the futures index value. With a futures index value of 11,914 points on January 4, 2013, one futures contract cost HKD 595,700 (USD 76,860). The tick size is one index point which corresponds to USD 6.5. The initial margin is set at HKD 39,100 (USD 5,045). Available contract months are the spot month, the next calendar month, and the next two calendar quarter months. Each contact's last trading day is the business day immediately preceding the last business day of the contract

[4]Relevant information from `http://www.hkex.com.hk/eng/prod/drprod/hshares/hhifut.htm` and own calculations.

month. The final settlement price is the average of all quotations of the HSCEI taken at five minute intervals during the last trading day.

Figure 1 depicts all three indices. All 50 constituents of the A50 index are included in the CSI300 index. Moreover, 28 stocks from the total of 40 stocks comprised in the HSCEI are part of the A50 and therefore the CSI300 also. Three stocks from the HSCEI are included in the CSI300, while nine stocks from the HSCEI are neither part of the A50 nor the CSI300 index.

Figure 1 about here.

Retailers account for 98 percent of CSI300 index futures market participants. The remaining 2 percent are institutional investors such as QFIIs, fund managers, insurance companies, securities companies and trusts. Retail investors account for 70 percent of total open interest in the market; the remaining 30 percent are dispensed with institutional investors. Since its launch in 2010, the market structure has largely remained unchanged. In comparison, roughly 80 percent of all participants in the A50 futures market are foreign institutional investors - most of them without the opportunity to invest in the CSI300 futures market as they are not part of the QFII scheme. In contrast, Chinese domestic investors as well as foreign institutional investors who can participate in the market through the QFII scheme generally prefer CSI300 index futures over A50 futures.

The CSI300 futures market has grown quickly. Based on trading volume, it now has 2.5 times the size of both the French CAC40 and the German DAX30 index futures markets.[5] However, its size is only 0.3 times that of the EuroStoxx50 index futures market. Based on average daily open interest, however, the CSI300 futures market is very small and corresponds to 0.15 times the CAC40, 0.3 times the DAX30 and 0.02 times the EuroStoxx50 index futures market.

[5] All data in this paragraph was taken from Thomson Reuters Datastream.

In comparison, the market for A50 index futures is even smaller. Based on trading volume, its size is comparable to that of the Dutch AEX index futures and has 0.03 times the size of the EuroStoxx50 index futures market. Based on open interest, its size is comparable to 0.2 times the DAX30 and 0.01 times the EuroStoxx50 futures market. Average daily trading volume of HSCEI index futures is comparable to 0.3 times that of the CAC40 and 0.04 times the EuroStoxx50 index futures. Its daily average open interest corresponds to 0.2 times the CAC40 and DAX30 and 0.98 times the AEX.

3 Literature Review

While it is well-established that futures markets are closely linked to the underlying spot markets through the process of arbitrage, two main lines of argument exist in the theoretical literature concerning the impact on underlying spot market volatility from the introduction of a futures market.

On the one hand, it is argued that futures markets have a stabilizing effect on the underlying spot market because futures trading improves price discovery, enhances market efficiency, increases market depth as well as information flows and contributes to market maturity. As a result, the introduction of futures trading reduces the volatility of the underlying spot market (Powers, 1970; Danthine, 1978; Bray, 1981; Kyle, 1985; Stoll and Whaley, 1988). Turnovsky (1983) demonstrates theoretically that derivatives trading has a stabilizing effect on spot prices. Danthine (1978) argues that futures traders are better informed than spot traders, and hence futures prices transmit information to relatively uninformed spot traders. In addition, Cox (1976) and Hiraki et al. (1995) present empirical evidence that futures traders are better informed than spot traders. This results in a stabilization in the spot market.

However, increasing spot market volatility following the introduction of futures trading need not have a negative connotation: if new information is effectively transmitted from the futures market to the cash market such that the information flow into the spot market is improved following the onset of futures trading, spot market volatility should increase (Ross, 1989).

Futures trading can destabilize the underlying spot market by increasing stock market volatility due to the impact of uninformed investors. Attracted by relatively low transaction costs, high degrees of leverage, and the ability to sell short, badly informed investors induce noise in the price discovery process and lower the information content of prices. This implies an increase in spot market volatility (Cox, 1976; Cagan, 1981; Stein, 1987).

Hart and Kreps (1986) argue that speculative activity is likely to destabilize prices regardless of how well these speculators are informed. They will buy when the chance of rising prices increases and they will sell as prices are likely to fall. This trading behavior raises price variability in the short term under otherwise equal conditions.

The theoretical literature prompted a number of empirical investigations yielding conflicting evidence. Most early empirical investigations focus on mature stock and futures markets that are typically viewed as being dominated by well-informed institutional investors.

Index futures markets were mainly introduced in the 1980s. At that time, institutional investors were the dominant players in developed international equity markets. Typically, the literature regards institutional investors as informed traders while individual investors are characterized as uninformed traders (e.g. Lee et al., 1999; Cohen et al., 2002; Barber and Odean, 2008; Kaniel et al., 2008).

Cohen et al. (2002) show that institutional investors' trading decisions are based on fundamental information. As a result, institutional investors drive stock prices to their fair values and thereby exert a stabilizing effect on prices. In comparison, individual investors are less well informed (Dennis and Weston, 2001). Therefore, their trading decisions are more biased by behavioral aspects (Kamesaka et al., 2003).

An obvious way to empirically investigate the impact of investor behavior on market stability is to examine the sources of changes in the volatility of returns. In addition, one may want to discriminate between mature and newly created markets for stock index futures. We consider select contributions to both strands of the literature.

Harris (1989) reports statistically but not economically significant increases in stock index returns volatility due to futures trading in the United States. Maberly et al. (1989) find that volatility rose subsequent to the introduction of index futures on the S&P 500. Lockwood and Linn (1990), Baldauf and Santoni (1991), Brorsen (1991) and Pericli and Koutmos (1997) confirm this. Damodaran (1990) finds that the daily price volatility of all the S&P 500 shares increased after the introduction of the S&P 500 futures contract, but that the increase was not statistically significant.

Antoniou and Holmes (1995) examine the British market and find increasing spot market volatilities after the introduction of the FTSE-100 Stock Index Futures. However, they report that the nature of volatility has not changed post-futures introduction. The authors find that the futures have improved the speed and quality of information flowing to the spot market.

Comparing markets in Germany, Japan, Spain, Switzerland, the United Kingdom and the United States, Antoniou et al. (1998) find that the futures introduction has not had a detrimental effect on the spot market. It appears that there has been an improvement in the way that news is transmitted into prices following the onset of futures trading. Therefore, the view that market turbulence results from the introduction of derivative trading appears unfounded.

Chang et al. (1999) confirm the hypothesis that future trading increases spot market volatility in Japan but that there is no volatility spillover to stocks against which futures are not traded.

Lee and Ohk (1992) show that, following the introduction of index futures, volatility of stock returns in Australia, Hong Kong and Japan did not change, but rose significantly in the United Kingdom and the United States. Kan (1997) supports the earlier findings for Hong Kong.

Edwards (1988a, b) reports a reduction of spot market volatility subsequent to the introduction of index futures on the S&P 500. Pericli and Koutmos (1997) find that the creation of S&P 500 stock index futures did not cause any shift in the volatility of index stock returns. Darrat et al. (2002) conclude that index futures trading is not to blame for the observed volatility in the S&P 500 spot market. Rather, they find more support for the alternative view that volatility in the futures market is an outgrowth of a turbulent cash market. Galloway and Miller (1997) document a significant decrease in return volatility and systematic risk as well as a significant increase in trading volume for the MidCap 400 stocks after the introduction of the corresponding index futures. Rahman (2001) shows that the introduction of index futures and futures options on the Dow Jones Industrial Average has produced no structural changes in the conditional volatility of the component stocks.

In line with the findings for the U.S. market, Bacha and Vila (1994) confirm the stabilization hypothesis for the Japanese market, Reyes (1996) for markets in France and Denmark and Dennis and Sim (1999) for the Australian market. On the other hand, Yu (2001) reports that the volatility of stock returns in the United States, France, Japan and Australia rose significantly subsequent to the introduction of the respective index futures but not in the United Kingdom and Hong Kong.

In a broad study, Gulen and Mayhew (2000) examine stock market volatility before and after the introduction of equity index futures trading in 25 countries consisting of a mix of mature and emerging markets. The authors find that futures trading is related to an increase in conditional volatility in the United States and Japan, but in nearly every other country, either no significant effect, or a volatility-dampening effect is reported.

A number of empirical papers specifically investigate the impact of the introduction of stock index futures trading on the underlying spot market in emerging markets. Chiang and Wang (2002) explore the market in Taiwan and report an increase in spot market volatility subsequent to the introduction of index futures. Baklaci and Tütek (2006) examine the Turkish market and find that the introduction of index futures significantly improves the rate at which new information is impounded into spot prices and reduces the persistence of information and volatility in the underlying spot market, resulting in improved efficiency. Caglayan (2011) reports that there have been significant changes in the structure of the volatility in the Turkish spot market following the onset of futures trading. However, both studies for Turkey cover a very short time span of less than two years. Kasman and Kasman (2008) report results in favor of the stabilization hypothesis for the Turkish ISE-30 index and suggest that the direction of both long- and short-run causality flows from spot prices to futures prices confirming the theory that futures markets enhance the efficiency of the underlying spot market. In line with this, Bohl et al. (2011) explore the Polish market where it is argued uninformed individuals are the dominant trader type in the futures markets. The authors are able, therefore, to investigate the destabilization hypothesis with a special focus on the influence of individuals trading in index futures on spot market volatility. Their results suggest that the introduction of index futures trading does not destabilize the spot market.

Turning to evidence for China, Arisoy (2008) examines the introduction of the SGX FTSE Xinhua China A50 index futures contract on the volatility and liquidity of its underlying spot market. The findings indicate a significant increase in spot volatility and liquidity in the post-futures period. Conditional volatility estimations suggest that the change in volatility is attributed to an increase in the rate of flow of information to the spot market, rather than speculative trading. After controlling for factors affecting liquidity, Arisoy confirms the finding that the introduction of futures trading induces migration of uninformed traders from spot market to futures market. His results imply an increased trading volume and more volatile, but more efficient markets. However, as noted previously, their results do not consider some of the institutional idiosyncrasies, notably the high barriers to entry, associated with the creation of this market which casts doubts on his findings.

We follow the majority of papers cited here in choosing a GARCH approach to model volatility spillovers for data at the daily frequency. However, owing to its recent creation the sample from the mainland Chinese market(s) is shorter than in some of the studies cited above. In general, samples based on the experience of emerging markets tend to be shorter than in papers that investigate the impact of futures markets on spot markets in mature economies.

4 Data and Methodology

4.1 Data

We analyze the impact of the introduction of the CSI300 index futures on different spot markets in the region. The spot index counterparts are the A50 spot index in Singapore and the HSCEI spot index in Hong Kong, in addition to the CSI300 spot market in Shanghai.

The times series for the CSI300 spot index begins with its introduction on April 8, 2005. The series for the A50 spot index series starts on January 4, 2000, the HSCEI spot index begins on January 3, 2000. Our sample ends on June 24, 2013. All data are taken from Thomson Reuters Datastream. Since CSI300 index futures are traded in CNY, A50 futures in USD and HSCEI futures in HKD, all data are expressed in CNY. As the relevant exchange rates become available to Datastream at 16:15 GMT each day, we use a one-day lag to account for time differences between GMT and GMT+8, the time zone in which all markets under consideration operate.

For each index, we calculate continuous returns in percent:

$$r_t = ln(P_t) - ln(P_{t-1})$$

After excluding non-trading days, our samples consist of 1991 usable observations for the CSI300 index, 3270 observations for the A50 index and 3294 observations for the HSCEI.[6]

4.2 Econometric Approach

Conditional variance is time-varying. Accordingly, we estimate varieties of GARCH models (Bollerslev, 1987) as these are frequently used in similar contexts and thus permit comparability with the extant literature. Frequently, disturbances are assumed to follow a *t*-distribution. However, we also estimate all models under the assumption of a normal conditional error distribution as additional robustness checks.[7]

The final model specifications are chosen by the general to specific approach. All models consist of the same mean equation and a number of different variance equations. To facilitate distinction between the three different spot markets considered, we add the respective superscripts CSI300, A50 and HSCEI to the estimated coefficients both in the text and in the output tables. Our mean equation is specified as follows:

$$r_t = \alpha_0 + \alpha_1 D^{GFC} + \alpha_2 r_{t-1} + \alpha_3 D^{GFC} r_{t-1} + \alpha_4 r_t^f + \alpha_5 D^{GFC} r_t^f + \alpha_6 r_{t-1}^f + \alpha_7 D^{GFC} r_{t-1}^f + \alpha_8 D^F + \epsilon_t \quad (1)$$

$$\epsilon_t | \Omega_{t-1} \sim t_\nu(0, h_t)$$

$$\epsilon_t | \Omega_{t-1} \sim \mathcal{N}(0, h_t)$$

[6] Besides the different raw indices, we also generate three different principal component series based on the presumption that the markets in question possess significant common features. Since the conclusions are unchanged, the relevant results are relegated to an appendix.

[7] Unless otherwise indicated, robustness checks support the findings discussed below.

It takes into account first-order autocorrelation in stock returns as well as international interdependence of the Chinese stock market; r_t^f and r_{t-1}^f denote the (lagged) logarithmic return on foreign stock markets measured by the return of the MSCI world index. In order to account for the effect of foreign stock market movements on all indices under consideration, a number of possible candidates were considered. Based on economic reasoning supported by correlation analysis, the MSCI has been found to best capture movements in international stock markets while not being overly correlated with the Chinese market.

The effect of the GFC on Chinese markets is captured by a crisis dummy variable D^{GFC}. To this end, various possible specifications of the GFC dummy were examined both economically and econometrically. A dummy taking on the value of one between June 7, 2007 and April 9, 2009 and zero otherwise has been found to best reflect the impact of the GFC. Its specification follows the St. Louis Fed's financial crisis timeline and starts on the day Bear Sterns suspended redemptions from its High-Grade Structured Credit Strategies Enhances Leverage Fund.[8] The timeline ends in March 2009. However, extreme return volatility in both international and broad Asian stock market indices can be found until early April 2009. Hence, the final specification of the GFC dummy reflects this feature of the data. To capture the various avenues through which the GFC may have impacted equity markets, the mean equation contains interaction terms.

D^F is a dummy variable equal to zero before and equal to one after the introduction of the respective futures markets under consideration. For the CSI300 index futures, it is equal to one following April 16, 2010. In the case of the A50 index futures, D^F equals one following September 5, 2006. For HSCEI index futures, the switching date is January 5, 2004. We create symmetric samples centered around these respective dates.

[8]See also Burdekin and Siklos (2012) for a discussion of alternative specifications of the D^{GFC} variable.

Assuming a GARCH(1,1) structure leads to the specification of two different variance equations:

$$h_t = \beta_0 + \beta_1 h_{t-1} + \beta_2 \epsilon_{t-1}^2 + \beta_3 D^{GFC} + \beta_4 h_t^f + \beta_5 h_{t-1}^{A50} + \beta_6 h_{t-1}^{HSCEI} + \beta_D D^F \tag{2}$$

$$\begin{aligned} h_t = \beta_7 + \beta_8 D^F + \beta_9 h_{t-1} + \beta_{10} D^F h_{t-1} + \beta_{11} \epsilon_{t-1}^2 + \beta_{12} D^F \epsilon_{t-1}^2 + \\ \beta_{13} D^{GFC} + \beta_{14} h_t^f + \beta_{15} h_{t-1}^{A50} + \beta_{16} h_{t-1}^{HSCEI} \end{aligned} \tag{3}$$

In equations (2) and (3), the estimated parameters on the dummy variable D^F, which capture the difference in volatility following the introduction of derivatives contracts, are most relevant for our research question: for example, if β_D (β_8) is positive, a positive shift in the conditional volatility process occurs after the introduction of index futures implying that the spot market volatility is higher after the introduction of futures. This would represent evidence in favor of the destabilizing hypothesis. If the coefficient is statistically significant but negative, index futures exhibit a dampening influence on conditional volatility levels, thereby providing empirical evidence in favor of the stabilizing hypothesis. The additive inclusion of the dummy variable in (3) captures possible changes in the overall level of the variance due to the introduction of index futures. The interaction terms β_{10} and β_{12} may further contribute or potentially offset a level shift in volatility following the introduction of futures depending upon the degree of volatility persistence.

To capture the impact of the GFC on spot market volatility, we also include the crisis dummy variable in all volatility equations. Moreover, we wish to account for possible volatility spillovers between international stock markets as well as the sister spot markets. To this end, we include three different variances into each volatility equation. They were obtained from basic GARCH(1,1) estimations taking into account the impact of the GFC. Due to differing time zones and trading hours, we include the contemporaneous value of the MSCI variances and one lag of the A50 and the HSCEI variances.[9]

To account for the fact that positive and negative shocks can have different effects on subsequent volatility, next we consider GJR-GARCH models as proposed by Glosten et al. (1993):

$$h_t = \gamma_0 + \gamma_1 h_{t-1} + \gamma_2 \epsilon_{t-1}^2 + \gamma_3 \epsilon_{t-1}^2 I_{t-1} + \gamma_4 D^{GFC} + \gamma_5 h_t^f + \gamma_6 h_{t-1}^{A50} + \gamma_7 h_{t-1}^{HSCEI} + \gamma_D D^F \quad (4)$$

$$\begin{aligned} h_t = {} & \gamma_8 + \gamma_9 D^F + \gamma_{10} h_{t-1} + \gamma_{11} h_{t-1} D^F + \gamma_{12} \epsilon_{t-1}^2 + \gamma_{13} \epsilon_{t-1}^2 D^F + \\ & \gamma_{14} \epsilon_{t-1}^2 I_{t-1} + \gamma_{15} \epsilon_{t-1}^2 I_{t-1} D^F + \gamma_{16} D^{GFC} + \gamma_{17} h_t^f + \gamma_{18} h_{t-1}^{A50} + \gamma_{19} h_{t-1}^{HSCEI} \end{aligned} \quad (5)$$

I_t takes on the value of zero if the return innovation is zero or positive, i.e., $\epsilon_{t-1} \geq 0$, and the value of one in case of negative return shocks, i.e., $\epsilon_{t-1} < 0$. A statistically significant and positive γ_3 (γ_{14}) coefficient indicates that negative return shocks increase the conditional variance more strongly than positive return shocks. Setting the asymmetry coefficient equal to zero yields the conventional GARCH(1,1) specification.

Lastly, we estimate an EGARCH model since this allows for asymmetric responses of conditional volatility to positive and negative shocks. Following Nelson (1991), the EGARCH models modified for our purposes are specified as follows:

$$\begin{aligned} \log(h_t) = {} & \theta_0 + \theta_1 log(h_{t-1}) + \theta_2 |\epsilon_{t-1}/\sqrt{h_{t-1}}| + \theta_3 (\epsilon_{t-1}/\sqrt{h_{t-1}}) \\ & + \theta_4 D^{GFC} + \theta_5 h_t^f + \theta_6 h_{t-1}^{A50} + \theta_7 h_{t-1}^{HSCEI} + \theta_D D^F \end{aligned} \quad (6)$$

[9] When estimating the models for the A50 (HSCEI) spot market, we only account for spillover effects to the HSCEI (A50) spot market. The CSI300 spot index was only introduced in 2005. Accounting for this fact would mean a considerable loss of observations.

$$\log(h_t) = \theta_8 + \theta_9 D^F + \theta_{10} log(h_{t-1}) + \theta_{11} log(h_{t-1}) D^F + \theta_{12} |\epsilon_{t-1}/\sqrt{h_{t-1}}| + \theta_{13} |\epsilon_{t-1}/\sqrt{h_{t-1}}| D^F + \theta_{14}(\epsilon_{t-1}/\sqrt{h_{t-1}}) + \theta_{15}(\epsilon_{t-1}/\sqrt{h_{t-1}}) D^F + \theta_{16} D^{GFC} + \theta_{17} h_t^f + \theta_{18} h_{t-1}^{A50} + \theta_{19} h_{t-1}^{HSCEI} \tag{7}$$

where $\log(h_t)$ is the logarithmic conditional volatility of ϵ_t. In (6), a positive θ_1 indicates the degree of volatility persistence; θ_2 captures the asymmetric effect, while θ_3 measures the magnitude effect. If θ_2 is statistically significant and negative, the negative shocks have a stronger impact on conditional volatility than positive shocks, implying the so-called leverage effect.

To generally ensure stationarity of the GARCH process, the estimated coefficients in front of the lagged variance and the lagged error term must sum to less than unity, i.e., in equation (2) $\beta_1 + \beta_2 < 1$ and in equation (4) $\gamma_1 + \gamma_2 < 1$. Moreover, these coefficients must be positive to ensure that the variance is always positive. However, our model specifications include additional explanatory variables in the variance equations whose estimated coefficients may well be negative. For instance, a negative β_D in equation (2) yields evidence in favor of the stabilizing hypothesis. It indicates that the variance falls after the introduction of futures trading. This does not imply that the variance becomes negative. Likewise, a negative β_4 highlights spillover effects between the MSCI and either of the three Chinese stock markets. Again, it does not mean that the variance becomes negative. In addition, the EGARCH model specification allows for all estimated coefficients to be negative: The implied value of h_t can never be negative regardless of the magnitude of $\log(h_t)$.

We estimate the mean equation (1) and the respective volatility equations (2) to (7) via maximum likelihood estimations based on the BHHH algorithm proposed by Berndt et al. (1974) and employ p-values based on Bollerslev and Wooldridge (1992) robust standard errors, if applicable.

5 Empirical Results

Table 1 provides summary statistics for the daily (exchange rate adjusted if applicable) spot return of the CSI300, the A50 and the HSCEI indices.

Table 1 about here.

Returns in all three markets indicate skewness and excess kurtosis, a finding that mirrors the properties of most financial time series. Kurtosis is higher before rather than after the introduction of CSI300 index futures in all three markets. One possible explanation may be that the futures introduction coincides with the end of the GFC. During the crisis, extreme market outcomes such as very high and very low daily returns were more likely than afterwards.

Both minima and maxima of all three indices considered are in line with the extrema for broad international stock indices. Ranging between plus and minus 15 percent, only the HSCEI's return varies a little more than the S&P500, the MSCI World Index or the FTSE All World index, whose daily returns fluctuate between plus and minus 10 percent during our sample period.[10]

Considerable differences are found when comparing the standard deviations of all three indices before and after the introduction of their respective index futures. Before the introduction of CSI300 index futures, the CSI300 spot index return's standard deviation is higher than afterwards. The same holds true for the A50 index and the HSCEI index. In contrast, the introduction of A50 index futures apparently increased standard deviation of the underlying A50 index. The introduction of HSCEI index futures does not alter the underlying indexes' standard deviation. The results suggest that the introduction of CSI300 index futures had a calming effect on all three spot market returns.

[10]Comparison based on authors' calculations; data obtained from Thomson Reuters Datastream.

Table 2 reports the regression results for the CSI300 spot market. Generally, the coefficients across all six different mean equations do not differ by much. α_4^{CSI} and α_6^{CSI} are positive and highly significant in all model specifications. This suggests that returns of the MSCI have a strong impact on returns of the CSI300 spot market. Neither the GFC nor the introduction of CSI300 index futures appears to have had a significant effect on the dependent variable. The finding for the GFC holds true for various robustness checks with different start and (or) end dates for the dummy specification (not all results are shown).

Table 2 about here.

The results of the estimation of equation (2) most interestingly yield empirical evidence in favor of the stabilizing hypothesis: β_D^{CSI} is negative and significant. Hence, the introduction of CSI300 index futures had a calming impact on CSI300 spot market volatility even if we control for the (end of the) GFC. Moreover, we find a high degree of volatility clustering as well as shock persistence. Neither the GFC-dummy itself nor the volatility of the HSCEI sister spot market are found to exert any impact on the volatility in the CSI300 spot market. However, there is empirical evidence for spillover effects between the CSI300 spot market and the A50 spot market (β_5^{CSI} is negative and significant). It is not an accident perhaps that the A50 market is located outside the influence, direct or indirect, of Chinese authorities who have, at the very least, moral suasion over behavior in the HSCEI market.

Generally, the foregoing findings are confirmed by the results of the estimation of equation (3): The introduction of CSI300 index futures had a calming effect on the volatility of its underlying spot market. Moreover, a positive and significant β_{16}^{CSI} now suggests spillover effects between the HSCEI spot market and the CSI300 spot market. Overall, as also shown below, it does not appear that spillover effects between the A50 and the CSI300 spot market are robust while the same cannot be said about the links between the HSCEI and the CSI300 markets.

As $\beta_1^{CSI} + \beta_2^{CSI} < 1$, the stationarity condition is fulfilled. Both parameters are positive. This equally holds for all of the following results. In all models, the variance is always positive, even if some of the coefficients are negative.

Estimation of equation (4) does not yield any significant impact of the CSI300 futures introduction on its spot market volatility. A negative and highly significant γ_1^{CSI} suggests a high degree of volatility clustering. γ_6^{CSI} is positive and highly significant, which shows spillover effects from the A50 spot market to its CSI300 sister spot market. This is confirmed by the results of the GJR-GARCH model in equation (5), where γ_{18}^{CSI} is positive and highly significant. Moreover, this model specification yields highly significant evidence in favor of the stabilizing hypothesis: negative and highly significant γ_9^{CSI}, γ_{11}^{CSI}, γ_{13}^{CSI} and γ_{15}^{CSI} strongly confirm that the introduction of CSI300 index futures had a calming effect on the volatility of the underlying spot market.

Generally, the results for both EGARCH model specifications confirm previous findings. Negative and highly significant estimated coefficients θ_D^{CSI}, θ_9^{CSI} and θ_{13}^{CSI} yield evidence in favor of the stabilizing hypothesis. A positive and significant θ_{18}^{CSI} substantiates the spillover effects between the A50 and the CSI300 spot markets.

Neither our results for the GJR-GARCH models nor the output for the EGARCH models report any significant leverage effect. The estimation output for both the GJR-GARCH II and EGARCH II model yields a significant and positive coefficient on the GFC dummy, suggesting that the crisis increased volatility in the CSI300 spot market.

Table 3 shows the regression results for the A50 spot market and the effect of the CSI300 futures introduction. Across all model specifications, strong evidence is found in favor of the stabilizing hypothesis. The introduction of CSI300 index futures had a calming effect on the volatility of the A50 spot market. Moreover, a positive and significant β_{16}^{A50}, γ_6^{A50} and γ_7^{A50} as well as γ_{18}^{A50} suggest spillover effects between the A50 spot market and both the CSI300 and the HSCEI sister spot markets. Again, no evidence for the existence of leverage effects is found.

Table 3 about here.

Table 4 summarizes the results obtained for the HSCEI spot market and the possible impact from the introduction of CSI300 futures. They confirm previous findings in favor of the stabilizing hypothesis. Moreover, negative and significant estimates of γ_{18}^{HSCEI}, θ_{6}^{HSCEI} and θ_{19}^{HSCEI} suggest negative spillover effects between the CSI300 spot market and its HSCEI sister market. Increases in the volatility of the CSI300 spot market tend to calm the HSCEI spot market.

Table 4 about here.

Finally turning to the examination of the two off-shore markets where index futures on Chinese stocks have been traded long before the introduction of CSI300 index futures, Table 5 shows the results for the A50 spot market and any possible impact of the introduction of A50 index futures. Overall, the different estimated coefficients on the dummy variable yield mixed results. For most model specifications, they are insignificant. In some cases, the evidence is favorable to the destabilizing hypothesis. β_{10}^{A50} and β_{12}^{A50}, γ_{11}^{A50}, θ_{D}^{A50} and θ_{11}^{A50} are positive and significant. However, the results have to be interpreted with caution. As outlined above and in the Appendix, A50 index futures trading was extremely narrow before the introduction of CSI300 futures. Table 6 summarizes our findings for the HSCEI spot market and its own index futures introduction. The relevant estimated coefficients are negative but insignificant. Hence, we find no evidence in favor of neither the stabilizing nor the destabilizing hypothesis.

Tables 5 and 6 about here.[11]

[11] As the CSI300 index was introduced in 2005, it has not been available long enough to be included in these estimations, which rely on samples centered around the introduction of A50 index futures on September 5, 2006 and HSCEI index futures on January 5, 2004, respectively. Therefore, we

6 Conclusions

This paper examines the impact of the introduction of CSI300 index futures on the volatility of its underlying spot market. Equally importantly, we contrast these findings with the A50 and HSCEI spot and derivatives markets, where index futures on Chinese stocks are also traded. At the same time, we model spillover effects between the three markets. To the best of our knowledge, this approach has not been considered and provides new insights into the relevant literature.

The CSI300 derivative market provides a unique setting for our analysis. It is controlled by the CSRC and characterized by high barriers to entry. Access is limited especially for international (institutional) investors. As a result, Chinese retail investors dominate the market. On the whole, this is rather atypical for an emerging market. In addition, the market exhibits very high average daily trading volume but low average open interest. No other market has been found to follow similar patterns over the sample period under consideration. This finding may hint at an increased activity of speculators.

Overall, we find robust evidence in favor of the stabilization hypothesis. Our regression results show that the introduction of CSI300 index futures had a significant and negative impact on the volatility of the CSI300 spot index, as well as on both the A50 and HSCEI spot markets. In contrast, the introduction of A50 and HSCEI index futures had unanimous but certainly not calming effects on their respective underlying spot markets. These findings also hold when controlling for the impact of the (end of the) GFC.

Differences in the types of investors, the tightly regulated nature of China's futures market, together with the existence of two sister markets in the region where comparable stocks are traded, may well combine to explain why China's market resembles

only include the volatility of one sister spot market in the different variance equations to account for possible spillover effects.

its counterparts in mature economies more so than in emerging markets. Of course, even allowing for spillover effects we cannot claim to have identified all of the sources of the stability inducing impact from the introduction of a futures market in China. Consequently, there is more research to be done to improve our understanding of the market structures examined. For example, a distinction has to be made between constituent and non-constituent stocks. In addition, firm-specific and possibly further macroeconomic factors apart from the GFC ought to be considered.

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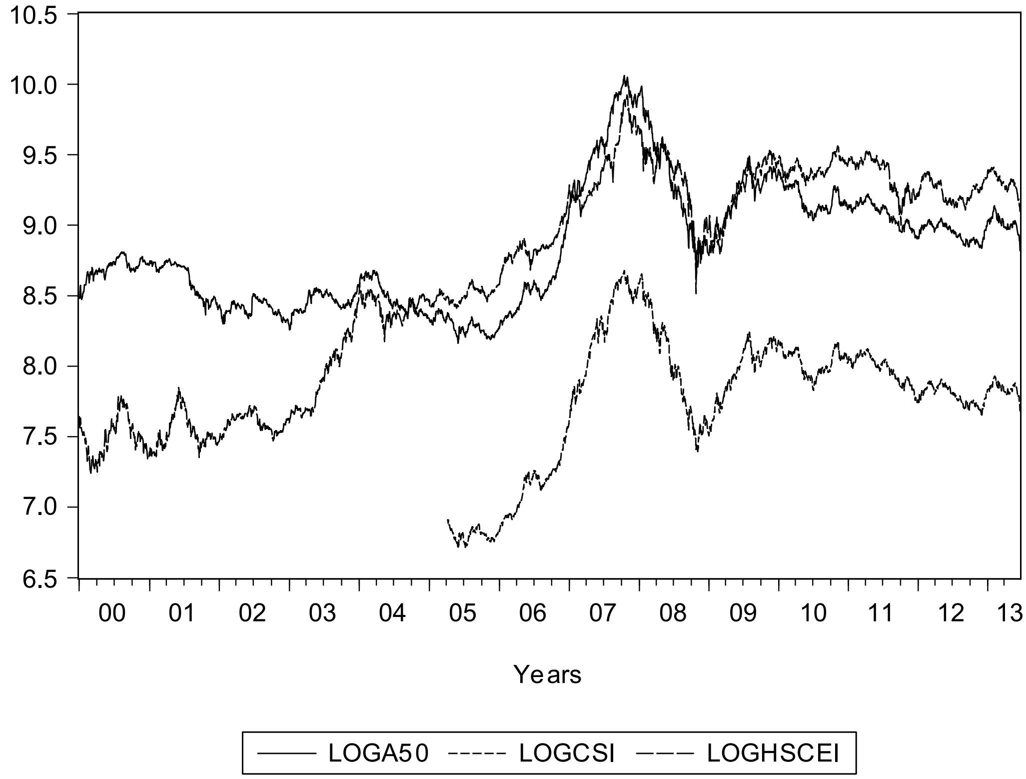
8 Figures and Tables

Figure 1: Index Comparison



Notes: All three indices (log of in index points) are taken from Thomson Reuters Datastream.

Table 1: Summary Statistics

	Mean	**Max.**	**Min.**	**Std. Dev.**	**Skew.**	**Kurt.**	**Obs.**
CSI 300							
Futures Dummy (CSI300)							
0	0.100	8.931	-9.695	2.150	-0.426	5.159	1221
1	-0.058	4.926	-6.516	1.431	-0.245	4.911	769
All	0.039	8.931	-9.695	1.906	-0.374	5.694	1990
A50							
Futures Dummy (A50)							
0	0.003	9.526	-5.797	1.315	0.965	9.680	1624
1	0.017	9.198	-9.861	2.006	-0.252	5.494	1645
Futures Dummy (CSI300)							
0	0.033	9.526	-9.861	1.782	0.029	7.047	2501
1	-0.064	5.472	-6.712	1.390	-0.157	5.358	768
All	0.010	9.526	-9.861	1.698	0.019	7.104	3269
HSCEI							
Futures Dummy (HSCEI)							
0	0.100	10.104	-8.312	2.065	0.230	5.191	985
1	0.009	15.511	-15.014	2.163	0.003	9.363	2308
Futures Dummy (CSI300)							
0	0.066	15.511	-15.014	2.277	0.043	8.026	2506
1	-0.059	7.666	-6.463	1.593	0.030	5.006	787
All	0.036	15.511	-15.014	2.134	0.062	8.290	3293

Our sample is defined as follows: CSI300 - April 8, 2005 to June 24 2013; CSI300 futures introduction on April 16, 2010. A50 - January 4, 2000 to June 24, 2013; A50 futures introduction on September 5, 2006. HSCEI - January 3, 2000 to June 24, 2013; HSCEI futures introduction on December 3, 2003. The table shows the summary statistics according to periods without futures trading (futures dummy equals zero), with futures trading (futures dummy equals one) and the entire sample (all). All data are taken from Thomson Reuters Datastream.

Table 2: Regression Results - Impact of CSI300 Futures Introduction on CSI300 Spot Market

GARCH I				**GJR-GARCH I**				**EGARCH I**			
Variable	**Coefficient**	**Std. Error**	**T-Stat.**	**Variable**	**Coefficient**	**Std. Error**	**T-Stat.**	**Variable**	**Coefficient**	**Std. Error**	**T-Stat.**
α_0^{CSI}	0.0865	0.1103	0.7849	α_0^{CSI}	0.1257	0.0824	1.5271	α_0^{CSI}	0.1393	0.1112	1.2534
α_1^{CSI}	−0.0226	0.1615	−0.1403	α_1^{CSI}	−0.1235	0.1388	−0.8904	α_1^{CSI}	−0.1146	0.1555	−0.7371
α_2^{CSI}	−0.0507*	0.0292	−1.7385	α_2^{CSI}	−0.0406	0.0283	−1.4383	α_2^{CSI}	−0.0486*	0.0281	−1.7326
α_3^{CSI}	0.0635	0.0477	1.3326	α_3^{CSI}	0.0678	0.0571	1.1900	α_3^{CSI}	0.0793	0.0485	1.6375
α_4^{CSI}	0.3120***	0.0475	6.5706	α_4^{CSI}	0.3250***	0.0479	6.7787	α_4^{CSI}	0.3191***	0.0521	6.1274
α_5^{CSI}	−0.0890	0.0885	−1.0060	α_5^{CSI}	−0.1015	0.0688	−1.4769	α_5^{CSI}	−0.0742	0.0755	−0.9832
α_6^{CSI}	0.2158***	0.0490	4.4072	α_6^{CSI}	0.2040***	0.0431	4.7306	α_6^{CSI}	0.2195***	0.0454	4.8337
α_7^{CSI}	0.0780	0.0804	0.9701	α_7^{CSI}	0.1234	0.0767	1.6093	α_7^{CSI}	0.1217*	0.0728	1.6732
α_8^{CSI}	−0.1429	0.1227	−1.1653	α_8^{CSI}	−0.1795*	0.0983	−1.8255	α_8^{CSI}	−0.2011*	0.1205	−1.6689
β_D^{CSI}	−0.0165***	0.0206	−3.8030	γ_D^{CSI}	−0.9670	1.0627	−0.9099	θ_D^{CSI}	−0.8186***	0.2592	−3.1581
β_0^{CSI}	0.0464	0.0314	1.4784	γ_0^{CSI}	2.0045*	1.1100	1.8059	θ_0^{CSI}	1.4009***	0.2869	4.8834
β_1^{CSI}	0.9602***	0.0131	73.4715	γ_1^{CSI}	0.9316***	0.1071	−8.6982	θ_1^{CSI}	−0.8509***	0.1781	−4.7784
β_2^{CSI}	0.0397***	0.0131	3.0442	γ_2^{CSI}	0.0136	0.0342	0.3983	θ_2^{CSI}	0.0634	0.0667	0.9502
β_3^{CSI}	0.0127	0.0339	0.3763	γ_3^{CSI}	0.0265	0.0495	0.5376	θ_3^{CSI}	−0.0181	0.0658	−0.2758
β_4^{CSI}	−0.0071	0.0088	−0.8198	γ_4^{CSI}	1.7800	1.3316	1.3368	θ_4^{CSI}	0.3547	0.2398	1.4796
β_5^{CSI}	−0.0131*	0.0071	−1.8571	γ_5^{CSI}	−0.1035	0.1594	−0.6497	θ_5^{CSI}	−0.0401	0.0447	−0.8967
β_6^{CSI}	0.0046	0.0042	1.1043	γ_6^{CSI}	1.1815***	0.2425	4.8715	θ_6^{CSI}	0.2404***	0.0413	5.8236
				γ_7^{CSI}	0.0843	0.1015	0.8306	θ_7^{CSI}	0.0073	0.0160	0.4577

GARCH II				**GJR-GARCH II**				**EGARCH II**			
Variable	**Coefficient**	**Std. Error**	**T-Stat.**	**Variable**	**Coefficient**	**Std. Error**	**T-Stat.**	**Variable**	**Coefficient**	**Std. Error**	**T-Stat.**
β_7^{CSI}	0.0690	0.0870	0.7931	γ_8^{CSI}	0.3424***	0.0994	3.4445	θ_8^{CSI}	1.1985***	0.2222	5.3942
β_8^{CSI}	2.9526***	0.8257	3.5757	γ_9^{CSI}	−0.3367***	0.1027	−3.2793	θ_9^{CSI}	−0.5629**	0.2348	−2.3978
β_9^{CSI}	0.9438***	0.0435	21.6839	γ_{10}^{CSI}	0.7987***	0.0112	71.1261	θ_{10}^{CSI}	−0.5967***	0.1333	−4.4764
β_{10}^{CSI}	−0.5273***	0.4830	−3.1620	γ_{11}^{CSI}	−0.1830***	0.0206	8.8766	θ_{11}^{CSI}	0.1003	0.2623	0.3826
β_{11}^{CSI}	0.0561	0.0435	1.2899	γ_{12}^{CSI}	0.0298**	0.0120	2.4799	θ_{12}^{CSI}	0.1278	0.0942	1.3573
β_{12}^{CSI}	−0.0755***	0.0471	−4.6034	γ_{13}^{CSI}	−0.0373***	0.0101	−3.7115	θ_{13}^{CSI}	−0.2668**	0.1341	−1.9896
β_{13}^{CSI}	0.0205	0.0683	0.3006	γ_{14}^{CSI}	0.1085***	0.0416	2.6090	θ_{14}^{CSI}	0.0496	0.0717	0.6927
β_{14}^{CSI}	−0.0324	0.0211	−1.5353	γ_{15}^{CSI}	−0.1166***	0.0445	−2.6185	θ_{15}^{CSI}	0.0070	0.0913	0.0778
β_{15}^{CSI}	−0.0203	0.0189	−1.0769	γ_{16}^{CSI}	0.2724*	0.1620	1.6812	θ_{16}^{CSI}	0.3693*	0.2176	1.6972
β_{16}^{CSI}	0.0139*	0.0084	1.6682	γ_{17}^{CSI}	0.0060	0.0117	0.5169	θ_{17}^{CSI}	−0.0500	0.0317	−1.5796
				γ_{18}^{CSI}	0.0197***	0.0075	2.6370	θ_{18}^{CSI}	0.1838***	0.0348	5.2890
				γ_{19}^{CSI}	−0.0005	0.0062	−0.0835	θ_{19}^{CSI}	0.0158	0.0139	1.1429

Notes:*,** ,*** denote statistical significance at the 10%, 5% and 1% level. The estimated α-coefficients are substantially the same for the second set of variance equations. For the sake of brevity, they are omitted here but available upon request. All data are taken from Thomson Reuters Datastream.

Mean Equation: $r_t = \alpha_0 + \alpha_1 D^{GFC} + \alpha_2 r_{t-1} + \alpha_3 D^{GFC} r_{t-1} + \alpha_4 r_t^f + \alpha_5 D^{GFC} r_t^f + \alpha_6 r_{t-1}^f + \alpha_7 D^{GFC} r_{t-1}^f + \alpha_8 D^F + \epsilon_t$

GARCH (I): $h_t = \beta_0 + \beta_1 h_{t-1} + \beta_2 \epsilon_{t-1}^2 + \beta_3 D^{GFC} + \beta_4 h_t^f + \beta_5 h_{t-1}^{A50} + \beta_6 h_{t-1}^{HSCEI} + \beta_D D^F$

GARCH (II): $h_t = \beta_7 + \beta_8 D^F + \beta_9 h_{t-1} + \beta_{10} D^F h_{t-1} + \beta_{11} \epsilon_{t-1}^2 + \beta_{12} D^F \epsilon_{t-1}^2 + \beta_{13} D^{GFC} + \beta_{14} h_t^f + \beta_{15} h_{t-1}^{A50} + \beta_{16} h_{t-1}^{HSCEI}$

GJR-GARCH (I): $h_t = \gamma_0 + \gamma_1 h_{t-1} + \gamma_2 \epsilon_{t-1}^2 + \gamma_3 \epsilon_{t-1}^2 I_{t-1} + \gamma_4 D^{GFC} + \gamma_5 h_t^f + \gamma_6 h_{t-1}^{A50} + \gamma_7 h_{t-1}^{HSCEI} + \gamma_D D^F$

GJR-GARCH (II): $h_t = \gamma_8 + \gamma_9 D^F + \gamma_{10} h_{t-1} + \gamma_{11} h_{t-1} D^F + \gamma_{12} \epsilon_{t-1}^2 + \gamma_{13} \epsilon_{t-1}^2 D^F + \gamma_{14} \epsilon_{t-1}^2 I_{t-1} + \gamma_{15} \epsilon_{t-1}^2 I_{t-1} D^F + \gamma_{16} D^{GFC} + \gamma_{17} h_t^f + \gamma_{18} h_{t-1}^{A50} + \gamma_{19} h_{t-1}^{HSCEI}$

EGARCH (I): $\log(h_t) = \theta_0 + \theta_1 log(h_{t-1}) + \theta_2 |\epsilon_{t-1}/\sqrt{h_{t-1}}| + \theta_3(\epsilon_{t-1}/\sqrt{h_{t-1}}) + \theta_4 D^{GFC} + \theta_5 h_t^f + \theta_6 h_{t-1}^{A50} + \theta_7 h_{t-1}^{HSCEI} + \theta_D D^F$

EGARCH (II): $\log(h_t) = \theta_8 + \theta_9 D^F + \theta_{10} log(h_{t-1}) + \theta_{11} log(h_{t-1}) D^F + \theta_{12} |\epsilon_{t-1}/\sqrt{h_{t-1}}| + \theta_{13} |\epsilon_{t-1}/\sqrt{h_{t-1}}| D^F + \theta_{14}(\epsilon_{t-1}/\sqrt{h_{t-1}}) + \theta_{15}(\epsilon_{t-1}/\sqrt{h_{t-1}}) D^F + \theta_{16} D^{GFC} + \theta_{17} h_t^f + \theta_{18} h_{t-1}^{A50} + \theta_{19} h_{t-1}^{HSCEI}$

Table 3: Regression Results - Impact of CSI300 Futures Introduction on A50 Spot Market

GARCH I				**GJR-GARCH I**				**EGARCH I**			
Variable	**Coefficient**	**Std. Error**	**T-Stat.**	**Variable**	**Coefficient**	**Std. Error**	**T-Stat.**	**Variable**	**Coefficient**	**Std. Error**	**T-Stat.**
α_0^{A50}	0.0431	0.1263	0.3418	α_0^{A50}	0.0896	0.0975	0.9188	α_0^{A50}	0.0779	0.1140	0.6838
α_1^{A50}	0.0665	0.2054	0.3239	α_1^{A50}	−0.0884	0.1413	−0.6261	α_1^{A50}	−0.0363	0.1624	−0.2241
α_2^{A50}	−0.0759**	0.0326	−2.3300	α_2^{A50}	−0.0372	0.0306	−1.2157	α_2^{A50}	−0.0619***	0.0181	−3.4166
α_3^{A50}	0.0613	0.0496	1.2368	α_3^{A50}	0.0386	0.0535	0.7225	α_3^{A50}	0.0503	0.0428	1.1775
α_4^{A50}	0.3112***	0.0423	7.3639	α_4^{A50}	0.3373***	0.0499	6.7567	α_4^{A50}	0.3019***	0.0528	5.7179
α_5^{A50}	−0.0666	0.0583	−1.1434	α_5^{A50}	−0.0679	0.0925	−0.7345	α_5^{A50}	−0.0258	0.0920	−0.2810
α_6^{A50}	0.2263***	0.0474	4.7798	α_6^{A50}	0.1973***	0.0401	4.9152	α_6^{A50}	0.2161***	0.0437	4.9460
α_7^{A50}	0.1061	0.1056	1.0053	α_7^{A50}	0.1956**	0.0812	2.4106	α_7^{A50}	0.1244	0.1055	1.1794
α_8^{A50}	−0.0921	0.1366	−0.6745	α_8^{A50}	−0.1492	0.1011	−1.4758	α_8^{A50}	−0.1376	0.1238	−1.1121
β_D^{A50}	−0.0166*	0.0319	−1.7228	γ_D^{A50}	−1.0585*	0.5917	−1.7891	θ_D^{A50}	−0.0214***	0.0326	−7.6559
β_0^{A50}	0.0546	0.0376	1.4529	γ_0^{A50}	1.5086**	0.7633	1.9763	θ_0^{A50}	−0.0237	0.0526	−0.4512
β_1^{A50}	0.9726***	0.0263	36.9854	γ_1^{A50}	0.9038***	0.0939	−9.6223	θ_1^{A50}	0.9654***	0.0599	16.1278
β_2^{A50}	0.0336***	0.0100	3.3626	γ_2^{A50}	0.0086	0.0230	−0.3762	θ_2^{A50}	0.0869**	0.0355	2.4501
β_3^{A50}	0.0368	0.0294	1.2540	γ_3^{A50}	0.0610**	0.0289	2.1146	θ_3^{A50}	−0.0304	0.0310	−0.9820
β_4^{A50}	−0.0010	0.0079	−0.1332	γ_4^{A50}	1.9792**	0.8314	2.3807	θ_4^{A50}	0.0098	0.0271	0.3647
β_5^{A50}	−0.0200	0.0159	−1.2591	γ_5^{A50}	−0.2615**	0.1147	−2.2803	θ_5^{A50}	−0.0050	0.0050	−1.0144
β_6^{A50}	0.0002***	0.0039	5.0699	γ_6^{A50}	1.1816***	0.1811	6.5254	θ_6^{A50}	0.0000	0.0063	−0.0069
				γ_7^{A50}	0.1790**	0.0833	2.1511	θ_7^{A50}	0.0021	0.0023	0.9251
GARCH II				**GJR-GARCH II**				**EGARCH II**			
Variable	**Coefficient**	**Std. Error**	**T-Stat.**	**Variable**	**Coefficient**	**Std. Error**	**T-Stat.**	**Variable**	**Coefficient**	**Std. Error**	**T-Stat.**
β_7^{A50}	0.0395	0.0395	1.0001	γ_8^{A50}	0.5458	0.4438	1.2298	θ_8^{A50}	0.1663	0.1184	1.4053
β_8^{A50}	−0.2944***	0.2515	13.1002	γ_9^{A50}	0.8745	0.9427	0.9278	θ_9^{A50}	0.6881***	0.2116	3.2526
β_9^{A50}	0.9694***	0.0180	53.7705	γ_{10}^{A50}	0.0250	0.3456	0.0724	θ_{10}^{A50}	0.7314***	0.1333	5.4883
β_{10}^{A50}	−1.8810***	0.0571	−32.9471	γ_{11}^{A50}	−0.9120**	0.3678	−2.4799	θ_{11}^{A50}	−1.3329***	0.2397	−5.5603
β_{11}^{A50}	0.0305*	0.0180	1.6920	γ_{12}^{A50}	−0.0067	0.0518	−0.1307	θ_{12}^{A50}	0.0441	0.0815	0.5420
β_{12}^{A50}	−0.0343*	0.0225	−1.5240	γ_{13}^{A50}	−0.0086	0.0564	−0.1530	θ_{13}^{A50}	−0.1183*	0.1450	−1.8160
β_{13}^{A50}	−0.0003	0.0347	−0.0095	γ_{14}^{A50}	0.0510	0.0686	0.7448	θ_{14}^{A50}	−0.1175**	0.0518	−2.2723
β_{14}^{A50}	−0.0317***	0.0102	−3.0969	γ_{15}^{A50}	0.0238	0.0865	0.2761	θ_{15}^{A50}	0.1442*	0.0809	1.7836
β_{15}^{A50}	−0.0120	0.0093	−1.2906	γ_{16}^{A50}	0.4451	0.6026	0.7388	θ_{16}^{A50}	0.0578	0.0546	1.0580
β_{16}^{A50}	0.0120***	0.0045	2.6932	γ_{17}^{A50}	−0.1338	0.1468	−0.9121	θ_{17}^{A50}	−0.0153	0.0143	−1.0751
				γ_{18}^{A50}	0.7706**	0.3094	2.4907	θ_{18}^{A50}	0.0300*	0.0238	1.7621
				γ_{19}^{A50}	0.0570**	0.0537	2.0610	θ_{19}^{A50}	0.0069**	0.0049	1.9898

Notes:*,** ,*** denote statistical significance at the 10%, 5% and 1% level. The estimated α-coefficients are substantially the same for the second set of variance equations. For the sake of brevity, they are omitted here but available upon request. All data are taken from Thomson Reuters Datastream.

Mean Equation: $r_t = \alpha_0 + \alpha_1 D^{GFC} + \alpha_2 r_{t-1} + \alpha_3 D^{GFC} r_{t-1} + \alpha_4 r_t^f + \alpha_5 D^{GFC} r_t^f + \alpha_6 r_{t-1}^f + \alpha_7 D^{GFC} r_{t-1}^f + \alpha_8 D^F + \epsilon_t$

GARCH (I): $h_t = \beta_0 + \beta_1 h_{t-1} + \beta_2 \epsilon_{t-1}^2 + \beta_3 D^{GFC} + \beta_4 h_t^f + \beta_5 h_{t-1}^{A50} + \beta_6 h_{t-1}^{HSCEI} + \beta_D D^F$

GARCH (II): $h_t = \beta_7 + \beta_8 D^F + \beta_9 h_{t-1} + \beta_{10} D^F h_{t-1} + \beta_{11} \epsilon_{t-1}^2 + \beta_{12} D^F \epsilon_{t-1}^2 + \beta_{13} D^{GFC} + \beta_{14} h_t^f + \beta_{15} h_{t-1}^{A50} + \beta_{16} h_{t-1}^{HSCEI}$

GJR-GARCH (I): $h_t = \gamma_0 + \gamma_1 h_{t-1} + \gamma_2 \epsilon_{t-1}^2 + \gamma_3 \epsilon_{t-1}^2 I_{t-1} + \gamma_4 D^{GFC} + \gamma_5 h_t^f + \gamma_6 h_{t-1}^{A50} + \gamma_7 h_{t-1}^{HSCEI} + \gamma_D D^F$

GJR-GARCH (II): $h_t = \gamma_8 + \gamma_9 D^F + \gamma_{10} h_{t-1} + \gamma_{11} h_{t-1} D^F + \gamma_{12} \epsilon_{t-1}^2 + \gamma_{13} \epsilon_{t-1}^2 D^F + \gamma_{14} \epsilon_{t-1}^2 I_{t-1} + \gamma_{15} \epsilon_{t-1}^2 I_{t-1} D^F + \gamma_{16} D^{GFC} + \gamma_{17} h_t^f + \gamma_{18} h_{t-1}^{A50} + \gamma_{19} h_{t-1}^{HSCEI}$

EGARCH (I): $\log(h_t) = \theta_0 + \theta_1 log(h_{t-1}) + \theta_2 |\epsilon_{t-1}/\sqrt{h_{t-1}}| + \theta_3(\epsilon_{t-1}/\sqrt{h_{t-1}}) + \theta_4 D^{GFC} + \theta_5 h_t^f + \theta_6 h_{t-1}^{A50} + \theta_7 h_{t-1}^{HSCEI} + \theta_D D^F$

EGARCH (II): $\log(h_t) = \theta_8 + \theta_9 D^F + \theta_{10} log(h_{t-1}) + \theta_{11} log(h_{t-1}) D^F + \theta_{12} |\epsilon_{t-1}/\sqrt{h_{t-1}}| + \theta_{13} |\epsilon_{t-1}/\sqrt{h_{t-1}}| D^F + \theta_{14}(\epsilon_{t-1}/\sqrt{h_{t-1}}) + \theta_{15}(\epsilon_{t-1}/\sqrt{h_{t-1}}) D^F + \theta_{16} D^{GFC} + \theta_{17} h_t^f + \theta_{18} h_{t-1}^{A50} + \theta_{19} h_{t-1}^{HSCEI}$

Table 4: Regression Results - Impact of CSI300 Futures Introduction on HSCEI Spot Market

GARCH I				GJR-GARCH I				EGARCH I			
Variable	**Coefficient**	**Std. Error**	**T-Stat.**	**Variable**	**Coefficient**	**Std. Error**	**T-Stat.**	**Variable**	**Coefficient**	**Std. Error**	**T-Stat.**
α_0^{HSCEI}	0.0210	0.0464	0.4537	α_0^{HSCEI}	0.0383	0.0696	0.5513	α_0^{HSCEI}	0.0148	0.0979	0.1520
α_1^{HSCEI}	0.2685***	0.0706	3.8038	α_1^{HSCEI}	0.2623**	0.1028	2.5528	α_1^{HSCEI}	0.1881	0.1459	1.2901
α_2^{HSCEI}	−0.1627***	0.0273	−5.9620	α_2^{HSCEI}	−0.1631***	0.0258	−6.3311	α_2^{HSCEI}	−0.1607***	0.0265	−6.0741
α_3^{HSCEI}	0.0330	0.0558	0.5927	α_3^{HSCEI}	0.0357	0.0578	0.6183	α_3^{HSCEI}	0.0434	0.0541	0.8037
α_4^{HSCEI}	0.5970***	0.0455	13.1128	α_4^{HSCEI}	0.6038***	0.0406	14.8773	α_4^{HSCEI}	0.5799***	0.0512	11.3281
α_5^{HSCEI}	0.2438**	0.1018	2.3952	α_5^{HSCEI}	0.2553**	0.0939	2.7180	α_5^{HSCEI}	0.2268**	0.1099	2.0648
α_6^{HSCEI}	0.6291***	0.0606	10.3879	α_6^{HSCEI}	0.6347***	0.0564	11.2493	α_6^{HSCEI}	0.6167***	0.0554	11.1267
α_7^{HSCEI}	0.2404**	0.1121	2.1449	α_7^{HSCEI}	0.2471**	0.1257	1.9653	α_7^{HSCEI}	0.1814*	0.1018	1.7826
α_8^{HSCEI}	−0.0770	0.0591	−1.3031	α_8^{HSCEI}	−0.0882	0.0784	−1.1251	α_8^{HSCEI}	−0.0849	0.1106	−0.7681
β_D^{HSCEI}	−0.0265	0.0218	−1.2168	γ_D^{HSCEI}	−0.0324***	0.0258	−3.2569	θ_D^{HSCEI}	−0.0401**	0.0481	−2.8345
β_0^{HSCEI}	0.0706*	0.0364	1.9420	γ_0^{HSCEI}	0.0828*	0.0457	1.8113	θ_0^{HSCEI}	0.0024	0.0427	0.0564
β_1^{HSCEI}	0.9431***	0.0119	79.2757	γ_1^{HSCEI}	0.9374***	0.0164	57.1636	θ_1^{HSCEI}	0.9155***	0.0815	11.2337
β_2^{HSCEI}	0.0568***	0.0119	4.7818	γ_2^{HSCEI}	0.0625***	0.0164	3.8116	θ_2^{HSCEI}	0.1077	0.0668	1.6145
β_3^{HSCEI}	0.0868**	0.0346	2.5140	γ_3^{HSCEI}	−0.0186	0.0158	−1.1807	θ_3^{HSCEI}	−0.0662*	0.0368	−1.8013
β_4^{HSCEI}	−0.0067	0.0091	−0.7441	γ_4^{HSCEI}	0.1157**	0.0543	2.1316	θ_4^{HSCEI}	0.1059	0.0749	1.4142
β_5^{HSCEI}	−0.0113	0.0160	−0.7078	γ_5^{HSCEI}	0.0017	0.0120	0.1431	θ_5^{HSCEI}	0.0140	0.0153	0.9198
β_6^{HSCEI}	−0.0021	0.0148	−0.1474	γ_6^{HSCEI}	−0.0173	0.0187	−0.9266	θ_6^{HSCEI}	−0.0083***	0.0166	−3.5049
				γ_7^{HSCEI}	0.0040	0.0182	0.2242	θ_7^{HSCEI}	−0.0013	0.0152	−0.0900

GARCH II				GJR-GARCH II				EGARCH II			
Variable	**Coefficient**	**Std. Error**	**T-Stat.**	**Variable**	**Coefficient**	**Std. Error**	**T-Stat.**	**Variable**	**Coefficient**	**Std. Error**	**T-Stat.**
β_7^{HSCEI}	0.0959*	0.0577	1.6622	γ_8^{HSCEI}	0.1214*	0.0673	1.8040	θ_8^{HSCEI}	0.0455	0.0552	0.8260
β_8^{HSCEI}	−0.0388	0.0565	−0.6886	γ_9^{HSCEI}	−0.0674***	0.0660	−5.0226	θ_9^{HSCEI}	−0.0026**	0.0934	−2.0883
β_9^{HSCEI}	0.8715***	0.0571	15.2705	γ_{10}^{HSCEI}	0.8814***	0.0637	13.8371	θ_{10}^{HSCEI}	0.8614***	0.0460	18.7437
β_{10}^{HSCEI}	0.0824	0.0569	1.4489	γ_{11}^{HSCEI}	−0.0846*	0.0662	1.9786	θ_{11}^{HSCEI}	−0.1077***	0.0388	4.7799
β_{11}^{HSCEI}	0.1284**	0.0571	2.2507	γ_{12}^{HSCEI}	0.1185*	0.0637	1.8606	θ_{12}^{HSCEI}	0.1095	0.0772	1.4187
β_{12}^{HSCEI}	−0.1123***	0.0628	−1.7893	γ_{13}^{HSCEI}	−0.1211*	0.0682	−1.7757	θ_{13}^{HSCEI}	−0.1378	0.1129	−1.2211
β_{13}^{HSCEI}	0.1170	0.0723	1.6197	γ_{14}^{HSCEI}	−0.0372	0.0234	−1.5923	θ_{14}^{HSCEI}	−0.1297***	0.0346	−3.7490
β_{14}^{HSCEI}	0.0195	0.0175	1.1210	γ_{15}^{HSCEI}	0.0631**	0.0290	2.1777	θ_{15}^{HSCEI}	0.1149***	0.0394	2.9169
β_{15}^{HSCEI}	−0.0325*	0.0169	−1.9219	γ_{16}^{HSCEI}	0.1657*	0.0868	1.9105	θ_{16}^{HSCEI}	0.1553***	0.0466	3.3341
β_{16}^{HSCEI}	0.0211	0.0163	1.2987	γ_{17}^{HSCEI}	0.0164	0.0146	1.1254	θ_{17}^{HSCEI}	0.0160***	0.0053	3.0180
				γ_{18}^{HSCEI}	−0.0338**	0.0140	−2.4145	θ_{18}^{HSCEI}	−0.0279***	0.0085	−3.2807
				γ_{19}^{HSCEI}	0.0214	0.0137	1.5662	θ_{19}^{HSCEI}	0.0185***	0.0071	6.6008

Notes:*,** ,*** denote statistical significance at the 10%, 5% and 1% level. The estimated α-coefficients are substantially the same for the second set of variance equations. For the sake of brevity, they are omitted here but available upon request. All data are taken from Thomson Reuters Datastream.

Mean Equation: $r_t = \alpha_0 + \alpha_1 D^{GFC} + \alpha_2 r_{t-1} + \alpha_3 D^{GFC} r_{t-1} + \alpha_4 r_t^f + \alpha_5 D^{GFC} r_t^f + \alpha_6 r_{t-1}^f + \alpha_7 D^{GFC} r_{t-1}^f + \alpha_8 D^F + \epsilon_t$

GARCH (I): $h_t = \beta_0 + \beta_1 h_{t-1} + \beta_2 \epsilon_{t-1}^2 + \beta_3 D^{GFC} + \beta_4 h_t^f + \beta_5 h_{t-1}^{A50} + \beta_6 h_{t-1}^{HSCEI} + \beta_D D^F$

GARCH (II): $h_t = \beta_7 + \beta_8 D^F + \beta_9 h_{t-1} + \beta_{10} D^F h_{t-1} + \beta_{11} \epsilon_{t-1}^2 + \beta_{12} D^F \epsilon_{t-1}^2 + \beta_{13} D^{GFC} + \beta_{14} h_t^f + \beta_{15} h_{t-1}^{A50} + \beta_{16} h_{t-1}^{HSCEI}$

GJR-GARCH (I): $h_t = \gamma_0 + \gamma_1 h_{t-1} + \gamma_2 \epsilon_{t-1}^2 + \gamma_3 \epsilon_{t-1}^2 I_{t-1} + \gamma_4 D^{GFC} + \gamma_5 h_t^f + \gamma_6 h_{t-1}^{A50} + \gamma_7 h_{t-1}^{HSCEI} + \gamma_D D^F$

GJR-GARCH (II): $h_t = \gamma_8 + \gamma_9 D^F + \gamma_{10} h_{t-1} + \gamma_{11} h_{t-1} D^F + \gamma_{12} \epsilon_{t-1}^2 + \gamma_{13} \epsilon_{t-1}^2 D^F + \gamma_{14} \epsilon_{t-1}^2 I_{t-1} + \gamma_{15} \epsilon_{t-1}^2 I_{t-1} D^F + \gamma_{16} D^{GFC} + \gamma_{17} h_t^f + \gamma_{18} h_{t-1}^{A50} + \gamma_{19} h_{t-1}^{HSCEI}$

EGARCH (I): $\log(h_t) = \theta_0 + \theta_1 log(h_{t-1}) + \theta_2 |\epsilon_{t-1}/\sqrt{h_{t-1}}| + \theta_3 (\epsilon_{t-1}/\sqrt{h_{t-1}}) + \theta_4 D^{GFC} + \theta_5 h_t^f + \theta_6 h_{t-1}^{A50} + \theta_7 h_{t-1}^{HSCEI} + \theta_D D^F$

EGARCH (II): $\log(h_t) = \theta_8 + \theta_9 D^F + \theta_{10} log(h_{t-1}) + \theta_{11} log(h_{t-1}) D^F + \theta_{12} |\epsilon_{t-1}/\sqrt{h_{t-1}}| + \theta_{13} |\epsilon_{t-1}/\sqrt{h_{t-1}}| D^F + \theta_{14} (\epsilon_{t-1}/\sqrt{h_{t-1}}) + \theta_{15} (\epsilon_{t-1}/\sqrt{h_{t-1}}) D^F + \theta_{16} D^{GFC} + \theta_{17} h_t^f + \theta_{18} h_{t-1}^{A50} + \theta_{19} h_{t-1}^{HSCEI}$

Table 5: Regression Results - Impact of A50 Futures Introduction on A50 Spot Market

GARCH I				GJR-GARCH I				EGARCH I			
Variable	**Coefficient**	**Std. Error**	**T-Stat.**	**Variable**	**Coefficient**	**Std. Error**	**T-Stat.**	**Variable**	**Coefficient**	**Std. Error**	**T-Stat.**
α_0^{A50}	−0.0024	0.0336	−0.0739	α_0^{A50}	−0.0159	0.0307	−0.5201	α_0^{A50}	0.0039	0.0403	0.0977
α_1^{A50}	0.0577	0.0714	0.8083	α_1^{A50}	0.0292	0.0578	0.5056	α_1^{A50}	0.0527	0.1171	0.4508
α_2^{A50}	−0.0154	0.0228	−0.6766	α_2^{A50}	−0.0104	0.0251	−0.4157	α_2^{A50}	−0.0091	0.0167	−0.5444
α_3^{A50}	0.0031	0.0344	0.0908	α_3^{A50}	−0.0004	0.0531	−0.0088	α_3^{A50}	0.0004	0.0393	0.0114
α_4^{A50}	0.1845***	0.0364	5.0752	α_4^{A50}	0.1832***	0.0380	4.8226	α_4^{A50}	0.1683***	0.0362	4.6515
α_5^{A50}	0.0720	0.0799	0.9015	α_5^{A50}	0.0776	0.0800	0.9700	α_5^{A50}	0.1087	0.0812	1.3395
α_6^{A50}	0.1497***	0.0296	5.0662	α_6^{A50}	0.1451***	0.0302	4.8074	α_6^{A50}	0.1326***	0.0339	3.9083
α_7^{A50}	0.2209***	0.0718	3.0779	α_7^{A50}	0.2052***	0.0603	3.4033	α_7^{A50}	0.2154**	0.0875	2.4608
α_8^{A50}	0.0166	0.0453	0.3680	α_8^{A50}	0.0276	0.0381	0.7248	α_8^{A50}	0.0016	0.0593	0.0280
β_D^{A50}	0.0092	0.0120	0.7714	γ_D^{A50}	0.0305	0.0225	1.3548	θ_D^{A50}	0.0153*	0.0090	1.7080
β_0^{A50}	0.0246*	0.0148	1.6637	γ_0^{A50}	0.0722**	0.0298	2.4210	θ_0^{A50}	−0.0976***	0.0207	−4.7134
β_1^{A50}	0.9220***	0.0216	42.7538	γ_1^{A50}	0.8895***	0.0297	29.9511	θ_1^{A50}	0.9666***	0.0131	73.6446
β_2^{A50}	0.0779***	0.0216	3.6130	γ_2^{A50}	0.0565***	0.0215	2.6253	θ_2^{A50}	0.1518***	0.0335	4.5341
β_3^{A50}	0.0383	0.0475	0.8063	γ_3^{A50}	0.0319	0.0260	1.2285	θ_3^{A50}	−0.0215	0.0170	−1.2668
β_4^{A50}	−0.0024	0.0051	−0.4847	γ_4^{A50}	0.1658*	0.0984	1.6843	θ_4^{A50}	0.0213	0.0151	1.4124
β_6^{A50}	−0.0018	0.0025	−0.7088	γ_5^{A50}	−0.0087	0.0100	−0.8722	θ_5^{A50}	−0.0047	0.0034	−1.3983
				γ_7^{A50}	0.0023	0.0047	0.5050	θ_7^{A50}	0.0016	0.0013	1.2118

GARCH II				GJR-GARCH II				EGARCH II			
Variable	**Coefficient**	**Std. Error**	**T-Stat.**	**Variable**	**Coefficient**	**Std. Error**	**T-Stat.**	**Variable**	**Coefficient**	**Std. Error**	**T-Stat.**
β_7^{A50}	0.0660*	0.0359	1.8385	γ_8^{A50}	0.1734**	0.0730	2.3773	θ_8^{A50}	−0.1313***	0.0473	−2.7752
β_8^{A50}	−0.0354	0.0393	−0.9016	γ_9^{A50}	−0.1395	0.0717	−1.9463	θ_9^{A50}	0.0727	0.0521	1.3953
β_9^{A50}	0.8260***	0.0558	14.8075	γ_{10}^{A50}	0.7743***	0.0705	10.9780	θ_{10}^{A50}	0.9149***	0.0385	23.7404
β_{10}^{A50}	0.1231**	0.0576	2.1401	γ_{11}^{A50}	0.1719**	0.0681	2.5242	θ_{11}^{A50}	0.0717*	0.0401	1.7883
β_{11}^{A50}	0.1739***	0.0558	3.1182	γ_{12}^{A50}	0.1041	0.0669	1.5571	θ_{12}^{A50}	0.2301***	0.0859	2.6793
β_{12}^{A50}	0.1335**	0.0579	−2.3047	γ_{13}^{A50}	−0.0666	0.0659	−1.0118	θ_{13}^{A50}	0.1343	0.0944	−1.4228
β_{13}^{A50}	0.0381	0.0466	0.8173	γ_{14}^{A50}	0.0498	0.0650	0.7661	θ_{14}^{A50}	−0.0191	0.0477	−0.4008
β_{14}^{A50}	−0.0070	0.0081	−0.8726	γ_{15}^{A50}	−0.0438	0.0658	−0.6660	θ_{15}^{A50}	0.0134	0.0513	0.2624
β_{15}^{A50}	0.0022	0.0042	0.5340	γ_{16}^{A50}	0.0279	0.0386	0.7232	θ_{16}^{A50}	0.0001	0.0103	0.0185
				γ_{17}^{A50}	−0.0138	0.0092	−1.5127	θ_{17}^{A50}	−0.0066**	0.0026	−2.5369
				γ_{19}^{A50}	0.0061	0.0048	1.2889	θ_{19}^{A50}	0.0023**	0.0010	2.3482

Notes:*,** ,*** denote statistical significance at the 10%, 5% and 1% level. The estimated α-coefficients are substantially the same for the second set of variance equations. For the sake of brevity, they are omitted here but available upon request. All data are taken from Thomson Reuters Datastream.

Mean Equation: $r_t = \alpha_0 + \alpha_1 D^{GFC} + \alpha_2 r_{t-1} + \alpha_3 D^{GFC} r_{t-1} + \alpha_4 r_t^f + \alpha_5 D^{GFC} r_t^f + \alpha_6 r_{t-1}^f + \alpha_7 D^{GFC} r_{t-1}^f + \alpha_8 D^F + \epsilon_t$

GARCH (I): $h_t = \beta_0 + \beta_1 h_{t-1} + \beta_2 \epsilon_{t-1}^2 + \beta_3 D^{GFC} + \beta_4 h_t^f + \beta_5 h_{t-1}^{A50} + \beta_6 h_{t-1}^{HSCEI} + \beta_D D^F$

GARCH (II): $h_t = \beta_7 + \beta_8 D^F + \beta_9 h_{t-1} + \beta_{10} D^F h_{t-1} + \beta_{11} \epsilon_{t-1}^2 + \beta_{12} D^F \epsilon_{t-1}^2 + \beta_{13} D^{GFC} + \beta_{14} h_t^f + \beta_{15} h_{t-1}^{A50} + \beta_{16} h_{t-1}^{HSCEI}$

GJR-GARCH (I): $h_t = \gamma_0 + \gamma_1 h_{t-1} + \gamma_2 \epsilon_{t-1}^2 + \gamma_3 \epsilon_{t-1}^2 I_{t-1} + \gamma_4 D^{GFC} + \gamma_5 h_t^f + \gamma_6 h_{t-1}^{A50} + \gamma_7 h_{t-1}^{HSCEI} + \gamma_D D^F$

GJR-GARCH (II): $h_t = \gamma_8 + \gamma_9 D^F + \gamma_{10} h_{t-1} + \gamma_{11} h_{t-1} D^F + \gamma_{12} \epsilon_{t-1}^2 + \gamma_{13} \epsilon_{t-1}^2 D^F + \gamma_{14} \epsilon_{t-1}^2 I_{t-1} + \gamma_{15} \epsilon_{t-1}^2 I_{t-1} D^F + \gamma_{16} D^{GFC} + \gamma_{17} h_t^f + \gamma_{18} h_{t-1}^{A50} + \gamma_{19} h_{t-1}^{HSCEI}$

EGARCH (I): $\log(h_t) = \theta_0 + \theta_1 log(h_{t-1}) + \theta_2 |\epsilon_{t-1}/\sqrt{h_{t-1}}| + \theta_3(\epsilon_{t-1}/\sqrt{h_{t-1}}) + \theta_4 D^{GFC} + \theta_5 h_t^f + \theta_6 h_{t-1}^{A50} + \theta_7 h_{t-1}^{HSCEI} + \theta_D D^F$

EGARCH (II): $\log(h_t) = \theta_8 + \theta_9 D^F + \theta_{10} log(h_{t-1}) + \theta_{11} log(h_{t-1}) D^F + \theta_{12} |\epsilon_{t-1}/\sqrt{h_{t-1}}| + \theta_{13} |\epsilon_{t-1}/\sqrt{h_{t-1}}| D^F + \theta_{14}(\epsilon_{t-1}/\sqrt{h_{t-1}}) + \theta_{15}(\epsilon_{t-1}/\sqrt{h_{t-1}}) D^F + \theta_{16} D^{GFC} + \theta_{17} h_t^f + \theta_{18} h_{t-1}^{A50} + \theta_{19} h_{t-1}^{HSCEI}$

Table 6: Regression Results - Impact of HSCEI Futures Introduction on HSCEI Spot Market

GARCH I				**GJR-GARCH I**				**EGARCH I**			
Variable	**Coefficient**	**Std. Error**	**T-Stat.**	**Variable**	**Coefficient**	**Std. Error**	**T-Stat.**	**Variable**	**Coefficient**	**Std. Error**	**T-Stat.**
α_0^{HSCEI}	0.1900***	0.0592	3.2088	α_0^{HSCEI}	0.2028***	0.0564	3.5961	α_0^{HSCEI}	0.1581	0.1905	0.8301
α_1^{HSCEI}	0.2693**	0.1123	2.3980	α_1^{HSCEI}	0.2721***	0.0976	2.7876	α_1^{HSCEI}	0.2604	0.1941	1.3413
α_2^{HSCEI}	−0.0353*	0.0196	−1.8013	α_2^{HSCEI}	−0.0363**	0.0173	−2.1002	α_2^{HSCEI}	−0.0426	0.0396	−1.0773
α_3^{HSCEI}	−0.0935***	0.0315	−2.9731	α_3^{HSCEI}	−0.0912**	0.0379	−2.4094	α_3^{HSCEI}	−0.0786	0.1569	−0.5009
α_4^{HSCEI}	0.4319***	0.0357	12.0834	α_4^{HSCEI}	0.4418***	0.0335	13.2034	α_4^{HSCEI}	0.4311***	0.1005	4.2887
α_5^{HSCEI}	0.4019***	0.0892	4.5064	α_5^{HSCEI}	0.4107***	0.0709	5.7934	α_5^{HSCEI}	0.3883	0.3716	1.0453
α_6^{HSCEI}	0.5047***	0.0380	13.2720	α_6^{HSCEI}	0.5101***	0.0346	14.7266	α_6^{HSCEI}	0.5084***	0.1104	4.6045
α_7^{HSCEI}	0.3651***	0.0959	3.8090	α_7^{HSCEI}	0.3726***	0.0770	4.8399	α_7^{HSCEI}	0.3236	0.3067	1.0552
α_8^{HSCEI}	−0.1768***	0.0668	−2.6494	α_8^{HSCEI}	−0.1808***	0.0616	−2.9334	α_8^{HSCEI}	−0.1523	0.2183	−0.6982
β_D^{HSCEI}	−0.0133	0.0130	−1.0233	γ_D^{HSCEI}	−0.0147	0.0149	−0.9905	θ_D^{HSCEI}	−0.0089	0.0115	−0.7789
β_0^{HSCEI}	0.0371**	0.0173	2.1452	γ_0^{HSCEI}	0.0407**	0.0192	2.1288	θ_0^{HSCEI}	−0.0829***	0.0112	−7.4078
β_1^{HSCEI}	0.9315***	0.0102	90.9993	γ_1^{HSCEI}	0.9265***	0.0100	92.8091	θ_1^{HSCEI}	0.9754***	0.0089	109.6190
β_2^{HSCEI}	0.0684***	0.0102	6.6898	γ_2^{HSCEI}	0.0734***	0.0100	7.3534	θ_2^{HSCEI}	0.1397***	0.0267	5.2269
β_3^{HSCEI}	0.0694**	0.0321	2.1661	γ_3^{HSCEI}	−0.0210***	0.0081	−2.5971	θ_3^{HSCEI}	−0.0051	0.0147	−0.3504
β_4^{HSCEI}	−0.0096	0.0073	−1.3133	γ_4^{HSCEI}	0.0976***	0.0326	2.9952	θ_4^{HSCEI}	0.0416	0.0420	0.9907
β_6^{HSCEI}	−0.0027	0.0044	−0.6290	γ_5^{HSCEI}	−0.0007	0.0081	−0.0924	θ_5^{HSCEI}	0.0014	0.0017	0.8781
				γ_7^{HSCEI}	−0.0004	0.0043	−0.1099	θ_7^{HSCEI}	−0.0016	0.0041	−0.4173

GARCH II				**GJR-GARCH II**				**EGARCH II**			
Variable	**Coefficient**	**Std. Error**	**T-Stat.**	**Variable**	**Coefficient**	**Std. Error**	**T-Stat.**	**Variable**	**Coefficient**	**Std. Error**	**T-Stat.**
β_7^{HSCEI}	0.0124	0.0196	0.6331	γ_8^{HSCEI}	0.0417	0.0306	1.3652	θ_8^{HSCEI}	0.9100***	0.2803	3.2473
β_8^{HSCEI}	0.0228	0.0222	1.0322	γ_9^{HSCEI}	−0.0030	0.0334	−0.0907	θ_9^{HSCEI}	−1.0042***	0.2855	−3.5177
β_9^{HSCEI}	0.9268***	0.0317	29.2399	γ_{10}^{HSCEI}	0.9178***	0.0299	30.7129	θ_{10}^{HSCEI}	−0.2408	0.2644	−0.9111
β_{10}^{HSCEI}	−0.0098	0.0289	−0.3426	γ_{11}^{HSCEI}	−0.0037	0.0301	−0.1235	θ_{11}^{HSCEI}	1.2105***	0.2634	4.5964
β_{11}^{HSCEI}	0.0731**	0.0317	2.3064	γ_{12}^{HSCEI}	0.0820**	0.0299	2.7471	θ_{12}^{HSCEI}	0.2831**	0.1095	2.5847
β_{12}^{HSCEI}	−0.0140	0.0317	−0.4438	γ_{13}^{HSCEI}	−0.0335	0.0325	−1.0305	θ_{13}^{HSCEI}	−0.1362	0.1170	−1.1648
β_{13}^{HSCEI}	0.1321**	0.0542	2.4384	γ_{14}^{HSCEI}	−0.0315	0.0242	−1.3008	θ_{14}^{HSCEI}	0.0632	0.0747	0.8465
β_{14}^{HSCEI}	0.0053	0.0126	0.4262	γ_{15}^{HSCEI}	0.0546*	0.0317	1.7277	θ_{15}^{HSCEI}	−0.0783	0.0767	−1.0212
β_{16}^{HSCEI}	0.0017	0.0056	0.3041	γ_{16}^{HSCEI}	0.1339**	0.0545	2.4555	θ_{16}^{HSCEI}	0.0469**	0.0208	2.2558
				γ_{17}^{HSCEI}	0.0050	0.0137	0.3717	θ_{17}^{HSCEI}	0.0035	0.0027	1.3423
				γ_{19}^{HSCEI}	0.0019	0.0062	0.3188	θ_{19}^{HSCEI}	−0.0022	0.0023	−1.0071

Notes:*,**,*** denote statistical significance at the 10%, 5% and 1% level. The estimated α-coefficients are substantially the same for the second set of variance equations. For the sake of brevity, they are omitted here but available upon request. All data are taken from Thomson Reuters Datastream.

Mean Equation: $r_t = \alpha_0 + \alpha_1 D^{GFC} + \alpha_2 r_{t-1} + \alpha_3 D^{GFC} r_{t-1} + \alpha_4 r_t^f + \alpha_5 D^{GFC} r_t^f + \alpha_6 r_{t-1}^f + \alpha_7 D^{GFC} r_{t-1}^f + \alpha_8 D^F + \epsilon_t$

GARCH (I): $h_t = \beta_0 + \beta_1 h_{t-1} + \beta_2 \epsilon_{t-1}^2 + \beta_3 D^{GFC} + \beta_4 h_t^f + \beta_5 h_{t-1}^{A50} + \beta_6 h_{t-1}^{HSCEI} + \beta_D D^F$

GARCH (II): $h_t = \beta_7 + \beta_8 D^F + \beta_9 h_{t-1} + \beta_{10} D^F h_{t-1} + \beta_{11} \epsilon_{t-1}^2 + \beta_{12} D^F \epsilon_{t-1}^2 + \beta_{13} D^{GFC} + \beta_{14} h_t^f + \beta_{15} h_{t-1}^{A50} + \beta_{16} h_{t-1}^{HSCEI}$

GJR-GARCH (I): $h_t = \gamma_0 + \gamma_1 h_{t-1} + \gamma_2 \epsilon_{t-1}^2 + \gamma_3 \epsilon_{t-1}^2 I_{t-1} + \gamma_4 D^{GFC} + \gamma_5 h_t^f + \gamma_6 h_{t-1}^{A50} + \gamma_7 h_{t-1}^{HSCEI} + \gamma_D D^F$

GJR-GARCH (II): $h_t = \gamma_8 + \gamma_9 D^F + \gamma_{10} h_{t-1} + \gamma_{11} h_{t-1} D^F + \gamma_{12} \epsilon_{t-1}^2 + \gamma_{13} \epsilon_{t-1}^2 D^F + \gamma_{14} \epsilon_{t-1}^2 I_{t-1} + \gamma_{15} \epsilon_{t-1}^2 I_{t-1} D^F + \gamma_{16} D^{GFC} + \gamma_{17} h_t^f + \gamma_{18} h_{t-1}^{A50} + \gamma_{19} h_{t-1}^{HSCEI}$

EGARCH (I): $\log(h_t) = \theta_0 + \theta_1 log(h_{t-1}) + \theta_2 |\epsilon_{t-1}/\sqrt{h_{t-1}}| + \theta_3 (\epsilon_{t-1}/\sqrt{h_{t-1}}) + \theta_4 D^{GFC} + \theta_5 h_t^f + \theta_6 h_{t-1}^{A50} + \theta_7 h_{t-1}^{HSCEI} + \theta_D D^F$

EGARCH (II): $\log(h_t) = \theta_8 + \theta_9 D^F + \theta_{10} log(h_{t-1}) + \theta_{11} log(h_{t-1}) D^F + \theta_{12} |\epsilon_{t-1}/\sqrt{h_{t-1}}| + \theta_{13} |\epsilon_{t-1}/\sqrt{h_{t-1}}| D^F + \theta_{14} (\epsilon_{t-1}/\sqrt{h_{t-1}}) + \theta_{15} (\epsilon_{t-1}/\sqrt{h_{t-1}}) D^F + \theta_{16} D^{GFC} + \theta_{17} h_t^f + \theta_{18} h_{t-1}^{A50} + \theta_{19} h_{t-1}^{HSCEI}$

9 Appendix

9.1 Additional Institutional Information about Spot and Derivatives Markets in Asia

- Even though A and B shares were identical in terms of ownership rights, market capitalization of the B-shares segment remained low. As of December 2007, total market capitalization of all A-shares traded in Shanghai (Shenzhen) was about 170 (40) times the total value of B-shares. B-shares typically traded at a considerable discount to A-shares (Fernald and Rogers, 2002).

- The QFII system allows licensed professional foreign investors to trade CNY denominated securities in China's mainland stock exchanges by converting foreign currency to CNY with a quota obtained from the relevant authorities. QFIIs have to satisfy minimum requirements regarding assets under management, paid-in capital and experience in trading.

- The CSI300 index components are adjusted every six months based on their size and liquidity by examination of daily average trading value.

- The settlement price of the nearby CSI300 futures contract was CNY 3431.2 on the first day of trading, giving each futures contract a notional value of CNY 1,029,360 (USD 150,811 at the exchange rate prevailing at that time). As the CSI300 futures market is a pure order-driven trading mechanism without market makers, trading is conducted by a central computer system which matches buy and sell orders.

- The A50 index itself accounts for approximately 47 percent of the total market capitalization of the entire A-share market. Right after the creation of A50 index futures in Singapore, the CFFEX was established in Shanghai and started preparing China's own index futures with four years of mock trading for large qualified domestic institutions. Most interestingly, there was almost no action in the A50 futures market until the introduction of CSI300 futures in April 2010. Since the market revisions following the introduction of CSI300 index futures, both T and T+1 sessions offer extended trading hours in the A50 futures market. Lunch break was canceled for a continuous T session from 09:00 to 15:25 local time (GMT+8h) and the T+1 session now trades from 16:40 to 02:00 the next day. The initial margin was reduced and is now USD 500; the maintenance margin is USD 550. The tick size is 5 index points worth USD 5 each.

- In the HSCEI index futures market, trading hours are from 09:15 to 12:00 noon and from 13:00 to 16:15. Since April 8, 2013, there exists an additional T+1 session from 17:00 to 23:00. Trading of expiring contracts closes at 16:00 on the last trading day, which is the business day immediately preceding the last business day of the contract month.

- The correlation between the CSI300 and the A50 spot index is 0.97. The correlation between the CSI300 and the HSCEI is 0.92 and the one between the A50 and the HSCEI is 0.84. The extremely high correlation between the CSI300 and the A50 stems from the fact that the 50 stocks with the highest weight in the CSI300 index are those forming the A50 index.

- With an average of 400,025 contracts traded per day since their introduction, trading volume in the CSI300 futures market is much higher than in the A50 (15,439 contracts for the same period since August 2010) and the HSCEI futures market (43,245 contracts). Since the third quarter of 2012, the CSI300 futures' trading volume rose to extremely high levels while the other two index futures remained at levels around their average. As noted above, A50 index futures were only lightly traded soon after their introduction in September 2006 (average daily turnover: 94 contracts) and not traded at all between October 2008 and late August 2010. Only the direct competition from CSI300 index futures induced reforms in the contract specifications and market set-up. Subsequently, the number of contracts traded increased to a daily average of 36,000. This is summarized in Figure 2. Figure 3 shows that open interest of CSI300 index futures rose steadily since their introduction but has remained below that of A50 and HSCEI index futures. Open interest of A50 futures remains low until 2012 (average of 11,138 contracts per day up to the end of December 2011) and shows significant increases during late 2012 and early 2013 (daily average of 181,221). The relatively high trading volume of the CSI 300 index futures compared to relatively low open interest could mirror an increased market activity of speculative investors. It may also reflect the large contract size, and therefore relatively high price, in comparison to the other two index futures. Figure 4 shows the ratio of trading volume to open interest for all three futures markets. The average ratio of 6.7 is extremely high for CSI300 futures, compared to averages of 0.3 and 0.5 for A50 and HSCEI futures respectively. An international comparison shows that more markets tend to fluctuate around the same ratios as the latter: For the sample period between April 2010 and June 2013, the average ratio for S&P index futures is 0.1, for EuroStoxx50 futures 0,5 and for Nikkei index futures 0.3. The extraordinarily high ratio of trading volume to open interest for the CSI300 futures may simply reflect the large contract size, possibly leading to a small number of existing contracts that are frequently traded. One other possible reason for the small open interest may be strong market regulation. If the regulator limits market supply of futures contracts, high demand is very likely to result in large trading volume.

Figure 2: Trading Volume - Total Number of Contracts Traded per Day

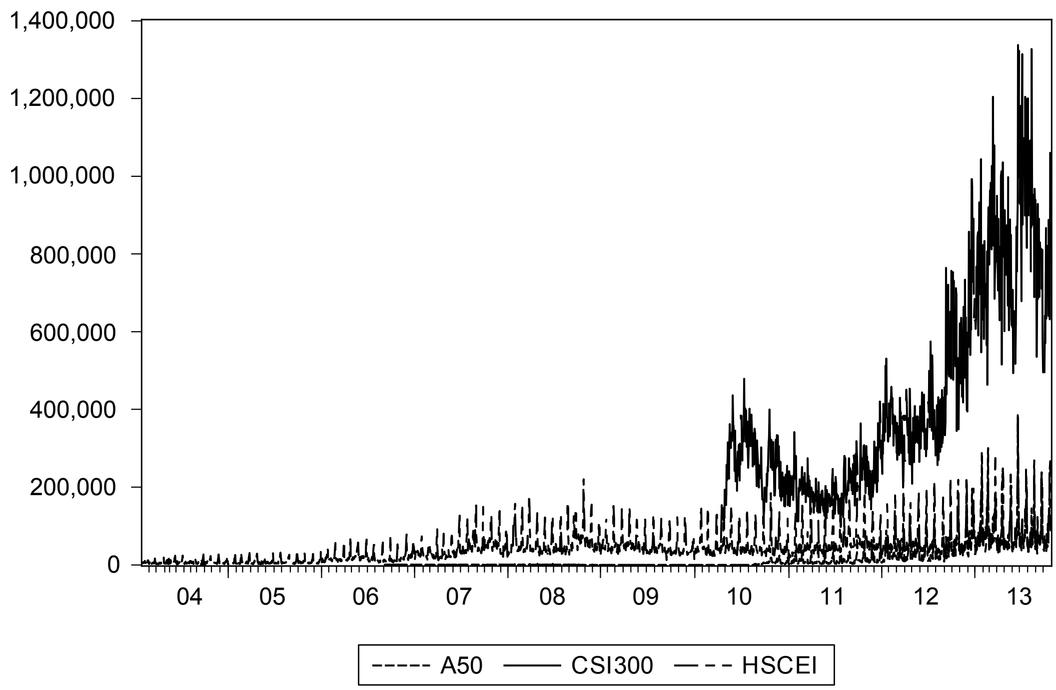
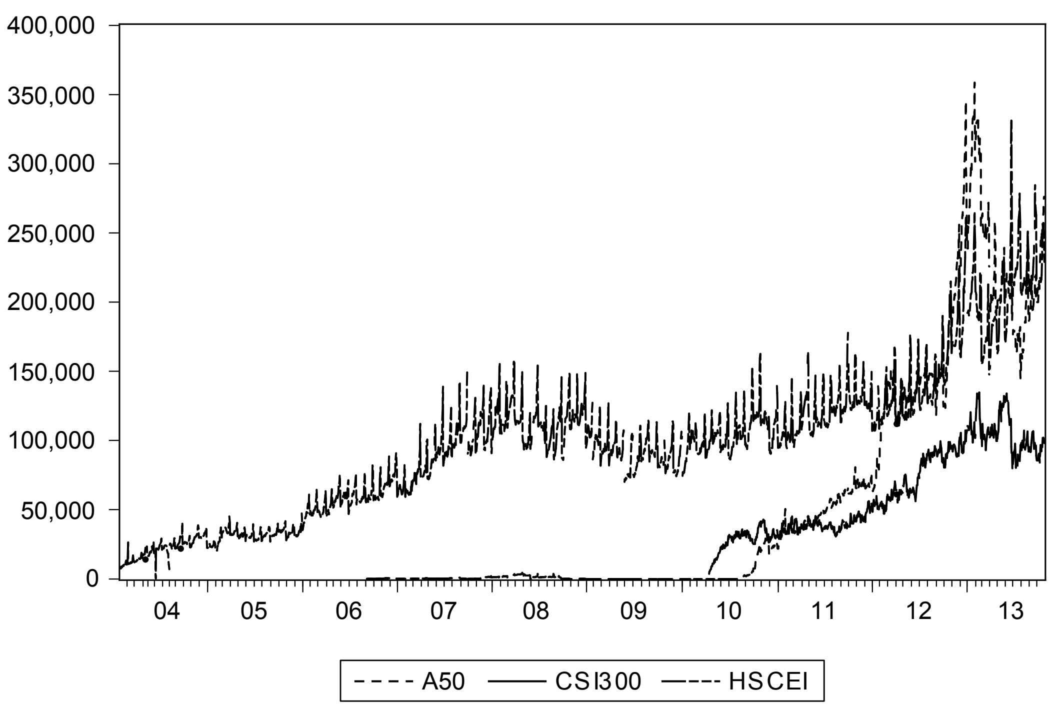
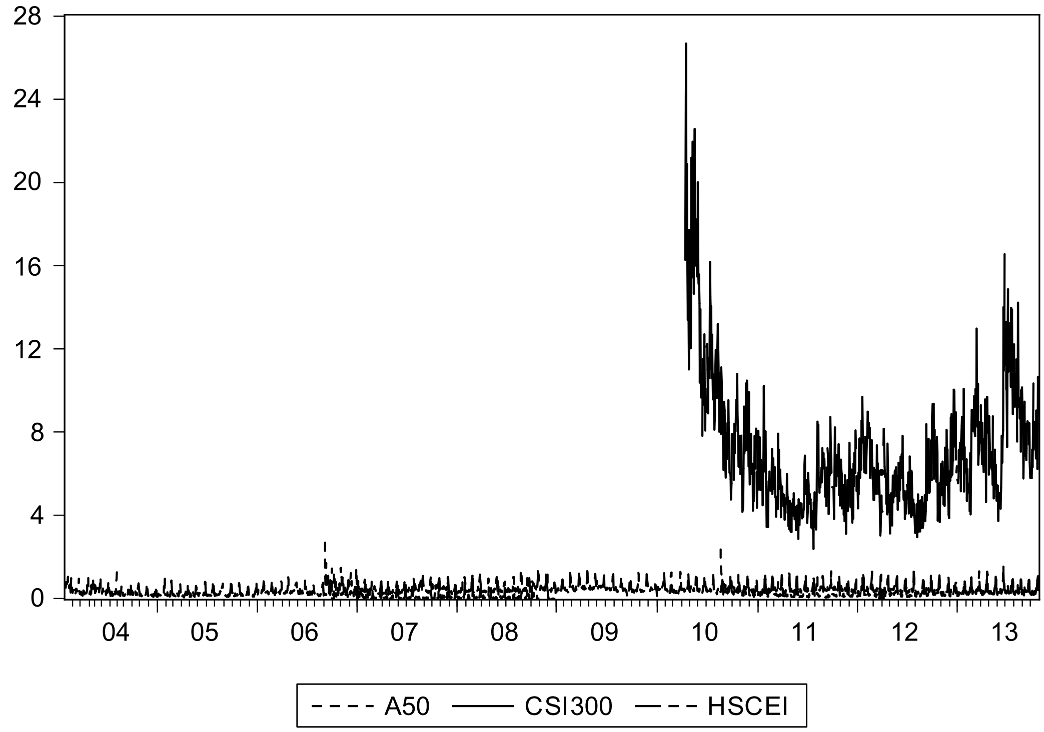


Figure 3: Open Interest - Total Number of Outstanding Contracts per Day



Notes: All data is taken from Thomson Reuters Datastream.

Figure 4: Trading Volume to Open Interest Ratio



Notes: All data is taken from Thomson Reuters Datastream.

9.2 Principal Component Estimation Results

Tables 7, 8 and 9 show the regression results for three different principal component series and the possible impact of the CSI300 index futures introduction. The first series (Table 7) captures the principal components of the CSI300, the A50 and the HSCEI spot indices. Generally, we find empirical evidence in favor of the stabilizing hypothesis. Table 8 summarizes our findings for a series containing the principal components of the CSI300, the A50, the HSCEI and the MSCI index. The results are not unanimous. While the estimated coefficients of the GARCH I, GJR-GARCH I and EGARCH I models show no significant impact of the futures introduction, the GARCH II, GJR-GARCH II and EGARCH II models yield evidence in favor of the stabilizing hypothesis. Lastly, estimating our models with a principal component series that combines the three Asian indices, the Chinese B35 index, the EuroStoxx50 index and the S&P500 index shows no significant impact of the futures introduction at all (Table 9). Therefore, we can summarize that this robustness check strongly confirms the results outlined above.

Tables 7, 8 and 9 about here.[12]

[12] As the PC series mirror the CSI300, the A50 and the HSCEI, all summands referring to spillover effects across these markets are excluded. In line with this, all summands including the MSCI index are eliminated from the models when the MSCI itself enters the PC calculations.

Table 7: Regression Results - Impact of CSI300 Futures Introduction on Principal Component Series Asia 3

GARCH I				**GJR-GARCH I**				**EGARCH I**			
Variable	**Coefficient**	**Std. Error**	**T-Stat.**	**Variable**	**Coefficient**	**Std. Error**	**T-Stat.**	**Variable**	**Coefficient**	**Std. Error**	**T-Stat.**
α_0^{PC}	0.0016	0.0385	0.0438	α_0^{PC}	0.0116	0.0558	0.2087	α_0^{PC}	0.0379	0.0506	0.7500
α_1^{PC}	0.0313	0.0581	0.5395	α_1^{PC}	0.0303	0.0823	0.3684	α_1^{PC}	−0.0341	0.0747	−0.4569
α_2^{PC}	−0.0925***	0.0276	−3.3550	α_2^{PC}	−0.0931***	0.0291	−3.1971	α_2^{PC}	−0.0887***	0.0311	−2.8524
α_3^{PC}	0.0679	0.0482	1.4108	α_3^{PC}	0.0731*	0.0440	1.6640	α_3^{PC}	0.0629	0.0613	1.0272
α_4^{PC}	0.1684***	0.0245	6.8815	α_4^{PC}	0.1686***	0.0253	6.6720	α_4^{PC}	0.1813***	0.0241	7.5104
α_5^{PC}	−0.0437	0.0436	−1.0017	α_5^{PC}	−0.0400	0.0444	−0.9019	α_5^{PC}	−0.0611	0.0461	−1.3251
α_6^{PC}	0.1254***	0.0229	5.4807	α_6^{PC}	0.1235***	0.0232	5.3147	α_6^{PC}	0.1175***	0.0212	5.5448
α_7^{PC}	0.0331	0.0365	0.9090	α_7^{PC}	0.0384	0.0395	0.9744	α_7^{PC}	0.0414	0.0526	0.7885
α_8^{PC}	−0.0458	0.0462	−0.9924	α_8^{PC}	0.0529	0.0609	0.8698	α_8^{PC}	−0.0775	0.0549	−1.4134
β_D^{PC}	−0.0004***	0.0030	−4.1558	γ_D^{PC}	−0.0042**	0.0066	−2.6544	θ_D^{PC}	−1.4628***	0.2766	−5.2883
β_0^{PC}	0.0027	0.0031	0.9031	γ_0^{PC}	0.0087	0.0080	1.0977	θ_0^{PC}	0.0177	0.2184	0.0815
β_1^{PC}	0.9652***	0.0113	85.2251	γ_1^{PC}	0.9609***	0.0147	65.2999	θ_1^{PC}	−0.8228***	0.1413	−5.8229
β_2^{PC}	0.0347***	0.0113	3.0639	γ_2^{PC}	0.0390***	0.0147	2.8547	θ_2^{PC}	−0.0446	0.0528	−0.8455
β_3^{PC}	0.0000	0.0051	−0.0171	γ_3^{PC}	−0.0127	0.0111	−1.1402	θ_3^{PC}	−0.0170	0.0400	−0.4249
β_4^{PC}	−0.0004	0.0009	−0.5190	γ_4^{PC}	0.0057	0.0081	0.7113	θ_4^{PC}	1.0485***	0.2852	3.6771
				γ_5^{PC}	−0.0002	0.0014	−0.1867	θ_5^{PC}	0.0560	0.0343	1.6341

GARCH II				**GJR-GARCH II**				**EGARCH II**			
Variable	**Coefficient**	**Std. Error**	**T-Stat.**	**Variable**	**Coefficient**	**Std. Error**	**T-Stat.**	**Variable**	**Coefficient**	**Std. Error**	**T-Stat.**
β_7^{PC}	0.0200	0.0145	1.3810	γ_8^{PC}	0.0823**	0.0408	2.0179	θ_8^{PC}	−0.1505***	0.0514	−2.9307
β_8^{PC}	−0.0140*	0.0147	−1.9834	γ_9^{PC}	−0.5067***	0.0679	7.4592	θ_9^{PC}	−1.0048*	0.5991	−1.6773
β_9^{PC}	0.8938***	0.0467	19.1386	γ_{10}^{PC}	0.8204***	0.0551	14.8802	θ_{10}^{PC}	0.9079***	0.0592	15.3255
β_{10}^{PC}	−0.0770***	0.0461	3.6720	γ_{11}^{PC}	−0.4510***	0.0879	−11.8897	θ_{11}^{PC}	−1.5691***	0.5251	−2.9886
β_{11}^{PC}	0.1061**	0.0467	2.2721	γ_{12}^{PC}	0.0596	0.0482	1.2370	θ_{12}^{PC}	0.1960***	0.0703	2.7882
β_{12}^{PC}	−0.0913*	0.0476	−1.9193	γ_{13}^{PC}	−0.2792***	0.0606	−4.6116	θ_{13}^{PC}	−0.3712*	0.2147	−1.7294
β_{13}^{PC}	0.0040	0.0148	0.2716	γ_{14}^{PC}	0.0692	0.0565	1.2261	θ_{14}^{PC}	−0.0485	0.0434	−1.1185
β_{14}^{PC}	0.0004	0.0012	0.3568	γ_{15}^{PC}	0.2650	0.2086	1.2710	θ_{15}^{PC}	0.0553	0.1392	0.3981
				γ_{16}^{PC}	0.0702	0.0449	1.5641	θ_{16}^{PC}	0.0447	0.0537	0.8333
				γ_{17}^{PC}	0.0032	0.0068	0.4821	θ_{17}^{PC}	0.0021	0.0037	0.5695

Notes:*,**,*** denote statistical significance at the 10%, 5% and 1% level. The estimated α-coefficients are substantially the same for the second set of variance equations. For the sake of brevity, they are omitted here but available upon request. All data are taken from Thomson Reuters Datastream.

Mean Equation: $r_t = \alpha_0 + \alpha_1 D^{GFC} + \alpha_2 r_{t-1} + \alpha_3 D^{GFC} r_{t-1} + \alpha_4 r_t^f + \alpha_5 D^{GFC} r_t^f + \alpha_6 r_{t-1}^f + \alpha_7 D^{GFC} r_{t-1}^f + \alpha_8 D^F + \epsilon_t$

GARCH (I): $h_t = \beta_0 + \beta_1 h_{t-1} + \beta_2 \epsilon_{t-1}^2 + \beta_3 D^{GFC} + \beta_4 h_t^f + \beta_5 h_{t-1}^{A50} + \beta_6 h_{t-1}^{HSCEI} + \beta_D D^F$

GARCH (II): $h_t = \beta_7 + \beta_8 D^F + \beta_9 h_{t-1} + \beta_{10} D^F h_{t-1} + \beta_{11} \epsilon_{t-1}^2 + \beta_{12} D^F \epsilon_{t-1}^2 + \beta_{13} D^{GFC} + \beta_{14} h_t^f + \beta_{15} h_{t-1}^{A50} + \beta_{16} h_{t-1}^{HSCEI}$

GJR-GARCH (I): $h_t = \gamma_0 + \gamma_1 h_{t-1} + \gamma_2 \epsilon_{t-1}^2 + \gamma_3 \epsilon_{t-1}^2 I_{t-1} + \gamma_4 D^{GFC} + \gamma_5 h_t^f + \gamma_6 h_{t-1}^{A50} + \gamma_7 h_{t-1}^{HSCEI} + \gamma_D D^F$

GJR-GARCH (II): $h_t = \gamma_8 + \gamma_9 D^F + \gamma_{10} h_{t-1} + \gamma_{11} h_{t-1} D^F + \gamma_{12} \epsilon_{t-1}^2 + \gamma_{13} \epsilon_{t-1}^2 D^F + \gamma_{14} \epsilon_{t-1}^2 I_{t-1} + \gamma_{15} \epsilon_{t-1}^2 I_{t-1} D^F + \gamma_{16} D^{GFC} + \gamma_{17} h_t^f + \gamma_{18} h_{t-1}^{A50} + \gamma_{19} h_{t-1}^{HSCEI}$

EGARCH (I): $\log(h_t) = \theta_0 + \theta_1 log(h_{t-1}) + \theta_2 |\epsilon_{t-1}/\sqrt{h_{t-1}}| + \theta_3 (\epsilon_{t-1}/\sqrt{h_{t-1}}) + \theta_4 D^{GFC} + \theta_5 h_t^f + \theta_6 h_{t-1}^{A50} + \theta_7 h_{t-1}^{HSCEI} + \theta_D D^F$

EGARCH (II): $\log(h_t) = \theta_8 + \theta_9 D^F + \theta_{10} log(h_{t-1}) + \theta_{11} log(h_{t-1}) D^F + \theta_{12} |\epsilon_{t-1}/\sqrt{h_{t-1}}| + \theta_{13} |\epsilon_{t-1}/\sqrt{h_{t-1}}| D^F + \theta_{14} (\epsilon_{t-1}/\sqrt{h_{t-1}}) + \theta_{15} (\epsilon_{t-1}/\sqrt{h_{t-1}}) D^F + \theta_{16} D^{GFC} + \theta_{17} h_t^f + \theta_{18} h_{t-1}^{A50} + \theta_{19} h_{t-1}^{HSCEI}$

Table 8: Regression Results - Impact of CSI300 Futures Introduction on Principal Component Series Asia 3 plus MSCI

GARCH I				**GJR-GARCH I**				**EGARCH I**			
Variable	**Coefficient**	**Std. Error**	**T-Stat.**	**Variable**	**Coefficient**	**Std. Error**	**T-Stat.**	**Variable**	**Coefficient**	**Std. Error**	**T-Stat.**
α_0^{PCMSCI}	0.0292	0.0563	0.5196	α_0^{PCMSCI}	0.0419	0.0609	0.6886	α_0^{PCMSCI}	0.0470	0.0678	0.6940
α_1^{PCMSCI}	−0.0083	0.0894	−0.0934	α_1^{PCMSCI}	−0.0095	0.0976	−0.0974	α_1^{PCMSCI}	−0.0675	0.0998	−0.6762
α_2^{PCMSCI}	−0.0173	0.0278	−0.6220	α_2^{PCMSCI}	−0.0184	0.0295	−0.6243	α_2^{PCMSCI}	−0.0037	0.0338	−0.1109
α_3^{PCMSCI}	0.0143	0.0491	0.2913	α_3^{PCMSCI}	0.0178	0.0536	0.3335	α_3^{PCMSCI}	0.0011	0.0564	0.0211
α_8^{PCMSCI}	−0.0685	0.0611	−1.1216	α_8^{PCMSCI}	−0.0762	0.0669	−1.1405	α_8^{PCMSCI}	−0.0929	0.0773	−1.2032
β_D^{PCMSCI}	−0.0020	0.0056	−0.3643	γ_D^{PCMSCI}	−0.0056	0.0068	−0.8321	θ_D^{PCMSCI}	−0.0385	0.0210	−1.8379
β_0^{PCMSCI}	0.0057	0.0070	0.8231	γ_0^{PCMSCI}	0.0139	0.0110	1.2659	θ_0^{PCMSCI}	−0.0754***	0.0245	−3.0866
β_1^{PCMSCI}	0.9508***	0.0225	42.1906	γ_1^{PCMSCI}	0.9433***	0.0282	33.4736	θ_1^{PCMSCI}	0.9320***	0.0303	30.8130
β_2^{PCMSCI}	0.0491**	0.0225	2.1822	γ_2^{PCMSCI}	0.0566**	0.0282	2.0112	θ_2^{PCMSCI}	0.1018***	0.0286	3.5577
β_3^{PCMSCI}	0.0015	0.0079	0.1913	γ_3^{PCMSCI}	−0.0174	0.0131	−1.3264	θ_3^{PCMSCI}	−0.0569*	0.0333	−1.7102
				γ_4^{PCMSCI}	0.0130	0.0156	0.8419	θ_4^{PCMSCI}	0.0427	0.0295	1.4484
GARCH II				**GJR-GARCH II**				**EGARCH II**			
Variable	**Coefficient**	**Std. Error**	**T-Stat.**	**Variable**	**Coefficient**	**Std. Error**	**T-Stat.**	**Variable**	**Coefficient**	**Std. Error**	**T-Stat.**
β_7^{PCMSCI}	0.0210	0.0196	1.0758	γ_8^{PCMSCI}	0.0276*	0.0150	1.8411	θ_8^{PCMSCI}	−0.1292***	0.0378	−3.4223
β_8^{PCMSCI}	1.0251***	0.0894	11.4629	γ_9^{PCMSCI}	0.1773	0.1616	1.0977	θ_9^{PCMSCI}	−0.4189***	0.1535	−4.7287
β_9^{PCMSCI}	0.8876***	0.0545	16.2906	γ_{10}^{PCMSCI}	0.8847***	0.0418	21.1568	θ_{10}^{PCMSCI}	0.9151***	0.0572	15.9999
β_{10}^{PCMSCI}	−1.7061***	0.1106	−15.4201	γ_{11}^{PCMSCI}	−0.2521	0.2661	−0.9475	θ_{11}^{PCMSCI}	−1.2214***	0.0928	−13.1599
β_{11}^{PCMSCI}	0.1123**	0.0545	2.0625	γ_{12}^{PCMSCI}	0.1151***	0.0418	6.7544	θ_{12}^{PCMSCI}	0.1695**	0.0662	2.5598
β_{12}^{PCMSCI}	−0.1434***	0.0546	−2.6273	γ_{13}^{PCMSCI}	−0.1927***	0.0433	−4.4498	θ_{13}^{PCMSCI}	−0.4449***	0.1171	−3.7977
β_{13}^{PCMSCI}	0.0137	0.0270	0.5081	γ_{14}^{PCMSCI}	−0.0288	0.0208	−1.3831	θ_{14}^{PCMSCI}	−0.0539	0.0605	−0.8907
				γ_{15}^{PCMSCI}	0.1996***	0.0499	4.0003	θ_{15}^{PCMSCI}	−0.0777	0.0966	−0.8046
				γ_{16}^{PCMSCI}	0.0342	0.0251	1.3683	θ_{16}^{PCMSCI}	0.0573	0.0458	1.2510

Notes:*,** ,*** denote statistical significance at the 10%, 5% and 1% level. The estimated α-coefficients are substantially the same for the second set of variance equations. For the sake of brevity, they are omitted here but available upon request. All data are taken from Thomson Reuters Datastream.

Mean Equation: $r_t = \alpha_0 + \alpha_1 D^{GFC} + \alpha_2 r_{t-1} + \alpha_3 D^{GFC} r_{t-1} + \alpha_4 r_t^f + \alpha_5 D^{GFC} r_t^f + \alpha_6 r_{t-1}^f + \alpha_7 D^{GFC} r_{t-1}^f + \alpha_8 D^F + \epsilon_t$

GARCH (I): $h_t = \beta_0 + \beta_1 h_{t-1} + \beta_2 \epsilon_{t-1}^2 + \beta_3 D^{GFC} + \beta_4 h_t^f + \beta_5 h_{t-1}^{A50} + \beta_6 h_{t-1}^{HSCEI} + \beta_D D^F$

GARCH (II): $h_t = \beta_7 + \beta_8 D^F + \beta_9 h_{t-1} + \beta_{10} D^F h_{t-1} + \beta_{11} \epsilon_{t-1}^2 + \beta_{12} D^F \epsilon_{t-1}^2 + \beta_{13} D^{GFC} + \beta_{14} h_t^f + \beta_{15} h_{t-1}^{A50} + \beta_{16} h_{t-1}^{HSCEI}$

GJR-GARCH (I): $h_t = \gamma_0 + \gamma_1 h_{t-1} + \gamma_2 \epsilon_{t-1}^2 + \gamma_3 \epsilon_{t-1}^2 I_{t-1} + \gamma_4 D^{GFC} + \gamma_5 h_t^f + \gamma_6 h_{t-1}^{A50} + \gamma_7 h_{t-1}^{HSCEI} + \gamma_D D^F$

GJR-GARCH (II): $h_t = \gamma_8 + \gamma_9 D^F + \gamma_{10} h_{t-1} + \gamma_{11} h_{t-1} D^F + \gamma_{12} \epsilon_{t-1}^2 + \gamma_{13} \epsilon_{t-1}^2 D^F + \gamma_{14} \epsilon_{t-1}^2 I_{t-1} + \gamma_{15} \epsilon_{t-1}^2 I_{t-1} D^F + \gamma_{16} D^{GFC} + \gamma_{17} h_t^f + \gamma_{18} h_{t-1}^{A50} + \gamma_{19} h_{t-1}^{HSCEI}$

EGARCH (I): $\log(h_t) = \theta_0 + \theta_1 log(h_{t-1}) + \theta_2 |\epsilon_{t-1}/\sqrt{h_{t-1}}| + \theta_3 (\epsilon_{t-1}/\sqrt{h_{t-1}}) + \theta_4 D^{GFC} + \theta_5 h_t^f + \theta_6 h_{t-1}^{A50} + \theta_7 h_{t-1}^{HSCEI} + \theta_D D^F$

EGARCH (II): $\log(h_t) = \theta_8 + \theta_9 D^F + \theta_{10} log(h_{t-1}) + \theta_{11} log(h_{t-1}) D^F + \theta_{12} |\epsilon_{t-1}/\sqrt{h_{t-1}}| + \theta_{13} |\epsilon_{t-1}/\sqrt{h_{t-1}}| D^F + \theta_{14} (\epsilon_{t-1}/\sqrt{h_{t-1}}) + \theta_{15} (\epsilon_{t-1}/\sqrt{h_{t-1}}) D^F + \theta_{16} D^{GFC} + \theta_{17} h_t^f + \theta_{18} h_{t-1}^{A50} + \theta_{19} h_{t-1}^{HSCEI}$

Table 9: Regression Results - Impact of CSI300 Futures Introduction on Principal Component Series 6

GARCH I				**GJR-GARCH I**				**EGARCH I**			
Variable	**Coefficient**	**Std. Error**	**T-Stat.**	**Variable**	**Coefficient**	**Std. Error**	**T-Stat.**	**Variable**	**Coefficient**	**Std. Error**	**T-Stat.**
α_0^{PC6}	0.0047	0.0557	0.0855	α_0^{PC6}	0.0156	0.0534	0.2936	α_0^{PC6}	0.0395	0.0617	0.6414
α_1^{PC6}	0.0209	0.0812	0.2584	α_1^{PC6}	0.0202	0.0776	0.2614	α_1^{PC6}	−0.0469	0.0921	−0.5093
α_2^{PC6}	−0.0872***	0.0275	−3.1752	α_2^{PC6}	−0.0875***	0.0305	−2.8728	α_2^{PC6}	−0.0845***	0.0312	−3.7074
α_3^{PC6}	0.0722	0.0481	1.5015	α_3^{PC6}	0.0765	0.0540	1.4164	α_3^{PC6}	0.0706	0.0661	1.0685
α_4^{PC6}	0.1117***	0.0230	4.8599	α_4^{PC6}	0.1116***	0.0267	4.1789	α_4^{PC6}	0.1217***	0.0271	4.4881
α_5^{PC6}	−0.0515	0.0432	−1.1952	α_5^{PC6}	−0.0468	0.0466	−1.0061	α_5^{PC6}	−0.0669	0.0596	−1.1234
α_6^{PC6}	0.1343***	0.0194	6.9436	α_6^{PC6}	0.1323***	0.0253	5.2414	α_6^{PC6}	0.1315***	0.0243	5.4092
α_7^{PC6}	0.0369	0.0303	1.2209	α_7^{PC6}	0.0435	0.0483	0.9019	α_7^{PC6}	0.0398	0.0560	0.7118
α_8^{PC6}	0.0518	0.0616	0.8425	α_8^{PC6}	0.0595	0.0623	0.9554	α_8^{PC6}	−0.0814	0.0679	−1.1991
β_D^{PC6}	−0.0007	0.0055	−0.1402	γ_D^{PC6}	−0.0046	0.0064	−0.7216	θ_D^{PC6}	−1.4733	0.3185	−4.6262
β_0^{PC6}	0.0034	0.0057	0.6019	γ_0^{PC6}	0.0098	0.0079	1.2519	θ_0^{PC6}	0.0818	0.2249	0.3642
β_1^{PC6}	0.9639***	0.0146	66.1110	γ_1^{PC6}	0.9582***	0.0151	63.4566	θ_1^{PC6}	−0.8602***	0.2605	−3.3019
β_2^{PC6}	0.0360**	0.0146	2.4717	γ_2^{PC6}	0.0417***	0.0151	3.7617	θ_2^{PC6}	−0.0190	0.0577	−0.3302
β_3^{PC6}	0.0000	0.0083	−0.0086	γ_3^{PC6}	−0.0130	0.0104	−1.2491	θ_3^{PC6}	−0.0078	0.0471	−0.1659
β_4^{PC6}	−0.0005	0.0011	−0.5325	γ_4^{PC6}	0.0061	0.0093	0.6583	θ_4^{PC6}	1.0527***	0.3345	3.1472
				γ_5^{PC6}	−0.0002	0.0016	−0.1895	θ_5^{PC6}	0.0619*	0.0367	1.6868
GARCH II				**GJR-GARCH II**				**EGARCH II**			
Variable	**Coefficient**	**Std. Error**	**T-Stat.**	**Variable**	**Coefficient**	**Std. Error**	**T-Stat.**	**Variable**	**Coefficient**	**Std. Error**	**T-Stat.**
β_7^{PC6}	0.0237	0.0378	0.6278	γ_8^{PC6}	0.0916*	0.0487	1.8813	θ_8^{PC6}	−0.1645***	0.0493	−3.3368
β_8^{PC6}	0.8938	0.0913	9.7933	γ_9^{PC6}	0.5135	0.1022	5.0265	θ_9^{PC6}	−0.7622	0.2340	−3.2575
β_9^{PC6}	0.8956***	0.1189	7.5312	γ_{10}^{PC6}	0.7978***	0.0636	12.5505	θ_{10}^{PC6}	0.9019***	0.0606	14.8938
β_{10}^{PC6}	1.7265***	0.1959	−8.8141	γ_{11}^{PC6}	−1.1280	0.1655	−6.8169	θ_{11}^{PC6}	−1.4235	0.1848	−7.7037
β_{11}^{PC6}	0.1043	0.1189	0.8773	γ_{12}^{PC6}	0.0770	0.0554	1.3914	θ_{12}^{PC6}	0.2191***	0.0637	3.4424
β_{12}^{PC6}	−0.1285	0.1171	−1.0979	γ_{13}^{PC6}	−0.0527	0.2399	−0.2201	θ_{13}^{PC6}	−0.4359*	0.1469	−1.7684
β_{13}^{PC6}	0.0101	0.0208	0.4885	γ_{14}^{PC6}	0.0672	0.0701	0.9594	θ_{14}^{PC6}	−0.0500	0.0491	−1.0185
β_{14}^{PC6}	−0.0037	0.0041	−0.9192	γ_{15}^{PC6}	0.0000	0.3696	0.0002	θ_{15}^{PC6}	0.0950	0.0795	1.1959
				γ_{16}^{PC6}	0.0782	0.0485	1.6146	θ_{16}^{PC6}	0.0466	0.0446	1.0456
				γ_{17}^{PC6}	0.0045	0.0095	0.4802	θ_{17}^{PC6}	0.0024	0.0048	0.5035

Notes:*,**,*** denote statistical significance at the 10%, 5% and 1% level. The estimated α-coefficients are substantially the same for the second set of variance equations. For the sake of brevity, they are omitted here but available upon request. All data are taken from Thomson Reuters Datastream.

Mean Equation: $r_t = \alpha_0 + \alpha_1 D^{GFC} + \alpha_2 r_{t-1} + \alpha_3 D^{GFC} r_{t-1} + \alpha_4 r_t^f + \alpha_5 D^{GFC} r_t^f + \alpha_6 r_{t-1}^f + \alpha_7 D^{GFC} r_{t-1}^f + \alpha_8 D^F + \epsilon_t$

GARCH (I): $h_t = \beta_0 + \beta_1 h_{t-1} + \beta_2 \epsilon_{t-1}^2 + \beta_3 D^{GFC} + \beta_4 h_t^f + \beta_5 h_{t-1}^{A50} + \beta_6 h_{t-1}^{HSCEI} + \beta_D D^F$

GARCH (II): $h_t = \beta_7 + \beta_8 D^F + \beta_9 h_{t-1} + \beta_{10} D^F h_{t-1} + \beta_{11} \epsilon_{t-1}^2 + \beta_{12} D^F \epsilon_{t-1}^2 + \beta_{13} D^{GFC} + \beta_{14} h_t^f + \beta_{15} h_{t-1}^{A50} + \beta_{16} h_{t-1}^{HSCEI}$

GJR-GARCH (I): $h_t = \gamma_0 + \gamma_1 h_{t-1} + \gamma_2 \epsilon_{t-1}^2 + \gamma_3 \epsilon_{t-1}^2 I_{t-1} + \gamma_4 D^{GFC} + \gamma_5 h_t^f + \gamma_6 h_{t-1}^{A50} + \gamma_7 h_{t-1}^{HSCEI} + \gamma_D D^F$

GJR-GARCH (II): $h_t = \gamma_8 + \gamma_9 D^F + \gamma_{10} h_{t-1} + \gamma_{11} h_{t-1} D^F + \gamma_{12} \epsilon_{t-1}^2 + \gamma_{13} \epsilon_{t-1}^2 D^F + \gamma_{14} \epsilon_{t-1}^2 I_{t-1} + \gamma_{15} \epsilon_{t-1}^2 I_{t-1} D^F + \gamma_{16} D^{GFC} + \gamma_{17} h_t^f + \gamma_{18} h_{t-1}^{A50} + \gamma_{19} h_{t-1}^{HSCEI}$

EGARCH (I): $\log(h_t) = \theta_0 + \theta_1 log(h_{t-1}) + \theta_2 |\epsilon_{t-1}/\sqrt{h_{t-1}}| + \theta_3 (\epsilon_{t-1}/\sqrt{h_{t-1}}) + \theta_4 D^{GFC} + \theta_5 h_t^f + \theta_6 h_{t-1}^{A50} + \theta_7 h_{t-1}^{HSCEI} + \theta_D D^F$

EGARCH (II): $\log(h_t) = \theta_8 + \theta_9 D^F + \theta_{10} log(h_{t-1}) + \theta_{11} log(h_{t-1}) D^F + \theta_{12} |\epsilon_{t-1}/\sqrt{h_{t-1}}| + \theta_{13} |\epsilon_{t-1}/\sqrt{h_{t-1}}| D^F + \theta_{14} (\epsilon_{t-1}/\sqrt{h_{t-1}}) + \theta_{15} (\epsilon_{t-1}/\sqrt{h_{t-1}}) D^F + \theta_{16} D^{GFC} + \theta_{17} h_t^f + \theta_{18} h_{t-1}^{A50} + \theta_{19} h_{t-1}^{HSCEI}$