Regulatory Soft Interventions in the Chinese Market: Compliance Effects and Impact on Option Market Efficiency

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Abstract:

Securities Laws in China are administered by the Chinese Securities Regulatory Commission (CSRC). The CSRC has great flexibility in administering securities laws since the committee represents the will of the state. Under the state-controlled financial system, the CSRC works closely with state-controlled financial firms and suggests, but does not mandate, actions to be taken in the equity market, especially during periods of extreme market stress. These suggestions, or soft interventions, have been used to block trades associated with short-sales, significantly reducing short-sales volume. With daily and intraday data, we investigate the impact of these interventions on put-call parity and implied volatilities. There is overwhelming evidence of increased deviations from put-call parity and changes in implied volatility after soft interventions. Our results are robust after allowing for bid-ask spreads, taxes, transaction costs and Difference-in-Differences comparisons with control securities in the Hong Kong market.

Keywords: Chinese market, Soft Interventions, Options, Efficient markets, Put-call parity

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1. Introduction

One of the objectives of the China Securities Regulatory Commission (CSRC, the regulator) is to promote the development of a fair, transparent and complete Chinese market. To protect the public interest and especially that of individual investors, the regulator is expected to keep the market stable (Annual Report of China Securities Regulatory Commission, (2015)). Without written laws or mandates, the CSRC makes known the will of the state and compliance by state influenced firms is expected. We use the term soft intervention to describe such actions by the CSRC.

We investigate the effectiveness of soft intervention by the CSRC and focus on the non-intended effects on market efficiency as quantified by deviations from put-call parity and implied volatilities. We find the soft intervention in 2015 reduces short-sale volume significantly. Using the Huxia SSE 50 ETF and its options, we find overwhelming evidence that put-call parity deviations increase significantly and implied volatilities change as predicted after the soft intervention. We verify robustness with a difference-in-differences (DiD) analyses using futures options on a mainland index (HSCEI) in the Hong Kong market as a control. The Hong Kong market is not directly regulated by the CSRC.

The paper is organized as follows: Section 2 summarizes the regulatory features of the Chinese market and Section 3 is the literature review. Section 4 describes the securities and the data. Section 5 develops the effect of the regulator's soft intervention on market prices. Section 6 develops identification tests and Section 7 concludes.

2. The State Controlled Financial System and Soft Intervention

The financial system in China is tightly controlled by the central government and state-owned capital. This especially holds true for equity markets. Tight control is a result of governmental style (McKinnon, (1991)) and the questionable reputation of speculators in the market. At the end of 2016, nine out of the largest ten commercial banks and all of the largest ten brokers were essentially controlled by state-own capital. The two stock exchanges (the Shanghai Stock Exchange and Shenzhen Stock Exchange) are both governmental agencies that directly report to the CSRC. Under this state-controlled financial system, the regulator and financial firms interact with each other closely. This system makes another form of regulation available for the CSRC, the soft intervention.

Soft intervention is a strong form of moral suasion where target firms have no legal obligation to comply. Soft intervention is similar to the practice of "window guidance" found in other countries and especially notable in Japan. However, soft intervention in China is stronger and more efficient under the state-controlled financial system. Another notable difference is that while previous works (Hoshi, Scharfstein and Singleton (1993), Rhodes and Yoshino (1999), and Ongena, Popov, and Van Horen, (2016)) mainly documents moral suasion and window guidance in the banking industry, the CSRC and Chinese government effectively soft-intervene in equity and derivatives markets. The soft intervention in China is a much stronger tool than moral suasion and window guidance in other countries because state-controlled firms have a dominant market position and these firms tends to comply with the will of the state.

2.1 The Legal Basis of Securities Market Regulation

The *Securities Law of the People's Republic of China* grants authority to CSRC to regulate financial markets in China. The CSRC has multiple departments that work in different markets and on different issues. For instance, the Bureau of Futures Regulation focuses on the futures market and the Bureau of Investor Protection focuses on investors' issues. These departments make administrative rules and regulations as they deem appropriate. Such administrative rules and regulations are formal "hard" rules and regulations. In addition, the CSRC may "suggest" appropriate behavior. Compliance with these soft interventions is expected, especially by state-controlled financial firms.

The CSRC has an Administrative Punishment Committee. This committee identifies violators and decides how to they should be handled. When the CRSC determines (perhaps subjectively) that some actions by market participants are detrimental, it will first intervene by communicating with the potential violator in order to effect the desired result. The communication may be in a form of window guidance, a warning letter, or even an informal call. If this does not work and there is solid evidence showing that a market participant is violating existing laws, rules and regulations, the CSRC has the right to levy administrative punishment on the violator. The administrative punishment can be a fine or a restraining order forbidding the violator from trading on the market for a period of time. All these punishments are announced on the CSRC website. If the suspect in violations does not agree with the punishment, they can provide further evidence and ask the CSRC to review it. However, historical evidence shows that it is very unlikely that the punishment will be changed. To avoid hard-to-overturn punishment, financial firms tend to comply with soft interventions.

2.2 The Mission of the CSRC

The mission of the CSRC is to improve market efficiency, protect investors and develop a fair, transparent, and orderly market. Protecting investors and providing an efficient market are consistent goals in most cases. In part, the regulator seeks to protect investors by improving market efficiency. However, in some extreme cases, there is arguably a short-term conflict between protection and efficiency. The regulator may choose to sacrifice some degree of market efficiency to temporarily protect investors, especially individual investors.

2.3 Individual Investors

Individual investors are heavily represented in the Chinese equity market. At the end of February 2016, there were 101.3 million investment accounts associated with individual investors, comprising 99.71% of the total number of investment accounts. At the end of 2014, individual investors held 23.51% of the total market capital in the Shanghai Stock Exchange. More than 75% of individual investors holds a portfolio with less than ¥100,000 or $14,482[1] (Jiang, Qian and Gong, (2016)). The growing middle-class constitutes the main segment of individual investors. A long history of limited investment opportunities and stories of successful individual investors has presumably led to expectations of high return with little regard for market risk. Irrational behavior in this market has been documented by Demirer and Kutan (2006), Chen et al. (2007), Tian et al. (2008), and Hilliard and Zhang (2015) giving rise to the potential for bubbles. Investments in the stock market take a significant proportion of the individual investors' personal wealth, so a crisis in the equity market is viewed with alarm. Accordingly, the regulator is not hesitant to intervene in crisis situations.

[1] Prices in USD are estimated assuming exchange rate of 6.9051 CNY/USD, provided by Bank of China on Dec 3, 2016. All tests are based on CNY.

2.4 The Market Crash of 2015 and the Short-sale Constraint

The Chinese equity market suffered a major meltdown beginning in June 2015 (Figure 1). Within one month, A-shares on the Shanghai Stock Exchange lost approximately one third of their value. CSRC, the regulator, moved to stabilize the market in the third quarter of 2015, limiting daily short volume and short positions. The regulator did not post a formal regulation to ban short-sales. Instead, they used pressure based soft interventions and persuaded the largest investment companies, most of whom are state-controlled firms, to keep purchasing stocks and to stop creating short positions and lending securities (Figure 2).

In responding to the regulator's call, on July 4, 2015, the 21 largest investment companies published a joint statement that they would spend ¥120 billion on "Blue Chip" ETFs, including the SSE 50 ETF and would not sell these securities until the Shanghai Composite Index exceeded 4500 points[2]. In addition, these investment companies stopped shorting the market and lending securities. As a result, it was hard for other investors who wanted to sell-short equity to find a counterparty willing to lend stocks. The short-sale volume thus dropped sharply after these actions (Figure 3). From February 2015 to July 2015, the average short-sale volume of the 50 ETF was 144 million shares per day. After a series of soft interventions were carried out from July to August 2015, the short-sale volume fell sharply to an average of 4.3 million shares from July 2015 to July 2016. Even though short-sales were not banned, an effective short-sale constraint had been put in place. The soft interventions were effective in virtually eliminating short-sales. Thus, compliance with soft interventions seems to be both swift and effective. In fact, even before the soft interventions, the state-controlled financial firms anticipated the pressure

[2] Statement is from Securities Association of China, http://www.sac.net.cn/tzgg/201507/t20150704_123599.html, (in Chinese), accessed on December 3, 2016.

from the regulator and limited the short positions themselves to avoid unfavorable actions under this policy uncertainty.

In addition to the soft interventions, trading rules on short-sales were also changed. After August 3, 2015, the trading rule on short-sales switched from "T+0" to "T+1", in which short position cannot be covered before the next day of execution (T+1). This friction was expected to further reduced short-sales volume.

3. Literature

Window guidance and moral suasion are regulatory practices similar to soft intervention. Previous works on window guidance mainly document governments and central banks intervening in the banking industry. Romans (1966) provides an early discussion on the effect of moral suasion. Hoshi, Scharfstein and Singleton (1993), and Rhodes and Yoshino (1999) discuss window guidance in Japan. Hoshi, Scharfstein and Singleton (1993) find that window guidance on lending policy affects the firms' investment behavior. During the period of tight window guidance, firms without funding resources other than bank loans invested less and focused more on cash flow. Rhodes and Yoshino (1999) find that a large proportion of target banks comply with window guidance. While efficient in its early years, the effectiveness of window guidance dropped in the post-1982 period of financial liberalization. Ongena, Popov, and Van Horen (2016) find evidence that European governments encourage domestic commercial banks to hold domestic sovereign bonds during the European Debt Crisis. In US markets, a remarkable example of moral suasion is the US Federal Banks' effort to save Long-Term Capital Management in 1998 by persuading 16 financial institutions to recapitalize the hedge fund. Furfine (2006) discusses the benefit and cost of this rescue action led by Federal Reserve Bank of New York. He argues that the action stopped potential market disruption at the cost of higher risk exposure by participating institutions.

There is an extensive literature on violations of put-call parity in world markets. Klemkosky and Resnick (1979) review the role of options in the US market and provide early evidence supporting efficiency for the registered options market. Gould and Galai (1974), and Phillips and Smith (1980) discuss the effect of transactions costs on put-call parity. Other early works in the US market document that options on indexes such as the S&P 100 frequently violate put-call parity (Evnine and Rudd (1985)). Kamara and Miller (1995) point out that American options are used in such works and the early exercise premium contributes to the deviation from put-call parity. Further studies provide evidence of fewer and less frequent violations of put-call parity on European options (Kamara and Miller (1995), and Ackert and Tian, (2001)). International evidence is provided by Nisbet (1992) for Britain, Brunetti and Torricelli (2005) for Italy, Mittnik and Rieken (2000) for Germany, and Li (2006) for Japan. All of these works document at least some deviations from put-call parity due to short-sale constraints and transactions cost.

Our findings are largely consistent with previous works and strongly support the findings of Ofek, Richardson, and Whitelaw (2004). They explore the effect of short-sales on synthetic option prices and confirm that deviations from put-call parity are related to the cost and difficulty of short-sales. The effect of short-sales bans and their impact on options markets have also been studied by Battalio and Schultz (2011) and Grundy, Lim and Verwijmeren (2012). Hendershott, Namvar and Phillips (2013) review the literature on short-sale bans and report that their effect is pervasive in financial markets, including the market for options, convertible bonds, credit default swaps, and exchange traded funds.

Soft interventions and pressures from the regulator in the Chinese market vastly exceed normal market frictions. They are an effective ban on short-sales. And we that expect large violations of put-call parity will appear after the soft interventions.

4. Securities and Data

To quantify the effects of the soft intervention we examine put-call parity relations and implied volatilities for options on the Huaxia SSE 50 ETF and its underlying ETF. Our sample period extends from the introduction date of the SSE 50 ETF options, February 9, 2015 through July 15, 2016. The SSE 50 European option was the first and only standardized option traded on the Shanghai Stock Exchange. Contracts are physically settled and each contract represents the right to purchase or sell 10,000 shares of the underlying security, the Huaxia SSE 50 ETF. The settle price for each day is determined by the average executed price in the closing call auction. During the sample period, the average call price on one underlying share was ¥0.255 ($0.0369) and the average put price was ¥0.209 ($0.0302). The minimum option price is ¥0.0001. Based on data from July 25, 2016 to August 25, 2016, the average bid-ask spread of the 50 ETF option was 2.28% for calls and 5.85% for puts.

Typically, the option contracts have four maturities; the current month, next month, and the first months of the following two quarters. The maximum days to maturity is approximately 244 days. The exercise days are the third Fridays of these months. At initiation, there will be five different exercise prices. The 50 ETF option has a daily fluctuation limit and the price of option is bounded by a formula based on exercise price, previous closing price, and previous settle price[3].

[3] Daily fluctuation limit for call = max$\{0.002K, \min(2S\text{-}K, 0.1S)\}$, and limit for put = max$\{0.002K, \min(2K\text{-}S, 0.1S)\}$. S is the previous closing price.

The SSE50 ETF option contract is dividend adjusted. There were no dividend distributions on SSE 50 ETF during the time period of our study.

The underlying asset of the option is the Huaxia SSE 50 ETF. The SSE 50 ETF trades on the Shanghai Stock Exchange and was the first ETF traded in China. The ETF tracks the SSE 50 index that includes 50 of the most active and reputable stocks listed on the Shanghai Stock Exchange. It is one of the most traded ETFs in China, with about 913 million shares average trading volume per day (Table 1). Most of the components in the SSE 50 ETF are stocks of financial firms. At the end of March 2016, 65.3% of this ETF was from the financial industry, 16.84% from manufacturing and 17.86% from all others industries. In addition, 92% (46 out of 50) of ETF firms are state-controlled and the remaining 8% are believed to be highly influenced by state-owned capital. The average price of the SSE 50 ETF was ¥2.45 per share during the period from February 2015 to July 2016. The bid-ask spread for the EFT is about 0.1%. The daily fluctuation limit on the SSE 50 ETF is ±10% of the previous close. Figure 4 shows the distribution of returns on the SSE 50 ETF. The daily returns on the SSE 50 ETF usually range from -3.5% to 3.5%. During the period from February 2015 to July 2016, the limit was touched once on August 24, 2015.

Short-sales were introduced to the Chinese stock market on March 2010 and component stocks of the SSE 50 index were the first stocks that were permitted to be short-sold. Prior to soft interventions, the SSE 50 ETF was one of the most shorted securities on the Shanghai Stock Exchange.

Two sets of data are used in this study, a daily dataset and an intraday dataset. Both of these datasets were provided by Wind Info, Inc. The Shanghai Stock Exchange provides other basic information on the SSE 50 ETF options including strike price and maturity.

The intraday dataset contains trade information at the end of each minute during the trading hours of the Shanghai Stock Exchange from January 4, 2016 to July 15, 2016. All dates and times are in UTC+08:00, the time zone of the Shanghai Stock Exchange. Observations with less than one trade per minute are excluded. From the intraday dataset, we obtain prices at the end of each minute or the price of the last executed trade within each minute during trading hours. We use a model with Poisson arrivals to evaluate the synchronicity of the intraday dataset. The estimated average time between put and call transactions is 4.02 seconds, the time between put and ETF transactions is 1.86 seconds, and the time between call and ETF transactions is 3.63 seconds (see Appendix A and Table A.1).

The daily dataset includes settle prices and volume on the Huaxia SSE 50 ETF and the SSE 50 ETF from February 9, 2015 to July 15, 2016. As shown in Table 1, ETF daily settle price ranges from ¥1.919 to ¥3.41 with mean ¥2.44 ($0.3534). The average trading volume is 913.8 million shares per day and short-sale volume is about 48.5 million shares per day. In empirical tests, days with less than 10 trades are excluded.

The Shanghai interbank offer rate (Shibor) provided by the National Interbank Funding Center is the proxy for the risk free rate. The Shibor rate is a winsorized average of the interbank offer rates among the18 largest commercial banks in China. The rate is posted at 11:00 a.m. every day. The rate used in tests is calculated by linear interpolation and matches the option's term to maturity. Other complementary information is obtained from Bloomberg (price of SSE 50 ETF and short-sales volume of SSE 50 ETF), Sina.com (short-sales volume of SSE 50 ETF), the Shanghai Stock Exchange (taxes and transaction fees), and the CSRC. All information about the Hong Kong market is from Bloomberg.

5. The Effect of Soft Interventions on Market Prices

The Wind datasets do not include the bid and ask price for options and their underlying. We assess arbitrage violations by developing a model for bid-ask spreads in Section 5.4. In this section, we use the daily dataset with settle prices and argue that the effect of bid and ask spreads are small in comparison to the magnitude of arbitrage deviations.

Using put-call parity we propose two alternatives. First, we compute the price of the synthetic call and compute the difference between the synthetic (*Syn*) and market (*Act*) price:

$$c_{it}^{Syn} = p_{it}^{Act} + S_t - K_i e^{-r_t T_{it}} \,, \tag{1}$$

$$Diffc_{it} = c_{it}^{Syn} - c_{it}^{Act}, \tag{2}$$

Similarly, we compute the implied interest rate and compare it to the actual risk-free rate matching time-to-maturity:

$$r_{it}^{Imp} = \frac{\ln(K_i) - \ln\left(S_t + p_{it}^{Act} - c_{it}^{Act}\right)}{T_{it}}, \tag{3}$$

$$Diffr_{it} = r_{it}^{Imp} - r_{it}^{Act}. \tag{4}$$

The bottom line is that both *Diffc* and *Diffr* should be close to zero if arbitrage opportunities are economically insignificant, consistent with put-call parity. “Economical significant” is a subjective conceptive. We arbitrarily (and conservatively) designate a difference as economically significant if the difference between price of synthetic call and that of actual call is more than 10% of actual call price.

5.1 Put-Call Parity Tests Over the Entire Sample Period

We first do a global analysis of put-call parity deviations pooling data from before and after the soft interventions. Table 2 shows that the average price of a synthetic call is 15.87% higher than that of the traded call and the average implied risk-free rate is about 11 % lower than the actual risk-free rate for the daily dataset (Panel A). For the intraday dataset (Panel B), the price of the synthetic call is 22% higher than that of actual call and the implied risk-free rate is about 8% lower than the actual risk-free rate. From put-call parity, the implied rate being "too low" means that the implied bond price is "too high" and this is consistent with the synthetic price of the call being higher than the market call.

Diffc is positively related to days to maturity and negatively related to the moneyness of the option. Most of the *Diffc*s and *Diffr*s of subsamples in Panel A and Panel B are both statistically significant at 1% and economically significant. The distribution of *Diffc* should be symmetric around zero if friction costs are symmetric. As shown in Figure 5, the distributions of *Diffc* are not symmetric for either dataset as both are clearly right skewed.

5.2 Soft Interventions and Deviations from Put-Call Parity

The soft interventions had a predictable effect on put option price. Not only were financial firms not selling short but they were increasing their equity exposure. In short, firms had large deltas. Our premise is that the rational response to reduce portfolio delta is to buy puts (negative delta) and sell calls (negative delta). In fact, net of frictions and dividends, long puts and short calls have payoffs equivalent to a short stock. In any case, there was buying pressure on puts and selling pressure on calls. These pressures led to large and frequent violations of put-call parity. But there is also the related question. Why were arbitrage profits not sufficient to restore a no-arbitrage equilibrium? Selling a synthetic call requires a short position in equity. But lending equity for shorts was difficult if not impossible due to pressure from the regulator. In summary, there were two related effects of the soft interventions: The emergence of overpriced puts/underpriced calls and the inability to short equity to remove the resulting arbitrage opportunities.

Our premise can be challenged on two fronts: First, did the regulator soft intervene on equity shorts but remain silent on put longs and call shorts? We can find no evidence that pressure was exerted to discourage participants from buying puts or selling calls. Furthermore, we find put volume increased significantly after the soft interventions (Figure 6). Second, who would sell the puts or buy the calls? Our thesis is that large state-controlled firms have incentives to buy puts (and/or sell calls). But for every put bought there must be a seller. And the put seller is effectively long equity. Arbitraugers who wish to hedge their long position must then short the equity. But this possibility has been effectively removed by the soft intervention. And so, who takes the other side of the transaction? Because of heavy demand for puts, dear prices for puts would attract investors because of a favorable risk-return ratios. Therefore, we expect that the sellers of puts (buyers of calls) would not be arbitraugers but would be investors attracted by favorable risk-return ratios.

We document the effect of the intervention on short-sales and its subsequent effect on put-call parity. We choose July 15, 2015 as the breakpoint. The results in Table 3 are consistent with the premise that the huge overall deviation from put-call parity is the consequence of soft interventions. As shown in Panel A of Table 3, mean *Diffc* is only ¥0.0020 (0.65% of mean call price) and is not *economically* significant before the interventions. On the other hand, much larger deviations are observed in Panel B during the period after the intervention. Mean *Diffc* is about

0.045, or about 33.22% of mean call price and is both statistically significant at 1% and economically significant. The results in both panels of Table 3 are similar to the full sample results in Table 2 with respect to the effect of moneyness and maturity. Thus, the results of the full sample period appear to be driven in large part by the after-intervention period.

Figure 7 visually documents the effect of the soft interventions. Before the soft interventions (Panel A), *Diffc* is more or less symmetrically distributed with a mean slightly above zero. In Panel B, *Diffc* is highly skewed to the right with most of the observations being positive. The contrast in positive skew between the distributions in Panel A and Panel B is further evidence of the effect of soft intervention.

Overall, we find compelling evidence that synthetic calls are overpriced. To eliminate arbitrage profits, investors would sell the synthetic call and buy the market call. However, the synthetic call cannot be sold because that strategy requires that the ETF be shorted. Even though short volume is not zero, arbitrage opportunities cannot be fully exploited by available trades in the market.

5.3 Soft Interventions and the Impact on Implied Volatility

Given that synthetic calls are expensive relative to traded calls, we investigate the relative mispricing of puts and calls. We have argued that puts (calls) are expensive (cheap), and that the condition cannot be corrected due to short sale constraints. But, unlike put-call parity, evaluating mispricing requires an equilibrium pricing model. We gain some insight using Black-Scholes implied volatilities. In fact, the application here comports well with the Black-Scholes model assumptions since the SSE 50 ETF option is European and the underlying did not pay dividends during our sample period.

Table 4 depicts implied volatilities before intervention, after intervention, and for the full sample period. For the full period, put and call volatilities are significantly different as are the differences between volatilities before and after the intervention. Before the soft interventions, the call implied volatility was 44.36%. After the soft interventions, call volatility dropped to 32.05% signalling lower prices. Conversely, put volatility increased from 42.03 to 44.22% after the soft interventions. In fact, for all maturities and moneyness levels, call volatility decreased (Panel A) and put volatility increased (Panel B) after the intervention. These results suggest that there was increased buying pressure on puts and selling pressure on calls. Both effects support our argument that overexposed investment firms were motivated to decrease their deltas after the intervention by buying puts and selling calls. Visual evidence to support Table 4 is given by implied volatility plots in Figures 8 and 9. The ratio of call IV to put IV is given in Figure 10. The ratio is greater than one just before the intervention and falls sharply below one after the intervention.

5.4 A Model for Bid-Ask Spreads

Securities are typically assumed to be bought at the ask and sold at the bid. The bid-ask spread acts a friction that slows or eliminates convergence of market prices to an equilibrium. When available, these bid-ask spreads are used in tests of put-call parity. The daily datasets provided by Wind Info, Inc. do not include bid and ask prices. Using data obtained from Sina.com during the period from July 27, 2016 to August 27, 2016[4], we develop models to estimate bid- ask prices for the Wind database and the full sample period. Ask (bid) prices from

[4] After August 17, we can only collect options expired in August or September, 2016 because of a problem with the Sina.com website.

the Sina.com are regressed on closing prices, volume, and contract information using the following models:

$$Ask\ price_{it} = \beta_1 price_{it} + \beta_2 K_i + \beta_3 T_{it} + \beta_5 Volume_{it} + \varepsilon_{it}, \tag{6}$$

$$Ask\ price_{it} = \beta_1 price_{it} + \beta_2 |K_i - S_t| + \beta_3 T_{it} + \beta_5 \log(Volume_{it}) + \varepsilon_{it,}. \tag{7}$$

$$Ask\ price_{it} = \beta_1 price_{it} + \beta_2 \frac{S_t}{K_i} + \beta_3 T_{it} + \beta_5 \log(Volume_{it}) + \varepsilon_{it}, \tag{8}$$

where *price* is last executed price of the option, *K* is the exercise price, *S* is the price of ETF, *T* is the days to maturity, and *Volume* is the daily trading volume of the option. Identical models were used for bid prices. Parameter estimates are given in Table 5. The R^2 of each model rounds to 100% with accuracy to four places. With an intercept term, the R^2 were 99.99%. In our implemented model did not include the intercept since it has no economic meaning and was not significant in all but one of three models. With parameters estimated from the model in equation (7), we infer bid and ask prices for the Wind database and the entire period from February 9, 2015 to July 15, 2016.

To test whether the bid-ask spread affects our results, we construct arbitrage portfolios to evaluate deviations from put-call parity. In Strategy A, we sell a synthetic call at bid prices and buy a market call at ask price. This mimics the strategy used to construct *diffc* but with imbedded bid-ask frictions. In Strategy B, we sell a market call at bid price and buy a synthetic call at ask prices. Portfolios formed by these two strategies should generate no arbitrage profit if put-call parity holds. Define the arbitrage profit by ε_{it}. Then, initial cash is

$$\varepsilon_{it}^{A} = (p_{it}^{Bid} + S_t^{Bid} - K_i e^{-r_t T_{it}}) - c_{it}^{Ask}, \tag{9}$$

$$\varepsilon_{it}^{B} = c_{it}^{Bid} - \left(p_{it}^{Ask} + S_t^{Ask} - K_i e^{-r_t T_{it}}\right). \tag{10}$$

Under frictionless put-call parity, both portfolios have zero cash flows. If there are bid-ask frictions, both portfolios should produce negative cash flows because *Ask>Bid*. Since we have found that puts (calls) are overpriced (underpriced) we expect more positive cash flow violations from Strategy A. Results are reported in Table 6.

The first six columns in Table 6 specify the bid-ask inputs used in equations (9) and (10). During the sample period, the average ask price is about 0.64% higher than the executed price for calls and 2.40% for puts. The bid price is 1.64% lower than the executed price for calls and 3.45% lower for puts. Bid-ask parameter estimated from equation (7) are used in the last row of Panels A and B. The bid (ask) for the SSE 50 ETF is 0.05% lower (higher) than reported transaction prices. Mean arbitrage profits with assumed inputs or estimated inputs are shown in columns seven and eight. The last column is the number of violations of put-call parity (either positive ε_{it}^{A} or positive ε_{it}^{B} is a violation). There are average positive arbitrage profits for Strategy A under for both daily and intraday data. The average arbitrage profit is negative under Strategy B. Even under more extreme bid-ask assumptions (not shown) Strategy A remains positive. For our daily dataset (Panel A), put-call parity is violated between 77% and 94% of the time. For the intraday dataset (panel B) put-call parity is violated between 79% and 91% of the time. After taking bid-ask spread into consideration, we conclude as before that no-arbitrage conditions are frequently violated and the culprit is a combination of an overpriced put and underpriced call.

5.5 A Mean-reverting Process for Arbitrage Profit

Technically, a single violation of put-call parity is all that is needed to reject the no-arbitrage assumption. More typically, the size and frequency of violations are used as conventional means of testing the no-arbitrage hypothesis. In well-functioning markets, violations are usually rare.

Recent work has focused on less demanding measures of no-arbitrage. There are the well cited limits to arbitrage papers that focus on capital constraints as in Shleifer and Vishney (1997), asymmetric costs as in Ofek, Richardson and Whitlaw (2004) and the hedging pressure arguments of Bollen and Whaley (2003). The physics and quantitative finance literature has seen the emergence of models of short-lived arbitrage, as in Otto (2000), Hilliard and Hilliard (2017), and Deville and Riva (2007). These models admit short lived arbitrage but deviations are immediately (or eventually) corrected to zero or to some economically insignificant number. The rationale for the mean regressive approach is that as an arbitrage opportunity grows, rational investors will increasingly be drawn into the market to correct violations.

To further complement our results on put-call parity, we assume that the arbitrage profit from put-call parity follows a mean-reverting Ornstein-Uhlenbeck process. A weak requirement is that the long-term mean of this process is zero if put-call parity holds. Furthermore, the speed of adjustment coefficient will be higher in markets with fewer frictions. In the context of bid-ask spreads, the long term mean of the model will be negative if there is no economically meaningful arbitrage. Since short-sales are not easily available because of the soft interventions, we expect to observe a positive long term mean for a strategy that depends on short sales.

We define the arbitrage profit for Strategy A and the mean-reverting process expressed in diffusion form as follows:

$$de_{it} = \kappa_i(\theta_i - e_{it})dt + \sigma_i dZ_{it}, \tag{11}$$

where $de_{it} = \varepsilon_{it}^A - \varepsilon_{it-1}^A$, κ is the speed of adjustment coefficient, and θ is the long term mean. As in previous sections, we match put options, call options and the ETF to form put-call pairs with the same strike price and time to maturity. The setup for Strategy B is similar and follows from equation (10).

We use maximum likelihood to estimate the parameters of the discrete AR(1) model

$$e_{it} = \kappa_i\theta_i + (1 - \kappa_i)e_{it-1} + u_{it} \tag{12}$$

for the entire sample period and in the before- and after-intervention periods[5]. Table 7 reports the summary statistics for the estimated parameters from Strategy A and Strategy B. Since Strategy A requires shorting the ETF we expect more violations in Strategy A than in strategy B and the violations should be concentrated in the after-intervention period. As shown in table 7, all long term means are significant at the one percent level. For strategy A, the average (over pairs denoted by i) long-term mean of the full sample is positive (θ = ¥0.0113). As expected, the average long term mean is negative (θ = ¥-0.0229) for the before-intervention period and positive (θ = ¥0.0273) for the after-intervention period. Compared to average call price (¥0.255) and average put price (¥0.206), the long-term mean of the arbitrage profit in the after-intervention period is about 10 % of option price.

The speed of adjustment estimate is higher in the before intervention period (κ= 0.3960 versus 0.2290). Using the exponential model of half-life and assuming convergence to θ =0 gives a before (after) intervention half-life of $(1/\kappa)ln(2)$ = 2.52 (3.3) days. Both the long term mean and speed of adjustment coefficient are consistent with the hypothesis that violations of no-

[5] To be consistent with previous sections, 07/15/2015 is used as the cutoff date for before- and after-intervention periods. Some series may start or end around the cutoff date since the observations of such pairs may be insufficient to estimate the autoregression parameters in the before- or after-intervention period. Thus, we exclude all pairs that do not have more than 15 consecutive observations within the period.

arbitrage conditions were greater after the soft interventions. Furthermore, arbitrage violations occur in the strategy (A) that requires shorting equity. Strategy B deviations in both periods have significantly negative long term means, consistent with the absence of arbitrage opportunities for that setup.

The maximum likelihood estimates of these parameters are biased due to the lack of dynamics of the series (Ball and Torous (1996), and Tang and Chen, (2009)). The relatively large speed of adjustment (Panel A of Table 7) and the short interval (one day) imply that our results should not be strongly affected by this bias. However, the magnitudes of some estimated parameters are very small and may be sensitive to lack of dynamics. Thus, we correct the bias with the bootstrap method proposed by Tang and Chen (2009). Summary statistics for this procedure are reported in the Panel B. The long-term means and speeds of adjustment are marginally adjusted downward. Both the mean and the median of the long term estimates are significantly positive and larger than those of the before-intervention period. The speed of adjustment estimate of the after-intervention period remains significantly lower than that of before-intervention period. In general, we find results similar to those in Panel A, further supporting the argument that arbitrage opportunities from put-call parity are created by soft interventions.

6. Identification

There is sufficient evidence to conclude that put-call parity does not hold and implied volatilities change after soft interventions on short-sales. The soft interventions were motivated by the market crisis in 2015. But were the soft interventions the proximate cause of the adverse effects on market efficiency? Were there other markets not subject to the intervention with prior similar behavior? Could the deviation from put-call parity be a result of taxes, transactions cost, or dividends? Apparently not. Transaction fees are negligible compared to the huge deviations we observe from put-call parity. At the end of October 2016, the Shanghai Stock Exchange charged 0.0045% transaction fee on the contract value for ETFs and even less if the trading size was large. The exchange also charged ¥2 per option contract (¥0.0002 or $0.00003 on each underlying) but this ¥0.0002 fee is small compared to the price of options (on average ¥0.255 for call and ¥0.209 for put). Taxes and dividends were also not a factor. During our sample period, neither taxes on interest, capital gains, nor stamp duty had to be paid for trades on the ETF and its options. And finally, no dividends on the ETF were paid during the sample period.

Another plausible culprit leading to violations of put-call parity was the tubulent market. Quite apart from soft interventions it could be argued that the failure of put-call parity was due to the fear of a market crash. Extreme crash fear would result in buying pressures on puts and selling pressures on calls. We further cement the effect of the soft intervention by identifying a control asset affected by the same market exposure except those related to the short-sale constraint. The Hang Seng China Enterprise Index (HSCEI) options serve as our control. We use the control group and a difference-in-differences (DiD) analysis to isolate the effect of the soft-intervention on put-call parity deviations and changes in implied volatilities.

6.1 Differences in Differences Analysis of Put-Call Parity Deviations

HSCEI options (European) are traded on the Hong Kong Stock Exchange. The HSCEI includes stocks traded on the Shanghai Stock Exchange (SSE) and Shenzhen Stock Exchange (SZSE). These stocks are accessible to Hong Kong investors through special arrangements called "Shanghai-Hong Kong Stock Connect" and "Shenzhen-Hong Kong Stock Connect". The HSCEI Index closely mirrors mainland Chinese markets (SSE and SZSE). See Figure 11. Like investors in mainland China, investors in Hong Kong could not short a basket of component stocks after the short-sale constraint in mainland markets. This restriction is largely mitigated, however, since futures contracts on the HSCEI index are available for shorting. Thus, the proximate market conditions that impact the SSE 50 option also impacts the HSCEI option except for the short-sale constraint. As noted earlier, the CSRC does not have direct regulatory power in Hong Kong and thus the shorting intervention is not binding on this market.

We match calls and puts by the strike and maturity, and then match futures and put-call pairs with the same maturity. We construct deviation from put-call parity (*Diffc*) of HSCEI options with these put-call-future pairs[6]

$$Diffc_{it} = P_{it} - C_{it} + F_{it}e^{-r_{it}T} - K_i e^{-r_{it}T}, \tag{13}$$

where F_{it}, P_{it} and C_{it} are the settle prices for contract-i on day t. The risk-free rate for each day and maturity, r_{it}, is proxied by the Hang Seng Interbank Offer Rate (HIBOR). We use the *Diffc's* of the SSE options and the HSCEI options and OLS to implement the DiD model

$$Diffc_{kt} = \alpha + \beta_1 SH_k + \beta_2 After_t + \beta_3 SH_k * After_t + e_{kt}. \tag{14}$$

where SH_k indicates the group (Shanghai or Hong Kong) and $After_t$ is a dummy indicating whether day t is before or after the soft intervention. We use 07/15/2015 as the cut-off date and the sample period covers 95 days before and after the cut-off date. We only include the near-the-money options with $0.9 \leq S/K \leq 1.1$. for the Shanghai market and $0.0 \leq Fe^{-rT}/K \leq 1.1$ for the Hong Kong market.

[7]The discounted futures price on the underlying can take the role of the spot when options on the underlying are European options. See Brenner, Courtadon and Subrahmanyam (1985).

The coefficient of the interaction term, β_3 , captures the intervention effect. Results are reported in panel A of table 8. The estimated coefficient of β_3 is 5.39 significant, implying that there is sufficient evidence to conclude that deviations from put-call parity of SSE 50 ETF options become significantly higher than that of the HSCEI options after the soft interventions,

Because the component stocks of HSCEI are traded in Mainland China and the exchange rate may affect the arbitrage process, we adjust *Diffc* of HSCEI options with the exchange rate between HKD and CNY. With this adjustment, the coefficient of the interaction term is 7.04 (Panel B), larger than that of no-exchange rate case. The coefficient is also positive and significant, confirming the result in panel A. We also use the Randomization Inference (RI) procedure following Bertrand, Duflo and Mullainathan (2004) to correct for possible violations in OLS standard errors[7]. See also Donohue III and Ho (2007). Tests using the RI estimator confirm that the β_3 estimates in the differences-in-differences setup fall outside the 99% confidence interval. Results are given in Panels A and B in table 8.

6.2 Difference in Differences on Implied Volatilities

As a further robustness check, we do a DiD analysis of implied volatilities of puts and calls. We use the same set up and data construction as that used to test the put-call parity DiD. Results for calls is shown in Table 9 and Panel A. Consistent with our earlier analysis, the coefficient of the interaction term is significant and equal to -0.12904. Put results are shown in Panel B, where the coefficient of the interaction term is significant and equal to 0.05587. Thus, under our DiD

[7] We use the following procedure: 1. Use OLS to estimate β_3 in equation (14). 2. Randomly assign 95 days with short-sale restrictions. Other days have no short-sale restriction. Estimate the coefficient of the interaction term, $\widehat{\beta_3^*}$. Repeat step 2 for M =100,000 times to get the empirical distribution of $\widehat{\beta_3^*}$. This corresponds to a null of no treatment effect. 3. Establish upper and lower confidence limits for the distribution and determine if the estimate of β_3 in step one falls outside the confidence interval.

model, there is sufficient evidence to conclude that the soft intervention resulted in cheaper calls and more expensive puts. The conclusions remain unchanged when we adjust standard errors by the RI procedure.

7. Conclusions

The deviations from put-call parity are consistent with the regulator's pressure and soft interventions that discourage short-sales. Soft interventions are not rule-based but a communication of policies favored by the regulator. During the 2015 crisis in the Chinese equity market, the regulator soft-intervened in order to support the market. While there was no explicit ban on short-sales, short-sale volume became extremely low during this period. Evidently, the management of state-controlled financial giants tends to work with the regulator in exchange for potential benefits that include protection from further intervention.

In our analysis of put-call parity and implied volatilities, we find that puts are overpriced and calls are underpriced. Thus, the synthetic call will sell for more than the traded call, violating put-call parity. The evidence suggests that these violations were due to the soft interventions by the regulator. Complying with this series of soft interventions, large state-owned firms became heavily exposed to equity risk. This exposure can be mitigated by buying puts and selling calls to decrease their portfolio deltas. Buying pressure on puts and selling pressure on calls increased put prices relative to call prices. The result was that the synthetic call was overpriced. This arbitrage condition persisted because participants could not sell the synthetic call. Selling the synthetic call required a short position in equity and this was difficult if not impossible due to pressure from the regulator against short-sales.

The results are robust compared to a control group of options that trade on the Hong Kong market. A differences-in-difference analysis shows that the soft intervention in the Shanghai market led to significantly higher deviations in put-call parity than those found in the Hong Kong market. A similar analysis of implied volatility differences shows that the lower implied call volatility and higher put implied volatility was due to the soft intervention in the Chinese options market.

Soft intervention was effective in reducing short-sales. And the market was temporally stabilized. However, there were winners and losers from the resulting market inefficiencies. The benefits of the soft intervention apparently accrued to participants not subject to regulatory pressure. During this period of market turbulence, it appears that they sold overpriced puts and bought underpriced calls. It is reasonable to assume that the other side of these transactions consisted primarily of state-controlled firms. They paid dear prices for delta protection and compliance with the will of the state.

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Appendix A: Synchronicity

We establish synchronicity of observations using a model of Poisson arrivals. Our intraday dataset includes prices of the last transactions executed on a minute-by-minute basis. A model is developed to estimate the expected value of the absolute value of the last arrival time difference (*LATD*) between two securities. In this model, the arrival of transactions is assumed to follow a Poisson distribution with parameter λ, different for each type of security. The arrival interval between security arrivals, $t_{p+1} - t_p$ follows an exponential distribution with parameter λ. The pth arrival time, t_p follows a gamma distribution with parameters p and $\frac{1}{\lambda}$. Thus, the distribution of last arrival time of one security within time period T, $g_{t_p}(x)$ is

$$
\begin{aligned}
g_{t_p}(x) &= P\left(t_p = x \middle| t_p < T, t_{p+1} > T\right) \\
&= \frac{P\left(t_p = x, t_p < T,\ t_{p+1} - t_p > T - t_p\right)}{P\left(t_p < T,\ t_{p+1} - t_p > T - t_p\right)} \\
&= \frac{f_{t_p}(x) 1_{\{x<T\}} \int_{T-x}^{\infty} f_{t_{p+1}-t_p}(y) dy}{\int_0^T f_{t_p}(x) \int_{T-x}^{\infty} f_{t_{p+1}-t_p}(y) dy\, dx} \qquad \text{(A.1)} \\
&= \frac{px^{p-1}}{T^p}.
\end{aligned}
$$

The expected arrival difference of two securities, given one has p arrivals and another has q arrivals, is

$$E\left(|t_p - s_q|\,\middle|\,number\ of\ arrivals = p\ and\ q\right)$$

$$= \int_0^T \int_0^x g_{t_p}(x) g_{s_q}(y)\,(x-y)dydx + \int_0^T \int_0^y g_{t_p}(x) g_{s_q}(y)\,(y-x)dxdy$$

$$= \frac{T}{p+q+1}\left(\frac{p}{q+1} + \frac{q}{p+1}\right). \tag{A.2}$$

where $t_p\ and\ s_q$ are last arrival times of two different types of securities within one minute. For tractability, security arrivals are assumed to be independent. Given p and q arrivals of securities and the distribution of last arrival time within period T, the last arrival time difference (*LATD*), or time displacement, within each minute is defined as

$$LATD = E\left[E\left(|t_p - s_q|\,\middle|\,number\ of\ arrivals = p\ and\ q\right)\right]$$

$$= \sum_{q=0}^{\infty}\sum_{p=0}^{\infty} \frac{e^{-T\lambda_t} T{\lambda_t}^p}{p!} \frac{e^{-T\lambda_s} T{\lambda_s}^q}{q!} \frac{T}{p+q+1}\left(\frac{p}{q+1} + \frac{q}{p+1}\right), \tag{A.3}$$

where λ_t and λ_s are arrival rates of securities. T is set as 1 minute and arrival rates have to be estimated for each 1-minute interval. An estimate of the arrival rate is given by the number of transactions per period. However, the number of transactions is not included in our dataset. Instead, we have trading volume for each 1-minute interval. If the trading volume is not zero, there is at least be one transaction executed in this 1-minute interval. By counting the number of 1-minute intervals with non-zero trading volume, we determine the minimum number of transactions arriving each day. Thus, we necessarily underestimate arrival rates and displacement intervals between securities. During the sample period of the intraday dataset, call options on average had 94 non-zero intervals (94.62) and put option had 82 non-zero intervals (82.79) per day. The ETF generally trades every minute (total 240 minute). Arrival rates per minute for options and the ETF are estimated by these average numbers of non-zero volume intervals. Using these arrival rates we compute *LATD*s using equation A.3.

Table A.1 reports *LATD*s for different securities pairs. The last arrival time difference is 4.02 seconds for call-put pairs, 1.86 for call-ETF pairs and 3.63 for put-ETF pairs. The differences are reasonably small and we argue that synchronicity is acceptable for the intraday dataset. We acknowledge the derivations of Mr. Yinan Ni in providing this model.

Table 1: Summary Statistics

Statistics for the daily dataset. The price of options is the settle price determined by the closing call auction of each trading day. The bid-ask spread is estimated during July 25, 2016-August 25, 2016. A minimum option price is set at ¥0.0001.

	N	Min	Max	Mean	Median	STD
ETF Price	349	1.919	3.41	2.447	2.349	0.368
ETF Volume (million shares)	349	82.79	9,146.83	913.85	437.37	1,170.93
Short-sale Volume (10,000 shares)	349	0.33	29,552.1	4,854.03	490.6	7,517.68
Call Price	19,519	0.0001	1.785	0.255	0.161	0.277
Call volume	349	5,656	338,671	84,620	84,974	53,004
Bid-ask spread	295	0.04%	40.00%	2.28%	0.76%	1.23%
Days to Maturity	19,519	1	244	80.81	62	63.79
Strike price	19,519	1.8	3.6	2.51	2.45	0.43
Put Price	19,519	0.0001	1.785	0.209	0.144	0.216
Put volume	349	3,322	220,188	67,529	67,461	42,874
Bid-ask spread	277	0.09%	66.67%	5.85%	1.12%	7.02%
Days to Maturity	19,519	1	244	80.81	62	63.79
Strike price	19,519	1.8	3.6	2.51	2.45	0.43

Table 2: Deviation of Put-call Parity

Moneyness is proxied by the price-to-strike ratio. The synthetic call portfolio is established by borrowing cash to buy a put and the underlying. The implied rate is the rate required to satisfy put-call parity. Differences (*Diffc and Diffr*) are differences between test proxies (Diffc= synthetic call price – actual call price). We use both the daily dataset and minute-level dataset. %*Diffc* is the percentage of average *Diffc* to average actual call price.

Days to Maturity	Moneyness	N	$Call_{syn}$	$Call_{act}$	*Diffc*	%*Diffc*	*Implied rate*,%	*Interest rate*,%	*Diffr*,%
					Panel A: Daily				
Overall		16,175	0.2227	0.1922	0.0305***	15.87%	-7.8844	3.0626	-10.9470***
	<0.9	1,775	0.0380	0.0067	0.0313***	465.22%	-31.1852	2.6408	-33.8260***
	0.9-0.97	1,220	0.0508	0.0322	0.0186***	57.63%	-17.4790	2.7999	-20.2789***
<45	0.97-1.03	1,264	0.0908	0.0738	0.0169***	22.89%	-12.4316	2.9557	-15.3873***
	1.03-1.1	1,305	0.1867	0.1754	0.0113***	6.42%	-5.9123	2.9556	-8.8678***
	>1.1	1,667	0.4569	0.4568	0.0002	0.04%	0.3738	2.7814	-2.4076***
	<0.9	1,249	0.0905	0.0343	0.0563***	164.24%	-6.3424	3.0238	-9.3662***
	0.9-0.97	922	0.1228	0.0869	0.0359***	41.25%	-4.2829	3.1328	-7.4157***
45-120	0.97-1.03	1,030	0.1700	0.1350	0.0350***	25.91%	-4.6644	3.3087	-7.9732***
	1.03-1.1	982	0.2474	0.2146	0.0329***	15.31%	-4.5367	3.3245	-7.8612***
	>1.1	1,418	0.4769	0.4657	0.0113***	2.43%	0.5006	3.2894	-2.7888***
	<0.9	538	0.1750	0.1003	0.0747***	74.53%	-3.2379	3.2048	-6.4427***
	0.9-0.97	623	0.2152	0.1581	0.0570***	36.05%	-2.1935	3.2676	-5.4612***
>120	0.97-1.03	718	0.2680	0.2065	0.0615***	29.81%	-2.3745	3.4006	-5.7751***
	1.03-1.1	641	0.3325	0.2728	0.0597***	21.88%	-2.5257	3.4275	-5.9533***
	>1.1	709	0.5170	0.4783	0.0386***	8.08%	-0.6730	3.4528	-4.1257***
					Panel B: Intraday				
Overall		277,749	0.0988	0.0810	0.0178***	22.00%	-5.3778	2.7348	-8.1183***
	<0.9	10,593	0.0184	0.0046	0.0138***	298.84%	-6.3138	2.7169	-9.0350***
	0.9-0.97	47,383	0.0254	0.0150	0.0104***	69.04%	-4.4432	2.6954	-7.1431***
<45	0.97-1.03	89,449	0.0559	0.0462	0.0097***	21.03%	-4.4550	2.6641	-7.1311***
	1.03-1.1	52,081	0.1343	0.1233	0.0110***	8.95%	-6.4041	2.6958	-9.1022***
	>1.1	11,533	0.2659	0.2547	0.0112***	4.38%	-7.6065	2.6377	-10.2455***
	<0.9	3,613	0.0674	0.0177	0.0497***	281.04%	-7.2113	2.9508	-10.1621***
	0.9-0.97	9,718	0.0752	0.0404	0.0348***	86.06%	-5.2000	2.9080	-8.1081***
45-120	0.97-1.03	19,186	0.1060	0.0754	0.0307***	40.69%	-5.3111	2.8887	-8.1998***
	1.03-1.1	12,921	0.1787	0.1449	0.0337***	23.26%	-6.5022	2.8938	-9.3959***
	>1.1	8,827	0.3271	0.2848	0.0423***	14.84%	-7.9462	2.9013	-10.8476***
	<0.9	362	0.1633	0.0519	0.1113***	214.36%	-7.4655	3.1013	-10.5668***
	0.9-0.97	2,230	0.1328	0.0616	0.0713***	115.73%	-4.4766	2.9506	-7.4272***
>120	0.97-1.03	3,081	0.1755	0.1081	0.0674***	62.38%	-4.6821	2.9507	-7.6328***
	1.03-1.1	2,501	0.2401	0.1713	0.0688***	40.13%	-5.2690	2.9640	-8.2329***
	>1.1	3,005	0.3583	0.2907	0.0675***	23.23%	-5.2613	2.9241	-8.1854***

Table 3: Deviation of Put-call Parity and the Soft Interventions

Moneyness is proxied by the price-to-strike ratio. The synthetic call portfolio is established by borrowing cash to buy a put and the underlying. The implied rate is the rate required to satisfy put-call parity. Differences (*Diffc and Diffr*) are differences between test proxies (Diffc= synthetic call price – actual call price). %*Diffc* is the percentage of average *Diffc* to average actual call price. Only the daily dataset is used in this table.

Days to Maturity	Moneyness	N	$Call_{syn}$	$Call_{act}$	*Diffc*	%*Diffc*	*Implied rate*,%	*Interest rate*,%	*Diffr*,%
Panel A: Daily, Before 07/15/2015									
Overall		5,314	0.3136	0.3116	0.0020***	0.65%	0.1534	3.4822	-3.3288***
	<0.9	260	0.0416	0.0247	0.0170***	68.73%	-18.9335	2.8212	-21.7548***
	0.9-0.97	367	0.0701	0.0626	0.0075***	11.99%	-7.8880	3.1364	-11.0244***
<45	0.97-1.03	432	0.1167	0.1100	0.0067***	6.07%	-4.7482	3.4804	-8.2286***
	1.03-1.1	496	0.2240	0.2203	0.0037***	1.70%	-0.6629	3.3978	-4.0607***
	>1.1	862	0.5530	0.5557	-0.0028***	-0.50%	1.6931	2.9472	-1.2540
	<0.9	241	0.0938	0.0838	0.0100***	11.96%	-0.2350	3.1217	-3.3567***
	0.9-0.97	275	0.1508	0.1556	-0.0048***	-3.11%	3.5470	3.5274	0.0196
45-120	0.97-1.03	363	0.2028	0.2013	0.0014	0.72%	3.0509	3.9512	-0.9003***
	1.03-1.1	358	0.2903	0.2875	0.0029**	0.99%	2.7770	3.9642	-1.1872***
	>1.1	595	0.5880	0.5988	-0.0109***	-1.81%	5.3420	3.6972	1.6448***
	<0.9	174	0.1787	0.1787	0.0000	-0.03%	2.7983	3.2563	-0.4580
	0.9-0.97	177	0.2615	0.2704	-0.0089***	-3.29%	3.9714	3.6878	0.2835
>120	0.97-1.03	232	0.3018	0.2880	0.0138***	4.78%	2.7624	4.0031	-1.2407***
	1.03-1.1	213	0.3815	0.3677	0.0138***	3.76%	2.7403	4.0953	-1.3549***
	>1.1	233	0.6699	0.6670	0.0029*	0.43%	3.9323	4.1897	-0.2574*
Panel B: Daily, After 07/15/2015									
Overall		10,823	0.1786	0.1340	0.0445***	33.22%	-11.8441	2.8575	-14.7015***
	<0.9	1,508	0.0375	0.0036	0.0338***	931.88%	-33.4324	2.6095	-36.0420***
	0.9-0.97	849	0.0425	0.0191	0.0234***	122.50%	-21.7010	2.6551	-24.3561***
<45	0.97-1.03	829	0.0772	0.0550	0.0223***	40.52%	-16.4661	2.6833	-19.1494***
	1.03-1.1	807	0.1637	0.1479	0.0159***	10.73%	-9.1318	2.6845	-11.8163***
	>1.1	805	0.3541	0.3508	0.0033***	0.95%	-1.0389	2.6038	-3.6427***
	<0.9	1,001	0.0900	0.0224	0.0676***	301.79%	-7.8275	3.0014	-10.8289***
	0.9-0.97	643	0.1110	0.0576	0.0533***	92.58%	-7.6314	2.9657	-10.5971***
45-120	0.97-1.03	664	0.1522	0.0988	0.0534***	54.02%	-8.8829	2.9595	-11.8424***
	1.03-1.1	621	0.2228	0.1726	0.0502***	29.07%	-8.7445	2.9581	-11.7026***
	>1.1	821	0.3968	0.3695	0.0273***	7.39%	-2.9873	2.9949	-5.9821***
	<0.9	362	0.1734	0.0627	0.1107***	176.57%	-6.1391	3.1803	-9.3194***
	0.9-0.97	446	0.1968	0.1136	0.0832***	73.23%	-4.6402	3.1009	-7.7410***
>120	0.97-1.03	485	0.2518	0.1675	0.0843***	50.37%	-4.8249	3.1128	-7.9377***
	1.03-1.1	428	0.3081	0.2256	0.0825***	36.57%	-5.1465	3.0952	-8.2417***
	>1.1	476	0.4421	0.3860	0.0562***	14.55%	-2.9272	3.0920	-6.0193***

Table 4: Implied Volatility and the Soft Interventions

Implied volatilities (IVs) based on the Black-Scholes model are reported in this table. Panel A and Panel B report IVs from call options and put options separately. Panel C reports the difference between IVs from put options and those from call options. The cutoff date is 07/15/2015.

Panel A: IV from Call Options

Time to Maturity	Moneyness, S/K	Full Period	Before Interventions	After Interventions
	<0.9	48.62%	64.99%	47.14%
	0.9-0.97	34.21%	46.65%	30.59%
<45	0.97-1.03	28.74%	38.94%	24.70%
	1.03-1.1	31.68%	39.52%	26.60%
	>1.1	50.12%	53.15%	46.18%
	<0.9	37.48%	62.86%	35.29%
	0.9-0.97	32.27%	47.57%	27.18%
45-120	0.97-1.03	28.91%	39.96%	23.86%
	1.03-1.1	28.48%	39.06%	22.45%
	>1.1	41.14%	46.38%	35.65%
	<0.9	35.96%	55.05%	33.15%
	0.9-0.97	30.76%	41.01%	27.46%
>120	0.97-1.03	27.96%	34.76%	25.15%
	1.03-1.1	26.64%	34.54%	22.54%
	>1.1	31.00%	35.77%	26.72%

Panel B: IV from Put Options

Time to Maturity	Moneyness, K/S	Full Period	Before Interventions	After Interventions
	<0.9	46.49%	48.05%	53.31%
	0.9-0.97	36.03%	39.76%	42.24%
<45	0.97-1.03	35.70%	39.57%	43.54%
	1.03-1.1	43.81%	47.57%	53.49%
	>1.1	65.30%	63.47%	81.66%
	<0.9	38.96%	40.62%	41.82%
	0.9-0.97	37.11%	38.37%	43.38%
45-120	0.97-1.03	37.71%	38.74%	44.13%
	1.03-1.1	41.66%	44.03%	46.00%
	>1.1	58.25%	52.25%	64.27%
	<0.9	35.88%	35.57%	39.30%
	0.9-0.97	36.46%	34.43%	40.20%
>120	0.97-1.03	38.25%	35.57%	41.42%
	1.03-1.1	40.25%	38.64%	43.24%
	>1.1	52.42%	45.34%	51.23%

Panel C: IV Difference Pooled Over Strike and Moneyness

	Full Period	Before Interventions	After Interventions	After - Before	t-statistic	P value
Average IV from Call	35.44%	44.36%	32.05%	-12.31%	-51.81	<.0001
Average IV from Put	43.60%	42.03%	44.22%	2.19%	9.55	<.0001
Put - Call	8.16%	-2.33%	12.17%			
t-statistic	49.32	-8.09	63.54			
P value	<.0001	<.0001	<.0001			

Table 5: Linear Models to Estimate Ask Price and Bid Price of Options

Observations from July 27, 2016 to August 27, 2016 are used to estimate the coefficients of bid and ask prices. Linear Model 1 is from [Equation (6)], Linear Model 2 is from Equation (7) and Linear Model 3 is from Equation (8). These coefficients are subsequently used to estimate bid price and ask prices during the sample period (Feb 2015 – July 2016).

	Model 1				Model 2				Model 3			
	Bid		Ask		Bid		Ask		Bid		Ask	
	Coef	P value	Coef	P value	Coef	P value	Coef	P value	Coef	P value	Coef	P value
Panel A: Calls												
Option Price	0.99816	<.0001	1.0013	<.0001	0.99992	<.0001	1.00364	<.0001	0.9983	<.0001	1.00049	<.0001
T	-2.7E-06	<.0001	1.33E-06	0.0435	-2.7E-06	<.0001	1.55E-06	0.0057	-2.4E-06	0.0004	9.15E-07	0.2097
Volume	-2.01E-07	0.7683	-3.50E-07	0.6271								
Log(Volume)					4.97E-05	0.0454	4.59E-05	0.081	2.53E-05	0.5345	-7.3E-05	0.1572
K	4.92E-05	0.2406	7.29E-05	0.1007								
$\lvert S - K \rvert$					-1.70E-03	0.0659	-2.16E-03	0.0278				
S/K									2.21E-05	0.8804	4.24E-04	0.0496
R^2	100%		100%		100%		100%		100%		100%	
Panel B: Puts												
Option Price	0.99587	<.0001	1.00239	<.0001	0.99622	<.0001	1.00283	<.0001	0.99619	<.0001	1.00241	<.0001
T	-1.5E-06	0.0012	3.29E-07	0.4976	-1.4E-06	0.0014	4.05E-07	0.3777	-1.4E-06	0.0033	3.60E-07	0.4685
Volume	-4.01E-07	0.4679	-3.06E-07	0.5904								
Log(Volume)					1.04E-05	0.5788	4.00E-07	0.9835	1.19E-05	0.7097	-6.6E-06	0.8409
K	3.71E-05	0.2387	4.21E-05	0.1938								
$\lvert S - K \rvert$					6.37E-05	0.8381	3.09E-04	0.3356				
K/S									5.89E-06	0.9661	9.54E-05	0.5038
R^2	100%		100%		100%		100%		100%		100%	

Table 6: Deviation of Put-call parity based on Estimated Bid and Ask Price

The first six columns are the assumed or estimated values (inputs) used to estimate bid and ask prices. The Predicted by Model rows use coefficients obtained from the model in equation 7 to calculate bid and ask prices. Arbitrage strategy A sells a synthetic call and buys a market call. Strategy B sells a market call and buys a synthetic call. Mean deviations from no-arbitration and Percentage violations of no-arbitrage are given in the last three columns.

	Bid-Ask Assumptions						Results		
Number of Observations	Call ask	Call bid	Put ask	Put bid	ETF ask	ETF bid	Strategy A	Strategy B	%Violation
Panel A: Daily									
17,050	0.64%	1.64%	2.40%	3.45%	0.05%	0.05%	0.0211	-0.0417	77.21%
17,050	Predicted by Model				0.05%	0.05%	0.0295	-0.0336	93.17%
Panel B: Intraday									
277,749	0.64%	1.64%	2.40%	3.45%	0.05%	0.05%	0.0132	-0.0223	79.80%
277,749	Predicted by Model				0.05%	0.05%	0.0176	-0.0178	99.28%

Table 7: Mean Regressive Parameters Before and After Interventions

Mean regressive parameters for the daily dataset. The cutoff date of before-intervention or after-intervention periods is 07/15/2015. Panel A reports estimated parameters from equations (6) to (8). Panel B reports corrected parameters using a bootstrap method. We test means with a t-test and test medians with the Wilcoxon rank sum test. The full period includes 208 call-put-ETF pairs, the before-intervention period includes 104 pairs and the after-intervention period includes 204 pairs. Triple asterisks imply significance at the 0.01 level.

	Full Period			Before-intervention Period			After-intervention Period			After - Before	
	Mean	Median	STD	Mean	Median	STD	Mean	Median	STD	Mean	Median
Panel A: Raw, Strategy A											
θ	0.0113	0.0073	0.0218	-0.0229	-0.0163	0.0209	0.0273	0.0296	0.0180	0.0503	0.0372
	***	***	-	***	***	-	***	***	-	***	***
κ	0.2550	0.1608	0.2652	0.3960	0.3299	0.2557	0.2292	0.1699	0.2442	-0.1668	-0.0742
	***	***	-	***	***	-	***	***	-	***	***
σ	0.0165	0.0129	0.0099	0.0141	0.0107	0.0077	0.0184	0.0183	0.0103	0.0043	-0.0029
	***	***	-	***	***	-	***	***	-	***	***
Panel B: Boot Strap Correction, Strategy A											
θ	0.0047	0.0022	0.0191	-0.0268	-0.0179	0.0215	0.0180	0.0142	0.0212	0.0448	0.0394
	***	***	-	***	***	-	***	***	-	***	***
κ	0.1983	0.1261	0.2645	0.3393	0.2794	0.2625	0.1632	0.1299	0.2357	-0.1761	-0.0169
	***	***	-	***	***	-	***	***	-	***	***
σ	0.0169	0.0131	0.0101	0.0146	0.0109	0.0081	0.0189	0.0185	0.0105	0.0042	-0.0028
	***	***	-	***	***	-	***	***	-	***	***
Panel C: Raw, Strategy B											
θ	-0.0374	-0.0332	0.2743	-0.0077	-0.0159	0.0195	-0.0515	-0.0556	0.0187	-0.0438	-0.0397
	***	***	-	***	***	-	***	***	-	***	***
κ	0.2726	0.1773	0.0198	0.4368	0.4022	0.2550	0.2303	0.1682	0.2462	-0.2064	-0.2339
	***	***	-	***	***	-	***	***	-	***	***
σ	0.0164	0.0129	0.0099	0.0140	0.0105	0.0078	0.0185	0.0183	0.0102	0.0044	0.0078
	***	***	-	***	***	-	***	***	-	***	***
Panel D: Boot Strap Correction, Strategy B											
θ	-0.0309	-0.0283	0.0177	-0.0046	-0.0143	0.0207	-0.0422	-0.0381	0.0220	-0.0376	-0.0238
	***	***	-	***	***	-	***	***	-	***	***
κ	0.2174	0.1379	0.2740	0.3826	0.3072	0.2599	0.1648	0.1249	0.2381	-0.2178	-0.1823
	***	***	-	***	***	-	***	***	-	***	***
σ	0.0168	0.0132	0.0101	0.0146	0.0107	0.0082	0.0189	0.0185	0.0105	0.0043	0.0079
	***	***	-	***	***	-	***	***	-	***	***

Table 8. Difference in Difference: Put-Call Parity Deviations

The HSCEI option traded in the Hong Kong market is the control group. RI is the procedure that mitigates the over-rejection problem. *Diffc* of the Hong Kong market is computed from equation (13). The DiD model is given in equation (14). The sample period is 95 days before and 95 days after 07/15/2015. We include options with $0.9 \leq S/K \leq 1.1$ for the SSE 50 option and $0.9 \leq Fe^{-rT}/K \leq 1.1$ for the HSCEI option. The empirical confidence interval in the RI procedure is based on M=100,000 observations. *** means that the estimate of the interaction coefficient falls outside the RI 99% confidence interval.

Panel A: Not Adjusted for Exchange Rate

	Coef	SE	T	P
Intercept	18.04	0.70	25.79	<.0001
SH	-18.05	0.98	-18.39	<.0001
After	-5.32	0.98	-5.41	<.0001
SH*After	5.39***	1.39	3.87	0.0001
Adj R-squared	0.5744			
Confidence interval for β_3 from RI	0.5 Percentile	99.5 Percentile		
	-4.26	4.19		

Panel B: Adjusted for Exchange Rates

	Coef	SE	T	P
Intercept	22.51	0.86	26.03	<.0001
SH	-22.52	1.21	-18.56	<.0001
After	-6.97	1.22	-5.73	<.0001
SH*After	7.04***	1.72	4.09	<.0001
Adj R-squared	0.5765			
Confidence interval for β_3 from RI	0.5 Percentile	99.5 Percentile		
	-5.29	5.20		

Table 9. Difference in Differences: Implied Volatility Changes

The HSCEI option traded in Hong Kong is the control group. RI is the procedure that mitigates the over-rejection problem. Implied volatilities are computed for Hong Kong Futures options on the HSCEI and Shanghai options on the SSE 50 ETF. The sample period is 95 days before and 95 days after 07/15/2015. We include options with $0.9 \leq S/K \leq 1.1$ for the SSE option and $0.9 \leq Fe^{-rT}/K \leq 1.1$ for the HSCEI futures option. The empirical confidence interval in the RI procedure is based on M=100,000 observations. *** means that the estimate of the interaction coefficient falls outside the RI 99% confidence interval.

Panel A: Dependent Variable is IV from Call

	Coef	SE	T	P
Intercept	0.27	0.008	34.30	<.0001
SH	0.15	0.01	13.66	<.0001
After	0.02	0.01	2.16	0.0317
SH*After	-0.13	0.016	-8.19	<.0001
Adj R-squared	0.3629			
Confidence interval for β_3 from RI	0.5 Percentile	99.5 Percentile		
	-0.0455	0.0450		

Panel B: Dependent Variable is IV from Put

	Coef	SE	T	P
Intercept	0.26	0.01049	25.19	<.0001
SH	0.11	0.01473	7.69	<.0001
After	0.02	0.01476	1.63	0.1044
SH*After	0.06	0.02088	2.68	0.0078
Adj R-squared	0.3558			
Confidence interval for β_3 from RI	0.5 Percentile	99.5 Percentile		
	-0.0497	0.0465		

Table A.1: Last Arrival Time Difference

Arrival rate per day is estimated by the number of non-zero volume intervals during the sample period of the intraday dataset. Results are calculated by equation (A.3)

Panel A: Inputs

Security	Estimated arrival rate per day
Call	94
Put	82
ETF	240

Panel B: Results

Pairs	*LATD*, second(s)
Call-Put	4.02
Call-ETF	1.86
Put-ETF	3.63

Figure 1: **Shanghai Stock Exchange (SSE) Composite Index from January 2015 to March 2016.**

Major market crashes were June-July 2015, August 2015 and January 2016.

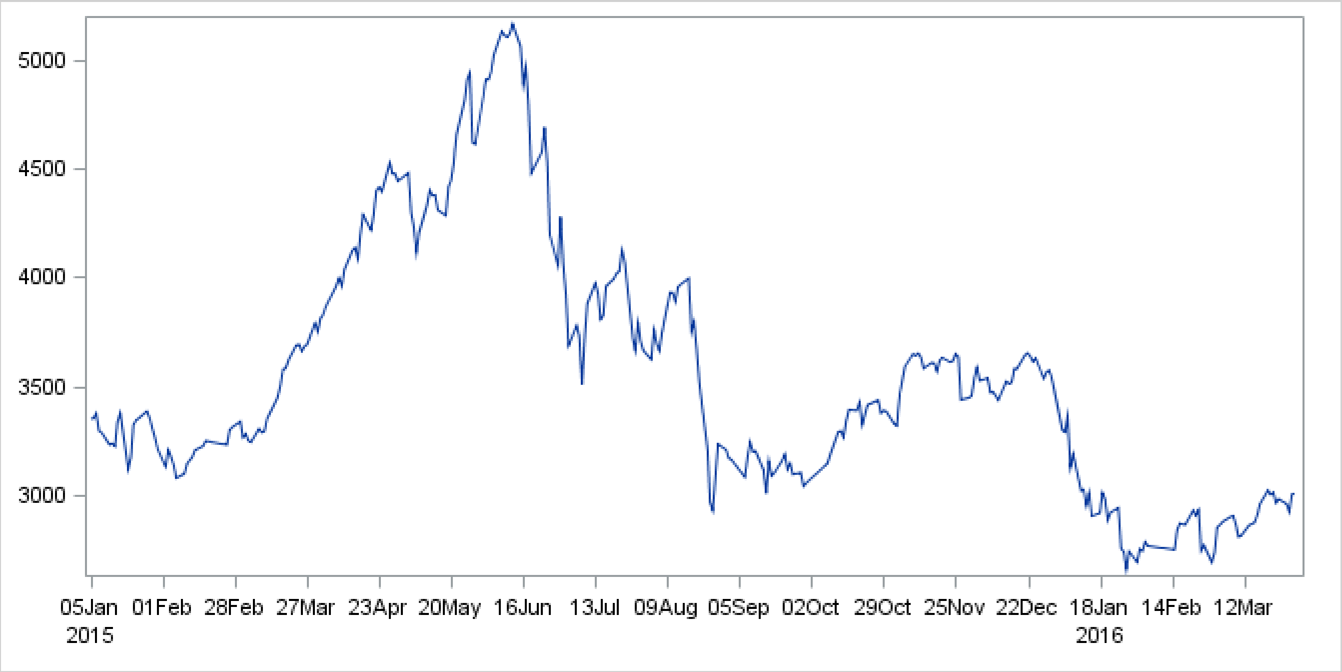
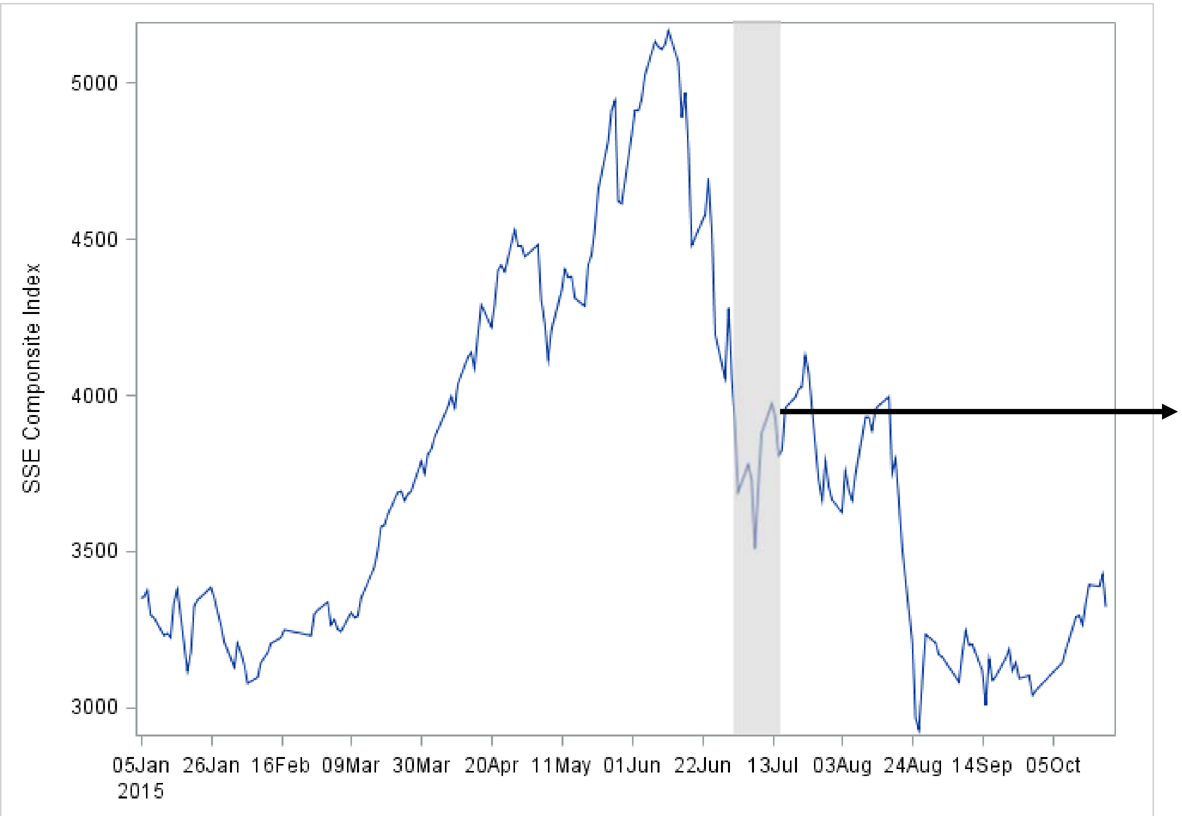


Figure 2: **Examples of the soft interventions during July 2015 in Chinese equity market**.



July 1, Shanghai Stock Exchange reduced the trading fees.

July 3, CSRC suspended IPOs. CSRC and brokers started to investigate arbitragers who shorted the market and to limit the short position. People's Bank of China stated it would provide liquidity to the market. At the end of July 3, the SSE Composite Index dropped 12.07% within one week and 28.6% within three weeks.

July 4, under the pressure from the CSRC, twenty-one investment companies and brokers published a statement that they would invest ¥120 billion in blue chip ETFs and guarantee that they would not sell the securities out before SSE Composite Index returns to 4500. The block holders of public firms published statements that they would not sell their securities until the market is stabilized.

July 5, The People's Bank of China stated that it would provide financial support to China Securities Finance Corporation to help stabilize the market.

July 8, CSRC asked managements and block holders of public firms who sold the firms' stocks within half a year to stop selling their own securities.

Figure 3: **Soft interventions and the collapse in short-sale volume.**

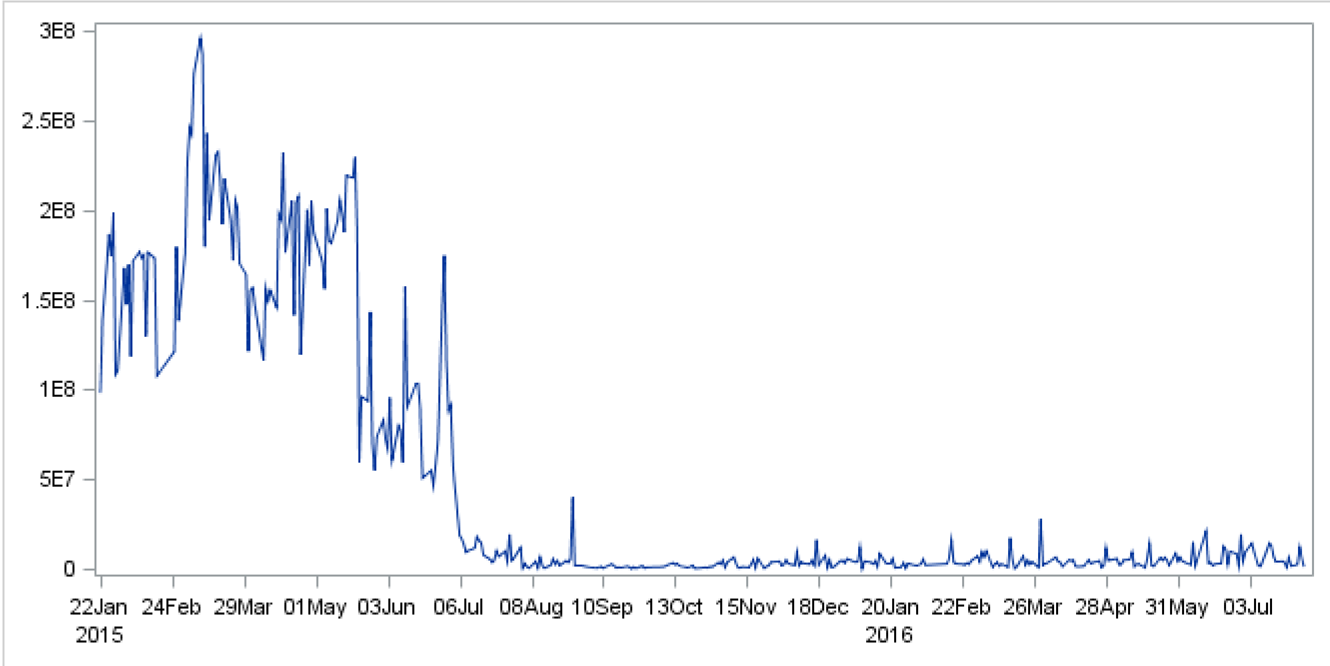


Figure 4. Distribution of SSE 50 ETF returns.

Daily returns are usually within ± 3.5% range. The 10% daily limit was touched only once during the sample period.

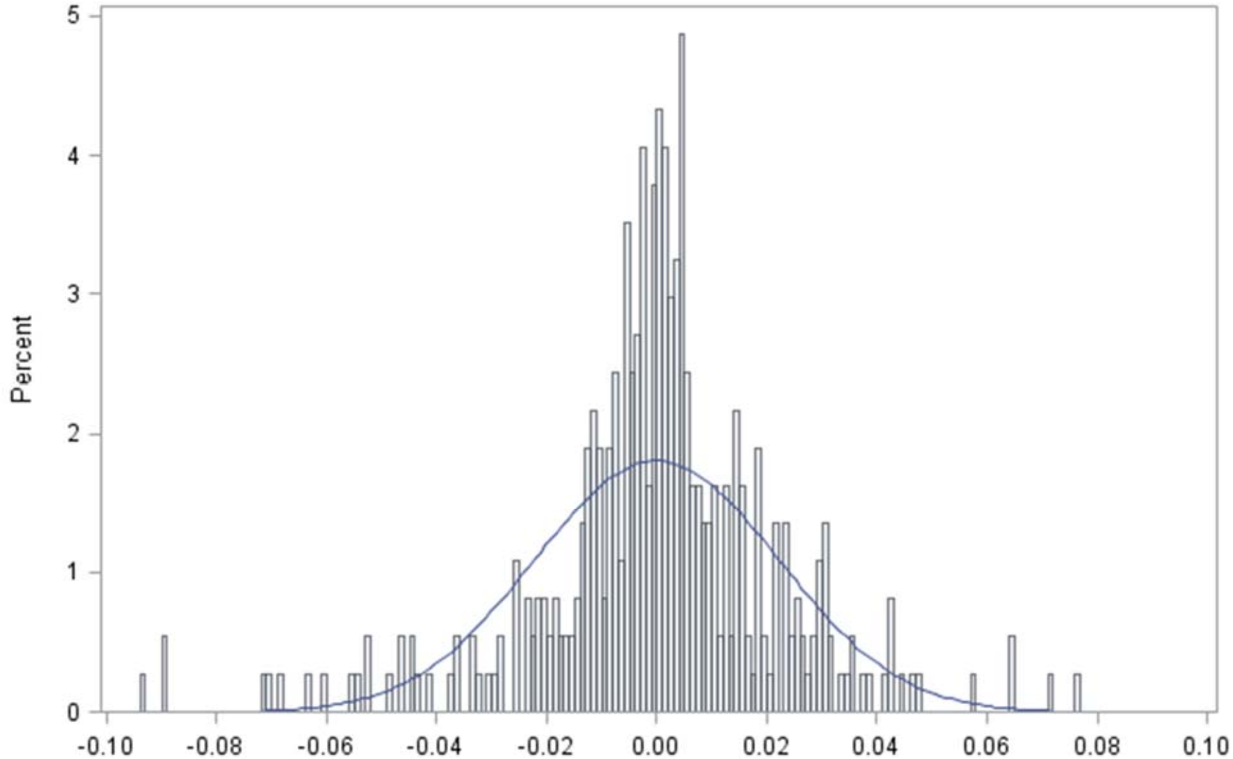
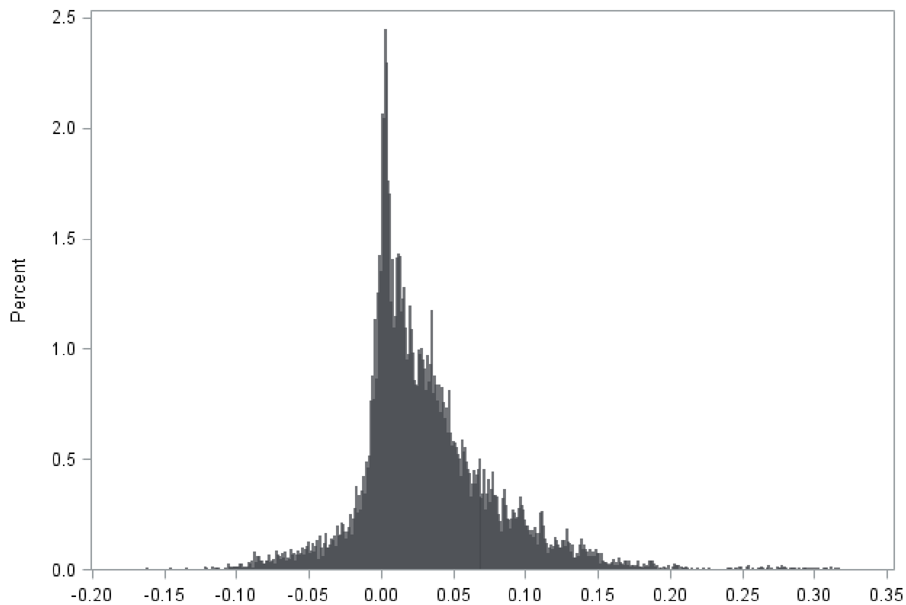


Figure 5: **Distribution of *Diffc*.**

The daily dataset includes observations from February 2015 to July 2016 and the intraday dataset includes observations from January 2016 to July 2016.

Panel A: Distribution of *Diffc,* daily



Panel B: Distribution of *Diffc*, intraday

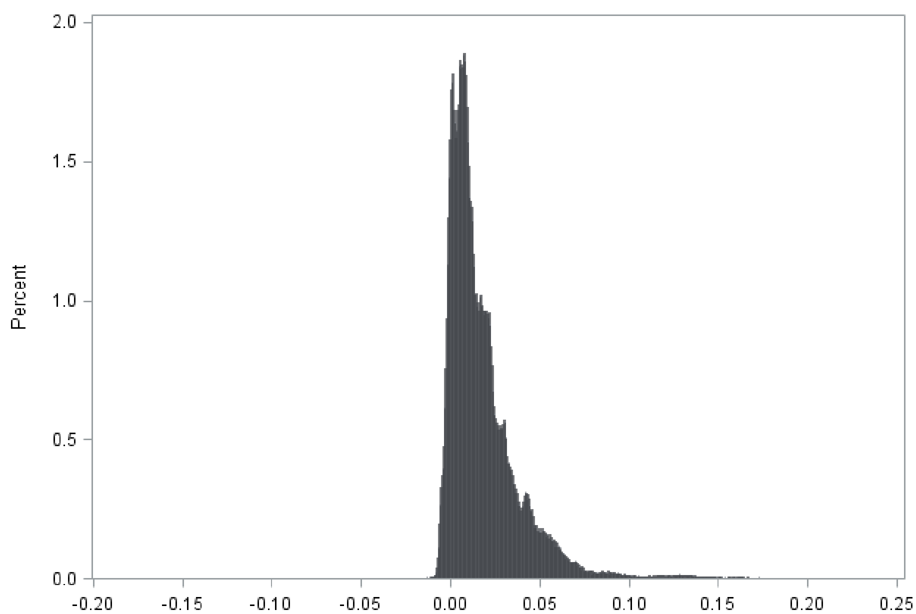


Figure 6: Daily volume of options.

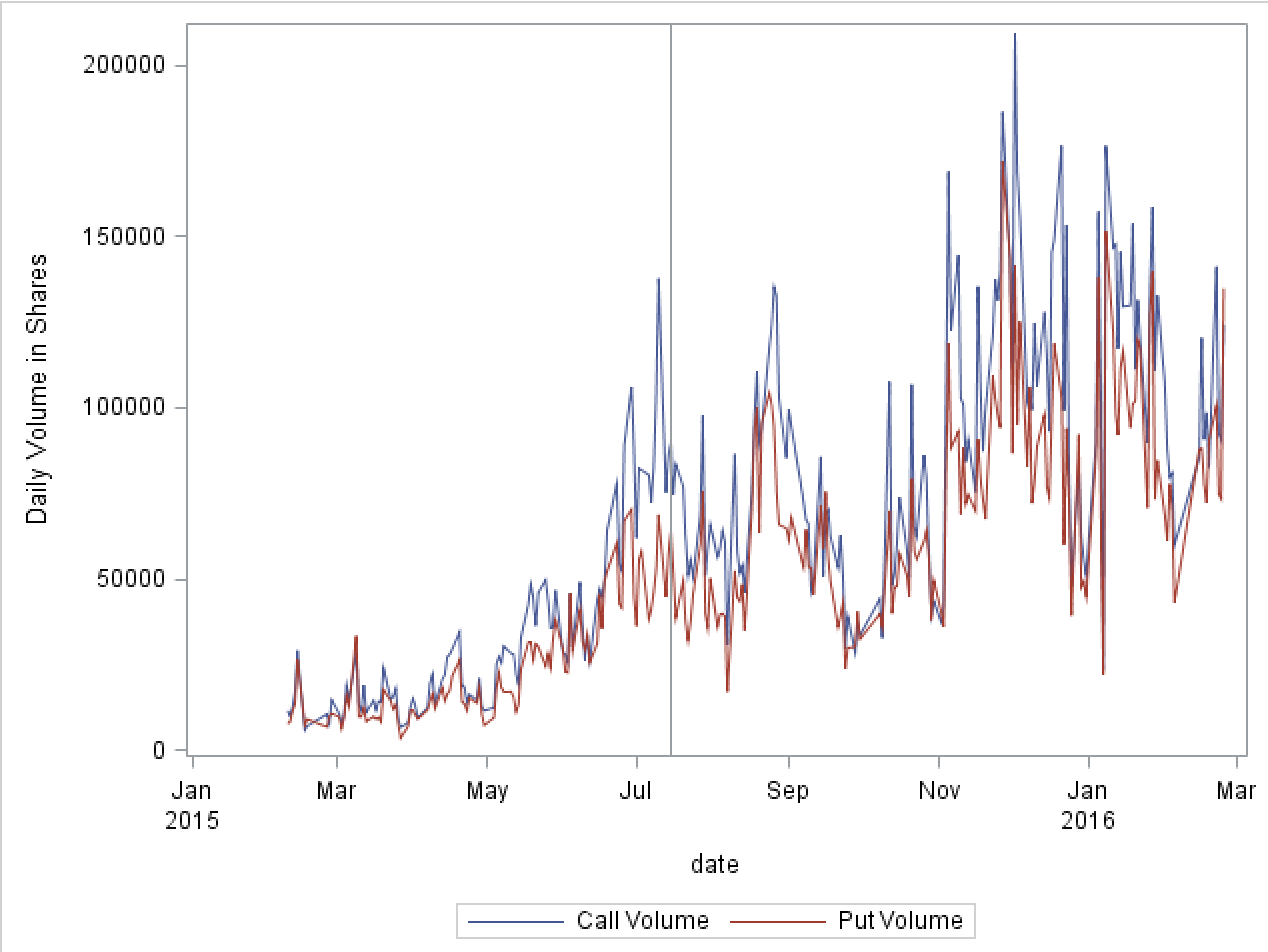
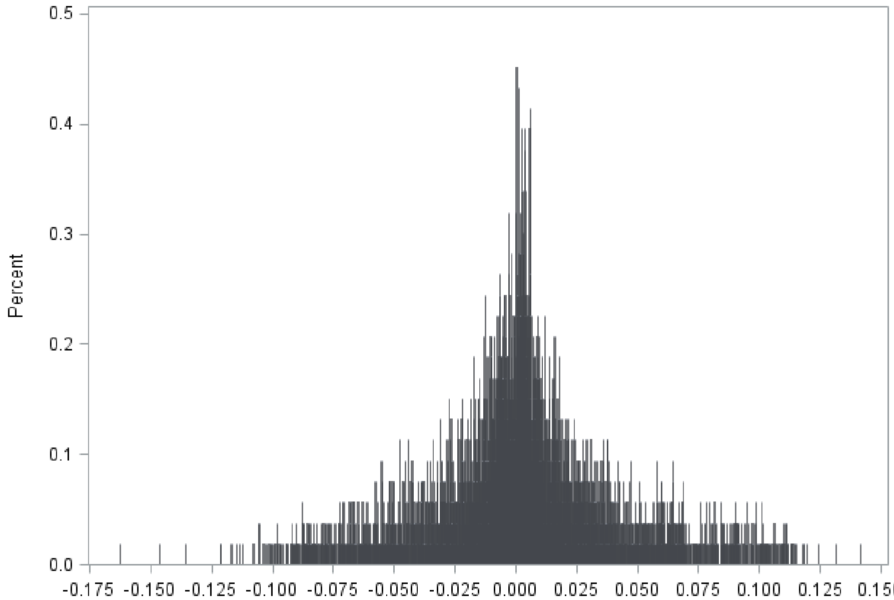


Figure 7: **Distribution of *Diffc* before and after the soft interventions.**

Panel A: Distribution of *Diffc*, before the soft interventions.



Panel B: Distribution of *Diffc,* after the soft interventions.

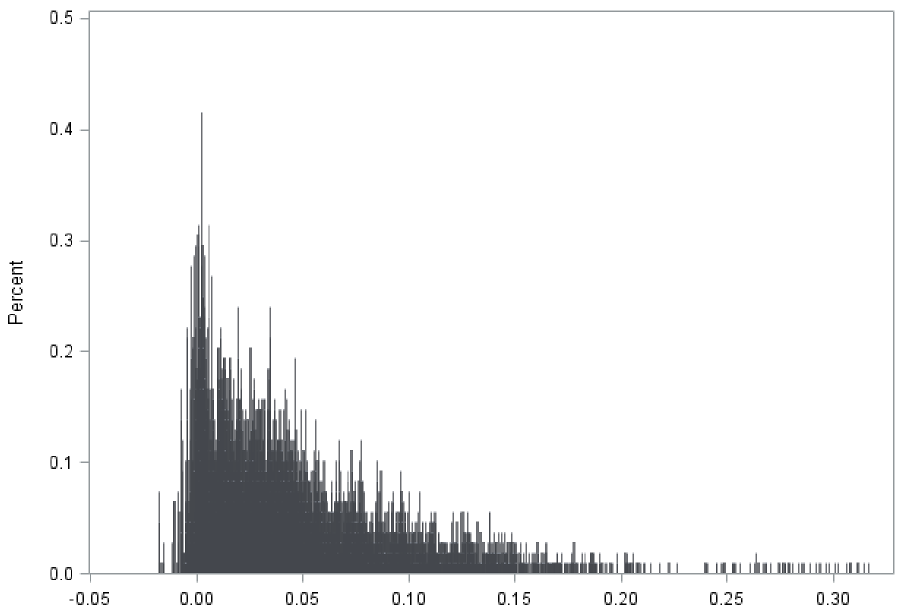


Figure 8: **Daily Average Implied Volatility (IV) for call options**.

The horizontal bars are the average IV before and after soft interventions. The cut-off date is July 15, 2015.

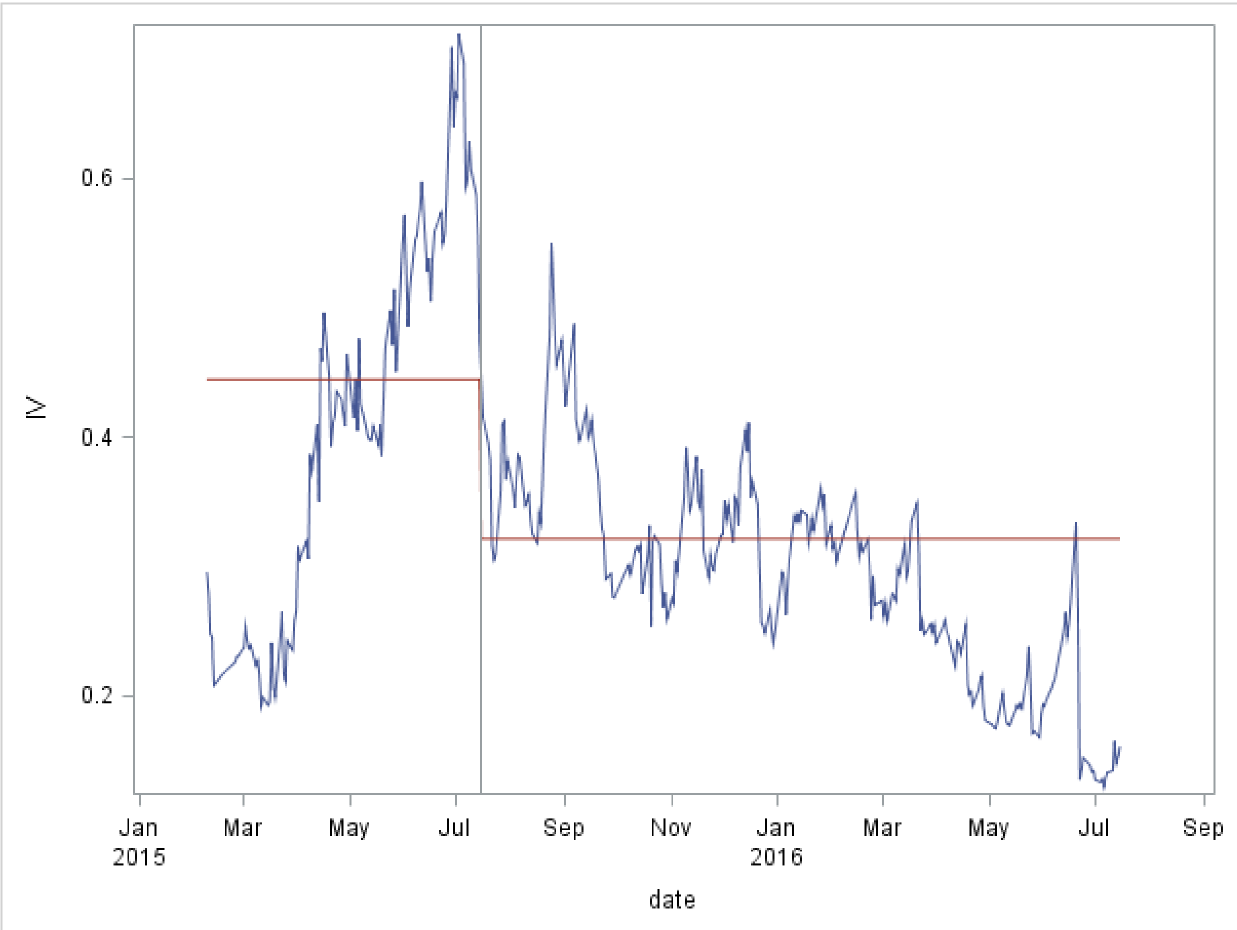


Figure 9: **Daily Average Implied Volatility (IV) for put options.**

The horizontal bars are the average IV before and after soft interventions. The cut-off date is July 15, 2015.

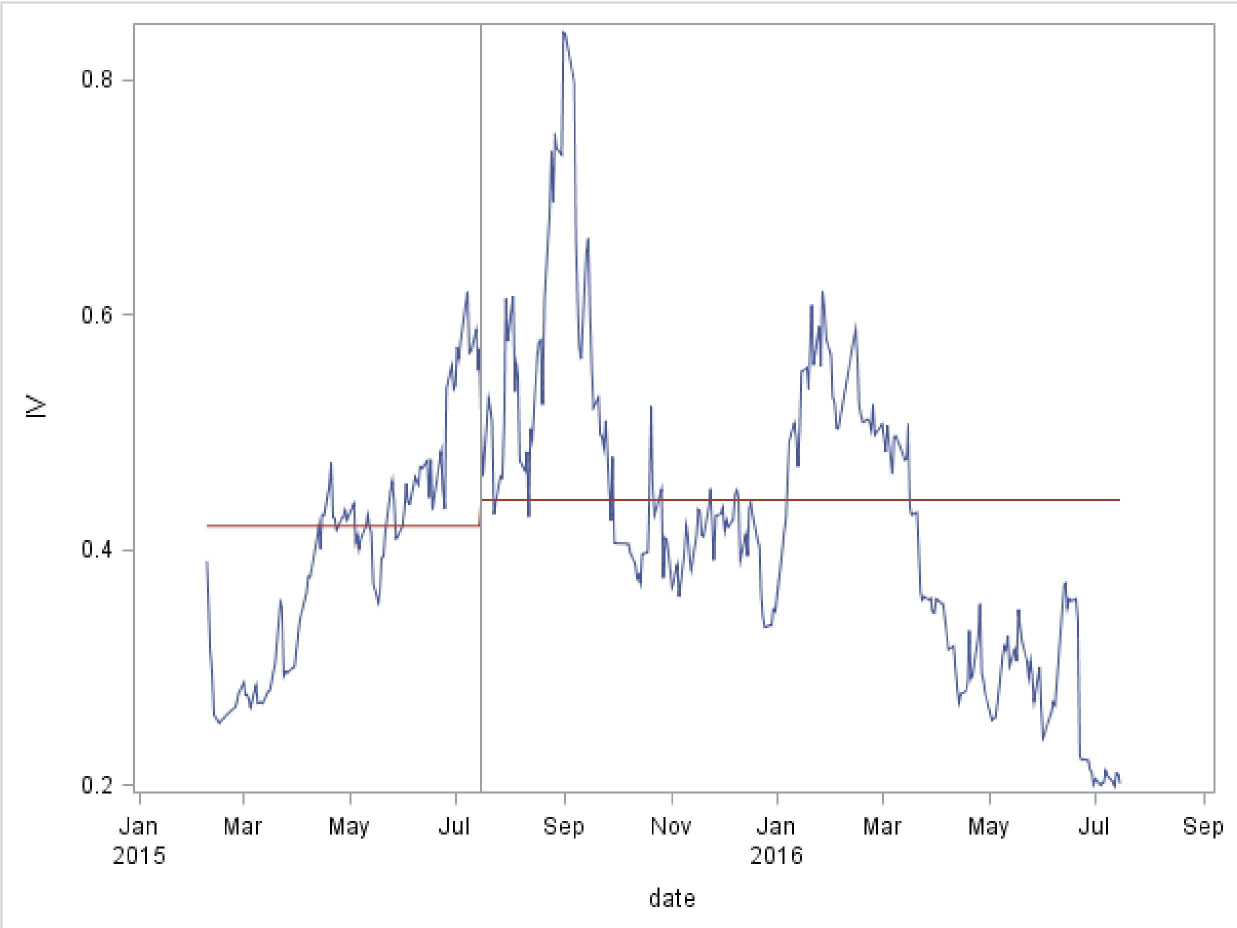


Figure 10: **The Average Ratio of Implied Volatility (IV) of call options to IV of put options**.

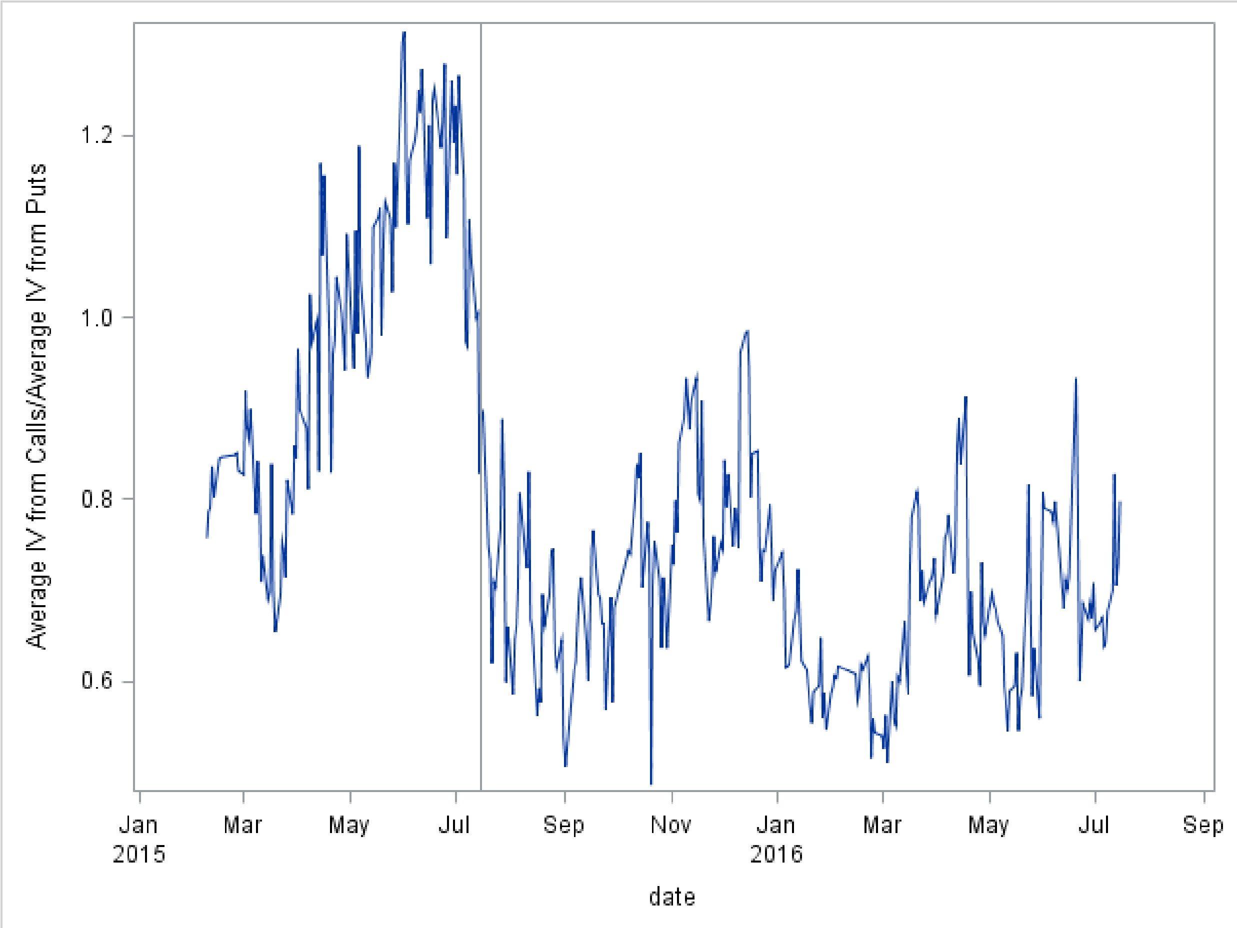


Figure 11. Price movement of Hang Seng China Enterprise Index and SSE 50 ETF around the 2015 market crisis.