Three Essays on Market Efficiency and Corporate Payout Policy

by

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A dissertation submitted to the Graduate Faculty of
Auburn University
In partial fulfillment of the
requirements for the Degree of
Doctor of Philosophy

Auburn, AL
August 3, 2019

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Abstract

Chapters 1 and 2 of this dissertation discuss a special form of regulation, soft intervention, in China. 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 positions, significantly reducing short-sales volume and futures trading volume. In Chapters 1 and 2, the impacts of these interventions on put-call parity and the cost of carry model are investigated. There is overwhelming evidence of increased deviations from put-call parity and the cost-of-carry model 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.

Chapter 3 focuses on how changes in dividend policy in 2008 as the financial crisis was unfolding influenced firm risk-adjusted returns in the following years. The sample consists of NYSE- and NASDAQ-traded firms that paid dividends in 2007. These firms are divided into four groups based on their dividend policy in 2008. Evidence shows that firms that decreased or eliminated dividends in 2008 had higher risk-adjusted returns in 2009. The higher risk-adjusted return is consistent with better corporate governance in 2007. This finding suggests that the firms

that quickly reacted to the deteriorating economic conditions by cutting dividends and preserving cash were able to better weather the coming financial crisis.

Acknowledgements

I would like to first express my deepest appreciation to my advisor, Dr. Jimmy Hilliard. He guides me through every stage of my doctoral study. I have learned a lot from him. I cannot reach this point without his encouragement, patience, and support. I would also like to extend my deepest gratitude to my co-author and committee member, Dr. Jitka Hilliard. Without her, I may not even start to pursue a life as a researcher. She has provided me extensive personal and professional support. I wish to thank Dr. John Jahera and Dr. James Barth for severing as my committee members. I received great support and invaluable advice from them. Thanks also to Dr. Denis Nadolnyak, who serves as the University Reader. This dissertation would not have been possible without their help. Finally yet importantly, I would like to express my gratitude to my wife, my family, and my friends. Their support and love inspire me every day.

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[1] This chapter is joint work with Dr. Jimmy E. Hilliard

1.1 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. We find the soft intervention in 2015 reduced short-sale volume significantly. Using the Huaxia SSE 50 ETF and its options, we find overwhelming evidence that put-call parity deviations increase significantly 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 1.2 summarizes the regulatory features of the Chinese market and Section 1.3 is the literature review. Sections 1.4 and 1.5 describe the securities and the data. Section 1.6 develops the effect of the regulator's soft intervention on put-call parity. Section 1.7 develops identification tests and Section 1.8 concludes.

1.2 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; 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.

1.2.1 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.

1.2.2 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 hold a portfolio with less than ¥100,000 or $14,482[2] (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.

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

The Chinese equity market suffered a major meltdown beginning in June 2015 (Figure 1.1). Within one month, A-shares on the Shanghai Stock Exchange lost approximately one third of

[2] 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.

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 1.2).

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[3]. 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 1.3). 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 was 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 from the regulator and limited the short positions themselves to avoid unfavorable actions under this policy uncertainty.

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

1.3 Related 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 to 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; 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 expect that large violations of put-call parity will appear after the soft interventions.

1.4 The Huaxia 50 ETF Option

The SSE 50 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. They are all

European options. 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 SSE 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[4]. The SSE 50 ETF option contract is dividend adjusted. In fact, however, 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 1.1). Most of the components in the SSE 50 ETF are stocks of financial firms. At the end of March 2016, 65.3% of the capitalization of this ETF was from the financial industry, 16.84% from manufacturing and 17.86% from all other 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

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

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 1.4 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 shorted. Prior to soft interventions, the SSE 50 ETF was one of the most shorted securities on the Shanghai Stock Exchange.

1.5 Data

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 average time between put and ETF transactions is 1.86 seconds, and the average time between call and ETF transactions is 3.63 seconds (see Appendix and Table A.1.1).

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 1.1, ETF daily settle price ranges from ¥1.919 to ¥3.41 with mean ¥2.447 ($0.3534). The average trading volume is 913.85 million shares per day and short-sale volume is about 48.5 million shares per day. In empirical tests, options 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.

1.6 The effect of soft interventions on market prices

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:

$$c_{it}^{Syn} = p_{it}^{Act} + S_t - K_i e^{-r_t T_{it}}, \tag{1.1}$$

$$Diffc_{it} = c_{it}^{Syn} - c_{it}^{Act}, \tag{1.2}$$

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

$$r_{it}^{Imp} = \frac{\ln(K_i) - \ln\left(S_t + p_{it}^{Act} - c_{it}^{Act}\right)}{T_{it}}, \tag{1.3}$$

$$Diffr_{it} = r_{it}^{Imp} - r_{it}^{Act}. \tag{1.4}$$

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. "Economically 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.

1.6.1 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 1.2 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 1.5, the distributions of *Diffc* are not symmetric for either dataset as both are clearly right skewed.

1.6.2 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 option volume increased significantly after the soft interventions (Figure 1.6). 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 ratio. 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 1.3 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 1.3, 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 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 1.3 are similar to the full sample results in Table 1.2 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 1.7 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.

1.6.3 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[5], we develop models to estimate bid- ask prices for the Wind database and the full sample period. Ask (bid) prices from Sina.com are regressed on closing prices, volume, and contract information using the following models:

$$Ask\ price_{it} = \beta_1 price_{it} + \beta_2 K_i + \beta_3 T_{it} + \beta_4 Volume_{it} + \varepsilon_{it}, \tag{1.5}$$

$$Ask\ price_{it} = \beta_1 price_{it} + \beta_2 |K_i - S_t| + \beta_3 T_{it} + \beta_4 \log(Volume_{it}) + \varepsilon_{it}, \tag{1.6}$$

$$Ask\ price_{it} = \beta_1 price_{it} + \beta_2 \frac{S_t}{K_i} + \beta_3 T_{it} + \beta_4 \log(Volume_{it}) + \varepsilon_{it}, \tag{1.7}$$

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 1.4. 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

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

not significant in all but one of three models. With parameters estimated from the model in equation (1.7), 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

$$\varepsilon_{it}^{A} = (p_{it}^{Bid} + S_t^{Bid} - K_i e^{-r_t T_{it}}) - c_{it}^{Ask}, \tag{1.8}$$

$$\varepsilon_{it}^{B} = c_{it}^{Bid} - \left(p_{it}^{Ask} + S_t^{Ask} - K_i e^{-r_t T_{it}}\right). \tag{1.9}$$

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 1.5.

The first six columns in Table 1.5 specify the bid-ask inputs used in equations (1.8) and (1.9). 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 (1.7) 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.

1.6.5 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 impli 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:

$$de_{it} = \kappa_i(\theta_i - e_{it})dt + \sigma_i dZ_{it}, \tag{1.10}$$

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 (1.9).

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

$$e_{it} = \kappa_i\theta_i + (1 - \kappa_i)e_{it-1} + u_{it} \tag{1.11}$$

for the entire sample period and in the before- and after-intervention periods[6]. Table 1.6 reports the summary statistics for the estimated parameters from Strategy A and Strategy B. Since

[6] 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 and the observations from 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.

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 1.6, all long-term means are significant at the one percent level. For strategy A, the average 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-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 in the series (Ball and Torous, 1996; and Tang and Chen, 2009). The relatively large speed of adjustment (Panel A of Table 1.6) 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.

1.7 Identification

There is sufficient evidence to conclude that put-call parity does not hold 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 a 0.0045% transaction fee on the contract value for ETFs and even less if the trade 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 a call and ¥0.209 for a 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, the options are dividend adjusted and in fact no dividends from 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.

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"[7]. The HSCEI Index closely mirrors mainland Chinese markets (SSE and SZSE). See Figure 1.8. 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 affect 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[8]

[7] During our sample period, only the "Shanghai-Hong Kong Stock Connect" was available. The "Shenzhen-Hong Kong Stock Connect" was launched in December 2016.
[8] 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).

$$Diffc_{it} = p_{it} - c_{it} + F_{it}e^{-r_{it}T} - K_i e^{-r_{it}T}, \tag{1.12}$$

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 and the HSCEI options and implement the DiD model

$$Diffc_{kt} = \alpha + \beta_1 SH_k + \beta_2 After_t + \beta_3 SH_k After_t + e_{kt}. \tag{1.13}$$

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 $0.9 \leq Fe^{-rT}/K \leq 1.1$ for the Hong Kong market.

The coefficient of the interaction term, β_3, captures the intervention effect. Results are reported in Panel A of Table 1.7. The estimated coefficient of β_3 (5.39) is significant at the one percent level. We conclude that deviations from put-call parity of SSE 50 ETF options became significantly higher than those 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[9]. 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 1.7.

1.8 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, 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

[9] We use the following procedure: 1. Use OLS to estimate β_3 in equation (1.13). 2. Randomly assign 95 days with short-sale restrictions. Other days have no short-sale restriction. Estimate the coefficient of the interaction term, $\hat{\beta}_3^*$. Repeat step 2 for M =100,000 times to get the empirical distribution of $\hat{\beta}_3^*$. 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. Estimates outside the confidence interval correspond to a significant treatment effect.

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.

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.

The impact of the market break and the ensuing soft intervention can be further investigated using the SSE 50 Index futures contract that trades on the China Financial Futures Exchange (CFFEX). It stands to reason that investors who wanted to short the SSE 50 ETF can achieve a similar risk exposure by shorting the CFFEX SSE 50 Index futures contract. That said, calls and puts do not exist for the CFFEX futures contract making direct tests of the put-call parity no-arbitrage relationship impossible without further assumptions.

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Table 1.1: 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 1.2: 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	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 1.3: 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 1.4: 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. Model 1 is from equation (1.5), Model 2 is from equation (1.6) and Model 3 is from equation (1.7). 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	0.9982	<.0001	1.0013	<.0001	0.9999	<.0001	1.0036	<.0001	0.9983	<.0001	1.0005	<.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	0.9959	<.0001	1.0024	<.0001	0.9962	<.0001	1.0028	<.0001	0.9962	<.0001	1.0024	<.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 1.5: Deviation of Put-call parity based on Estimated Bid and Ask Price

The first six columns are the assumed or estimated values used to estimate bid and ask prices. The Predicted by Model rows use coefficients obtained from the model in equation (1.7) 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-arbitrage 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 1.6: 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 (1.8) to (1.11). 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 put-call-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 1.7: Difference in Difference: Put-Call Parity Deviations

The HSCEI option traded in the Hong Kong market is the control asset. RI is the procedure that mitigates the over-rejection problem. *Diffc* of the Hong Kong market is computed from equation (1.12). The DiD model is given in equation (1.13). 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. Triple asterisks imply 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 value
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 value
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		

Figure 1.1: **Shanghai Stock Exchange (SSE) Composite Index from January 2015 to March 2016.**

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

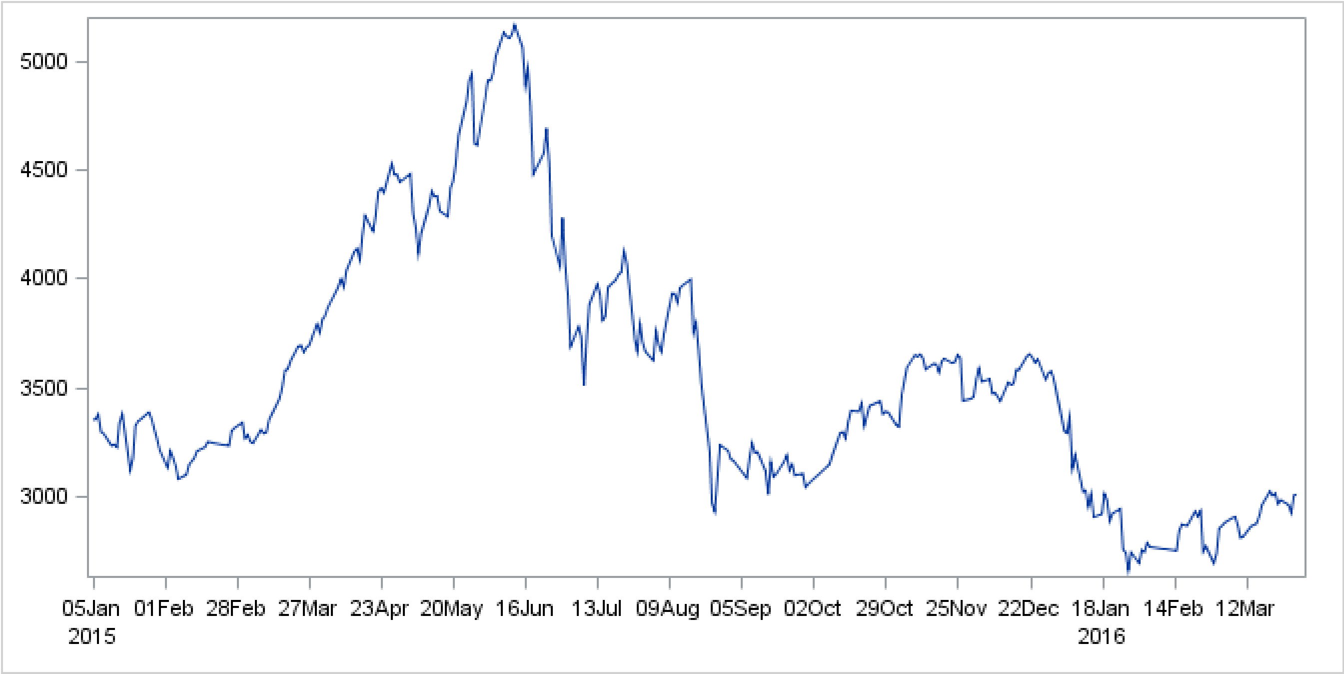
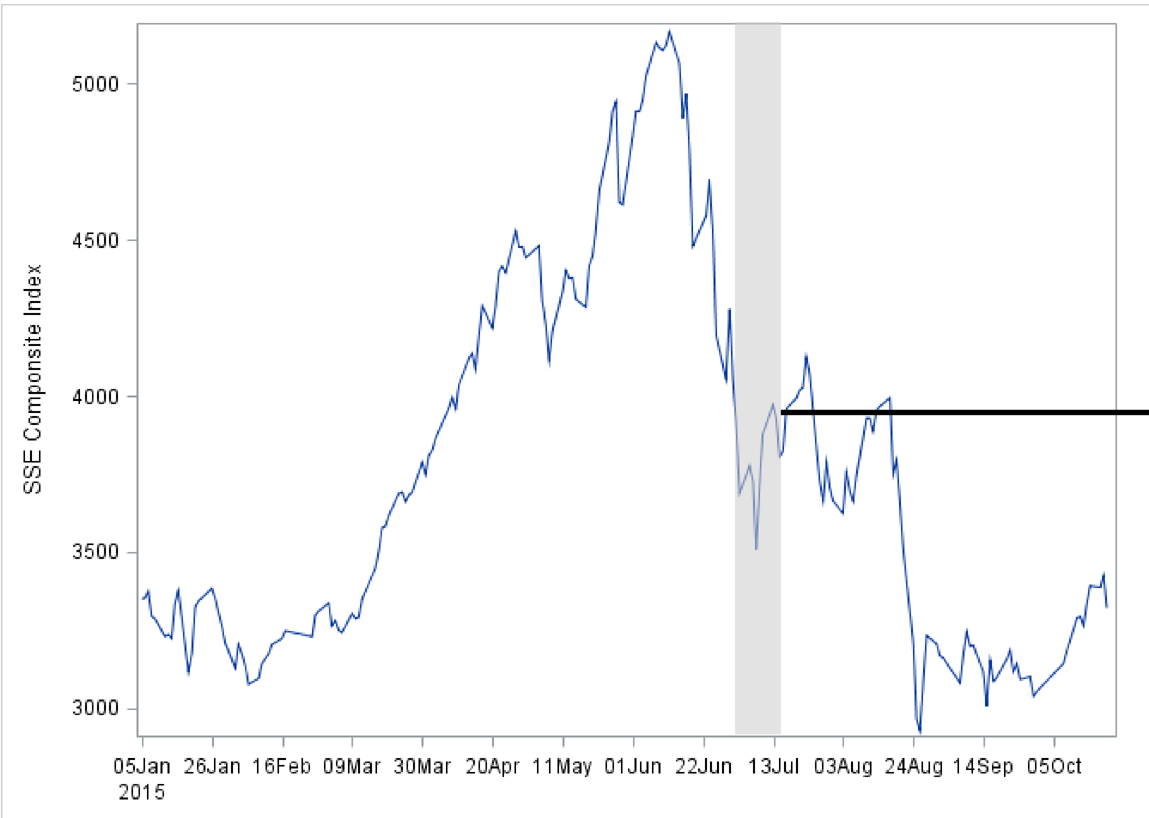


Figure 1.2: **Examples of the interventions during July 2015 in Chinese equity market**.



July 1, Shanghai Stock Exchange reduced the trading fees.

July 3, CSRC suspended IPOs. CSRC and brokers started to investigate arbitrageurs/speculators 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 was 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 1.3: **Soft interventions and the collapse in short-sale volume.**

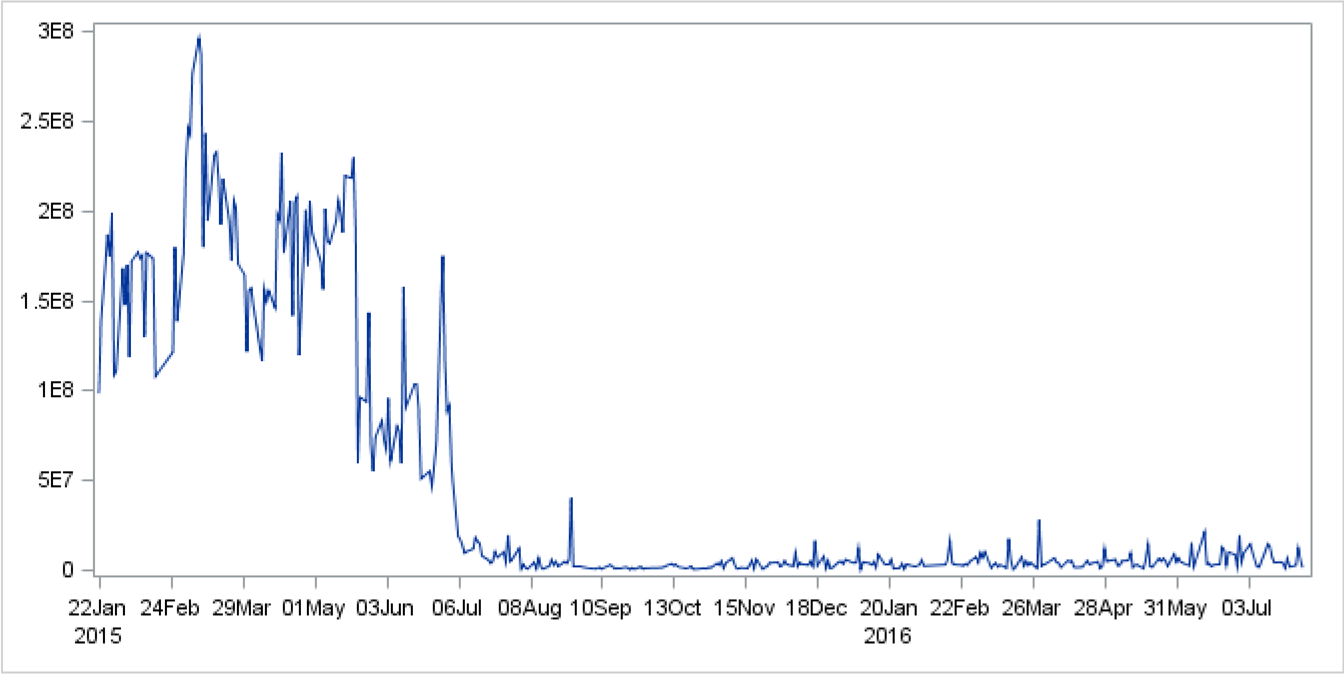


Figure 1.4: Distribution of SSE 50 ETF returns.

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

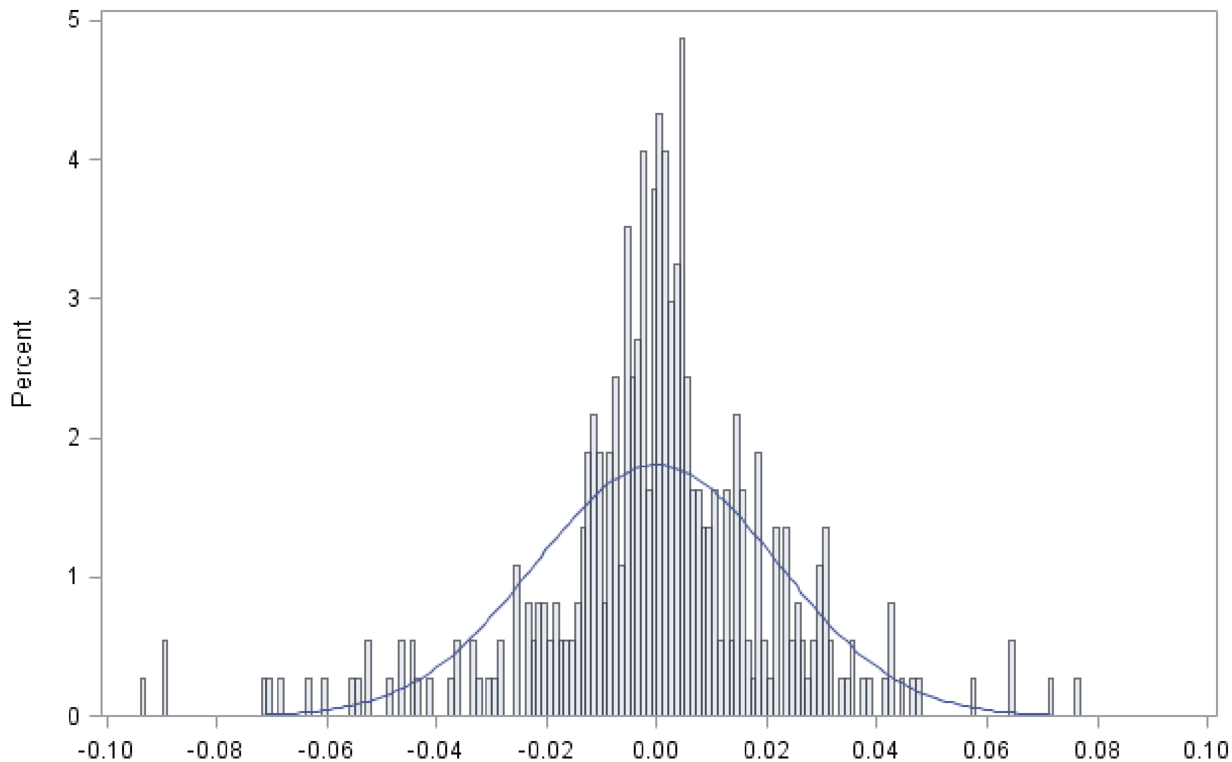
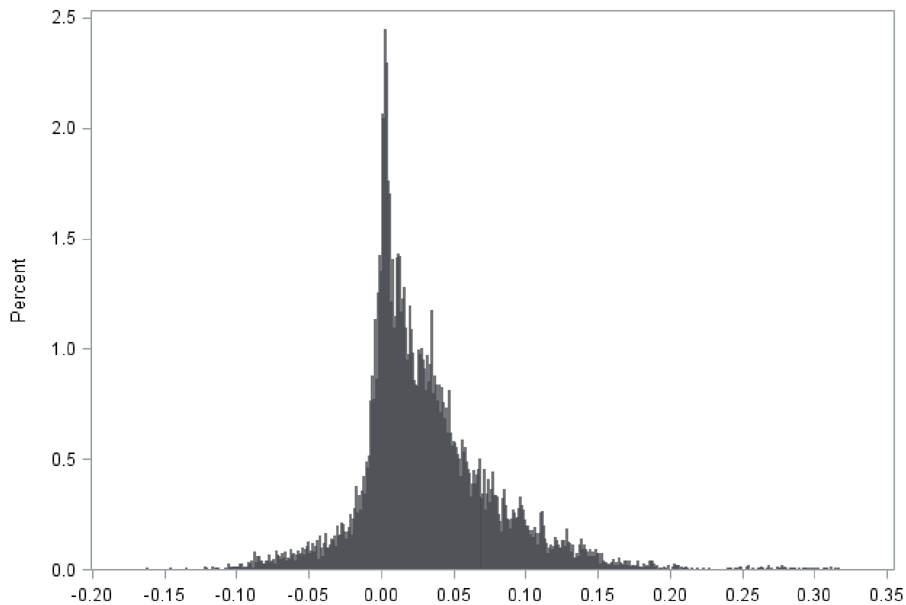


Figure 1.5: **Distribution of *Diffc*.**

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

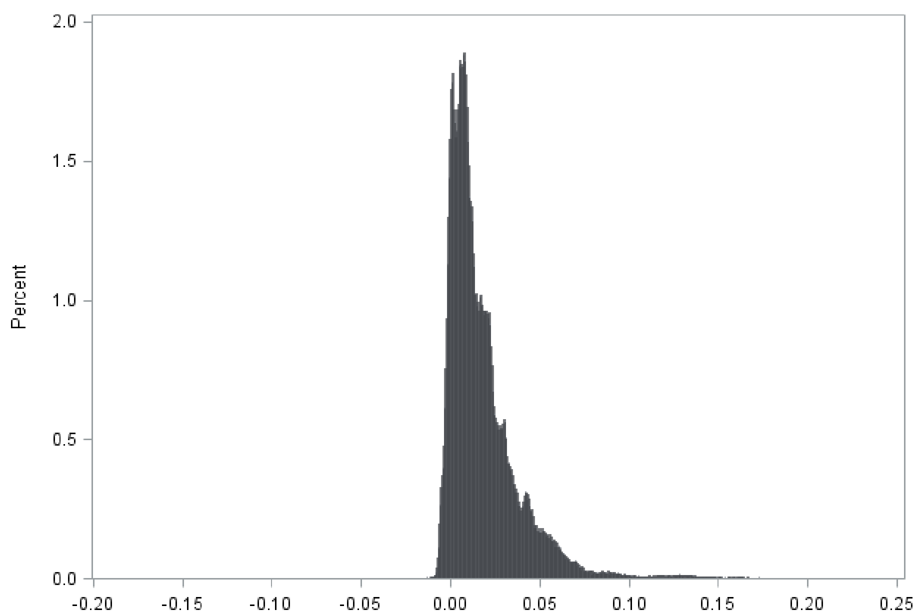


Figure 1.6: Daily volume of options.

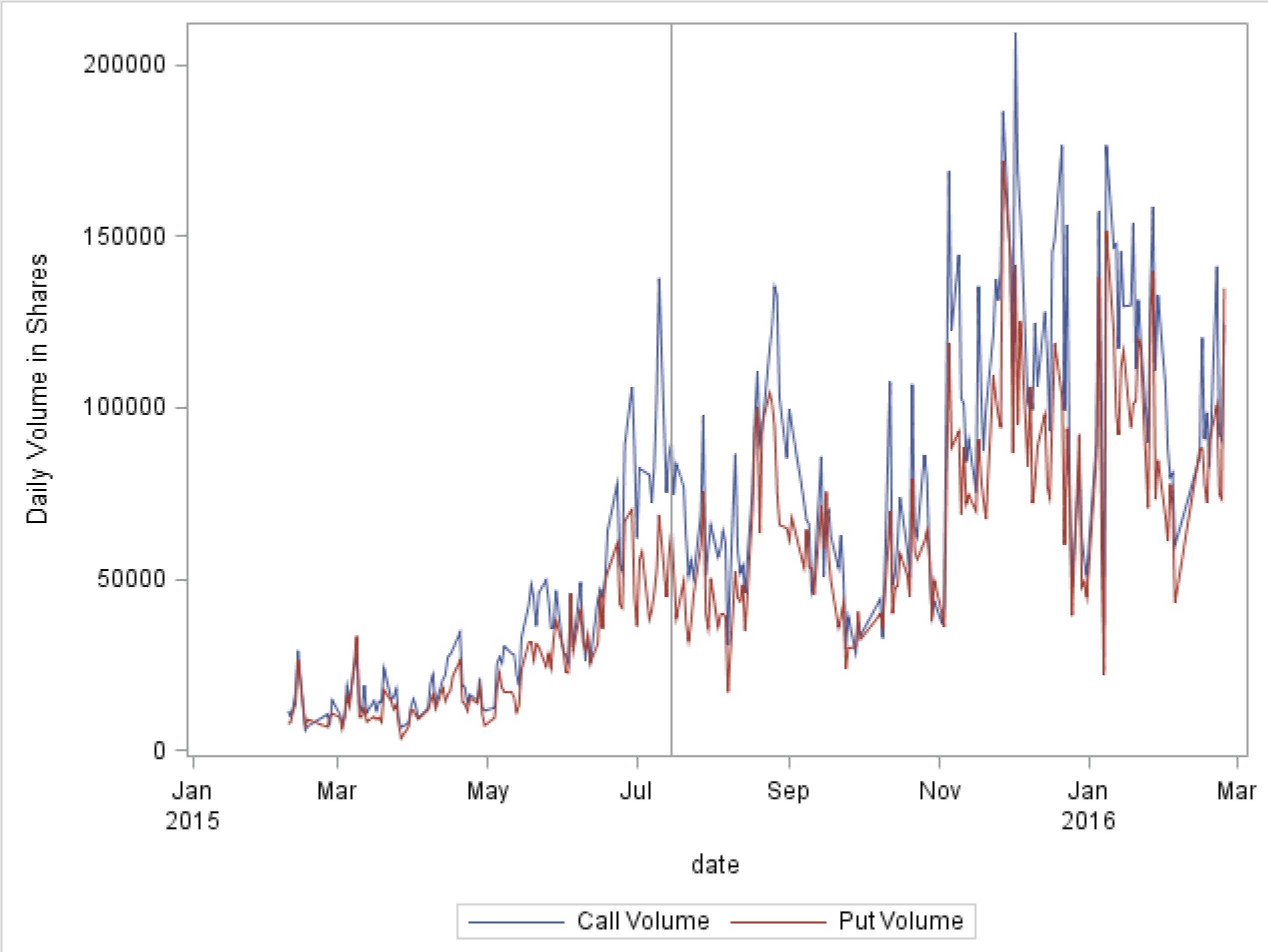
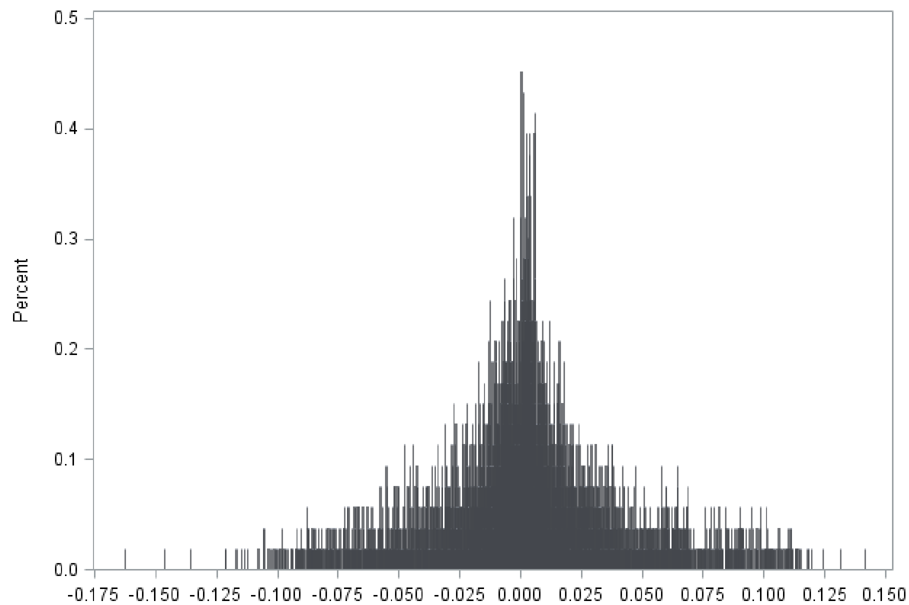


Figure 1.7: **Distribution of *Diffc* before and after the soft interventions.**

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



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

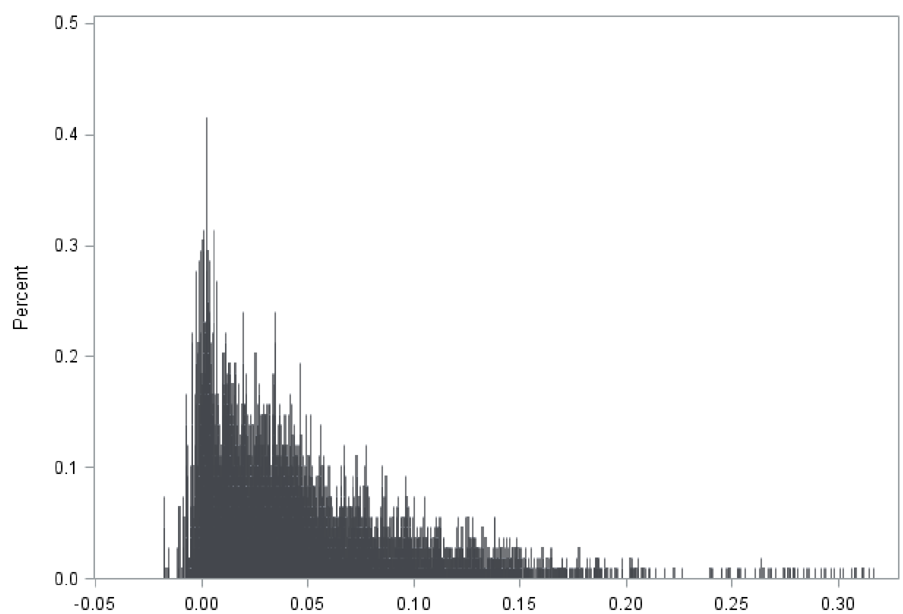
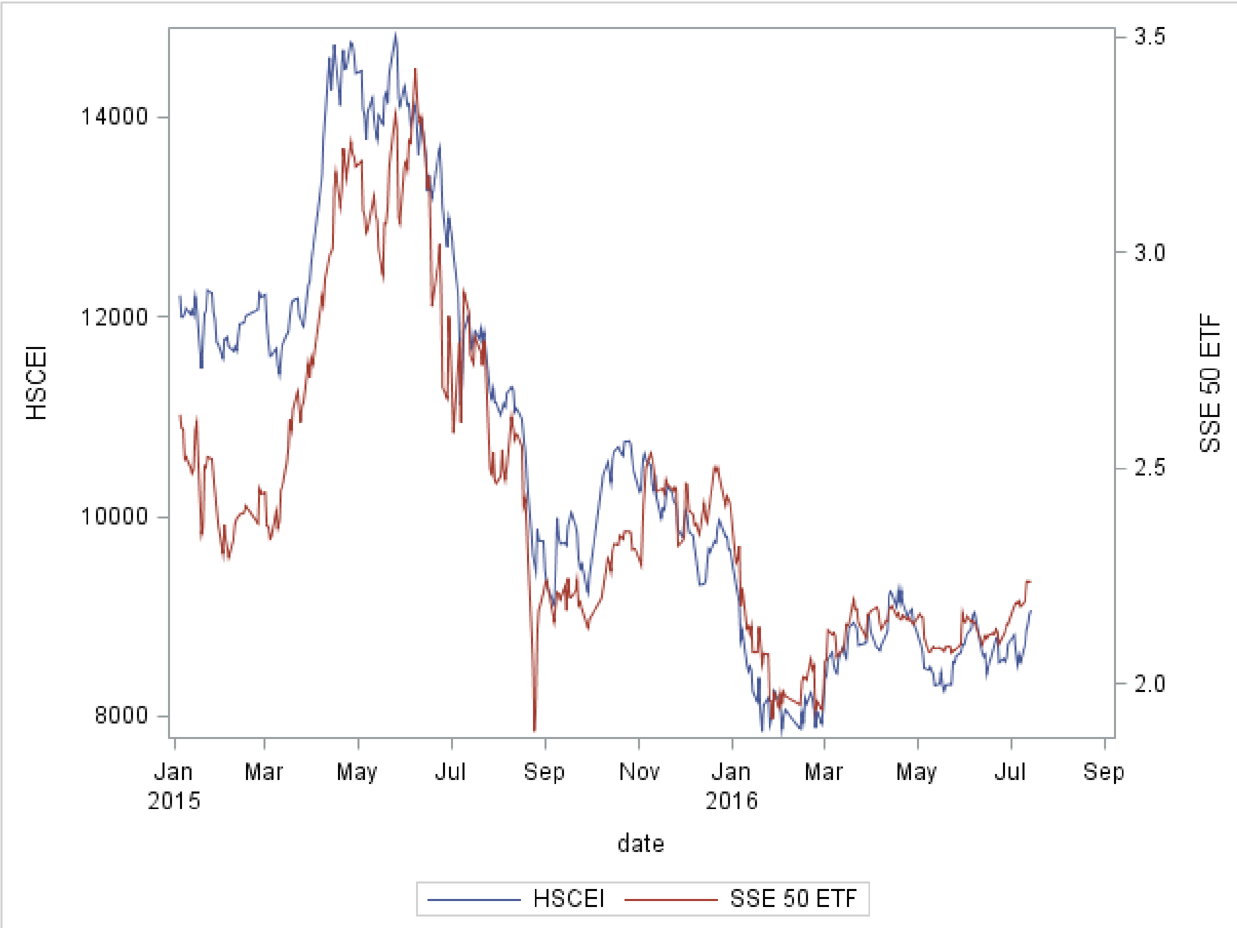


Figure 1.8: Price movement of Hang Seng China Enterprise Index and SSE 50 ETF around the 2015 market crisis.



Appendix: 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

$$\begin{aligned} g_{t_p}(x) &= P\left(t_p = x \middle| t_p < T, t_{p+1} > T\right) \\ &= \frac{P\left(t_p = x, t_p < T,\ t_{p+1} - t_p > T - t_p\right)}{P\left(t_p < T,\ t_{p+1} - t_p > T - t_p\right)} \\ &= \frac{f_{t_p}(x) 1_{\{x<T\}} \int_{T-x}^{\infty} f_{t_{p+1}-t_p}(y)dy}{\int_0^T f_{t_p}(x) \int_{T-x}^{\infty} f_{t_{p+1}-t_p}(y)dy\, dx} \qquad \text{(A.1.1)} \\ &= \frac{px^{p-1}}{T^p}. \end{aligned}$$

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

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

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

$$= \frac{T}{p+q+1}\left(\frac{p}{q+1} + \frac{q}{p+1}\right). \tag{A.1.2}$$

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

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

$$= \sum_{q=0}^{\infty}\sum_{p=0}^{\infty} \frac{e^{-T\lambda_t} T{\lambda_t}^p}{p!} \frac{e^{-T\lambda_s} T{\lambda_s}^q}{q!} \frac{T}{p+q+1}\left(\frac{p}{q+1} + \frac{q}{p+1}\right), \tag{A.1.3}$$

where λ_t and λ_s are arrival rates of the pair of securities. *T* is set at 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. Arrival rates per minute for options and the ETF are estimated by the average numbers of non-zero volume intervals. During the sample period of the intraday dataset, call options on average had 94 non-zero intervals (94.62) and put options had 82 non-zero intervals (82.79) per day. The ETF generally trades every minute (240 minutes). Using these arrival rates we compute *LATD*s using equation A.1.3. Because we underestimate arrivals, we necessarily underestimate arrival rates and displacement intervals between securities.

Table A.1.1 reports *LATD*s for different security 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 the level of synchronicity is acceptable for the intraday dataset. We acknowledge the derivations of Mr. Yinan Ni in providing this model.

Table A.1.1: 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.1.3)

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

Chapter 2. The Impact of Soft Intervention on the Chinese Financial Futures Market[10]

[10] This chapter is joint work with Dr. Jimmy Hilliard.

"*There was no official announcement, because it hasn't happened officially, but China just killed the biggest stock index futures market in the world.*"

- Linette Lopez, senior finance correspondent at Business Insider, (09/09/2015)

2.1 Introduction

Chinese financial futures markets have a relatively short history compared to financial futures markets in other countries. After unsuccessful pilot projects in the 1990s, the first financial futures contract was formally introduced in April, 2010. Currently, there are six financial futures index and bond contracts traded on the China Financial Futures Exchange (CFFEX).

The China Securities Regulatory Commission (CSRC) and the government tightly controls financial markets in China. The financial futures market is subjected to different forms of regulations, including soft intervention. Soft regulation is not based on written statutes. Instead, it is a form of regulation in which market participants do not have legal obligations to comply with the will of the regulator. There may be no "hard" ban or rule. Rather, the regulator uses its influence to affect decisions made by market participants. Under the state-controlled financial system, market participants are very likely to comply with such soft interventions even though although compliance is not required by law.

During the 2015 financial crisis in China, participants in the Chinese futures market faced the criticism that market manipulators and hostile shorts speculated in the bear market through financial futures contracts and thereby destabilized the equity (spot) market (Wildau, 2015; Han and Liang, 2017; Lin 2018). As a result, the CSRC tried to limit short positions on both spots and futures markets by soft interventions. In this study, we present evidence on the effects of soft intervention in the financial futures market. We use the cost-of-carry model to test the impact of these interventions on market efficiency.

The paper proceeds as follows: Section 2.2 reviews the cost-of-carry model for index futures. Section 2.3 describes the Chinese futures market and data. Section 2.4 summarizes soft interventions in the Chinese markets and Section 2.5 discusses the effect of soft intervention on market efficiency. Section 2.6 concludes.

2.2 Cost-of-carry model for financial futures

Futures contracts are similar to forward contracts. In a forward contract, bilateral participants agree on specifics of the underlying asset including the size of the contract, the date and time of delivery and the price to be paid at delivery. There are no intermediate cash flows. Hull (2015) summarizes the assumptions on the cost-of-carry model, 1) all investors can trade freely without any restrictions, 2) there are no transaction costs, 3) all investors pay the same tax rate on all net profit, and 4) all investors can borrow and lend freely at the risk-free rate. Under these assumptions, financial assets with no or known dividends can easily be priced by the cost-of-carry model. Violation of the model would imply the existence of arbitrage profits. The model describes the time-t relationship between spot market prices (S) and the forward (futures) market prices for a contract expiring time T. The forward price is

$$F(t,T) = [S - \mathrm{PV}(Div)]e^{r(T-t)}, \tag{2.1}$$

where r is the continuously compounded risk-free rate and PV(*Div)* is the present value of dividends received during the life of the contract.

Futures contracts share many features with forward contracts. However, futures contracts are traded on exchanges and are typically marked-to-market at the end of the trading day. Therefore, interest rate changes can come into play. For example, if the underlying is positively correlated with interest rates, an increase in rates tends to be accompanied by an inflow into the long's margin account. Conversely, a decrease in rates would tend to accompanied by outflows from the long's margin account. Under this scenario, the futures contract would have a slightly higher price than a corresponding forward contract. These differences are usually small, however, and it is typical to assume that futures contracts are priced like forward contracts. When interest rates are fixed, it can be shown that a futures contract has the same price as a forward contract.

The cost-of-carry model is the established standard for pricing financial futures contracts and used in joint tests of futures market efficiency. Unlike commodity futures, financial futures have no or economically trivial convenience yield. Therefore, it is easy to show that under standard assumptions violation of the model would produce arbitrage profits.

Cornell and French (1983a and 1983b) summarize the cost-of-carry model for index futures and discuss the role of dividends, interest rates, and taxes. Cornell (1985) finds the cost-of-carry model fails in index futures market by documenting deviations from the model with a daily dataset of S&P500 index prices and futures prices. Conversely, Chung (1991) provides empirical evidence supporting the cost-of-carry model with a transaction-level dataset.

Hull (2015) argues that the short-sale constraint should not have impact on the cost-of-carry model as long as some investors own enough shares and are able to sell them if there is an arbitrage opportunity. However, some empirical studies document the impact of the short-sale constraint on the spot-future relationship and the cost-of-carry model. Fung and Jiang (1999) find that lifting the short-sale constraint strengthens the lead-lag relationship between the spot market and the futures market in Hong Kong. Fung and Draper (1999) find that deviations from the cost-of-carry model decreases as short-sale constraints are relaxed in Hong Kong markets. Gay and Jung (1999) find persistent mispricing, especially underpricing of futures contracts in the Korean stock index futures market and such mispricing is associated with transactions cost and the short-sale constraint.

International evidence on the cost-of-carry model for index futures is provided by Bailey (1989) for Japan, Yadav and Pope (1994) for the UK, Bühler and Kempf (1995) for Germany, Lafuente and Novales (2003) for Spain, Wang (2011) and Fung and Draper (1999) for Hong Kong, Bohl, Salm, and Schuppli (2011) for Poland, Gay and Jung (1999) for Korea, and Wang and Hsu (2006) for Taiwan.

Other research considers the effect of additional state variables such as stochastic interest rates and stochastic volatility. Ramaswamy and Sundaresan (1985) modify the cost-of-carry model and develop a stochastic interest model to estimate the pice of index futures. Cakici and Chatterjee (1991) assume that the interest rate follows a mean-reverting square root process. They find empirical evidence that the cost-of-carry model with stochastic interest rates has better performance than the constant interest rate cost-of-carry model. Hemler and Longstaff (1991) propose a general equilibrium model based on the CIR (Cox, Ingersoll, and Ross, 1985) framework, considering both spot market volatility and interest rates.

The cost-of-carry model is used to study the contribution of the futures market to the price formation process (See, for example, Kawaller, Koch, and Koch, 1987, Stoll and Whaley, 1990, Chang, 1992; Kim et al., 1999, Yang et al., 2012, and Miao, Ramchander, Wang and Yang, 2017).

With respect to this study, here is our take: For short-terms futures contracts, the cost-of-carry performs quite well, net of transaction costs, for liquid financial assets. The model performs best when dividends are known or at least stable, borrowing and lending rates are equal, and when short sale constraints are not binding.

2.3 The Chinese financial futures market

In the early 1990s, the regulator and several exchanges started several pilot projects with financial futures, but all of them were terminated in short order because of thin trading volumes and questionable behavior by market participants. In 2010, financial futures were formally introduced into the Chinese market. Currently, there are six financial futures in China. Half of them are stock index futures and half of them are bond futures. All six futures are traded on China Financial Futures Exchange (CFFEX). The CFFEX, like other securities exchanges in China, operates like a government agency. And similar to the bond and equity market, it is regulated by the CSRC.

In this study, we focus on all three stock index futures contracts: The CSI 300 index futures (IF) contract, the CSI 500 index futures (IC) contract, and the SSE50 index futures (IH) contract. The first formal contract introduced into the Chinese market was the CSI 300 future contract, introduced on April 8, 2010. The CSI500 index future contract and the SSE50 index future contract were introduced on April 16, 2015.

The China Securities Index Co., Ltd publishes the prices of all underlying indices. Indices and futures contracts are not adjusted for dividend events. This information is available, however, and the present value of dividend flows are accounted for in the cost-of-carry model. All futures contracts are settled only by cash. The index multiplier is 300 for CSI 300 futures contracts, 200 for CSI 500 futures contracts and 300 for SSE 50 futures contracts. At each point in time, there are four maturities outstanding; the current month, next month, and first months of the next two quarters. The settle day is the third Friday of settle month. The daily price change is limited to ± 10% of the previous close. The trading hours of the CFFEX are 9:30 - 11:30 and 13:00 - 15:00 (local time, UTC+8).

Our sample includes all stock index futures contracts traded on the CFFEX. The sample period spans from 1/6/2015 to 12/30/2016. Daily prices, dividend points and volumes are from Bloomberg and the website of the CFFEX. All prices quoted are in local currency, CNY (¥). Contract information is from the website of the CFFEX. We use the Shanghai interbank offer rate (Shibor) as the risk-free rate. Historic rates are from the website (http://www.shibor.org). Information on the HSCEI index, HSCEI futures, and the risk-free rate (Hong Kong Interbank Offer Rate, HIBOR) of the Hong Kong market is from Bloomberg. Both Shibor and HIBOR are quoted benchmark rates. We convert them to continuously compounded rates by

$$r = \frac{365}{Time\ to\ maturity} \ \ln(1 + r^* \frac{Time\ to\ maturity}{365}). \tag{2.2}$$

where r^* is the interest rate calculated by linear interpolation of two nearest benchmark rates and matching the future's term to maturity.

Table 2.1 reports the summary statistics of all three index futures during the sample period. The settle price of future contracts has a mean of CNY3,484.6 for CSI 300 futures contracts, CNY2,322.4 for SSE 50 futures contracts and CNY6,509.9 for CSI 500 futures contracts[11]. The range of time to maturity of futures contracts is from 0 to 245 days. The present value of all dividend points in the remaining life of the contract has a mean of CNY16.4, 14.2 and 9.9 for CSI 300 futures contracts, SSE 50 futures contracts and CSI 500 futures contracts, respectively.

2.4 Soft interventions and the 2015 financial crisis in the Chinese markets

Hilliard and Zhang (2018) explore an alternative form of regulation, soft intervention, available to the regulator in the Chinese equity market. Soft intervention is a set of regulations that the

[11] The settle price is quoted per index unit. For example, the multiplier is 300 for CSI 300 futures contracts. The actual price is ¥1,045,380.

regulator recommends as desired behavior, although market participants have no legal obligations to comply. This form of regulation is sometimes referred to as moral suasion and window guidance in other markets. Because it is the will of the state, soft intervention is very powerful in the Chinese markets.

During the 2015 financial crisis, the regulator soft-intervened in the financial markets in order to stabilize the markets. They sought to limit short positions and the volume of short trading. In the equity/spot market, the regulator persuaded market participants, most of whom were state-owned financial firms, to avoid shorting the market and to avoid lending out securities to potential shorters. Investors who did not comply received extra regulatory attention (Lopez, 2015; Zhang and Zhang, 2015) and some were arrested for illegal trading (Wong et al., 2015). As a result of this soft intervention, short-sales were virtually eliminated in the Chinese equity/spot market after July 2015 (Figure 2.1). It was not a hard or complete ban since there was still some short volume in the market. However, trading volume was not comparable to the volume in previous periods.

In addition to the soft intervention in the equity/spot market, the regulator also soft intervened in the futures market. The futures market is a natural substitute for short-sales when there is a constraint on spots. Accordingly, investors used the futures market to undo the short-sale constraint. This was not unnoticed by the regulator. In response, the regulator further limited short positions in the futures market through soft intervention. This severely limited volume in the futures market (Figure 2.2).

In a similar study, Draper and Fung (2003) investigated government intervention in the Hong Kong market. In 2008, the Hong Kong government and the regulator, backed by the Mainland Chinese government, fought hostile shorts and speculators in an attempt to stabilize the markets. In August 2008, the Hong Kong government purchased a huge volume of securities to support market prices in a series of open market operations. The regulator also temporarily changed trading rules. Government intervention exacerbated mispricing (measured by deviations from non-arbitrage bounds) and had an adverse effect on market quality.

The soft intervention investigated here is different from the Hong Kong government's intervention in 1998 even though both governments attempted to increase buying pressure and limit shorting pressure. "Hard" regulations and open market operations were the main weapons in Hong Kong. But Hong Kong does not have a state-controlled financial system and the regulator and government could not effectively employ the soft intervention tactic that proved so effective in Mainland China.

There are two complicating factors in assessing soft intervention in the Mainland Chinese futures markets. The first challenge is in finding direct evidence of soft interventions. Soft interventions are more communication-based and pressure-based regulations, so it is not easy to obtain official statements or documents like traditional "hard" regulations. Lopez (2015) implies such regulations on the futures market but states "it hasn't happened officially". Wong et al. (2015) document efforts of regulators and the government to limit the short positions in the spot and futures markets. Figure 2.2 shows the change in in the volume futures contracts traded during the 2015 financial crisis. We find that the volume of futures contracts increased after the soft intervention in the equity/spot market and decreased substantially after the soft intervention on the futures market.

The second complicating factor is that the soft intervention in the futures market came contemporaneously with several "hard" regulations/changes in futures trading rules (Lin and Wang, 2018). These "hard" regulations presumably also had an impact on market volume and market quality. However, the changes in margin rate and transaction fees are hardly sufficient to bring trading volume to the low levels observed. On the other hand, the "hard" rule changes were also a form of pressure (soft intervention) from the regulator and government. These were strong signals to market participants that the regulator and government were not happy with these short positions in the futures market. We argue that because of these pressures the trading volume of futures contracts dropped significantly. That is, the first order effect on trading volume was due to soft intervention and not cosmetic changes in fees and margin rates.

2.5 Impact of soft interventions on the cost-of-carry model

We use the cost-of-carry model to evaluate the impact of soft interventions. During financial crises, other statistics like bid-ask spread, market breadth, and volumes are affected by the dramatic changes in market conditions. However, it is not easy to isolate the effect of soft interventions on these measures since we have no hard and fast mathematical theory on their equilibrium behavior. That is, there is no standard for assessing these measures. The cost-of-carry model, however, depends on an equilibrium enforced by the absence of arbitrage opportunities. Even in crisis periods we expect that participants prefer more to less and thus that a no-arbitrage condition would be binding. Furthermore, we argue that the "hard" rule changes in the Chinese futures market in the 2015 financial crisis should have limited impact on the cost-of-carry equilibrium since they only changed rates and transaction fees. Conversely, soft interventions set constraints on short positions in both the spot and futures market and hence have the potential to affect both the cost-of-carry equilibrium and other measures of Chinese market quality.

2.5.1 The soft intervention periods

During the 2015 crisis, the regulator intervened in both the spot market and futures markets. We choose 07/15/2015 as the intervention date of the spot market and 09/07/2015 as the intervention date of the futures market. The sample period is divided into three stages, Period 1: There are no restrictions on either the spot or futures market (01/06/2015 - 07/15/2015);

Period 2: There are soft interventions discouraging short-sales in the spot market. There is no evidence of intervention in future contracts (07/15/2015-09/07/2015);

Period 3: There is soft intervention discouraging short positions in both spots and futures. (09/07/2015-12/30/2016).

2.5.2 Deviations from the cost-of-carry equilibrium

Deviations from the cost-of-carry equilibrium can be computed as

$$Diff_{it} = [S_{it} - \mathrm{PV}(Div)]e^{r_{it}(T-t)} - F_{it}. \tag{2.3}$$

in assessing deviations/violations, we use the scaled measurement,

$$Diffp_{it} = Diff_{it}/F_{it}, \tag{2.4}$$

where *i* and *t* represent a futures-underlying pair *i* at time *t*, *T* is the maturity, *S* is the closing value of an underlying index, *F* is the closing price of a futures contract, and PV(*Div*) is the sum of the present values of all dividends received before contract expiration. Each observation is a spot-future pair.

Non-synchronous spot and futures observations compromises the cost-of-carry model. The underlying index itself cannot be traded. Instead, investors can trade a basket of component stocks that track the index. The basket of stocks trade as an exchange traded fund (ETF.) Table 2.2 reports the daily volumes of future contracts and related ETFs. The average daily volume of underlying ETFs range from 36 million shares to 2.7 billion shares in the three periods in our study. The average daily volume of future contracts ranges from 241 thousand to 1.8 million shares per contract in Period 1 and Period 2. Because of the soft intervention, the Period 3 average futures volume falls to a range from 10 thousand to 21 thousand shares per contract. The large volumes, especially in Periods 1 and 2, suggest that synchronicity is not a significant issue.

Here is how the arbitrage mechanism works: Large positive or negative values in equation (2.3) denoted by *Diff* suggest arbitrage opportunities. If *Diff* is positive, forwards are underpriced relative to spots (stocks). The arbitrageur takes a long position in the forward contract and shorts stocks in the index with value S. Funds from the short in the amount PV(Div) are invested in risk-free asset(s) with maturities that match the stocks' dividend flow(s). The remainder of the funds [S - PV*(Div*)] are invested in a risk-free asset with a maturity that matches that of the forward contract. During the life of the contract, funds from the dividend investments are used to pay dividends required of the short position. At contract expiration, the arbitrageur has $[S - \text{PV}(Div)]e^{r(T-t)}$ to pay for the forward contract. But by assumption *Diff* = $[S - \text{PV}(Div)]e^{r(T-t)} - F > 0$ and there are arbitrage profits. Under this scenario, there will be buying pressure on forwards and selling pressure on spots to initiate movement towards a no-arbitrage equilibrium.

If *Diff* is negative, forwards are overpriced relative to spots (stocks). The arbitrageur sells the forward contract and borrows *S* at rate *r* to buy stocks in the index. The borrowing is composed of two or more maturities. Borrow PV*(Div)* with maturities matching that of stock dividend flows. Repay this borrowing with dividends received from the long stock position. Borrow the remaining $S - \text{PV}(Div)$ with maturity equal to that of the forward contract. At maturity, furnish stocks to unwind the short forward and repay borrowing equal to $[S - \text{PV}(Div)]e^{r(T-t)}$. By assumption *Diff* = $[S - PV(Div)]e^{r(T-t)} - F < 0$ and there are arbitrage opportunities. Under this scenario, forwards are sold and spots bought to initiate movement towards a no-arbitrage equilibrium.

If the cost-of-carry model holds, *Diff* and *Diffp* should be economically small and symmetrically distributed about zero. There may be some temporal deviations but the deviations, net of transaction frictions and dividend uncertainties, should not persist in a no-arbitrage market.

2.5.3 Distribution and Statistics

Figure 2.3 shows the average *Diffp* per contract. The soft intervention in the spot market imposed a short-sale constraint. Investors could not short stocks so they used futures contracts to build short positions, leading to a higher futures volume in early July (Figure 2.2) and a relatively lower price of future contracts. As a result, *Diffp* becomes significantly positive, deviating significantly from zero in Period 2 and Period 3. Then the regulator soft intervened in the futures market in Period 2 and limited the short positions of futures contracts. This soft intervention prevented pessimistic opinions from being imbedded into futures prices, reversing the downward market pressure and pushing the price of futures contracts to a higher level. Subsequently, the magnitude of *Diffp* dropped to a lower level but remained positive.

Table 2.3 reports summary statistics of *Diffp*, confirming the visual results shown in Figure 2.3. *Diffp* is 4.17% of the index price overall. It increases from 0.23% in Period 1 to 8.45% in Period 2 and then drops back to 4.72% in Period 3. Average *Diffp* in Period 1 (0.23%) is statistically insignificant at the 1% level and supports the argument that the cost-of-carry model approximately holds in this period. *Diffp*s in the other two periods are both economically and statistically significant (at the 1% level). Overall *Diffp*s for the CSI 300, SSE 50, and CSI 500 futures contracts are 3.16%, 2.14%, and 7.36%, respectively. They all increase significantly from Period 1 to Period 2 and decrease in Period 3. Figure 2.4 shows distributions of *Diffp* during the three periods. If the cost-of-carry model holds, we expect to see *Diffp* symmetrically and tightly distributed around a mean of zero. The D'Agostino and Cureton (1972) tests for symmetry (Table 2.4) imply that *Diffp* is significantly skewed to the right in each of the three periods. Right skewness implies that there can be large positive deviations, presumably due to short-selling frictions.

2.5.4 Bid-ask spread

The bid-ask spread is a transaction cost that impacts the cost-of carry equilibrium. Unfortunately, our current dataset does not include bid and ask prices for futures contracts. As a proxy, we use the bid-ask spread on index-related ETFs/mutual funds. These funds have correspondingly large trading volumes and small bid-ask spreads. Han and Liang (2018) document the mean relative bid-ask spread as 0.13% for the index during the period from May 4, 2015 to September 30, 2015. Liu at al (2016) finds the bid-ask spread for the commodity futures contracts in Shanghai Futures Exchange ranges from 0.02% (copper) to 0.0378% (aluminum) during the period from January 4, 2010 to June 30, 2015.

Based on previous work, we assume, as a point estimate, that the bid-ask spread on all securities is 0.13%. We further analyze a worst case scenario by assuming that the bid-ask spread on all securities is 1%. We compute the ask (bid) price as the bid-ask spread/2 higher (lower) than the closing price. To profit from apparent opportunities, arbitrageurs have two strategies: selling the index and buying futures (Strategy A) or selling futures and buying the index (Strategy B).

Strategy A produces scaled returns

$$e_{it}^{A} = \{[S_{it}^{Bid} - \mathrm{PV}(Div)]e^{r_{it}(T-t)} - F_{it}^{Ask}\}/F_{it}, \tag{2.5}$$

where e_{it}^{A} is the scaled deviation of future-index pair i at time t under Strategy A, F_{it}^{Ask} is the ask price of the futures contract and S_{it}^{Bid} is the bid price of the index. For Strategy B take opposite positions in spots and futures, always buying at the ask and selling at the bid. The no-arbitrage condition predicts zero profits (e_{it}) if there are no market frictions. Otherwise allowing for bid-ask spreads, the profit should be negative under both strategies. A positive arbitrage opportunity under either strategy is a violation of the cost-of-carry model. Table 2.5 gives a summary of arbitrage opportunities under the two strategies in Periods 1, 2 and 3.

In Panel A, we assume a bid-ask spread of 0.13%. Under Strategy A, the mean (scaled) arbitrage profit in Period 1 is 0.1%. Even though mean profit is positive, there is still insufficient evidence to reject the cost-of-carry model in Period 1. The mean arbitrage profit is 8.31% in Period 2 and 4.58% in Period 3. Both profit statistics are significantly positive, violating the predictions of the cost-of-carry model. The mean arbitrage opportunities are negative under Strategy B, arguably because the strategy does not involve short-selling in the spot market. We observe the same pattern as that noted in Section 2.5.3: The deviation from the cost-of-carry model widens significantly from Period 1 to Period 2 and narrows in Period 3. In fact, overall, 91% of our observations violate the cost-of-carry model. We document the least violations (63.54%) in Period 1 and the most violations (99.53%) in Period 2.

In Panel B, we increase the bid-ask spread to 1%. This implausibly high spread serves as a worst case scenario. The results are similar to those in Panel A. Under Strategy A, the mean arbitrage profits are still significantly positive except that in Period 1. The mean arbitrage profits are negative under Strategy B. Period 1 still provides least violations and Period 2 provides the most.

How can these apparent arbitrage opportunities exist in a liquid market? The most obvious answer is that short selling restrictions in the spot market in Period 2 led to relative overpricing of spots and this mispricing could not be corrected by arbitrageurs. In Period 3, additional pressures placed on futures market participants attenuated but did not remove the relative mispricing.

2.5.5 Arbitrage and the mean-reverting process

In a prefect markets, we should not observe non-zero deviations from the cost-of-carry model. Either positive or negative deviations can be profitable since negative deviations are equivalently positive when spot and forward positions are reversed. However, we expect to observe some non-zero deviations because of frictions and/or policies imposed during periods of market turbulence. The bottom line is that such deviations or arbitrage opportunities should vanish quickly as arbitrageurs act to remove mispricing.

To assess the effect of some market frictions on the cost-of-carry model, we now assume that deviations (arbitrage profits) from the cost-of-carry model follow a process that is mean-reverting toward zero. The mean-reverting process allows for some short-term deviations, but as deviations increase there is stronger economic incentives to remove them. We expect that the speed of reversion should be higher for a relatively more efficient market. We also expect that the long term mean should be closer to zero in these markets. In the mean-regressive model, we also take the bid-ask spread into consideration.

Arbitrage profit is calculated from equation (2.5) and the mean-reverting process for Strategy A is defined as

$$de_i^A = \kappa_i^A\left(\theta_i^A - e_i^A\right)dt + \sigma_i^A dZ_t, \tag{2.6}$$

We use the equivalent equation is the same for Strategy B. We rewrite the diffusion in difference form and estimate parameters by an AR(1) model**.**

Table 2.6 reports the estimated parameters in each period based on assumptions about the bid-ask spread. The bid-ask spread is assumed to be 0.13% in Panel A and bid-ask spread is assumed to be 1% in Panel B. In both panels, The speed of reversion coefficient, κ, falls from about 0.33 in Period 1 to 0.28 in Period 2 and then to 0.23 in Period 3. The differences in the coefficient between periods are significant at the 1% level. The half-life of the speed of reversion $(1/\kappa \ln 2)$ is about 2.1 days in Period 1, 2.48 days in Period 2, and 3.01 days in Period 3. The result was not unexpected. It took longer for the deviation/mispricing to adjust toward equilibrium after interventions. Contrary to the findings in Lin and Wang (2018), our findings imply that soft interventions adversely affected market efficiency.

Positive long term means suggest arbitrage opportunities. The long-term means in both panels are negative under Strategy B. In Panel A, based on the assumption that the bid-ask spread is 0.13%, all long-term means under Strategy A are positive. The long-term mean is 1.62% in Period 1, 14.63% in Period 2 and 2.67% in Period 3. However, the long-term mean in Period 1 was not statistically significant even at 10% level, supporting the view that the cost-of-carry model cannot be rejected Period 1. After the soft intervention and short-sale constraint in the spot market, the long-term mean under Strategy A increases significantly in Period 2. This confirms our previous results that soft intervention in the spot market led to significant deviations from the cost-of-carry model. As the regulator further soft intervened in the futures market, the long-term mean drops back to 2.67% but is statistically significant at 1% level.

In Panel B, we assume that the bid-ask spread is 1%. Overall the long-term mean under Strategy A is positive and is significant at the 5% level, implying that the cost-of-carry model is still rejected under this more extreme assumption. Similar to Panel A, the long-term mean in Period 1 was not statistically significant at the 10% level. We still see the pattern that long-term point estimates of the mean increases from Period 1 (0.77%) to Period 2 (13.7%) and then drops in Period 3 (1.78%).

Both the estimate of the long-term mean and the speed of reversion coefficient indicates that market quality suffered as a result of the soft interventions. Market quality as measured by the mean regressive model can be assessed by two parameters: one the long term deviation of the mean deviation from zero and the other is the speed of adjustment in price toward the mean. Larger mean estimates and slower speeds of adjustment implies a deterioration in market quality. Consistent with our observations in Section 2.5.4, we argue that the magnitude of the deviations from Period 2 to Period 3 follows from the offsetting effect of the short constraint on the futures market in Period 3.

2.5.6 Identification

Many risk factors during the 2015 financial crisis have the potential to affect the cost-of-carry model. To identify the impact of soft interventions during the crisis, we use the Hang Seng China Enterprise Index (HSCEI) futures traded on the Hong Kong market as a control group. We calculate *Diffp*s of HSCEI futures using the same equations (2.3 and 2.4), to test the causal impact of soft interventions in a Difference-in-Difference (DiD) framework.

The CSRC does not have direct authority to regulate the Hong Kong markets, so it could not soft intervene in the Hong Kong markets. The treatment effect, soft intervention, is only available in the mainland Chinese markets. On the other hand, the HSCEI is exposed to similar risk factors as the three underlying financial futures indices in mainland China. The component stocks of the HSCEI are issued by mainland Chinese firms and listed on the Hong Kong Stock Exchange. The plot of HSCEI prices in Figure 2.5 shows that the HSCEI moves in a pattern similar to that of the CSI 300 index, the underlying index of IF futures contracts on the CFFEX. Figure 2.6 is a plot of *Diffp* of HSCEI futures. During our sample period, *Diffp* in Hong Kong is generally distributed around zero, mainly in a range of -1% to 1%, implying that the cost-of-carry model works well in the Hong Kong market.

The DiD model is

$$Diffp_{kt} = \alpha + \beta_1 SH_k + \beta_2 After_t + \beta_3 SH_k After_t + e_{kt}, \tag{2.7}$$

where SH_k indicates the market (Shanghai or Hong Kong) and $After_t$ is a dummy indicating whether time-*t* is before or after cutoff dates. The impact of soft interventions is measured by β_3.

Table 2.7 reports the regression results from the difference-in-difference model. We compare *Diffp*s in two periods. In Panel A, β_3 is 0.0861, postive and significant. It implies that *Diffp* is 8.61% higher in CFFEX (in Shanghai) in Period 2, evidence that the soft intervention and short-sale constraint significantly contributed to deviations from the cost-of- carry model.

In Panel B, β_3 is -0.0376, negative and significant. The deviations decreases after the soft intervention on the futures market. The results are consistent with Figure 2.3, Table 2.3, Table 2.5 and Table 2.6. We conclude that soft interventions significantly impacted the Chinese futures market both in Periods 2 and 3.

2.5.7 Hard rule changes or soft intervention?

The soft intervention in the futures market comes was accompanied by some "hard" changes in trading rules. Panel A of Table 2.8 (from Table 2 in Lin and Wang, 2018) summarizes the changes during the 2015 financial crisis. The regulator made notable efforts to stabilize the market. Our results suggest that "hard" trading rule changes were not as effective as the soft intervention. The regulator set limits on daily trading volume of each investor, increased transactions cost and margin rates. We argue that limiting daily trading volume and increasing margin rates did not result in the huge devations from the cost-of-carry model that we observed in the previous sections. As long as investors could build up arbitrage portfolios without interference, arbtrage oppotuntiesy would attract more investors into this market to fill the mispricing gap between the spot and futures market. The peak transaction cost of trading in the futures market was 0.23% of the transaction size. Compared to the overall 8.45% (4.72%) value of *Diffp* in Period 2 (Peiod 3), the changes in transaction cost cannot be the main contributitor of the devations from the cost-of-carry model.

And, in addition, these rule changes themselves should not diminish the trading volume to the very low level observed in Figure 2.2. Instead, these rule changes can be viewed as signals that the regulator and the government are not happy with the short positions built through futures contracts. By changing these trading rules, they pressured financial firms not to build short positions through futures contracts. In response to soft intervention, financial firms stopped shorting future contracts and the trading volume dropped precipitiously.

Panel B of Table 2.8 reports three trading rule changes after 2015 financial crisis. The regulator loosened trading rules by decreasing margin rates, reducing transaction costs and lifting limits on daily trading volume of each investor. There were three rounds of changes after the 2015 crisis in 02/17/2017, 9/18/2017 and 12/3/2018. As shown in Figure 2.7, the "hard" rule changes do not boost the trading volume. Even though there is a minor upward trend in trading volume, the magnitude of futures volume after the crisis is not comparable to that before the crisis. As long as the pressure from the regulator and the government is still there, investors hesitated to short futures contracts and re-enter the futures market. In contrast to previous work (Lin and Wang, 2018; Han and Liang, 2018), we argue that soft interventions contributed more significantly to the changes in market quality and efficiency than changes in trading rules.

2.6 Conclusion

We investigate the soft intervention in the Chinese futures market during the 2015 financial crisis. We find evidence that the regulator and the government soft intervened in the futures market and influenced market participants, especially state-controlled financial firms, to limit or liquidate short positions. The trading volume of futures contracts approached a very low level after the intervention. Using the cost-of-carry model as a test instrument, we find significant deviations after the soft intervention in the spot market. Shortly after the intervention in the spot market, the futures market was also soft intervened and short positions in future contracts were effectively limited. The magnitude of overall deviations from the cost-of-carry model dropped significantly because the short constraint on the futures market partly offset the effect of the short constraint in the spot market. However, the net effect of both interventions was a deterioration in market efficiency.

For robustness, we use two additional tests of the effect of soft interventions. First, we assume that the deviation from the cost-of-carry model follows a mean-reverting process and find that the speed of reversion coefficient dropped after two rounds of soft interventions (in the spot market and then in the futures market). The the long term mean of deviations also increased after the soft interventions. Secondly, we used the Hong Kong futures market as a control group and set up a Difference-in-Difference model to determine if the same effect is observed in a proxy market not subject to the soft interventions. Our findings from the Difference-in-Difference model confirm the previous results and indicate that in fact the deviations from the cost-of-carry market were a result of the soft intervention in the Chinese futures market.

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Table 2.1: Summary Statistics

Summary statistics for three index futures and underlying indices. The Futures Price is the settle price of a futures contract at the end of each day. The present value of dividends is the sum of present values of all index's dividend points in the future's remaining life. The sample period spans from 1/6/2015 to 12/30/2016. SSE 50 futures contracts and CSI 500 futures contracts are available after 4/6/2015.

	Mean	Median	StDev	Minimum	Maximum
		Panel A: CSI 300 Futures			
Futures Price	3,484.6	3,302.7	588.6	2,490.4	5,360.8
Days to Maturity	90	62	73	0	245
Present value of dividends	16.4	3.8	22.1	0.0	70.5
Index Value	3,579.7	3,371.1	538.5	2,853.8	5,353.8
		Panel B: SSE 50 Futures			
Future Price	2,322.4	2,207.0	385.0	1,745.8	3,604.0
Days to Maturity	91	63	73	0	245
Present value of dividends	14.2	3.3	20.0	0.0	61.8
Index Value	2,397.0	2,286.9	343.7	1,912.7	3,458.7
		Panel C: CSI 500 Futures			
Future Price	6,509.9	6,166.6	1,317.3	4,269.8	11,502.0
Days to Maturity	91	63	73	0	245
Present value of dividends	9.9	2.4	13.2	0.0	43.2
Index Value	6,841.9	6,435.1	1,219.9	5,271.2	11,545.9

Table 2.2: Daily Volumes of Futures Contracts and ETFs

The average volume in shares of futures contracts per day per contract and the average volume in shares of related ETFs per day. The ETFs are the largest in market capitalization as of 03/25/2019 that follow same indices. The sample period spans from 1/6/2015 to 12/30/2016. The SSE 50 futures contracts and CSI 500 futures contracts are available after 4/6/2015. Period 1 is the period before 07/15/2015, Period 2 is the period between 07/15/2015 and 09/07/2015 and Period 3 is the period after 09/07/2015.

	Overall	Period 1	Period 2	Period 3
All Futures	334,291	827,816	965,916	17,374
CSI 300 Futures	558,226	1,001,218	1,794,865	20,947
Huatai-Pinebridge CSI 300 ETF	563,882,500	1,418,408,354	457,115,016	240,064,789
SSE 50 Futures	135,096	449,430	354,746	10,075
Huaxia SSE 50 ETF	1,056,072,296	2,664,655,509	1,199,813,242	364,122,203
CSI 500 Futures	94,712	407,601	241,197	19,511
Nanfang CSI 500 ETF	49,204,533	77,951,235	52,193,512	36,738,390

Table 2.3: Summary of cost-carry-violations (*Diffp*)

Diffp is calculated from equation (2.3) and equation (2.4). The sample period spans from 1/6/2015 to 12/30/2016. SSE 50 futures contracts and CSI 500 futures contracts are available after 4/6/2015. Period 1 is the period before 07/15/2015, Period 2 is the period between 07/15/2015 and 09/07/2015 and Period 3 is the period after 09/07/2015. *Diffp* is reported in the first row and the P-values of the t-test are reported in the second row. The last two columns report the difference between Period 2 and Period 1, and the difference between Period 3 and Period 2.

Contract	Overall	Period 1	Period 2	Period 3	Period 2 - 1	Period 3 - 2
All	0.0417***	0.0023**	0.0845***	0.0472***	0.0822***	-0.0373***
	0.0000	0.0202	0.0000	0.0000	0.0000	0.0000
CSI 300 Futures	0.0316***	-0.0061**	0.0748***	0.0418***	0.0810***	-0.0331***
	0.0000	0.0202	0.0000	0.0000	0.0000	0.0000
SSE 50 Futures	0.0214***	-0.0133***	0.0551***	0.0242***	0.0684***	-0.0310***
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
CSI 500 Futures	0.0736***	0.0354***	0.1234***	0.0753***	0.0880***	-0.0481***
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

*,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 2.4: Test statistics for symmetry

We test for the symmetry of distributions of *Diffp* by using a skewness statistic. The first row gives skewness and the second row gives P-values of the D'Agostino test. The sample period spans from 1/6/2015 to 12/30/2016. SSE 50 futures contracts and CSI 500 futures contracts are available after 4/6/2015. Period 1 is the period before 07/15/2015, Period 2 is the period between 07/15/2015 and 09/07/2015 and Period 3 is the period after 09/07/2015.

	Overall	Period 1	Period 2	Period 3
All	1.6074***	1.6771***	1.2086***	1.7843***
	0.0000	0.0000	0.0000	0.0000
CSI 300 Futures	1.1535***	1.3482***	1.3763***	1.0877***
	0.0000	0.0000	0.0000	0.0000
SSE 50 Futures	1.1437***	1.4738***	1.6680***	1.2897***
	0.0000	0.0000	0.0000	0.0000
CSI 500 Futures	1.0506***	0.8212***	0.4486**	1.0268***
	0.0000	0.0000	0.0301	0.0000

*,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 2.5: Implied Arbitrage Profits

Implied arbitrage profits are calculated by equation (2.5). Strategy A shorts the index and longs futures. Strategy B shorts futures and longs the underlying index. The first and third rows in each panel provide the mean implied arbitrage profits under each strategy. The second and fourth rows give the P-values of t-tests under the zero null. Violation (%) is the proportion of observations that with positive profits under either strategy. The sample period spans from 1/6/2015 to 12/30/2016. Period 1 is the period before 07/15/2015, Period 2 is the period between 07/15/2015 and 09/07/2015 and Period 3 is the period after 09/07/2015.

	Overall	Period 1	Period 2	Period 3	Period 2 -1	Period 3 - 2
Panel A: Bid-ask spread is 0.13%						
e^A	0.0404***	0.0010	0.0831***	0.0458***	0.0821***	-0.0373***
	0.0000	0.3206	0.0000	0.0000	0.0000	0.0000
e^B	-0.0514***	-0.0164***	-0.0881***	-0.0564***	0.0821***	-0.0373***
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Violation (%)	0.9087	0.6354	0.9953	0.9701		
Panel B: Bid-ask spread is 1%						
e^A	0.0315***	-0.0078***	0.0740***	0.0369***	0.0818***	-0.0371***
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
e^B	-0.0603***	-0.0251***	-0.0971***	-0.0654***	-0.0720***	0.0318***
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Violation (%)	0.7310	0.3505	0.9671	0.8036		

*,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 2.6: Mean reverting process for cost-of-carry deviations (Diffp)

The mean-reverting process is defined by equation (2.5) and equation (2.6). Strategy A shorts the index and longs futures. Strategy B shorts futures and longs the underlying index. κ^A, θ^A and σ^A (κ^B, θ^B and σ^B) are estimated parameters from Strategy A (B). The first row provides estimate of parameters and the second row gives the P-value of t-test. The sample period spans from 1/6/2015 to 12/30/2016. Period 1 is the period before 07/15/2015, Period 2 is the period between 07/15/2015 and 09/07/2015 and Period 3 is the period after 09/07/2015.

Contract	Overall	Period 1	Period 2	Period 3	Period 2 - 1	Period 3 - 2
			Panel A: bid-ask spread is 0.13%			
κ^A	0.2164***	0.3340***	0.2792***	0.2327***	-0.0548***	-0.0465***
	0.0000	0.0000	0.0082	0.0000	0.0000	0.0000
θ^A	0.0257***	0.0162	0.1463**	0.0266***	0.1301***	-0.1197***
	0.0036	0.1404	0.0295	0.0002	0.0000	0.0000
σ^A	0.0001	0.0002	0.0003	0.0001		
	NA	NA	NA	NA		
κ^B	0.2164***	0.3340***	0.2792***	0.2326***	-0.0548***	-0.0465***
	0.0000	0.0000	0.0082	0.0000	0.0000	0.0000
θ^B	-0.0283***	-0.0187*	-0.1491**	-0.0293***	-0.1304***	0.1198***
	0.0014	0.0978	0.0270	0.0001	0.0000	0.0000
σ^B	0.0001	0.0002	0.0003	0.0001		
	NA	NA	NA	NA		
			Panel B: Bid-ask spread is 1%			
κ^A	0.2164***	0.3339***	0.2792***	0.2328***	-0.0546***	-0.0465***
	0.0000	0.0000	0.0082	0.0000	0.0000	0.0000
θ^A	0.0169**	0.0077	0.1370**	0.0178**	0.1292***	-0.1192***
	0.0482	0.3159	0.0396	0.0119	0.0000	0.0000
σ^A	0.0001	0.0002	0.0003	0.0001		
	NA	NA	NA	NA		
κ^B	0.2163***	0.3341***	0.2792***	0.2326***	-0.0549***	-0.0466***
	0.0000	0.0000	0.0082	0.0000	0.0000	0.0000
θ^B	-0.0371***	-0.0272**	-0.1584**	-0.0381***	-0.1312***	0.1203***
	0.0000	0.0195	0.0198	0.0000	0.0000	0.0000
σ^B	0.0001	0.0002	0.0003	0.0001		
	NA	NA	NA	NA		

*,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 2.7: Difference in Difference

Futures traded in the Hong Kong market are the a control group for the Difference-in-Difference setup. *Diffp*s of HSECI future contracts are calculated from equation (2.3) and equation (2.4). SH is a dummy set to 1 if the observation is from Shanghai Financial Futures Exchange.

	Coef	SE	T	P
Panel A: Comparison between Period 1 (After=0) and Period 2 (After=1)				
Intercept	-0.0028*	0.0016	-1.8100	0.0715
SH	0.0007	0.0022	0.3300	0.7442
After	0.0017	0.0033	0.5200	0.6008
SH*After	0.0861***	0.0047	18.3000	0.0000
Adj R-squared	0.7030			
Panel B: Comparison between Period 2 (After=0) and Period 3 (After=1)				
Intercept	-0.0011	0.0028	-0.3900	0.6999
SH	0.0868***	0.0040	21.8800	0.0000
After	-0.0012	0.0030	-0.4100	0.6848
SH*After	-0.0376***	0.0042	-8.9400	0.0000
Adj R-squared	0.7287			

*,**, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 2.8: Hard rule changes on the Chinese financial futures market

Date	Change details
	Panel A: Changes during the 2015 financial crisis*
7/6/2015	The maximum daily trading volume in each CSI 500 futures contract is set to 1200 contracts.
7/8/2015	The margin rate to short CSI 500 futures contracts for non-hedging purpose is increased from 10 to 20%.
7/9/2015	The margin rate to short CSI 500 futures contracts for non-hedging purpose is increased from 20 to 30%.
8/3/2015	The transaction fee is increased to 0.0023% of the transaction size; The order fee is increased to ¥1 per order.
8/26/2015	The maximum daily total trading volume in each index futures contracts for non-hedging purpose is increased 600 contracts; The transaction fee to close CSI 300, SSE 50 and CSI 500 futures contracts is increased to 0.0115% of transaction size; The margin rate to trade CSI 300 and SSE 50 futures contracts for non-hedging purpose is increased from 10% to 12%; The margin rate to long CSI 500 futures contracts for non-hedging purpose is increased from 10% to 12%.
8/27/2015	The margin rate to trade CSI 300 and SSE 50 futures contracts for non-hedging purpose is increased to 15%; The margin rate to long IC futures contracts for non-hedging purpose is increased to 15%.
8/28/2015	The margin rate to trade CSI 300 and SSE 50 futures contracts for non-hedging purpose is increased to 20%; The margin rate to long CSI 500 futures contracts for non-hedging purpose is increased to 20%.
8/31/2015	The margin rate to trade CSI 300 and SSE 50 futures contracts for non-hedging purpose is increased from 20% to 30%; The margin rate to long CSI 500 futures contracts for non-hedging purpose is increased from 20% to 30%.
9/7/2015	The maximum daily total trading volume in each index futures contracts for non-hedging purpose is set to ten contracts; The transaction fee to close an index futures contracts is increased to 0.23% of transaction size; The margin rate to trade all stock index futures contracts for non-hedging purpose is increased from 30% to 40%; The margin rate to trade all stock index futures contracts for hedging purpose is increased from 10% to 20%.
	Panel B: Changes after the 2015 financial crisis
2/17/2017	The margin rate to trade CSI 300 and SSE 50 futures contracts for non-hedging purpose is reduced from 40% to 20%; The margin rate to trade CSI 500 futures contracts for non-hedging purpose is reduced from 40% to 30%; The transaction fee is reduced to 0.092% of transaction size.
9/18/2017	The margin rate to trade CSI 300 and SSE 50 futures contracts is reduced from 20% to 15%; The transaction fee is reduced to 0.069% of transaction size.
12/3/2018	The margin rate to trade CSI 300 and SSE 50 futures contracts is reduced to 10%; The margin rate to trade CSI 500 futures contracts is reduced to 15%; The transaction fee is reduced to 0.046% of transaction size.

*Source: Panel A is from Table 2 in Lin and Wang (2018).

Figure 2.1: Total daily short volume on the Chinese equity market.

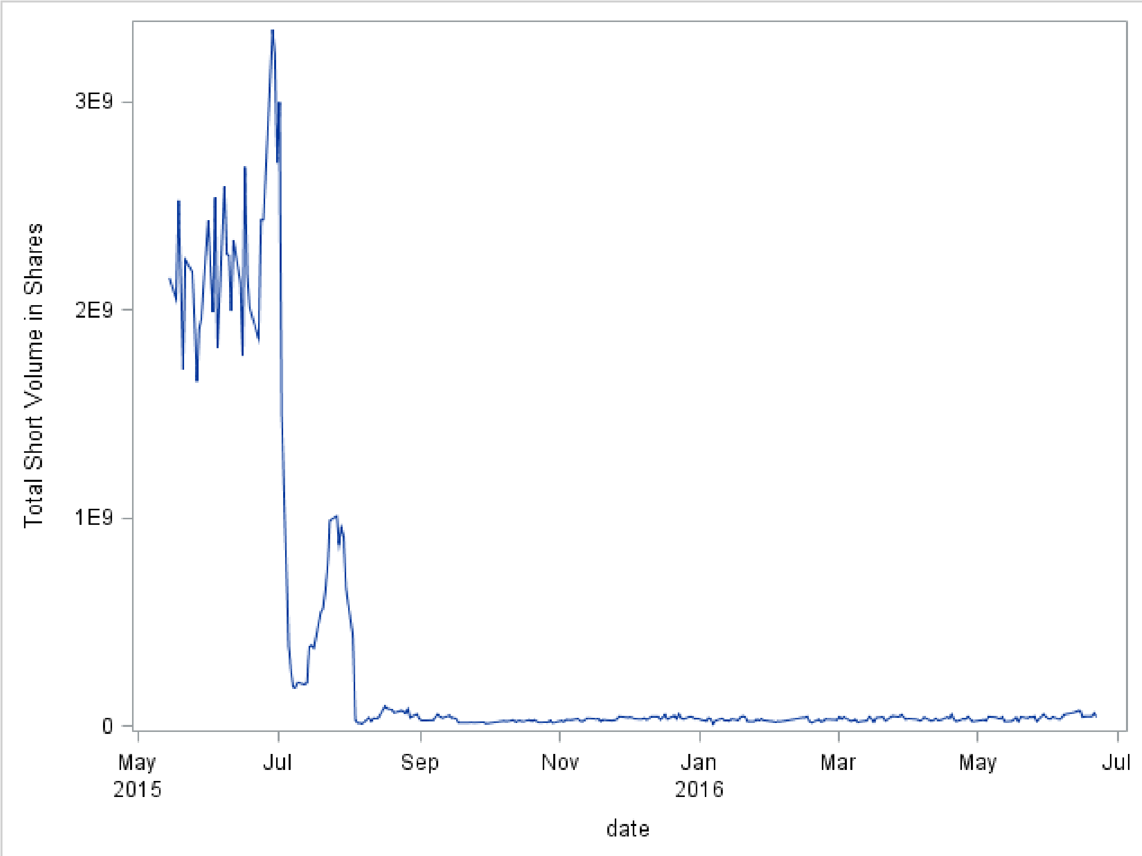


Figure 2.2: Total daily trading volume of futures contracts.

Dates for the vertical reference lines are 07/15/2015, the soft intervention cut-off day in the spot market, and 09/07/2015, the soft intervention cut-off day in the futures market.

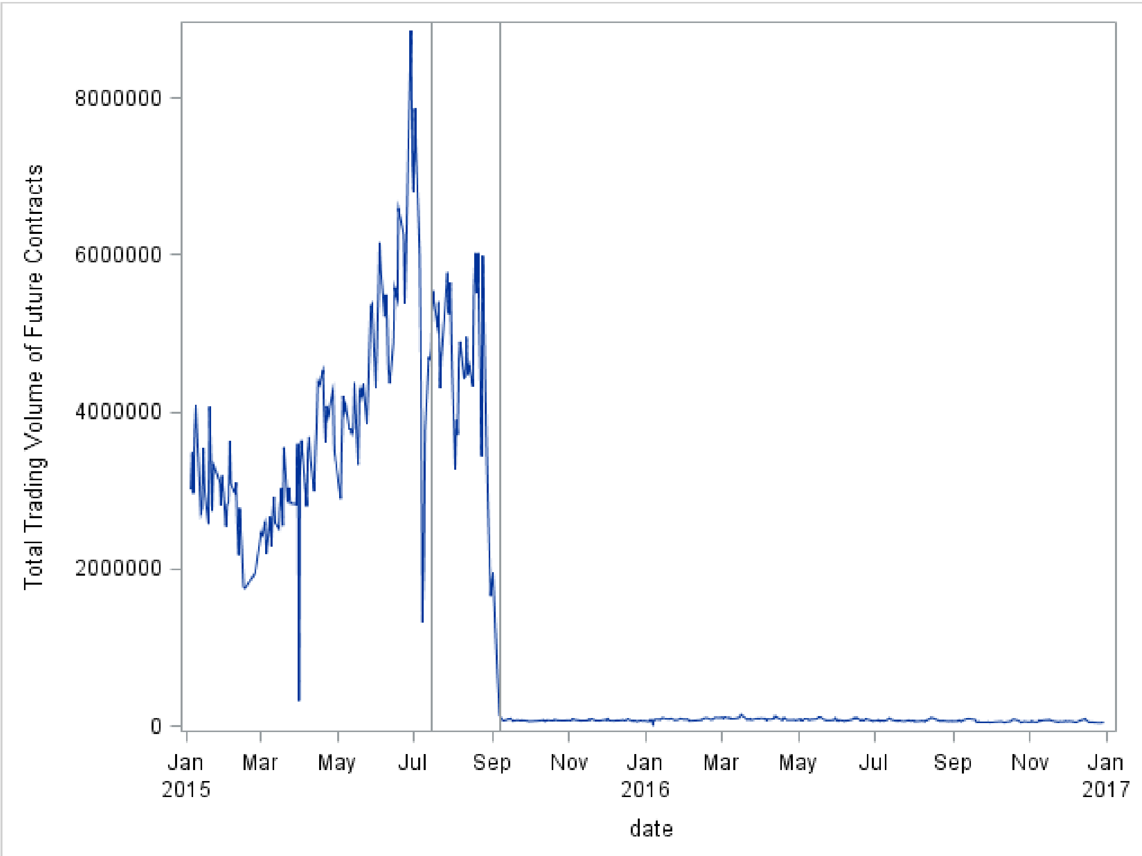


Figure 2.3: Average daily cost-of-carry violations (*Diffp)* over time.

Dates for the two reference lines are 07/15/2015, the soft intervention cut-off day in the spot market, and 09/07/2015, the soft intervention cut-off day in the futures market.

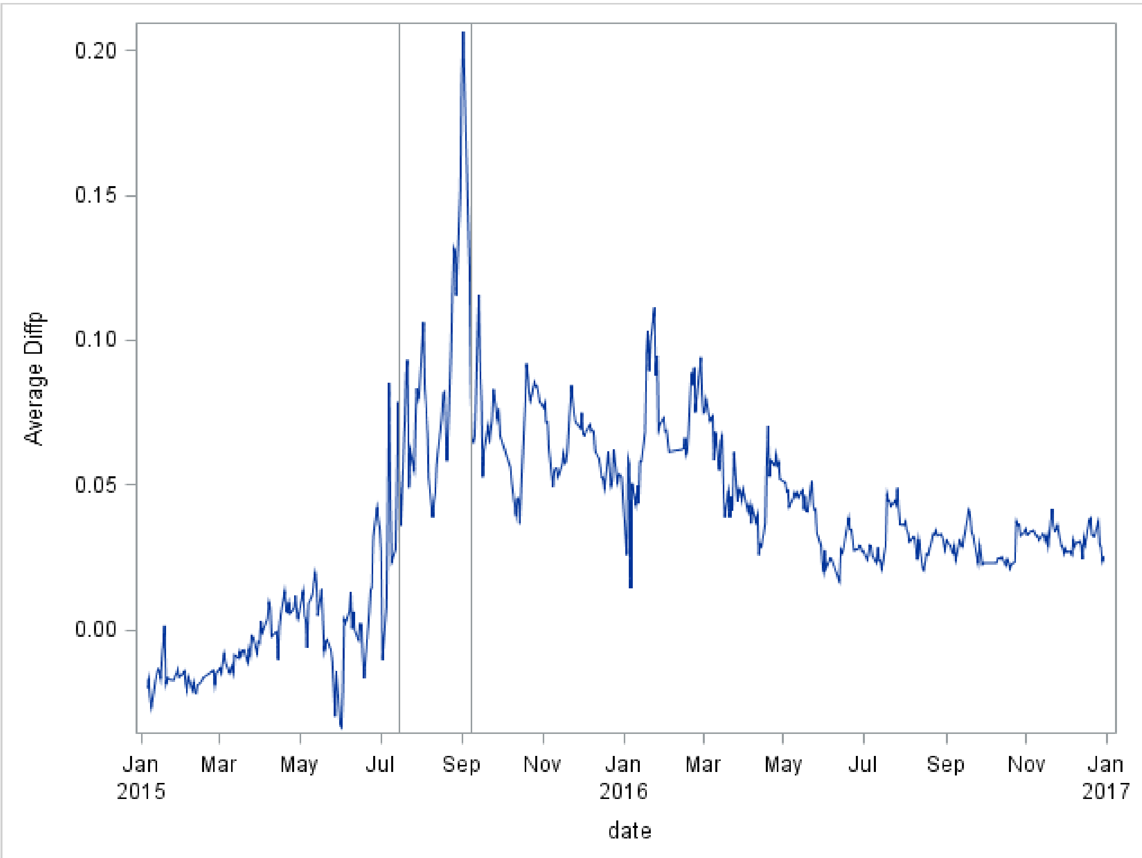
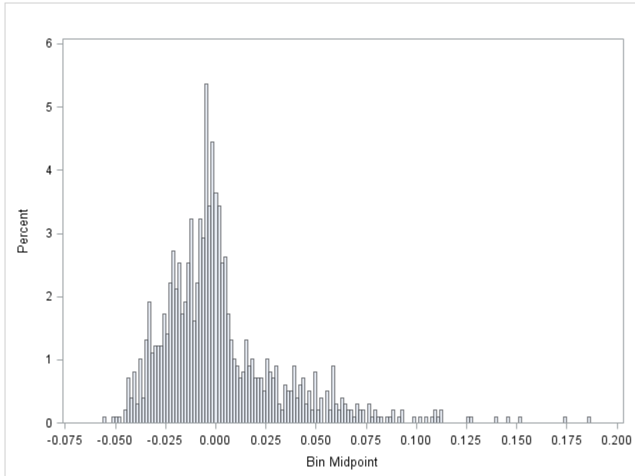
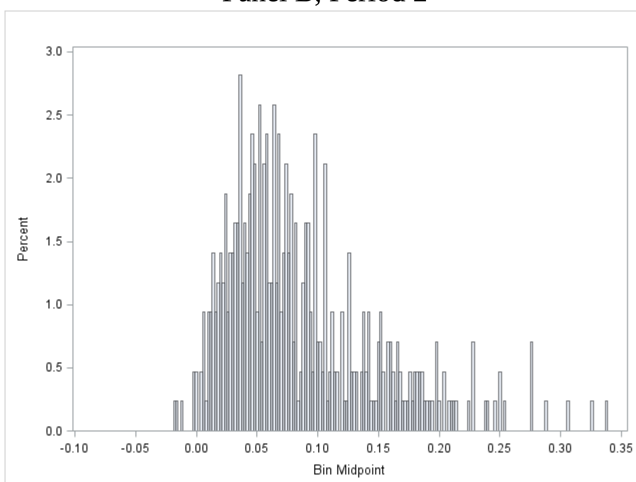


Figure 2.4: Distributions of cost-of-carry violations (*Diffp)*.

Panel A, Period 1



Panel B, Period 2



Panel C, Period 3

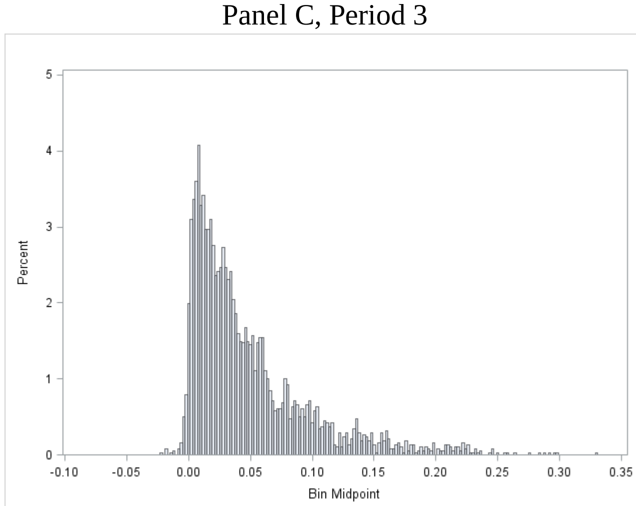


Figure 2.5: HSCEI and CSI 300 index prices.

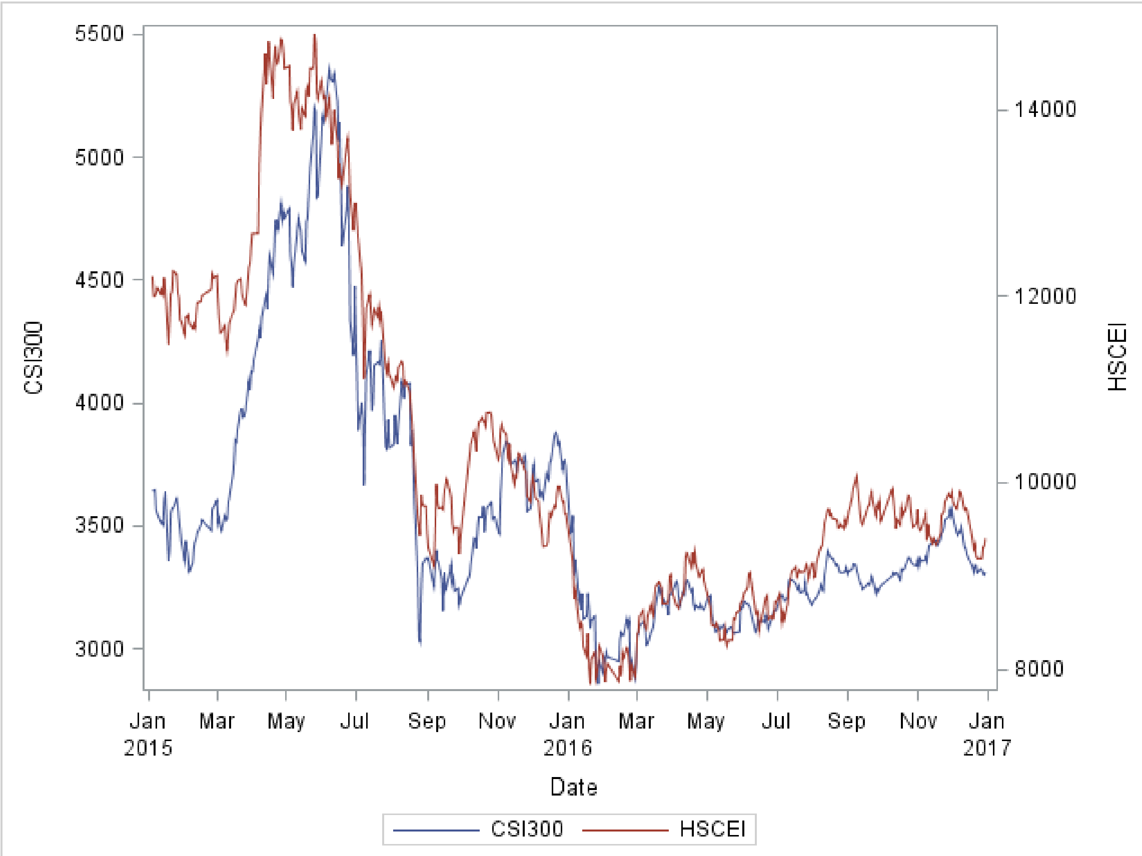


Figure 2.6: Average daily violation-of-carry (*Diffp)* in the Hong Kong market.

Dates for the vertical reference lines are 07/15/2015, the soft intervention cut-off day in the Mainland Chinese spot market, and 09/07/2015, the soft intervention cut-off day in the Mainland Chinese futures market.

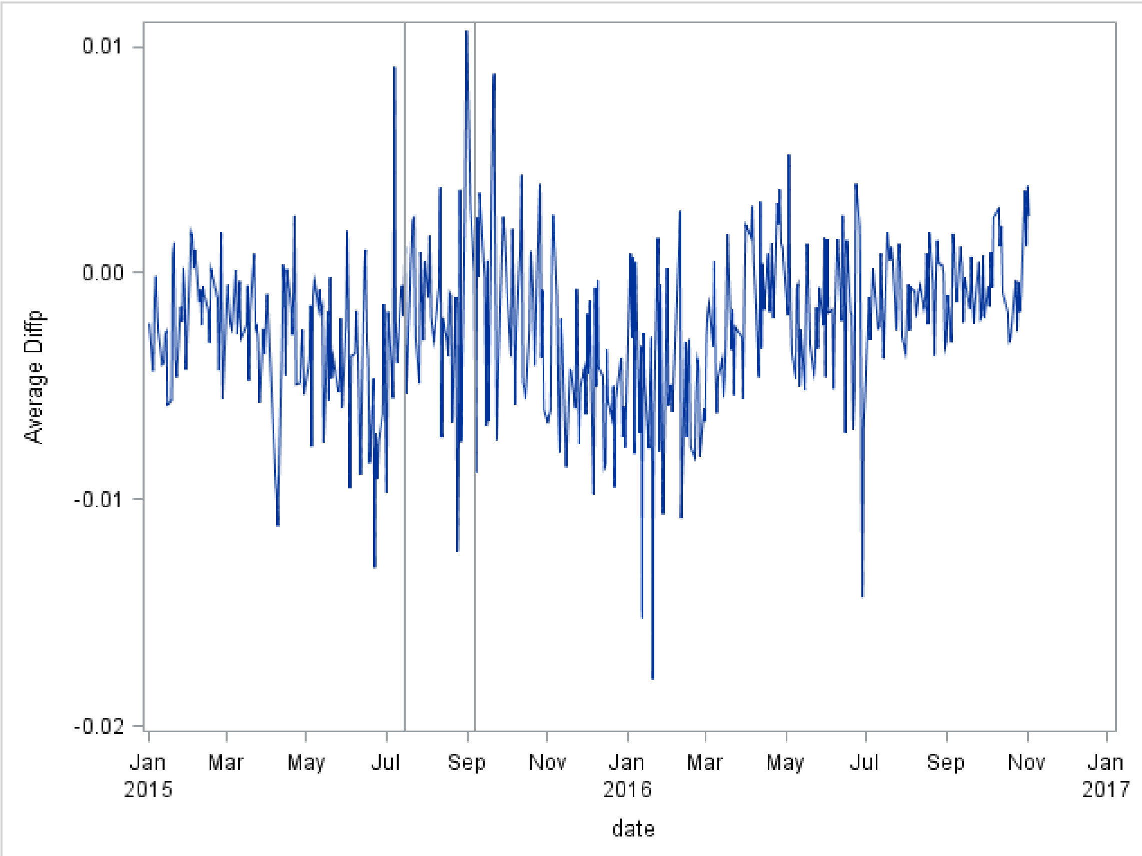
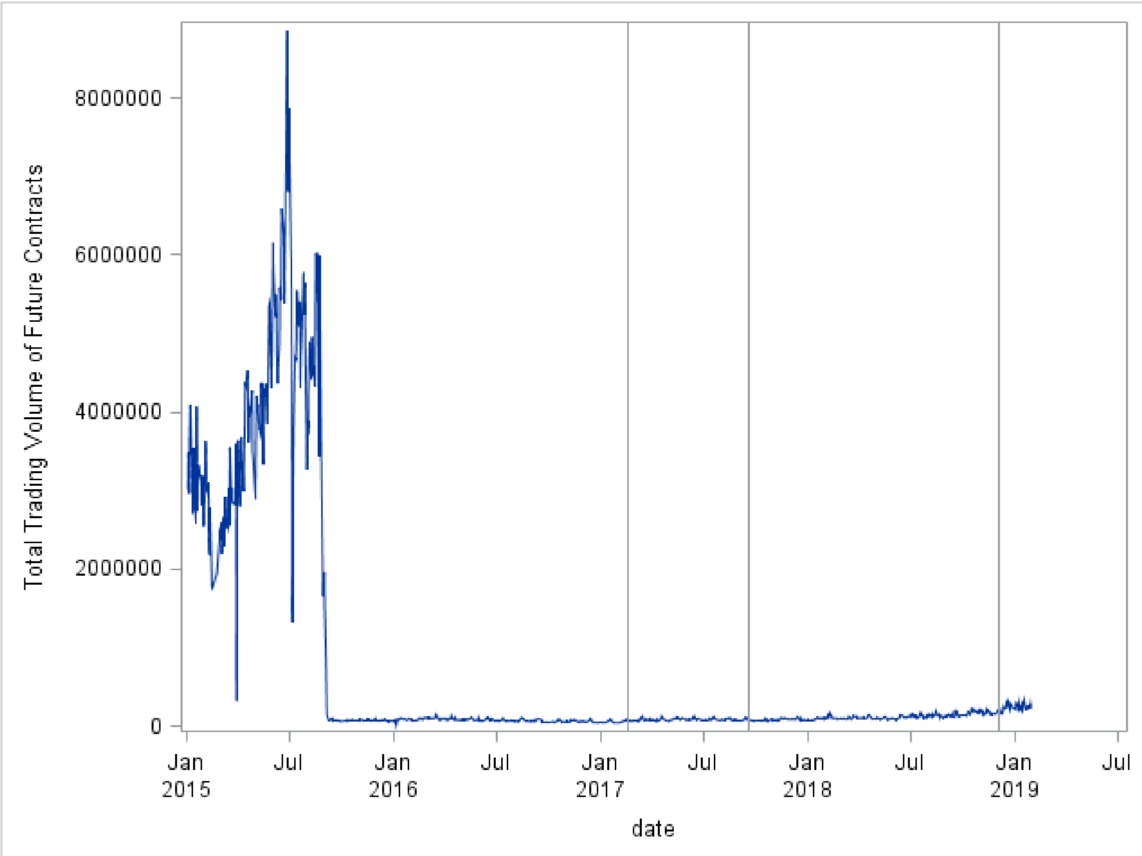


Figure 2.7: Total daily trading volume of futures contracts and trading rule changes after the 2015 financial crisis.

The three vertical reference are the dates of three rule changes on 02/17/2017, 9/18/2017 and 12/3/2018. These changes were made to loosen the trading constraints set during the 2015 financial crisis.



Chapter 3. The US Financial Crisis and Corporate Dividend Reactions: For Better or for Worse?[12]

[12] This chapter is joint work with Dr. John Jahera and Dr. Jitka Hilliard.

3.1 Introduction

Corporate dividend policy has been the subject of finance and economic research for decades as new factors are considered in determining why firms pay dividends, why they choose to initiate dividends as well as why they choose to reduce/suspend dividends. The recent financial crisis offers a somewhat unique situation in terms of examining the dividend behavior of U.S. firms in the face of somewhat dire economic conditions. Generally speaking, a reduction in dividends has been viewed as a negative signal in terms of firm value. However, the financial crisis represented such a significant event not only in the U.S. but globally, that it is of interest to further examine the dividend behavior from the pre-crisis period and on throughout the crisis period.

It is the objective of this research to examine firms that reduced or eliminated their cash dividends at the beginning of the financial crisis. Firms are categorized according to their crisis-related dividend behavior. That is, our data sample considers firms that made no changes at all in their dividend policy; those that reduced their dividends to zero; those that reduced their dividends but not totally; and finally those that actually increased their dividends. Financial returns of these four groups are followed through until the end of 2009. The methodology is designed to assess whether the changes in dividend policy during the crisis period impacted the risk-adjusted returns of the sample firms. The general conclusions show that firms that eliminated or reduced their dividends had significantly higher risk-adjusted returns in 2009, a finding somewhat contrary to traditional theory. The overall conclusion is that it was beneficial for firms to react quickly to the deteriorating economic conditions in 2008 by adjusting their dividend policy to preserve cash.

The paper will continue with a brief literature review followed by a discussion of the data utilized and then the specific empirical methodology. The results will be discussed and followed by the final conclusions and implications.

3.2 Related Literature

The body of research regarding corporate dividend policy is very extensive and we will provide just a brief review of the more important literature. Of course, Miller and Modigliani (1961) offer the classic work in this area where they argued that firm value is unaffected by the choice of distribution methods under certain assumptions. Many others have built upon this early work with studies examining the tax effects on dividends also (See Talmor and Titman, 1990; Change and Rhee, 1990; Naranjo, Nimalendran and Ryngaert, 1998; Kuo and Lee, 2013). Additional dividend research has considered the information content of dividends (See Healy and Palepu, 1988; Gonedes, 1978; Benartzi, Michaely and Thaler, 1997; Best and Best, 2001). The argument in that body of work is that dividends convey information that investors use in their assessment of the overall risk and future of the firm and hence firm value. Generally speaking, decreases or omissions of dividends are viewed as conveying negative information regarding a firm's prospects for the future. Another line of research has addressed the agency relationship and how that may influence dividends. One argument is that a higher payout firms have less in retained earnings and are forced to turn to the capital markets when they need additional equity. The scrutiny of the capital market serves to mitigate any agency issues that may have developed if the firm only retained earnings. In other words, this agency effect emphasizes the role of investment bankers and analysts in insuring that management is indeed acting in the best interest of the shareholders. Rozeff (1982) examined this issue by looking at the tradeoff between agency costs and the cost of external financing. His empirical work provides evidence to support the conclusion that investment policy does indeed affect dividend policy. This was expanded and reinforced by Lloyd, Jahera and Goldstein (1986). Firms with greater investment opportunities exhibit lower dividend payout ratios. Many other studies have considered the agency issues as related to dividend policy (See for example Easterbrook, 1984; Jensen et al., 1992; Schooley and Barney 1997; Fenn and Liang, 2001).

Frankfurter and Wood (2002) review the conflicts among the results from earlier work on dividend policies. Their overall conclusion is that explanatory models for dividends are likely to continue to be inconclusive due to the various factors and the difficulty in capturing all the relevant factors. A more recent work by Baker, Powell and Veit (2002) reexamines the dividend puzzle to see if "all the pieces now fit." This work offers a review of much of the major research as well as discussion of the reasons for dividends and also results of various surveys on dividends. The general conclusion is that the many studies regarding dividends have helped in putting the "puzzle" together, but it is still not complete nor may it ever be complete. Baker et al. (2002) list the main factors from their review of the work; market imperfections, behavioral issues, firm specific characteristics, and management preferences. A more "practical" research work is by Brav, Graham, Harvey and Michaely (2005) and is based on survey research. They survey a large number of financial executives and also conduct actual interviews to gain a better understanding of the elements that determine dividends as well as stock repurchases. Their conclusions are not surprising. First, they conclude that management still hesitates to cut dividends given the perceived adverse reaction on the part of investors. That is, dividends tend to be "sticky" in the sense that firms tend to maintain existing dividend policies for long periods of time. In addition, many of the respondents in their survey indicated that they would have preferred to not pay dividends but once dividends were initiated they were hesitant to cut them. Another finding is that share repurchases have gained in importance given the relative flexibility of that means of distribution. Jagannathan, Stephens, and Weisbach (2000) point out that financial flexibility is an important consideration when the firms make decision on payout policy. They focus on the choice between cash dividends and repurchases, finding that firms that generate stable cash flows tend to pay cash dividends while firms with unstable and uncertain cash flows tend to distribute through share repurchases. Iyer, Feng and Rao (2017) confirm that mangers want to maintain a flexible payout policy by using stock repurchases rather than dividend. This flexibility allows the managers to better meet future capital expenditures of the firm. The authors find that capital expenditures are significantly negatively related to repurchases, especially under financial constraints. They do not find any significant relation between capital expenditures and cash dividend payouts.

Another body of research has considered dividend changes and the reaction and reasons for such changes. Lie (2005) examines a large number of dividend decreases and omissions for the time frame 1980 to1998. He relates the dividend changes to changes in earnings. His conclusions are that earnings generally suffer at the announcement time but then tend to recover in subsequent periods. He does find a negative stock price effect with the view that the market overreacts to any negative inferences. Jensen, Lundstrum and Miller (2010) look at firms that had dividend reductions from 1967 to 2006. Their methodology considers both the standard stock return reaction to the announcement and then also a consideration of financial characteristics. As shown in much of the earlier research, there is a negative market reaction to a reduction in dividends but this is followed by a recovery in earnings after the dividend reduction period. When looking at other characteristics, they find that the earnings recovery is due to the reduction in certain other costs such as capital investments, R&D as well as the level of employment. Lacina and Zhang (2008) investigate dividend initiations of high-tech firms and non-high-tech firms. They find that the market performance of high-tech firms after dividend initiations is better than that of non-high-tech firms. They also argue that higher liquidity of assets held by high-tech firms strengthens investor confidence and hence leads to better market reaction on the dividend initiations.

Another study by Chay and Suh (2009) empirically studies the dividend behavior of over 5,000 firms from Australia, Canada, France, Germany, Japan, the UK and the U.S. Their research determines that cash flow uncertainty is a major driver of dividend policy while controlling for other relevant factors. This is consistent with the idea that uncertainty resulting from a financial crisis can indeed affect dividend policy and in a very short time frame.

More directly related to our research are works related to the financial crisis and dividends. Campello, Graham and Harvey (2010), using survey methodology, focus on some broader aspects of financial change during a crisis. They study how financial constraints impacted firms in terms of employment levels, capital investment, marketing and technology spending. Their survey coveres 1,050 CFOs in 39 countries. The results show that the above items all faced reductions in funding levels. The survey results further indicate that firms were burning cash quickly which led to dividend cuts that were greater than anticipated. Floyd, Li and Skinner (2015) examine dividend paying behavior for both financial as well as industrial firms. Citing earlier evidence that dividends for industrial firms have been in something of a long run decline, they find that the reluctance to reduce dividends remains quite high (See Fatemi and Bildik, 2012). In a somewhat related paper by Fuller and Goldstein (2011), dividends are found to have greater importance in declining markets. They consider the time period from 1970 to 2007 and examine the stock returns for a sample of dividend paying firms as well as those not paying dividends. While their results do capture the 37-year effect, it stops short of the period of the 2008 financial crisis which is the focus of our current research. Che, Liebenberg, Liebenberg, and Morris (2008) document the effect of dividend cuts during 2008 financial crisis. They confirm a negative market reaction to dividend cuts and find that this market reaction is related to the firm’s growth opportunities. Higher abnormal returns on dividend cut are found for firms with better growth opportunities.

Of direct relevance to our research is a work by Abreu and Gulamhussen (2013) on the dividend payout behavior of 462 bank holding companies in the U.S. Their findings are not surprising. Overall macroeconomic conditions do influence dividend behavior. Further, firm specific characteristics play a major role with, as expected, stronger institutions paying greater dividends. Abreu and Gulamhussen feel that their results offer continuing support for the signaling effect of dividends. In another interesting study for firms on the London Stock Exchange, Bozos, Nikolopoulos and Ramgandhi (2011) consider signaling effects of dividend announcements, comparing reactions between periods of economic stability and economic turmoil. They confirm the continuing information importance of dividends but do find that dividend changes and their impact are related to overall economic stability. Another study by Pathan, Faff, Fernandez, and Masters (2014) considered a large sample of dividend increase announcements by US firms for the period 1989-2012. Their general conclusions are that firms that are financially constrained actually displayed higher post increase performance relative to unconstrained firms. In explaining this finding, they suggest that there is a timing effect to dividend increase announcements made in anticipation of a seasoned equity offering. They cite this as evidence of a signaling effect for those firms. They further find that dividend increasing firms that are also financially constrained exhibited weaker returns during the financial crisis.

Hauser (2013) asks whether corporate dividend policy changed during the recent U.S. financial crisis. Hauser used 2006 as a base year to insure that management had not yet gained knowledge of the impending problems with our financial system. Using data from Compustat and the time period 2006-2009, Hauser utilized logistic regression. In summary, he found a decline in the likelihood of dividends being paid for 2008 and 2009 ceteris paribus. Not surprising is his finding that dividend cuts increased during his sample period as firms preserved cash during the time of greater uncertainty. One other paper by Lee, Lusk and Halperin (2013) considers dividend payout as well as stock repurchases during the financial crisis. Their results, like many others, are not terribly surprising. Overall, firms must exhibit a sound financial condition if they are to increase dividends in a crisis period. Further, such firms tended to continue also with stock repurchase programs. This suggests that they were not diverting funds from a repurchase plan simply to continue paying dividends. Bliss, Cheng and Denis (2013) examine financial policies and any adjustments made during the recent financial crisis. Specifically, they focus on credit availability and find that those firms with more leverage, greater growth and less liquidity displayed reductions in dividends. Simply stated, they find that firms paid out less but used the funds to support growth and investment.

Clearly, the more recent literature offers some insights into the dividend policy reaction to the U.S. financial crisis. Given the breadth and depth of the financial crisis, a better understanding of firm reactions is of importance in guiding corporate dividend policy. A summary view of the literature is that firms did indeed respond to the crisis through preservation of cash, reduction in capital investment, R&D, etc. Our research is designed to consider further the reaction for a broad set of firms that may have eliminated dividends, reduced dividends or actually increased dividends.

3.3 Data

Our sample consists of all companies trading on the NYSE and NASDAQ. To avoid biases associated with highly regulated financial companies, we exclude all companies with SIC code 6000-6999 (Finance). We use information on dividends and daily returns from CRSP, the risk-free rate and factor loadings from the Fama-French database, and fundamental data from Compustat. Institutional holding data comes from Thomson Reuters.

First, we provide basic information on dividends and stock repurchases for NYSE- and NASDAQ-traded companies from 2000 to 2015 (Table 3.1). The number of firms included varies from year to year. For NYSE firms, the number ranges from 1567 in 2009 to 1945 in 2000. For NASDAQ firms, the number ranges from 2221 in 2012 to 4442 in 2000. The ratio of cash dividend paying stocks traded on the NYSE was increasing until the year 2007 when it reached 62.7 percent of firms in our sample. Starting in 2008, the ratio of dividend payers was declining. It reached the bottom of 56.76 percent in 2010 and then started to increase again recovering to 61.27 percent in 2012. For NASDAQ-traded firms, the ratio of dividend payers reached its high of 16.7 percent in 2008, then declined to 16.0 percent in 2009 and started to increase again in 2010. The year 2009 was also the year of the lowest rate of stock repurchases for both NYSE and NASDAQ-traded stocks.

3.4 Grouping the firms based on their dividend policy

To examine the consequences of changes in dividend policy, we identify all firms that paid cash dividends in 2007. Our sample contains 861 dividend-paying firms on NYSE and 350 on NASDAQ (Table 3.2). These are our sample firms and we use 2007 as the benchmark year. We use this year because the financial crisis is generally thought to have begun at the end of 2007 and it was well underway in 2008. Also, the National Bureau of Economic Research (NBER) defines the beginning of the crisis as December of 2007. So, it is unlikely firms would have had sufficient time to react to deteriorating economic conditions via dividend policy changes in 2007. In other words, we view 2007 as a “clean” year in terms of normal dividend policies.

We divide these sample firms into four groups based on their dividend policy in 2008 (Table 3.2). We use the dividend payout information (DIVAMT, RCRDDT, DISTCD) in the CRSP monthly stock file. Dividend policy change is proxied by changes in the total amount of dividends and frequency of dividends. Group 0 consists of firms that decreased both the amount and frequency of dividends to zero in 2008. This group represents 8.48% of the sample firms for NYSE and 8.86% for NASDAQ. Group 1 includes firms that decreased either the amount or frequency of dividends, from 2007 to 2008 (16.03% of the sample firms on NYSE and 15.71% on NASDAQ). Group 2 contains firms that made no change to their dividends (19.28% of the sample firms on NYSE and 18.57% on NASDAQ). Group 3 includes firms that increased either the amount or frequency of their dividends. This is the largest group, representing 56.21% of the sample firms on NYSE and 56.86% on NASDAQ. This is not surprising because this group represents the most typical dividend policy when firms increase their dividends over the years. To address possible distribution by stock repurchases in our sample, Table 3.3 reports firms in our sample that reported stock repurchases from 2007 to 2009. Only very small proportion of these firms repurchased during our study period. In fact, only 9 out of 861 NYSE firms and 10 out of 350 NASDAQ firms in our sample repurchased shares between 2007 and 2009. Therefore, we can assume that repurchases were not an important way of distribution to shareholders in our sample.

Basic characteristics of different groups are shown in Table 3.4. As can be seen, the group of firms that stopped paying dividends in 2008 (group 0) had on average the lowest profitability, the highest level of debt, and the highest book-to-market ratios. These firms were also the smallest firms. Such firms were clearly encountering more difficulty related to profitability, debt, etc. and had the need to preserve cash. On the other hand, the group of firms that increased dividends in 2008 (group 3) had the highest profitability, lowest leverage, lowest book-to-market ratios and the highest market value. For the NYSE firms, the institutional holding levels are highest for group 0, i.e. the group of firms that stopped paying dividends and lowest for group 3, i.e. the group that increased their dividends. For NASDAQ firms, the levels of institutional holdings are just opposite with the lowest institutional holdings for the group of firms that stopped paying dividends (group 0) and the highest institutional holdings for the groups that continued or increased their dividends (groups 2 and 3). Average daily returns for individual groups in 2009 are also shown in Table 3.4. The highest daily returns were for group 0 on NYSE and group 1 on NASDAQ.

We follow all four groups until 2009 and examine whether dividend policy in the crucial year of 2008 influenced their risk-adjusted returns. Note here that the groups were created based on their dividend policy in 2008 and no further adjustments to the groups were made. That is, the assigned group number remains the same regardless of subsequent changes. Changes in dividend policy in the 2009 year did not result in reclassification.

3.5 Differences in Risk-Adjusted Returns among Groups

We ask a question whether the changes in dividend policy in the crucial year of 2008 influenced the market performance of the firms in a following year. Therefore, we sort firms into groups based on changes in dividend policy that they had made in 2008 and examine their risk-adjusted returns in 2009. We believe that firms that quickly reacted to the upcoming financial crisis by preserving cash were able to compensate, at least to some extent, for the lack of internal and external financing sources during this crisis. For dividend-paying firms, of course, the elimination of cash dividends represents an important cash source. Therefore, we expect that firms that adjusted their dividends downward in 2008 had higher risk-adjusted returns in 2009. To estimate the risk-adjusted returns, we use the four-factor model

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_1(r_{m,t} - r_{f,t}) + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 UMD_t + \varepsilon_{i,t}, \quad (3.1)$$

where $r_{i,t}$ is the daily return on the asset *i* in 2009, $r_{f,t}$ is the risk-free rate, $r_{m,t}$ is the market return, and SMB_t, HML_t and UMD_t are the Fama-French factors representing the returns corresponding to size, book-to-market and momentum portfolios.

The average risk-adjusted returns for each group in 2009 are shown in Table 3.5. We test the stocks trading on NYSE and NASDAQ separately and show the results in panels A and B. The portfolio of firms that decreased their dividends or stopped paying dividends in 2008, i.e. groups 0 and 1, have positive and significant alphas in 2009 for both NYSE and NASDAQ-traded stocks. In addition, the firms that decreased dividends (group 1) have positive and significant alphas for both NYSE and NASDAQ while the firms that stopped paying dividends entirely (group 0) have alpha significant at the 10 percent level only for NYSE. These results suggest that reducing dividends at the beginning of financial crises was a beneficial decision that resulted in higher risk-adjusted returns in 2009.

We further test whether alphas among groups are significantly different using modified GRS test (detail is provided in the appendix). The modified GRS test follows the method of Gibbons, Ross and Shanken (1989), and Follmann (1996) to test the difference between alphas under one universe. We find a positive and significant difference in four-factor alphas between the groups that reduced or stopped paying dividends (group 0 and 1) and groups that did not make changes to their dividend policy (group 2) or increased their dividends (group 3). This applies to both NYSE and NASDAQ exchanges (Table 3.6). These results support our previous findings and the notion that the firms who reduced the dividend during the 2008 crisis had significantly stronger recovery.

3.5.1 Robustness Check with Matched Benchmarks

To address concerns that these differences in mid/long-run performance are due to other factors than changes in dividend policy, we use the propensity score matching to find a benchmark for each dividend payer. We match each dividend-payer with a nonpayer based on similar fundamental information. Specifically, we use the industry, size, leverage, turnover, book-to-market ratio (BM), profit margin, and return on assets (ROA) as matching criteria in 2009. To ensure that a non-dividend payer mimics the fundamental characteristics of the dividend-payer, we first run a logistic model,

$$Logit(Dividendpayer_i = 1) = \alpha + \beta_1 Size_i + \beta_2 Leverage_i + \beta_3 Turnover_i + \beta_4 BM_i + \beta_5 Margin_i + \beta_6 ROA_i + \varepsilon_i. \quad (3.2)$$

Then, using the predicted value of logit regression as a score, we match each dividend-payer with the closest nonpayer within the same industry.

Table 3.7 reports the returns/alphas of each group and its benchmark. Our variables of interest are variables *Difference in returns* and *Difference in alphas. Difference in returns* is the excess return of each dividend-policy group over the excess return of its matched benchmark. *Difference in alphas* is the difference in alphas of each group and their matched benchmarks. Consistent with our previous results, the groups 0 and 1, i.e. groups that stopped paying dividends or reduced dividends, have higher excess returns and alphas than their non-payer counterparts. Groups 2 and 3, i.e. groups that continued with their dividend policy or increased dividends, had on the other hand, significantly lower returns than their non-dividend matches.

3.5.2 The Effect of Dividend Omissions

In this paper, we argue that decreasing dividends at the beginning of 2008 financial crisis was a correct decision that enabled the firms to preserve much needed cash and work through the financial crisis period. Consistent with this premise, we find that firms that stopped paying dividends or those that decreased dividends were rewarded by higher risk-adjusted returns in 2009. Empirical research documents that decreases in dividends are usually associated with significantly lower returns surrounding the announcement day (see for example Dhillon and Johnson, 1994; Michaely, Thaler and Womack, 1995; Che et al., 2008). Therefore, higher risk-adjusted returns in a year following decrease in dividends may not be due to benefits of improved cash flows during the crisis but rather to a depressed stock price resulting from the change in dividend policy. In other words, our findings may not be specific to the severe financial crisis of 2008. Instead they may be driven by the dividend omissions and consequent recovery effect in long-run performance. To address this concern, we expand the time period and examine the effect of changes in dividend policy on risk-adjusted returns from 1999 to 2015. We use the same methodology and identify dividend-paying firms in year *t-2*. In year *t -1*, we sort these firms into groups based on changes in their dividend policy. We follow these groups and evaluate their performance in year *t*. The results are plotted in Figures 3.1 (NYSE) and 3.2 (NASDAQ). As can be seen from these figures, the large increase in risk-adjusted returns for groups 0 and 1 is present only during the 2008 financial crisis, implying that higher risk-adjusted returns for firms that decreased their dividends are not driven by effects associated with dividend-omission. Figures 3.1 and 3.2 cover time period from 2001 to 2015.

3.6 Cross-Sectional Tests on Returns

3.6.1 The Effect of Dividend Policy Change

To further support our finding, we conduct cross-sectional tests on risk-adjusted returns. We regress risk-adjusted return (alpha or average excess return) on firm characteristics and a group variable (*Group*):

$$Alpha_i = \alpha + \beta_1 Size_i + \beta_2 Leverage_i + \beta_3 Turnover_i + \beta_4 BM_i + \beta_5 Margin_i$$

$$+\beta_6 ROA_i + \gamma Group_i + \varepsilon_i. \tag{3.3}$$

The *Alpha* is the four-factor model alpha generated from 2009 daily returns [equation (3.1)]. We also use average excess return as another dependent variable. The control variables are firm characteristics in 2009; *Group* is the group number. We do not further expand the set of our control variables because of concern of losing more observations. Missing values in Compustat may introduce bias leading our sample towards larger firms and value firms and significantly reducing observations, especially in Group 0.

Panel A of Table 3.8 reports results from the full sample including NYSE observations and NASDAQ observations. All of the *Group* coefficients (γ) are negative and significant (at 1% level), indicating that alphas/excess returns are significantly higher for groups with lower group numbers, i.e. the groups that decreased or stopped paying dividends in 2008. Panel B reports similar results for NYSE firms. For NASDAQ firms, the effect of change in dividend policy is similar but weaker (panel C) with all γ coefficients negative but only three significant at 5% level and one not significant. In general, we confirm the previous results that dividend policy change in 2007 does affect the risk-adjusted returns after the crisis.

3.6.2 Survival Bias

Some firms in our sample may have been acquired by other firms, gone bankrupt and delisted during our time period. Therefore, our results may suffer survivorship bias. To address this problem, we add back missing observations and conduct the Heckman correction to the tests. First, we collect information of delisted firms and add them back into our sample prior to the date they delisted in 2009. Second, we identify those firms that are present in our 2007 sample but disappear in the 2009 sample. We calculate the inverse mills ratio (IMR) for each observation and add IMR as an independent variable using following equations:

$$P(Drop_i = 1) = \alpha_i + \sum_{k=1}^{6} \beta_k Control_{ik}^{2007} + \varepsilon_i, \tag{3.4}$$

$$IMR_i = \frac{\phi(Predicted\ value_i)}{\Phi(Predicted\ value_i)}, \tag{3.5}$$

$$Aplha_i = \alpha_i + \sum_{k=1}^{6} \beta_k Control_{ik}^{2009} + \gamma Group_i + \delta IMR_i + \varepsilon_i. \tag{3.6}$$

Control variables include the *size*, *leverage*, *turnover*, *BM*, *margin* and *ROA*. *IMR* is the inverse mills ratio, which is estimated from Equations (3.4) and (3.5). $\phi(\cdot)$ denotes the normal density function and $\Phi(\cdot)$ denotes the normal cumulative distribution function. Table 3.9 shows the results of the Heckman correction test. The *Group* coefficients (γ) remain negative and significant confirming that our results reported in Table 3.8 hold. Moreover, the effect of a change in dividend policy for NASDAQ firms is stronger after Heckman correction.

3.7 The Managerial Effort

In this study, we argue that the strong recovery of groups 0 and 1 is a result of managements' fast reaction to the financial crisis. Managers, who were able to identify the coming crisis and reduce their dividends, mitigated the effect of liquidity constrains on the firm during the financial crisis. Therefore, we believe that managerial effort played a significant role in firms recovering through correctly reducing dividends during the crisis.

3.7.1 The Cross-sectional Tests with a Proxy of Managerial Effort

To test this hypothesis, we add institutional holding as a variable that proxies for managerial effort and investigate the relationship between managerial effort in 2007 and the group effect on return in 2009. A huge body of literature focuses on institutional investors' effort to improve corporate governance (See for example Shleifer and Vishny, 1986; Bertrand and Mullainathan, 2001; Velury, Reisch, O'reilly, 2003). In general, institutional investors are seen as watchdogs that push managers to make right choices. Therefore, a higher level of institutional ownership is associated with better managerial effort. That is, institutional investors bring a level of oversight and monitoring that may influence better management. We are not necessarily interested in the overall effect of the managerial effort on returns but rather in the effect of managerial effort concerning the change in dividend policy. Our argument is that decisions that led to preserving cash, such as the decision to decrease dividends, were crucial decisions at the beginning of the financial crisis and that companies benefitted from these decisions in 2009. Therefore, we test the effect of the managerial effort through a model,

$$Aplha_i = \alpha + \sum_{k=1}^{6} \beta_k Control_{ik}^{2009} + \gamma_1 Group_i + \gamma_2 IH_i^{2007} + \gamma_3 Group_i IH_i^{2007} + \varepsilon_i, \qquad (3.7)$$

where *IH* is the institutional holding in 2007. Control variables include *size*, *leverage*, *turnover*, *BM*, *Margin* and *ROA*. The dependent variables are risk-adjusted returns in 2009.

We expect better managerial decisions concerning the dividend policy to be reflected in a negative and significant coefficient on the interaction term ($Group_i IH_i^{2007}$). Consistent with our expectations, the interaction coefficients are negative and significant at 5% level for the full sample

(Panel A of Table 3.10). After the interaction term is added into the model, the *Group* coefficient loses its significance and becomes positive. This finding implies that the effect of dividend policy change on future recovery is indeed associated with managerial effort during the crisis. We find similar results for NYSE firms (Panel B). The results for NASDAQ firms are weaker (Panel C), probably due to smaller sample size.

3.7.2 Persistence of Institutional Holdings

The managerial effort may have affected returns in 2009 through two channels. First, the management that reduced dividends at the beginning of crisis preserved cash that benefited the firm during and after crisis. Second, the management that was effective in 2007 kept the position and remained effective in 2009. Because institutional holdings (a proxy for managerial effort) may not change dramatically year to year, the better returns in 2009 may not be due to fast managerial reaction to the upcoming crisis but rather to good corporate governance in 2009.

To address this concern, we use a two-stage regression to exclude the effect of institutional holding in 2009. The first stage regression is:

$$Alpha_i = \alpha + \beta IH_i^{2009} + u_i. \tag{3.8}$$

The residuals of the first regression are then used in the second stage to exclude the effect of corporate governance in 2009:

$$\hat{u}_i = \alpha + \sum_{k=1}^{6} \beta_k Control_{ik}^{2009} + \gamma_1 Group_i + \gamma_2 IH_i^{2007} + \gamma_3 Group_i IH_i^{2007} + \varepsilon_i. \tag{3.9}$$

The results are reported in Table 3.11. The coefficients on interaction term ($Group_i IH_i^{2007}$) (except one for NASDAQ) remain negative and significant (at 10% level). These results confirm our argument that fast managerial reaction during crisis contributed to better market performance during recovery period.

3.7.3 The Performance over Matched Benchmarks

We use institutional holdings as a proxy for managerial effort but other factors, however, may affect returns, dividend policy and institutional holdings at the same time. To address a possible endogeneity issue, we exclude the effect of these factors by matching each firm in our sample with a similar firm that did not pay dividends in 2007 and therefore is not included in our sample (a benchmark firm). The benchmark firm should react to similar factors as the matched firm.

$$Logit(Dividendpayer_i = 1) = \alpha + \beta_1 Size_i + \beta_2 Leverage_i + \beta_3 Turnover_i + \beta_4 BM_i$$
$$+\beta_5 Margin_i + \beta_6 ROA_i + IH_i^{2009} + \varepsilon_i. \quad (3.10)$$

With the predicted value of logit regression, we match each of our sample firms with the closest nonpayer within the same industry. Then we exclude the effect of potential other factors by calculating the excess risk-adjusted returns,

$$Excess\ Aplha_i = Aplha_i - Aplha_i^{Benchmark}, \quad (3.11)$$

$$Excess\ Aplha_i = \alpha + \sum_{k=1}^{6} \beta_k Control_{ik}^{2009} + \gamma_1 Group_i + \gamma_2 IH_i^{2007} + \gamma_3 Group_i IH_i^{2007} + \varepsilon_i. \quad (3.12)$$

The coefficients on interaction term ($Group_i IH_i^{2007}$) are still negative and significant for full sample and NYSE (Panels A and B of Table 3.12). For NASDAQ firms the results are weaker with coefficients being negative but not significant. In general, these results support the argument that change in dividend policy during crisis positively affects future performance because of managerial efforts. The effect of dividend change is concentrated mainly in the NYSE sample firms.

3.8 Conclusions

Overall, the objective of this research is to examine the effect of dividend behavior during the period of recent U.S. financial crisis. Given the critical decline in economic activity, many firms felt the need to preserve cash and took action to insure sufficient cash levels to survive the crisis. We examine firms that made no changes in dividends, those that eliminated dividends totally, those that reduced but did not totally eliminate dividends and then finally those that actually increased dividends. Overall we find that firms that were able to quickly react to deteriorating economic conditions in 2008 by adjusting their dividend policy had higher risk-adjusted returns in the subsequent year. Reducing dividends is usually seen as a “bad” signal by the market and followed by negative market reaction. Under exceptionally adverse market conditions, however, a reduction in dividends may signal the ability of managers to quickly react to the changing market conditions and the firms may be rewarded by the market in a long run. Hence, earlier works on the signaling hypothesis may have had some element of time specificity. That is, the results may be driven by financial crises for instance. Clearly, the U.S. financial crisis has been the most significant since the Great Depression with many of the belief that corporate decision making may have been permanently altered. The dividend payout decision is but one area in which the resulting changes are of interest. That is, despite any negative connotations, many firms felt they had to reduce or eliminate their cash dividends. We further looked at a longer time period to provide more evidence of firm reaction. More research will be needed of course to trace the longer run implication of many of the corporate policy changes that may have occurred since 2008.

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Table 3.1: Dividend paying and repurchasing firms

We use the dividend payout information (DIVAMT, RCRDDT, DISTCD) in CRSP monthly stock file. Cash dividend is dividend with distribution code (DISTCD) starting with 1 and Repurchase are distribution with code starting with 5 but not 5523.

	NYSE				NASDAQ			
Year	N	Cash dividends	Repurchase	Overlap	N	Cash dividends	Repurchase	Overlap
2000	1945	54.29%	7.25%	3.14%	4442	8.24%	8.80%	0.65%
2001	1872	54.17%	4.38%	2.35%	3958	8.44%	5.38%	0.61%
2002	1785	52.89%	4.65%	2.02%	3387	9.21%	5.82%	0.74%
2003	1709	57.99%	3.98%	2.34%	2989	12.45%	5.59%	0.74%
2004	1715	59.83%	6.71%	4.96%	2797	14.44%	5.18%	1.64%
2005	1728	63.43%	8.04%	5.84%	2729	15.76%	5.79%	1.72%
2006	1737	62.52%	6.22%	4.84%	2683	15.32%	5.29%	1.38%
2007	1706	62.72%	5.86%	4.16%	2675	16.19%	3.85%	0.97%
2008	1608	61.88%	2.80%	2.05%	2541	16.69%	3.38%	0.55%
2009	1567	57.18%	2.04%	1.08%	2422	16.06%	1.69%	0.21%
2010	1589	56.77%	2.71%	1.76%	2362	19.18%	4.15%	0.51%
2011	1626	58.36%	3.14%	2.34%	2300	21.35%	3.39%	0.74%
2012	1629	61.26%	3.13%	2.33%	2221	27.10%	4.37%	0.45%
2013	1683	60.01%	3.03%	2.08%	2245	26.24%	2.94%	0.45%
2014	1728	59.90%	2.37%	1.68%	2408	27.41%	2.74%	0.66%
2015	1714	60.44%	2.98%	1.87%	2518	27.32%	3.34%	0.48%

Table 3.2: Groups of firms based on their dividend policy

The dividend payout information comes from CRSP monthly stock file. We focus on cash payout. Companies are sorted into groups based on the change in their dividend policy from 2007 to 2008. We calculate total amount of dividends and frequency of dividends for each firm. Group 0 consists of firms that decreased both amount and frequency of dividends to zero in 2008. Group 1 includes firms that decreased either the amount or frequency of dividends (but not zero). Group 2 contains firms that made no change to their dividends. Group 3 includes firms that increased either amount or frequency of their dividends.

Dividend policy	Group number	Number of firms	
		NYSE	NASDAQ
Decreased to zero	0	73	31
Decreased, but not to zero	1	138	55
No change	2	166	65
Increased	3	484	199
Total		861	350

Table 3.3: Number of Repurchase in Each Group

Repurchases are distributions with code starting from 5 but not 5523. Repurchase information comes from CRSP monthly stock file. Change in dividend policy refers to change in cash dividend.

Group	Change in dividend policy	2007	2008	2009	2007-2009
		Panel A: NYSE			
0	Decreased to zero	1	0	0	1
1	Decreased	2	0	0	2
2	No change	2	2	3	3
3	Increased	1	1	3	3
		Panel B: NASDAQ			
0	Decreased to zero	0	0	0	0
1	Decreased	1	1	0	2
2	No change	1	0	0	1
3	Increased	4	3	0	7

*Adding numbers of firms in 2007, 2008 and 2009 may not get number of firms 2007-2009 since same firm may repurchase in multiple years.

Table 3.4: Group characteristics: Means of key variables

Firms' characteristics in 2009 come from Compustat. Size is the natural logarithm of total asset, leverage is total asset over total debt (estimated by total asset – total equity), asset turnover is the revenue over total asset, BM ratio is the total equity over total market value, profit margin is the net income over revenue, ROE is the net income over total equity, and ROA is the net income over total asset. Institutional holding is the percentage of market value held by institutional investors. Return is average daily return of stocks.

Group	Change in dividend policy	Size	Leverage	Asset Turnover	BM	Profit margin	ROE	ROA	Institutional Holding	Return	Market value
Panel A: NYSE											
0	Decreased to zero	7.7792	1.4052	0.9579	1.5212	-0.0317	-0.2076	-0.0655	0.8962	0.0037	1948.99
1	Decreased	8.0617	1.7556	0.8654	0.7213	0.0181	-0.1048	-0.0074	0.8138	0.0035	5069.72
2	No change	7.7868	1.9408	1.0355	0.6656	0.0114	-0.0988	-0.0069	0.7920	0.0023	4849.31
3	Increased	8.4135	4.5107	0.9383	0.5793	0.0779	6.6832	0.0592	0.7262	0.0018	12483.03
Panel B: NASDAQ											
0	Decreased to zero	5.5456	3.8579	0.8057	2.5036	-0.2593	-0.6567	-0.1441	0.3683	0.0030	245.74
1	Decreased	5.7611	2.8912	1.2482	1.2748	-0.1038	-0.1194	-0.0245	0.4827	0.0037	867.61
2	No change	5.7154	3.0976	1.3853	0.9152	0.0075	-0.0232	-0.0047	0.5968	0.0016	379.97
3	Increased	6.3336	4.4340	0.9892	0.6227	0.0426	0.1560	0.0574	0.5630	0.0020	3920.71

Table 3.5: The risk-adjusted returns for each group in 2009

The monthly returns for each group are regressed on risk factors using the four-factor model [equation (1)].

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_1(r_{m,t} - r_{f,t}) + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 UMD_t + \varepsilon_{i,t}.$$

Input data are average returns of all groups and four-factor model loadings in 2009. All information comes from CRSP.

	Group 0: Dividends decreased to zero		Group 1: Dividends decreased		Group 2: No change in dividends		Group 3: Dividends increased		Groups 0 and 1	
	coef	p-value	coef	p-value	coef	p-value	coef	p-value	coef	p-value
					Panel A: NYSE					
Alpha	0.0019	0.0711	0.0011	0.0278	0.0003	0.1931	0.0001	0.6645	0.0012	0.0163
MPR	1.0584	<.0001	1.0927	<.0001	1.1214	<.0001	1.0075	<.0001	1.0879	<.0001
SMB	1.0135	<.0001	0.8395	<.0001	0.7258	<.0001	0.3333	<.0001	0.8610	<.0001
HML	0.4737	0.0006	0.2597	0.0002	0.0448	0.1678	-0.1674	<.0001	0.2873	<.0001
UMD	-0.3311	0.0002	-0.3697	<.0001	-0.1858	<.0001	-0.1599	<.0001	-0.3643	<.0001
R^2	0.7760		0.9276		0.7749		0.9749		0.9299	
					Panel B: NASDAQ					
Alpha	0.0014	0.3543	0.0017	0.0134	-0.0002	0.6488	0.0003	0.1788	0.0016	0.0109
MPR	1.0227	0.8847	0.7575	<.0001	0.9233	<.0001	0.8913	<.0001	0.6490	<.0001
SMB	0.7853	0.0004	0.7392	<.0001	0.8496	<.0001	0.5389	<.0001	0.7464	<.0001
HML	0.1832	0.3502	-0.0700	0.4297	-0.0083	0.8524	-0.1230	0.0001	-0.0328	0.6950
UMD	-0.5049	0.0001	-0.3397	<.0001	-0.1718	<.0001	-0.1905	<.0001	-0.3645	<.0001
R^2	0.9368		0.2375		0.7715		0.9601		0.7725	

Table 3.6: GRS test for alpha difference

This table reports the modified GRS test results of abnormal returns. In GRS tests, we test the difference between abnormal returns of two different groups. Sign is the sign of the difference in abnormal returns of group pairs. Detail of modified GRS tests is provided in the appendix. ***, ** and * represent significance at 1%, 5% and 10% level, respectively.

	NYSE		NASDAQ	
Group pairs	Sign	GRS	Sign	GRS
Group 0 – Group 1	+	0.652	-	0.0219
Group 0 – Group 2	+	2.55	+	0.626
Group 0 – Group 3	+	3.44*	+	0.306
Group 1 – Group 2	+	2.45	+	3.71*
Group 1 – Group 3	+	5.51**	+	2.67
Group 0 and 1 – Group 2	+	3.09*	+	2.78*
Group 0 and 1– Group 3	+	6.47**	+	3.92**

Table 3.7: Returns over matched benchmark

We collect information for dividend payers and dividend non-payers and match them up in 2009. We use property score matching to find a unique benchmark from non-payers for each payer. Industry, size, leverage, asset turnover, BM and profit margin are used to match a payer to a non-payer. Matched nonpayers for each group serve as the benchmark for each group. This table reports average risk-adjusted returns of each group and its benchmark group, and the difference between them.

	Excess Return	Benchmark Excess return	Difference in excess returns	t	Alpha	Benchmark alpha	Difference in alphas	t
				Panel A: NYSE				
Group 0	0.0050	0.0032	0.0018	1.75	0.0023	0.0010	0.0013	1.06
Group 1	0.0049	0.0035	0.0013	0.98	0.0025	0.0010	0.0016	0.99
Group 0 and 1	0.0049	0.0034	0.0014	1.17	0.0025	0.0009	0.0016	1.10
Group 2	0.0022	0.0031	-0.0008	-3.16	0.0002	0.0008	-0.0006	-2.22
Group 3	0.0017	0.0025	-0.0009	-6.89	0.0000	0.0004	-0.0004	-3.39
				Panel B: NASDAQ				
Group 0	0.0031	0.0017	0.0013	0.71	0.0016	0.0003	0.0013	0.68
Group 1	0.0035	0.0030	0.0005	1.11	0.0015	0.0010	0.0005	1.03
Group 0 and 1	0.0034	0.0027	0.0006	1.34	0.0015	0.0009	0.0006	1.25
Group 2	0.0015	0.0028	-0.0013	-2.94	-0.0002	0.0012	-0.0015	-2.72
Group 3	0.0020	0.0029	-0.0009	-4.2	0.0002	0.0011	-0.0009	-2.92

Table 3.8: Cross-sectional tests

We use cross-sectional regressions to further investigate the relationship between risk-adjusted returns and dividend policy changes.

$$Alpha_i = \alpha + \beta_1 Size_i + \beta_2 Leverage_i + \beta_3 Turnover_i + \beta_4 BM_i + \beta_5 Margin_i + \beta_6 ROA_i + \gamma Group_i + \varepsilon_i.$$

Daily excess return and alpha in 2009 serve as the dependent variables. The interested variable is *Group*, representing the dividend policy change from 2007 to 2008. Control variables include fundamental information of each firm in 2009. Fundamental information comes from Compustat.

	Dependent Variable: Alpha, 2009				Dependent Variable: Average excess return, 2009			
	Model 1		Model 2		Model 3		Model 4	
	Coefficient	P value	Coefficient	P value	Coefficient	P value	Coefficient	P value
Panel A: All								
Group	-7.53E-04	0.00	-8.08E-04	0.00	-9.84E-04	0.00	-9.54E-04	0.00
Control Variables	No		Yes		No		Yes	
N	1037		976		1037		976	
Adj R-square	976		0.0098		0.0318		0.0337	
Panel B: NYSE								
Group	-9.20E-04	0.00	-9.59E-04	0.00	-1.13E-03	0.00	-1.15E-03	0.00
Control Variables	No		Yes		No		Yes	
N	734		692		734		692	
Adj R-square	0.015		0.009		0.036		0.038	
Panel C: NASDAQ								
Group	-3.70E-04	0.03	-2.82E-04	0.14	-4.50E-04	0.00	-3.02E-04	0.05
Control Variables	No		Yes		No		Yes	
N	303		284		303		284	
Adj R-square	0.0125		0.0964		0.0324		0.0996	

Table 3.9: Cross-sectional tests: Heckman correction

We address the survival bias by adding missing observations and conducting Heckman correction. First, we collect information of delisted firms and add them back into our sample prior to the date they delisted. Second, we identified those firms that are in the 2007 sample but disappear in the 2009 sample and calculate inverse mills ratio (*IMR*) for observations in 2009 sample through equation (4) - (5).

$$P(Drop_i = 1) = \alpha_i + \sum_{k=1}^{6} \beta_k Control_{ik}^{2007} + \varepsilon_i,$$

$$IMR_i = \frac{\phi(Predicted\ value_i)}{\Phi(Predicted\ value_i)},$$

then we add *IMR* to the equation,

$$Aplha_i = \alpha_i + \sum_{k=1}^{6} \beta_k Control_{ik}^{2009} + \gamma Group_i + \delta IMR_i + \varepsilon_i.$$

	Dependent Variable: Alpha, 2009				Dependent Variable: Average excess return, 2009			
	Model 1		Model 2		Model 3		Model 4	
	Coefficient	P value	Coefficient	P value	Coefficient	P value	Coefficient	P value
Panel A: All								
Group	-8.26E-04	0.00	-8.44E-04	0.00	-1.08E-03	0.00	-9.95E-04	0.00
Control Variables	No		Yes		No		Yes	
Inverse Mills Ratio	Yes		Yes		Yes		Yes	
Delisted Firms	Yes		Yes		Yes		Yes	
N	960		950		960		950	
Adj R-square	0.0141		0.0100		0.0330		0.0394	
Panel B: NYSE								
Group	-1.01E-03	0.00	-9.86E-04	0.00	-1.32E-03	0.00	-1.16E-03	0.00
Control Variables	No		Yes		No		Yes	
N	677		673		677		673	
Inverse Mills Ratio	Yes		Yes		Yes		Yes	
Delisted Firms	Yes		Yes		Yes		Yes	
Adj R-square	0.0143		0.0079		0.0368		0.0375	
Panel C: NASDAQ								
Group	-4.25E-04	0.02	-3.41E-04	0.08	-5.38E-04	0.00	-3.65E-04	0.01
Control Variables	No		Yes		No		Yes	
Inverse Mills Ratio	Yes		Yes		Yes		Yes	
Delisted Firms	Yes		Yes		Yes		Yes	
N	283		277		283		277	
Adj R-square	0.0238		0.0395		0.0456		0.1271	

Table 3.10: Effect of corporate governance on future performance of each group

We test the effect of management on the return effect of dividend policy changes. We use institutional holding as a measure of managers' effort in 2007. Institutional holding comes from Thomson Reuters.

$$Aplha_i = \alpha + \sum_{k=1}^{6} \beta_k Control_{ik}^{2009} + \gamma_1 Group_i + \gamma_2 IH_i^{2007} + \gamma_3 Group_i IH_i^{2007} + \varepsilon_i.$$

Alphas and excess returns in 2009 are dependent variables, firms' fundamentals in 2009 are control variables.

	Dependent Variable: Alpha, 2009				Dependent Variable: Average excess return, 2009			
	Model 1		Model 2		Model 3		Model 4	
	Coefficient	P value	Coefficient	P value	Coefficient	P value	Coefficien	P value
Panel A: All								
Institution holding	2.15E-04	0.77	4.42E-03	0.03	1.24E-03	0.05	6.45E-03	0.00
Institution holding* Group			-1.77E-03	0.03			-2.19E-03	0.00
Group	-8.22E-04	0.00	4.72E-04	0.46	-9.36E-04	0.00	6.66E-04	0.22
Control Variables	Yes		Yes		Yes		Yes	
N	959		959		959		959	
Adj R-square	0.0092		0.0131		0.0376		0.0465	
Panel B: NYSE								
Institution holding	6.47E-04	0.56	7.00E-03	0.06	1.33E-03	0.16	8.75E-03	0.01
Institution holding* Group			-2.56E-03	0.07			-2.99E-03	0.02
Group	-9.64E-04	0.00	1.09E-03	0.36	-1.13E-03	0.00	1.27E-03	0.22
Control Variables	Yes		Yes		Yes		Yes	
N	679		679		679		679	
Adj R-square	0.0089		0.012		0.0403		0.0471	
Panel C: NASDAQ								
Institution holding	-5.05E-04	0.39	1.54E-03	0.33	2.32E-04	0.62	2.20E-03	0.08
Institution holding* Group			-8.64E-04	0.17			-8.32E-04	0.09
Group	-2.91E-04	0.14	1.98E-04	0.62	-2.96E-04	0.05	1.74E-04	0.58
Control Variables	Yes		Yes		Yes		Yes	
N	280		280		280		280	
Adj R-square	0.0228		0.0261		0.0728		0.0792	

Table 3.11: Effect of corporate governance on future performance of each group: The persistence effect of institutional holding

We test the effect of management on the return effect of dividend policy changes controlling the persistence effect of institutional holding. We use institutional holding as a measure of managers' effort in 2007. A two-stage regression is used to exclude the effect of institutional holding in 2009. Alphas and excess returns in 2009 are dependent variables in first stage regressions,

$$Alpha_i = \alpha + \beta IH_i^{2009} + u_i.$$

Residual from first stage is the dependent variable in second stage.

$$\hat{u}_i = \alpha + \sum_{k=1}^{6} \beta_k Control_{ik}^{2009} + \gamma_1 Group_i + \gamma_2 IH_i^{2007} + \gamma_3 Group_i IH_i^{2007} + \varepsilon_i.$$

The interested variable is Group and its interaction term with institutional holding.

	Dependent Variable: Residual, Alpha				Dependent Variable: Residual, Average excess return			
	Model 1		Model 2		Model 3		Model 4	
	Coefficient	P value	Coefficient	P value	Coefficient	P value	Coefficient	P value
				Panel A: All				
Institution holding	8.95E-04	0.00	3.11E-03	0.00	8.95E-04	0.00	3.11E-03	0.00
Institution holding* Group			-9.32E-04	0.00			-9.32E-04	0.00
Group	-4.33E-04	0.00	2.49E-04	0.25	-4.33E-04	0.00	2.49E-04	0.25
Control Variables	Yes		Yes		Yes		Yes	
N	934		934		934		934	
Adj R-square	0.072		0.0824		0.0720		0.0824	
				Panel B: NYSE				
Institution holding	1.55E-03	0.00	6.03E-03	0.00	1.74E-03	0.00		0.00
Institution holding* Group			-1.81E-03	0.00			-2.38E-03	0.00
Group	-4.56E-04	0.00	9.92E-04	0.00	-7.06E-04	0.00	1.20E-03	0.00
Control Variables	Yes		Yes		Yes		Yes	
N	668		668		668		668	
Adj R-square	0.1154		0.1434		0.1902		0.2257	
				Panel C: NASDAQ				
Institution holding	1.58E-04	0.76	1.55E-03	0.25	3.72E-04	0.45	2.34E-03	0.07
Institution holding* Group			-5.92E-04	0.26			-8.38E-04	0.10
Group	-2.84E-04	0.08	5.41E-05	0.87	-3.26E-04	0.04	1.52E-04	0.64
Control Variables	Yes		Yes		Yes		Yes	
N	266		266		266		266	
Adj R-square	0.0196		0.0205		0.0704		0.0766	

Table 3.12: Effect of corporate governance on future performance of each group: performance over matched benchmarks

We test the effect of management on the return effect of dividend policy changes. We use institutional holding as a measure of managers' effort in 2007. Institutional holding comes from Thomson Reuters.

$$Excess\ Aplha_i = Aplha_i - Aplha_i^{Benchmark},$$

$$Excess\ Aplha_i = \alpha + \sum_{k=1}^{6} \beta_k Control_{ik}^{2009} + \gamma_1 Group_i + \gamma_2 IH_i^{2007} + \gamma_3 Group_i IH_i^{2007} + \varepsilon_i.$$

Excess alphas and excess returns in 2009 are dependent variables, firms' fundamentals in 2009 are control variables.

	Dependent Variable: Excess Alpha, 2009				Dependent Variable: Excess Return, 2009			
	Model 1		Model 2		Model 3		Model 4	
	Coefficient	P value	Coefficient	P	Coefficient	P value	Coefficient	P
Panel A: All								
Institution holding	-8.67E-05	0.00	5.56E-03	0.00	6.32E-04	0.39	7.21E-03	0.00
Institution holding* Group			-2.36E-03	0.00			-2.74E-03	0.00
Group	-4.58E-04	0.00	1.29E-03	0.00	-6.08E-04	0.00	1.43E-03	0.00
Control Variables	Yes		Yes		Yes		Yes	
N	935		935		935		935	
Adj R-squared	0.0085		0.0059		0.0087		0.0197	
Panel B: NYSE								
Institution holding	-5.93E-04	0.19	4.86E-03	0.00	-9.04E-05	0.86	7.03E-03	0.00
Institution holding* Group			-2.19E-03	0.00			-2.86E-03	0.00
Group	-3.83E-04	0.00	1.38E-03	0.00	-5.02E-04	0.00	1.80E-03	0.00
Control Variables	Yes		Yes		Yes		Yes	
N	673		673		673		673	
Adj R-squared	0.0677		0.0861		0.0757		0.0471	
Panel C: NASDAQ								
Institution holding	-7.24E-04	0.48	2.79E-03	0.30	2.36E-04	0.80	3.47E-03	0.16
Institution holding* Group			-1.48E-03	0.16			-1.37E-03	0.16
Group	-8.66E-05	0.79	7.73E-04	0.27	-2.47E-04	0.40	5.45E-04	0.39
Control Variables	Yes		Yes		Yes		Yes	
N	262		262		262		262	
Adj R-squared	0.0122		0.0198		0.0186		0.0263	

Figure 3.1: Daily alpha difference in the third year, NYSE

We form three-year sets from 1999 to 2015. First two years are used to classify dividend policy change groups and we calculate alphas in the third year through the four-factor model for each group in each set.

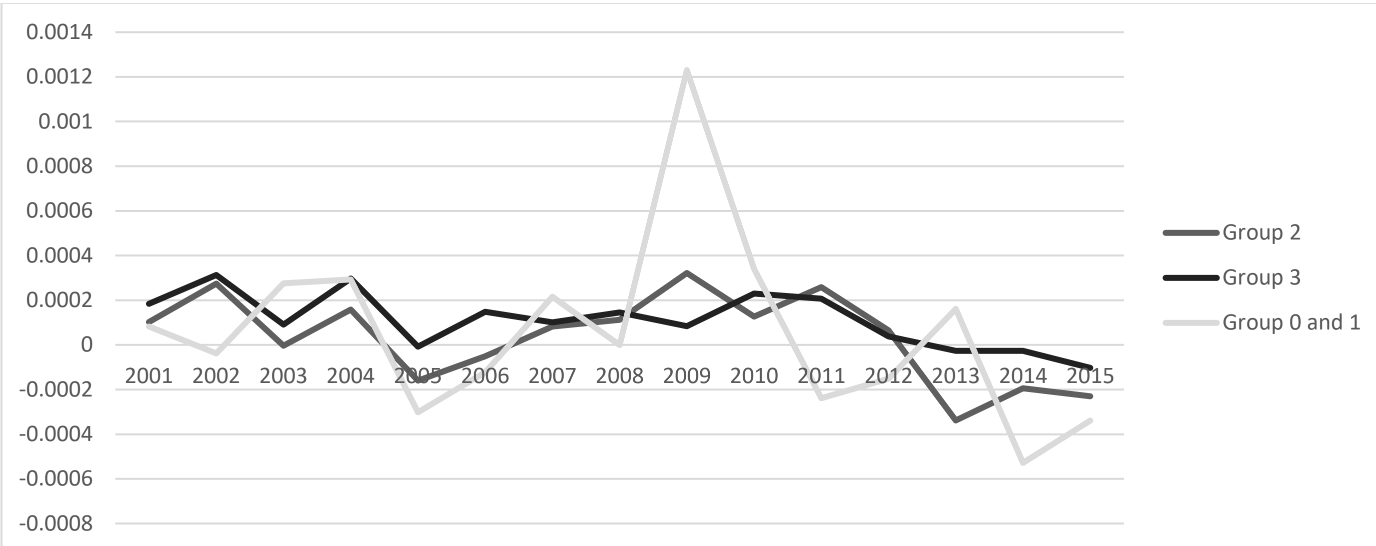
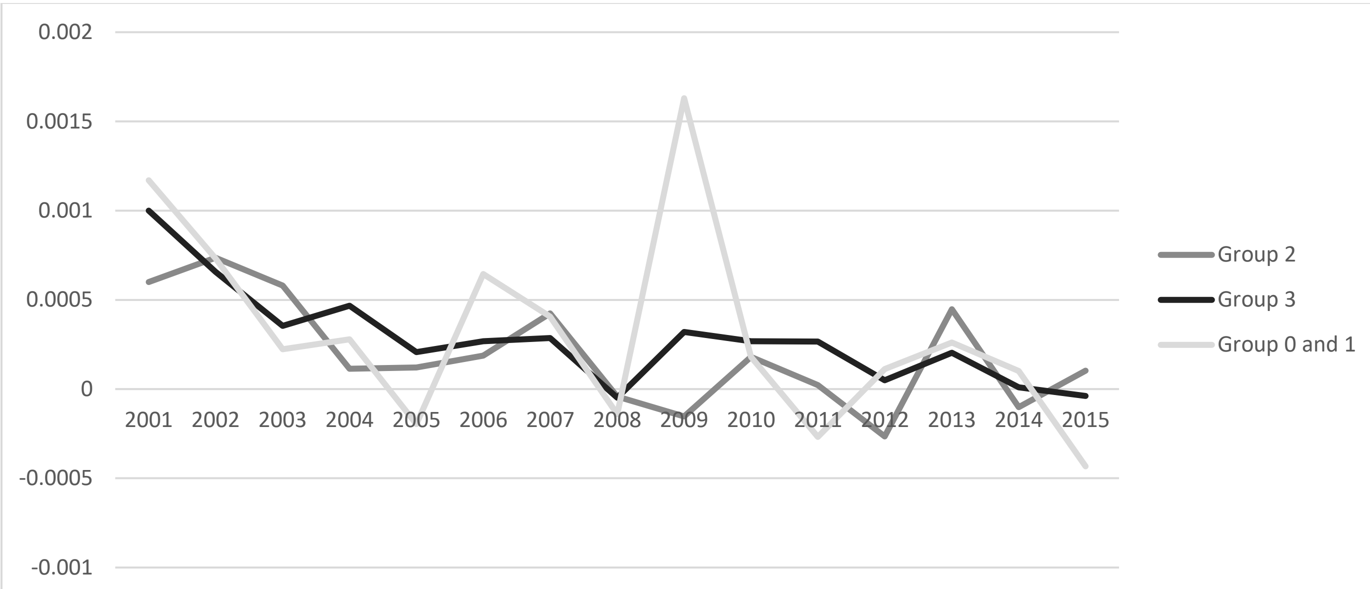


Figure 3.2: Daily Alpha Difference in the Third Year, Nasdaq

We form three-year sets from 1999 to 2015. First two years are used to classify dividend policy change groups and we calculate alphas in the third year through the four-factor model for each group in each set.



Appendix: Modified GRS test

Gibbons, Ross and Shanken (1989) provide their GRS test on abnormal returns. The null hypothesis of GRS test is all *α*s equal to zero. In our work, we want to compare abnormal returns between groups. Therefore, we make a modification to GRS test. Following Morrison (2005), we have

$$H_0: \alpha_i - \alpha_j = 0 \ or\ R'\alpha = 0$$

$$\sqrt{\frac{T}{1+\hat{\theta}}}\hat{\alpha} \sim N\left(\sqrt{\frac{T}{1+\hat{\theta}}}\alpha, \Sigma\right). \quad \text{(A.3.1)}$$

$$\sqrt{\frac{T}{1+\hat{\theta}}}R'\hat{\alpha} \sim N\left(\sqrt{\frac{T}{1+\hat{\theta}}}R'\alpha, R'\Sigma R\right). \quad \text{(A.3.2)}$$

$R'\hat{\alpha}$ and $R'\Sigma R$ are independent. $(T-2)R'\Sigma R$ follows Wishart distribution. Then apply GRS's conclusion,

$$F = \frac{T(T-N-K)}{N(T-2)}\frac{(R'\hat{\alpha})'(R'\hat{\Sigma}R)^{-1}(R'\hat{\alpha})}{1+\hat{\theta}^2} \sim F_{N,T-N-K}. \quad \text{(A.3.3)}$$

N is the number of restriction, which is 1 in our tests. *K* is the number of factors, which is 4 since we use four-factor model. $\hat{\theta} = \hat{\mu}_f{}'\hat{\Omega}^{-1}\hat{\mu}_f$, where $\hat{\mu}_f$ is the sample mean of factor loadings and $\hat{\Omega}$ is the max-likelihood estimation of covariance matrix of factor loadings.

We are interested whether alpha of one group is significantly larger than alpha of another group. So

$$H_1: \alpha_i - \alpha_j > 0 \ or\ R'\alpha > 0.$$

Null is rejected when $F < F_{2a,N,T-N-K}$ and $\alpha_i - \alpha_j > 0$ (Follmann, 1996).