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On the relation between liquidity and the futures-cash basis: evidence from a natural experiment ^{*}

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&
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Abstract

As a response to the 2015 Chinese stock market crash, regulators prohibited arbitrage activities in the index futures and cash markets. We use this natural experiment to test the hypothesis that liquidity and pricing efficiency causally affect each other. We find that resulting shift in the arbitrage boundary led to the breakdown of the two-way causality relation between liquidity and the absolute futures-cash basis. We thus confirm that the relation between liquidity and the absolute futures-cash basis is not driven by the omitted variable bias, but is indeed due to arbitrage.

JEL classification: G01, G14, G18

Keywords: Futures-cash basis; Liquidity; Trading restrictions; Arbitrage

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1 Introduction

The law of one price is the economic theory that two traded or synthesized instruments with the same future cash flows should trade at the same price due to arbitrage trades. The effectiveness of arbitrage in enhancing pricing efficiency should depend on liquidity. Roll, Schwartz, and Subrahmanyam (2007) test this notion by comprehensively investigating the intertemporal association between stock market liquidity and the absolute futures-cash basis in the context of the New York Stock Exchange (NYSE) index futures/cash markets. Using a vector autoregressions (VAR) approach, they find that the innovations to the absolute futures-cash basis and spreads are positively correlated, and there is a positive two-way Granger causality relation between them. The underlying mechanism of this phenomenon, as surmised by Roll, Schwartz, and Subrahmanyam (2007), is that a liquid market would facilitate arbitrage trades and then eliminate market mispricing, while the arbitrage triggered trades in response to a wide futures-cash basis could also reduce liquidity due to order imbalances.¹ This two-way relation also exists in the international markets (e.g., Lee, Chien, and Liao, 2012; Kadapakkam and Kumar, 2013).

However, there remains one potential issue in Roll, Schwartz, and Subrahmanyam (2007) and other relevant studies, which is the “*omitted variable bias*.” Testing if and how market liquidity and the absolute futures-cash basis interacts with each other poses a tricky identification challenge. According to Granger (1980), Lütkepohl (1982), and Stock and Watson (2001), among others, the results on Granger causality could be spurious or measure wrong feedback relations, if as is likely, there are omitted variables (such as interest rate, market volatility, and market sentiment, etc. in our context)² that simultaneously affect liquidity and the absolute futures-cash basis. In our context, to overcome the potential for omitted

¹The interplay between market efficiency and liquidity is an enduringly important research question in the financial economics literature. For instance, Kumar and Seppi (1994) point out, arbitrage activities, and hence, the futures-cash basis, may be affected by liquidity. In the reverse direction, market-wide order imbalances resulting from arbitrage trades may have a contemporaneous and a persistent impact on liquidity (e.g., Stoll, 1978a; O’Hara and Oldfield, 1986; Chordia, Roll, and Subrahmanyam, 2002).

²For instance, numerous theoretical and empirical studies have demonstrated the role volatility plays in driving illiquidity (e.g., Stoll, 1978b, 2000; Amihud and Mendelson, 1989; Chordia, Roll, and Subrahmanyam, 2001; Chordia, Sarkar, and Subrahmanyam, 2005), while Chen, Cuny, and Haugen (1995) document that stock market volatility is a key determinant of the index futures-cash basis.

variable bias, the commonly used approaches in the ordinary least squares (OLS) regression, i.e., instrument variables or exogenous shocks to independent variable(s), can prove difficult since we have two series of lagged independent variables.³

In this study, we formally test whether the interplay between liquidity and the absolute futures-cash basis is caused by the forces of arbitrage. We employ a natural experiment to “shut down” the driving force (arbitrage activities) and test whether the two-way relation between liquidity and the futures-cash basis still holds or not. Specifically, recent trading restrictions on short sales and index futures trading in the Chinese financial markets provide us with an ideal laboratory setting for such an identification strategy.⁴ As a response to the Chinese stock market crash starting in the middle of June 2015, since July 2015, regulators successively restricted the positions for the “speculation or arbitrage” purpose in the index futures market by limiting the number of trades and sharply increasing the transaction costs and margin rates. Regulators also de facto banned short positions in the stock market.⁵ Under these restrictions, arbitrage trades, which need to set up simultaneous positions in both markets and are sensitive to transaction costs, are in fact infeasible. Hence, in this restriction experiment, the positive two-way relation between the absolute futures-cash basis and illiquidity should break down if their relation is indeed due to the arbitrage activities other than the endogeneity problem.

We first investigate the relation between the Chinese Securities Index 300 (CSI 300) absolute futures-cash basis and the aggregate liquidity of the CSI 300 using the VAR approach and impulse response analysis for the sample period from January 2, 2012 to May 29, 2015 (a half month before the market crash). In this pre-restriction period, results are in line with the findings in both U.S. and international markets: the absolute futures-cash basis and market illiquidity have a positive two-way causality relation both statistically and

³Roll, Schwartz, and Subrahmanyam (2007) mention the possible existence of the omitted variable bias and control for volatility and signed index returns, the possible common drivers, in the VAR estimation. However, as it is impossible to control for all the known and unknown factors in one system, we adopt a different identification strategy based on the economic mechanism behind the statistical relation.

⁴Stock and Watson (2001) also suggest that, although not commonly used in the literature, the natural experiment approach could be a remedy for the omitted variable bias problem in the Granger causality test.

⁵We provide a more detailed introduction of this restriction experiment in Section 2 and Appendix A.

economically, and the results are stronger for the effective spread measure compared to the quoted spread measure, possibly due to the fact that the effective spread is a more accurate estimate of arbitrage cost (Blume and Goldstein, 1997).

We next examine the sample period that covers the quasi-natural experiment (July 7, 2015 to June 30, 2016). We find that the significant two-way causality relation in the pre-restriction period disappears in this restriction period for all the futures contracts. The impulse response analyses also show that shocks to spreads (bases) are uninformative towards the future movements of bases (spreads) and the mean values of response are statistically different from those in the pre-restriction period. The insignificant impulse responses also reveal that the economic significance of the cross-effects between liquidity and the futures-cash basis is negligible. To ensure the robustness, we also use a more strict definition for the restriction period (August 3, 2015 to June 30, 2016), and the results are qualitatively unaltered. Moreover, we use the Z-test to statistically compare the VAR coefficients in the two sample periods (pre-restriction and restriction) and the results indicate that the coefficients are significantly different between these two sample periods. Overall, our results confirm the hypothesis that arbitrage is the underlying mechanism that drives the interplay between spreads and the futures-cash basis.

One remaining concern for our central conclusion is the market crash effect. Lien et al. (2013) argue that when market liquidity decreases and the absolute futures-cash basis increases (a typical phenomenon during the 2015 Chinese market crash), the dependence structure between these two variables may break down. Since our restriction period overlapped the Chinese market crash period, our treatment effect (restriction) might therefore be confounded by the market crash effect that can potentially provide explanatory power for our results. To alleviate this concern, we first conduct a Granger causality test in the post-crash sample period from September 1, 2015 to June 30, 2016. The relation between spreads and the absolute futures-cash basis, however, is still insignificant for this stable period in the market. Second, we use the Hang Seng China Enterprise Index (HSCEI)⁶ in the Hong Kong

⁶The HSCEI was established on October 3, 2001, based on companies listed in Hong Kong but registered in mainland China (“H” shares). This index comprises the 40 largest and most liquid H shares.

Stock Exchange (HKEx) as a control group. Since the variation in “H” shares’ stock prices reflects operating information in mainland China, the HSCEI is highly integrated with the mainland China stock markets. As a result, during the 2015 Chinese stock market crash, the HSCEI also experienced severe turmoil. However, in contrast to mainland China, there is no trading restriction imposed on either the futures or cash markets in Hong Kong. We find that a positive two-way relation prevails in both pre-restriction and restriction periods in the Hong Kong market. Collectively, our findings effectively rule out the likelihood that the treatment effect in the restriction period is driven by the market crash effect.

Our study contributes to two strands of literature. First, this paper complements and extends, both methodologically and substantively, a rigorous analysis of the relation between liquidity and the futures-cash basis. To the best of our knowledge, this is the first study that formally addresses the omitted variable bias problem in the bulk of the literature on this topic. Based on a novel identification strategy, we conclude that the interplay between liquidity and pricing efficiency is “casual” other than “correlated” and confirm that arbitrage is indeed the underlying mechanism.

Second, our paper also joins the literature on the consequences of regulations during a market crash. Using the 2007-2009 global financial crisis as a natural experiment, researchers have mainly focused on the impact of short selling bans on liquidity and pricing efficiency separately across different markets (e.g., Boulton and Braga-Alves, 2010; Beber and Pagano, 2013; Boehmer, Jones, and Zhang, 2013; Trebbi and Xiao, 2015). Focusing on the recent 2015 Chinese market crash, we tackle the real effects of regulations on liquidity and market efficiency jointly. We utilize the restrictions in both futures and stock markets in China and document that the regulations triggered arbitrage constraint shuts down the interaction between liquidity and market efficiency during and after the 2015 Chinese market crash.

The rest of the paper proceeds as follows. We provide the institutional background in Section 2. In Section 3, we describe the variable construction methods and outlines our data. In section 4, we present the empirical results. Concluding remarks are given in Section 5.

2 Institutional background

In this section, we focus on introducing the institutional background of the natural experiment, including the 2015 Chinese market crash, the short sale bans in the stock market and the trading restrictions in the index futures market, and the uniqueness of this Chinese regulatory experiment comparing to the regulation shocks in other markets.

As shown in Figure 1, after a sharp rise from the middle of March to the middle of June, the Chinese stock market started to crash on June 15, 2015 and in the consecutive 17 trading days, the CSI 300 index dropped from 5335.11 to 3663.04, or 31.34%. After three stable weeks, the CSI 300 index collapsed again on August 24, falling 8.49%, marking the largest decline since 2007, and continued to drop by 7.63% on August 25.⁷ Since September 1, the market started to improve and became steady. By the end of December 2015, the CSI 300 index had recovered from the crash and outperformed the S&P 500 Index for 2015. In the first week of 2016, on both January 4 (Monday) and January 7 (Thursday), trading in the Chinese stock market and index futures market was halted after a 7% drop in the CSI 300 index from the time markets opened because of the newly issued circuit-breaker rule.⁸ Regulators suspended the circuit-breaker rule on January 8.⁹ In January, the CSI 300 index decreased by 17.74%. Beginning in February, the Chinese stock market slowly recovered from the panic caused by the circuit-breaker rule and the CSI 300 index has remained around 3,200. As of October 24, 2016, the CSI 300 index is at the level of 3367.58.

< **Insert Figure 1 here** >

During the 2015 Chinese crash period (June 15, 2015 to August 31, 2015), the index futures trading was commonly blamed by the public as the catalyst for the market decline.¹⁰

⁷These two days are known as “Black Monday and Tuesday.” Since there is a 10% downside limit in the Shanghai and Shenzhen stock markets, a drop of 8.49% means that the majority of the stocks in the market had hit the limit ban.

⁸The complete trading session on Thursday lasted only 29 minutes, including a 15-minute halt in trading that was triggered after an initial 5% drop in the index. See a related report at: <http://www.bloomberg.com/news/articles/2016-01-07/china-s-29-minutes-of-chaos-stunned-brokers-and-a-race-to-sell>.

⁹We remove the first week of January 2016 from our sample due to the consideration that the measurement of futures-cash basis and spreads would be inaccurate in these extremely short-ended sessions.

¹⁰See a related report at: <http://english.caixin.com/2015-09-09/100847961.html>.

Beginning on July 7, 2015, a bundle of policies were implemented by regulators to restrict speculative contracts in index futures and other shorting behaviors.¹¹ In the Chinese index futures market, all the futures positions are divided into two groups: hedging positions and speculative positions. To open hedging positions, investors should apply to the China Financial Futures Exchange (CFFEX), and the number of contracts they can open is limited to cover their long-term stock investments. Typically, hedging positions are opened by institutional investors such as mutual funds and brokers. All other positions are classified by the regulators as speculative positions, which include positions for arbitrage and speculative purposes.

The policies for the futures market are designed to primarily restrict speculative positions, while hedging positions are only slightly influenced (increasing margin rate from 10% to 20%). Currently, the restrictions on speculative positions include limiting the number of opening contracts to no more than 10 per day per investor, increasing the margin rate to 40% (which was 10% before) and increasing transaction cost to 0.230% (which was 0.005% before). In Appendix A, we further discuss these policies.

Without official announcements, short selling is de facto frozen in the Chinese stock market. In Figure 2, we plot the daily volume of short selling, with the data obtained from Shanghai and Shenzhen Stock Exchanges. Since July 7, 2015, the trading volume dropped dramatically. On August 4, 2015, regulators changed the trading rule for short sales from “ $T+0$ ” to “ $T+1$ ”, which the market interpreted as a signal to comprehensively restrict short selling. It is evident that starting from that date, trading volume is negligible compared to the pre-restriction period. Trading restrictions for both markets dramatically increase the cost of arbitrage and make them infeasible, which provides an ideal quasi-natural experiment to identify the channel underlying the relation between liquidity and the futures-cash basis.¹²

¹¹See related reports at: http://english.gov.cn/news/top_news/2015/07/07/content_281475142013234.htm and <http://www.reuters.com/article/china-markets-futures-idUSB9NOVJ02P20150826>.

¹²Trading restrictions, especially the short selling ban, could lead to increased volatility (e.g., Boulton and Braga-Alves, 2010; Boehmer, Jones, and Zhang, 2013). In untabulated results, we also control for volatility and the results remain qualitatively the same. Therefore, our identification strategy would not be confounded by the volatility effect.

< Insert Figure 2 here >

During the 2007-2009 global financial crisis, most regulators around the world imposed bans or constraints on short sales, either for financial stocks only or for the entire stock market (Beber and Pagano, 2013). As recently as 2011 and 2012, Belgium, France, Italy, and Spain imposed renewed short selling restrictions on stocks. Even though without restrictions on the index futures market, restrictions on short sales in the cash market would also prohibit the arbitrage trades in the presence of negative futures-cash basis, thus making our testing strategy possibly feasible in these markets. However, compared to other markets, the Chinese stock and futures markets provide a better laboratory setting for our research question.

First, the index futures market in China is active and has a large trading volume. In 2014, the trading volume of the CSI 300 futures contracts was more than 216 million and ranked in the top-10 worldwide Equity Index Futures & Options Contracts by the Futures Industry Association.¹³ In July 2015, the China Financial Futures Exchange was ranked by the World Federation of Exchanges as the most active market for index futures.¹⁴ Among all the markets that issued short selling bans, only the U.S. and Japanese markets have comparable futures trading volumes. Second, the restrictions in the Chinese market are comprehensive. Since July 2015, regulators in China restricted transactions on both the futures and stock markets. In other markets, the index futures trading was unaffected. For short sales in the stock market, some market restrictions only applied to financial stocks (e.g., U.S., U.K., Canada, and South Korea) instead of the entire market or were only in the form of a naked ban other than a covered ban (e.g., Japan, Spain, Switzerland, and Italy). Under these circumstances, arbitrage in the futures/stock market is still possible. For instance, Karmaziene and Sokolovski (2015) show that short selling equity ETFs was a viable method of circumnavigating the ban in the U.S. market and they estimated that close to \$5.5 billion new short positions were established using the ETFs. Third, the trading restriction period in China is long and covers both a market crash period and a more settled period, thus alleviating the concern that our results may be driven by a market crash. In summary,

¹³<https://fimag.fia.org/>.

¹⁴<http://www.world-exchanges.org/>.

to the best of our knowledge, China might be the only market that can satisfy all three conditions: (i) active with large trading volume, (ii) incurring comprehensive restrictions, and (iii) having a sufficiently long restriction period. All these three conditions are crucial for our identification strategy to be feasible and effective.

3 Data

In this section, we introduce the data sources and explain the methods used to construct the futures-cash basis and liquidity measures. Our analysis focuses on the CSI 300 cash index and the CSI 300 index futures. The CSI 300 index was initiated by the China Securities Index Company Ltd on April 8, 2005 to measure the performance of the aggregate Chinese stock market. It consists of the top 300 stocks with the largest market capitalization from the Shanghai Stock and Shenzhen Stock Exchanges, the total value of which accounts for 70% of the total market capitalization of these two markets. To provide investors with a hedging instrument, the China Financial Futures Exchange introduced index futures against the CSI 300 index on April 16, 2010.¹⁵

3.1 Futures-cash basis

Following MacKinlay and Ramaswamy (1988), the absolute value of the relative index futures basis (henceforth, ABAS) can be defined as:

$$ABAS = \frac{|Fe^{-(r-\delta)t} - S|}{S}, \quad (1)$$

where F is the index futures price; S is the cash stock market index; r is the risk-free rate over the remaining life of the contract; t is the time to contract expiration; and δ is the dividend yield over the contract's remaining lifetime.

Specifically, the absolute futures-cash basis is empirically constructed with the following components: F is the daily closing futures price on the CSI 300 index futures contract, while

¹⁵For details about the CSI 300 index and the CSI 300 index futures market, see Yang, Yang, and Zhou (2012).

S is the daily closing value of the CSI 300 index.¹⁶ The risk-free rate r is the Shanghai Interbank Offered Rate (SHIBOR) maturing as close to the futures expiration date as possible.¹⁷ The dividend yield δ is the (continuously compounded) difference between the CSI 300 total return index and the CSI 300 index. All the data used in constructing the absolute futures-cash basis are obtained from Datastream.

The expiration day of the CSI 300 index futures contracts is the third Friday of the contract (delivery) month. Contract (delivery) months include the current month, next month, and the final months of next quarter and next two quarters, which are called quarter-months. We plot the daily trading volumes of these four contracts from January 2, 2012 to June 30, 2016 in Figure 3. As clearly shown, the current-month contract has the highest trading volume and the contracts for the final months of next quarter and next two quarters are inactively traded with volumes negligible compared to the other two contracts. Therefore, we focus only on the first two contracts in the following analysis.

< **Insert Figure 3 here** >

We construct two absolute futures-cash basis series by starting with a contract with certain months to maturity and rolling over into a successive contract at the reset date with the same original time to maturity. We name these two basis series as current-month basis ($ABAS1$) and next-month basis ($ABAS2$).

3.2 Liquidity measures

Following Roll, Schwartz, and Subrahmanyam (2007), we use two cost-based liquidity measures for each stock, quoted spread and effective spread, and these spreads are not scaled by

¹⁶There is a slight asynchronicity between the hours of operation of the Shanghai and Shenzhen Stock Exchanges and the China Financial Futures Exchange (where the futures contracts trade). Specifically, while both the Shanghai and Shenzhen Stock Exchanges operate from 9:30 a.m. to 11:30 a.m., and then from 1:00 p.m. to 3:00 p.m. (Beijing time), the trading hours of the China Financial Futures Exchange are from 9:15 a.m. to 11:30 a.m., and from 1:00 p.m. to 3:15 p.m. (Beijing time). According to Roll, Schwartz, and Subrahmanyam (2007), although this asynchronicity will introduce some measurement errors in the basis, it should not affect the statistical inferences. To ensure the robustness, we also use the intraday trading data of the CSI 300 index futures contracts from TRTH to obtain the futures price at 3:00 pm. The untabulated results show that our conclusion remains the same.

¹⁷The maturities for SHIBOR we use are overnight, 1 week, 2 weeks, 1 month, and 3 months.

price to avoid attributing variations in stock prices to variations in liquidity. These are two widely used liquidity measures in both short-horizon and long-horizon liquidity research.¹⁸

For a given stock, the quoted spread for the s^{th} time interval is defined as:

$$Quoted\ Spread_s = Ask_s - Bid_s, \quad (2)$$

where Ask_s and Bid_s are the best ask and bid quotes for the s^{th} time interval. The daily quoted spread, $Quoted\ Spread_i$, is the time-weighted average of $Quoted\ Spread_s$ computed over all the time intervals within trading day i .

For a given stock, the effective spread for the k^{th} trade is defined as:

$$Effective\ Spread_k = 2|P_k - M_k|, \quad (3)$$

where P_k is the price of the k^{th} trade and M_k is the midpoint of the consolidated Best Bid Offer (BBO) prevailing immediately prior to the time of the k^{th} trade. Daily effective spread, $Effective\ Spread_i$, is the volume-weighted average of $Effective\ Spread_k$ computed over all the trades within trading day i .

Daily spread measures are averaged and value-weighted, across stocks (with weights proportional to market capitalizations of the tradable shares at the end of last month¹⁹) to obtain the aggregate market illiquidity measures.

To construct these two liquidity measures, we obtain intraday trades and quotes data of all the constituents of the CSI 300 index from the Thomson Reuters Tick History (TRTH) database, which is supplied by the Securities Industry Research Centre of Asia-Pacific (SIRCA). TRTH is a survivor-bias-free database that contains historical Reuters data feeds beginning January 1996 on over 5 million instruments from various exchanges. Fong, Holden, and Trzcinka (2014) documents that TRTH is a comparable database for the international

¹⁸Since our study focuses on a daily basis, we do not use the other commonly used liquidity measures, including the price impact measure of Amihud (2002), which typically measures liquidity over a relatively long time period. For a recent comprehensive review on liquidity measures, see Holden, Jacobsen, and Subrahmanyam (2014).

¹⁹Here we use the market value of tradable shares other than the total market value as it is hard to measure the market value of non-tradable shares accurately. See Li et al. (2011) for more detailed discussions on the tradable and non-tradable shares in China.

markets to that of the Trade and Quote (TAQ) for the U.S. market in terms of liquidity research.

We collect the CSI 300 index composition information from TRTH and adjust the sample of individual stocks for the aggregate liquidity measures whenever there is any adjustment in the CSI 300 index composition.

3.3 Summary statistics

We report the summary statistics of the absolute futures-cash bases and spreads in Table 1. In Panel A, we find that in the pre-restriction period, the mean values of the absolute futures-cash bases increase monotonically along the maturities, indicating the possible presence of arbitragers in the Chinese market as short-term contracts are more actively traded. The mean value of quoted spread (0.014 CNY (Chinese yuan)) is lower than that of effective spread (0.020 CNY). This is because in China the security trading scheme is order driven instead of market making. As shown in Panel B, in the restriction period, the mean values of the absolute futures-cash bases increased dramatically for both the current-month and next-month futures contracts. For instance, for the current month contract, the mean percentage absolute basis in the pre-restriction period is close to zero (0.407%), reflecting the effectiveness of arbitrage activities, while in the restriction period, it is as high as 2.083%. The high level of absolute basis is consistent with our argument that in the restriction period, arbitrage activities were prohibited and the pricing gap thereby cannot be closed. Consistent with the observations in the other markets, market liquidity strains during a market crash. Comparing Panel A with Panel C, it is evident that the spread measures increased dramatically during the 2015 Chinese stock market crash period. For instance, the mean value of the effective spread rises 35% from 0.020 CNY to 0.027 CNY. Considering that the CSI 300 index dropped more than 36% in the crash period, the percentage-based spread measures increased even more. In Panel D, we can observe that the level of market liquidity recovers to some extent after the market crash with mean values of spread measures close to those in the pre-restriction period.

< **Insert Table 1 here** >

We also plot the dynamics of the futures-cash bases and two spread measures in Figures 4 and 5. During the restriction period, the futures-cash bases were generally negative and with large magnitudes, and spreads increased sharply. In the restriction period, the least restricted position in the futures market was the hedging position and short selling in the cash market was frozen. As a result, the high magnitude of negative futures-cash bases as shown in Figure 4 might largely reflect the premiums investors were willing to pay in the futures market to hedge their long positions in the cash market.

< **Insert Figure 4 and Figure 5 here** >

Futures-cash basis and spread measures show calendar regularities and time trends (e.g., Gallant, Rossi, and Tauchen, 1992). To address this issue, following Roll, Schwartz, and Subrahmanyam (2007) and Kadapakkam and Kumar (2013), we adjust the raw absolute futures-cash bases and spreads by controlling for the weekday effect, monthly effect, pre- and post- holiday effects, and linear and quadratic time trends. For bases, we also control for the time to maturity. The residuals from these regressions are then used in the analysis.

Table 2 reports the pair-wise correlation matrix among two adjusted futures-cash basis measures ($ABAS1$ and $ABAS2$) and two spread measures ($QSPR$ and $ESPR$) in the pre-restriction period and restriction period in Panels A and B respectively. In the pre-restriction period, all correlations are positive and significant at the 1% level. The two absolute basis measures are highly correlated, and the two spread measures are also significantly related. In addition, the correlations of the bases with spreads are all positive. In contrast, we find that in Panel B, the positive correlations of the bases with spreads disappear. This finding indicates a potential structural break during the restriction period.

< **Insert Table 2 here** >

4 Results

In this section, we first show that the general pattern of the relation of the futures-cash basis and liquidity in the pre-restriction period (January 2, 2012 to May 29, 2015). Then,

to address the omitted variable bias, we adopt a natural experiment identification design and test their relation in the restriction period (July 7, 2015 to June 30, 2016). Finally, to provide further evidence that our conclusion is not driven by the market crash effect, we also conduct a sub-sample analysis and use the Hong Kong market as a control group.

4.1 Results in the pre-restriction period

In this section, the sample period is from January 2, 2012 to May 29, 2015. Our analysis mainly relies on the vector autoregressions (VAR) model, which provides evidence with a rich dynamic structure. The vector we use mainly includes two variables: adjusted absolute bases and adjusted quoted spread (or adjusted effective spread). The number of lags is chosen as the minimum of the values selected by Akaike and Schwarz information criteria, which is four in our case. Four VARs are estimated, pairing each of the two adjusted absolute bases (two futures contracts for current month and next month) with two spread measures (adjusted quoted spread and adjusted effective spread).

The VAR model that captures the joint dynamics of bases and spread measures can be expressed as:

$$y_t = \sum_{i=1}^4 \alpha_i y_{t-i} + \sum_{j=1}^4 \beta_j x_{t-j} + \epsilon_t, \quad (4)$$

where y represents the column variable, while x represents the row variable and ϵ denotes the residuals. The null hypothesis is that row variable does not Granger-cause the column variable. Hence, it is a joint test of whether all β_j equal to 0.

Panel A in Table 3 reports the F-statistics of all the pairwise Granger causality tests. The results show that *ABAS1* and *ABAS2* highly significantly Granger-cause *QSPR* and *ESPR*, suggesting that arbitrage forces, triggered by the futures-cash bases, lead to inventory imbalance and strain the liquidity in the stock market. In the other direction, *ESPR* also Granger-causes the absolute bases, especially for the next-month contract, indicating that illiquidity does impede pricing efficiency. The stronger effect for the longer-term contracts is consistent with the findings in Roll, Schwartz, and Subrahmanyam (2007), in which they argue that liquidity concerns are more relevant for arbitrageurs in longer-term, relatively

less-active contracts. In contrast to *ESPR*, the effects of *QSPR* on bases are not found to be significant. This observation is largely in parallel with Roll, Schwartz, and Subrahmanyam (2007), suggesting that effective spread, which accounts for transactions executing within and outside the quotes (Blume and Goldstein, 1997), is a more relevant estimate of arbitrage cost.

< **Insert Table 3 here** >

To have a clear picture of the Granger causality relation, we also conduct impulse response analyses. An impulse response function (IRF) depicts the current and future responses of endogenous variables to a one-time, unit standard deviation, positive shock to one of the variables. We use the inverse of the Cholesky decomposition of the residual variance-covariance matrix to orthogonalize the impulses. Figures 6 and 7 present the impulse responses of the cross effects between the absolute futures-cash basis and spread. Monte Carlo simulations (1,000 replications) are applied to get the 95% confidence intervals of the responses.²⁰

< **Insert Figure 6 and Figure 7 here** >

In Figure 6, for the responses of *QSPR* to *ABAS1*, consistent with the Granger causality result, a shock to the current-month absolute futures-cash basis has a significantly positive and persistent effect on the adjusted quoted spread. Meanwhile, even though *QSPR* does not Granger-cause absolute bases, after accounting for the joint dynamics by including the persistence of the absolute basis and liquidity variables, a shock to *QSPR* also leads to a higher absolute futures-cash basis. As shown in Figure 6, the cross-effect of *ESPR* and *ABAS1* exhibits a similar pattern. For the next month contract (Figure 7), we find both spreads (bases) shocks are informative towards future movements of bases (spreads). The results in the impulse response analysis reinforce our findings in the Granger causality test.

Next, we gauge the economic significance in a similar way to that of Roll, Schwartz, and Subrahmanyam (2007).²¹ Specifically, we measure economic significance using both

²⁰To save space and make the main results more clearly presented, we leave the impulse responses of bases (spreads) to their own shocks in the Online Appendix Figures A1-A4. The results show that these responses decay overtime, indicating that these variables are stationary.

²¹By doing so, we can also compare the results in the pre-restriction period and the restriction period economically. We thank an anonymous referee for this suggestion.

CNY value and percentage. When the response variable is *QSPR* (or *ESPR*), the economic significance in terms of CNY value is the annualized extra trading cost of a daily round-trip trade of one million shares in the basket of CSI 300 stocks caused by a one standard deviation shock from *ABAS1* (or *ABAS2*); the economic significance in terms of percentage for spread is measured as extra trading cost over the average total trading cost. When the response variable is *ABAS1* (or *ABAS2*), the economic significance in terms of CNY value is the annualized extra divergence between the futures and its cash value for a trade of one million shares of a 40 CNY stock, caused by a one standard deviation shock from *QSPR* (or *ESPR*); the economic significance measured in percentage is the extra divergence value over the average total divergence value. The specific formulas for these measures are in the Note portion of Table 4. Information used to calculate these measures is from Panel A in Table 1 and Figures 6 and 7.

We summarize the results with respect to the economic significance of the IRFs in Table 4. As shown, for a daily round-trip trade of one million shares of CSI 300 stocks, a one standard deviation shock from *ABAS1* impacts *ESPR* and aggregates to an annualized extra trading cost of 0.1375 million CNY (or 2.75% of the average total trading cost). A value of 2.75% is non-trivial and close to the effect of three-month absolute basis on the *ESPR* in the U.S. market (3%) as reported in Roll, Schwartz, and Subrahmanyam (2007, p. 2022). The effect is stronger for the other way around. When the response variable is *ABAS1*, a one standard deviation shock from *ESPR* can bring extra an annualized 4 million CNY divergence between the futures and cash value for a trade of one million shares of a 40 CNY stock. This is equivalent to 9.8% of the average total divergence value, which is about 1.67 times of the effect of *ESPR* on the three-month absolute basis in the U.S. case. In line with the findings in Table 3, when *ABAS2* is considered, the percentage value can increase to around 16%, reflecting that arbitragers in longer-term (less active) contracts suffer more from the liquidity shock.

< **Insert Table 4 here** >

Overall, our results indicate that there exists a two-way positive relation between spreads

and the absolute futures-cash bases in the Chinese market both statistically and economically, and are thus consistent with the findings in Roll, Schwartz, and Subrahmanyam (2007) and Kadapakkam and Kumar (2013) for the U.S. and Indian markets.

4.2 Results in the restriction period

We define two restriction periods with different starting points. First, although the official announced restriction policies on the CSI 300 index futures trading took place on August 3, 2015, on July 7, 2015 it was reported that opening speculating positions on CSI 300 index futures may be rejected without any notification.²² Moreover, arbitragers need to hold opposing positions in both markets. Restrictions that sharply increase the cost of arbitrage in one market would largely impede the arbitrage activities. Since the restrictions on the short selling of stocks started July 7, 2015, we define the first restriction period as being from July 7, 2015 to June 30, 2016.²³

Second, August 3, 2015 is the day that regulators announced the restrictions on futures trading for the CSI 300 index futures. One day later (August 4, 2015), it was announced that the short selling scheme was switched from “ $T+0$ ” to “ $T+1$.” Henceforth, we use a more strict definition of restriction period (August 3, 2015 to June 30, 2016) to ensure our central conclusion is robust.

Our hypothesis is that in the restriction period, since the arbitrage activities are frozen, the absolute futures-cash bases should have no causal effects on liquidity and vice versa. We test this hypothesis using the Granger causality test, together with the impulse response analysis. Panel B of Table 3 reports the F -statistics and p -values for all the tests pairing two absolute bases and two spread measures for the restriction period from July 7, 2015 to June 30, 2016. In contrast to Panel A, all the F -statistics are insignificant in both directions for both current-month and nex-month futures contracts. The results in the second restriction period (August 3, 2015 to June 30, 2016), as presented in Panel C, further reinforce the

²²For example, on July 13, 2015, after 3 p.m., all opening long position orders in the futures market were rejected. See news at: <http://cn.reuters.com/article/2015/07/13/cn-drv-idCNKCS0PN11H20150713>.

²³June 30, 2016 is the last date in our sample. The restrictions on these two markets are as of October 24, 2016.

evidence that the interplay between absolute futures-cash bases and spreads is absent under restriction. Overall, the Granger causality tests indicate that the absolute futures-cash bases do not Granger cause liquidity and vice versa when arbitrage activities are prohibited.²⁴

In Figures 6 and 7, we plot the impulse responses for the VAR models estimated using the sample data in the first restriction period for the current-month and next-month contracts, together with the IRFs in the pre-restriction period. First, it is evident that in the restriction period, the responses of *ESPR* (*QSPR*) to shocks of *ABAS1* (*ABAS2*) are not significantly different from zero.²⁵ The shocks of *ESPR* (*QSPR*) also contain no information about the future movements of *ABAS1* (*ABAS2*). All these results are consistent with the breakdown of Granger causality, as documented in Panel B of Table 3. Second, we compare the IRFs in the restriction period with the confidence intervals in the pre-restriction period. The underlying null hypothesis in this comparison is that the IRFs in the restriction period are indifferent from the ones in the pre-restriction period. However, we can find that the lines for restriction period are out of the confidence intervals of responses for the pre-restriction period for most cases, especially for the next-month contract in Figure 7, indicating rejection of the null hypothesis. This evidence that the impulse response patterns in these two periods are distinctly different. Third, as shown in Table 4, the IRFs in the pre-restriction period are economically significant and comparable to the findings for the U.S. market as reported in Roll, Schwartz, and Subrahmanyam (2007). However, in the restriction period, since the mean values of IRFs are indifferent from zero and significantly different from those in the pre-restriction period, the economic meaning thereby is negligible.

As a further test, we also compare the coefficients in the VAR models across two regimes (pre-restriction and restriction) using the Z-test.²⁶ Considering that the regressors in the VAR model with four lags are likely to be highly collinear, we test the coefficient differences

²⁴As the restriction period has more than 230 observations, the likelihood that insignificance is due to the power issue of small sample size is trivial. Moreover, in the augmented VAR analysis below, we estimate the model using the combined sample from two periods, further alleviating the concern of small sample bias. We thank an anonymous referee for articulating the issue of small sample size.

²⁵We have not plotted the confidence intervals for the IRFs in the restriction period here to make the presentation of results clear. The results in Figures A5-A8 of the Online Appendix show that the lower confidence intervals are always below zero and the upper confidence intervals are always above zero.

²⁶We thank an anonymous referee for this suggestion.

based on the VAR model with only one lag²⁷ as follows:

$$y_{t,j} = \alpha_j y_{t-1,j} + \beta_j x_{t-1,j} + \epsilon_{t,j}, \quad (5)$$

where j denotes the sample periods (i.e., $j = 1$ denotes the pre-restriction period and $j = 2$ denotes the restriction period), y represents the column variable, x represents the row variable, and ϵ denotes the residuals. We are particularly interested in testing whether the β s are different in the two regimes for the same set of y and x variables. This can be achieved by the Z-test, with the statistic equals to $\frac{\beta_1 - \beta_2}{\sqrt{(SE(\beta_1))^2 + (SE(\beta_2))^2}}$, where $SE(\beta_i)$ denotes the standard deviation of β_i .

Table 5 reports the testing results. At first glance, the patterns are in sharp contrast in two sample periods: the estimates of β , which measure the cross effect between spreads and absolute based, are all significantly positive in the pre-restriction period, but non of them are significant in the restriction period. This confirms again our previous findings in the Granger casualty tests in Table 3. The last two columns report the Z statistics and the associated p values for the Z-test. For instance, when the y variable is *QSPR*, and the x variable is *ABAS1*, the estimates of β are 0.022 and -0.003 in the pre-restriction period and restriction period, respectively. The statistic of Z-test turns out to be 9.652, which is positively significant at 1% level. This indicates that compared to the restriction period, the effect of lagged *ABAS1* on *QSPR* is statistically larger in the pre-restriction period. The columns show that all of the other Z statistics are positive and significant at conventional levels. As a result, we can conclude that the coefficients in two regimes are statistically different and the coefficients in the pre-restriction regime are predominately larger than the

²⁷Since all the absolute futures-cash basis and spread measures are highly autocorrelated, the independent variables would have the multicollinearity issue, making the Z-test lacking of power (see e.g. Enders, 2015, p.290). In order to test whether the coefficients in the two regimes are different, we have also used an augmented VAR model with 4 lags that uses dummy variables to distinguish two regimes. We use the F-test to test whether the coefficients of the interaction terms jointly equal to zero. Since multicollinearity influences the individual parameter estimates but not the overall level of variance accounted for, the F-test is reliable even in the presence of multicollinearity. As reported in Table A5 in the Online Appendix, we reject the null hypothesis of indifference and thus confirm that the coefficients in the two regimes are statistically different. The drawback of this F-test approach, however, is that it cannot tell the directions of the differences i.e., we cannot know whether the coefficients are statistically larger in the restriction period or in the pre-restriction period. With this in mind, we mainly rely on the simple version of VAR model with 1 lag to test the regime differences by the Z-test.

ones in the restriction regime.

< **Insert Table 5 here** >

Taken together, the evidence suggests that the two-way positive relation breaks down both statistically and economically in the restriction period. We thus confirm the hypothesis that the arbitrage force is the underlying mechanism that drives the interplay between liquidity and the absolute futures-cash basis.

4.3 Controlling the market crash effect

The results show that during the restriction period, the significant two-way positive relation between market illiquidity and the absolute futures-cash basis no longer exists. One remaining concern for this interpretation is the effect of the 2015 Chinese market crash. Lien et al. (2013) show that when the market liquidity decreases and the absolute basis increases, the dependence structure between these two variables may break down in an extreme case. After the Chinese stock market crash in 2015, market liquidity significantly dropped. Table 1 shows that the effective bid-ask spread increased from 0.020 CNY in the pre-restriction period to 0.027 CNY in the crash period and to 0.021 CNY in the whole restriction period. Given that the market index significantly dropped (around 37%) during the market crash, the percentage spreads experienced a larger increase while the market liquidity significantly decreased. As a result, since the first one-six of the restriction period overlaps the crash period, the relation between the absolute futures-cash basis and liquidity could dissipate due to the significant decrease in market liquidity, not the absence of arbitrage activities.

To ensure our findings in the restriction period are not confounded by the market crash effect, we conduct two robustness checks. We first conduct a Granger causality test using the post-crash sample period. From September 1, 2015 to June 30, 2016, market conditions became relatively stable and were much less noisy, as shown in Figure 1. However, from Table 6, the F -statistics indicate that we cannot reject the null hypothesis that spreads (absolute futures-cash bases) contain information towards future absolute bases (spreads) movements for both current month and next month contracts. We draw a similar conclusion

from unreported results on impulse response analyses. Henceforth, our results for a more settled market alleviate concerns regarding the market crash effect.

< **Insert Table 6 here** >

Furthermore, we use the index futures/cash markets in Hong Kong as a control group.²⁸ The Hong Kong financial market is increasingly integrated with the mainland China market, especially as a growing number of Chinese enterprises go public in the Hong Kong stock market (e.g., Wang and Jiang, 2004; Wang, Miao, and Li, 2013).²⁹ For firms listed in Hong Kong but registered in mainland China (H shares), their share prices reflect operating information in mainland China, and therefore have close proximity to mainland China stock markets. From January 2, 2012 to December 31, 2015, the correlation between the HSCEI, which captures the performance of the 40 largest H share stocks, and the CSI 300 index is 50.9% in terms of return and 63.2% in terms of realized volatility.³⁰

During the Chinese market crash period in 2015, as we can see in Figure 1, the HSCEI also collapsed, dropping from 13,984 to 9,741.41 (46%). In contrast to the mainland China markets, however, regulators in Hong Kong did not impose any restrictions on the HSCEI futures/cash markets.³¹ Different regulations in these two markets, thereby, provide us with an institutional setting to address the market crash effect further. If the disappearance of the two-way positive relation is a result of the market crash instead of the arbitrage restrictions,

²⁸Our analysis is in the spirit of a difference-in-difference (DID) approach, but not a formal one. We do not employ a formal DID analysis as the typical DID analysis is used to test the difference in means while we care about the change of joint coefficients in a VAR system, making the DID approach methodologically difficult.

²⁹By the end of 2015, there were 229 H share companies listed in the Hong Kong stock market, including the Big Four state-owned banks in mainland China. The market capitalization of H share companies was HK \$ 5,157 billion, 21.11% of the total market capitalization in the Hong Kong stock market. When “Red chips” stocks, stocks of mainland China companies incorporated outside China and listed in Hong Kong, are also counted in, the China-related stocks had a market share of 42.15% in the Hong Kong market. Source: HKEx Monthly Market Highlights (https://www.hkex.com.hk/eng/stat/smstat/chidimen/cd_mc.htm) and HKEx Securities Market Statistics (https://www.hkex.com.hk/eng/stat/smstat/chidimen/cd_mc.htm).

³⁰We use 5-minute CSI 300 index and HSCEI data from TRTH to construct the simple realized volatility measures at a daily frequency by taking a square root of the summation of all the 5-minute return squares within a trading day.

³¹In practice, the Hong Kong Stock Exchange manages a shortable list and updates it quarterly. Short selling is permitted only for specific stocks on the list. However, during our sample period, the ETFs on the HSCEI were always shortable.

we should also observe a structural break in the HSCEI futures/cash market after the Chinese market crash, given the high similarity between the mainland China market and H share stocks. Otherwise, the crash effect is unlikely to be the main driving force for the breakdown of the interaction between spreads and the absolute futures-cash bases.

To test this hypothesis, we construct spreads and the absolute futures-cash basis measures for the HSCEI futures/cash markets in a similar way as for the CSI 300 futures/cash markets.³² Similar to the CSI 300 index futures contracts, the delivery months for the HSCEI futures also include current month, next month, and the final months of the next quarter and the next two quarters.³³ To be consistent, we only include the first two contracts in the analysis and denote these two basis series as *HKABAS1* and *HKABAS2*.³⁴

In line with the analysis for the mainland China market, we estimate the VAR model for the Hong Kong market in two sample periods: one from January 2, 2012 to May 29, 2015, and the other from July 7, 2015 to June 30, 2016. Table 7 presents the estimation results for these two sample periods. Panel A shows that in the pre-restriction period, in the HSCEI futures/cash markets, there is a two-way Granger causality relation between stock market illiquidity and the absolute futures-cash bases for both the current-month and the next-month contracts. As in the Chinese and U.S. markets, the spreads have stronger effects on the bases for the longer-term contracts. The evidence in Panel B for the restriction period is striking: wider bases still lead to larger spreads for both contracts due to the arbitrage-triggered order imbalance and larger spreads also cause wider absolute futures-cash bases, at least for the next month contract, as illiquidity impedes arbitrage and thereby the pricing efficiency.³⁵ Considering that the HSCEI experienced a larger drop than the CSI 300 index

³²The risk-free rate is the Hong Kong Interbank Offer Rate (HIBOR), with maturities including overnight, 1-week, 2-week, 1-month, 2-months, and 3-months. The dividend yield is the difference between the (continuously compounded) difference between the HSCEI total return index and the HSCEI index. For liquidity measures, we weight the quoted spreads/effective spreads for the individual firms in the HSCEI by their market value in the last month.

³³The H-shares index futures were introduced on December 8, 2003. Its underlying asset is the HSCEI. It is a top-10 derivatives market product in the Hong Kong market and has a trading volume comparable to the Hang Seng Index futures. For more details on the futures contracts, we refer readers to: <https://www.hkex.com.hk/eng/prod/drprod/hshares/hhifut.htm>.

³⁴The time series of the spread and basis measures are presented in the Online Appendix Figures A9-A10.

³⁵The results for the F-test with dummy variables, as reported in the Online Appendix Table A6, show that the F-statistics are all insignificant, indicating that we cannot reject the null that the coefficients are

during the market crash, our results provide strong evidence that arbitrage activities are still the driving force for the interplay between liquidity and pricing efficiency even during market upheaval. The results show that the absence of arbitrage activities is the driving force behind the break down of the two-way Granger causality relation in the Chinese market.

< **Insert Table 7 here** >

5 Conclusion

In this paper, we explore the relation between the absolute futures-cash basis and liquidity in the Chinese CSI 300 index futures/cash market from 2012 to 2016. Our main purpose is to address the omitted variable bias. We first use the restrictions on the futures trading and stocks short sales imposed by the regulators as a response to the 2015 Chinese market crash as a natural experiment. We find that during this restriction period, in which the arbitrage channel is shut off, the significant two-way relation between the absolute futures-cash basis and liquidity in the pre-restriction period dissipates both statistically and economically. Using the Hong Kong market as a control sample, we confirm that there is no market crash effect driving the results. Our results suggest that the two-way positive causality relation between the absolute futures-cash basis and liquidity is indeed causal through the arbitrage channel, and is not due to endogeneity. Our evidence indicates that arbitrage is the force to be reckoned with in shaping the interplay between liquidity and market efficiency.

indifferent in two regimes in the Hong Kong market.

References

- Amihud, Yakov (2002), “Illiquidity and stock returns: cross-section and time-series effects,” *Journal of Financial Markets*, vol. 5, 31–56.
- Amihud, Yakov and Haim Mendelson (1989), “The Effects of Beta, Bid-Ask Spread, Residual Risk, and Size on Stock Returns,” *The Journal of Finance*, vol. 44, 479–486.
- Beber, Alessandro and Marco Pagano (2013), “Short-selling bans around the world: Evidence from the 2007–09 crisis,” *The Journal of Finance*, vol. 68, 343–381.
- Blume, Marshall E and Michael A Goldstein (1997), “Quotes, order flow, and price discovery,” *The Journal of Finance*, vol. 52, 221–244.
- Boehmer, Ekkehart, Charles M Jones, and Xiaoyan Zhang (2013), “Shackling short sellers: The 2008 shorting ban,” *Review of Financial Studies*, vol. 26, 1363–1400.
- Boulton, Thomas J and Marcus V Braga-Alves (2010), “The skinny on the 2008 naked short-sale restrictions,” *Journal of Financial Markets*, vol. 13, 397–421.
- Chen, Naf-Fu, Charles J Cuny, and Robert A Haugen (1995), “Stock volatility and the levels of the basis and open interest in futures contracts,” *The Journal of Finance*, vol. 50, 281–300.
- Chordia, Tarun, Richard Roll, and Avanidhar Subrahmanyam (2001), “Market liquidity and trading activity,” *The Journal of Finance*, vol. 56, 501–530.
- Chordia, Tarun, Richard Roll, and Avanidhar Subrahmanyam (2002), “Order imbalance, liquidity, and market returns,” *Journal of Financial Economics*, vol. 65, 111–130.
- Chordia, Tarun, Asani Sarkar, and Avanidhar Subrahmanyam (2005), “An empirical analysis of stock and bond market liquidity,” *Review of Financial Studies*, vol. 18, 85–129.
- Enders, Walter (2015), *Applied econometric time series*, John Wiley & Sons.
- Fong, Kingsley YL, Craig W Holden, and Charles Trzcinka (2014), “What are the best liquidity proxies for global research?” *Available at SSRN 1558447*.
- Gallant, A Ronald, Peter Eric Rossi, and George Tauchen (1992), “Stock prices and volume,” *Review of Financial Studies*, vol. 5, 199–242.
- Granger, Clive WJ (1980), “Testing for causality: a personal viewpoint,” *Journal of Economic Dynamics and Control*, vol. 2, 329–352.

- Holden, Craig W, Stacey E Jacobsen, and Avanidhar Subrahmanyam (2014), “The empirical analysis of liquidity,” *Foundations and Trends in Finance*, vol. 8, 263–365.
- Kadapakkam, Palani-Rajan and Umesh Kumar (2013), “Impact of Liquidity on the Futures-Cash Basis: Evidence from the Indian Market,” *Journal of Futures Markets*, vol. 33, 266–298.
- Karmaziene, Egle and Valeri Sokolovski (2015), “Beware of the Spider: Exchange Traded Funds and the 2008 Short-Sale Ban,” *Swedish House of Finance Research Paper*.
- Kumar, Praveen and Duane J Seppi (1994), “Information and index arbitrage,” *Journal of Business*, vol. 67, 481–509.
- Lee, Hsiu-Chuan, Cheng-Yi Chien, and Tzu-Hsiang Liao (2012), “Commonality in trading activity and futures-cash basis: Evidence from the Taiwan futures and stock markets,” *Journal of Futures Markets*, vol. 32, 964–994.
- Li, Kai, Tan Wang, Yan-Leung Cheung, and Ping Jiang (2011), “Privatization and risk sharing: Evidence from the split share structure reform in China,” *Review of Financial Studies*, vol. 24, 2499–2525.
- Lien, Donald, Gerui Lim, Li Yang, and Chunyang Zhou (2013), “Dynamic Dependence Between Liquidity and the S&P 500 Index Futures-Cash Basis,” *Journal of Futures Markets*, vol. 33, 327–342.
- Lütkepohl, Helmut (1982), “Non-causality due to omitted variables,” *Journal of Econometrics*, vol. 19, 367–378.
- MacKinlay, A Craig and Krishna Ramaswamy (1988), “Index-futures arbitrage and the behavior of stock index futures prices,” *Review of Financial Studies*, vol. 1, 137–158.
- O’Hara, Maureen and George S Oldfield (1986), “The microeconomics of market making,” *Journal of Financial and Quantitative analysis*, vol. 21, 361–376.
- Roll, Richard, Eduardo Schwartz, and Avanidhar Subrahmanyam (2007), “Liquidity and the Law of One Price: The Case of the Futures-Cash Basis,” *The Journal of Finance*, vol. 62, 2201–2234.
- Stock, James H and Mark W Watson (2001), “Vector autoregressions,” *Journal of Economic Perspectives*, vol. 33, 101–115.
- Stoll, Hans R (1978a), “The pricing of security dealer services: An empirical study of NASDAQ stocks,” *The Journal of Finance*, vol. 33, 1153–1172.

- Stoll, Hans R (1978b), “The supply of dealer services in securities markets,” *The Journal of Finance*, vol. 33, 1133–1151.
- Stoll, Hans R (2000), “Presidential address: friction,” *The Journal of Finance*, vol. 55, 1479–1514.
- Trebbi, Francesco and Kairong Xiao (2015), “Regulation and Market Liquidity,” Tech. rep., National Bureau of Economic Research.
- Wang, Kent, Li Miao, and Jiawei Li (2013), “Two-Factor Decomposition Analysis for Correlation between Mainland China and Hong Kong Stock Markets,” *International Review of Finance*, vol. 13, 93–110.
- Wang, Steven Shuye and Li Jiang (2004), “Location of trade, ownership restrictions, and market illiquidity: Examining Chinese A-and H-shares,” *Journal of Banking & Finance*, vol. 28, 1273–1297.
- Yang, Jian, Zihui Yang, and Yinggang Zhou (2012), “Intraday price discovery and volatility transmission in stock index and stock index futures markets: Evidence from China,” *Journal of Futures Markets*, vol. 32, 99–121.

Table 1 Summary statistics for CSI 300 futures-cash bases and liquidity measures

Summary statistics are for the absolute futures-cash bases (in percentages relative to the cash index value), and (in CNY) for the CSI 300 value-weighted quoted and effective spreads. *ABAS1* and *ABAS2* represent unadjusted absolute bases for the two futures contracts (current month and next month). *QSPR* represents the unadjusted quoted bid-ask spread. *ESPR* represents the unadjusted effective spread .

Panel A: Pre-restriction Period (January 2, 2012 - May 29, 2015)			
Variables	Mean	Median	Std. Dev.
<i>ABAS1</i>	0.407%	0.297%	0.425%
<i>ABAS2</i>	0.652%	0.480%	0.167%
<i>QSPR</i>	0.014	0.014	0.002
<i>ESPR</i>	0.020	0.020	0.004
Panel B: Restriction Period (July 7, 2015 - June 30, 2016)			
Variables	Mean	Median	Std. Dev.
<i>ABAS1</i>	2.083%	1.536%	1.893%
<i>ABAS2</i>	4.225%	3.584%	2.330%
<i>QSPR</i>	0.016	0.016	0.002
<i>ESPR</i>	0.021	0.020	0.002
Panel C: Crash Period (June 15, 2015 - August 30, 2015)			
Variables	Mean	Median	Std. Dev.
<i>ABAS1</i>	2.940%	2.232%	2.480%
<i>ABAS2</i>	4.752%	4.484%	3.241%
<i>QSPR</i>	0.019	0.018	0.003
<i>ESPR</i>	0.027	0.027	0.004
Panel D: Post-crash Period (September 1, 2015 - June 30, 2016)			
Variables	Mean	Median	Std. Dev.
<i>ABAS1</i>	1.629%	1.342%	1.384%
<i>ABAS2</i>	3.784%	3.140%	1.963%
<i>QSPR</i>	0.015	0.015	0.001
<i>ESPR</i>	0.020	0.019	0.003

Table 2 Correlation matrix

ABAS1 and *ABAS2* represent adjusted absolute bases for the two futures contracts (current month and next month). *QSPR* represents the quoted bid-ask spread (adjusted by calendar effects and time trends). *ESPR* represents the effective spread (adjusted by calendar effects and time trends). * and *** denote statistical significance at the 10% and 1% levels, respectively.

Panel A: Normal Period (January 1, 2012 - May 29, 2015)				
	<i>ABAS1</i>	<i>ABAS2</i>	<i>QSPR</i>	<i>ESPR</i>
<i>ABAS1</i>				
<i>ABAS2</i>	0.89***			
<i>QSPR</i>	0.30***	0.27***		
<i>ESPR</i>	0.30***	0.26***	0.97***	
Panel B: Restriction Period (July 7, 2015 - June 30, 2016)				
	<i>ABAS1</i>	<i>ABAS2</i>	<i>QSPR</i>	<i>ESPR</i>
<i>ABAS1</i>				
<i>ABAS2</i>	0.91***			
<i>QSPR</i>	0.08	-0.12		
<i>ESPR</i>	0.14*	-0.03	0.90***	

Table 3 Granger causality tests

ABAS1 and *ABAS2* represent adjusted absolute bases for the two futures contracts (current month and next month). *QSPR* represents the quoted bid-ask spread (adjusted by calendar effects and time trends). *ESPR* represents the effective spread (adjusted by calendar effects and time trends). F-statistics are reported with the *p*-values in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Panel A: Pre-restriction Period (January 2, 2012 - May 29, 2015)				
	<i>ABAS1</i>	<i>ABAS2</i>	<i>QSPR</i>	<i>ESPR</i>
<i>ABAS1</i>			4.830*** (0.001)	6.318*** (0.000)
<i>ABAS2</i>			2.279* (0.058)	3.422*** (0.008)
<i>QSPR</i>	1.527 (0.197)	1.770 (0.138)		
<i>ESPR</i>	2.411** (0.050)	2.831** (0.027)		
Panel B: Restriction Period I (July 7, 2015 - June 30, 2016)				
	<i>ABAS1</i>	<i>ABAS2</i>	<i>QSPR</i>	<i>ESPR</i>
<i>ABAS1</i>			0.444 (0.776)	1.713 (0.147)
<i>ABAS2</i>			0.514 (0.725)	1.322 (0.262)
<i>QSPR</i>	0.555 (0.457)	0.023 (0.980)		
<i>ESPR</i>	0.743 (0.389)	0.256 (0.613)		
Panel C: Restriction Period II (August 1, 2015 - June 30, 2016)				
	<i>ABAS1</i>	<i>ABAS2</i>	<i>QSPR</i>	<i>ESPR</i>
<i>ABAS1</i>			0.951 (0.435)	1.061 (0.376)
<i>ABAS2</i>			0.943 (0.439)	1.010 (0.402)
<i>QSPR</i>	1.535 (0.216)	0.343 (0.558)		
<i>ESPR</i>	0.648 (0.421)	0.229 (0.633)		

Table 4 Economic significance

This table presents economic significance in million CNY value and percentages. When the response variable is $QSPR$ (or $ESPR$), the economic significance in terms of CNY value is measured as: $Value(Spread) = Response(Spread) \times 1million \times 250$, where $Response(Spread)$ is the sum of the four response coefficients for spread in Figure 6 and 7, and 250 is the total trading days per year. The economic significance in terms of percentage is measured as: $Percentage(Spread) = \frac{Response(Spread) \times 1million \times 250}{AverageSpread \times 1million \times 250}$, where $AverageSpread$ is the average spread as reported in Panel A of Table 1. When the response variable is $ABAS1$ (or $ABAS2$), the economic significance in terms of CNY value is measured as: $Value(Basis) = Response(Basis) \times 1million \times 40 \times 250$, where $Response(Basis)$ stands for the sum of the four response coefficients for basis in Figure 6; the economic significance in terms of percentage can be expressed as: $Percentage(basis) = \frac{Response(basis) \times 1million \times 40 \times 250}{AverageBasis \times 1million \times 40 \times 250}$, where $AverageBasis$ refers to the average absolute futures-cash basis as reported in Panel A of Table 1.

Response Variables:				
	$ABAS1$	$ABAS2$	$QSPR$	$ESPR$
$ABAS1$			0.085 (1.70%)	0.1375 (2.75%)
$ABAS2$			0.047 (0.93%)	0.085 (1.70%)
$QSPR$	4.030 (9.87%)	4.600 (11.27%)		
$ESPR$	4.000 (9.80%)	6.500 (15.93%)		

Table 5 Z-test for regime differences

This table reports the Z-test results for the coefficients difference in the VAR models with only one lag. The VAR model is $Y_t = \alpha_i Y_{t-1} + \beta_i X_{t-1} + \epsilon_t$. The VAR models are estimated for the pre-restriction period, which is from January 2, 2012 to May 29, 2015, and the restriction period, which is from July 7, 2015 to June 30, 2016. The pair-wise estimates of β and associated t -statistics are reported. Z-statistic denotes statistic for testing the difference between two coefficients in two sample periods, and the associated p -values are in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Panel A: Spread measures as dependent variables						
Independent Variable	Pre-restriction Period		Restriction Period		Difference Tests	
	<i>QSPR</i>	<i>ESPR</i>	<i>QSPR</i>	<i>ESPR</i>	<i>QSPR</i>	<i>ESPR</i>
	Coefficient	Coefficient	Coefficient	Coefficient	Z-Statistic (p -value)	Z-Statistic (p -value)
<i>Lag(ABAS1)</i>	0.022*** (4.213)	0.057*** (4.055)	-0.003 (-0.490)	0.004 (0.190)	9.652*** (0.000)	4.431*** (0.000)
<i>Lag(ABAS2)</i>	0.014*** (4.473)	0.037*** (4.274)	-0.005 (-1.176)	-0.006 (-0.404)	12.952*** (0.000)	6.195*** (0.000)
Panel B: Absolute basis measures as dependent variables						
Independent Variable	Pre-restriction Period		Restriction Period		Difference Tests	
	<i>ABAS1</i>	<i>ABAS2</i>	<i>ABAS1</i>	<i>ABAS2</i>	<i>ABAS1</i>	<i>ABAS2</i>
	Coefficient	Coefficient	Coefficient	Coefficient	Z-Statistic (p -value)	Z-Statistic (p -value)
<i>Lag(QSPR)</i>	0.207*** (3.971)	0.170*** (2.961)	-0.008 (-0.320)	-0.204 (-0.686)	13.830*** (0.000)	1.525* (0.064)
<i>Lag(ESPR)</i>	0.109*** (4.134)	0.094*** (3.239)	0.015 (0.372)	-0.041 (-0.416)	3.807*** (0.000)	1.727** (0.042)

Table 6 Robustness: Granger causality tests in the post-crash period

ABAS1 and *ABAS2* represent the daily adjusted absolute bases for the two futures contracts (current month and next month). *QSPR* represents the daily quoted bid-ask spread (adjusted by calendar effects and time trends). *ESPR* represents the daily effective spread (adjusted by calendar effects and time trends). F-statistics are reported with the *p*-values in parentheses. The time period is from September 1, 2015 to June 30, 2016.

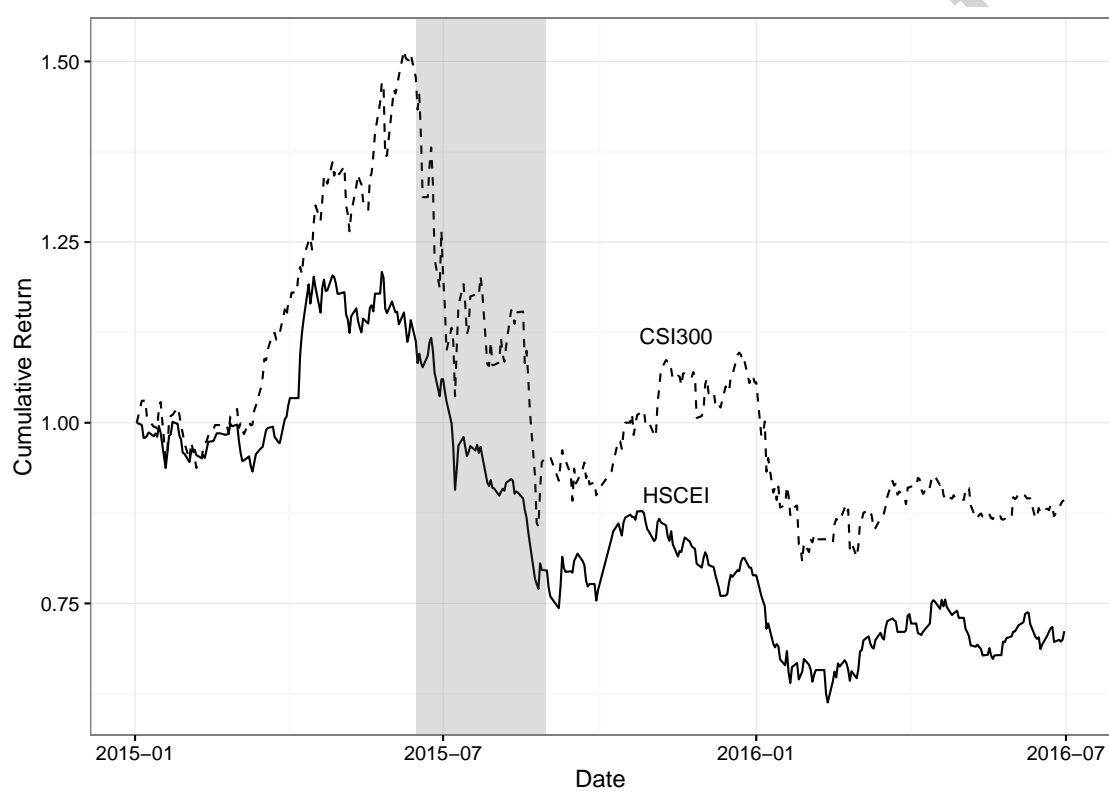
Post-crash period (September 1, 2015 - June 30, 2016)				
	<i>ABAS1</i>	<i>ABAS2</i>	<i>QSPR</i>	<i>ESPR</i>
<i>ABAS1</i>			0.651 (0.527)	1.760 (0.138)
<i>ABAS2</i>			0.130 (0.971)	1.258 (0.288)
<i>QSPR</i>	0.643 (0.633)	1.128 (0.345)		
<i>ESPR</i>	0.109 (0.979)	0.666 (0.617)		

Table 7 Granger causality tests in the Hong Kong market

HKABAS1 and *HKABAS2* represent the daily adjusted absolute bases for two futures contracts (current month and next month) for HSCEI index of Hong Kong market. *HKQSPR* represents the daily quoted bid-ask spread (adjusted by calendar effects and time trends). *HKESPR* represents the daily effective spread (adjusted by calendar effects and time trends). F-statistics are reported with the p -values in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

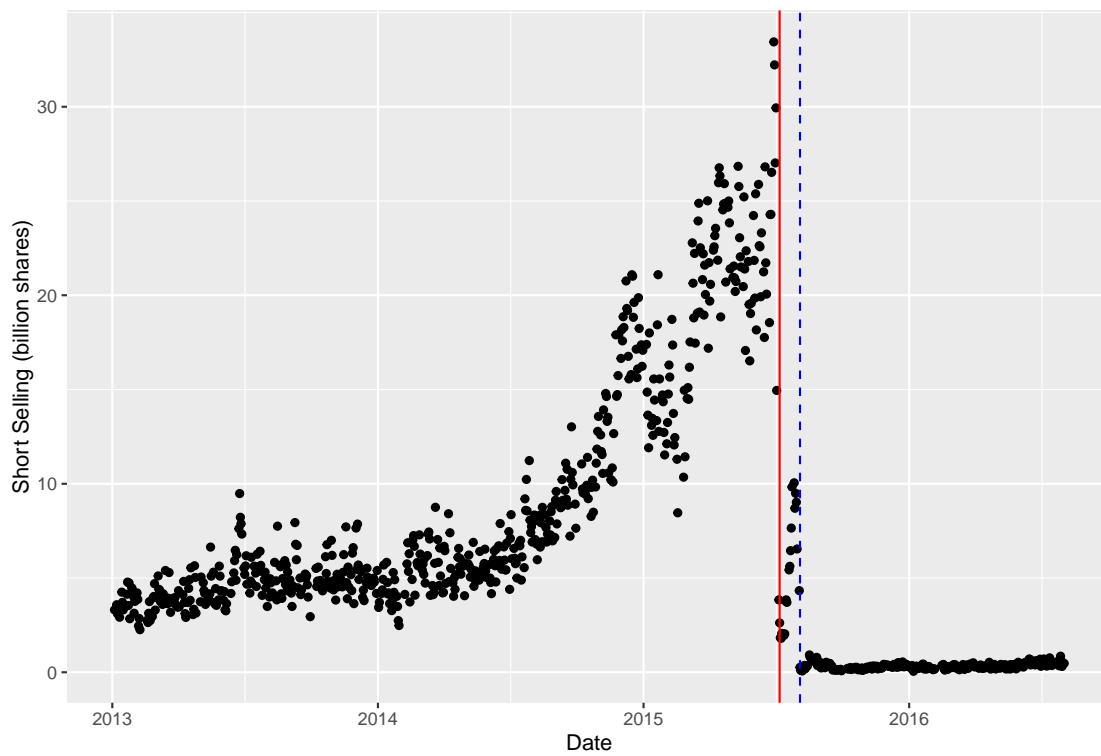
Panel A: Pre-restriction period (January 1, 2012 - May 29, 2015)				
	<i>HKABAS1</i>	<i>HKABAS2</i>	<i>HKQSPR</i>	<i>HKESPR</i>
<i>HKABAS1</i>			2.566*	2.750**
			(0.053)	(0.041)
<i>HKABAS2</i>			2.205*	3.495**
			(0.086)	(0.015)
<i>HKQSPR</i>	2.101*	7.156***		
	(0.085)	(0.000)		
<i>HKESPR</i>	2.466*	3.369**		
	(0.061)	(0.018)		
Panel B: Restriction period (July 7, 2015 - June 30, 2016)				
	<i>HKABAS1</i>	<i>HKABAS2</i>	<i>HKQSPR</i>	<i>HKESPR</i>
<i>HKABAS1</i>			2.381*	2.870**
			(0.069)	(0.036)
<i>HKABAS2</i>			2.152*	3.201**
			(0.093)	(0.023)
<i>HKQSPR</i>	2.174*	6.480***		
	(0.090)	(0.000)		
<i>HKESPR</i>	1.853	4.908***		
	(0.137)	(0.002)		

Figure 1 Cumulative returns of CSI 300 and HSCEI

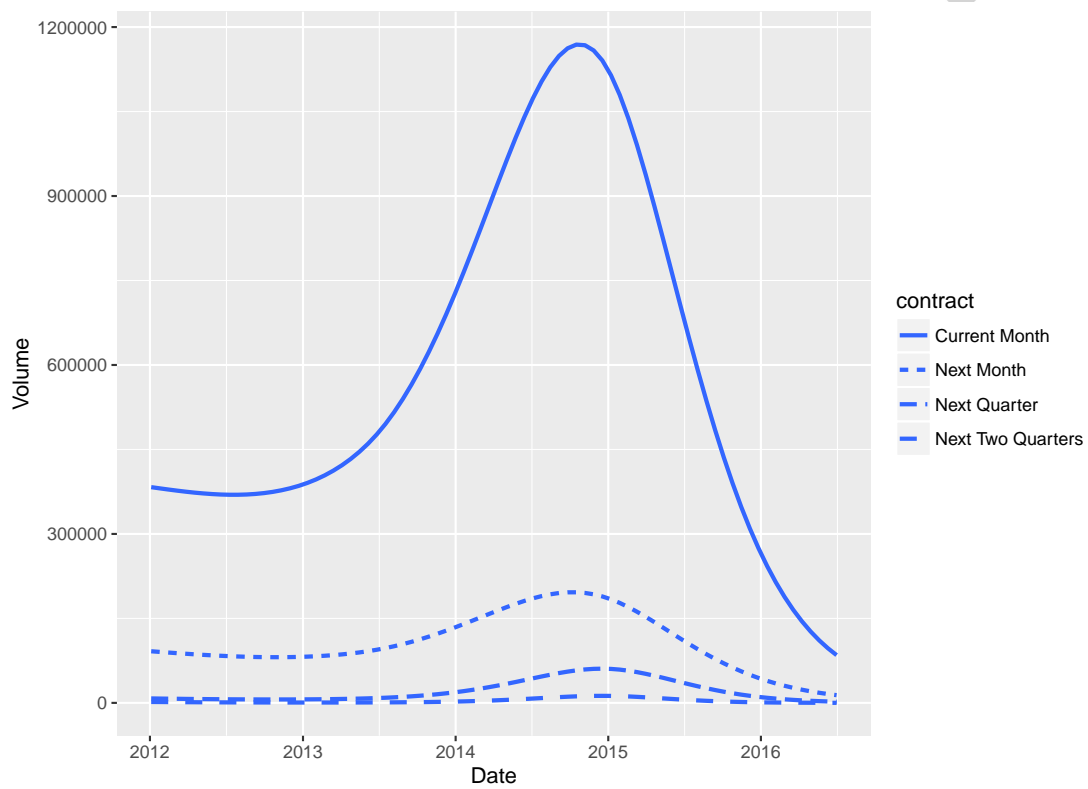


In this figure, we plot the cumulative returns of the CSI 300 and HSCEI. The time period is from January 2, 2015 to June 30, 2016.

Figure 2 Short sale volume

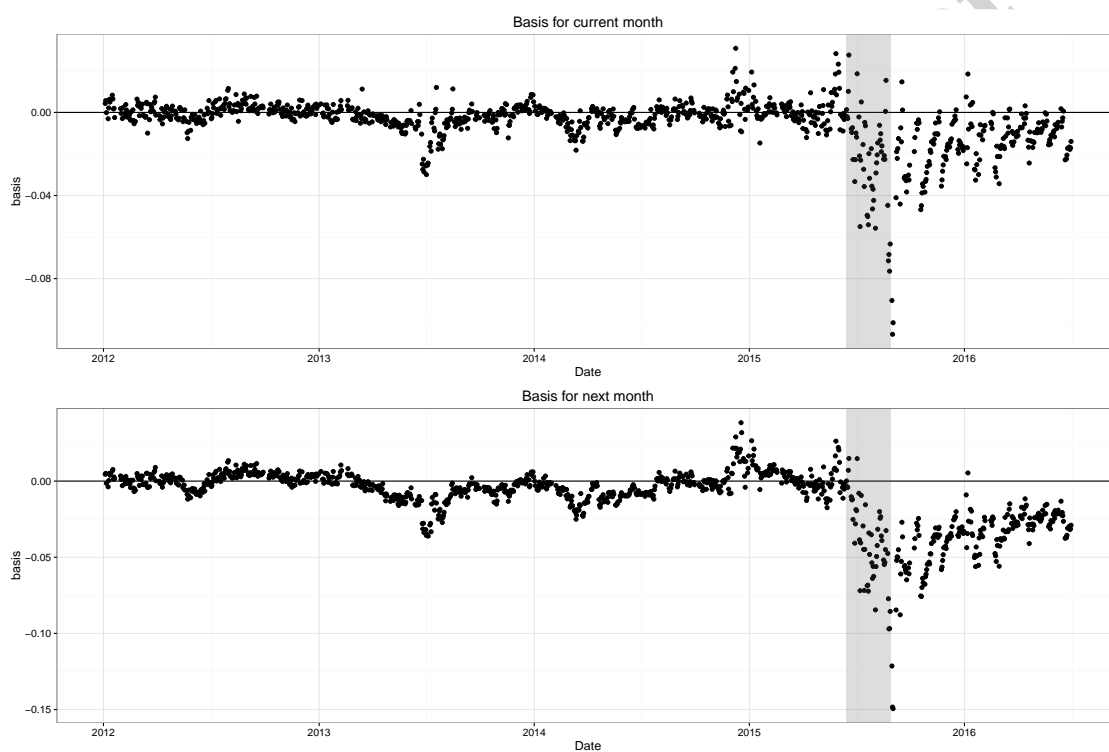


In this figure, we plot the daily volume of aggregate short selling (billion shares) in the Chinese stock market from January 2, 2013 to June 30, 2016. The solid vertical line denotes the date of July 7, 2015. The dashed vertical line denotes the date of August 4, 2015.

Figure 3 Trading volume of CSI 300 futures contracts

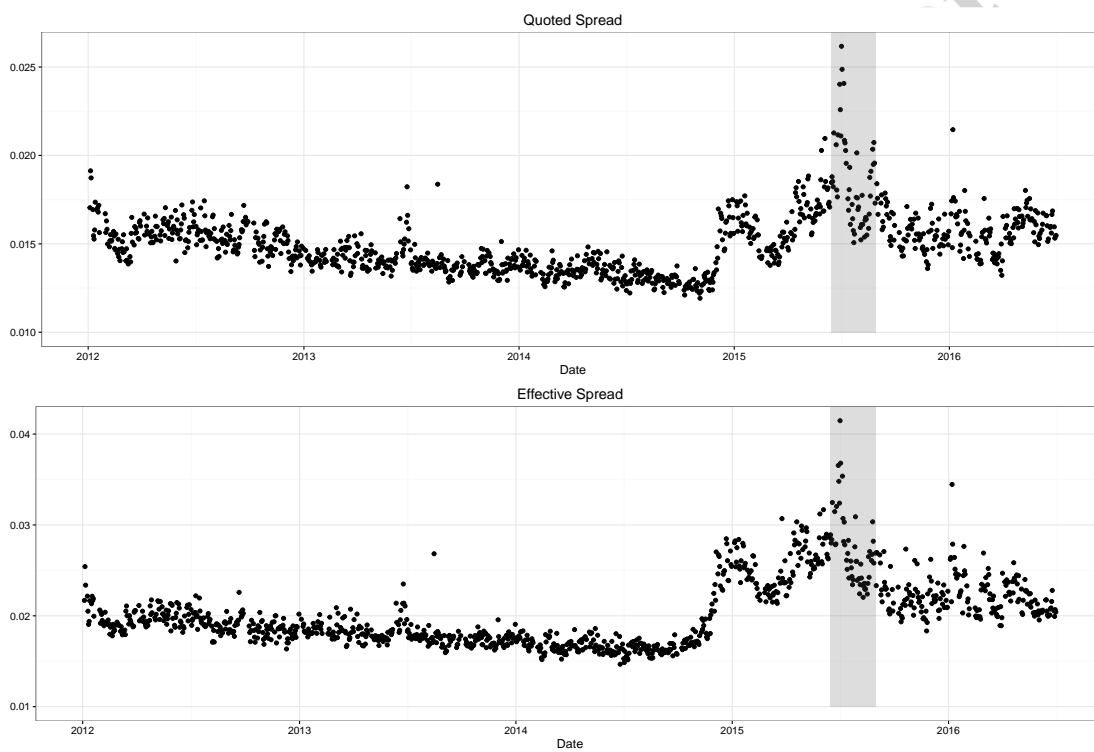
In this figure, we plot the smoothed trading volumes for four contracts of CSI 300 index futures: current month, next month, next quarter month and next two quarters month. The time period is from January 2, 2012 to June 30, 2016.

Figure 4 Futures-cash bases for the CSI 300



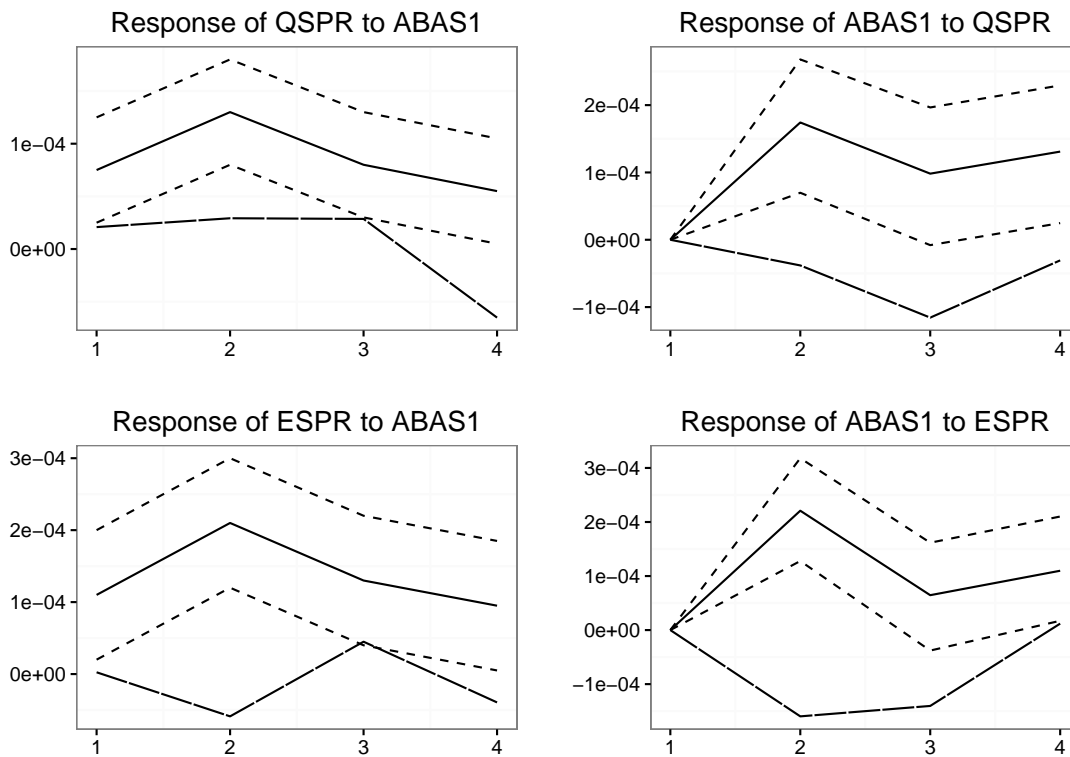
In this figure, we plot the CSI 300 index futures-cash bases for the current month and next month contracts. The series are from January 2, 2012 to June 30, 2016. The shaded area denotes the 2015 Chinese stock market crash period, which is from June 15, 2015 to August 30, 2015.

Figure 5 Spread measures for CSI 300



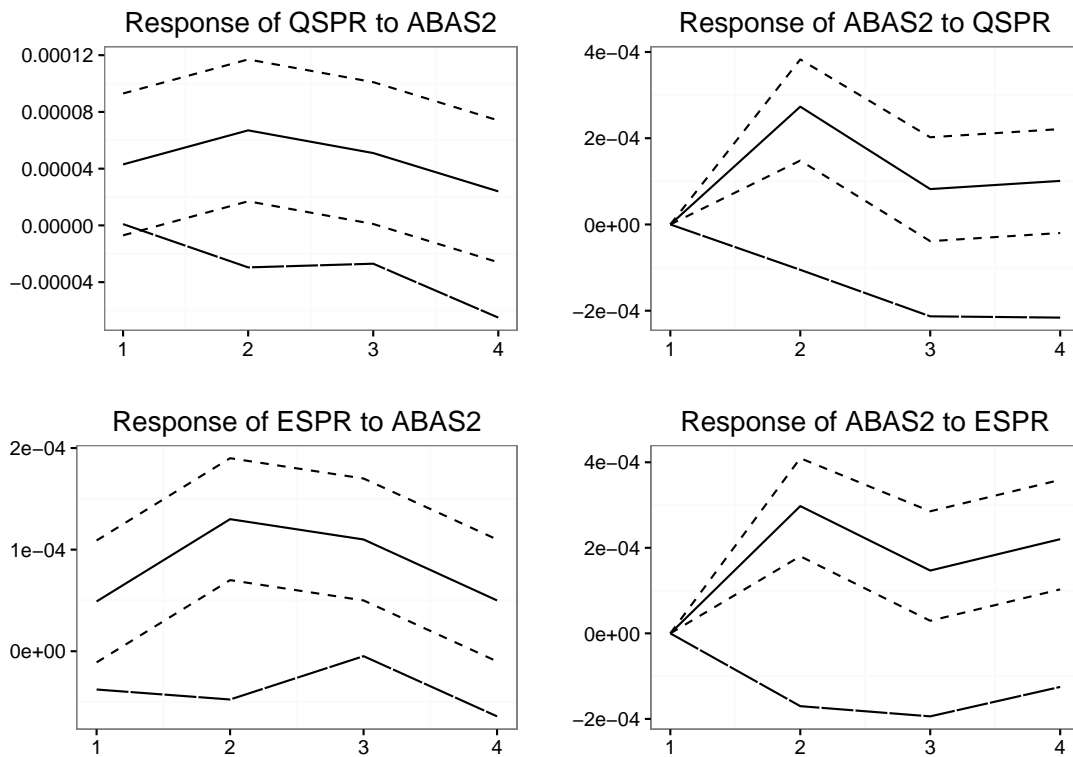
In this figure, we plot the CSI 300 index quoted spread and effective spread. The series are from January 2, 2012 to June 30, 2016. The shaded area denotes the 2015 Chinese stock market crash period, which is from June 15, 2015 to August 30, 2015.

Figure 6 Impulse responses comparison I: current-month futures contract



In this figure, we plot the impulse responses of *ABAS1* and *QSPR* (*ESPR*) in the pre-restriction period (January 2, 2012 to May 29, 2015) and the restriction period (July 7, 2015 to June 30, 2016). The solid lines denote the mean response values in the pre-restriction period, and the short dashed lines are the corresponding 95% confidence intervals based on 1,000 simulations. The long dashed lines represent the mean response values in the restriction period.

Figure 7 Impulse responses comparison II: next-month futures contract



In this figure, we plot the impulse responses of *ABAS2* and *QSPR* (*ESPR*) in the pre-restriction period (January 2, 2012 to May 29, 2015) and the restriction period (July 7, 2015 to June 30, 2016). The solid lines denote the mean response values in the pre-restriction period, and the short dashed lines are the corresponding 95% confidence intervals based on 1,000 simulations. The long dashed lines represent the mean response values in the restriction period.

Appendix A Restrictions on futures trading

In this Appendix, we briefly summarize the restrictions on index futures trading issued by the China Financial Futures Exchange. We obtain these announcements from the official weibo (Chinese version of Twitter) of the China Financial Futures Exchange.³⁶ We introduce these restrictions based on the time line of announcement dates.

July 6, 2015

Starting from July 7, 2015, transactions on the China Security Index 500 (CSI 500)³⁷ futures is limited to 1,000 contracts per client per day for one direction of trading (either long or short).

July 8, 2015

Starting from July 8, 2015, the margin rate for CSI 500 index futures increases from 10% to 20% (except for the hedging position). Since July 9, 2015, the margin rate for CSI 500 index futures has increased to 30%.

July 31, 2015

Starting from August 3, 2015, for clients with speculative positions (including arbitrage and speculation) in all the index futures (including the CSI 300 index futures), for a single contract, cancelling more than 400 orders for a single contract or more than five trades a day would be considered as “irregular trading.”

August 25, 2015

On August 26, 2015, the margin rates for speculative positions in the CSI 300 and SSE 50³⁸ index futures increased from 10% to 12%. Since August 27, 2015, the margin rates for speculative positions in the CSI 300, SSE 50 index futures increased to 15%, while the margin rate for the long (speculative) positions in the CSI 500 index futures is increased to 15%. Starting from August 28, 2015, the margin rates for speculative positions in the CSI 300, SSE 50 index futures increased to 20%, while the margin rate for the long (speculative) positions in the CSI 500 index futures increased to 20%.

Starting from August 26, 2015, transactions on the CSI 300, SSE 50, and CSI 500 index futures are limited to 600 contracts per day per client for speculative positions on each futures product.

Starting from August 26, 2015, the transaction fee for the intraday delivery (opening and closing position in the same day) increased from 0.05‰ to 0.115‰.

August 28, 2015

³⁶<http://weibo.com/cffexfabu>.

³⁷CSI 500 was launched on January 15, 2007, and it is designed to capture the aggregate performance of the small-cap stocks in the Chinese stock market. The index futures (CSI 500 index futures) was launched on April 16, 2015 by the China Financial Futures Exchange.

³⁸SSE 50 index was launched on January 2, 2004, and it is designed to capture the aggregate performance of the 50 stocks with the largest market capitalizations in the Shanghai stock market. The index futures (SSE 50 index futures) was launched on April 16, 2015 by the China Financial Futures Exchange.

Since August 31, transactions on the CSI 300, SSE 50, and CSI 500 index futures are limited to 100 contracts per day per client for speculative positions on each futures product. Since August 31, 2015, the margin rates for speculative positions increased to 30%.

September 2, 2015

Since September 7, 2015, transactions on the CSI 300, SSE 50, and CSI 500 index futures are limited to 10 contracts per day per client for speculative positions on each futures product.

Since September 7, 2015, the margin rates in the CSI 300, SSE 50, and CSI 500 index futures increased from 30% to 40% for the speculative positions and 20% for the hedging positions.

Since September 7, 2015, the transaction fee for the intraday delivery (opening and closing position in the same day) increased from 0.115‰ to 2.30‰.

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