On the Relation between Liquidity and the Futures-Cash Basis:
Evidence from a Natural Experiment

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ABSTRACT
We use a natural experiment to test the hypothesis that liquidity and pricing efficiency causally affect each other. During and after the 2015 Chinese market crash, regulators prohibit the arbitrage activities in the index futures and cash markets. The resulting shift in the arbitrage boundary leads to the breakdown of the two-way positive causality relation between spreads and the absolute futures-cash bases, and this treatment effect is not confounded by the market crash effect. We thus confirm that the relation between liquidity and basis is not driven by the omitted variable bias, but is indeed due to the arbitrage force.

JEL classification: G01, G14, G18
Keywords: Futures-cash basis; Liquidity; 2015 Chinese stock market crash; Arbitrage

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PREFACE

Thesis title: Three Essays in Finance

Supervisors: Professor Tom Smith, Professor Karen Benson, Dr. Martina Linnenluecke

The thesis focuses on addressing causality of finance issues by adopting instrument variables or natural experimental designs. The three issues I explore can be seen as follows:

1. CEO Inside Debt and Investment-Cash Flow Sensitivity

It provides a new explanation for the firm’s investment-cash flow sensitivity from the perspective of CEO inside debt holdings. We examine the effect of CEO pensions and deferred compensation (inside debt) on investment-cash flow sensitivity for a sample of U.S. manufacturing firms from 2006 to 2012. We find that firms with higher relative CEO leverage ratios (CEO’s debt/equity ratio scaled by the firm’s debt/equity ratio) generate higher investment-cash flow sensitivity. This positive relationship still holds after we address endogeneity using state income tax rate as the instrument variable. The paper based on this essay has been published in Accounting and Finance.

2. Politically Connected Boards, Value or Cost: Evidence from a Natural Experiment in China

This essay investigates the net effect of a politically connected board for a firm. Using a natural experiment in China— a regulatory change to forbid bureaucrats from sitting on the board of public firms, we address the causality of the net effect of a politically connected board by testing the market reaction of the shares of firm targeted by the regulatory change to the policy announcement. The paper based on this essay is forthcoming in Accounting and Finance.

3. On the Relation between Liquidity and the Future-Cash Basis: Evidence from a Natural Experiment

This essay uses a natural experiment to test the hypothesis that liquidity and pricing efficiency causally affect each other. During and after the 2015 Chinese market crash, regulators prohibit the arbitrage activities in the index futures and cash markets. The resulting shift in the arbitrage boundary leads to the breakdown of the two-way positive causality relation between spreads and the absolute futures-cash bases, and this treatment effect is not confounded by the market crash effect. The paper based on this essay is forthcoming in Journal of Financial Markets.

The paper I present is based on the third essay.
1 Introduction

The Law of One Price states 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 et al. (2007) test this notion by comprehensively investigating the intertemporal association between the stock market liquidity and the 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 basis and spreads are positively correlated, and there is a two-way positive Granger causality relation between them. The underlying mechanism of this phenomenon, as surmised by Roll et al. (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 basis could also reduce liquidity due to order imbalances.1 Using a similar empirical design, literature documents that this two-way relation also exists in the international markets (see e.g. Lee, Chien, and Liao, 2012; Kadapakkam and Kumar, 2013).

However, there remains one potential issue in Roll et al. (2007) and other relevant studies, which is the ‘omitted variable bias’. Testing if and how market liquidity and the 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, 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 futures-cash basis. To overcome such a problem of ‘omitted variable bias’ in our context, 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 article, we formally test whether the interplay between liquidity and basis is caused by the arbitrage force. We adopt a natural experiment to ‘shut down’ the driving force (arbitrage activities) that underlies the hypothesis and test whether the hypothesis still holds or not. Specifically, recent trading restrictions 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 the 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 futures-cash basis should have no impact on liquidity any more if their relation is indeed due to the basis triggered arbitrage activities other than the endogeneity problem; further, if liquidity affects the futures-cash basis through the arbitrage channel, one would then predict that market liquidity should also have no effect on the futures-cash basis.

Empirically, we first investigate the relation between the Chinese Securities Index 300 (CSI 300) futures-cash basis and the aggregate liquidity of the CSI 300 index 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 two-way positive causality relation both statistically and

\(^3\)Roll et al. (2007) mention the possible existence of the ‘omitted variable bias’ and control for volatility and index returns, the possible common drivers, in the VAR estimation. However, as it is impossible to control for all the possibly known and unknown factors in one system, our paper adopts a different identification strategy based on the economic mechanism behind the statistical relations.

\(^4\)Stock and Watson (2001) also appeal that, though 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.

\(^5\)We provide a more detailed introduction of this restriction experiment in Section 2.2.1 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 then turn to 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 the ones in the pre-restriction period. The insignificant impulse responses also reveal the economic significance of the cross-effects between liquidity and bases 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 two sample periods (pre-restriction and restriction). Imposing this testing procedure still supports our previous findings. Overall, by interpreting these results together, we confirm the hypothesis that arbitrage is the underlying mechanism that drives the interplay between spreads and bases.

One remaining concern for our central conclusion is the market crash effect. Lien et al. (2013) argue that when the market liquidity decreases and the absolute 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 is overlapped with the market crash period, our treatment effect (restriction) might therefore be confounded by the market crash effect that potentially can explain our results. To alleviate this concern, we first re-conduct the Granger causality test in the post-crash sample period from September 1, 2015 to June 30, 2016. The relation between spreads and bases, however, is still insignificant under this stable market condition. Second, we use the Hang Seng China Enterprise Index (HSCEI) in the Hong Kong Stock Exchange (HKEx) as a control group. The HSCEI

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6We acknowledge an anonymous referee for suggesting to statistically comparing the coefficients in these two regimes.

7The HSCEI index was established on October 3, 2001, based on companies listed in Hong Kong but registered in mainland China (‘H’ shares). This index comprises the largest and most liquid 40 H shares.
captures the performance of large Chinese firms registered in mainland China but listed in Hong Kong (‘H’ shares). Since the variation in ‘H’ shares’ stock prices reflects operating information in mainland China, HSCEI is highly integrated with the mainland China stock markets. As a result, during the Chinese market crash, HSCEI also experienced a severe turmoil. However, in contrast to mainland China, there is no trading restriction imposed on both the futures and cash markets in Hong Kong. If the breakdown of the linkage between liquidity and the futures-cash basis in mainland China is a result of the market crash, we expect to observe a similar pattern in the HSCEI futures/cash markets. However, we find that a two-way positive 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 article 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 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 force is indeed the underlying mechanism.

Second, our paper also joins the literature on the consequences of regulations during a market crash. Using the 2007 to 2009 crisis as a natural experiment, previous literature mainly focuses on the impact of the short selling bans on liquidity and pricing efficiency separately across different markets (see 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 regulation on liquidity and market efficiency jointly. We utilize the restrictions in both futures and stock markets simultaneously and document that the regulation triggered arbitrage constraint ‘shuts down’ the interaction between liquidity and market efficiency.

The rest of the article proceeds as follows. Section 2 introduces the background. Section 3 describes the variable construction methods and outlines our data. Section 4 presents the
empirical results. Section 5 concludes.

2 Institutional Background

As shown in Figure 1, after a sharp rise from middle March to middle June, the Chinese stock market started to crash on June 15, 2015 and in 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 by 8.49 percent, marking the largest fall since 2007, and continued to drop by 7.63% on August 25.\(^8\) Since September 1, market started to move up and became steady. In the end of December 2015, Chinese stock market 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 for the day after a 7% drop in the CSI 300 index from the time markets opened because of the newly issued circuit-breaker rule.\(^9\) The circuit-breaker rule was then announced to be suspended by regulators since January 8.\(^{10}\) In January, the CSI 300 index decreased by 17.74%. Since February, the Chinese stock slowly recovered from the panic caused by the circuit-breaker system and CSI 300 index moved steady around 3,200.

During the crash period, the index futures trading was commonly blamed by public as the catalyst for the market decline.\(^{11}\) From July 7, 2015, a bundle of policies were successively adopted by the China Financial Futures Exchange (CFFEX) to restrict the speculative contracts in index futures and other shorting behaviours.\(^{12}\) In the Chinese index futures market, all the futures positions are divided into two groups: hedging position and

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\(^8\)These 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 by 8.49% means that the majority of the stocks in the market had hit the limit ban.


\(^{10}\)We remove the first week of January 2016 out of our sample due to the consideration that the measurement of futures-cash basis and spreads would be inaccurate in these extremely short-ended sessions.


This figure plots the cumulative returns of CSI 300 index and HSCEI. The time period is from January 2, 2015 to June 30, 2016.
speculative position. To open hedging positions, investors should apply to 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 the other positions are classified by the regulators as speculative positions, which include both positions for the arbitrage and speculative purposes.

The bundle of policies for the futures market are mainly aiming to restrict the speculative positions, while hedging positions are only slightly influenced (increasing margin rate from 10% to 20%). At the current stage, the restrictions on the 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 2.30‰ (which was 0.05‰ before). In Appendix A, we provide a detailed introduction of these policies.

Though without official announcements, short selling is *de facto* frozen in the stock market. Figure 2 plots the daily volume of short selling, with the data obtained from Shanghai and Shenzhen Stock Exchanges. We can see that since July 7, 2015 (the red vertical line), the trading volume dropped dramatically. Since August 4, 2015 (the blue vertical line), regulators changed the trading rule for short sales from ‘T+0’ to ‘T+1’, which was regarded by the market as the signal to comprehensively restrict short selling. It is evident that starting from that date, the trading volume is negligible compared to the “pre-restriction” period. As a result, the restrictions on both markets dramatically increase the cost of arbitrage activities and make the arbitrage activities infeasible, which provide an ideal quasi-natural experiment to identify the channel underlying the relation between liquidity and the futures-cash basis.\(^\text{13}\)

During the global financial crisis from 2007 to 2009, many markets imposed bans or constraints on short sales, either for financial stocks only or for the whole stock market (Beber and Pagano, 2013). As recently as 2011 and 2012, Belgium, France, Italy and Spain imposed

\(^{13}\text{Trading restrictions, especially the short selling ban, could lead to increased volatility (see 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.}
Daily volume of aggregate short selling (billion shares) in the Chinese stock market are plotted for the period January 2, 2013 to June 30, 2016. The red vertical line is the date of July 7, 2015. The blue vertical line is the date of August 4, 2015.
renewed short selling restrictions. 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 basis, thus making our testing strategy possibly feasible in these markets. However, we believe that compared to other markets, the Chinese market provides 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 for the CSI 300 futures contracts was more than 216 millions and ranked as the Top-10 worldwide Equity Index Futures & Options Contracts by the Futures Industry Association\textsuperscript{14}. In July 2015, the China Financial Futures Exchange was ranked by the World Federation of Exchanges as the most active market for index futures.\textsuperscript{15} 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. China restricted transactions on both futures and cash markets. In other markets, the index futures trading were unaffected. For short sales in the cash market, some markets only applied to the financial stocks (e.g. U.S., U.K., Canada and South Korea) instead of whole stocks or were only in the form of naked ban other than covered ban (e.g. Japan, Spain, Switzerland and Italy). Under these circumstances, arbitrage in the futures/cash 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 USD of 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 market crash. In summary, to the best of our knowledge, China might be the only market that can satisfy all the three conditions: (i) active with large trading volume, (ii) incurring comprehensive restrictions, and (iii) having a sufficiently long restriction period.

\textsuperscript{14}https://fimag.fia.org/
\textsuperscript{15}http://www.world-exchanges.org/
3 Data

This section introduces data sources and explains the methods used to construct the futures-cash basis and liquidity measures. In this paper, our analysis focuses on the CSI 300 cash index and the CSI 300 index futures. The CSI 300 index was published 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 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.\(^\text{16}\)

3.1 Futures-cash basis

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

\[
\text{ABAS} = \frac{|Fe^{-(r-\delta)t} - S|}{S}
\]  

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 \(\delta\) is the dividend yield over the contract’s remaining lifetime.

Specifically, basis is empirically constructed with following components: \(F\) is the daily closing futures price on the CSI 300 index futures contract, while \(S\) is the daily closing value of the CSI 300 index.\(^\text{17}\) The risk-free rate \(r\) is the Shanghai Interbank Offered Rate

\(^{16}\)For details about the CSI 300 index and the CSI 300 index futures market, we refer readers to Yang et al. (2012).

\(^{17}\)There 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 Shanghai and Shenzhen stock exchanges open 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 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 et al. (2007), though 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.
This figure plots 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, 2015 to June 30, 2016.

(SHIBOR) maturing as close to the futures expiration date as possible. The dividend yield $\delta$ 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 is obtained from Datastream.

The expiration day of the CSI 300 index futures contracts is the third Friday of the contract (delivery) month, and contract (delivery) months include current month, next month, and 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 final months of next quarter and next two quarters are inactively

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18 The available maturities for SHIBOR used in the current study are overnight, 1-week, 2-weeks, 1-month and 3-months.
traded with volumes negligible compared to the other two contracts. Therefore, we focus only on the first two contracts in the following analysis.

We construct two 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 et al. (2007), we use two cost-based liquidity measures for each stock, i.e. the *Quoted Spread* and *Effective Spread*, and these spreads are not scaled by 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.\(^ {19} \)

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

\[
Quoted\ Spread_s = \text{Ask}_s - \text{Bid}_s
\]

where \( \text{Ask}_s \) and \( \text{Bid}_s \) 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 the trading day \( i \).

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

\[
Effective\ Spread_k = 2|P_k - M_k|
\]

where \( P_k \) is the price of the \( k^{th} \) spread 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 \( i \).

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\(^ {19}\)Since 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 the liquidity over a relatively long time period. For a recent comprehensive review on liquidity measures, we refer readers to Holden et al. (2014).
Daily spread measures are averaged, value-weighted, across stocks (with weights proportional to market capitalizations of the tradable shares at the end of last month\textsuperscript{20}) 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. One recent study by Fong et al. (2014) documents that TRTH is a comparable database for the international 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 futures-cash bases and spreads in Table 1. In Panel A, we can find that in the \textit{pre-restriction} period, the mean values of absolute 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 consistent with the fact in China the security trading scheme is order driven instead of market making. As shown in Panel B, in the \textit{restriction} period, the mean values of the absolute bases has increased dramatically for both current month and next month futures contracts. For instance, for the current month contract, the mean percentage absolute basis in the \textit{pre-restriction} period is close to zero (0.407%), reflecting the effectiveness of arbitrage activities, while in the \textit{restriction} period, it is as high as 2.083%. The high level of

\textsuperscript{20}Here we use the market value of tradable shares other than the total market value due to the consideration that 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.
absolute basis is consistent with our argument that in the *restriction* period, the 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 and Panel C, it is evident that the spread measures has increased dramatically in the crash period. For instance, the mean value of effective spread rises from 0.020 CNY to 0.027 CNY by 35%. Considering that the CSI 300 index has dropped more than 36% in the crash period, the percentage based spread measures has increased even much more. In Panel D, we can see that the level of market liquidity recovers to some extent after the market crash with mean values of spread measures close to the ones in the *pre-restriction* period.

We also plot the dynamics of the futures-cash bases and two spread measures in Figure 4 and Figure 5. It is obvious that during the *restriction* period, the futures-cash bases were generally negative and with large magnitudes, and spreads also increased sharply. Since 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, the high magnitude of negative bases as shown in Figure 4 might largely reflect the premiums that investors were willing to pay in the futures market in order to hedge their long positions in the cash market.

Futures-cash basis and spread measures show calendar regularities and time trends (see e.g. Gallant, Rossi, and Tauchen, 1992). To address this issue, following Roll et al. (2007) and Kadapakkam and Kumar (2013), we adjust the raw absolute 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 empirical analysis.

Table 2 reports the pair-wise correlation matrix among two adjusted bases measures (ABAS1 and ABAS2) and two spread measures (QSPR and ESPR) in both *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. Two absolute basis measures are highly correlated, and two spread measures are also significantly related. Meanwhile, 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 provides some
Table 1 Summary Statistics for CSI300 Futures-Cash Bases and Liquidity Measures

Summary statistics are for absolute bases (in percentages relative to the cash index value) for the current month and next month futures contracts, and (in CNY) for the CSI300 value-weighted quoted and effective spreads.

<table>
<thead>
<tr>
<th>Panel A: Pre-restriction Period (Jan 2, 2012 - May 29, 2015)</th>
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<tbody>
<tr>
<td>Variables</td>
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<tr>
<td>Current month absolute basis</td>
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<td>Next month absolute basis</td>
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<tr>
<td>Quoted spread</td>
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<td>Effective spread</td>
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<th>Panel B: Restriction Period (July 7, 2015 - June 30, 2016)</th>
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<tr>
<td>Variables</td>
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<tr>
<td>Current month absolute basis</td>
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<td>Next month absolute basis</td>
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<td>Quoted spread</td>
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<td>Effective spread</td>
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<th>Panel C: Crash Period (June 15, 2015 - August 30, 2015)</th>
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<td>Current month absolute basis</td>
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<td>Next month absolute basis</td>
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<td>Quoted spread</td>
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<td>Effective spread</td>
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<th>Panel D: Post-crash Period (September 1, 2015 - June 30, 2016)</th>
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<td>Next month absolute basis</td>
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<td>Quoted spread</td>
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<td>Effective spread</td>
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This figure plots 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.
This figure plots 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.
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 calender effects and time trends). ESPR represents the effective spread (adjusted by calender effects and time trends). * and *** denote the significances at 10% and 1% levels, respectively.

<table>
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<tr>
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<th>ABAS1</th>
<th>ABAS2</th>
<th>QSPR</th>
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<td>ABAS1</td>
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<td>ABAS2</td>
<td>0.89***</td>
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<td>0.30***</td>
<td>0.27***</td>
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<tr>
<td>ESPR</td>
<td>0.30***</td>
<td>0.26***</td>
<td>0.97***</td>
<td></td>
</tr>
</tbody>
</table>


Panel B: Restrictions Period (July 7, 2015 - June 30, 2016)
preliminary evidence that there could have a structural break during the restriction period, for which we prove its existence with a more rigorous analysis in the following section.

4 Empirical 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 covers from January 2, 2012 to May 29, 2015. Our empirical 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 4 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

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

where $y$ represents the column variable, while $x$ represents the row variable and $\epsilon$ 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 $\beta_j$ 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
ABAS1 and ABAS2 represent the daily adjusted absolute bases for 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 significance at the 5%, and 1% levels, respectively.

<table>
<thead>
<tr>
<th>Panel A: Pre-restriction Period (2012.01-2015.05)</th>
<th>ABAS1</th>
<th>ABAS2</th>
<th>QSPR</th>
<th>ESPR</th>
</tr>
</thead>
<tbody>
<tr>
<td>ABAS1</td>
<td>4.830***</td>
<td>6.318***</td>
<td>(0.001)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>ABAS2</td>
<td>2.279**</td>
<td>3.422***</td>
<td>(0.058)</td>
<td>(0.008)</td>
</tr>
<tr>
<td>QSPR</td>
<td>1.527</td>
<td>1.770</td>
<td>(0.197)</td>
<td>(0.138)</td>
</tr>
<tr>
<td>ESPR</td>
<td>2.411**</td>
<td>2.831**</td>
<td>(0.051)</td>
<td>(0.027)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel B: Restriction Period I (2015.07-2016.06)</th>
<th>ABAS1</th>
<th>ABAS2</th>
<th>QSPR</th>
<th>ESPR</th>
</tr>
</thead>
<tbody>
<tr>
<td>ABAS1</td>
<td>0.444</td>
<td>1.713</td>
<td>(0.776)</td>
<td>(0.147)</td>
</tr>
<tr>
<td>ABAS2</td>
<td>0.514</td>
<td>1.322</td>
<td>(0.725)</td>
<td>(0.262)</td>
</tr>
<tr>
<td>QSPR</td>
<td>0.555</td>
<td>0.023</td>
<td>(0.457)</td>
<td>(0.980)</td>
</tr>
<tr>
<td>ESPR</td>
<td>0.743</td>
<td>0.256</td>
<td>(0.389)</td>
<td>(0.613)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel C: Restriction Period II (2015.08-2016.06)</th>
<th>ABAS1</th>
<th>ABAS2</th>
<th>QSPR</th>
<th>ESPR</th>
</tr>
</thead>
<tbody>
<tr>
<td>ABAS1</td>
<td>0.951</td>
<td>1.061</td>
<td>(0.435)</td>
<td>(0.376)</td>
</tr>
<tr>
<td>ABAS2</td>
<td>0.943</td>
<td>1.010</td>
<td>(0.439)</td>
<td>(0.402)</td>
</tr>
<tr>
<td>QSPR</td>
<td>1.535</td>
<td>0.343</td>
<td>(0.216)</td>
<td>(0.558)</td>
</tr>
<tr>
<td>ESPR</td>
<td>0.648</td>
<td>0.229</td>
<td>(0.421)</td>
<td>(0.633)</td>
</tr>
</tbody>
</table>
ESPRES, suggesting that the bases triggered arbitrage force leads to inventory imbalance and strains the liquidity in the stock market. In the other direction, ESPRES also Granger-causes the absolute bases, especially for the next month contract, indicating that illiquidity does impede the pricing efficiency. The stronger effect for the longer-term contracts is consistent with the findings in Roll et al. (2007), in which they argue that liquidity concerns are more relevant for arbitrageurs in longer-term, relatively less-active contracts. In contrast to ESPRES, the effects of QSPRES on bases are not found to be significant. This observation is largely in parallel with Roll et al. (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.

To have a clear picture of the Granger-causality relation, we also conduct the 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 to 7 present the impulse responses of the cross effects between the absolute futures-cash basis and spread. Monte Carlo simulations (1000 replications) are applied to get the 95% confidence intervals of the responses.21

In Figure 6, for the responses of QSPRS to ABAS1, consistent with the Granger-causality result, a shock to the absolute futures-cash basis has a significantly positive and persistent effect on the adjusted quoted spread. Meanwhile, even though QSPRS 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 QSPRS also leads to future higher basis for the current month contract. As shown in Figure 6, the cross-effect of ESPRS and ABAS1 exhibits a similar pattern. For the next month contract (Figure 7), we can find both spreads (bases) shocks are informative towards future movements of bases (spreads). The results in the impulse response analysis reinforces our findings in the Granger-causality test.

21To 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 1-4. The results show that these responses decay overtime, indicating that these variables are stationary.
Figure 6 Impulse Responses Comparison I: Current-month Futures Contract

This figure plots 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 black lines denote the mean response values in the pre-restriction period, and the dashed lines are the corresponding 95% confidence intervals based on 1,000 simulations. The red lines represent the mean response values in the restriction period.
This figure plots 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 black lines denote the mean response values in the pre-restriction period, and the dashed lines are the corresponding 95% confidence intervals based on 1,000 simulations. The red lines represent the mean response values in the restriction period.
Next, we gauge the economic significance in a similar way to that of Roll et al. (2007). Specifically, we measure economic significance using both 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 can be found in the Note part 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 ABAS 1 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 percentage of 2.75% is non-trivial and close to the effect of 3-month absolute basis on the ESPR in the U.S. market (3%) as reported in Roll et al. (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 3-month absolute basis in the U.S. case. In line with the findings in Table 3, when ABAS 2 is considered, the percentage value can be even increased to around 16%, reflecting the fact that arbitragers in longer-term (less active) contracts suffer more from the liquidity shock.

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22 By 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.
Table 4 Economic Significance

This table presents economic significance in million CNY value and percentage. ABAS1 represents adjusted absolute bases for the current month future contract. ESPR represents the effective spread (adjusted by calendar effects and time trends). 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 formula is \( \text{Value(Spread)} = \text{Response(Spread)} \times 1\text{million} \times 250 \), where \( \text{Response(Spread)} \) stands for the sum of the four response coefficients for spread in Figure 6 and 250 is the total trading days per year. The economic significance in terms of percentage is measured as the extra trading cost over the average total trading cost. The formula is \( \text{Percentage(Spread)} = \frac{\text{Response(Spread)} \times 1\text{million} \times 250}{\text{AverageSpread} \times 1\text{million} \times 250} \), where \( \text{AverageSpread} \) refers to 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 the annualized extra divergence between the futures and its cash value for average stock price of 40 CNY and a trade of one million shares, caused by a one-standard deviation shock to QSPR (or ESPR). The formula is specified as: \( \text{Value(Basis)} = \text{Response(Basis)} \times 1\text{million} \times 40 \times 250 \), where \( \text{Response(Basis)} \) stands for the sum of the four response coefficients for basis in Figure 6; the economic significance in terms of percentage is the extra divergence value over the average total divergence value. The formula can be expressed as: \( \text{Percentage(basis)} = \frac{\text{Response(basis)} \times 1\text{million} \times 40 \times 250}{\text{AverageBasis} \times 1\text{million} \times 40 \times 250} \), where \( \text{AverageBasis} \) refers to the average absolute futures-cash basis as reported in Panel A of Table 1.

<table>
<thead>
<tr>
<th>Response Variables:</th>
<th>ABAS1</th>
<th>ABAS2</th>
<th>QSPR</th>
<th>ESPR</th>
</tr>
</thead>
<tbody>
<tr>
<td>ABAS1</td>
<td>0.085</td>
<td>0.1375</td>
<td>(1.700%)</td>
<td>(2.75%)</td>
</tr>
<tr>
<td>ABAS2</td>
<td>0.047</td>
<td>0.085</td>
<td>(0.93%)</td>
<td>(1.700%)</td>
</tr>
<tr>
<td>QSPR</td>
<td>4.030</td>
<td>4.600</td>
<td>(9.874%)</td>
<td>(11.270%)</td>
</tr>
<tr>
<td>ESPR</td>
<td>4.000</td>
<td>6.500</td>
<td>(9.800%)</td>
<td>(15.925%)</td>
</tr>
</tbody>
</table>
Overall, our results indicate that there exists a two-way positive relation between spreads and absolute bases in the Chinese market both statistically and economically, and are thus consistent with the findings in Roll et al. (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, though the official announced restriction polices on the CSI 300 index futures trading took place on August 3, 2015, it was reported that opening speculating positions on CSI 300 index futures may be rejected without any notification since July 7, 2015. Moreover, arbitrages need to hold opposite 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 since July 7, 2015, we define the first ‘restriction’ period from July 7, 2015 to June 30, 2016.

Second, August 3, 2015 is the first day that regulators explicitly announced the restrictions on the futures trading for the CSI 300 index futures. One day later (August 4, 2015), it was also announced that the short selling scheme was switched from ‘T+0’ to ‘T+1’. Henceforth, we also use another 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 first restriction period. We can see that, in contrast to Panel A, all the F statistics are insignificant in both directions for both contracts. The results in the second restriction period, as presented in Panel C, further reinforce the evidence that the interplay between absolute bases and spreads is absent under

23 For example, on July 13, 2015, after 3pm, all opening long position orders in the futures market were rejected. See news http://cn.reuters.com/article/2015/07/13/cn-driver-idCNKCS0PN11H20150713
24 June 30, 2016 is the last date in our sample. The restrictions on these two markets are still valid now.
restriction. Overall, the Granger-causality tests indicate that the futures-cash bases do not Granger-cause liquidity and vice versa when arbitrage activities are prohibited.\footnote{As our 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.}

Figures 6 and 7 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 (in red lines), together with the IRFs in the pre-restriction period (in black lines). Firstly, it is evident that in the restriction period, the responses of ESPR (QSPR) to shocks of ABAS1 (ABAS2) are not significantly different from zero.\footnote{We have not plotted the confidence intervals for the IRFs in the restriction period here to make the presentation of results clear. From the detailed results as reported in Figures 5-8 of the Online Appendix, we can see that the lower confidence intervals are always below zero and the upper confidence intervals are instead always above zero.} Simultaneously, the shocks of ESPR (QSPR) contain no information against the future movements of ABAS1 (ABAS 2) as well. All these results are consistent with the breakdown of Granger causality as documented in Panels B and C in Table 3. Second, we compare the IRFs in the restriction period (red lines) with the confidence intervals in the pre-restriction period (dashed lines). 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 red lines are out of the confidence interval of responses for the pre-restriction period for most cases, especially for the next-month contract in Figure 7, indicating the rejection of the null hypothesis. This comparison thus provides us with another evidence that the impulse response patterns in these two periods are in sharp distinctions from a simulation perspective. Third, as shown in Table 4, the IRFs in the pre-restriction period are economically significant and comparable to the findings in the U.S. market. However, in the restriction period, since the mean values of IRFs are indifferent from zero and significantly different from the ones in the pre-restriction period, the economic meaning thereby is negligible.

As a further test, we also statistically compare the coefficients in the VAR models across two regimes (pre-restriction and restriction) with the widely used Z-test.\footnote{We thank an anonymous referee for this suggestion.} Considering that
the regressors in the VAR model with 4 lags are likely to be highly collinear, we test the
coefficient differences based on the VAR model with only one lag as follows:

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

where \( j \) denotes the sample periods i.e., \( j = 1 \) refers to the pre-restriction period and \( j = 2 \) stands for the restriction period, \( y \) represents the column variable, \( x \) represents the row variable and \( \epsilon \) denotes the residuals. We are particularly interested in testing whether the two coefficient \( \beta \)s are different in 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 \( \beta_i \).

Table 5 reports the testing results. At first glance, the patterns are in sharp contrast in two sample periods: the estimates of \( \beta \), 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 \( \beta \) 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

28Since all the absolute 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 5 in the On-line 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.
Table 5 Z-test for Regime Difference

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 in two separate time periods i.e., the pre-restriction period that covers from January 2, 2012 to May 29, 2015, and the restriction period spans from July 7, 2015 to June 30, 2016. ABAS1 and ABAS2 represent the daily adjusted absolute bases for 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). The pair-wise estimates of $\beta$ and associated t statistics are reported. Z-Test denotes the Z-statistic for testing the difference between two coefficients in two sample periods, and the associated p values are in parentheses. *, ** and *** denote the significance at 10%, 5% and 1% levels, respectively.

Panel A: Spread Measures as Dependent Variables

<table>
<thead>
<tr>
<th>Independent Variable</th>
<th>Pre-restriction Period:</th>
<th>Restriction Period:</th>
<th>Difference Tests:</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>QSPR</td>
<td>ESPR</td>
<td>QSPR</td>
</tr>
<tr>
<td>Lag(ABAS1)</td>
<td>0.022***</td>
<td>0.057***</td>
<td>-0.003</td>
</tr>
<tr>
<td></td>
<td>(4.213)</td>
<td>(4.055)</td>
<td>(-0.490)</td>
</tr>
<tr>
<td>Lag(ABAS2)</td>
<td>0.014***</td>
<td>0.037***</td>
<td>-0.005</td>
</tr>
<tr>
<td></td>
<td>(4.473)</td>
<td>(4.274)</td>
<td>(-1.176)</td>
</tr>
</tbody>
</table>

Panel B: Absolute Basis Measures as Dependent Variables

<table>
<thead>
<tr>
<th>Independent Variable</th>
<th>Pre-restriction Period:</th>
<th>Restriction Period:</th>
<th>Difference Tests:</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>ABAS1</td>
<td>ABAS2</td>
<td>ABAS1</td>
</tr>
<tr>
<td>Lag(QSPR)</td>
<td>0.207***</td>
<td>0.170***</td>
<td>-0.008</td>
</tr>
<tr>
<td></td>
<td>(3.971)</td>
<td>(2.961)</td>
<td>(-0.320)</td>
</tr>
<tr>
<td>Lag(ESPR)</td>
<td>0.109***</td>
<td>0.094***</td>
<td>0.015</td>
</tr>
<tr>
<td></td>
<td>(4.134)</td>
<td>(3.239)</td>
<td>(0.372)</td>
</tr>
</tbody>
</table>
different and the coefficients in the pre-restriction regime are predominately larger than the ones in the restriction regime.

Taken together, all above 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 basis.

4.3 Controlling the market crash effect

Above results show that during the ‘restriction’ period, the significant two-way positive relation between market illiquidity and the futures-cash bases no longer exists. One remaining concern for this interpretation is the effect of 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, the market liquidity significantly dropped. In Table 1, we can see 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 market index significantly dropped (around 37%) during the market crash, the percentage spreads experienced an even much larger increase and thus the market liquidity should have significantly decreased. As a result, since the first one-six of the restriction period is overlapped with the crash, the relation between futures-cash basis and liquidity could break down as a result of the lasting effect of the significant decrease in market liquidity other than due to the absence of arbitrage activities.

To ensure our treatment effect in the restriction period is not confounded by the market crash effect, we conduct two robustness checks. We first re-conduct the Granger-causality test using the post-crash sample period. From September 1, 2015 to June 30, 2016, the market condition became relatively stable and was much less noisy as shown in Figure 1. However, from Table 6, F-statistics still indicate that we cannot reject the null hypothesis that spreads (absolute bases) contain information towards future bases (spreads) movements for both current month and next month contracts. Unreported results on impulse response
Table 6 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 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.

<table>
<thead>
<tr>
<th></th>
<th>ABAS1</th>
<th>ABAS2</th>
<th>QSPR</th>
<th>ESPR</th>
</tr>
</thead>
<tbody>
<tr>
<td>ABAS1</td>
<td>0.651</td>
<td>1.760</td>
<td>(0.527)</td>
<td>(0.138)</td>
</tr>
<tr>
<td>ABAS2</td>
<td>0.130</td>
<td>1.258</td>
<td>(0.971)</td>
<td>(0.288)</td>
</tr>
<tr>
<td>QSPR</td>
<td>0.643</td>
<td>1.128</td>
<td>(0.633)</td>
<td>(0.345)</td>
</tr>
<tr>
<td>ESPR</td>
<td>0.109</td>
<td>0.666</td>
<td>(0.979)</td>
<td>(0.617)</td>
</tr>
</tbody>
</table>
analyses draw a similar conclusion. Henceforth, our results in a more settled market alleviate the concerns regarding the peculiarity of the restriction period.

Furthermore, we rely on the index futures/cash markets in Hong Kong as a control group.\(^{29}\) It has been long recognized that the Hong Kong financial market has been increasingly integrated with the mainland China market, especially as an increasing number of Chinese enterprises go public in the Hong Kong stock market (see e.g. Wang and Jiang, 2004; Wang, Miao, and Li, 2013; Li, 2013)\(^{30}\). 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 index, 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.\(^{31}\)

During the China market crash period, as we can see in Figure 1, the HSCEI index also collapsed, dropping from 13984 to 9741.41 (46\%). In contrast to the mainland China markets, however, regulators in Hong Kong did not impose any restriction on both cash and futures markets.\(^{32}\) 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 market crash instead of the arbitrage restrictions, highly likely, we should also observe a structural break in the HSCEI index cash/futures

\(^{29}\)The analysis below is in the spirit of a difference-in-difference (DID) approach, but not a formal one. We do not adopt a formal DID analysis due to the following consideration: the typical DID analysis aims at testing the difference in mean while we care about the change of joint coefficients in a VAR system, making the DID approach methodologically difficult.

\(^{30}\)By the end of 2015, there were 229 ‘H’ share companies listed in the Hong Kong stock market, and 1866 companies in total, including the ‘Big Four’ state-owned banks in mainland China. The market capitalisation of ‘H’ shares companies was HK $ 5,157 billion, 21.11\% of the total market capitalisation 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/smsstat/chidimen/cd_mc.htm) and HKEx Securities Market Statistics (https://www.hkex.com.hk/eng/stat/smsstat/chidimen/cd_mc.htm)

\(^{31}\)We use 5-minute CSI 300 index and HSCEI index 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.

\(^{32}\)In practice, Hong Kong Stock Exchange manages a shortable list and updates it quarterly. Short selling is permitted only for specific stocks that are on the list. However, during our sample period, the ETFs on the HSCEI were always shortable.
market after the China market crash, given the high similarity between the mainland China market and ‘H’ share stocks. Otherwise, the crash effect is unlike to be the main driving force for the breakdown of the interaction between spreads and bases.

To test above hypothesis, we construct spreads and the futures-cash bases measures for the HSCEI futures/cash markets in a similar way as for the CSI 300 futures/cash markets. 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 next quarter and next two quarters. To be consistent, we only include the first two contracts in empirical analysis and name these two basis series as HKABAS1 and HKABAS2.

In line with the empirical analysis in the mainland China market, we estimate the VAR model in the Hong Kong market in two sample periods, one from January 2, 2012 to May 29, 2015, and the other one 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 the stock market illiquidity and absolute bases for both current month and next month contracts. As same as in the Chinese market and U.S. market, 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 bases, at least for the next month contract, as illiquidity impedes arbitrage and thereby the pricing

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33 The 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. All the data used in constructing the absolute futures-cash bases for Hong Kong market is from Datastream. For liquidity measures, we weight the quoted spreads/effective spreads for the individual firms in HSCEI by their market value in last month. All the data for constructing the liquidity and volatility measures are from TRTH via SIRCA. All the spreads and bases measures are adjusted 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.

34 The H-shares index futures were introduced on December 8, 2003. Its underlying asset is the HSCEI index. It is a Top-10 derivatives market product in 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/hhfut.htm

35 The time series of the spread and basis measures are presented in the Online Appendix.

36 For the latter sample period, we also use August 3, 2015 to June 30, 2016 and June 30, 2016 for robustness checks and the results are qualitatively unaltered.
### Table 7 Hong Kong Granger-Causality Tests

HKABAS1 and HKABAS2 represent the daily adjusted absolute bases for two futures contracts (current month and next month) for SCEI index of HK 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 significance at the 10%, 5%, and 1% levels, respectively.

#### Panel A: ‘Pre-restriction’ Period (2012.01-2015.05)

<table>
<thead>
<tr>
<th></th>
<th>HKABAS1</th>
<th>HKABAS2</th>
<th>HKQSPR</th>
<th>HKESPR</th>
</tr>
</thead>
<tbody>
<tr>
<td>HKABAS1</td>
<td>2.566*</td>
<td>2.750**</td>
<td>(0.053)</td>
<td>(0.041)</td>
</tr>
<tr>
<td>HKABAS2</td>
<td>2.205*</td>
<td>3.495**</td>
<td>(0.086)</td>
<td>(0.015)</td>
</tr>
<tr>
<td>HKQSPR</td>
<td>2.101*</td>
<td>7.156***</td>
<td>(0.085)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>HKESPR</td>
<td>2.466*</td>
<td>3.369**</td>
<td>(0.061)</td>
<td>(0.018)</td>
</tr>
</tbody>
</table>

#### Panel B: ‘Restriction’ Period (2015.07-2016.06)

<table>
<thead>
<tr>
<th></th>
<th>HKABAS1</th>
<th>HKABAS2</th>
<th>HKQSPR</th>
<th>HKESPR</th>
</tr>
</thead>
<tbody>
<tr>
<td>HKABAS1</td>
<td>2.381*</td>
<td>2.870**</td>
<td>(0.069)</td>
<td>(0.036)</td>
</tr>
<tr>
<td>HKABAS2</td>
<td>2.152*</td>
<td>3.201**</td>
<td>(0.093)</td>
<td>(0.023)</td>
</tr>
<tr>
<td>HKQSPR</td>
<td>2.174*</td>
<td>6.480***</td>
<td>(0.090)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>HKESPR</td>
<td>1.853</td>
<td>4.908***</td>
<td>(0.137)</td>
<td>(0.002)</td>
</tr>
</tbody>
</table>
efficiency.\footnote{The impulse response analyses, unreported for brevity, are consistent with the Granger-causality test results. The results for the F-test with dummy variables, as reported in the Online Appendix, show that the F statistics are all insignificant, indicating we cannot reject the null that the coefficients are indifferent in two regimes.} Considering that the HSCEI index experienced a larger drop than the CSI 300 index during the market crash, our results provide strong evidence that arbitrage activities still work as the driving force for the interplay between liquidity and pricing efficiency even during a market turbulence. As a result, the market crash should not be the leading effect that can explain the break down of the two-way causality relation in the Chinese market. Instead, the absence of arbitrage activities is the driving force to be reckoned with.

\section*{4.4 Two Additional Tests}

Besides the natural experiment approach, to further corroborate our empirical findings, we conduct two more tests in the \textit{pre-restriction} period (January 2, 2012 to May 29, 2015) and report the detailed discussions and analysis in the Online Appendix. First, in the Chinese financial market, there is a severe asymmetry between the costs of shorting index futures and stocks: it is much cheaper to short the futures compared to the stocks (see e.g. Chang, Luo, and Ren, 2014; Lu, Ren, and Zhao, 2015). Hence, if the arbitrage is the underlying mechanism, the effect of the futures-cash basis on liquidity would also be asymmetric: given the same level of magnitude, positive basis has a larger effect on the liquidity than does the negative basis. We test this prediction in the \textit{pre-restriction} period and the results confirm the existence of the asymmetric effect both statistically and economically. Second, if the underlying mechanism is arbitrage force, we should also observe that the effect of basis on liquidity is stronger when basis is beyond the arbitrage cost. We test this convention based on a time-varying arbitrage cost measure and the estimation results confirm our prediction. Collectively, by interpreting these results together, our findings suggest that the relation between liquidity and the futures-cash basis is not driven by the ‘\textit{omitted variable bias}’, but is indeed driven by the arbitrage activities.
5 Conclusion

In this paper, we explore the relation between the futures-cash basis and liquidity in the Chinese market. Our main purpose is to address the ‘omitted variable bias’. We first use the restrictions on the futures trading and stocks short sales 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 basis and illiquidity in the pre-restriction period disappears 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. All of these tests suggest that the two-way positive causality relation between the futures-cash basis and liquidity is not due to endogeneity, but is indeed casual through the arbitrage channel. By doing so, we prove and highlight that arbitrage is the force to be reckoned with in shaping the interplay between liquidity and market efficiency.
References


Fong, Kingsley YL, Craig W Holden, and Charles Trzcinka (2014), “What are the best liquidity proxies for global research?” *Available at SSRN 1558447*.


Appendix A   Restrictions on The 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. We introduce these restrictions based on the time line of announcement dates.

July 6, 2015

Starting from July 7, 2015, transactions on China Security Index 500 (CSI 500)\textsuperscript{39} futures is limited to 1,000 contracts per client per day for one direction of trading (either longing or shorting).

**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 increases 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 the speculative positions in the CSI 300 and SSE 50\textsuperscript{40} index futures are increased from 10\% to 12\%. Since August 27, the margin rates for the speculative positions in the CSI 300, SSE 50 index futures are increased to 15\%, the margin rate for the long (speculative) positions in the CSI 500 index futures is increased to 15\%. Starting from August 28th, the margin rates for the speculative positions in the CSI 300, SSE 50 index futures are increased to 20\%, the margin rate for the long (speculative) positions in the CSI 500 index futures is increased to 20\%.

Starting from August 26, 2015, transactions on 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) is increased from 0.05\% to 0.115\%.

**August 28, 2015**
Since August 31, transactions on 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 are increased to 30\%.

**September 2, 2015**
Since September 7, 2015, transactions on 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 were increased to 15\%.

\textsuperscript{39}CSI 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.

\textsuperscript{40}SSE 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.
futures are 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) is increased from 0.115% to 2.30%.