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Abstract

This paper documents the existence of primary dealers' losses in Treasury bond markets and investigates how these losses affect dealers' market value. Using a novel data set that tracks more than 2,350 primary-to-secondary transactions, we find that bond losses for primary dealers are prevalent and were severe during the financial crisis. Our results indicate that liquidity constraints are a major source of bond losses observed in primary-to-secondary trades. We also find that financial sector value is correlated with these losses. Using an alternating market experiment, we show that bond losses are higher under discriminatory auctions as compared to uniform auctions.

JEL Classification: C57, C58, D44.

Keywords: Bond Losses, Treasury Bonds, Liquidity Constraint, Auction Mechanisms.

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'On Friday afternoon, the volume-weighted average rate of the benchmark seven-day REPO traded in the interbank market, considered the best indicator of general liquidity in China, was 2.6024 percent, or 4.92 basis points higher than the previous week's closing average rate of 2.5532 percent. The Shanghai Interbank Offered Rate (SHIBOR) for the same tenor stayed flat at 2.6290 percent, up 3 basis points from the previous week's close of 2.5990 percent. The one-day or overnight rate stood at 2.3400 percent and the 14-day REPO stood at 2.4459 percent. A trader at a regional bank in Shanghai said liquidity conditions tightened on Friday following a 50-year bond auction by China's finance ministry that attracted stronger-than-expected demand. "Yields fell a lot, and traders came in chasing them," she said.'

(Reuters, November 16, 2018)

1 Introduction

Recent studies have shown that the trading of bonds is a major part of banks' activities and accounts for a significant share of their revenues (King, Massoud, and Song, 2013; Begenau, Piazzesi, and Schneider, 2015). Hence, losses in this market can have significant consequences for banks as well as for the stability of the banking sector. The 2007-2008 global financial crisis, for instance, has shown how bank losses can cause instability in global financial systems and lead to severe macroeconomic fluctuations (De Bandt, Hartmann, and Peydro, 2010).

A *carry trade* strategy based on the purchase of risky sovereign debts using funds provided by government banks (Acharya and Steffen, 2015; Popov and Van Horen, 2014) and financial repression (Reinhart and Sbrancia, 2015; Becker and Ivashina, 2018) have been documented as important causes of bank losses in the sovereign bond markets. The authors note that these losses can lead to a decrease in a bank's capitalization value and also a reduction in credit supply. Another way of incurring losses is through participation in Treasury bond markets where financial institutions buy securities in primary market auctions and sell them in the secondary market. As the most optimistic primary market dealer wins the auction, and may end up paying more than the amount they could extract from the secondary market, the financial institution could be exposed to winner's curse (Bukhchandani and Huang, 1989, 1993; Nyborg, Rydqvist, and Sundaresan, 2002).

In this paper, we show that banks make subtancial losses in the process of buying (bidding for) on-the-run Treasury bonds in the primary markets and reselling them in the secondary market due to tight liquidity conditions. Using a novel data set that tracks primary-to-secondary transactions in the Treasury bond market, we measure the loss or gain as the difference between primary and secondary market returns on the debut-day (the initial secondary market trading day for a given bond).[1] We show that, when this inter-market margin is negative, the primary market dealer incurs a loss in their market value, which is a possible source of financial market instability.

This paper has three objectives. First, we show that significant losses exist in the bond market even after controlling for bond and market characteristics. Using a unique data set from China, which contains trades of more than 2,350 Treasury bonds in primary and secondary markets from 2004–2017, we calculate the difference between primary and secondary market returns—the effective return for a bond.[2] We exploit the rare timing structure of the Chinese government bond issuance process where short trades are strictly prohibited. Due to the simple market structure and the no-short-trade regulation, we are able to investigate the channel and information structure of systemic risk observed in post-auction periods. Another advantage of our measurement is that it allows us to focus on an analysis of potential liquidity constraints rather than a combination of liquidity and short-position constraints. Differently, previous studies had to develop empirical strategies to measure bond losses (or gains) as it is required to disentangle speculative short trades under the intricate information revelation environment (Jordan and Jordan, 1997; Nyborg and Strebulaev, 2003).

We document negative margins for about 20% of the observed transactions even after adjusting for bond and market conditions. This result shows that primary dealer losses are prevalent in Treasury bond markets. Given our temporally extensive data set, which includes the 2007-2008 financial crisis, we are able to show the magnitude of losses before, during, and after the crisis. Our results indicate that, during the crisis, more than 50% of post-auction Treasury transactions led to losses. These findings could be informative for policymakers who are interested in understanding financial markets during a recession or who are interested in government security market (in)stability.

The second objective of this paper is to explore the question: if financial losses are prevalent for primary market dealers, what is the possible market mechanism behind these losses? In line with the Reuters (2018) quote above, we hypothesize that, when facing high borrowing costs, primary market dealers are willing to liquidate their on-the-run bonds at a loss in order to minimize their financial distress. To test this possible explanation for bond market losses, we examine whether a change in the REPO rate can predict individual bond losses.[3] As

[1]Our definition of gain/loss is motivated by IPO literature and for example, see Ljungqvist (2007). Another reason behind our focus on on-the-run bonds is that these bonds are relatively liquid while off-the-run issues are substantially illiquid, as reported by Fleming (2002).

[2]Note that China's government bond market was about $5.8 trillion in 2017. The total market, including corporate bonds, was about $9 trillion in 2017. See https://www.spglobal.com/our-insights/China-Bond-Market-Development-2017-in-Review.html.

[3]The REPO rate is the volume-weighted average rate of the benchmark seven-day repurchase agreement

suggested by Reuters, the REPO rate is considered the best indicator of general liquidity in China. Further, we investigate the volume of secondary market debut-day trades when the REPO rate is high. We expect the volume of bond trades to be higher when primary market dealers face high borrowing costs as they can generate cash using bond sales (meaning that the supply of bonds in the secondary market is higher). The results indicate that, when REPO rates are high, the probability of observing bond losses is higher and the secondary market volume is also higher.

Third, having documented the existence of bond losses and their liquidity channels, we inquire whether bond losses can lead to financial market instability. As liquidity constraints constitute private information within a primary dealer, bond losses inevitably generate new public information among financial market participants. As a consequence, this new public information could become a common reference point for all traders, possibly resulting in a banking sector-wide capitalization value shock.

To investigate this hypothesis further, we examine the movements of the Chinese FTSE Russel financial indexes on debut-days when Chinese primary market dealers suffer significant secondary market bond losses.[4] In this exercise, we first identify secondary market debut-days with significant bond losses using all secondary market debut-dates in which we observe only all positive or all negative margins. We then create a balanced panel for these secondary market transactions with FTSE banking and security sector indexes two days prior to and two days after the secondary market debut date. Using this data, we estimate a model in the difference-in-difference (DID) spirit to examine the impact of bond losses on the financial sector. We find that FTSE indexes fell significantly—by about 0.5-0.7 percent—following bond loss days compared to all positive days. This means that a negative return on an initial secondary market trading day transaction (which could have been caused by just one primary dealer) generates a disturbance in the entire Chinese financial sector's capitalization value. This finding further supports our hypothesis that bond losses can lead to financial market instability and also indicates that bond losses play a sizable informational role. Similarly, the fact that REPO rates remain the same after negative transaction days also suggests that bond losses can lead to financial market instability.

This study contributes to the literature on government security auctions and their market design. Preceding studies of Treasury auctions and related bond markets have concentrated on

rate in the interbank market.

[4]FTSE Chinese financial indices include 600 large and mid-cap A-share stocks listed on the Shanghai and Shenzhen stock exchanges. As these indices provide broad coverage of Chinese financial institutions and stock markets, they contain information about the financial health of banks and insurance companies in China overall. Further, note that more than 90 percent of financial institutions that represent the FTSE banking, security, and insurance indexes are also primary dealers who participate in government security auctions.

which auction format generates higher revenues (i.e., lower yields) for Treasuries.[5] However, yield (or price) gaps in financial assets, specifically between primary and secondary markets, have been called to attention by financial economists as well as scholars studying friction in financial markets. Among a few influential studies, Nyborg and Sundaresan (1996) investigate mark-ups and information flow before and after bid submissions.[6] We contribute to this literature by investigating the inter-market yield gap and its informational role in market stability.[7]

This paper also contributes to the existing literature on bond losses. Previous studies show that bond losses during 2007-2012 were caused by the acquisition of the risky GIPSI (Greece, Ireland, Portugal, Spain and Italy) sovereign bonds (Acharya and Steffen, 2015; Popov and Van Horen, 2014; Becker and Ivashina, 2018). Acharya and Steffen (2015) show that those bank losses were derived from the European banks' carry trade strategy: the purchase of risky sovereign debt using funding provided by the European Central Bank (ECB). Popov and Van Horen (2014) find that banks with sizeable holdings of GIPSI sovereign bonds saw a decline in their credit supply, and Becker and Ivashina (2018) show that financial repression led to bank losses and the crowding out of corporate lending. Differently, we show that large fluctuations in the money market rates could generate bond losses that decrease the financial sector's market value.

In addition, our study contributes to the literature on government security issuance market (in)stability. Preceding studies focus on instability related to short squeezes (e.g., Jegadeesh, 1993; Jordan and Jordan, 1996; and Nyborg and Strebulaev, 2003). In the spirit of this literature, our study investigates potential policy options that could curb abnormal market behavior. Specifically, we investigate which auction mechanism–uniform or discriminatory–is better at reducing losses. As we show, negative margins in the bond market can have a significant effect on the capitalization value of the financial sector. Thus, a government interested in promoting financial stability would benefit from knowing which auction mechanism best mitigates bond losses. To the best of our knowledge, this paper is the first to show a linkage between bond losses (a possible indicator of winner's curse), liquidity constraints, auction mechanisms, and

[5] For example, Hortasçsu and McAdams (2010) and Kastl (2011) have reported Counterfactual simulation-based methods for revenue comparisons. On the other hand, Brenner (2009) indicates that financial institutions tend to prefer the discriminatory-pricing rule to the uniform rule because of the direct controllable payment upon winning.

[6] Nyborg and Sundaresan (1996) define 'mark-up' as the gap between the auction yield and the when-issued market transaction yield, which is also the return obtained by a dealer in the bond market. They find mixed statistically significant difference in mark-ups between uniform and discriminatory auctions. However, they do show that the size and frequency of pre-auction transactions are higher for uniform auctions, suggesting a higher degree of information release to mitigate winner's curse.

[7] Another strand of the winner's curse literature concentrates on procurement auctions of oil-drilling leases. For instance, the presence of winner's curse in off-shore oil drilling was first noted by Capen et al. (1971). This phenomenon in oil-lease auctions has been extensively studied by Hendricks and Porter (1988).

financial sector-wide instability, as well as clarifying the information transmission channels behind them.[8]

In order to evaluate which auction mechanism (uniform or discriminatory) alleviates possible bond losses, we use an alternating market experiment conducted by two Chinese government bond issuers. We find that the share of transactions with bond losses is higher in discriminatory auctions than in uniform auctions. This result suggests that a government–as a bond issuer–could adopt uniform auctions to reduce bond losses and mitigate financial distress. As far as we know, earlier studies have not investigated bond losses linked to financial sector instability under an alternating-rule market experiment to answer this policy-relevant question.

The remainder of the paper proceeds as follows: The next section gives a background to the Chinese government bond-issuing institutions, and their primary and secondary markets. Section 3 describes the data, employing summary statistics. Section 4 defines the debut-day measure of returns in the Chinese bond market. Section 5 investigates borrowing cost-based liquidity constraints and bond losses. Section 6 reports results on the relationship between bond losses and financial stability. Section 7 evaluates the policy question of which auction mechanism best mitigates bond losses, based on a market experiment conducted by the Chinese government bond issuers. Section 8 concludes the analysis.

2 Institutional background

2.1 Government bond issuers

In this subsection, we describe the institutional backgrounds of the Chinese Government Bond Issuers: the Chinese Ministry of Finance (MOF), the Chinese Development Bank (CDB), the Export-Import Bank (EIB), and the Agriculture Development Bank of China (ADB).

2.1.1 The Chinese Ministry of Finance

Initiated by the MOF, the history of Chinese government securities was closely related to the establishment and economic development of the People's Republic of China (PRC). In 1949, the MOF launched their first bonds, called "People's Victory Bonds," to fund large military expenditures and regenerate the national economy. In 1953, three years after the founding of the PRC, to rebuild the economy and complete "The Plan of the First Five Years," the MOF

[8] It is worth mentioning that, with resale opportunities, the theoretical literature on multiple-unit common-value auctions does not provide a clear-cut conclusion as to which auction mechanism (uniform or discriminatory) best minimizes winner's curse (see Mester, 1995.) See the seminal works of Bukhchandani and Huang (1989 and 1993), Nyborg and Sundaresan's (1996), and Nyborg, Rydqvist, and Sundaresan, (2002) for an early analysis of winner's curse in bond markets.

decided to issue bonds to cover a large financial deficit. These securities were called "National Economic Construction Government Bonds," and the bond issuance lasted until 1958. These two bonds were regarded as the precursors to today's Chinese government securities. However, between 1958 and 1980, China did not issue any bonds.

In 1979, the Chinese government implemented a profit-retention scheme among state-owned companies, which led to an increase in the discrepancy between fiscal revenue and expenditure.[9] Accordingly, in early 1980s, the Chinese government suffered from a fiscal deficit. In 1981, to solve this fiscal challenge, the Chinese government decided to resume issuing bonds.[10] Since the early 1980s, the contemporary Chinese bond market has developed rapidly, and the MOF began to use a system of primary dealers in 1993. In 1995, for the first time, the MOF used auctions as a mechanism to sell government securities. Subsequently, in 1996, auctions became the only method used to issue bonds in the primary market.

In 2002, some Chinese treasury bonds experienced failure in the primary market, as their cut-off rate exceeded the MOF-set upper limit, which was based on the secondary market yield from the previous trading day. As the MOF used only the uniform-price auction format (an auction format in which there is a unique market-clearing yield) at that time, the auctions failed to sell bonds, if the cut-off yield exceeded the upper limit. In 2003, to mitigate this operational challenge, the MOF introduced the discriminatory auction rule (an auction in which bidders pay what they bid). Additionally, starting in 2004, the MOF decided to employ the Spanish (hybrid) auction format to further alleviate the issues with upper rate limit. The MOF used weighted-average winning rates, instead of the secondary market yield, as a reference point to set the upper rate limit.[11] However, since 2016, the MOF has discontinued using discriminatory auctions, and has started using only hybrid auctions to sell bonds with maturities of less than one year. Accordingly, the MOF currently only uses uniform and Spanish auctions to sell its bonds.

2.1.2 The Chinese Development Bank

In 1994, the CDB was founded, and its main financial missions are middle- and long-term fund operations for national projects initiated by the central government. Administratively, the CDB is governed by the Central Bank. In 1994, the CDB started to issue policy-bank bonds for the first time. However, the CDB was initially unsuccessful in allocating bonds, especially in terms of attracting dealers and, as a consequence, was required to reform its

[9] Shen and Cao (2014. p4).

[10] From 1981 to 1984, the Chinese government issued securities worth ¥ 4 billion per year. The total volume increased to ¥ 6 billion per year during 1985-1986.

[11] If a bid deviated from the weighted-average winning rate more than a certain and discretionary range in an auction, the bid was treated as invalid. Note that the range is announced five working days before the auction, and could be different for each bond.

issuance mechanism. In 1995, the bank began to use auctions to issue bonds in the primary market. In the early periods, the CDB issued mainly short- and middle-term bonds (less than or equal to five years), and later expanded their bond maturities to long-term bonds (more than five years). The CDB also issued bonds with different payment mechanisms to satisfy financial market demand. Interestingly, the CDB also offers bonds with floating interest rates. Currently, the CDB uses uniform auctions to sell its bonds.

2.1.3 The Export-Import Bank and the Agriculture Development Bank

The EIB and the ADB were both founded in 1994. Like the CDB, the EIB and ADB are administered by the Central Bank, and their missions are to implement national projects determined by the central government. Note that, throughout the auction history of the EIB and ADB, both institutions have offered some bonds with floating interest rates.

The EIB's main mission is to provide financial support to promote the international trade of Chinese products, especially mechanical and electronic products. It also provides funding to Chinese high-tech companies to develop an advantage in international competition. In 1999, the EIB started using auction mechanisms to issue bonds, mainly through the uniform-price rule, but also occasionally through discriminatory auctions. We will provide further descriptions of the EIB's auction formats in Section 7.

Lastly, the ADB is a policy bank that supports national projects related to the Chinese agricultural sector by providing loans and funds. The bank was established in 1994, but began to use auctions to issue bonds in 2004. Notably, the ADB has only ever employed the uniform-price format in its auctions. Compared to other policy banks, the ADB's bond auctions have smaller volumes.

2.2 Chinese bond issuers and credit ratings

In this subsection, we discuss the credit ratings associated with the four Chinese government and policy bank security-issuing institutions. There are three major institutional rating characteristics and they are: (i) credit ratings are homogeneous within each year during our period of analysis; (ii) bonds issued by the four institutions are all backed by the Chinese government; (iii) ratings for individual bonds are non-existent. Tables A.1 and A.2 report the long- and short-term credit ratings issued by three foreign agencies: Moody's, Standard & Poor's, and Fitch.

First, regarding the ratings for the four institutions, we observe that the four bond issuers are awarded the same credit ratings by each agency within the same calendar year, with the exception of the CDB's short-term rating in 2004. However, ratings vary over the years due to macro-level economic fluctuations and China's fiscal/taxation ability. Note that, in our empirical analysis, we primarily use data from 2004-2017, where all four institutions were actively selling their bonds.

Second, China has distinctive political characteristics regarding its fiscal and national project operations under the framework of the socialistic market economy. Specifically, the MOF is directly governed by the State Council. In addition, the People's Bank of China (the Central Bank)–which administers the CDB, EIB, and ADB–is operated by the National People's Congress.[12] However, the State Council and the National People's Congress are both under the administration of the Presidency of China, which represents the Chinese Communist Party government. Indeed, it is widely accepted by bond market participants that the bonds issued by the four institutions are all backed by the Chinese government (e.g., Chen, 2010). As a consequence, during our sample period, the four bond-issuing institutions have the same within-year long-term credit ratings, awarded by the three foreign rating agencies.

Third, although credit ratings were awarded for the four bond-issuing institutions (i.e., institutional ratings), to the best of our knowledge, these four institutions had not solicited any credit rating agencies to rate their individual bonds until the middle of 2017.[13] Thus until recently, each Government Security auction was held without an individual bond credit rating.

2.2.1 The selection of primary dealers

In order to bid in Chinese government security auctions, primary dealers must be prequalified. The MOF's primary dealer groups were organized once a year from 2000 to 2008, and the frequency changed to once every three years since 2009. In order to identify qualified primary dealers, the MOF created a document of prequalification rules, known as *Management Rules of Organizing Treasury Bond Underwriting Groups*. The prequalification is based on each dealer's financial capacity, past performance, value, and volume of trading over the past three years. An independent committee of experts ranks primary dealers according to these criteria. Based on this ranking, the MOF chooses the primary dealers that can participate in the primary market. For the MOF, for instance, if the target number of primary bidders is 50. The top 45 primary dealers are allowed to continue for another year (or term), and other dealers compete for the remaining five seats.[14] The CDB, EIB, and ADB also use a similar method to

[12] The Governor of the People's Bank of China is appointed by the National People's Congress; yet the nomination of the Governor is made by the Premier of the People's Republic of China, the leader of the State Council. See the following Bloomberg article regarding the relation between the policies of the Chinese Government and the People's Bank of China: https://www.bloomberg.com/view/articles/2018-03-11/people-s-bank-of-china-gains-a-little-independence

[13] Chen (2014) indicates that the three Chinese policy banks enjoy Chinese government-guaranteed sovereign credit ratings.

[14] At the MOF, after the selection of primary dealers, the top 20 primary dealers in the group become high-ranked primary dealers, and the rest of the primary dealers are identified as lower-ranked primary dealers. High-

build their primary groups, but they do not impose a bidding minimum volume for primary dealers.[15] In this study, we refer to all prequalified dealers as "primary" dealers.[16]

One of the most distinctive characteristics of primary dealers in China is their overlapping nature across the four bond-issuing institutions. As Figure 1 shows, during the period 2004-2017, more than 50 percent of primary dealers submitted bids to all all four institutions' auctions (MOF, CDB, EIB, ADB). Moreover, around 25 percent of primary dealers submitted bids across the CDB, EIB, and ADB. Given these facts, we can reasonably conclude that, in Chinese government-related Treasury auctions, a bidder faces the same group of competing financial institutions. This nearly-duplicated competitor environment is an appealing situation for an empirical study, as auction outcomes across different institutions are reasonably comparable.

2.2.2 Secondary market of government and policy bank bonds

In this study, following the IPO initial return literature, we use spot market data from the secondary market debut-days for each on-the-run bond, extracted from the inter-bank and security markets in China. The secondary market debut-day is the date on which primary market participants are allowed to trade a new issuance in the secondary market for the first time.

Chinese government and policy bank bonds have a rigorous timeline regarding secondary market appearance. Specifically, primary market participants are prohibited from trading newly issued bonds at a secondary market for a certain period after an auction—typically five business days.[17] Compared to the U.S., in China, the number of when-issued transactions (that take place between the announcement of a security auction and the issuing date) is almost non-existence. In fact, the only permitted short-trade transactions are of MOF notes with a maturity of 7 years, and when-issued trades for other government securities are strictly prohibited.[18] Thus, in China, financial market participants are typically informed of the

and low-ranked primary dealers have different obligations in terms of minimum volumes: While high-ranked primary dealers need to bid at least four percent of the total volume in an auction, lower-ranked primary dealers only need to bid at least one percent.

[15] Differently from the MOF, these policy banks do not classify their primary dealers as high- and low-ranked.

[16] The number of registered bidders is plotted in Figure A.1, while Figure A.2 plots the year-to-year continuing incumbents. More than 90 percent of bidders continue from the previous year, and more than 50 percent of bidders who participated in 2004 are still in the market in 2017 (see Figure A.3).

[17] The typical length of no-resale-activity restrictions is five business days, although it varies across institutions and auction dates, primarily due to public holidays.

[18] In China, when-issued transactions started in 2013. The Shanghai Security Exchange (SSE), which organizes trades in the when-issued markets for Chinese bonds, began by stimulating trades of MOF notes with a maturity of 7 years. However, since the start, the market has failed to attract potential participants, and only a small number of infrequent transactions have occurred. Indeed, we observe no when-issued transactions for the 7-year MOF issuances since December 2015. For this reason, when-issued transactions are not considered in this paper. Visit the website for details: http://www.sse.com.cn/services/tradingservice/tbondp/home/.

secondary market price/yield of an on-the-run issue five business days after an auction.

3 Data

3.1 Primary and secondary market data

We obtain data on primary and secondary market transactions of the Chinese bond market from two data sources–the Wind Database and Chinabond.com.cn. The Wind Database is obtained from the Wind Information Co. Ltd., a financial data and information provider in China. Chinabond.com.cn is the official website of the China Central Depository & Clearing Co., Ltd. (CCDC), which is the only government bond deposit authorized by the MOF. The CCDC is responsible for the establishment and operation of the government bond depository system.[19]

The Chinese inter-bank market consists of three sections: spot, call, and REPO markets. Throughout this research, we focus on spot market data as bond IDs are available for spot market transactions and we are able to match them with primary auction market outcomes. During our sample period of 2004-2017, the spot market trading volumes of the inter-bank market are far larger than those in the security markets.[20] Further, our study use data only from bonds issued through auctions, as information about issue rates (or prices) are only available for auctioned bonds. Note that since 2004 all institutions started relying only on auctions to sell their bonds.

The Wind Database provides access to details of primary market data on bond auctions held by the MOF, CDB, EIB and ADB from 1998 to 2017. Our data contains not only information of auctioned bonds, such as bond ID, maturity, auction method, size of each auction, and tender subjects (e.g., price or rate), but also the auction outcomes of weighted-average winning rate (or price), low and high winning rates, total demand, number of bidders, number of bids, number of winners, number of winning bids, and final coupon rate for each auction, as well as the presence or absence of floating coupons. We collected supplementary information from Chinabond.com, such as bond types, subsidies, coupon payment, and the frequency for each bond. These two datasets provide more than 2,900 primary market auctions. The Wind Database also provides relevant data of secondary resale markets. From this data, we obtain information on more than 2,350 secondary market debut-day transactions and, as

[19]The CCDC is a State Council-approved agency system (also authorized by the China Banking Regulatory Commission) which conducts registrations; principal, coupon, and interest payments; and depository and other government bond-related transactions. Note that the CCDC was formerly known as China Government Securities Depository Trust & Clearing Co., Ltd.

[20]For example, in the calendar year 2009, the trading volume of the interbank spot market was ¥ 48,868 billion, while it was only ¥ 179 million in the security markets. Source: ChinaBond.com and the People's Bank of China Report in 2009.

in the primary market data, we observe the bond ID and the yield rate (or price) of bonds in the secondary market.[21] This allows us to match each primary and secondary transaction by bond ID, which is a unique feature of our data.

The Wind Database also provides secondary market yield data. As in Keloharju et al., (2005), we use the secondary market yield curve to calculate resale market volatilities by maturity. On each business day, the CCDC announces yield curves for bonds issued by the MOF, CDB, EIB, and ADB. These yield curves are based on the previous period's resale market transactions and provide official bond market information to investors. Daily yield curve data for each institution is available, since 2002 for the MOF and CDB, and since 2008 for the EIB and ADB. Using this data, we calculate the within-five-business-day variance of the corresponding maturity, and use the volatility as a control variable for each issuance in our regression analyses.

3.2 Descriptive statistics

As mentioned earlier, all institutions started using auctions to sell their bonds in 2004. Therefore, in our sample, we use data from 2004 to 2017. During this period, we have 2,951 primary market auction records. We observe that 2,371 of these primary auctions could successfully be matched with secondary market debut-day transactions using their unique bond IDs. Note that these secondary market data contain only the debut-day transactions of a bond. We begin our analysis by providing descriptive statistics for these matched transactions.[22]

Table 1 presents summary statistics of the data used in the analysis. In Panel A, we report summary statistics for auction-level characteristics. Out of the 2,371 auctions, for which we matched primary and secondary market information, 1,521 used the uniform auction (UA) format, and 285 used the discriminatory auction (DA) format. The rest were auctioned off using the Spanish auction format (also known as hybrid auction [HA]). The average yield for these bonds in the primary market rate is 3.63%.[23] In our sample, most of the financial instruments fall into the category of notes (maturities ranging from more than one year to 10 years). Of these bonds, 168 had a floating coupon rate, and were auctioned off only using the uniform format, starting in 2007. Further, they were used only for notes. We observe that, on average, there were about 40 bidders per auction.

[21] Due to small trading volumes, we excluded over-the-counter transactions from this research.

[22] First, in Table A.3, we present the number of bonds by institution and bond type. In the sample, we observe that the CDB is the largest auction organizer in terms of auction numbers, and the majority of the bonds are auctioned off as notes. In Table A.4, we report the tabulations of bonds by auction mechanism and maturity period. One can observe that all three auction types are used for different types of bonds.

[23] In China, primary dealers receive subsidies when they acquire bonds in government auctions. Those subsidies take the form of rebate on the auction value of the bond. All bond rates in our dataset account for these subsidies.

In Panel B, we report secondary market information. The average secondary market yield is about 3.75%. These bonds could be traded in the Chinese inter-bank market, or in the Shanghai or Shenzhen stock exchanges. However, the inter-bank market accounted for 94.9% (2,213 out of 2,371) of secondary market transactions. Additionally, all floating bonds were traded in the inter-bank market. In our analysis, we use the time lag variable to capture idiosyncratic market variations within this short period. We also include monthly traded volume to control for the intensity of transactions by bond type and maturity. The average monthly volume is about ¥ 886 billion by bank.

In Panel C, we present the variables that capture possible changes in market conditions. Note that unobserved macroeconomic conditions and associated inflation expectations (or any other economic fundamentals) could change in the short time between the auction and the secondary market debut-days. We first show the average volatility of yield curves five days before the secondary market. This variable varies by bond type and maturity, and the calculated value is 0.03. We also use the five-day volatility of the FTSE Chinese Bank Index (and Security Index) to control for unobserved heterogeneity of the financial sector.[24] Further, in our regression, we include a change in the yield curve (at a corresponding maturity and at each institution) as a control variable, controlling for financial market events occurring between the auction and debut-days.[25] Additionally, we use the total value of maturing bonds by institution for a given month, to control for issuer-level monthly demand for money (backlog). We also report the REPO rate, which is about 3% on average during the sample period.

4 Returns in the Chinese bond market

4.1 Definition of the adjusted margin

Primary bond dealers in China purchase bonds in Treasury auctions to resell them in the secondary market. As mentioned before, given the non-existence of short-trade opportunities, these bidders know their effective margin only after selling these bonds in the secondary market, which typically does not open until five business days after a Treasury auction.

Interestingly, we notice that more than 80 percent of the on-the-run bonds (i.e. about 1,900 issuances out of 2,371) were sold on their first trading days in the secondary market. This prosperity of debut-day trades provides a great opportunity to quantify possible bond losses in the Chinese bond market, as we can observe both primary and debut-day secondary rates for a given bond. Therefore, following the convention of the IPO initial return literature, we

[24] Note that the Insurance Index started from 2007.

[25] Our outcome variable is the difference between the primary and secondary market yields. Hence, any unobserved variables, which affect both primary and secondary market rates in the same way, could cancel out.

define the margin for a given bond as the primary market rate minus the debut-day secondary market rate.

Figure 2 shows the cumulative distribution (CDF) of this raw margin for our data. As we can see, many transactions are negative. However, we caution against the direct interpretation of this gap (or return) as bond losses, because this distribution is not controlled by any auction, bond, and financial market characteristics, which could vary between the primary auction day and the debut-day. Hence, our next step is to remove the observable effects of auction, bond, and market characteristics from this raw margin. This removal will allow us to obtain a measure of the *adjusted margin* that is not driven by observables. Specifically, given the unique market and information structure, our measurement has a noisy public signal interpretation, which may reveal liquidity constraints within a primary market bidder (or bidders). The procedure to obtain this conditional measure is as follows. Specifically, we follow a bid homogenization introduced by Haile et al. (2006), which is widely used in empirical auction studies. First, we estimate the following regression, explaining the observed margin for a given bond (i) by institution (j) as a function of auction (x), bond (z), and market characteristics (m), as seen in Equation 1.

$$\text{margin}_{ijt} = \alpha + x_{ij}^{'}\beta + z_{ij}^{'}\gamma + m_{it}^{'}\omega + \theta_j + \tau_t + \epsilon_{ijt}, \tag{1}$$

where τ is the time fixed-effects, θ is the institution effect, α is the constant, and ϵ is the residual. First, in the right-hand side of Equation (1), x, z ,m and fixed effect terms are known to the financial market participants. Thus, ϵ captures the unobservable variation of the return that is not explained by the observable variables, including the privately-possessed liquidity constraint information. Here, the term of "unobservable" means unobserved information to researchers and general financial market participants, except bidders who sell on-the-run issues on debut-days (and who know the reasons behind the debut-day reselling activities). Second, ϵ plays a role of a noisy public signal.[26] ϵ is noisy because financial market participants (except bidders who sell on-the-run issues) do not know the exact motive behind the trade. On the other hand, as the transacted secondary market yields are publicly posted on the interbank market and other websites with bond IDs (but without the identities of the traders), every financial market participant can monitor ϵ.[27] Third, the homogenized margin captures

[26]Noisy public signals play a substantial role in financial markets. See Morris and Shin (2002) and Allen, Morris, and Shin (2006) for models of noisy public signal information and coordinated reactions of financial market participants.

[27]Specifically, such secondary market bond trade transaction information with bond IDs (but without identities) is officially posted on the websites of: China Foreign Exchange Trade System and National Interbank Funding Center (www.chinamoney.com.cn); Shanghai Stock Exchange (http://www.sse.com.cn); Shenzhen Stock Exchange (http://www.szse.cn), as well as commercial banks' websites. In addition, financial information companies (Bloomberg, Wind, etc.) post daily transaction data for their subscribers, who can obtain quotes from their terminals.

informational revelation, especially related to trades with negative margins. Although general financial market participants (and researchers) know neither the economic incentives behind the negative margin trades, nor the identity of involved primary bidders, the negative margin trade itself reveals an urgent demand for liquidating the on-the-run issue. We will later test this information revelation hypothesis.

As the residuals in Equation 1 by construction have a mean of zero, we subtract the mean market rate of return from the residuals to obtain the adjusted margin (Equation 2).

$$\text{margin}^*_{ijt} = \widehat{\epsilon}_{ijt} - \overline{\widehat{\text{margin}}}. \tag{2}$$

This is our noisy public signal measure of the adjusted margin, which is later used to investigate the informational channel of post-Treasury-auction market instability.

Table 2 presents the estimated parameters and explains the market gap (i.e. return), as in Equation 1. In Column 1, we present results from the model that are estimated while excluding our financial market volatility and trend measures. This is our baseline model, to which we compare the sensitivity of parameters when re-estimated with market controls. Results indicate that floating coupon bonds reduce the margin compared to bonds without any coupons. The log number of bidders in an auction tends to induce aggressive bidding and increase the market gap, which is consistent with auction theory. Results indicate that, if the time lag between the primary and secondary market debut-day is longer, primarily due to public holidays, then this time lag tends to increase the margin. Additionally, the coefficient of the previous month's trading volume indicates that, if the trading intensity is high, then the margin is low, which is consistent with liquidity premium theories. Finally, the volatility, constructed using the previous five days' yield curve information at a given maturity, indicates that, if the market is volatile, then the margin is high.

Considering other controls, we see that the Spanish or discriminatory auction methods do not affect the margin any differently than the uniform auction format. Securities with maturities beyond one year do not affect the market gap any differently than bills.

In Column 2, we include the FTSE volatility as a control. The coefficient is statistically insignificant. In Column 3, we also include the yield curve difference (between auction and debut-days) to control for market trends. In Column 4, we also control for volatility of FTSE bank index at the day before the secondary market transaction. In Column 5, we include the variable that controls for money demand by institutions. The results indicate that the margin is not affected by the value of maturing bonds by institution for a given month. The main point is that, even after controlling for market conditions, our main bond- and auction-specific parameters stay consistent, including the coefficient of determination.

Note that not all of the on-the-run bonds are resold on their debut-days. A concern one might have with these margin regressions is selection bias after controlling for covariates, and bonds that were traded are not randomly selected. Given that we observe all primary and debut-day secondary market transactions, we address this concern by using a Heckman-based correction model. We specify the probability of selling on the first allowed trading day in the secondary market (the selection equation) using the same variables in the outcome equation given in Column 5 of Table 2, excluding trading location controls (Shenzhen Stock Exchange and Shenzhen Stock Exchange dummies). Because we do not have an exclusion restriction(s), we leverage the nonlinearity of the functional form of the selection equation. The estimates are presented in Column 6, and the results indicate that selection bias is not a concern.

Next, we want to confirm whether the patterns we observe in the mean regression hold throughout the entire distribution of the margins. Therefore, we estimate the empirical model described in Column 5 of Table 2, using the quantile regression method proposed by Koenker and Bassett (1982). We report these results in Table A.5 in Appendix A. Qualitative interpretations of the coefficients are similar to what we observed in Table 4 and, hence, we do not discuss these results in detail. The main point is that the patterns discussed in the mean regression hold throughout the distribution of margins as well.

However, in all models, the controls explain some variation, but not all. In Figure 3, we plot the fitted margins (from Equation 1) and adjusted margins (from Equation 2). In the figure, we use predicted margins and residuals obtained after estimating the empirical model described in Column 5 in Table 2, and use them to construct the adjusted margins as described in Equation 2. Now, we compare the CDFs of fitted (un-adjusted) margins (Figure 2) with the adjusted margins (Figure 3). The natural question is whether one could still observe this negative return after removing the observable variation. Now, consider the distribution of the adjusted margin. Looking at Figure 3, we observe that, on average, the market generates positive returns (adjusted margins). However, about 20% of transactions suffer losses. In Table 3, we present the distributional statistics of the adjusted margins with 95% confidence intervals. We observe that, at the bottom part of the distribution, negative values indicate the losses with statistical significance.

In the above analysis, we do not control for secondary market volume, which may affect the secondary market rates. Our data set contains 1,128 secondary market debut transactions with volume information for non-reissued bonds. Note that the Wind data do not provide secondary transaction volumes for re-issued bonds and floating bonds.

Next, we re-estimate the market gap regressions (Equation 1), previously seen in Table 2, with the control for the secondary market volume. These regression results are reported in

Table 4 and they are qualitatively similar to those reported in Table 2.[28] However, these data provide an opportunity to calculate the gains and losses for the volumes sold in the secondary market.

In Table 5, we report the summary statistics for the gains and losses (positve and negative adjusted margins) based on regression results presented in Column 5 of Table 4. We observe that there are 816 and 312 observations with positive and negative adjusted margins respectively. The average adjusted margin for positive values was 0.060%, while the average negative adjusted margin was -0.082%. We also calculate the change in price between primary and secondary market debut transactions. For all the positive margins, the adjusted price change was 0.052. For the negative margins, it was -0.121. Given this information, we then calculate the average and total gains (or losses) for the traded instruments in the secondary market compared to the primary market. We observe that, for all positive adjusted margin transactions between 2004 and 2016, the average gain per transaction was about ¥ 42.6 million, while the average loss was about ¥ 71.70 million for negative adjusted margin transactions. Even though the individual losses were higher than the gains, the total gains were ¥ 34.76 trillion (approximately $ 5.27 trillion) while the losses were ¥ 22.37 trillion (approximately $ 3.39 trillion).

4.2 Adjusted margins by period

Given our data span, we are in a unique position to examine the adjusted margins and the magnitude of losses during a financial crisis, as observed in 2008-2009. Here, we use the same predicted margins and residuals as the empirical model estimated in Column 5 in Table 2.[29] However, we now construct the adjusted margins before, during, and after the crisis. These results are presented in Table 6. We also draw the CDF of these homogenized margins, and they are presented in Figure 4.

The results indicate that, during the crisis years, the adjusted margins were negative and with higher magnitudes in the bottom half of the distribution, including the 50th percentile. This pattern was not observed before or after the financial crisis, indicating that bond losses were more prevalent during 2008-2009. However, after 2009, our results in Table 6 show that the adjusted profit margins have increased for primary dealers and this difference is statistically significant.

In Table 7, we breakdown the gains and losses by period. The basic interpretation is similar to Table 5. However, during the 2008-2009 period, the average losses were about 2.8 times

[28]We have drawn the adjusted margins in the Appendix Figure A.4, which is also similar to Figure 3.

[29]We also estimate these models using dummies to indicate the crash and after-crash periods. These OLS and quantile models are presented in Table A.6 and Table A.7 respectively. The results indicate that the market gaps were higher during and after the crash, compared to the time before the financial crisis.

larger than the average gains. To be specific, during the financial crisis, the average gains were about ¥ 45.90 million, while the average losses were ¥ 128 million per transaction.

Next, as we noticed, in Table 2, the market gap of the floating bonds are quite different from non-floating bonds. This may be due to the inherent structure of floating bonds. Hence, we re-estimate the models described in Equation 1, using only uniform bonds sold since 2007. Details of the analysis and regression results are presented in Appendix B.

5 Liquidity constraints and bond losses

Having defined bond losses, in this section, we examine whether we can predict bond losses when the financial market faces high money market borrowing costs, i.e., when the costs of intertemporal substitutions for alleviating current liquidity shortage are high. First, we identify secondary market transactions and days in which all traded bonds generated negative adjusted margins, and at least one transaction generated a loss that fell below the bottom 10^{th} of the distribution. This explains the observation of a negative adjusted margin of 15.7%.[30] We identify 52 days (out of 1,185 days) where all transactions incurred losses. This classification works as our most restrictive sample, and we later relax the cut-off threshold on these definitions of losses. We denote a transaction with a loss ($loss = 1$) and a day where all transaction incurred losses ($all\ losses = 1$).

As represented by the Reuters' report, the best indicator of general liquidity in China is the seven-day REPO rate. Hence, we use the REPO rate as a proxy for liquidity constrains in China. A testable hypothesis is that when primary dealers face high borrowing-costs, which we use as a measurement of liquidity constraints, the primary dealers choose to generate cash using on-the-run bond sales. Hence, we examine whether we can use the REPO rate to predict bond losses, especially on trading days when all adjusted margins are negative. We also investigate the predictability of trading volume based on the REPO rate.

First, at the transaction level, we use a simple probit to examine the probability of observing bond losses on trades given the REPO rate of the debut-day. We report these results in Table 8, Column 1 Panel A. Note that these losses are based on our adjusted margins, and hence they have been estimated after controlling for bond, auction, and market characteristics. The positive and significant coefficient of the REPO rate indicates that when the market observes a high REPO rate, there is a higher probability of observing bond losses in the secondary market. In Column 2, we report the results for auctions with available records of secondary market volumes. The results are similar to what we observe in Column 1. Next in Column 3, we examine a different construction of the dependent variable, which is equal to one on

[30] Note that 78 transactions generated less than -15.7% returns.

a debut-day when all adjusted margins are negative, and otherwise zero. Our probit results indicate that when the REPO rate is high on a given day, then there is a higher probability that all secondary market transactions are losses on that day.

Next we examine whether the traded volume is affected by the REPO rate, at both transaction and debut-day levels. Here our dependent variable is either (i) secondary market traded volume by bond (in logs), compared to its primary market auctioned volume (in logs), or (ii) the total secondary market volume of all bonds for a given trading day (in logs), compared to these bonds' total primary market volume (in logs). In Columns 4 and 5 we report these results estimated using OLS. Both columns indicate that when liquidity constrains are tighter, secondary market trading volumes are higher, compared to low liquidation cost days. It is possible that our results from this analysis are driven by the market crash in 2008 and 2009. Hence, we re-estimate these models without bond transactions between 2008 and 2009. These results are presented in Panel B. The results indicate that our findings are not sensitive to the market crash, and are thus robust.

Next we reduce our loss threshold to 10% and re-estimate all models. Our general qualitative results are similar, indicating that they are robust to different thresholds of losses as well. We do not report these results, but they are available upon request.

6 Bond losses and financial stability

Now we turn our attention to the effect of bond losses on financial instability by analyzing what happened to the FTSE Russel Chinese financial indexes – consisting of representative bank, security, and insurance sector public companies – on the days when Chinese primary market dealers suffered substantial bond losses. As we mentioned earlier, the FTSE Chinese financial indexes provide broad coverage of the Chinese stock market and financial institutions. Hence, any movement on these indexes reveals information about the financial health of banks and insurance companies in China. We exploit the fact that more than 90 percent of financial institutions that represent the FTSE banking, security, and insurance indexes are also primary dealers. In Table A.8, we present a breakdown of the number of primary banks that represent the FTSE indexes.

By investigating the effect of bond losses on Chinese financial indexes, we hypothesize that, if primary dealers are exposed to bond losses on a secondary market debut-day, then their market capitalization value could decline, lowering the FTSE financial indexes. To test this informational hypothesis, we conduct the following empirical exercise.

First, as above, we use secondary market debut-days with at least one transaction where the adjusted margins fall below the bottom 10^{th} (-15.7%) of the distribution. Next, we drop all secondary market dates where we observe both positive and negative adjusted margin transactions. This condition drops 121 secondary market dates with 454 transactions. This gives us a sample of 1,064 secondary market debut-dates, which consist of transactions with either all positive (1,606) or or all negative (313) adjusted margins. As in the liquidity constraint exercise, we identify days where all transactions were negative (52) with at least one transaction generating adjusted margins at or below the 10th percentile of the distribution. Next, we create a balanced panel for the 1,917 secondary transactions involving banking and security indexes, using data from two days prior and two days after the secondary market debut date. This creates a sample of 9,585 observations. Using this data, we estimate the following simple panel regression model, similar to a difference-in-difference (event study) model, to examine the impact of bond losses on the financial sector as

$$I_{it} = \beta_1 N_i + \beta_2 T_t + \beta_3 N_i \times T_t + \alpha_{it} + \varepsilon_{it}, \tag{3}$$

where I is the banking or security index at time t based on i^{th} bond transaction, N is an indicator to identify all negative adjusted margin transactions with the corresponding trading date, and T identifies a period of two days after the secondary market debut trading date.

We are primarily interested in the value of the coefficient of β_3 which measures the difference in indexes between the days with all negative adjusted margin transactions and days with all positive ones. We present the results for the banking index of this exercise in Table 9, Panel A. Note that all +/- day indexes values are normalized by the corresponding secondary market trading day value.

We estimate the above model with a plus-minus one day time span, as well as with a plus-minus two days span. Further, we estimate these models without years 2008 and 2009. The results indicate that banking index fell by about 0.6-0.8 percent following days with bond losses. These panel regression results support our hypothesis that bond losses could lead to financial market instability, at least in (but not limited to) the financial sectors' capitalization values. Similar patterns are observed for the security index (See Panel B in Table 9).

Next, we estimate a similar model where the dependent variable is the REPO rate, normalized by the debut date value. The coefficient of interest, β_3, indicates that the REPO rate is not responsive to the observed bond losses (Panel C in Table 9). This result further support our hypotheses that financial indexes respond to bank losses, while money market rates do not.[31]

[31] As in our 'liquidity constraints' exercise, we re-estimate these models using a 10% cut-off for the negative adjusted margin threshold. Results are qualitatively similar and we can provide them upon request.

7 Auction mechanisms and bond losses

In the previous section, we demonstrated that bond losses are prevalent in bond markets, and that such losses generate a drop in the entire Chinese banking sector's stock capitalization value. A government that cares about financial stability may consider all available policy instruments to stabilize the market. In the context of the financial bond market, the government, as a bond issuer, can use different auction mechanisms to reduce bond losses. However, there is no clear policy recommendation, based on the empirical and/or theoretical literature, about which mechanism should be used for this purpose.[32]

In this section, we evaluate which auction mechanism best mitigates bond losses in the market. China, again, is the perfect ground to investigate this question. During the period May 2012-July 2014 for the CDB, and July 2013-May 2015 for the EIB, these two institutions conducted alternating auction rule market based experiment to sell bonds using discriminatory and uniform-pricing auction formats. As the use of the different auction mechanisms was experimented, we can estimate the effect of the adoption of the discriminatory and uniform auctions on the distribution of the adjusted margin. Our results suggest that bidders are more exposed to bond losses in discriminatory auctions than in uniform-price auctions.

7.1 Alternating auction rule experiment

Throughout the experiment period, the CDB held weekly auctions on Tuesdays, while the EIB held their auctions mostly on Thursdays or Fridays. Note that, in the early parts of the sample, the EIB held auctions fortnightly or monthly while, later, they held weekly auctions. Within each week, the CDB sold 2 to 5 different maturities of bonds in separate auctions, and the EIB followed a similar pattern. A representative pattern of their alternating experimental auction format choices are as follows:

Each week, the CDB auctioned off bonds with maturity lengths of 3, 5, and 7 years. However, as shown in Table A.9, each week they alternated the auction mechanism between the discriminatory and uniform formats. The CDB repeated this pattern of alternating auction rules between May 2012 and July 2014.[33] The EIB also implemented a similar experiment design with the alternation of uniform- and discriminatory- auction formats. As shown in Table A.10 Panel A, in the early part of their experiment, the EIB alternated between auction formats every two or three months. In the second half of the experiment, the EIB alternated the auction format for the same type of bond (identified by bond ID and initial and reissue

[32]See Bikhchandani and Huang (1993), Mester (1995), and Kastl (2017) for a survey of the literature on the economics of Treasury security auctions.

[33]Note that all bills (with maturities of less than or equal to one year) and bonds (with maturities equal to or more than 10 years) were sold using the uniform auction format.

status). We note this market experimentation for two bonds in Table A.10 Panel B.

We observe 348 auctions during this experimental period. Out of these, 160 auctions were held using the discriminatory auction format. The CDB held 269 auctions and 130 of then were using discriminatory auction format while 139 were sold using uniform autions format. The EIB used 30 and 49 discriminatory and uniform auctions respectively. Accordingly, we exploit this experimental alternation between auction formats a source of exogenous variation. The total value of the experiment is ¥ 1.96 trillion (approximately $ 291 billion).[34]

An important feature of experiment conducted by the CDB and EIB is that bidders know the format of a given auction only five days before it occurs. This means that, when they are participating in a typical auction, they do not know the format of the upcoming auctions. This is an important feature of the experiment, as bidders will not be able to time their entry into the auction based on the format of the auction that is coming up next.

Given this setting, we re-estimate our models (as in Equations 1 and 2) for this period. OLS and quantile results are presented in Tables 10 and A.11.[35] Although we do not see a difference in market gap between uniform and discriminatory auction formats during this period, our main interest is the adjusted margins. We obtain adjusted margins for this period without controlling for auction mechanisms. In Figure 7, we plot these adjusted margins by uniform and discriminatory auction formats.

Figure 7 reveals that the share of transactions with a negative adjusted margin is higher in discriminatory auctions than in uniform ones. It also shows that the distribution of adjusted margins for uniform auctions are higher than the the adjusted margins of discriminatory auctions. The result of Kolmogorov-Smirnov test reports that the hypothesis of distributional equivalence is rejected at the p-value of less than 0.01.[36] Table 11 supports the evidence provided in Figure 7 and indicates that the margins generated from uniform auctions are larger than the margins generated from discriminatory auctions.[37]

Next, we also re-estimate the market gap (Equation 1) controlling for volume. We have only

[34]Barbosa et al. (2018) show that, during the experiment period, the value of the market yield the day before the primary market, secondary market volatility, and the value of maturing bonds by the institution for a given month are not statistically different between the uniform and discriminatory format. Barbosa et al. (2018) also find that, between the two auction formats, bidders' entry behavior does not reveal any statistical difference.

[35]We do not estimate this using a Heckman model, as more than 94% (328 out of 348) of bonds sold in primary market auctions during this experiment period had experienced secondary market sales on their debut days.

[36]We further investigate the Goldman-Kaplan point-by-point equivalence test (Goldman and Kaplan 2018) shows that, with a familywise error rate at a 5% level, the CDF equivalence is rejected in the ranges of [-0.013, -0.0124], [-0.012, -0.008], [0.007, 0.019], and [0.039, 0.869].

[37]However, one may argue that margins in discriminatory auctions may be different for a given bond based on the highest and lowest accepted primary rates they observe. To address this concern, we construct margins using high and low primary bids. The margins regression is presented in Table A.12 in the Appendix A. Table A.13 and Figure A.5 present adjusted margins that have been constructed by using high, low, and weighted average winning primary rates. The results indicate that, regardless of the primary market rate, negative margins prevail in the bottom 10th percentile.

74 observations (out of 348) with volume records during the experimental period. However, our results indicate that the basic findings are similar to the ones we find in Table 4.[38] In this exercise, we also calculate the average gains and losses. With respect to uniform auctions, we observe that the average gain per transaction—based on 33 positive adjusted margins—was ¥ 5.10 million while the average loss was ¥ 3.34 million based on 10 negative adjusted margin transactions. When considering discriminatory auctions, the average gain per auction is ¥8.60 million (25 transactions with positive adjusted margins) while the average loss was ¥ 15.78 million (6 transactions with negative adjusted margins).

7.2 Policy Implications

The above results indicate that, if a government wishes to stabilize the financial sector, it could adopt uniform auctions that lead to a lower probability of bond losses. However, the government may have other objectives that may conflict with mitigating bond losses. For instance, the uniform format could potentially reduce revenues to the government. Barbosa et al. (2019) show that there is no difference in the primary market auction outcomes between discriminatory and uniform auction methods using the same Chinese experimental data. Therefore, from the point of view of a government's revenue, the two auction mechanisms generate the desired funds with statistically indistinguishable yield rates.

8 Conclusion

In this paper, we show that the existence of bond losses is prevalent in bond markets in post-Treasury auction periods. We exploit the market structure of the Chinese government security issuance process, where short trades are strictly prohibited, which allows us to focus on an analysis of potential liquidity constraints. By computing the difference between the primary market yield in bond auctions and its respective secondary market yield from resale market transactions, we obtain the effective return (adjusted margin) of a primary bond dealer, which has a straightforward interpretation. Using a unique data set containing the transactions of bonds in the primary and secondary markets, we show the prevalence of bond losses even after adjusting for auction, bond, and market conditions. Next, we show that tight liquidity conditions, proxied by REPO rates in the money market, are a source of bond losses. Also, we finds that bond losses are related to the decline in capitalization values, measured by FTSE index. Importantly, we also find that market indexes fall after observing bond losses, clarifying the informational channel through which financial market instability propagates.

[38] We do not report these results but can provide upon request.

Finally, we determine which auction mechanism (uniform vs. discriminatory) best mitigates these bond losses, using an alternating market-based experiment conducted by two Chinese government bond issuers. We find that the share of transactions with bond losses is higher in discriminatory auctions than in uniform ones. Also, the results show that the dealers' average expected returns are lower in discriminatory auctions. This may support the discontinuation of discriminatory auctions since 2016 by Chinese bond issuers, as well as the global trend of switching from the discriminatory to the uniform format. Thus, our finding of auction-rule effect could be informative to governments, who may wish to achieve financial stability through Treasury security markets designs.

References

[1] Acharya, V. and Steffen, S. (2015). "The Greatest Carry Trade Ever? Understanding Eurozone Bank Risks." Journal of Financial Economics, 115, 215-236.

[2] Allen, F., S. Morris, and H.S. Shin (2006). "Beauty contests and iterated expectations in asset markets." The Review of Financial Studies, 19(3): 719-752.

[3] Back, K. and J.F. Zender (1993). "Auctions of divisible goods: on the rationale for the Treasury experiment." Review of Financial Studies 6, 733–764.

[4] Barbosa, Klenio, Dakshina G. De Silva, Liyu Yang, and Hisayuki Yoshimoto (2018). "Auction Mechanisms and Treasury Revenues: Evidence from the Chinese Experiment" *Mimeo*.

[5] Becker, Bo and Ivashina, Victoria (2018). "Financial Repression in the European Sovereign Debt Crisis." Review of Finance, 22 (1), 83–115.

[6] Begenau, J., M. Piazzesi, and M. Schneider (2015). Banks' Risk Exposures. NBER Working Paper No. 21334.

[7] Bikhchandani, S. and C. Huang (1989). "The Economics of Treasury Securities Markets." The Journal of Economic Perspectives, 7(3), 117-134.

[8] Brenner, Menachem, Dan Galai, and Orly Sade (2009), "Sovereign debt auctions: Uniform or discriminatory?" Journal of Monetary Economics, 56: 267–274.

[9] Bukhchandani, Sushil and Chi-fu Huang (1989), "Auctions with resale markets: An exploratory model of treasury bill markets." Review of Financial Studies, 2: 311–339

[10] Capen, E. C., R. V. Clapp, and W. M. Campbell (1971). "Competitive Bidding in High-Risk Situations." Society of Petroleum Engineers. 23(06): 641-653

[11] Chen, Jian (2014). "Research on the Financial Bonds issued by Policy Banks in the Process of Reform and Transition." Zhong guo jing rong chu ban she (Li xing Press)

[12] Chen, Ying (2010). "Problems about current credit rating system of bonds in China and strategies-the example of credit rating system in interbank bond market." Financial Teaching and Research, 2: 59-62.

[13] De Bandt, O., P.Hartmann, and J. Peydro (2010). "Systemic Risk in Banking." In The Oxford Handbook of Banking, Second Edition (2ed.) Edited by Allen N. Berger, Philip Molyneux, and John O. S. Wilson.

[14] Fleming, M.J. (2002), "Are larger treasury issues more liquid? Evidence from bill reopenings." Journal of Money, Credit and Banking, 707-735.

[15] Goldman, M. and D.M. Kaplan (2018). "Comparing distributions by multiple testing across quantiles or CDF values." Journal of Econometrics, 206(1):143-166.

[16] Haile, P.A., H. Hong, and M. Shum (2006). "Nonparametric Tests for Common Values in First Price Sealed-bid Auctions," Working Paper

[17] Hendricks, Kenneth and R. Porter (1988). "An Empirical Study of an Auction with Asymmetric Information." American Economic Review, 78 (5): 865-883.

[18] Hortacsu, Ali and David McAdams (2010). "Mechanism choice and strategic bidding in divisible good auctions: An empirical analysis of the Turkish treasury auction market." Journal of Political Economy, 118: 833–865.

[19] Jordan, Bradford and Susan Jordan (1997). "Special Repo Rates: An Empirical Analysis." 52 (5): 2051-2072.

[20] Kastl, Jakub (2011), "Discrete bids and empirical inference in divisible good auctions." Review of Economic Studies, 78: 974–1014.

[21] Kastl, Jakub (2017). Recent Advances in Empirical Analysis of Financial Markets: Industrial Organization Meets Finance. In B. Honoré, A. Pakes, M. Piazzesi, & L. Samuelson (Eds.), Advances in Economics and Econometrics: Eleventh World Congress (Econometric Society Monographs, pp. 231-270). Cambridge: Cambridge University Press.

[22] Keloharju, M., K. G. Nyborg, and K. Rydqvist (2005). "Strategic behavior and underpricing in uniform price auctions: Evidence from Finnish treasury auctions." The Journal of Finance, 60: 1865-1902.

[23] King, M.R., N. Massoud, and K. Song (2013). "How Does Bank Trading Activity Affect Performance? An Investigation Before and after the Crisis," mimeo.

[24] Koenker, R., G. Bassett Jr. (1982). "Robust tests for heteroscedasticity based on regression quantiles." Econometrica 50 (1): 43–61.

[25] Mester, L. (1995). "Theres More than One Way to Sell a Security: The Treasury's Auction Experiment." Business Review. Federal Reserve Bank of Philadelphia, July-August, 3-17.

[26] Morris, S. and H.S. Shin (2002). "Social value of public information." American Economic Review, 92(5): 1521-1534.

[27] Nyborg, K. G. and I. A. Strebulaev (2003). "Multiple unit auctions and short squeezes." The Review of Financial Studies, 17(2): 545-580.

[28] Nyborg, Kjell G. and Suresh Sundaresan (1996). "Discriminatory versus uniform treasury auctions: Evidence from when-issued transactions." Journal of Financial Economics, 42, 63–104.

[29] Nyborg, Kjell G, Kristian Rydqvist, and Suresh M Sundaresan (2002). "Bidder behavior in multiunit auctions: Evidence from Swedish treasury auctions." Journal of Political Economy, 110, 394–424.

[30] Papke, Leslie E. and Jeffrey M. Wooldridge (1996). "Econometric Methods for Fractional Response Variables with an Application to 401 (K) Plan Participation Rates." Journal of Applied Econometrics, 11(6):619-632.

[31] Popov, Alexander and Van Horen, Neeltje (2015). "Exporting Sovereign Stress: Evidence from Syndicated Bank Lending during the Euro Area Sovereign Debt Crisis." Review of Finance, 19 (5), 1825–1866.

[32] Reinhart, Carmen and Sbrancia M. Belen (2015). "The Liquidation of Government Debt." Economic Policy, 30(82), 291-333.

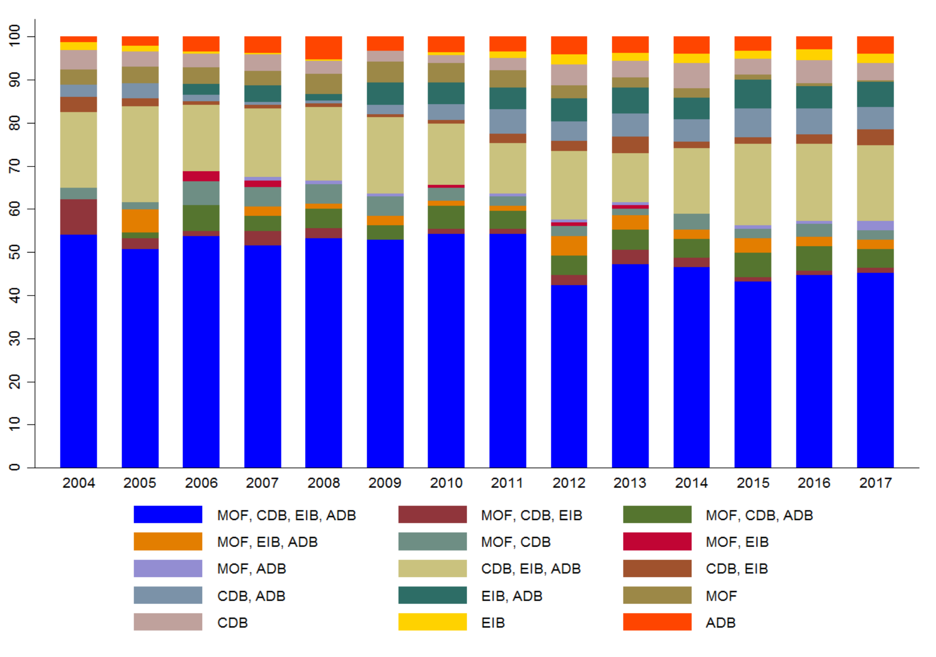
[33] Rock, K. (1986). "Why New Issues are Underpriced." Journal of Financial Economics, 15, 187–212.

[34] Shen, Bingxi and Yuanyuan Cao (2014). "China Bond Market Reform and Development in the Past 30 Years." Beijing da xue chu ban she (Bo wen Press)

[35] Umlauf, Steven R. (1993). "An empirical study of the Mexican treasury bill auction." Journal of Financial Economics, 33, 313–340.

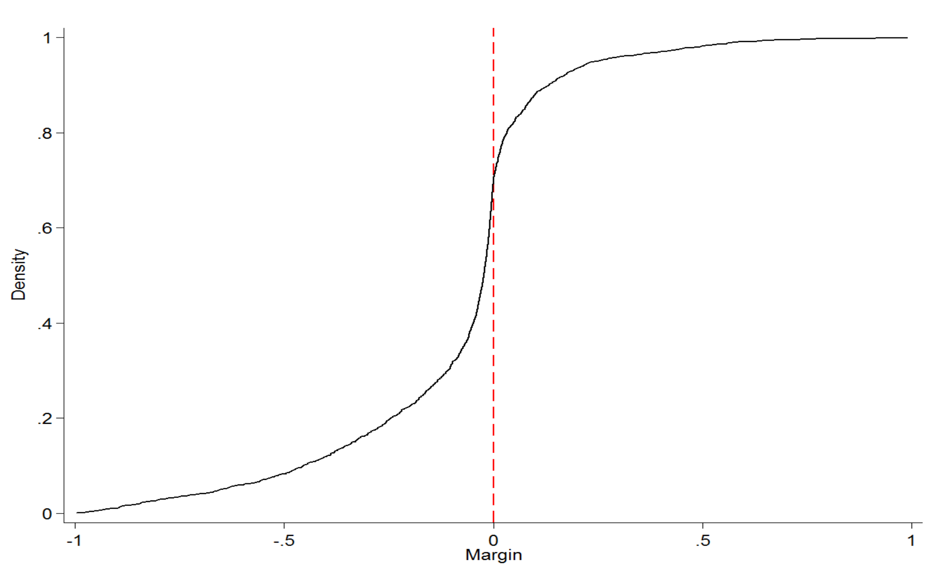
[36] Welch, I. (1989). "Seasoned Offerings, Imitation Costs, and the Underpricing of Initial Public Offerings." Journal of Finance, 44, 421–449.

Figure 1: Primary dealer overlap



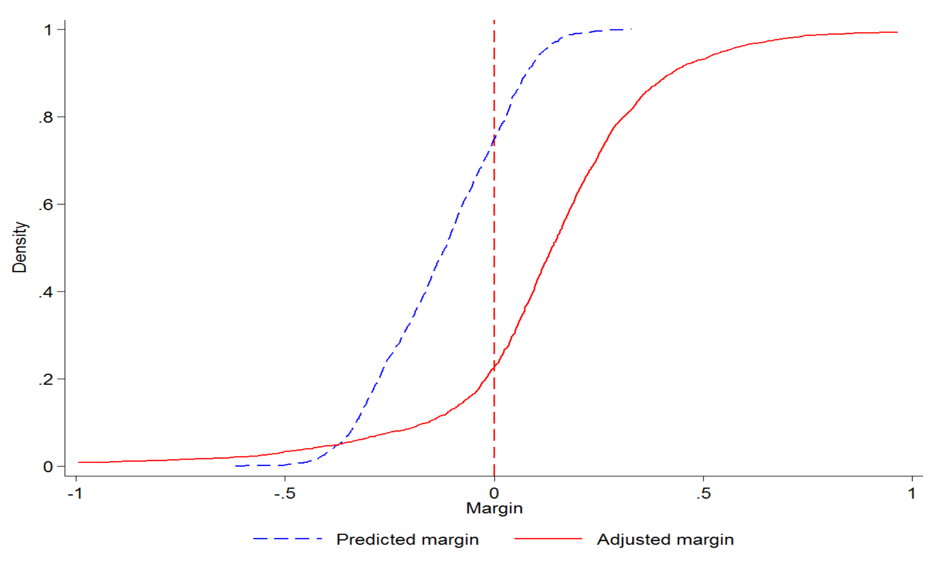
In this figure, we show the overlapping nature across the four bond-issuing institutions. During the period 2004-2017, about 50 percent of primary dealers submitted their bids in all MOF, CDB, EIB, and ADB auctions.

Figure 2: Fitted (un-adjusted) margin



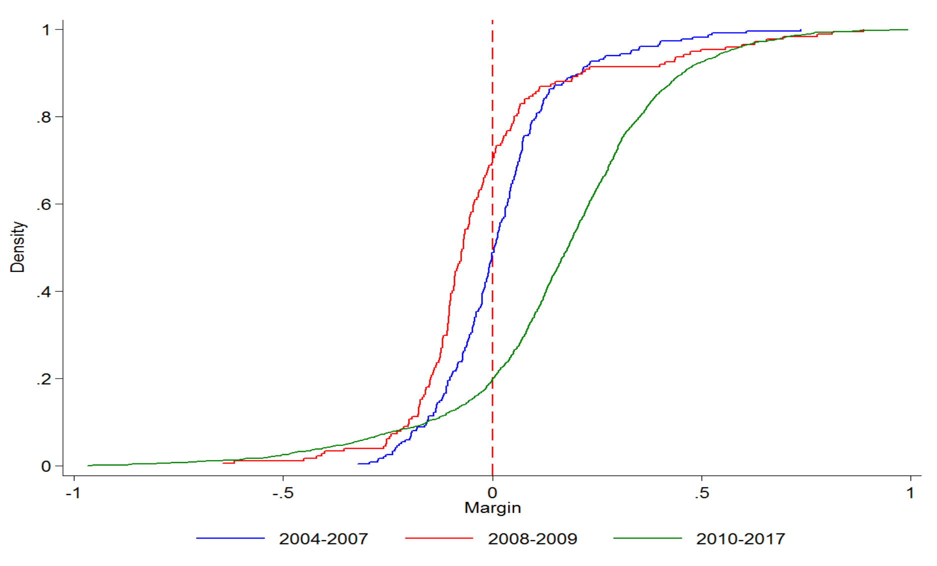
This figure shows the cumulative distribution (CDF) of the margin. We define the margin for a given bond as the primary minus secondary market rates.

Figure 3: Adjusted margin



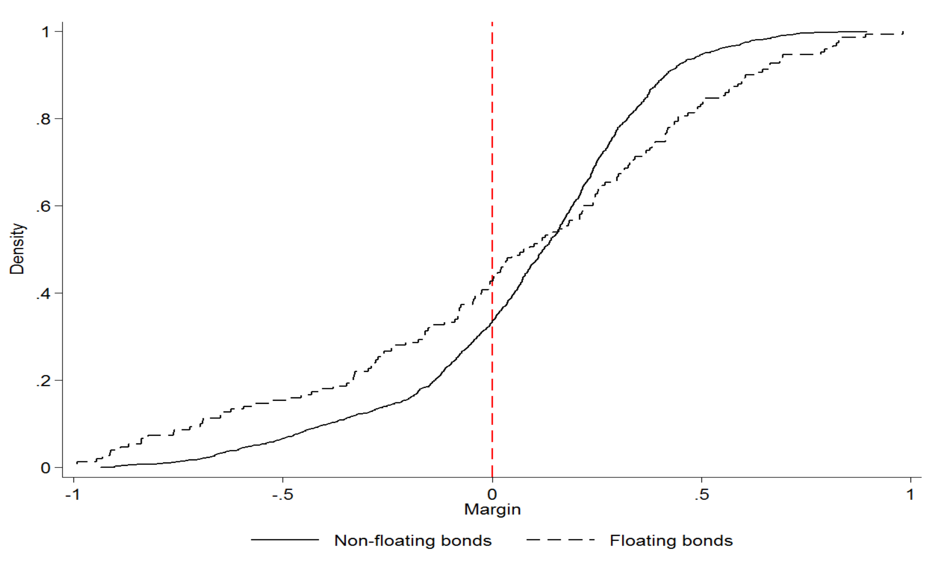
In this figure, we plot the fitted margins and adjusted margins. Here, we use predicted margins and residuals obtained after estimating the empirical model described in Column 5 in Table 4. Then we use them to construct the adjusted margins as described in Equation 2.

Figure 4: Adjusted margins by period



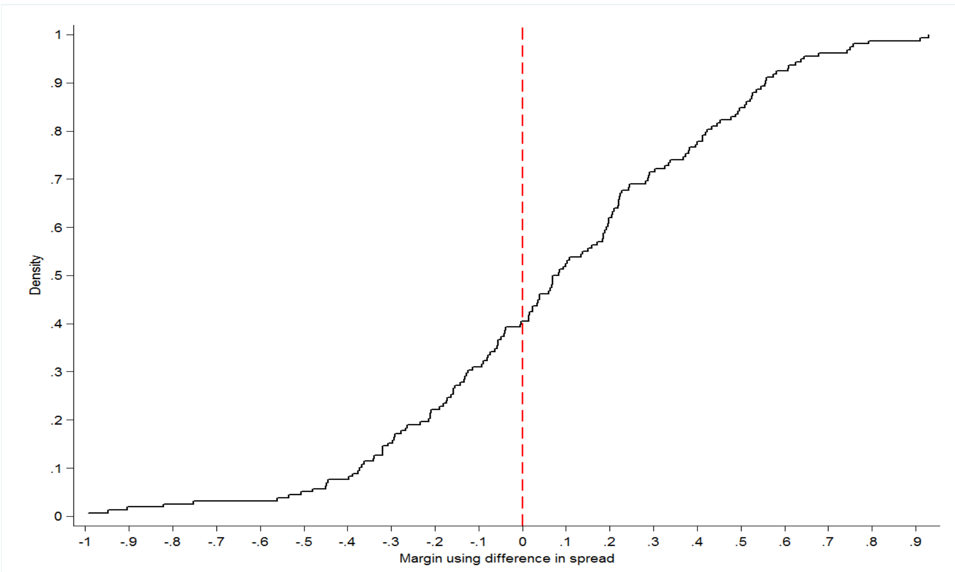
In this figure, we plot the adjusted margins before, during, and after the crisis. We use predicted margins and residuals obtained after estimating the empirical model described in Column 5 in Table 4 to construct the adjusted margins by period.

Figure 5: Adjusted margins for floating and non-floating bonds



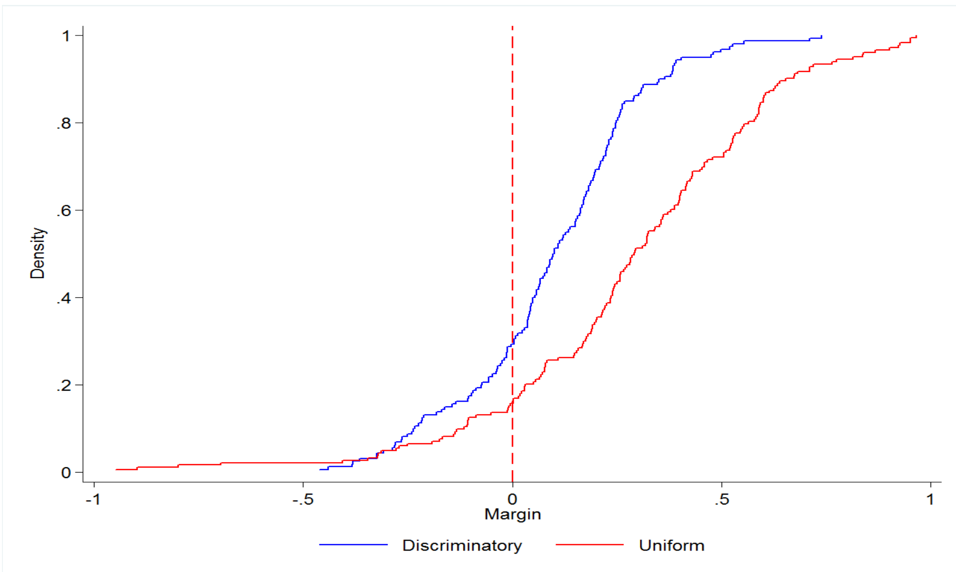
In this figure, we show the adjusted margins by bond type. Note that floating bonds were sold using only the uniform auction format.

Figure 6: Adjusted margins for floating bonds using spreads



In this figure, we show the adjusted margin using the spread for floating bonds. There were 168 floating bonds during our sample period. The detailed description of the spread construction is explained in the Appendix B.

Figure 7: Adjusted margins for uniform and discriminatory auctions during randomized



In this figure, we plot the adjusted margins for uniform and discriminatory auction formats during the alternating-rule experiment period.

Table 1: Summary statistics

Variable	Mean / Counts
Panel A	
Number of bonds sold in the secondary market	2,371
HA (Spanish)	565
DA	285
UA	1,521
Average primary market rate	3.628
	(0.951)
Bills	572
Notes	1,357
Bonds	442
Floating Bond	168
Number of bidders	43.762
	(11.205)
Panel B	
Average secondary market rate	3.750
	(0.962)
Inter-Bank Market	2,213
Shanghai Stock Exchange	99
Shenzhen Stock Exchange	59
Time lag (in calendar days)	8.522
	(4.681)
Trading volume (in ¥ billions)	886.00
	(729.00)
Panel C	
Volatility	0.030
	(0.030)
Volatility of FTSE bank index before a secondary market debut day	0.017 (0.011)
REPO rate	3.062
	(1.131)
Government yield gap between a primary auction date and a day before the secondary market	-0.003 (0.093)
Value of maturing bonds by institution for a given month (in ¥ 100,000)	2,823,731.00 (3,270,008.00)

This table reports summary statistics of data used in the analysis. Panel A reports summary statistics for auction-level characteristics. Panel B reports secondary market statistics and variables. Panel C reports other variables, including those capture possible changes in market conditions between auction and secondary market debut days. Standard deviations are in parentheses.

Table 2: Regression results for market gap

Variable	Primary rate – secondary rate					
	OLS					Heckman
	(1)	(2)	(3)	(4)	(5)	(6)
HA (Spanish)	-0.048	-0.048	-0.046	-0.046	-0.045	-0.042
	(0.029)	(0.029)	(0.029)	(0.029)	(0.029)	(0.043)
DA	0.033	0.033	0.034	0.034	0.035	0.034
	(0.022)	(0.022)	(0.022)	(0.022)	(0.023)	(0.028)
Fixed coupon bond	-0.002	-0.002	-0.002	-0.001	-0.002	-0.003
	(0.027)	(0.026)	(0.027)	(0.026)	(0.026)	(0.037)
Floating coupon bond	-0.140**	-0.140**	-0.142**	-0.142**	-0.143**	-0.143***
	(0.061)	(0.061)	(0.061)	(0.061)	(0.061)	(0.048)
Notes	0.009	0.009	0.009	0.009	0.009	0.009
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.022)
Bonds	0.038	0.038	0.037	0.037	0.037	0.037
	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.025)
Log number of bidders	0.162***	0.161***	0.160***	0.159***	0.158***	0.158***
	(0.048)	(0.048)	(0.048)	(0.048)	(0.048)	(0.036)
Shanghai Stock Exchange	0.016	0.016	0.016	0.016	0.015	
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	
Shenzhen Stock Exchange	0.028	0.028	0.027	0.027	0.028	
	(0.061)	(0.061)	(0.061)	(0.061)	(0.061)	
Log of days between primary and secondary market	0.144***	0.144***	0.144***	0.144***	0.143***	0.145***
	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)	(0.025)
Log of trading volume in the previous month	-0.101***	-0.101***	-0.102***	-0.101***	-0.101***	-0.101***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Volatility	0.473**	0.486**	0.521**	0.532**	0.537**	0.533**
	(0.201)	(0.203)	(0.210)	(0.211)	(0.212)	(0.258)
Volatility of FTSE bank index at the day before		-0.323		-0.282	-0.285	-0.292
secondary market		(0.882)		(0.886)	(0.886)	(0.727)
Government yield gap between primary auction			0.116	0.115	0.115	0.115
date and the day before the secondary market			(0.072)	(0.073)	(0.073)	(0.074)
Log value of maturing bonds by institution for a					-0.001	-0.001
given month					(0.001)	(0.002)
Selection						
λ						0.025
						(0.062)
Institution effects	Yes	Yes	Yes	Yes	Yes	Yes
Month & year effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,371	2,371	2,371	2,371	2,371	2,371
R^2	0.182	0.182	0.183	0.183	0.183	
Wald χ^2						529.890

This table presents the estimated parameters and explains the market gap (margin), as in Equation 1. We define the margin for a given bond as the primary minus secondary market rates. The OLS results are presented in first five columns. As we have primary and secondary market debut day records (including the records of no debut-day transactions), we also report the Heckman-based correction model, presented in Column 6. Robust standard errors are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 3: Adjusted margins

Variable	Percentile				
	0.10	0.25	0.50	0.75	0.90
Adjusted margins	-0.157	0.017	0.139	0.272	0.426
	[-0.171, -0.144]	[0.003, 0.030]	[0.125, 0.152]	[0.259, 0.286]	[0.412, 0.440]

This table presents the distributional statistics of the adjusted margins. 95% confidence intervals are in parentheses. For constructing the adjusted margins, as described in Equation 2, we use predicted margins and residuals obtained after estimating the empirical model described in Column 5 in Table 4.

Table 4: Regression results for market gap with volume

Variable	Primary rate – secondary rate				
	OLS				
	(1)	(2)	(3)	(4)	(5)
HA (Spanish)	-0.007	-0.007	-0.003	-0.003	-0.003
	(0.015)	(0.015)	(0.015)	(0.015)	(0.014)
DA	-0.008	-0.008	-0.008	-0.008	-0.009
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)
Fixed coupon bond	-0.025	-0.025	-0.024	-0.024	-0.024
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
Notes	0.001	0.001	0.001	0.002	0.002
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Bonds	0.023	0.023	0.021	0.021	0.021
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Log of volume	0.008	0.008	0.006	0.006	0.007
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Log number of bidders	0.026	0.026	0.020	0.020	0.020
	(0.029)	(0.029)	(0.027)	(0.027)	(0.027)
Log of days between primary and secondary market	-0.003	-0.003	-0.005	-0.005	-0.004
	(0.025)	(0.025)	(0.025)	(0.025)	(0.024)
Log of trading volume in the previous month	-0.006	-0.005	-0.006	-0.006	-0.006
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Volatility	0.065	0.071	0.163	0.168	0.163
	(0.091)	(0.092)	(0.129)	(0.129)	(0.132)
Volatility of FTSE bank index at the day before		-0.203		-0.178	-0.175
secondary market		(0.454)		(0.462)	(0.460)
Government yield gap between primary auction			0.217***	0.217***	0.216***
date and the day before the secondary market			(0.075)	(0.076)	(0.076)
Log value of maturing bonds by institution for a					0.001
given month					(0.001)
Institution effects	Yes	Yes	Yes	Yes	Yes
Month & year effects	Yes	Yes	Yes	Yes	Yes
Observations	1,128	1,128	1,128	1,128	1,128
R^2	0.039	0.039	0.052	0.052	0.052

This table presents the estimated parameters and explains the market gap (margin), as in Equation 1. We define the margin for a given bond as the primary minus secondary market rates. The OLS results are presented in the five columns. Robust standard errors are in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% level, respectively.

Table 5: Gains and losses

Variable	Adjusted margins	
	≥ 0	< 0
Number of observations	816	312
Average adjusted margin – in %	0.060	-0.082
	(0.069)	(0.308)
Average adjusted margin – change in price between primary market date and secondary market debut date	0.052	-0.121
	(0.069)	(1.0380)
Average volume traded in the secondary market (in millions of ¥)	697.00	757.00
	(764.00)	(659.00)
Average gains (in millions of ¥)	42.60	-71.70
	(126.00)	(599.00)

Standard deviations are in parentheses.

Table 6: Adjusted margins during 2004–2007, 2008–2009, and 2010-2017

Variable	Percentile				
	0.10	0.25	0.50	0.75	0.90
2004 – 2007	-0.161	-0.071	0.004	0.073	0.214
	[-0.195, -0.127]	[-0.105, -0.037]	[-0.030, 0.038]	[0.039, 0.107]	[0.180, 0.248]
2008 – 2009	-0.200	-0.124	-0.069	0.033	0.234
	[-0.250, -0.149]	[-0.174, -0.074]	[-0.120, -0.019]	[-0.017, 0.083]	[0.183, 0.284]
2010 – 2017	-0.172	0.042	0.180	0.311	0.460
	[-0.187, -0.157]	[0.026, 0.057]	[0.165, 0.195]	[0.296, 0.326]	[0.445, 0.475]

For constructing the adjusted margins before, during, and after the 2008–2009 financial crisis, we use the predicted margins and residuals obtained from the empirical model estimated in Column 5 in Table 4. 95% confidence intervals are in parentheses.

Table 7: Gains and losses by period

Variable	2004–2007		2008–2009		2010–2017	
	Adjusted margin		Adjusted margin		Adjusted margin	
	≥ 0	< 0	≥ 0	< 0	≥ 0	< 0
Number of observations	131	43	110	35	575	234
Average adjusted margin – in %	0.076	-0.146	0.055	-0.086	0.057	-0.066
	(0.063)	(0.452)	(0.054)	(0.126)	(0.072)	(0.283)
Average adjusted margin – change in price between	0.065	-0.048	0.023	-0.029	0.016	-0.018
primary market date and secondary market debut date	(0.075)	(0.146)	(0.023)	(0.036)	(0.023)	(0.064)
Average volume traded in the secondary market	672.00	700.00	766.00	854.00	689.00	753.00
(in millions of ¥)	(1,320.00)	(659.00)	(548.00)	(623.00)	(615.00)	(665.00)
Average gains	60.80	-32.60	45.90	-128.00	37.80	-70.40
(in millions of ¥)	(268.00)	(52.40)	(80.50)	(307.00)	(71.60)	(681.00)

All margins reported in this table are adjusted margins. Standard deviations are in parentheses.

Table 8: Effect of REPO rate on adjusted margins and volume

Variables	Probability of observing losses			Log of volume	
	All trades	With volume	Trading day	By trade	Total per day
	(1)	(2)	(3)	(4)	(5)
Panel A: All years					
REPO rate	0.012***	0.007***	0.012***	0.104***	0.072**
	(0.003)	(0.002)	(0.004)	(0.028)	(0.032)
Log of initial volume		0.003		1.108***	
		(0.004)		(0.043)	
Log of total initial volume			-0.050***		1.008***
			(0.008)		(0.072)
Observations	2,371	1,128	1,185	1,128	877
Loglikelihood	17.20	8.618	50.63		
R-squared				0.301	0.201
Panel B: Without 2008–2009					
REPO rate	0.010***	0.007***	0.010**	0.107***	0.104***
	(0.003)	(0.002)	(0.004)	(0.032)	(0.038)
Log of initial volume		0.001		1.079***	
		(0.003)		(0.044)	
Log of total initial volume			-0.052***		0.984***
			(0.009)		(0.076)
Observations	2,190	983	1,039	983	752
Loglikelihood	-414.9	-69.14	-202.7		
R^2				0.302	0.199

Robust standard errors are in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% level, respectively.

Table 9: Bank and security index variation

Variables	All years		Without 2008-2009	
	+/- One day	+/- Two days	+/- One day	+/- Two days
	(1)	(2)	(3)	(4)
Panel A: Bank index				
Negative adjusted margin trades	0.003***	0.003**	0.003***	0.003**
	(0.001)	(0.001)	(0.001)	(0.001)
After the secondary market trades	0.000	0.001	0.000	0.001
	(0.001)	(0.000)	(0.000)	(0.000)
Negative adjusted margin trades ×	-0.007**	-0.007***	-0.006**	-0.007***
after the secondary market trades (β_3)	(0.003)	(0.002)	(0.003)	(0.002)
Observations	5,742	9,570	5,217	8,695
R^2	0.002	0.001	0.002	0.001
Panel B: Security index				
Negative adjusted margin trades	0.002	0.001	0.002*	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
After the secondary market trades	-0.000	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Negative adjusted margin trades ×	-0.006**	-0.005**	-0.005*	-0.005**
after the secondary market trades (β_3)	(0.003)	(0.002)	(0.003)	(0.002)
Observations	5,751	9,585	5,226	8,710
R^2	0.001	0.001	0.001	0.001
Panel C: REPO rate				
Negative adjusted margin trades	0.267***	0.267***	0.173**	0.173**
	(0.086)	(0.070)	(0.088)	(0.072)
After the secondary market trades	-0.000	-0.000	0.000	0.000
	(0.034)	(0.025)	(0.035)	(0.026)
Negative adjusted margin trades ×	0.000	0.000	-0.000	-0.000
after the secondary market trades (β_3)	(0.149)	(0.111)	(0.152)	(0.113)
Observations	5,742	9,570	5,217	8,695
R^2	0.002	0.002	0.001	0.001

This table reports results for the panel regression (event study) model to examine the impact of bond losses on the financial sector. The first two columns report results for all years, while the last two columns report results without 2008 and 2009 We are interested in the value of the coefficient of β_3, which measures the difference in indices that occurs after the secondary market trades (one or two days) on all negative adjusted margin transaction days compared to all positive days. Robust standard errors are in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% level, respectively.

Table 10: Regression results for market gap during the alternating-rule experiment

Variable	Primary rate – secondary rate				
	(1)	(2)	(3)	(4)	(5)
DA	-0.043	-0.050	-0.042	-0.049	-0.050
	(0.033)	(0.034)	(0.033)	(0.034)	(0.034)
Floating coupon bond	-0.791***	-0.799***	-0.792***	-0.800***	-0.801***
	(0.089)	(0.087)	(0.089)	(0.087)	(0.087)
Log number of bidders	0.350**	0.341**	0.350**	0.341**	0.342**
	(0.169)	(0.164)	(0.170)	(0.165)	(0.166)
Lag of days between primar market and secondary market	-0.036	-0.045	-0.034	-0.042	-0.038
	(0.045)	(0.046)	(0.044)	(0.046)	(0.047)
Log of trading volume on the previous month	-0.099**	-0.122***	-0.096**	-0.119***	-0.119***
	(0.041)	(0.044)	(0.041)	(0.044)	(0.044)
Volatility	0.392	0.115	0.516	0.289	0.301
	(0.655)	(0.664)	(0.701)	(0.706)	(0.711)
Volatility of FTSE bank index at the day before		4.758**		4.908**	4.983**
secondary market		(2.212)		(2.218)	(2.229)
Government yield gap between primary auction			0.092	0.135	0.142
date and day before the secondary market			(0.153)	(0.154)	(0.155)
Log value of maturing bonds by institution for a					0.007
given month					(0.010)
Institution effects	Yes	Yes	Yes	Yes	Yes
Month & year effects	Yes	Yes	Yes	Yes	Yes
Observations	348	348	348	348	348
R^2	0.553	0.559	0.553	0.560	0.560

This table reports the OLS results for the market gap between uniform and discriminatory auction formats during the alternating experiment period. Robust standard errors are in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% level, respectively.

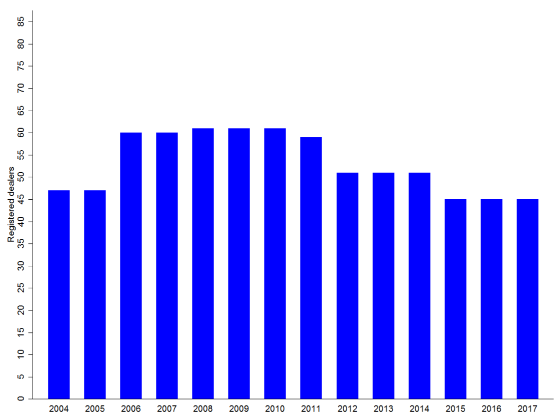
Table 11: Adjusted margins during the alternating-rule experiment by auction mechanism

Variable	Percentile				
	0.10	0.25	0.50	0.75	0.90
DA	-0.235	-0.026	0.098	0.229	0.358
	[-0.270, -0.200]	[-0.061, 0.009]	[0.064, 0.133]	[0.194, 0.264]	[0.323, 0.393]
UA	-0.132	0.082	0.295	0.529	0.711
	[-0.188, -0.077]	[0.027, 0.137]	[0.240, 0.350]	[0.474, 0.584]	[0.656, 0.766]

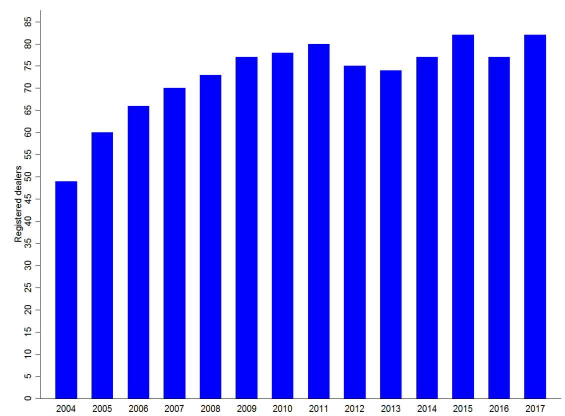
This table reports the adjusted margins for discriminatory and uniform auctions for selected percentiles.
In this exercise, we use the data from the alternating-rule market experiment period only.
95% confidence intervals are in parentheses.

Appendix A

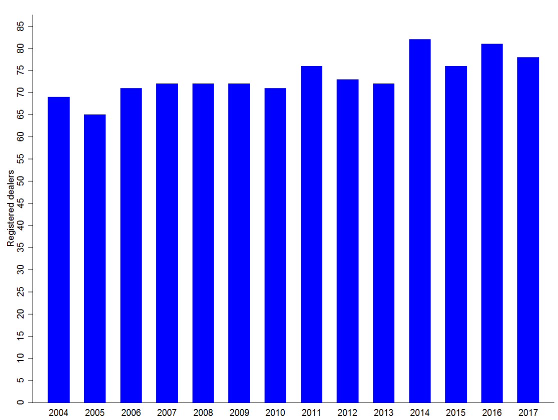
Figure A.1: Registered primary dealers



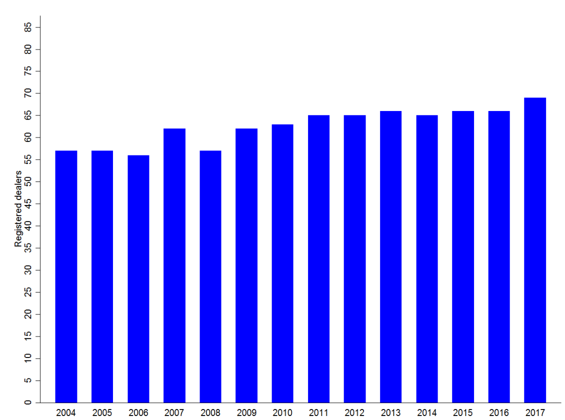
Panel A: MOF



Panel B: ABD



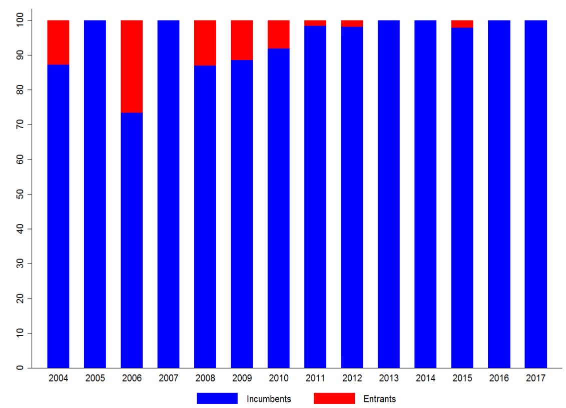
Panel C: CDB



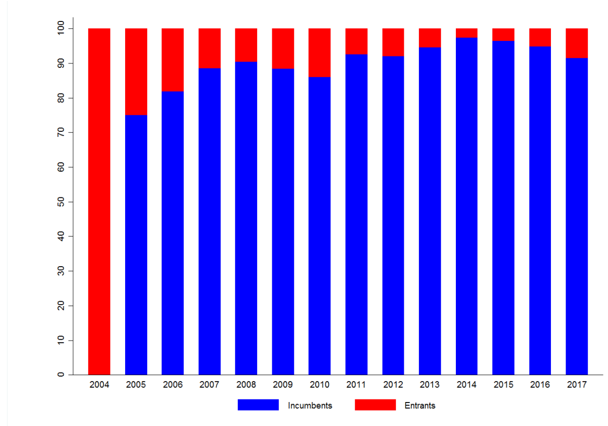
Panel D: EIB

In this figure, we show the number of prequalified (primary) dealers by institution from 2004 to 2017. Panel A presents the statistics for the Chinese Ministry of Finance (MOF), Panel B for the Agriculture Development Bank (ADB), Panel C for the Chinese Development Bank (CDB), and Panel D for the Export-Import Bank (EIB).

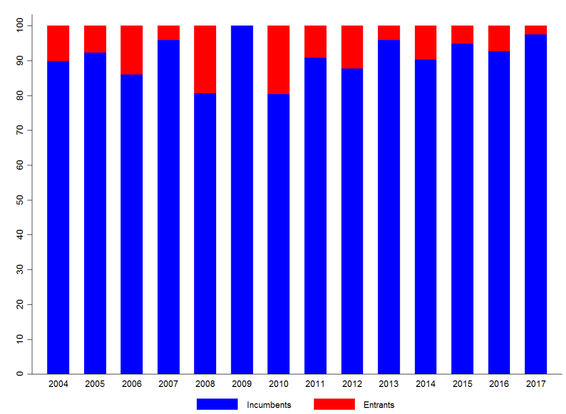
Figure A.2: Ratios of incumbents and entrants



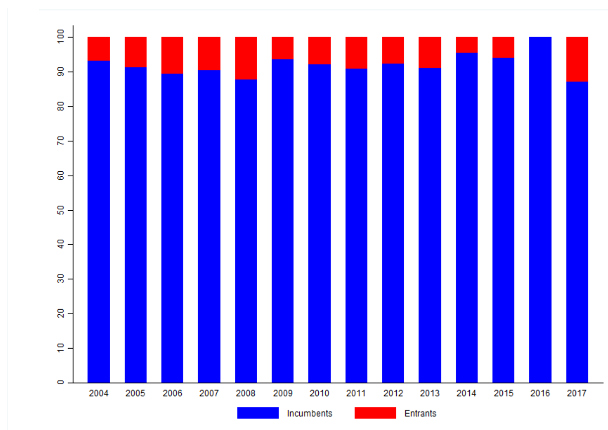
Panel A: MOF



Panel B: ADB



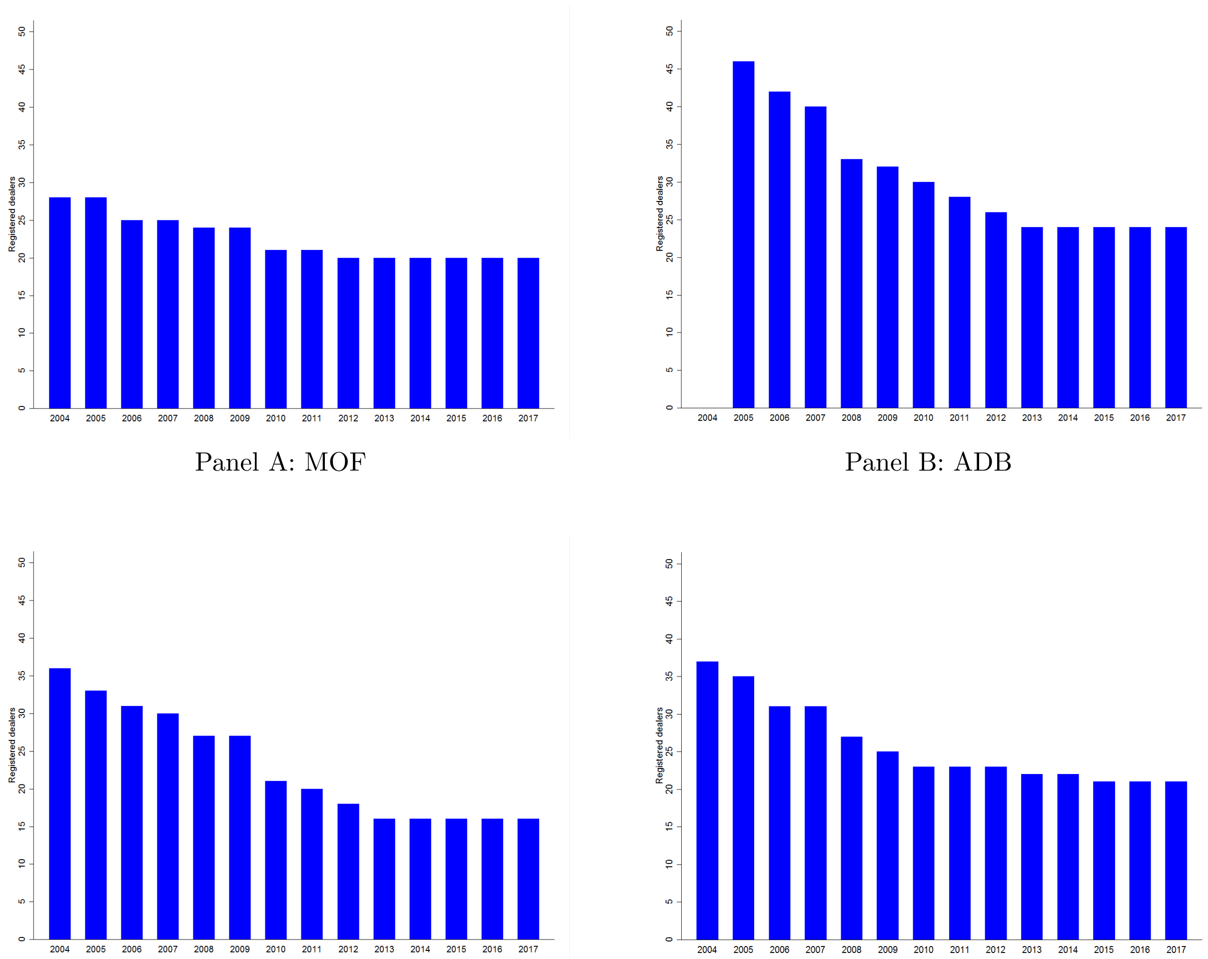
Panel C: CDB



Panel D: EIB

In this figure, we plot the ratio of entrants and incumbents for each institution from 2004 to 2017. Note that the ADB started selling bonds in 2004 and hence all participants are considered entrants.

Figure A.3: The number of continuing primary dealers



Panel A: MOF

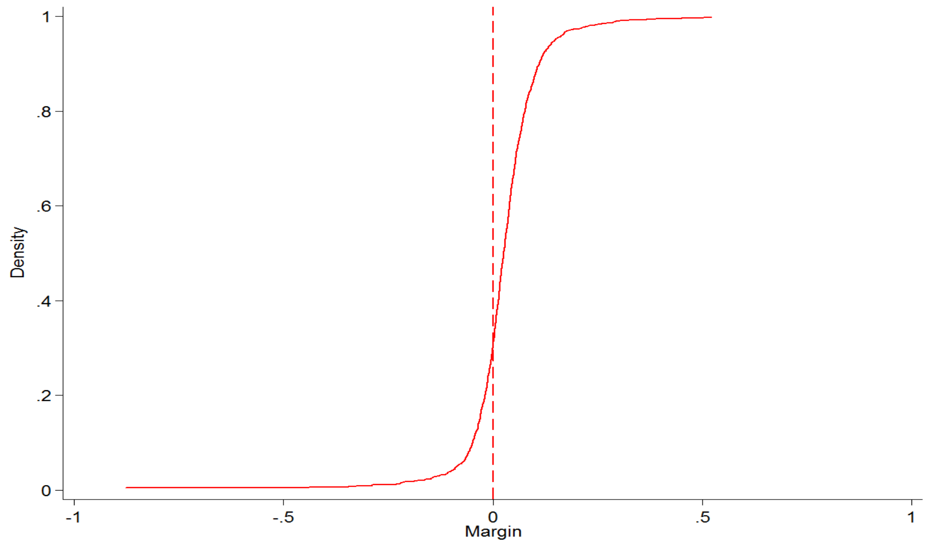
Panel B: ADB

Panel C: CDB

Panel D: EIB

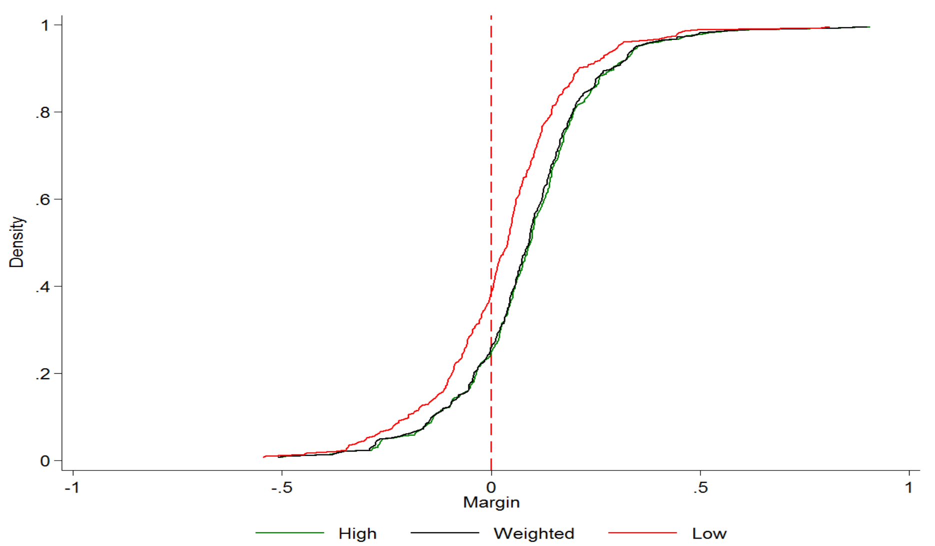
In this figure, we plot the year-to-year continuing incumbents for each institution from 2004 to 2017. More than 90 percent of bidders continue from the previous year and more than 50 percent of bidders who participated in 2004 are still in the market in 2017.

Figure A.4: Adjusted margins while controlling for volume



In this figure, we show the adjusted margins while controlling for volume.

Figure A.5: Margins for discriminatory auctions



This figure present adjusted margins that have been constructed by using the highest, lowest, and weighted average winning primary rates in discriminatory auctions.

Table A.1: Chinese government and policy banks' long term security credit ratings

Year	Fitch				Moody's				Standard & Poor's			
	MOF	CDB	EIB	ADB	MOF	CDB	EIB	ADB	MOF	CDB	EIB	ADB
2004	A-	A-	—	—	A2	A2	A2	—	BBB+	BBB+	BBB+	—
2005	A	A	—	—	A2	A2	A2	—	A-	A-	A-	—
2006	A	A	A	—	A2	A2	A2	—	A	A	A	—
2007	A+	A+	A+	—	A1	A1	A1	—	A	A	A	—
2008	A+	A+	A+	A+	A1	A1	A1	A1	A+	A+	A+	A+
2009	A+	A+	A+	A+	A1	A1	A1	A1	A+	A+	A+	A+
2010	A+	A+	A+	A+	Aa3	Aa3	Aa3	Aa3	AA-	AA-	AA-	AA-
2011	A+	A+	A+	A+	Aa3	Aa3	Aa3	Aa3	AA-	AA-	AA-	AA-
2012	A+	A+	A+	A+	Aa3	Aa3	Aa3	Aa3	AA-	AA-	AA-	AA-
2013	A+	A+	A+	A+	Aa3	Aa3	Aa3	Aa3	AA-	AA-	AA-	AA-
2014	A+	A+	A+	A+	Aa3	Aa3	Aa3	Aa3	AA-	AA-	AA-	AA-
2015	A+	A+	A+	A+	Aa3	Aa3	Aa3	Aa3	AA-	AA-	AA-	AA-
2016	A+	A+	A+	A+	Aa3	Aa3	Aa3	Aa3	AA-	AA-	AA-	AA-
2017	A+	A+	A+	A+	A1	A1	A1	A1	AA-	AA-	AA-	AA-

This table reports the long-term credit ratings issued by three foreign agencies: Moody's, Standard & Poor's, and Fitch. If a rate was updated in the middle of a calendar year, the updated rate is listed. "—" denotes that no rate was given by a credit rating agency.

Table A.2: Chinese government and policy banks' short term security credit ratings

Year	Fitch				Moody's				Standard & Poor's			
	MOF	CDB	EIB	ADB	MOF	CDB	EIB	ADB	MOF	CDB	EIB	ADB
2004	F1	F2	—	—	P-1	—	—	—	A-2	A-2	A-2	—
2005	F1	F1	—	—	P-1	—	—	—	A-1	A-1	A-1	—
2006	F1	F1	F1	—	P-1	—	—	—	A-1	A-1	A-1	—
2007	F1	F1	F1	—	P-1	—	—	—	A-1	A-1	A-1	—
2008	F1	F1	F1	F1	P-1	—	—	P-1	A-1+	A-1+	A-1+	A-1+
2009	F1	F1	F1	F1	P-1	—	—	P-1	A-1+	A-1+	A-1+	A-1+
2010	F1	F1	F1	F1	P-1	—	—	P-1	A-1+	A-1+	A-1+	A-1+
2011	F1	F1	F1	F1	P-1	—	—	P-1	A-1+	A-1+	A-1+	A-1+
2012	F1	F1	F1	F1	P-1	—	—	P-1	A-1+	A-1+	A-1+	A-1+
2013	F1	F1	F1	F1	P-1	—	—	P-1	A-1+	A-1+	A-1+	A-1+
2014	F1	F1	F1	F1	P-1	P-1	—	P-1	A-1+	A-1+	A-1+	A-1+
2015	F1	F1	F1	F1	P-1	P-1	—	P-1	A-1+	A-1+	A-1+	A-1+
2016	F1	F1	F1	F1	P-1	P-1	—	P-1	A-1+	A-1+	A-1+	A-1+
2017	F1+	F1+	F1+	F1+	P-1	P-1	—	P-1	A-1	A-1	A-1	A-1

This table reports the short-term credit ratings issued by three foreign agencies: Moody's, Standard & Poor's, and Fitch. If a rate was updated in the middle of a calendar year, the updated rate is listed. "—" denotes that no rate was given by a credit rating agency.

Table A.3: Secondary market T–bill distribution

Bond type	Financial institution				Total
	ADB	CDB	EIB	MOF	
Bills	83	159	58	272	572
Notes	306	565	201	285	1,357
Bonds	38	191	46	167	442
Total	427	915	305	724	2,371

Table A.4: Secondary market T–bill distribution by maturity

Auction mechanism	Maturity type			Total
	Bills	Notes	Bonds	
Discriminatory auctions (DA)	125	160	–	285
Spanish auctions (SA)	145	281	139	565
Uniform auctions (UA)	302	916	303	1,521
Total	572	1,357	442	2,371

Table A.5: Quantile regression results for market gap

Variable	Primary rate – secondary rate				
	Quantile				
	0.10	0.25	0.50	0.75	0.90
HA (Spanish)	-0.031	-0.036	-0.026	0.002	0.029
	(0.034)	(0.022)	(0.017)	(0.014)	(0.020)
DA	0.030	0.001	0.006	0.013	-0.014
	(0.025)	(0.020)	(0.011)	(0.011)	(0.021)
Fixed coupon bond	-0.051*	-0.027	-0.000	-0.014	-0.027
	(0.028)	(0.021)	(0.014)	(0.008)	(0.019)
Floating coupon bond	-1.078***	-0.452***	0.014	0.320***	0.522***
	(0.117)	(0.123)	(0.065)	(0.044)	(0.063)
Notes	0.054*	0.031	0.007	0.015**	0.018*
	(0.029)	(0.019)	(0.007)	(0.007)	(0.010)
Bonds	0.075***	0.050**	0.019*	0.034***	0.042***
	(0.026)	(0.021)	(0.010)	(0.007)	(0.015)
Log number of bidders	0.135*	0.080**	0.032*	-0.002	-0.019
	(0.071)	(0.039)	(0.019)	(0.016)	(0.022)
Shanghai Stock Exchange	0.008	0.015	0.011	0.021*	0.024
	(0.017)	(0.015)	(0.010)	(0.012)	(0.022)
Shenzhen Stock Exchange	0.075**	0.048**	0.024	0.096***	0.120**
	(0.035)	(0.022)	(0.019)	(0.023)	(0.061)
Log of days between primary and secondary market	0.168***	0.100***	0.051***	0.045***	0.046**
	(0.029)	(0.022)	(0.016)	(0.017)	(0.019)
Log of trading volume in the previous month	-0.082***	-0.051***	-0.037***	-0.047***	-0.040***
	(0.013)	(0.009)	(0.008)	(0.006)	(0.013)
Volatility	-0.035	0.068	0.304**	0.383***	0.886***
	(0.239)	(0.136)	(0.148)	(0.139)	(0.222)
Volatility of FTSE bank index at the day before	-0.841	-0.177	-0.074	-0.056	-0.492
secondary market	(0.941)	(0.479)	(0.390)	(0.239)	(0.645)
Government yield gap between primary auction	0.132**	0.062	0.066	0.120**	0.327***
date and the day before the secondary market	(0.062)	(0.049)	(0.046)	(0.056)	(0.053)
Log value of maturing bonds by institution for a	-0.000	-0.001	-0.001	-0.000	-0.001
given month	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
Institution effects	Yes	Yes	Yes	Yes	Yes
Month & year effects	Yes	Yes	Yes	Yes	Yes
Observations	2,371	2,371	2,371	2,371	2,371
R^2	0.341	0.236	0.078	0.080	0.222

This table presents results for margins using the quantile regression method proposed by Koenker and Bassett (1982). Bootstrapped standard errors are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table A.6: Regression results for market gap by period

Variable	Primary rate – secondary rate					
	OLS					Heckman
	(1)	(2)	(3)	(4)	(5)	(6)
2008 – 2009	0.157***	0.159***	0.157***	0.159***	0.163***	0.146***
	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)	(0.040)
2010 – 2017	0.127***	0.121***	0.126***	0.120***	0.126***	0.109***
	(0.034)	(0.034)	(0.034)	(0.034)	(0.033)	(0.040)
HA (Spanish)	0.020	0.017	0.019	0.017	0.018	-0.011
	(0.026)	(0.027)	(0.026)	(0.027)	(0.027)	(0.042)
DA	0.027	0.027	0.026	0.026	0.027	0.049*
	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.028)
Fixed coupon bond	-0.098***	-0.094***	-0.098***	-0.094***	-0.096***	-0.005
	(0.024)	(0.023)	(0.024)	(0.023)	(0.023)	(0.022)
Floating coupon bond	-0.153**	-0.150**	-0.153**	-0.150**	-0.152**	
	(0.064)	(0.064)	(0.064)	(0.064)	(0.064)	
Notes	-0.011	-0.010	-0.010	-0.010	-0.010	-0.040*
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.021)
Bonds	0.032	0.032	0.032	0.033	0.033	0.005
	(0.027)	(0.027)	(0.027)	(0.027)	(0.027)	(0.025)
Log number of bidders	0.210***	0.210***	0.211***	0.210***	0.207***	0.208***
	(0.045)	(0.045)	(0.045)	(0.045)	(0.045)	(0.036)
Shanghai Stock Exchange	-0.013	-0.013	-0.013	-0.013	-0.013	
	(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	
Shenzhen Stock Exchange	-0.038	-0.037	-0.037	-0.037	-0.037	
	(0.060)	(0.060)	(0.060)	(0.060)	(0.060)	
Log of days between primary and secondary market	0.136***	0.135***	0.136***	0.135***	0.132***	0.123***
	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.027)
Log of trading volume in the previous month	-0.059***	-0.057***	-0.058***	-0.057***	-0.056***	-0.053***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.013)
Volatility	0.243	0.265	0.230	0.251	0.253	0.278
	(0.187)	(0.188)	(0.188)	(0.188)	(0.188)	(0.248)
Volatility of FTSE bank index at the day before		-0.669		-0.680	-0.661	-0.862
secondary market		(0.777)		(0.779)	(0.780)	(0.697)
Government yield gap between primary auction			-0.041	-0.044	-0.044	-0.043
date and the day before the secondary market			(0.071)	(0.071)	(0.071)	(0.075)
Log value of maturing bonds by institution for a					-0.001	-0.001
given month					(0.001)	(0.002)
Selection						
λ						-0.009
						(0.026)
Institution effects	Yes	Yes	Yes	Yes	Yes	Yes
Month & year effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,371	2,371	2,371	2,371	2,371	2,371
R^2	0.123	0.123	0.123	0.123	0.123	
Wald χ^2						292.47

Robust standard errors are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table A.7: Quantile regression results for market gap by period

Variable	Primary rate – secondary rate				
	Quantile				
	0.10	0.25	0.50	0.75	0.90
2008 – 2009	0.358***	0.198***	0.129***	0.134***	0.156***
	(0.090)	(0.036)	(0.032)	(0.032)	(0.054)
2010 – 2017	0.511***	0.275***	0.183***	0.189***	0.168**
	(0.129)	(0.053)	(0.041)	(0.038)	(0.078)
HA (Spanish)	-0.031	-0.036	-0.026**	0.002	0.029
	(0.037)	(0.026)	(0.013)	(0.013)	(0.020)
DA	0.030	0.001	0.006	0.013	-0.014
	(0.031)	(0.026)	(0.018)	(0.013)	(0.023)
Fixed coupon bond	-0.051*	-0.027	-0.000	-0.014	-0.027
	(0.028)	(0.022)	(0.011)	(0.010)	(0.021)
Floating coupon bond	-1.078***	-0.452***	0.014	0.320***	0.522***
	(0.106)	(0.144)	(0.061)	(0.066)	(0.064)
Shanghai Stock Exchange	0.054*	0.031	0.007	0.015**	0.018
	(0.029)	(0.019)	(0.013)	(0.007)	(0.014)
Shenzhen Stock Exchange	0.075**	0.050**	0.019	0.034***	0.042**
	(0.030)	(0.022)	(0.014)	(0.010)	(0.020)
Notes	0.135**	0.080**	0.032*	-0.002	-0.019
	(0.068)	(0.040)	(0.017)	(0.020)	(0.031)
Bonds	0.008	0.015	0.011	0.021	0.024
	(0.019)	(0.014)	(0.012)	(0.018)	(0.026)
Log number of bidders	0.075*	0.048*	0.024	0.096***	0.120*
	(0.042)	(0.027)	(0.016)	(0.016)	(0.067)
Log of days between primary and secondary market	0.168***	0.100***	0.051***	0.045***	0.046**
	(0.026)	(0.015)	(0.010)	(0.014)	(0.022)
Log of trading volume in the previous month	-0.082***	-0.051***	-0.037***	-0.047***	-0.040**
	(0.018)	(0.010)	(0.008)	(0.008)	(0.016)
Volatility	-0.035	0.068	0.304***	0.383**	0.886***
	(0.250)	(0.159)	(0.105)	(0.188)	(0.281)
Volatility of FTSE bank index at the day before	-0.841	-0.177	-0.074	-0.056	-0.492
secondary market	(0.938)	(0.406)	(0.304)	(0.306)	(0.513)
Government yield gap between primary auction	0.132*	0.062	0.066**	0.120**	0.327***
date and the day before the secondary market	(0.068)	(0.056)	(0.033)	(0.049)	(0.064)
Log value of maturing bonds by institution for a	-0.000	-0.001	-0.001*	-0.000	-0.001
given month	(0.002)	(0.001)	(0.000)	(0.001)	(0.001)
Institution effects	Yes	Yes	Yes	Yes	Yes
Month & year effects	Yes	Yes	Yes	Yes	Yes
Observations	2,371	2,371	2,371	2,371	2,371
R^2	0.341	0.236	0.078	0.080	0.222

Bootstrapped standard errors are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table A.8: FTSE index institutions and the primary market dealers

Variable	FTSE Index		
	Bank	Security	Insurance
Total number of institutions in the FTSE index	23	33	4
FTSE index institutions as MOF primary dealers	22 (96%)	26 (79%)	4 (100%)
FTSE index institutions as ADB primary dealers	21 (91%)	24 (73%)	1 (25%)
FTSE index institutions as CDB primary dealers	22 (96%)	28 (85%)	4 (100%)
FTSE index institutions as EIB primary dealers	20 (87%)	21 (64%)	3 (75%)

Table A.9: Example of alternating pattern for the CDB

Date	Maturity (in years)	Auction mechanism
Jan 08, 2013	3, 5, 7	Discriminatory
Jan 15, 2013	3, 5, 7	Uniform
Jan 22, 2013	5, 7	Discriminatory
Jan 29, 2013	3, 5, 7	Uniform
Feb 05, 2013	3, 5, 7	Discriminatory
Feb 19, 2013	3, 5, 7	Uniform
Apr 09, 2013	3, 7	Discriminatory
Apr 16, 2013	3, 7	Uniform
Apr 23, 2013	3, 7	Discriminatory
May 07, 2013	3, 7	Uniform
May 14, 2013	3, 7	Discriminatory
May 21, 2013	3, 7	Uniform
Jul 16, 2013	3, 5, 7	Discriminatory
Jul 23, 2013	3, 5, 7	Uniform
Jul 30, 2013	3, 5, 7	Discriminatory

Note that all bills (maturity less than or equal to one year) and bonds (maturity equal or more than 10 years) were sold using the uniform auction format. The alternating-rule experiment period for CDB was from May 2012 – July 2014.

Table A.10: Example of alternating pattern for the EIB

Date	Bond ID	Maturity (in years)	Auction mechanism
Panel A: Experimentation by date			
Jul 31, 2013		2(t)	Discriminatory
Aug 15, 2013		2(t)	Discriminatory
Sep 24, 2013		2(t)	Discriminatory
Oct 21, 2013		2(t)	Uniform
Nov 04, 2013		2(t)	Uniform
Apr 11, 2014		3(t)	Discriminatory
May 15, 2014		3(t)	Uniform
May 23, 2014		3(t)	Discriminatory
Jun 06, 2014		3(t)	Uniform
Panel B: Experimentation by bond			
Nov 28, 2014	14 EXIM 78 (initial)	2	Discriminatory
Dec 04, 2014	14 EXIM 78 (reissue)	2	Uniform
Dec 17, 2014	14 EXIM 78 (reissue)	2	Discriminatory
Apr 15, 2015	15 EXIM 09 (initial)	3	Uniform
Apr 24, 2015	15 EXIM 09 (reissue)	3	Uniform
Apr 30, 2015	15 EXIM 09 (reissue)	3	Uniform
May 06, 2015	15 EXIM 09 (reissue)	3	Discriminatory
May 13, 2015	15 EXIM 09 (reissue)	3	Discriminatory
May 21, 2015	15 EXIM 09 (reissue)	3	Discriminatory

The alternating-rule experiment period for the EIB was from July 2013 – May 2015. Each reissued bond has a new id and an old id, which can be matched.

Table A.11: Quantile regression results for market gap during the alternating experiment

Variable	Primary rate – secondary rate				
	Quantile				
	0.10	0.25	0.50	0.75	0.90
DA	0.046	0.024	-0.044	-0.026	0.009
	(0.053)	(0.053)	(0.047)	(0.033)	(0.025)
Floating coupon bond	-1.381***	-1.095***	-0.822***	-0.269	0.058
	(0.243)	(0.173)	(0.191)	(0.234)	(0.172)
Log number of bidders	0.080	0.039	0.008	-0.007	-0.048
	(0.237)	(0.145)	(0.150)	(0.143)	(0.130)
Log days between the primary and secondary market	-0.076	-0.008	0.004	-0.052	-0.028
	(0.111)	(0.082)	(0.051)	(0.055)	(0.043)
Log of the trading volume in the previous month	-0.178**	-0.109	-0.026	-0.060	-0.038
	(0.074)	(0.089)	(0.066)	(0.043)	(0.029)
Volatility	0.207	1.068	0.970	0.360	-0.171
	(1.446)	(1.186)	(0.882)	(0.749)	(0.690)
Volatility of FTSE bank index at the day before	7.274*	1.208	-1.233	-1.817	-2.525
secondary market	(4.314)	(2.474)	(1.510)	(1.547)	(1.579)
Government yield gap between the primary auction	0.109	0.138	0.178	0.103	0.132
date and the day before secondary market	(0.221)	(0.206)	(0.203)	(0.202)	(0.162)
Log value of maturing bonds by institution for a	-0.010	-0.018	-0.001	-0.015	-0.011
given month	(0.034)	(0.039)	(0.039)	(0.014)	(0.017)
Institution effects	Yes	Yes	Yes	Yes	Yes
Month & year effects	Yes	Yes	Yes	Yes	Yes
Observations	348	348	348	348	348
R^2	0.575	0.475	0.312	0.240	0.331

This table reports the quantile regression results for the market gap between uniform and discriminatory auction formats during the alternating-rule experiment period. Bootstrapped standard errors are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table A.12: Regression results for market gap using discriminatory auctions

Variable	Primary rate – secondary rate		
	Highest	Lowest	Weighted avg.
	(1)	(2)	(3)
Notes	-0.039	-0.070	-0.054
	(0.073)	(0.072)	(0.072)
Log number of bidders	-0.285**	-0.395***	-0.269**
	(0.110)	(0.110)	(0.110)
Shanghai Stock Exchange	-0.003	-0.015	-0.001
	(0.040)	(0.040)	(0.040)
Shenzhen Stock Exchange	-0.325	-0.336	-0.324
	(0.513)	(0.507)	(0.512)
Log of days between primary and secondary market	-0.067	-0.071	-0.070
	(0.051)	(0.052)	(0.050)
Log of trading volume in the previous month	-0.109***	-0.095***	-0.115***
	(0.027)	(0.027)	(0.027)
Volatility	-0.439	-0.233	-0.436
	(0.494)	(0.479)	(0.491)
Volatility of FTSE bank index at the day before secondary market	-2.193*	-2.608*	-2.146
	(1.322)	(1.359)	(1.320)
Government yield gap between primary auction date and the day before the secondary market	-0.040	-0.070	-0.044
	(0.141)	(0.140)	(0.140)
Log value of maturing bonds by institution for a given month	-0.010**	-0.016***	-0.010**
	(0.005)	(0.005)	(0.005)
Institution effects	Yes	Yes	Yes
Month & year effects	Yes	Yes	Yes
Observations	285	285	285
R^2	0.370	0.430	0.376

Robust standard errors are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table A.13: Adjusted margins for discriminatory auctions

Variable	Percentile				
	0.10	0.25	0.50	0.75	0.90
Highest primary market winning rate	-0.137	0.002	0.095	0.176	0.294
	[-0.164, -0.110]	[-0.025, 0.029]	[0.068, 0.122]	[0.149, 0.203]	[0.267, 0.321]
Weighted average of the primary market winning rate	-0.139	-0.001	0.092	0.171	0.292
	[-0.166, -0.112]	[-0.028, 0.026]	[0.065, 0.119]	[0.144, 0.198]	[0.265, 0.319]
Lowest primary market winning rate	-0.198	-0.063	0.0.040	0.120	0.212
	[-0.225, -0.171]	[-0.090, -0.037]	[0.013, 0.067]	[0.093, 0.147]	[0.185, 0.239]

This table reports the adjusted margins in discriminatory auctions by the highest, weighted average, and lowest primary rates. 95% confidence intervals are in parentheses.

Appendix B: Adjusted margins by bond types

In this Appendix, we report the adjusted margins for floating bonds. Floating bonds were introduced to the Chinese bond market in 2007 and were sold using only the uniform auction format. In this subsection, we analyze the models described in Equation 1 using only uniform bonds sold since 2007. The regression results are presented in Table B.1, and the general conclusions are qualitative the same. To be complete and consistent, we estimate Column 5 in Table 10 using the quantile regression technique. The quantile results are presented in Table B.2, and are qualitatively similar to those presented in Table 10.

Next, to obtain our adjusted measure of margin for floating and non-floating bonds, we estimate the models described in Equation 1 without the bond-type dummies for the selected sample. In Figure B.1, we show the adjusted margins by bond type. As we can see, floating bonds tend to have a higher rate of bond losses. Table B.3 reports the adjusted margins by bond type for selected percentiles. While floating bonds make large negative adjusted margins, they also make large positive adjusted margins – twice in magnitude – compared to non-floating bonds.

One might consider why there are large tails for floating bonds. The returns of the floating bonds are tied to market conditions, while non-floating bonds are predetermined.[1] Hence, we argue that the difference in spreads in the primary and secondary market is a better measure of the margin for floating bonds.

Obtaining the spread is a challenging task, as it is not readily available for bonds traded in the secondary market. Hence, one could consider the following method to compute the spread. Based on the forward curve of the money market reference (e.g., deposit rate, LIBOR, SHIBOR, China Inter-Bank Offer Rate [CHIBOR]) of each floating bond, we compute its expected cash-flow payment at the secondary market trading date. That information, combined with the secondary market yield rate of that floating bond, allows us to obtain the implicit spread for every floating bond transacted in the secondary market.

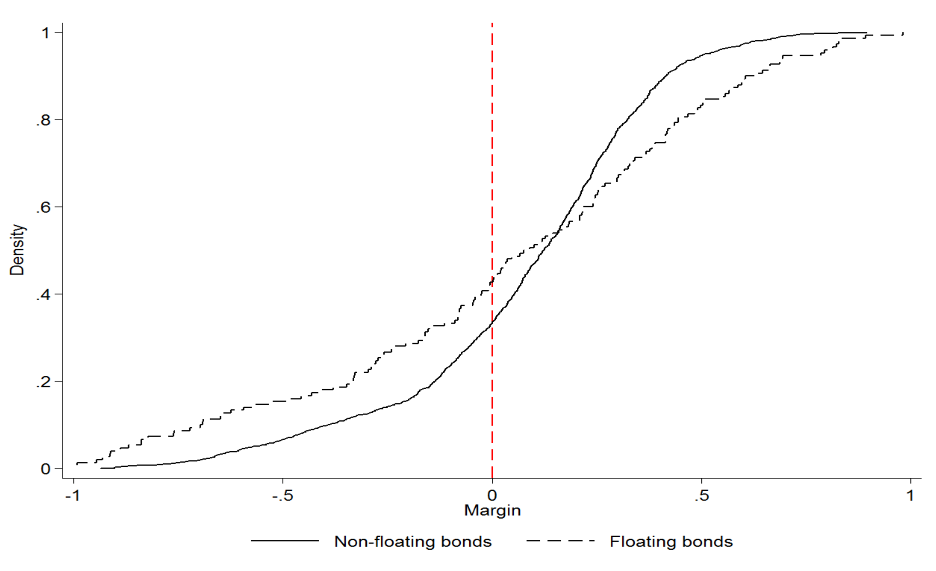
First, we estimate our standard set of empirical models with relevant variables for the floating bond sample of 168. These results are presented in Table B.2. Compared to short-term bills, bonds and notes have a smaller margin. Interestingly, the coefficient of the volatility of the bank index indicates larger, as the variation of the FTSE index increases. Using estimates from Column 5 in Table B.2, we construct the adjusted margins for the floating bonds.[2] In Figure B.2, we show the adjusted margins using the spread for floating bonds. We see that about 40 percent of them still face bond losses. To be complete, in Table B.3, we show the distribution of the adjusted margins constructed by spread with 95% confidence intervals.[3]

[1] Note that, in floating bonds, bidders bid for the spread. In these floating bonds, the effective return is the indexed interest rate – London Interbank Offered Rate (LIBOR) or Shanghai Interbank Offered Rate (SHIBOR) – plus the spread. Additionally, the spread already accounts for changes in the forwards rates.

[2] All floating bonds were sold in the secondary market and, hence, no selection model is estimated.

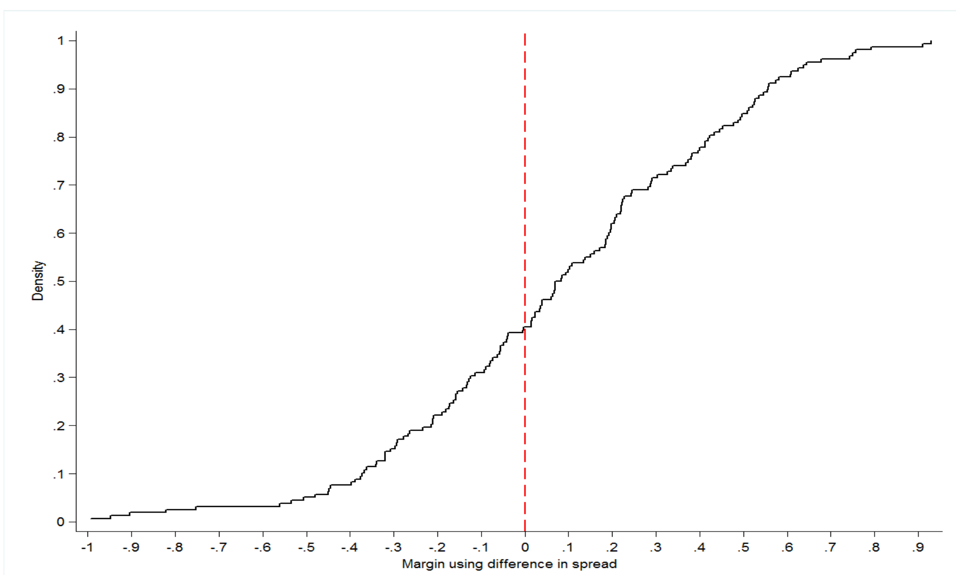
[3] We do not compare the floating and non-floating bonds' gains and losses as we do not have the volume of the floating bonds.

Figure B.1: Adjusted margins for floating and non-floating bonds



In this figure, we show the adjusted margins by bond type. Note that floating bonds were sold using only the uniform auction format.

Figure B.2: Adjusted margins for floating bonds using spreads



In this figure, we show the adjusted margin using the spread for floating bonds. There were 168 floating bonds during our sample period.

Table B.1: Regression results for uniform floating and other bonds' market gap

Variable	Primary rate – secondary rate				
	(1)	(2)	(3)	(4)	(5)
Fixed coupon bond	-0.031	-0.031	-0.037	-0.037	-0.037
	(0.064)	(0.064)	(0.063)	(0.064)	(0.064)
Floating coupon bond	-0.199**	-0.198**	-0.207**	-0.207**	-0.206**
	(0.081)	(0.082)	(0.080)	(0.081)	(0.081)
Notes	0.022	0.022	0.022	0.022	0.022
	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)
Bonds	0.047	0.047	0.046	0.046	0.046
	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)
Log number of bidders	0.143*	0.143*	0.140*	0.140*	0.141*
	(0.079)	(0.079)	(0.079)	(0.079)	(0.079)
Shanghai Stock Exchange	-0.006	-0.006	-0.006	-0.006	-0.006
	(0.068)	(0.069)	(0.065)	(0.066)	(0.066)
Log of days between primary and secondary market	0.144***	0.144***	0.144***	0.144***	0.144***
	(0.033)	(0.033)	(0.033)	(0.032)	(0.033)
Log of trading volume in the previous month	-0.143***	-0.143***	-0.144***	-0.145***	-0.144***
	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)
Volatility	0.698**	0.693*	0.753**	0.747**	0.747**
	(0.348)	(0.355)	(0.362)	(0.368)	(0.368)
Volatility of FTSE bank index at the day before secondary market		0.082 (1.266)		0.123 (1.271)	0.119 (1.274)
Government yield gap between primary auction date and the day before the secondary market			0.158 (0.113)	0.159 (0.113)	0.158 (0.115)
Log value of maturing bonds by institution for a given month					0.000 (0.002)
Institution effects	Yes	Yes	Yes	Yes	Yes
Month & year effects	Yes	Yes	Yes	Yes	Yes
Observations	1,442	1,442	1,442	1,442	1,442
R^2	0.199	0.199	0.200	0.200	0.200

This table presents the OLS results for margins by bond types – floating and non-floating bonds. Robust standard errors are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table B.2: Regression results for floating bonds' difference in spread

Variable	Difference in primary and secondary market spread				
	(1)	(2)	(3)	(4)	(5)
Notes	-0.693**	-0.675**	-0.687**	-0.661**	-0.660**
	(0.302)	(0.291)	(0.304)	(0.293)	(0.295)
Bonds	-0.921**	-0.887***	-0.907**	-0.855**	-0.859**
	(0.353)	(0.338)	(0.360)	(0.345)	(0.348)
Log number of bidders	0.542**	0.538*	0.539*	0.531*	0.532*
	(0.272)	(0.274)	(0.274)	(0.277)	(0.280)
Log of days between primary and secondary market	0.054	0.087	0.041	0.061	0.062
	(0.120)	(0.127)	(0.119)	(0.127)	(0.126)
Log of trading volume in the previous month	-0.165*	-0.194**	-0.179*	-0.226**	-0.227**
	(0.091)	(0.094)	(0.097)	(0.100)	(0.101)
Volatility	2.090	1.427	2.073	1.346	1.352
	(1.558)	(1.586)	(1.555)	(1.574)	(1.583)
Volatility of FTSE bank index at the day before		15.138***		16.170***	16.236***
secondary market		(5.193)		(5.385)	(5.415)
Government yield gap between primary auction			-0.846	-1.802	-1.839
date and the day before the secondary market			(1.343)	(1.477)	(1.500)
					-0.002
					(0.007)
Institution effects	Yes	Yes	Yes	Yes	Yes
Month & year effects	Yes	Yes	Yes	Yes	Yes
Observations	168	168	168	168	168
R^2	0.626	0.644	0.626	0.647	0.647

This table presents the OLS results for margins by floating bonds. The returns of the floating bonds are tied to market conditions, while non-floating bonds are predetermined. Hence, we use the difference in spreads in the primary and secondary market as a measure of the margin for floating bonds. Robust standard errors are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table B.3: Adjusted margins by bond type

Variable	Percentile				
	0.10	0.25	0.50	0.75	0.90
Non-floating coupon bond	-0.415	-0.090	0.121	0.284	0.415
	[-0.436, -0.395]	[-0.110, -0.070]	[0.101, 0.141]	[0.264, 0.305]	[0.394, 0.435]
Floating bond	-0.930	-0.341	0.035	0.416	0.665
	[-1.034, -0.826]	[-0.445, -0.237]	[-0.069, 0.139]	[0.312, 0.520]	[0.561, 0.770]

This table reports the adjusted margins by bond type for selected percentiles. Note that, to obtain our adjusted measure of margin for floating and non-floating bonds, we estimate the models described in Equation 1 without the bond-type dummies for the selected sample. 95% confidence intervals are in parentheses.

Table B.4: Adjusted margins for floating bonds using spread

Variable	Percentile				
	0.10	0.25	0.50	0.75	0.90
Floating spread	-0.326	-0.102	0.154	0.469	0.681
	[-0.400, -0.253]	[-0.176, -0.029]	[0.081, 0.228]	[0.396, 0.542]	[0.607, 0.754]

In this table, we report the distributional statistics of the adjusted margins constructed by spread with 95% confidence intervals.