Bond Losses in Post-Auction Resale Markets: Causes and Consequences*

Klenio Barbosa† Dakshina G. De Silva‡ Liyu Yang§ Hisayuki Yoshimoto¶

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Abstract

This paper examines the primary-dealers' returns in post-auction resale markets for treasury bonds, assesses the prevalence of losses and gains and their consequences for the financial sector. Using a novel database that tracks more than 2,350 primary-to-secondary transactions, we find that bond losses for primary-dealers are pervasive and were severe during the financial crisis. Our results indicate that liquidity constraint is a major source of the bond losses. We also find that financial sector value is correlated with these losses. Using an alternating market experiment, we show that primary-to-secondary losses are higher under discriminatory auctions as compared to uniform auctions.

JEL Classification: C57, C58, D44, G1, G2.

Keywords: Bond Losses, Treasury Bonds, Financial Sector Value, Auction Mechanisms.

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†Corresponding author. SKEMA Business School - Université Côte d'Azur, 60 Rue Fedor Dostoievski, Sophia Antipolis, 06902, France. Email: klenio.barbosa@skema.edu

‡Department of Economics, Lancaster University Management School, Lancaster LA1 4YX, UK. Email: d.desilva@lancaster.ac.uk

§School of Economics, Department of Finance, Jinan University, Guangzhou, Guangdong Province, 510632, China. Email: yang_liyu@qq.com

¶University of Glasgow, Adam Smith Business School, Glasgow, G12 8QQ, Scotland. Email: hisayuki.yoshimoto@glasgow.ac.uk

‘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

Several private or government-owned assets which are sold through auctions, such as buildings, vehicles, oil leases, and government securities, have resale opportunities. Resale opportunities introduce a common value element in auctions that affect bidders’ behavior. When bidders face an option to sell an object acquired in an auction in a secondary market, they shade their bids in the auction to reduce the risk of overpaying and making a loss in the secondary market. As a result, the most optimistic bidder wins the auction, but it may place a bid that exceeds the effective secondary market price. In this case, the winning bidder makes a loss, incurring a winner’s curse.[1]

In this paper, we investigate primary dealers’ returns in the post-auction resale market for treasury bonds, aiming to assess the prevalence of the bond losses, presumably explained by the winner’s curse. Additionally, we investigate the implications of these bond losses on the overall value of the financial sector. Our analysis is important because treasury bond dealers buy securities in the primary auction market and sell them in the secondary market. Since trading of bonds is a major part of dealers’/banks’ activities and accounts for a significant share of their revenues, losses in this market can have significant consequences for banks and the financial sector’s value.[2,3] For instance, the 2007-2008 global financial crisis has shown how bank losses can cause instability in global financial systems and lead to severe macroeconomic fluctuations (De Bandt, Hartmann, and Peydro, 2010).

Previous studies have empirically examined the bidding behavior, the losses and the winner’s

[1]Seminal works of Wilson (1967, 1977) and Milgrom and Weber (1982) provides a theoretical framework to analyze common value auctions, particularly bidding behavior and ‘winner’s curse’. Haile’s (1999) work is among the earliest to theoretically analyze auctions with resale and revenues. He notes that the revenue at the auction stage depends on the resale market structure and the information linkage between primary and secondary market.

[2]See King, Massoud, and Song (2013); Begenau, Piazzesi, and Schneider (2015).

[3]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, making a loss due to winner’s curse (Bukhchandani and Huang, 1989, 1993; Nyborg, Rydqvist, and Sundaresan, 2002).

curse in auctions for objects with resale opportunities. For instance, Capen, Clapp and Campbell (1971) and Hendricks and Porter (1988) examine the winner's curse in oil lease auctions. Hendricks, Pinkse and Porter (2003) document off-shore oil bidding behavior consistent with a winner's curse in equilibrium. Recently, Hafalir and Krishna (2008, 2009) and Cheng (2011) have also studied revenue generation and market efficiency in auctions with resale. Further, recent experimental studies by Georganas (2011), Georganas and Kagel (2011), Jabs-Saral (2012), and Jog and Kosmopoulou (2015) have examined the secondary market efficiency for objects that were first sold through auctions. As in these previous works, our paper also determines the primary-secondary market return and quantifies the prevalence of bond losses in auctions, theoretically explained by winner's curse in the bond market. However, different from these studies, our paper examines how winner's curse losses in the bond market spillover onto the financial market's value.

In the same spirit, Bonaldi, Hortaçsu and Kastl (2015) estimate the effects of financial cost shocks in individual banks on systemic risk. They show that the network structure of a bank determines the externality of its funding cost shocks on all other banks in the system, explaining the co-movements of banks' short-term funding costs. While Bonaldi, Hortaçsu, and Kastl (2015) focus on the network effect of liquidity shocks in the financial system, we look at how dealers' losses in post-auction resale markets for treasury bonds–a measure of individual bank's financial shock–shape the risk of an entire financial market. Given that the nature of our losses is linked to the common value aspect of the auction for bonds, we can draw, for the first time, important conclusions on how different auction mechanisms for selling bonds affect the financial system value and risk.

To perform our analysis, we divide our investigation into three parts. First, we quantify the effective return of a bond to primary dealers and assess the prevalence of their losses and gains in the market. Second, if financial losses are prevalent for primary market dealers, we ask "What is the possible market mechanism behind these losses?" Finally, in the presence of bond losses and their causes, we inquire whether bond losses can affect the value of the financial sector.

To examine the first part, we use a unique data set from China, containing trades of more than 2,350 Treasury bonds in primary and secondary markets from 2004 to 2017. Exploiting the rare timing structure of the Chinese government bond issuance process, where short trades are strictly prohibited, we calculate the effective return for a bond which is difference between primary and secondary market returns.[4] Next, we remove the observable effects of auction, bond, and market characteristics from this raw measure of bond return. This removal allows us to obtain an adjusted measure of bond return, which contains information about primary dealers' common valuation for bonds which is not driven by market conditions. Note that when this adjusted return is negative, it corresponds to a bond loss, which can be interpreted as winner's curse in the post-auction bond

[4]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.

market.

Due to the no-short-trade regulation and the simple information structure on dealer's returns, we are able to investigate whether some information about primary dealers' valuations and returns are revealed to the market when they sell bonds on the first trading day (debut-day), and how this revealed information affects the value of the financial sector in post-auction periods. Another advantage of our measurement is that it allows us to directly focus on an analysis of potential liquidity constraints rather than a combination of liquidity and short-position constraints.[5] Further, this paper analyzes what happens to the distribution of adjusted return and its risk in different auction mechanisms, whereas the previous literature only looks at average returns. That allows us to understand how different auction types affect the variability of the return in the auction for securities, which has not been investigated before.

Note that the construction of our post-auction effective bond return is in the spirit of Hendricks and Porter (1988), where they track the winning price in the auction and the price of the oil sold in the future. However, there are important differences in which we contribute to the literature. First, our time frame is very short (a few days) compared to the oil lease auctions studied by Hendricks and Porter (1988), which are years. The long period between primary and secondary outcomes in Hendricks and Porter (1988) could allow the players to hedge and prevent significant losses and potential bankruptcies. As we are looking at very short period, where the primary dealers are more likely to be surprised by the outcome in the secondary market. These losses can spillover onto the financial market, thereby affecting its value. Further, we compute the adjusted measure of bond return, which is not explained by observable institutional and market characteristics, an adjustment not made by Hendricks and Porter.

Our results indicate negative adjusted returns for about 20% of the observed transactions. Note that these bond losses are not occasional losses for primary dealers as they persist even after controlling for adverse changes in the yield between the auction date and the secondary trading day. 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-Treasury auction (secondary market) transactions led to negative adjusted returns. Our findings are interesting because they can be informative for policymakers interested in understanding financial markets during a recession or interested in government security market (in)stability.

To evaluate the possible market mechanism behind these losses, the second part of this paper explains why the bond auction dealers-winners liquidate their on-the-run bonds on the first trading day (debut-day) at a loss, rather than waiting for a better *market timing* to sell their bonds in the secondary market. We hypothesize that a high borrowing cost leads to primary dealer's liquidity

[5]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).

constraint, which makes the sales of on-the-run bonds at a loss the best dealers' strategy 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.[6] We also 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 bond losses (i.e., negative adjusted returns) is higher and the secondary market volume is also higher.

Finally, having documented the existence of bond losses and their causes, we turn to our third part–examining whether bond losses can affect the value of the financial sector. As liquidity constraints constitute private information within a primary dealer, bond losses inevitably generate new public information among financial market participants. Hence, in the spirit of De Silva et al. (2008), 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 bond losses in the secondary market.[7] In this exercise, we first identify secondary market debut-days with significant bond losses using all secondary market debut-dates where we observe only all positive or all negative adjusted 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 negative adjusted returns (i.e., bond losses) on the financial sector. We find that FTSE financial 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. As an additional robustness test, we estimate the same model using two placebo groups, FTSE Chinese Food and FTSE Chinese Health Care indexes. The results indicate that bond losses) have no effect on Food or Heath Care indexes. This result further validates our hypotheses that financial indexes respond to bank losses. Therefore, our findings support our hypothesis that bond losses affect the value of the financial sector and indicate that bond losses play a sizable informational role.

This study contributes to the recent empirical literature on multiunit auctions related to Trea-

[6]The REPO rate is the volume-weighted average rate of the benchmark seven-day repurchase agreement rate in the interbank market.

[7]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.

sury auctions. Seminal papers by Hortaçsu and McAdams (2010) and Kastl (2011) examine the revenues generated in the primary market for Treasury bills (also see Barbosa et at., 2022) in different auction mechanisms. Differently, our paper examines the relationship between auction design and the value of the financial sector by examining primary-secondary market transactions and computing the gains and the losses of primary dealers on government securities auctioned off through dissimilar auctions mechanism.

Further, our study contributes to the literature on government and corporate security underwriting issuance premia (for example, see Jegadeesh, 1993; Jordan and Jordan, 1996; and Nyborg and Strebulaev, 2003; Cai et al., 2007; Henderson and Tookes, 2012; Nikolova et al., 2020; Flanagan et al., 2022; Nikolova and Wang, 2022). 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. To evaluate which auction mechanism alleviates possible bond losses, we use an alternating market experiment conducted by two Chinese government bond issuers. Results indicate that the share of transactions with negative adjusted returns is higher in discriminatory auctions than in uniform auctions. Moreover, we show that these losses in the bond market can significantly affect the capitalization value of the financial sector. As far as we know, earlier studies have not investigated bond losses linked to the financial sector value under an alternating-auction rule market experiment to answer this policy-relevant question. This result suggests that a government–as a bond issuer–could adopt uniform auctions to reduce bond losses and mitigate financial distress.

Note that our results have important policy implications and contribute to the existing literature on bond losses. For example, Acharya and Steffen (2015) show that those bank losses were derived from the European banks' carry trade strategy–purchasing risky sovereign debt using funding provided by the European Central Bank (ECB). Popov and Van Horen (2014) show that banks with sizeable holdings of risky GIPSI (Greece, Ireland, Portugal, Spain and Italy) 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 summary, to the best of our knowledge, this paper is the first to show a linkage between bond losses, liquidity constraints, auction mechanisms, financial sector-wide value, and clarify the information transmission channels behind them.[8]

The remainder of the paper proceeds as follows: The next section gives the background of the Chinese government bond-issuing institutions and their primary and secondary markets. Section

[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.

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 sector value. 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 discusses the implications of our paper for global financial markets. Section 9 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

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.[9] In 1995, for the first time, the MOF used auctions as a mechanism to sell T-Bills. Subsequently, in 1996, auctions became the only method to issue bonds in the primary market. Note that, initially, T-Bills were traded only in the inter-bank market. Since 2000, with the permission of the State Council, the MOF began to allow primary dealers to trade T-Bills across the markets to attract long-term bondholders.

In 2002, some Chinese treasury bonds experienced failure in the primary market as the cut-off rate exceeded the MOF-set upper limit based on secondary market yield from the previous trading day. As uniform price auction (an auction format in which there is a unique market-clearing rate or price) was, by that time, the only auction mechanism used by the MOF to sell its bonds, auctions failed to sell bonds if the cut-off yield exceeded the upper limit. To mitigate auction failures in the presence of an upper rate limit, in 2003 the MOF introduced the discriminatory auction, an auction in which bidders pay what they bid. Additionally, from 2004, the MOF decided to employ the Spanish (hybrid) auction format to further alleviate 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.[10] 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

[9]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.

[10]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 it is different for each bond.

year. Accordingly, the MOF currently only uses uniform and hybrid 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 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. In Appendix A, Table A.1 and Table 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.[11] 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.[12] 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, then the top 45 primary dealers are allowed

[11] 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

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

to continue for another year (or term). Other dealers compete for the remaining five seats.[13] The CDB, EIB, and ADB also use a similar method to build their primary groups, but they do not impose a bidding minimum volume for primary dealers.[14] In this study, we refer to all prequalified dealers as "primary" dealers.[15]

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 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 first 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.[16] 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.[17] Thus, in China, financial market participants are typically informed of the secondary market price/yield of an on-the-run

[13]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- 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.

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

[15]The number of registered bidders is plotted in Figure A.1 in Appendix A, while Figure A.2 also in Appendix A 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 in Appendix A).

[16]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.

[17]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/.

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.[18]

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.[19] Further, our study use data only from bonds issued through auctions, as 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 in the primary market data, we observe the bond ID and the yield rate (or price) of bonds in the secondary market.[20] 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

[18]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.

[19]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.

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

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.[21]

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%.[22] 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.

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 eco-

[21]First, in Table A.3 in Appendix A, 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 also in Appendix A, 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.

[22]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.

nomic 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.[23] 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.[24]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 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 which contains information about primary-dealers common valuation for bonds which is not driven by market conditions. 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).

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

[24]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.

Note that we aim to obtain a measure of adjusted margin that captures the unobservable variation of return that is not explained by the observable variables, including the privately possessed liquidity constraint information. Here, the term "unobservable" means unobserved information to researchers and general financial market participants, except bidders who sell on-the-run issues on debut days (and know the reasons behind the debut-day reselling activities). Note that the adjusted margin should be a noisy public signal because financial market participants (except bidders who sell on-the-run issues) do not know the exact motive behind the trade.[25] 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), which every financial market participant can observe.[26]

The procedure to obtain the adjusted measure of return 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 raw 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 and α is the constant. The variable ϵ is the error term, which has mean zero and variance σ_ϵ. Note that in the right-hand side of Equation (1), x, z, m and fixed effect terms are known to the financial market participants.

As we are interested in the portion of the returns which is unexplained by observables, the predicted error term $\widehat{\epsilon}_{ijt}$ of estimated Equation 1 would be the natural candidate for a measure of adjusted margin. Nevertheless, $\widehat{\epsilon}_{ijt}$ has, by construction, a mean of zero, a property of the least square regression model. Thus, positive and negative values of $\widehat{\epsilon}_{ijt}$ cannot not represent, respectively, effective gains and losses not driven by observables (bond, bank, market, and financial market conditions). Aiming to obtain an adjusted measure of return that is meaningful in our context and contains information about primary-dealers common valuation for bonds, we subtract from $\widehat{\epsilon}_{ijt}$ the average market return $\overline{\widehat{margin}}_{ijt}$, which is the portion of the returns explained by observables (bond, bank, market, and financial market conditions). Note that we are removing a mean zero measure of return ($\widehat{\epsilon}_{ijt}$) from a return obtained by an average bank-dealer that replicates the market return ($\widehat{\epsilon}_{ijt}$), to obtain an individual bank-dealer return (margin^*_{ijt}). This is is our

[25]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.

[26]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.

measure of adjusted margin. Formally, our measure of adjusted margin is constructed as follows.[27]

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

This is our noisy public signal measure of the adjusted margin, which is later used to investigate how a revealed information about a bank-dealer loss in the bond market affects the value of financial sector in post-Treasury-auction periods. Note that our measure of adjusted margin in Equation 2 captures 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. Henceforward, all the analysis are based on the adjusted margin defined in Equation 2, which is the measure of a bond loss not related to market conditions, as discussed in the previous paragraphs.

Table 2 presents the estimated parameters and explains the market gap (i.e. raw margin), 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 increases rates (i.e., lower price) in the primary market, thereby increasing the primary and secondary market gap. This is not an unusual result in common value auctions.[28] Results show 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.[29] In Column 4, we also control for volatility of FTSE bank index

[27] This is, in spirit, similar to bid homogenization introduced by Haile et al., (2006).

[28] Giliberto and Varaiya (1989) note that, in common value auctions, in which winner's curse effect is likely to be prevalent, bidders pursue aggressive bidding strategies and they overpay. Gordy (1999), also show that greater the potential for winner's curse and larger the number of competing bidders, then the winning bids are upwardly biased.

[29] We also estimate this using the yield changes between the close of the primary and secondary market trading day and results are qualitatively similar. We can provide these results upon request. However, we prefer to use the yield rate announced at the beginning of the secondary market trading day to avoid endogeneity issues.

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 2 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. As one may note, these bond losses are not rare losses that even experience dealers may suffer. That is because the bond losses that we found exist even after controlling for adverse market changes, including a yield change between the auction date and the secondary trading day.[30]

[30]Note that in almost the entire support of return's distribution, the adjusted margin is higher than the predicted

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.[31] 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.[32] 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.[33]

margin. That means that the institutional and market conditions generate observable negative returns $\overline{\widehat{\text{margin}}}$. As a result, when we subtract $\overline{\widehat{margin}}_{ijt}$ from the $\widehat{\epsilon}_{ijt}$ to obtain the adjusted margin margin^*_{ijt}, we are scaling up the adjusted margins, which makes them higher than the raw margins.

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

[32] We also estimate these models using dummies to indicate the crash and after-crash periods. These OLS and quantile models are presented in Appendix A 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.

[33] Figure 5 displays the CDF of the adjusted margins by non-floating and floating bonds. Figure 6 presents the CDF of the adjusted margin using the spread for floating bonds. The detailed description of the spread construction is explained in the Appendix B. In the Appendix A, Figure A.4 shows the CDF of adjusted margins while controlling for volume presents, and Figure A.5 presents CDF of adjusted margins that have been constructed by using the highest, lowest, and weighted average winning primary rates in discriminatory auctions.

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 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.[34] Details of the analysis and regression results are presented in Appendix B.

5 Liquidity constraints and bond losses

Given the prevalence of bond losses in the post-auction resale markets, one may question the reason for the bond dealers to liquidate their on-the-run bonds on the debut-day at a loss, rather than waiting for better *market timing* to sell their bonds in the secondary market. In this section, we examine whether a high money market borrowing cost leads to primary dealer's liquidity constraint, which makes them sell their on-the-run bonds at a loss to minimize their financial distress. Doing so, we investigate 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. To pursue this empirical investigation, we consider three different definitions of a day with bond losses. We first define a day with bond losses as a day in which all secondary market transactions generated negative adjusted margins, and at least one transaction generated a loss below the bottom 10th of the distribution. The second definition of a day with bond losses is any day in which a transaction generates a negative adjusted margin. Lastly, we define a day with bond losses as a day in which all transactions on that day have led to a negative adjusted margin.

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

[34]Uniform auction was the only mechanism used to sell both floating and non-floating bonds.

trading volume based on the REPO rate.

First, at the transaction level, we use a simple probit to examine the probability of observing negative adjusted margins (i.e., bond losses) on trades given the REPO rate of the debut day. We report these results in Table 8. Note that these losses are based on our adjusted margins, and hence they have been estimated after controlling for bond, auction, and market characteristics. In Column 1 Panel A of Table 8 we consider the definition of a day with bond losses as a day in which all secondary market transactions generated negative adjusted margins, and at least one transaction generated a loss below the bottom 10th of the distribution. 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 consider a day with bond losses when any day a transaction generated a negative adjusted margin. In the estimations report in Column 2, we use only data for the days on which secondary market volumes are available. 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 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 will be loose on that day. Interestingly, our results are qualitatively the same, regardless of the definition of a day with bond losses used.[35]

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.

[35]We also estimate the adjusted margin as the dependent variable using a simple OLS. This regression also indicates that losses are higher during days when the REPO rate is high. However, even though the coefficient negative, results are statistically not significant. We can provide these results upon request.

6 Bond losses and financial sector value

Now we turn our attention to the effect of bond losses on the value of the financial sector by analyzing what happened to the FTSE Russel Chinese financial indexes – consisting of representative bank, security, and insurance sector publicly traded companies – on the days when Chinese primary market dealers suffered substantial bond losses (i.e., negative adjusted return). 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 Appendix A, Table A.8 presents 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 negative adjusted returns(bond losses not explained by observable institutional and markets conditions) 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 (i.e., negative adjusted margin). These panel regression results support our hypothesis that a negative adjusted return from a post-auction resale of bonds could lead to a decrease in the financial sectors' capitalization values. Similar patterns are observed for the security index (See Panel B in Table 9).[36]

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.[37]

Further, we use two placebo groups to check the validity of the original difference-in-difference (DID) results. Gruber (1994) notes that if the results with placebo groups are not statistically significant and are different from the DID with the original treatment group, then the original DID is likely to be unbiased. Thus, we consider FTSE Chinese Food and FTSE Chinese Health Care indexes provided by the Thomson Reuters as placebo groups, replacing the FTSE Chinese Financial Sector indexes in the estimation of Equation (3). Our assumption is that the performances of Banks or Insurance institutions have very little or no influence on the performances of Food or Health Care sector providers. We report these results in the last two columns of Table 10. Results indicate that observed bond losses have no effect on Food or Heath Care indexes. This result further validates our hypotheses that financial indexes respond to bank losses.

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 the volatility of financial sector value 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.[38]

[36]We have also estimated Equation 3 using the other two definitions of a day with bond losses described in Section 5. Our findings are qualitatively the same. Hence, our results are robust to less extreme definitions of day with bond losses.

[37]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.

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

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, that we describe next, suggest that bidders are more exposed to bond losses in discriminatory auctions than in uniform-price auctions.

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 in Appendix A, 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.[39] 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 Appendix 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 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).[40]

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

[39]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.

[40]Barbosa et al. (2022) 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. (2022) also find that, between the two auction formats, bidders' entry behavior does not reveal any statistical difference.

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 11 and Table A.11 in Appendix A.[41] 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 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.[42] Table 12 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.[43]

Next, we also re-estimate the market gap (Equation 1) controlling for volume. We have only 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.[44] 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).

8 Implications for global financial markets

Our paper demonstrates that when bank dealers incur losses during the post-auction resale of bonds, it negatively impacts the financial markets. This occurs because the immediate liquidation of on-the-run bonds at a loss, instead of waiting for more favorable conditions in the secondary

[41]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.

[42]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].

[43]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 in the Appendix A 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.

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

market, is interpreted by stock market investors as a negative indicator of the bank dealers' liquidity. Consequently, this perception prompts investors to sell off bank stocks.

These results have important implications for the global financial markets. First, it highlights a new channel through which bank losses affect financial markets, which proved to be a relevant issue in the 2007-2008 global financial crises. This is particularly important because bonds consist of a large share of bank assets, and trading of bonds accounts for a significant share of their revenues in several countries, as documented by Massoud, Song (2013) and Begenau, Piazzesi, and Schneider (2015). This indicates the economic relevance of trading bonds, their potential losses in several international markets, and their harmful effects on the financial markets.

Note that our findings are consistent with the liquidity deterioration effect described by Gorton (2010) in the U.S. bond market during the 2007-2008 financial crisis. Gorton notes that, during this period, banks were forced to sell their bonds to raise money while bond prices were falling due to enormous 'fire sales.' This shows that the liquidity constraint bond sales story that we detected in the Chinese secondary bonds markets shares important similarities with the banks' sell-off bonds during the most recent global financial crises. This indicates that our findings on the consequences of bond losses to the volatility of the financial market in China are related to what we observe in other countries.

Furthermore, our findings are valuable for policymakers aiming to design measures to prevent future financial crises. The documented impact of bank losses in the post-auction resale of bonds due to liquidity shocks indicates that central banks should provide increased liquidity in the inter-bank market on debut days. More broadly, policymakers should consider which auction mechanisms minimize bank losses in post-auction bond resales, as these losses contribute to financial market instability. In this context, our paper also offers insights for other financial markets. We show that the proportion of transactions involving bond losses is higher in discriminatory auctions than in uniform auctions. Thus, if a government seeks to reduce volatility in the financial sector's stock capitalization, it should adopt uniform auctions associated with a lower likelihood of bond losses.

9 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 of a primary bond dealer. Next, we remove the observable effects of auction, bond, and market characteristics from this raw measure of bond return. This removal allows us to obtain an adjusted measure of bond return, which contains information about primary dealers' common valuation for bonds not driven by market conditions. When this adjusted return is negative, it corresponds to a bond loss, which can be interpreted as winner's curse in the post-auction bond market.

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 losses propagates.

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.

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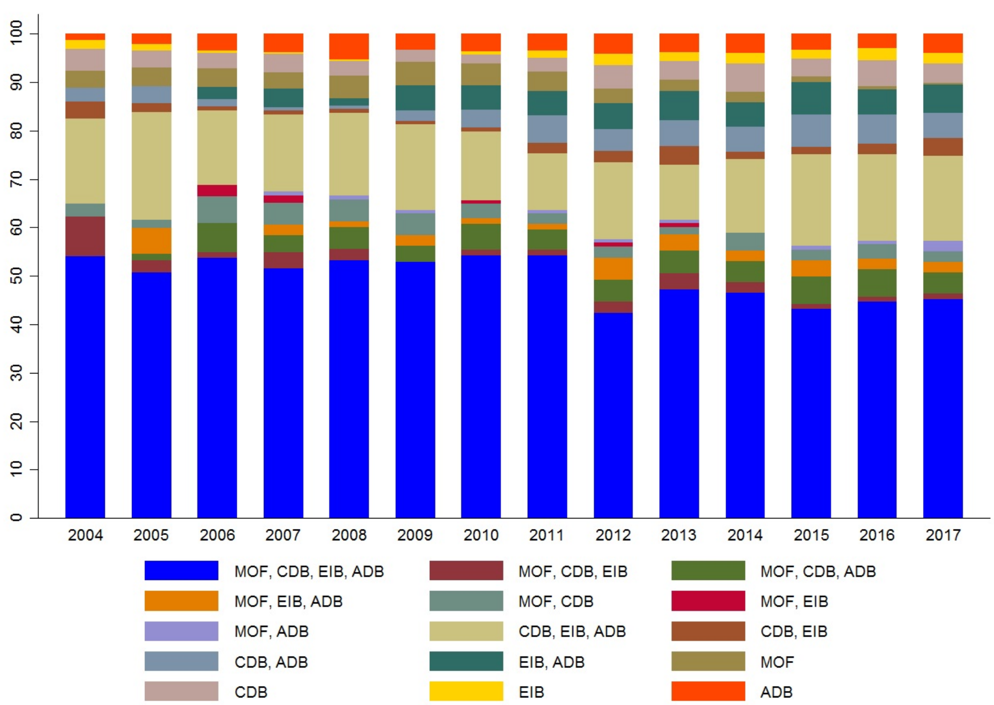
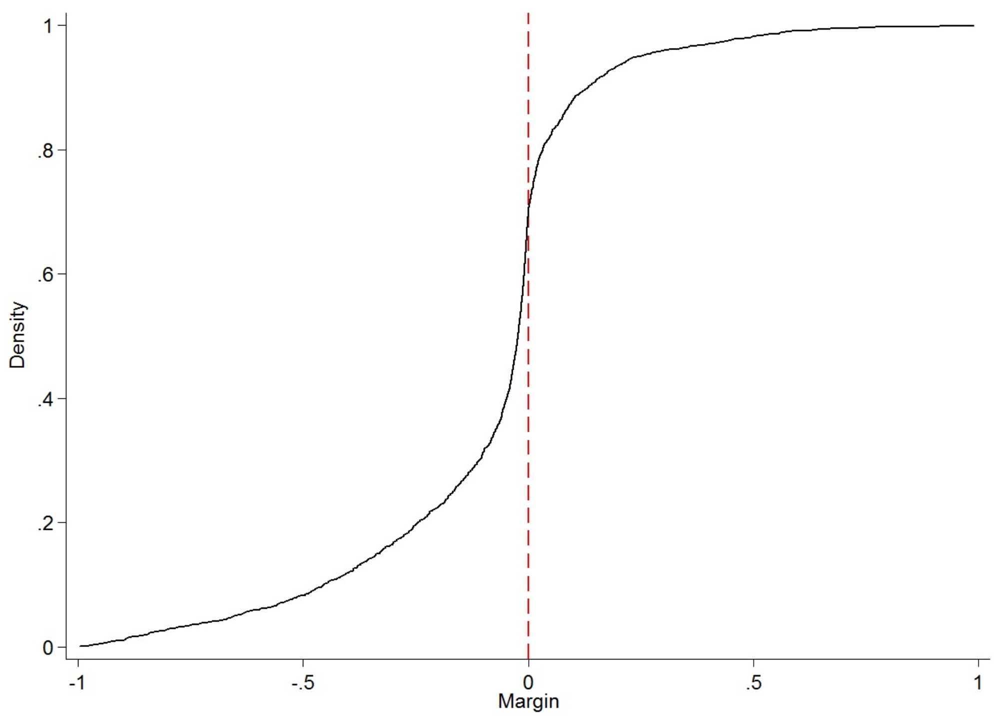
Figure 1: Primary dealer overlap



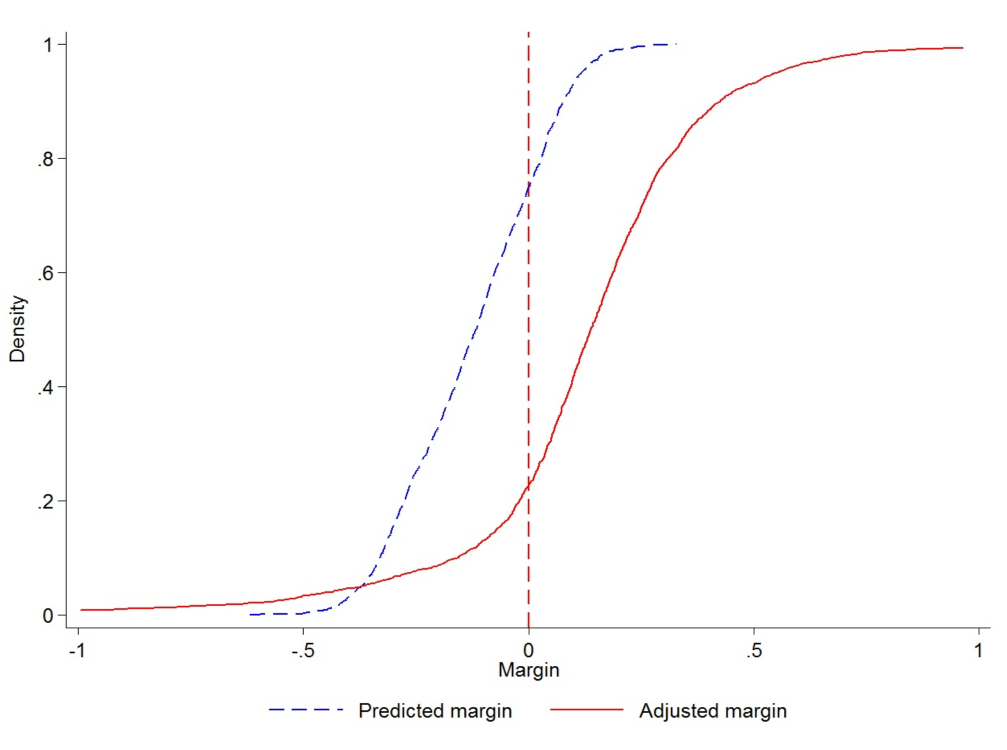
Notes: In this figure, we show the overlapping nature across the four bond-issuing institutions. During the period 2004-2017, about 50 percent of primary dealers submitted their bids in all MOF, CDB, EIB, and ADB auctions. Moreover, around 25 percent of primary dealers submitted bids across three policy banks: CDB, EIB, and ADB.

Figure 2: Raw margin



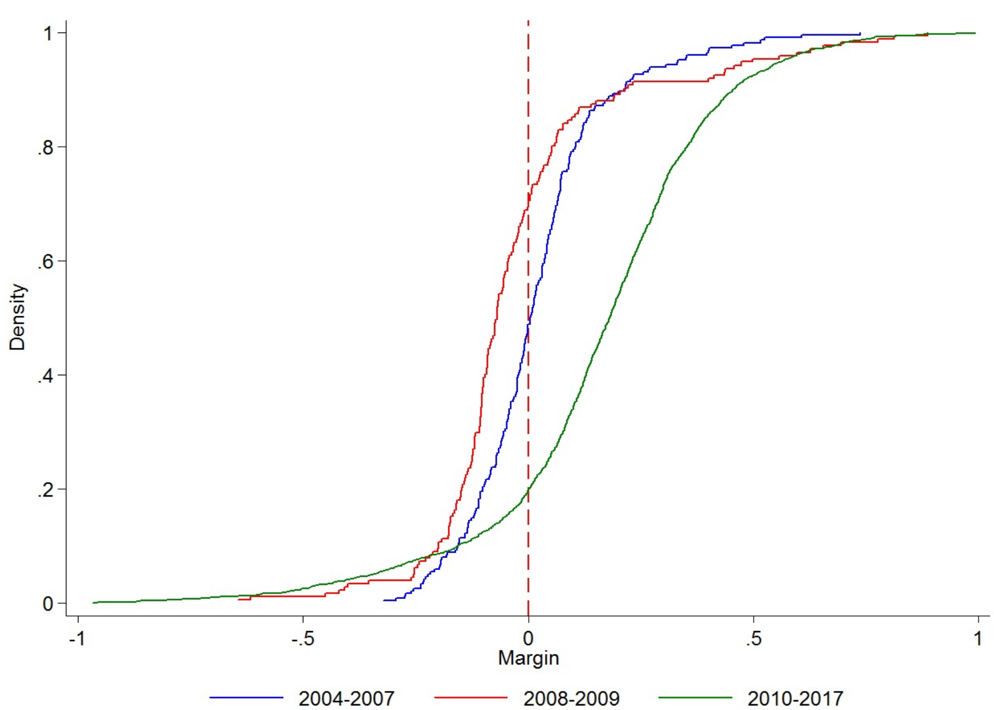
Notes: This figure shows the cumulative distribution (CDF) of the raw margin. We define the margin for a given bond as the primary minus secondary market rates. This distribution is not controlled by any auction, bond and financial market characteristics.

Figure 3: Adjusted margin



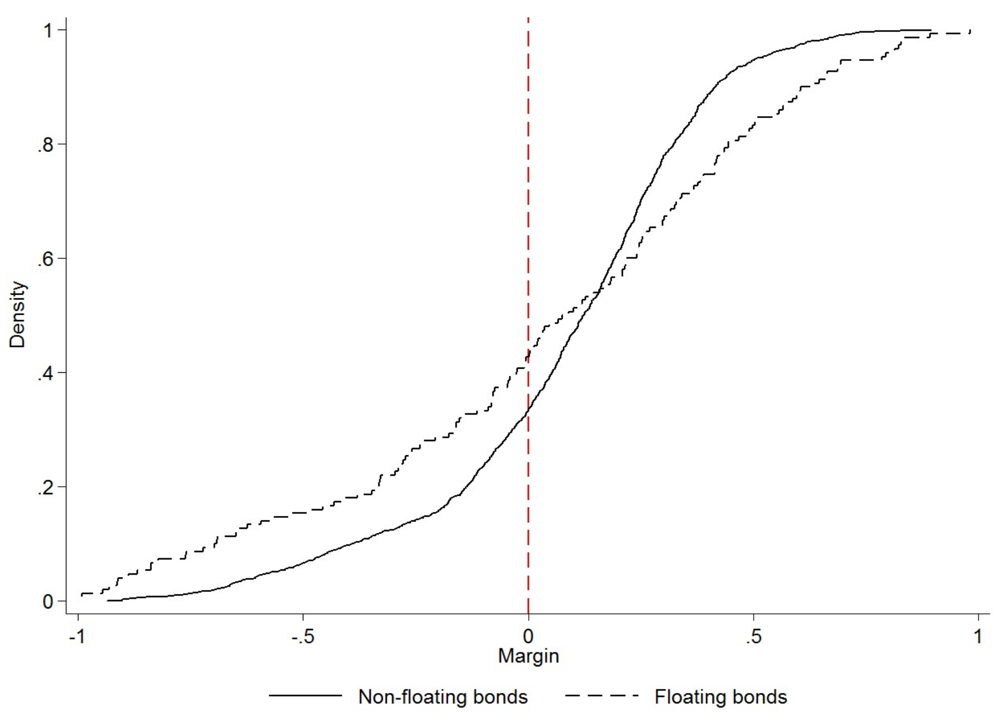
Notes: In this figure, we plot the CDF of fitted margins (From Equation 1) and adjusted margins (From Equation 2). Here, we use predicted margins and residuals obtained after estimating the empirical model described in Column 5 in Table 2. Then we use them to construct the adjusted margins as described in Equation 2.

Figure 4: Adjusted margins by period



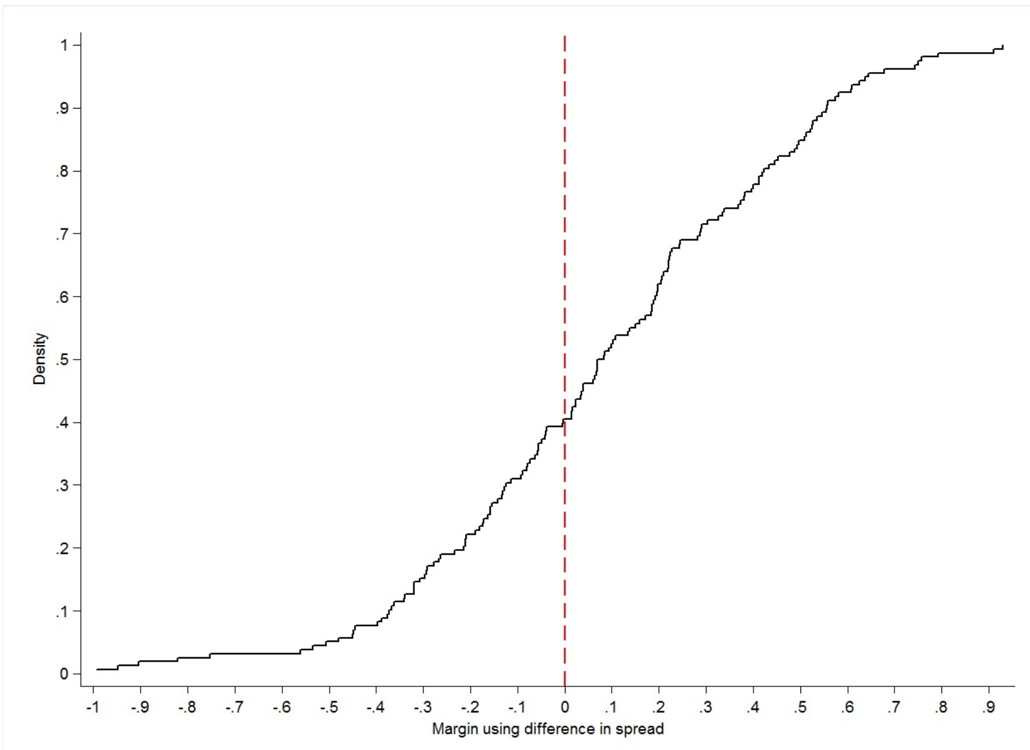
Notes: In this figure, we plot the CDF of adjusted margins before, during, and after the 2008-2009 crisis. We use predicted margins and residuals obtained after estimating the empirical model described in Column 5 in Table 2 to construct the adjusted margins by period.

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



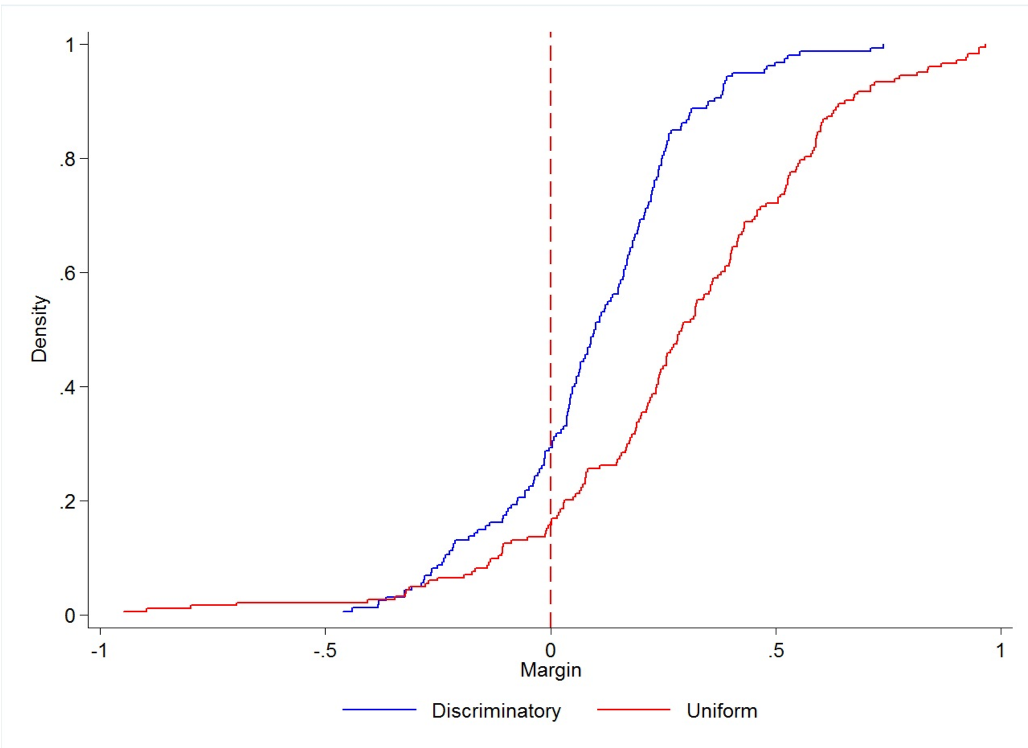
Notes: In this figure, we show the CDF of adjusted margins by bond type. Note that floating bonds were sold using only the uniform auction format since 2007.

Figure 6: Adjusted margins for floating bonds using spreads



Notes: 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



Notes: In this figure, we plot the CDF of adjusted margins for uniform and discriminatory auction formats during the alternating-rule experiment period. The alternating-rule experiment is conducted by two Chinese policy banks from 2012 to 2015.

Table 1: Summary statistics

This table reports summary statistics of data used in the analysis between 2014 and 2017. Panel A reports summary statistics for auction-level characteristics: auction formats, bond categories, floating bond and bidders' number per auction. 2371 auctions are matched with secondary market information. Panel B reports secondary market statistics and variables: list location, time lags and monthly traded volume. 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, when it applies.

Variable	Mean / Counts
Panel A	
Number of bonds sold in the secondary market	2,371
Number of bonds sold through Hybrid Auctions (HA)	565
Number of bonds sold through Discriminatory Auctions (DA)	285
Number of bonds sold through Uniform Auctions (UA)	1,521
Average primary market rate (in percentage)	3.628
	(0.951)
Number of Bills	572
Number of Notes	1,357
Number of Bonds	442
Number of Floating Bonds	168
Number of bidders	43.762
	(11.205)
Panel B	
Average secondary market rate (in percentage)	3.750
	(0.962)
Number of transactions in the Inter-Bank Market	2,213
Number of transactions in the Shanghai Stock Exchange	99
Number of transactions in the 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	0.017
market debut day	(0.011)
REPO rate (in percentage)	3.062
	(1.131)
Government yield gap between a primary auction date and a	-0.003
day before the secondary market (in percentage)	(0.093)
Value of maturing bonds by institution for a	2,823,731.00
given month (in ¥ 100,000)	(3,270,008.00)

Table 2: Regression results for market gap

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. HA is an indicator equalling to one if the auction format is the hybrid auction. DA is an indicator equalling to one if the auction format is the discriminatory auction. Fixed coupon bond equals to one if the bond coupon payment is fixed. Floating coupon bond equals to one if the bond coupon payment is float. Notes equals to one if the bonds' maturity is between one year and ten year. Bonds is an indicator equalling one when bonds' maturities are more than ten year. Log number of bidders is nature logarithm of number of bidders. Both Shanghai Stock Exchange and Shenzhen Stock Exchange are indicators of listing locations where bonds trading in the secondary market. Log of days between primary and secondary market is nature logarithm of time gap between two markets. Log of trading volume in the previous month is nature logarithm monthly trading volume one month prior to auctions. Volatility is calculated using the five-day daily government announced yield before secondary debut days. Volatility if FTSE bank index at the day before secondary market is constructed using the five-day FTSE China bank index one day prior to secondary initial trading days. Government yield gap between primary auction date and the day before secondary market is using the government daily yield at auction day minus the government yield one day before the secondary listing day. Log value of maturing bonds by institution for a given month is the nature logarithm of monthly maturing bond in the same month as the auction days. 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), This table 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.

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

Table 3: Adjusted margins

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.

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]

Table 4: Regression results for market gap with volume

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. Note, Log of volume is the nature logarithm of total volume of bonds which are traded in the secondary initial days. 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.

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

Table 5: Gains and losses

This table report the summary statistics for the gains (positive adjusted margins) and losses (negative adjusted margins) based on regressions results in Column 5 of Table 4. Standard deviations are in parentheses.

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)

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

This table presents the distributional statistics of the adjusted margins before, during and after the financial crisis in 2008 and 2009. 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.

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]

Table 7: Gains and losses by period

This table presents the statistics of the gains and losses before, during and after the 2008-2009 financial crisis. All margins reported in this table are adjusted margins. The predicted margins and residuals are obtained from the empirical model estimated in Column 5 in Table 4. All basic interpretation is similar to Table 5. Standard deviations are in parentheses.

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)

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

This table reports the effect of REPO rate on observing bond losses and trading volume for all years and years excluding 2008 and 2009 in Panel A and Panel B, respectively. A simple probit estimations are employed in the first three column, examining the probability of observing bond losses on trades given the REPO rate of the debut-day. All margins are adjusted margins. *All trades* is indicator equally one if the transaction suffers the loss. *With volume* records the transaction with volume information. It equals to one if the transaction obtains the negative margins. *Trading day* equals to 1 if all transactions in that day collect negative margins. Otherwise, it equals to 0. The Column 4 and 5 use the OLS estimations, examining the effects of REPO rate affect the trading volume. *Log of Volume by trade* (Column 4) is log of secondary market trading volume over log of total primary market auctioned volume. *Log of Volume total per day* (Column 5) is log of total market trading volume over log of total primary market auctioned volume in a given day. *REPO rate* is Chinese seven-day repo rates which are daily announced. *Log of initial volume* is nature logarithm of trading volume in first debut-day. *Log of total initial volume* is nature logarithm of total trading volume in a given day. Robust standard errors are in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% level, respectively.

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

Table 9: Bank and security index variation

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 China FTSE indexes (Bank, Security, Insurance) 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.

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

Table 10: Food and beverage and health care index variation

This table reports results for the panel regression (event study) model to examine the impact of bond losses on banking, food and beverage, and health care sectors for all years in our sample. We are interested in the value of the coefficient of β_3, which measures the difference in China FTSE indexes (Bank, Food and Beverage, Health Care) that occurs after the secondary market trades (one or two days) on all negative adjusted margin transaction days compared to all positive days. The first two columns report results for the China FTSE Bank Sector Index as the outcome variable. Columns (3) and (4) report results for the China FTSE Food and Beverage Sector Index, while the last two columns report results for the China FTSE Health Care Sector Index. Robust standard errors are in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% level, respectively.

Variables	Bank index		Food and beverage		Health care	
	+/- One day	+/- Two days	+/- One day	+/- Two days	+/- One day	+/- Two days
	(1)	(2)	(3)	(4)	(5)	(6)
Negative adjusted margin trades	0.003***	0.003**	-0.001	-0.003	-0.000	-0.001
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
After the secondary market trades	-0.000	-0.000	-0.002***	-0.002***	-0.001	-0.000
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)
Negative adjusted margin trades ×	-0.006**	-0.006***	-0.001	-0.002	-0.000	0.000
after the secondary market trades (β_3)	(0.003)	(0.002)	(0.004)	(0.004)	(0.004)	(0.003)
Observations	4,902	7,890	4,902	7,890	4,902	7,890
R^2	0.003	0.001	0.004	0.002	0.001	0.000

Table 11: Regression results for market gap during the alternating-rule experiment

This table reports the OLS results for the market gap between uniform and discriminatory auction formats during the alternating experiment period. All explanatory variables are similar as Table 2. Two policy banks, CDB and EIB, conducted auction experiment from 2012 to 2015. The experiment period of CDB is between May 2012 and July 2014, while the experiment period of EIB is between July 2013 and May 2015. Robust standard errors are in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% level, respectively.

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

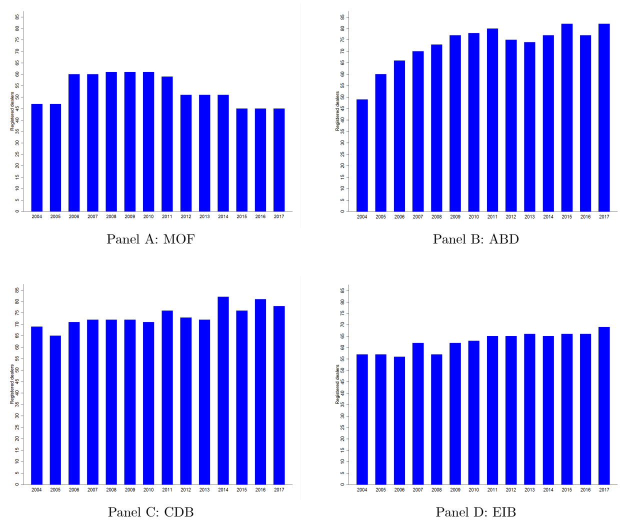
Table 12: Adjusted margins during the alternating-rule experiment by auction mechanism

This table reports the distributional 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. This experiment is conducted by CDB and EIB from 2012 to 2015. 95% confidence intervals are in parentheses.

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]

Appendix A

Figure A.1: Registered primary dealers



Panel A: MOF

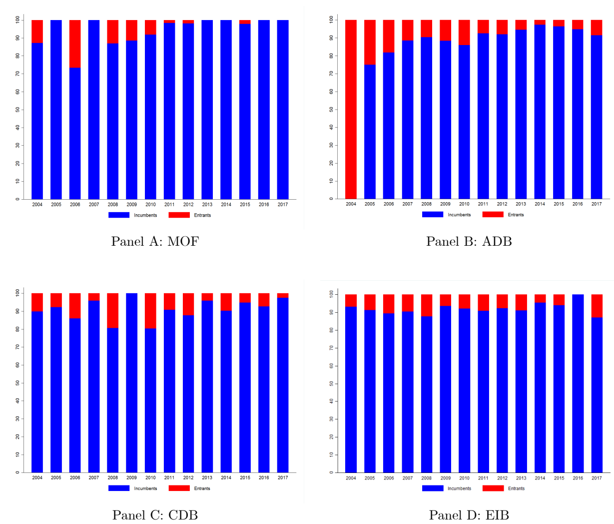
Panel B: ABD

Panel C: CDB

Panel D: EIB

Notes: 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

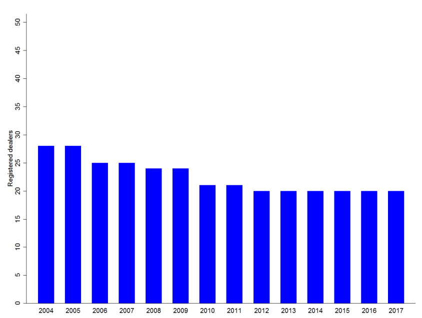
Panel B: ADB

Panel C: CDB

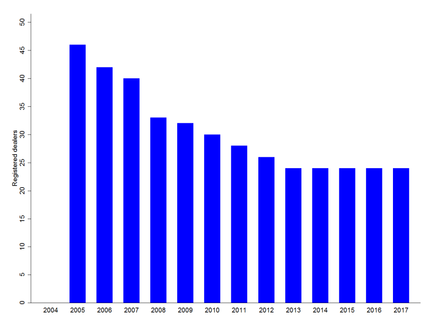
Panel D: EIB

Notes: In this figure, we plot the ratio of entrants and incumbents for each institution from 2004 to 2017. The ratio of entrants equals the entrants divided by total number of bidders in each year. The ratio of incumbents equals the incumbents divided by total number of bidders in each year. Entrants are primary dealers who first time to participate bond auctions in the specific institution. Incumbents are primary dealers who participate bond auctions in the institution at least once before. Notably, the ratio of entrants and incumbents is obtained based on statistics in 2013 for MOF, ADB and CDB. Note that the ADB started selling bonds in 2004 and hence all participants are considered entrants.

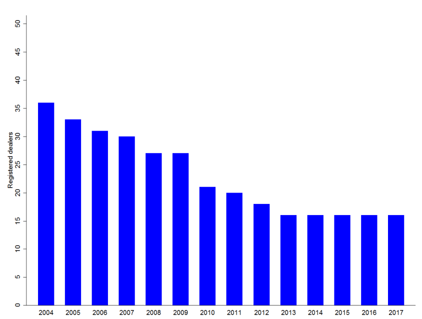
Figure A.3: The number of continuing primary dealers



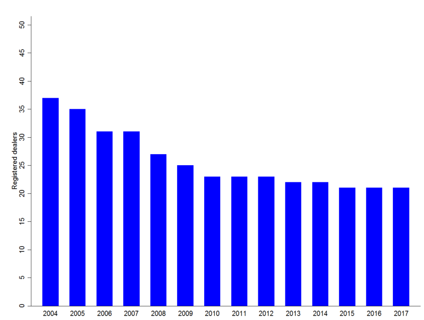
Panel A: MOF



Panel B: ADB



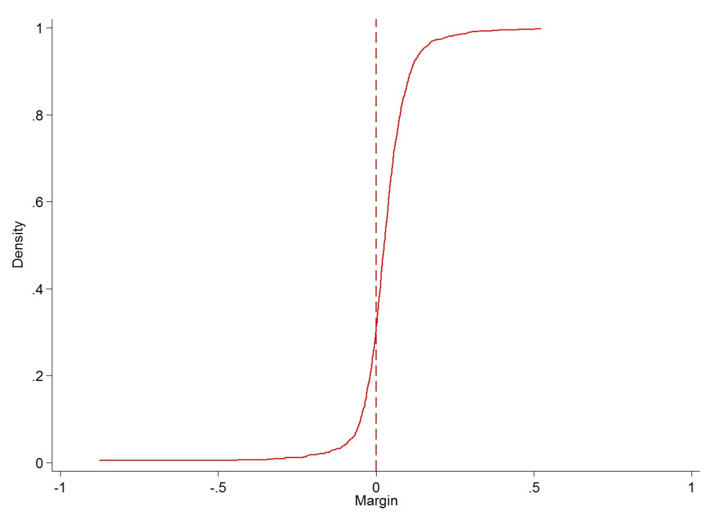
Panel C: CDB



Panel D: EIB

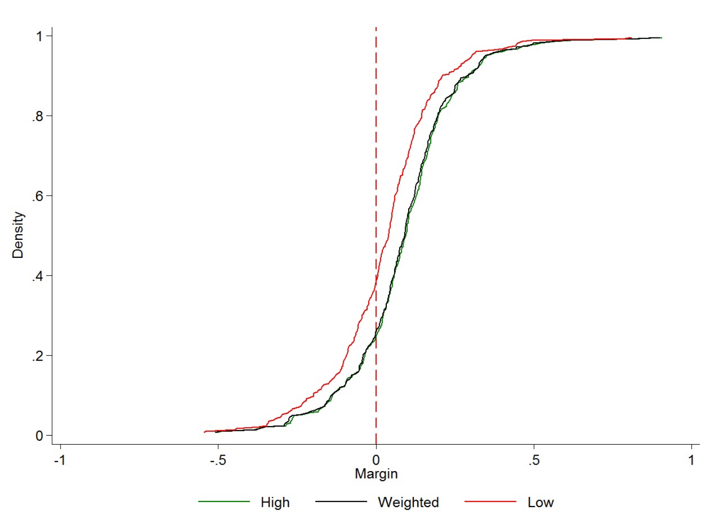
Notes: In this figure, we plot the year-to-year continuing incumbents for each institution from 2004 to 2017. Note that the continuing incumbents are primary dealers who are authorised by bond issuers as members to participate bond auctions every year during 2004 to 2017. Because ADB used auction since 2004, the continuing incumbents are collected from 2005. 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



Notes: In this figure, we show the CDF of adjusted margins while controlling for volume. Note that 1,128 out of 2,371 observations records information of volume for non-reissued bonds.

Figure A.5: Margins for discriminatory auctions



Notes: This figure presents CDF of adjusted margins that have been constructed by using the highest, lowest, and weighted average winning primary rates in discriminatory auctions. Since dealers need to pay what they bid in discriminatory auctions, 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. The distributions are plotted basing on Table A.12.

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

This table reports the long-term credit ratings issued by three foreign agencies: Moody's, Standard & Poor's, and Fitch from 2004 to 2017. 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.

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-

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

This table reports the short-term credit ratings issued by three foreign agencies: Moody's, Standard & Poor's, and Fitch from 2004 to 2017. If a rate was updated in the middle of a calendar year, the updated rate is listed. Note that except rating of CDB in 2004, four bond issuers are awarded the same credit rating by each agency within the same calendar year. '–' denotes that no rate was given by a credit rating agency.

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

Table A.3: Secondary market T–bill distribution

This table present the number of bonds by institution and bond type. The difference among three bond types is the maturity. Bills' maturity is less than one year. Notes' maturity is between one year and ten years. Bond's maturity is more than ten years.

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

This table show the number of bonds by bond type and auction format. Notably, discriminatory auctions are only used for bills and notes.

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

This table presents results for margins using the quantile regression method proposed by Koenker and Bassett (1982) based on the empirical model described in Column 5 of Table 2. Bootstrapped standard errors are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

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

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

This table displays the regression results for adjusted margins before, during and after the 2008-2009 financial crisis, based on the empirical model described in corresponding columns of Table 2. Notable, in the Heckman estimation, the indictor of fixed coupon bonds is excluded, compared to Column 6 of Table 2. Robust standard errors are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

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

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

This table shows the distributional estimation results of adjusted margins by period: before, during and after financial crisis. Bootstrapped standard errors are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

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

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

This table presents a breakdown of the number of primary banks that represent the FTSE indexes. Percentages are in parentheses, calculating by FTSE index institutions in each bond issuer (MOF, ADB, CDB, EIB) divided by total number if institutions in the corresponding FTSE indexes.

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

This table shows the CDB repeated pattern of alternation auction rules during the experiment period. 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 to July 2014.

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

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

This table shows the EIB pattern of alternation auction rules during the experiment period. The alternating-rule experiment period for the EIB was from July 2013 to May 2015. Panel A, we show the early part of experimental pattern by date. In Panel B, we show the second half of experimental pattern. Notably, EIB alternated the auction formats for the same type of bonds (identified by bond ID and initial and reissue status). Each reissued bond has a new id and an old id, which can be matched.

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

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

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.

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

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

This table presents the regression results of margins, calculated by highest, lowest and weighted-average winning yields in discriminatory auctions. Robust standard errors are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

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	-2.193*	-2.608*	-2.146
secondary market	(1.322)	(1.359)	(1.320)
Government yield gap between primary auction	-0.040	-0.070	-0.044
date and the day before the secondary market	(0.141)	(0.140)	(0.140)
Log value of maturing bonds by institution for a	-0.010**	-0.016***	-0.010**
given month	(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

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

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	-0.139	-0.001	0.092	0.171	0.292
market winning rate	[-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]

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 B.1 using the quantile regression technique. The quantile results are qualitatively similar to those presented in Table B.1 and can be provided upon request.

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.

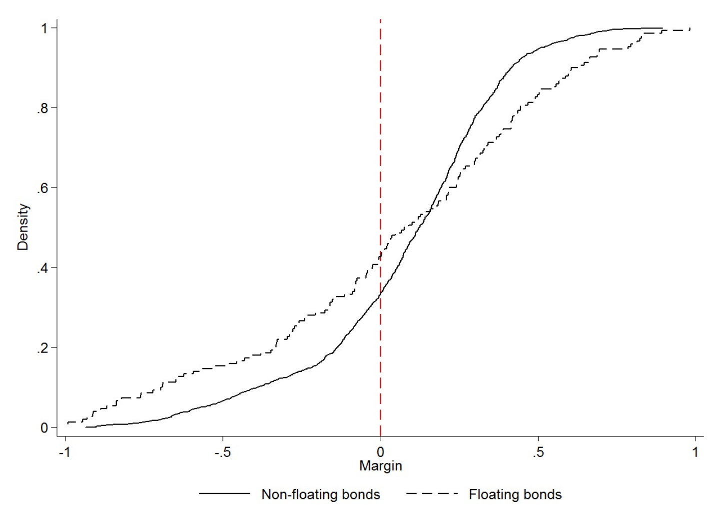
First, we estimate our standard set of empirical models with relevant variables for the floating bond sample of 168. These results are presented in Table B.2. Compared to short-term bills, bonds and notes have a smaller margin. Interestingly, the coefficient of the volatility of the bank index indicates 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.

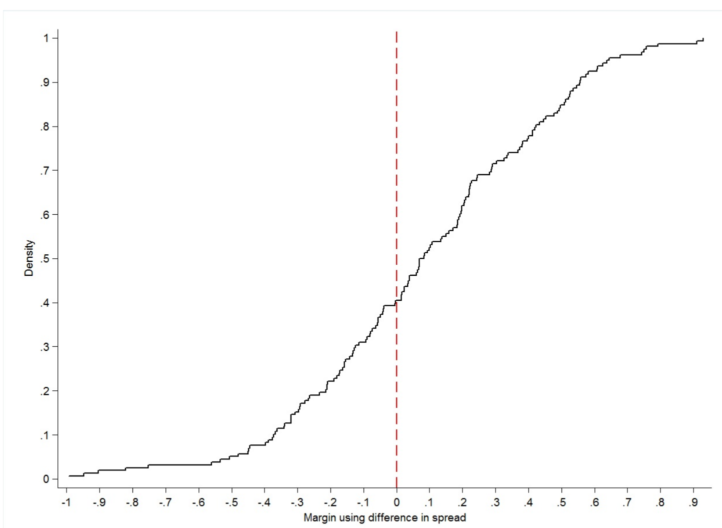
[3] We do not compare the floating and non-floating bonds' gains and losses as we do not have the volume of the floating bonds.

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



Notes: In this figure, we show the CDF of 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



Notes: In this figure, we show the CDF of adjusted margins for 168 floating bonds, based on Column 5 in Table B.2. The spread of floating bonds are constructed by expected cash-flow rates.

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

This table presents the OLS results for margins by bond types - floating and non-floating bonds, based on the empirical model described in Equation 1. The floating bond were introduced since 2007 and hence estimations in this tables are based on bond trading information from 2007 to 2017. Robust standard errors are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

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		0.082		0.123	0.119
secondary market		(1.266)		(1.271)	(1.274)
Government yield gap between primary auction			0.158	0.159	0.158
date and the day before the secondary market			(0.113)	(0.113)	(0.115)
Log value of maturing bonds by institution for a					0.000
given month					(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

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

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. All floating bonds were sold by uniform auctions. Hence, we use the difference in spreads in the primary and secondary market as a measure of the margin for floating bonds. To obtain the implicit spreads, we first compute the expected case-flow payment yields basing on the forward curve of market reference rates. Then these expected yields are considered as the secondary market yield to compute the margins. Robust standard errors are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

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

Table B.3: Adjusted margins by bond type

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.

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]

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

In this table, we report the distributional statistics of the adjusted margins constructed by spread with 95% confidence intervals. The computation process of spread is similar with in Table B. 2.

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]