Bond Issuance Mechanisms and their Effects on Revenues

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Abstract

This thesis consists of three essays on the discussion about superiority among different government security issuance mechanisms: book-building, discriminatory auctions, and uniform auctions. Using a large Chinese government primary and secondary bond market data set, I analyse the revenue rankings of these mechanisms. Results suggest that uniform auctions are superior to book building and discriminatory auctions in generating revenues. Further, results suggest that uniform auctions are better in mitigating bond losses compared to discriminatory auctions.

The first essay compares the primary rate between book building and uniform auctions, using data from Chinese local government bonds. Results show that book building procedures lead to a higher primary rate than uniform auction procedures, which reduces the issuers' revenue. These findings are robust across different revenue measurements: primary rates, primary rates normalized by T-bond daily yield rate one day prior to issuance day and primary rates normalized by five days' average T-bond daily yield rate before issuance day. Therefore, uniform auctions generate higher income than book building.

The second essay exploits a large-size auction experiment conducted by two Chinese Government bond issuers-the Chinese Development Bank and the Export-Import Bank-to investigate whether Treasury securities should be sold through uniform or discriminatory auction mechanisms. Based on the outcomes of more than 300 Treasury securities issued through an alternating auction-rule market experiment, the study finds that auction outcome yield rates of the two auction formats are not statistically different.

Further, these estimates indicate that there is no significant economic difference in terms of revenue between the two auction mechanisms. This result is robust across different bond-yield rate measurements and participation behaviour.

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

Declaration

I hereby declare that this thesis is my own work, and has not been submitted in substantially the same form for the award of a higher degree elsewhere.

Liyu Yang

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Chapter 1

Introduction

1.1 Importance of bond issuing mechanisms

Bond is an instrument for government and corporation to borrow money from public. Although stock market are commonly known by people, the size of bond markets are larger than stock market. According to report of Securities Industry and Financial Markets Association, the total value of US bond issuance size in 2019 is 8.17 trillion dollars while stock issuance size is 228 billion dollars. At the meanwhile, government bond markets, the largest security market, carry a big weight in national economy. In most countries with market economies, they usually use treasury as a very important macro-economic tool to adjust domestic economy and raise money for national development. Additionally, the circumstances of government bond markets affect the stabilization of whole financial markets. Governments can obtain more revenue and remain financial market stable by choosing a proper issuing mechanisms.

Auctions and book building are two main sales techniques used as issuing mechanisms in the equity and security markets. Existing literature discusses the advantages and disadvantages of each, to discover a superior technique. Three different auction formats are also considered in the existing literature: discriminatory auctions, hybrid auctions and uniform auctions since researchers were also interested in which auction format is better.

1.2 Objectives of this thesis

As mentioned earlier, it is importance for bond issuers to select an appropriate issuance technique. This thesis considers the superiority between different issuing mechanisms. In Chapter 2, Chinese local government bond data is used to compare the revenue generation between uniform auctions and book building. In Chapter 3, the revenue difference between discriminatory auctions and uniform auction is considered. To do this, data are looked at from a large-size auction experiment conducted by two Chinese government policy bond issuers (the Chinese Development Bank and the Export-Import Bank of China). Furthermore, Chapter 4 investigates the existence of bond loss and the possible source of bond losses. In addition, this study attempts to explore the correlation between the bond loss and instability of financial markets. Eventually, auction experiment data from two policy banks are used to compare differences in bond losses under uniform auctions and discriminatory auctions in this chapter.

1.3 Results of this study

Book building mechanisms were originally designed for Initial Public Offering (IPO) markets. Previous literature has focused on comparing under-price levels between book building and auctions, using IPO settings. This is because IPO market issuers tend to focus on how to promote their shares. Under the IPO setting, many researchers claim that book building is better overall compared to uniform auctions. Reasons for this cover many areas, including long term relationship between underwriters and their investors, level of analyst coverage, classifying investors into high-quality and low-quality, and information disclosure. However, previous research agrees that auctions generate more revenue than book building, for issuers in the IPO markets. In contrast to IPO market settings, bond market issuers tend to focus on revenue, because financing is a critical goal for bond issuers.

Chinese local government have used both uniform auctions and book building to issue their bonds since 2015. This study differs from others, as it uses bond market data to compare revenue generation between book building and auctions. In Chapter 2, three different revenue measurements are used: primary rate, primary rate normalized by T-bond yield one day before bond issuing day, and primary rate normalized by five-day average T-bond yield before bond issuing day. The OLS approach and Heckman approach are used to estimate the empirical model. Results show that book building leads to a higher primary rate, which lowers the bond issuers' revenue.

In Chapters 3 and 4, work is conducted with Klenio Barbosa, Dakshina G. De Silva and Hisayuki Yoshimoto, to analyse the Chinese bond auctions from two perspectives: revenue and bond losses.

Governments who issues bonds are interested in knowing which auction format could generate the most revenue. This is because their goal is to create finances in order to support national projects. In Chapter 3, revenue superiority between uniform auctions and discriminatory auctions is examined, using data during the experimental period from 2012 to 2015. Previous literature focuses on understanding which multi-unit auction format could acquire a lower yield rate, and therefore a higher price for bond issuers. However, Ausubel (2008) found that the revenue ranking between uniform auctions and discriminatory auctions is ambiguous. This seminal paper has encouraged empirical researchers to further study the differences in auction formats. The empirical analysis in this paper is conducted using two different approaches: comparing the outcome yield between the two auction formats directly, and comparing the outcome yield normalized by the prior day's government-announced corresponding yield across the two auction formats. In both approaches, results show that auction yield rates are not statistically different between uniform and discriminatory auction formats. Furthermore, the estimates suggest that there is no significant revenue difference between the two auction mechanisms.

As there is no revenue difference between uniform auctions and discriminatory auctions, differences in bond losses among auction types are examined (shown in Chapter 4). Bond losses are also a concern for policy makers, since it will lead to the instability of financial markets.

Recent studies show that the trading of bonds is a major part of banks' activities, and accounts for a significant share of their revenues. Losses in the bond market can therefore have significant consequences for banks, and for the stability of the banking sector as a whole. One way of incurring losses is through participation in Treasury bond markets, where financial institutions buy securities in primary market auctions, and sell them in the secondary market.

Chapter 4 first investigates the existence of bond loss in the bond market, using a unique Chinese bond market dataset.[1] Margins are defined as the gap between the primary market and secondary market return rate, after controlling for bond and market characteristics. Negative margins are found for about 20% of the observed transactions, again even after adjusting for bond and market characteristics. This result shows that

[1] Data is obtained from Wind database and Chinabond.com.cn

primary dealers' losses are prevalent in Treasury bond markets. Additionally, the results indicate a correlation between the bond losses and financial recession. During the financial crisis from 2008 to 2009, more than 50% of post-auction Treasury transactions led to losses.

Next, the possible mechanisms behind bond losses are considered. Basing on Reuters's claim, it is hypothesized that, when facing high borrowing costs, primary market dealers are willing to liquidate their on-the-run bonds at a loss, in order to minimize their financial distress. To test this possible explanation for bond market losses, this study examines whether a change in REPO rate (the best indicator of general liquidity in the Chinese market) can predict bond losses. Furthermore, the volume of secondary market trades when the REPO rate is high is investigated. The volume of bond trades is expected to be higher when primary market dealers face high borrowing costs, as they can generate cash using bond sales. To examine these two hypotheses, a simple probit regression and OLS regressions are used.

Furthermore, after documenting the existence of bond losses and their liquidity channels, this study considers whether bond losses can lead to financial market instability. We select the 10th bottom of distribution and delete all dates including both positive and negative margins. FTSE indexes are chosen as the indicators of Chinese bond market health. Finally, the difference estimation is used to examine how bond loss affects the stability of the financial market. The results confirm that bond loss negatively affects the stability of the Chines financial market.

As bond losses can lead to financial market instability, governments could reduce the risk of bond loss by selecting a proper auction mechanism. Data are examined from a randomized experiment by two Chinese government bond issuers: CDB and EIB.

Results show that uniform auctions could reduce bond losses and therefore help to stabilize the financial sector.

1.4 Importance of this thesis

This thesis provides three important empirical evidences to policy makers. The first study, entitled "Revenue Comparison between Book Building and Uniform auctions", indicates that uniform auction performs better than book building on revenue collection. According to results from the first study, policy makers should adopt uniform auctions if they want to obtain more revenue, comparing to book-building. The second essay, named "Auction Mechanisms and Treasury Revenue: Evidence from the Chinese Experiment", finds that there is no statistical difference between uniform auctions and discriminatory auctions from the revenue perspective. In the following study, "Bond Losses and Systemic Risk", results show that uniform auctions can reduce bond loss, stabilizing financial markets, comparing to discriminatory auctions. These threes evidences recommend bond issuers and policy makers select uniform auctions as issuance mechanisms in bond markets.

1.5 Organization of this thesis

This thesis is structured as follows: Chapter 2, entitled "Revenue Comparison between Book Building and Uniform auctions", compares the revenue between book building and uniform auctions. Chapter 3 presents the second study: "Auction Mechanisms and Treasury Revenue: Evidence from the Chinese Experiment". This study analyses the revenue superiority between discriminatory auctions and uniform auctions. The third essay, "Bond Losses and Systemic Risk", are presented in Chapter 4. It explores the prevalence of bond losses and its major forming mechanisms, then considers which auction mechanism can best reduce bond losses. Finally, Chapter 5 provides the conclusion of the thesis.

Chapter 2

Revenue Comparison between Book Building and Uniform Auctions

2.1 Introduction

Auction and book building are two main sales procedures, which are commonly used in equity and security markets. There is a growing body of literature that recognises the importance of studying on the advantages and disadvantages of alternative selling mechanisms, since firms or bond issuers have to pay unnecessary issuing cost when they choose an improper issuing mechanism (Kutsuna and Smith, 2003; Pettway et al., 2008). However, there is no clear conclusion regarding the revenue ranking superiority between auction and book building formats. Hence, in this study, I utilize a unique dataset from Chinese local governments that use both uniform auction and book building designs, to sell government securities to study which mechanisms is better in revenue generation.

In the previous literature, the question regarding superiority between auctions and book buildings exists due to many countries introduced both mechanisms into the same market, especially the IPO market. Therefore, most of the past research on the comparisons between auction and book building mechanisms have concentrated on the IPO market. Further, bond markets rarely introduce both auctions and book buildings as the issuing mechanisms. The majority of literature claim that book building performs better than uniform auctions in the IPO market from a theoretical and empirical perspective, though book building will lead to higher initial rate and under-pricing.

In his theoretical paper, Sherman (2000) claims that the main advantage of book building is the long-term stable relationship between the underwriters and their investors as it is beneficial for improving the under-pricing in the IPO market. Further, Jovanovic and Szentes (2007) demonstrate that book building can disclose more information to distinguish between high-quality investors and low-quality investors; the auction cannot accomplish this and can lead to adverse selection in the market.

Meanwhile, many empirical studies support the advantage of book building on information disclosure and long-term relationships between the underwriters and investors. Pettway et al. (2008), using the Japanese IPO data, point out that analyst coverage is higher in the book building than in the uniform auction. Additionally, Kutsuna and Smith (2000, 2003) compare auctions and book buildings in the Japanese IPO market. They show that the uniform auction method leads to adverse selection in the Japanese IPO market. Also, they mention that the level of under-pricing varies with the scale of issuers, even though the under-pricing is significantly higher in the book building than in the auction on average. They find that under-pricing improves when the issuer is a large company. Furthermore, they argue that researchers should consider the opportunity cost of the underinvestment and loss because of the inaccurate pricing in uniform auctions when they compare the auction and book building. In addition, Ma and Faff (2007) claim that, in the Chinese IPO market, book building is better than the uniform auction format, especially in low return and high volatility markets.

Moreover, studies on both the European and US markets also prove the superiority of book building from the information revealing aspect compared to uniform auctions. Degeorge et al. (2007), using French IPO data of 1991, observe that the coverage of favorable research is higher in book buildings than in auctions and that higher analyst coverage can provide more confidence to the lead underwriter promoting the company. After studying the US IPO market, Degeorge et. al. (2010) agree that the reason why underwriters prefer book building is due to the long-term relationship. Meanwhile, they point out that failed auctions are excluded in their study, leading to a bias in their results when they investigate the under-pricing and price between uniform auction and book-building.

Apart from the research in specific countries, Sherman (2001) and Jagannathan et al. (2015) list countries using auctions and book buildings. From these global evidences, they summarise that the auction method is driven out by book building in IPO markets because auction needs more sophistication bidders. From their perspective, auctions are designed for the large scale companies, which is the key reason that auctions can succeed in the government bond. In addition, Anand (2005) traces the IPO transaction data from a specific company, Google, highlighting that book buildings perform better than auctions.

Although the major view supports book building in IPO markets, most studies cannot deny that auctions can reduce under-pricing, especially for the small size companies. From the information dimension, Derrien and Womack (2003) suggest that the auction offering incorporates more information about the current and recent past market condition than the book building offering. Furthermore, Pukthuanthong et al. (2007) use 11 pair of strictly matching companies in US IPO market to compare the price discovery, one of advantages of book building, between the uniform auction and book building. They note the conclusion of superiority on price disclosure between auctions and book building is ambiguous due to the long-run under-performing in book building scenarios. Moreover, auctions have advantages over book building on lowering underwriter spread and increasing turnover in the secondary market.

Therefore, there is no clear conclusion regarding the revenue generation ranking between auction and book building formats. Further, as previously mentioned, the comparison between the auction and book building focuses on the IPO market due to the lack of book building examples and relevant data in bond markets. My study is the first which use bond market data to investigate revenue superiority between uniform auctions and book building.

The Chinese central government added the book building format to sale mechanisms for issuing the local government bonds beginning in 2015, providing me a good opportunity to study the superiority between uniform auctions and book buildings. In this study, I compare the primary rate and two different normalized primary rates between auctions and book building by using the data gathered on Chinese local government bonds from 2015 to 2019. My results show that book building leads to a higher primary rate than uniform auctions, reducing the bond issuers' revenue. My results are consistent with Kaneko and Pettway (2003).

This study is organized with the following structure. In section 2.2, I introduce the market background about Chinese local government bond, including the history of Chinese local government bonds, issuing procedures and issuers of local government bonds and the construction of T-bond daily yields. In section 2.3, I show the data description: data source and statistical summary. In the fourth section, I display my main estimations and robustness checks. Finally, section 2.5 provides the conclusion.

2.2 Market Background

This section will first describe the development of Chinese local government bonds, and introduce the two issuing procedures (book building and uniform auctions). Next, the issuers of local government bonds will be described. Finally, the yield curve daily data (used for normalizing the bond-level yield rates) will be discussed.

2.2.1 The development of Chinese local government bonds

Before 2009 local governments were prohibited from issuing bonds unless required by law or the State Council (The Budget Law of the People's Republic of China, 1994).[2] The 1994 tax reform consolidated more than half of the national tax revenue to the central government, causing local governments' income to fall sharply. Local governments were forced to borrow money from national banks and increase administrative fees to cover the fiscal deficit. In 1995, the central government reformed national banks' technology and property, to control the non-performing assets, and also cancelled more than 20,000 types of administrative fees. This caused local government debts to increase significantly. Furthermore, the central government introduced expansionary fiscal policies in 2008, which local governments could not abide by due to lack of funds. As a result, the central government decided to allow local governments to issue their own bonds. The local government bond market began to gradually open (Jin et al., 2009).

[2] the 28th rule in the *The Budget Law of the People's Republic of China*

In 2009, the Chinese Minister of Finance (MOF), began to issue and payback local government bonds.[3] Initially, local governments could not issue bonds independently, and bonds shared the sovereign credit rating. In 2011, the State Council approved Shanghai, Zhejiang, Guangdong, and Shenzhen as pilot provinces to issue bonds independently. In 2013 and 2014, Jiangsu, Shandong, Beijing, Jiangxi, and Ningxia were added to the list of pilot provinces. The central government finally decided to allow all local governments to issue bonds independently in 2015 (Li and Qian, 2017; Shen and Cao, 2010).

Alongside the opening of the local government bond market, the issuing and trading volume of local government bonds increased significantly between 2009 to 2018 (Figure 2.1). As shown in Figure 2.1, since 2014 there has been a steep rise in the annual issuing and trading volumes, reflecting when the central government opened local government bond markets. The issuing and trading volumes continue to rise until it peaked in 2016, then it declined slightly.

2.3 Issuing procedures: book buildings and uniform auctions

Book building is widely used in both developed countries and emerging markets. It was originally designed for the US Initial Public Offering (IPO) issuance in the 1990s and is still a popular practice in the IPO market. However, book building is rarely applied to bond markets for pricing the bonds of companies (Sherman, 2001).

Three parties are involved in book building: the issuer, the book manager and a syndicate group. In a typical book building scenario, the issuer hires a book manager

[3] In February 2009, the Chinese MOF claimed, in their official document *The Budget Management of Local Government Bonds in 2009*, that all local government bonds and their issuing fees are issued and paid by the Chinese MOF on behalf of local governments

(usually a merchant bank) and builds a syndicate group. The book manager announces the price band and total supply to the syndicate group, after discussing this with the issuer. Next, syndicate group members submit their bids and demand volume, based on orders placed by their customers within the time prescribed. The bids and demand volume are made in accordance with the price range and supply volume. This process builds the price and demand "book", whereby the book manager obtains the list of aggregate demands at each price level. The issuer and book manager set a final price based on the demand information in the book, which is usually the weighted average price or interest rate. In the final stage, the book manager will allocate shares to winning members according to his discretion.

Uniform auctions, on the other hand, are more popular in bond issuance than IPO issuance, and issuers employ different auction techniques to issue their bonds. There are three main differences between book building and uniform auctions. First, uniform auctions only have two parties: the issuer and the syndicate group. Second, in uniform auctions, issuers cannot disclose any demand information before bids are submitted. This is due to the absence of book managers. The third difference between book building and uniform auctions is the allocation procedure. For example, the winners in a bond auction are those who bid higher than the market-clearing price or lower than the market-clearing yield rate.[4] Afterward, the bond volume that winners receive is the sum of their bidding volume at each winning price or yield level.

Uniform auctions and book building are both used for Chinese local government bonds. Since 2009, Uniform auctions were used to issue 73% of bonds, while 27% of the

[4] The market clearing means that at the price or yield rate that all bonds are sold. They are lowest winning price and highest winning yield.

securities were issued using book building in the Chinese local government bond market. The Chinese MOF has formulated rules for these two issuing mechanisms.

For local government bonds issued by uniform auctions, the Chinese MOF allows local governments to build their own syndicate groups. Potential members need to be prequalified by the local MOF, based on their financial capacity, performance and credit rating in the last three years.[5] After selecting the syndicate group members, local governments announce if they plan to use uniform auctions or book building to issue securities. This announcement must be made at least five working days before the bond's issuance.[6] All details about the upcoming bond auction are announced at least one working day before the auction.[7] On the auction day, all members in the syndicate group submit their bids, and results are released on the same day. The lowest winning price is the bond price and the highest winning interest rate is the coupon rate. Following the payment rule of uniform auctions, the bond volume that winners are allocated to is the sum of their bidding volume at each winning price or yield level. Furthermore, winners of auctions pay the bond price or the coupon rate depending on auction tenders which are listed in the pre-announced documents.[8]

For local government bonds issued by book building, the Chinese MOF gives local governments two options regarding the syndicate group; they can either build a new syndicate group (with at least four participants) or use the syndicate group used for uniform auctions.[9][10]

[5] Local governments create similar pre-qualification rules for selecting members of syndicate groups.
[6] The 11th rule of *The Standards of Auction of Local Government Bonds' Issuing*
[7] The 11th rule of *The Standards of Auction of Local Government Bonds' Issuing*
[8] The 9th and 10th rule of *The Standards of Auction of Local Government Bonds' Issuing*
[9] The 7th rule of Chapter 2 in The Standards of Book Building of Local Government Bonds' Issuing
[10] There is no official evidences shows that local governments build independent syndicate groups for book building and auctions respectively

Like the IPO book building, the book manager is selected from the syndicate group by local governments. The book manager collects and records demand prices from each syndicate group member. The book manager and other main group members then negotiate with the local government, to decide the price (interest rate) range based on investors' bidding intention and average T-bond yield rate of five days prior to the bond issuing day. All details about the bond issuing (including the price range, book building process, principle of price decision, sale rules and issuing system) are released five days prior to the bond issuing day. On the bond issuing day, all participants (except the book manager) in the syndicate group submit their bids. Local governments collect members' demand information and announce the lowest winning price or the highest interest rate. Ultimately, the payment process of book building is the same as uniform auctions (which differs from IPO book building).[11][12]

2.3.1 Issuers of local government bond

In the *The Budget Management of Local Government bonds* in 2009, the Chinese MOF defined the issuers of local government bonds are provinces, autonomous regions and municipalities. Since the _rst local government bond issued in 2009, there are 31 provinces issued their own bonds in ten years. Figure 2.2 shows the total number of local government bonds by each issuer since 2009. Notably, most bonds are issued by Liaoning, the second most by Shandong, and the least amount by Tibet.

[11] The Chapter 3 of *The Standards of Book Building of Local Government Bonds' Issuing provides all rules of book building process*

[12] Book managers allocate shares to dealers based on their discretion (Sherman, 2000; Jovanovic and Szentes, 2007)

2.3.2 The T-bond daily yield rate data

The market T-bond yield data is created by the China Central Depository Clearing Co. Ltd. (CCDC). The CCDC is a State Council-approved agency (also authorized by the China Banking Regulatory Commission) that records all government bond-related transactions. The T-bond is a government bond issued by the Chinese MOF. The CCDC releases the yield data for different maturities of T-bond on each business day (depending on the T-bond transaction data on the same day).

The market T-bond yield curve is used to normalize the primary market rate, and as a proxy for market volatility. Local governments use the average T-bond yield rate for five days prior to the bond issuing day as a reference to set the price range. Therefore, the yield curve is used to calculate volatility. The volatility measurement is separated by different maturities.

2.4 Data Description

Data were collected from three sources: the Wind database, Chinabond.com.cn and the National Bureau of Statistics of China. The Wind database is maintained by Wind Information. Co. Ltd., who is one of the largest financial data and information providers in China. Chinabond.com.cn is the official website of the China Central Depository & Clearing Co. Ltd. The National Bureau of Statistics of China is a national agency (directly governed by the State Council of China), responsible for collecting, investigating and publishing national economic statistics.

Uniform auction and book building data were collected from the Wind database. This data include bond characteristics as such as bond name, maturity, total supply, bond type, and tender subjects (price and interest rate). Issuing information (including auction and announcement dates, issuers, and issuing methods) and outcome details (including final winning yield, primary rate, and subsidies) were also collected from the Wind database. Chinabond.com.cn was used to obtain daily T-bond yield data, monthly issuing volumes and trading sizes. Finally, the total annual GDP and population for each province were acquired from the Nation Bureau of Statistics of China. This data was used to calculate the provincial GDP per capita.

2.4.1 Summary statistics

Chinese local governments use both book building and uniform auctions to issue bonds. To compare the differences in generated revenue between the two techniques, Chinese local government bond data from 2015 to 2018 is analysed. In the sample, only bonds with maturity ranging from one to ten years are included. This is because local governments only use book building for issuing bonds with maturities in this range. Table 2.1 shows the summary statistics of the sample. Furthermore, the central MOF recommends that local governments use book building procedures to issue their bonds when the total bond size is small.[13] Book building is only used when the total supply value is less than 27.65 billion yuan. Hence, bonds valued higher than 27.65 billion yuan were not included in the analysis. Therefore, in this study, I initially match securities offered using uniform auctions and book building by maturity and volume.

As shown in Table 2.1, 2,868 local government bonds were issued between 2015 and 2018. Of these, 2,107 bonds were issued through uniform auctions, and 761 bonds through book building. The average primary market rate overall is 3.609. The mean primary market rate under uniform auctions is 3.607, which is slightly lower than the

[13] The 3rd rule in Chapter 1 of *The Standards of Book Building of Local Government Bonds' Issuing*

primary market rate under book building (3.615). The means of other important control variables in the empirical model are as follows: T-bond yield one day prior to bond issuing day (3.230), maturity (6.259), total supply (41.963), volatility (0.020) and monthly aggregated volume of matured bonds (602.218). The unit of total supply and monthly aggregated volume of matured bonds is one hundred million.

2.5 Estimation results

2.5.1 Main estimation

To compare the revenue ranking between book building and uniform auction procedures, I use the empirical model as follow:

$$y_{ijt} = \beta D_{ijt} + X'_{ijt}\emptyset + \alpha_j + \tau_i + \varepsilon_{ijt}, \qquad (2.1)$$

The dependent variable, is for a given bond *i*, issued by the province *j* in the period *t*. In this study, I employ three different dependent variables in my model: the primary rate, the primary rate normalized by T-bond yield one day prior to bond issuing day (normalized rate A) and the primary rate normalized by five-day average T-bond yield prior to bond issuing day (normalized rate B). The variable D is the dummy variable which identifies the issuing mechanism, which equals one when the bond is issued by book building, otherwise, it equals zero. The coefficient β captures the difference of revenue from book building and uniform auction. Also, I control bond characteristics and market conditions (X) in my model. The α and τ are province and time effects, and ε denote the error term.

The empirical analysis is conducted using the ordinary least squares (OLS) method. Firstly, primary rate is used as the dependent variable, and the results are shown in Table

2.2 (columns 1 and 2). Column 1 shows the regression of the primary rate on the indicator of book building, t-bond yield one day prior to the bond-issuing day, province effects, month effects, and year effects. Yield is controlled for because the central MOF recommends local governments and their syndicate groups use the t-bond yield as the reference to bid. Therefore, dealers' bids may be affected by the T-bond yield rate. In column 2, variables of bond characteristics and market conditions are shown. These include maturity, total supply, volatility, and the monthly volume of matured local government bonds in the model.

Next, normalized rate A (the primary rate minus T-bond yield one day prior to the bond issuing days) is used as the dependent variable, and the parameters are re-estimated using the equation (2.1). The regression results are presented in Table 2.2 (columns 3 and 4). Using normalized rate A is advantageous, as the unobserved economic factors across bonds can be captured (Hortacsu et al., 2018). Column 3 shows the regression of normalized rate A on the indicator of book building, province effects and time effects. Column 4 shows the regression results when the same variables as in column 2 are included in the model.

In columns 5 and 6, the normalized rate B (the primary rate minus five working days' average T-bond yield before the bond issuing days) is used as the dependent variable. The Chinese central MOF requires local governments to use the average T-bond daily yield for the five days prior to the bond issuing day, as a reference to set the bid range for both uniform auctions and book building. Accordingly, the bidding behaviours are affected by previously short-run market conditions. Therefore, this analysis uses the five days average T-bond yield instead of the one-day T-bond yield rate to remove the unobserved heterogeneity of pre-issuance market conditions across the bonds. As before, initially, the simple regression estimate only includes the proxy of book building after controlling the province and time effects. Next, all variables of market conditions and bond characteristics are controlled for.

The results in column 1 show that book building procedures lead to higher primary yield and lower revenue for bond issuers, compared to uniform auction procedures. This result is statistically significant. Column 2 shows that, after controlling other market conditions and bond characteristics, the result is consistent with that in column 1. Furthermore, columns 3 to 6 use different measurements of local governments' revenue, and estimation results are also consistent with the first two regressions.

The above results are consistent with previous literature regarding the Japanese IPO market (Kaneko and Pettway, 2003). The coefficient of the book building dummy variable captures the difference in primary rate between uniform auctions and book building, ranging from 0.188 to 0.194. Book building bidders are thought to have more bargaining power than in uniform auctions, because of the advantage of information disclosure in the book building process. This is especially true of sophisticated and experienced bidders. Higher analyst and research coverage in the book building process can help bidders to price the bond more accurately and bid rationally, leading to fewer over-bids (Derrien and Womack, 2003). However, in uniform auctions, participants may bid more aggressively, as they only need to pay the market-clearing yield. As a result, the final winning rate rises.

2.5.2 Selection

Local governments may follow specific rules when they select issuing mechanisms for their bonds, which could lead to selection bias in the results.[14]

To address this concern, a Heckman model is used. The probability of using book building as the issuing mechanism (the selection equation) is specified. All the same variables used in the outcome equation (shown in Table 2.2, column 2) are included. In this case, there are no exclusion restrictions, so the nonlinearity of the functional form of the selection equation is leveraged.[15] Results are shown in Table 2.3 (column 1) and indicate that selection is not a concern.

Furthermore, the dependent variable is changed from primary rate, to normalized rate A and normalized rate B. The same method is used to re-estimate the Heckman model. Results are shown in Table 2.3 (column 2 and 3) and are the same as in the main estimation. There is a significant positive correlation between primary rate and book building techniques, which shows that book building generates less revenue for local governments.

2.5.3 Robustness Check

2.5.3.1 Top provinces versus bottom provinces

The previous estimations included all provincial issuers in the empirical model. However, it could be argued that the revenue ranking results between book building and uniform auctions may differ across provinces with varying economic strength. To

[14] According to the 3rd rule in Chapter 1 of *The Standards of Book Building of Local Government Bonds' Issuing*, the central MOF recommend book building formats to issue small size bonds.
[15] Barbosa et al. (2019) also use the heckman model without the exclusion restriction to correct the selection bias.

address this, all Chinese provinces are ranked based on their GDP per capita per year. The bonds issued by the annual top five and bottom five provinces between 2015 to 2018 are analysed; a total of 494 bonds issued by the top five provinces, and 382 bonds issued by the bottom five provinces. The empirical model is adjusted for the two groups, using the variables given by the main OLS estimations (excluding the province effects). The results from these regression estimations are presented in Table 2.4. This further supports the conclusion from the main estimations: book building decreases the revenue for local government bond issuers.

2.6 Conclusion

In this study, I investigate the superiority of revenue between book building and uniform auctions by using the Chinese local bonds from 2015 to 2018. From the results, I find that book building procedures lead to higher primary rate, lowering the revenue for the bond issuers, compared to the uniform auctions.

In previous research, the comparison between the book building and auction mechanisms are concentrate on the IPO market. My finding makes an important contribution to the field of comparison between book building and auctions by first using bond market data. Although Chinese local government bond issuing market and Japanese IPO issuing market use different auction formats,[16] my results support the conclusion from empirical studies about the Japanese IPO market that book building brings higher initial rate than auctions (Kaneko and Pettway, 2003; Kutsuna and Smith, 2003).

[16] Chinese local government bonds are issued by uniform auctions while Japanese IPO issuance employs discriminatory auctions.

Although, this research shows that book building procedures will make issuers lose money, the Chinese central government still keeps the book building format as one of the alternatives for local governments to issue bonds. There are two conjectures about this. First, the central government may use the advantage of book building on information revealing to avoid the adverse selection in the local bond market, even though they need to pay extra cost. Second, according to the rules, the higher return in book building for bidders can attract primary bidders to participate in the local government primary market, helping local government and book managers promote their bonds to the investors.

This study only focuses on the revenue superiority between book building and auctions for the issuers. The main contribution of my study is to provide strong empirical evidence, recommending auction formats, to bond issuers when they decide the issuing methods from the revenue dimension. From the IPO literature, most researchers have focused on the under-pricing, which combined the issuing market and resale market. It is worthy to study the problem of under-pricing by using the bond data from the primary market and the secondary market. Thus, I leave this advanced topic for future study once I obtain local government bond data from the secondary bond market.

2.7 Figures and Tables

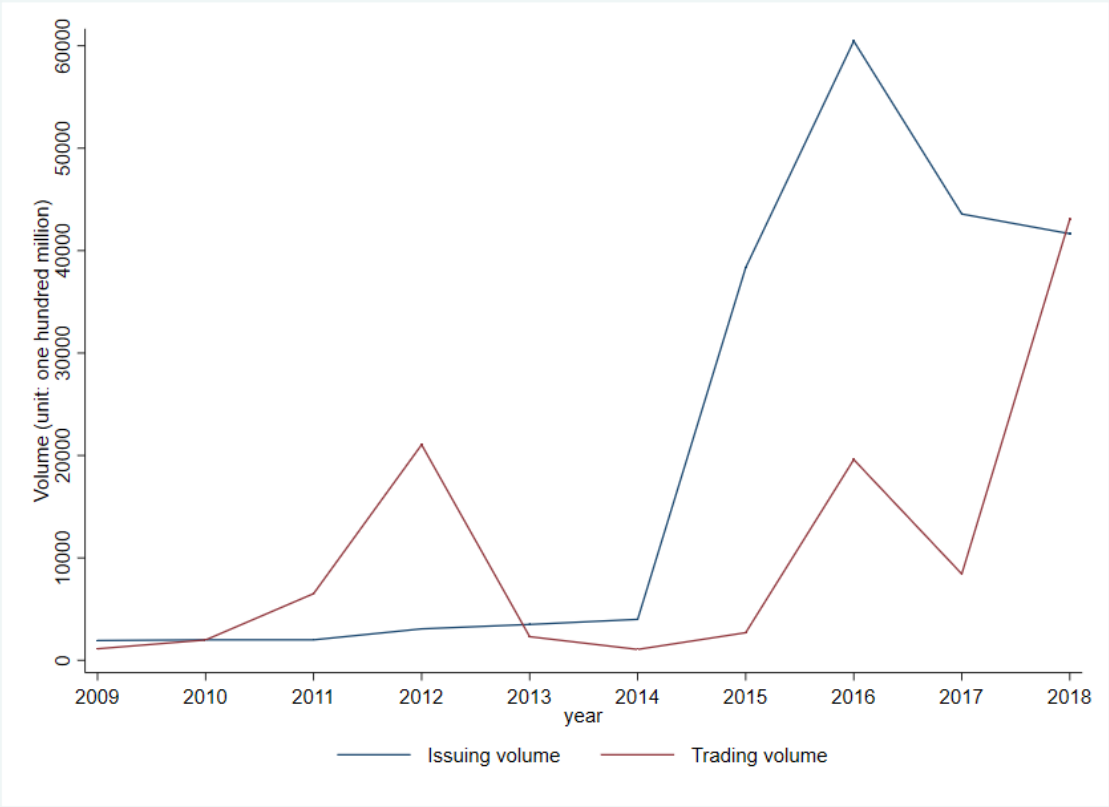

Figure 2.1: Annual issuing volume and issuing size

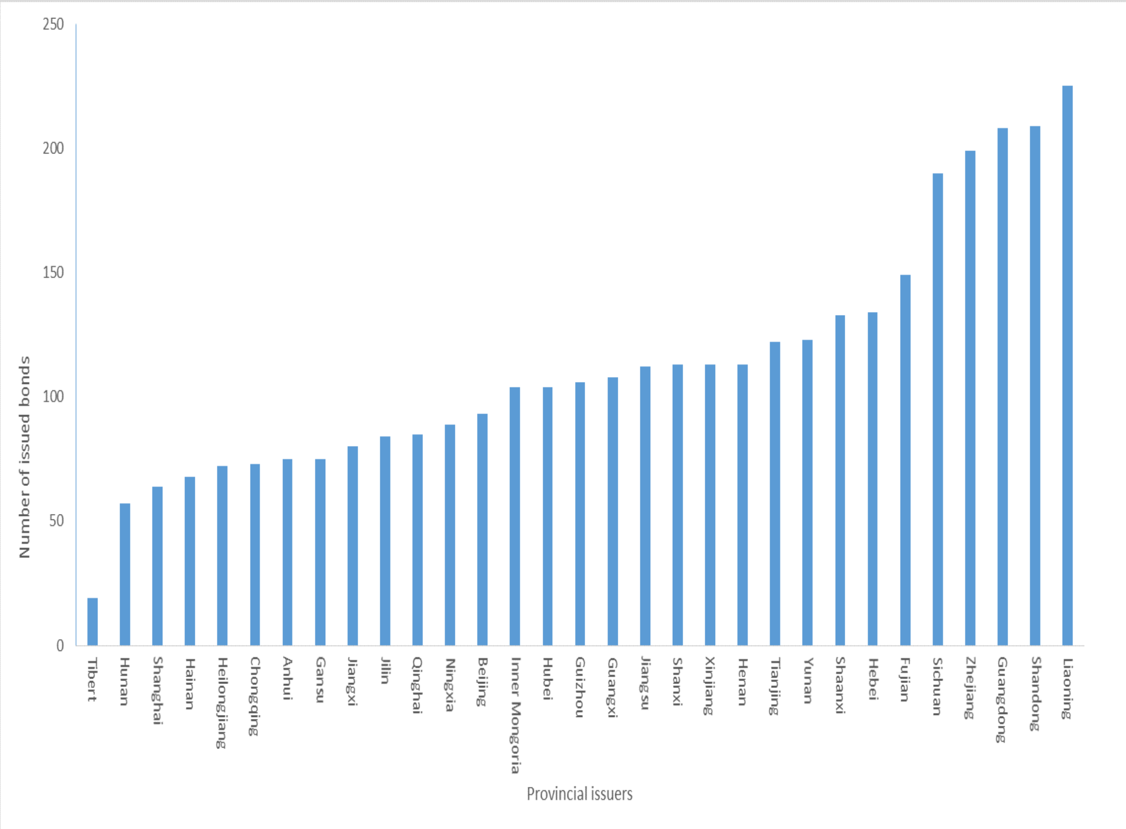

Figure 2.2: Number of bonds issued by each province

Table 2.1: Summary statistics

Variable	Mean / Counts
Number of bonds sold in the primary market	2,868
Uniform-auction	2,107
Book-building	761
Average primary market rate	3.609
	(0.496)
Average primary market rate under the uniform auction	3.607
	(0.510)
Average primary market rate under the book building	3.615
	(0.455)
T-bond Yield one day prior to bond issuing day	3.230
	(0.388)
Maturity	6.259
	(2.452)
Total supply	41.963
	(42.232)
Volatility	0.020
	(0.013)
Monthly matured bond	602.218
	(446.732)

This table reports the number of total bonds sold in the primary market, the number of bonds using uniform auction and the number of bonds using book building. Also, this table presents means and standard deviations of average primary market rate, the average primary rate under uniform auctions and book building respectively. In addition, this table shows the mean and standard deviation of control variables in the empirical model, including T-bond yield one day prior to bond issuing day, maturity, total supply, volatility and volume of monthly matured bonds. Standard deviations are in parentheses.

Table 2.2: Main estimation

Variables	Primary rate		Normalized rate A		Normalized rate B	
	(1)	(2)	(3)	(4)	(5)	(6)
Book Building	0.191***	0.188***	0.190***	0.189***	0.194***	0.192***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
T-bond Yield one day prior to bond issuing day	1.089***	0.857***				
	(0.014)	(0.023)				
Log of maturity		0.121***		0.076***		0.072***
		(0.008)		(0.005)		(0.005)
Log of total supply		-0.001		-0.001		-0.001
		(0.002)		(0.002)		(0.002)
Volatility		-0.254		-0.310		0.144
		(0.229)		(0.235)		(0.216)
Log of monthly matured bond		-0.001		0.007**		-0.004
		(0.004)		(0.003)		(0.003)
Month effects	Yes	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Province effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,868	2,868	2,868	2,868	2,868	2,868
R-squared	0.947	0.951	0.595	0.626	0.616	0.643

This table reports the main OLS estimation results for primary rate, Normalized rate A and Normalized B. Normalized rate A is calculated as primary rate minus T-bond yield one day prior to bond issuing days. Normalized rate B is calculated as primary rate minus five days average T-bond yield before bond issuing days. All columns are controlled the indicator of book building, month effects, year effects and province effects. Additionally, Column 2 and 3 are controlled T-bond yield one day prior to bond issuing day. In Column 2, 4 and Column 6, I control the log of maturity, log of total supply, volatility and log of volume of monthly matured bond. 95% confidence intervals calculated based on robust standard errors are in brackets, and p-values are denoted by asterisks according to the following scheme: *** p <0.01, ** p <0.05, * p <0.1.

Table 2.3: Heckman estimation

Variables	Primary rate	Normalized rate A	Normalized rate B
	(1)	(2)	(3)
Book building	0.187***	0.188***	0.192***
T-bond Yield one day prior to bond issuing day	0.784***		
	(0.038)		
Log of maturity	0.153***	0.084***	0.077***
	(0.016)	(0.006)	(0.006)
Log of total supply	-0.020**	-0.022**	-0.017**
	(0.008)	(0.009)	(0.008)
Log of monthly matured bond	-0.008*	0.005	-0.005
	(0.005)	(0.004)	(0.004)
Volatility	-0.118	-0.198	0.225
	(0.192)	(0.189)	(0.184)
Month effects	Yes	Yes	Yes
Year effects	Yes	Yes	Yes
Province effects	Yes	Yes	Yes
Observations	2,868	2,868	2,868
R-squared	0.951	0.626	0.643

One potential concern is that local governments may select issuing mechanisms based on specific rules. To address this concern, I use Heckman model to correct selection bias. I re-estimate three different measurements on the indicator of book building, log of maturity, log of total supply, log of monthly matured bond, volatility, month effects, year effects and province effects. In addition, the T-bond yield one day prior to bond issuing days is controlled in Column 1. The calculation of Normalized A and B is same as Table 2.2. Robust standard errors are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 2.4: Top provinces versus bottom provinces

Variables	Primary rate		Normalized rate A		Normalized rate B	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Top provinces						
Book building	0.254***	0.283***	0.256***	0.283***	0.262***	0.284***
	(0.010)	(0.011)	(0.010)	(0.011)	(0.011)	(0.012)
T-bond Yield one day prior to bond issuing day	1.064***	1.013***				
	(0.026)	(0.047)				
Log of maturity		0.049***		0.053***		0.050***
		(0.019)		(0.010)		(0.011)
Log of total supply		0.012**		0.012**		0.012**
		(0.005)		(0.005)		(0.005)
Volatility		0.321		0.321		1.092**
		(0.435)		(0.433)		(0.435)
Log of monthly matured bond		0.098***		0.097***		0.072***
		(0.010)		(0.009)		(0.009)
Month and year effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	494	494	494	494	494	494
R-squared	0.942	0.953	0.596	0.672	0.611	0.664
Panel B: Bottom provinces						
Book building	0.175***	0.169***	0.175***	0.170***	0.175***	0.175***
	(0.011)	(0.013)	(0.012)	(0.013)	(0.011)	(0.013)
T-bond Yield one day prior to bond issuing day	1.078***	0.804***				
	(0.034)	(0.058)				
Log of maturity		0.148***		0.087***		0.083***
		(0.022)		(0.013)		(0.013)
Log of total supply		-0.002		-0.001		0.002
		(0.005)		(0.005)		(0.005)
Volatility		-0.233		-0.431		0.090
		(0.387)		(0.400)		(0.434)
Log of monthly matured bond		0.024**		0.036***		0.015
		(0.011)		(0.010)		(0.011)
Month and year effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	382	382	382	382	382	382
R-squared	0.957	0.964	0.641	0.690	0.661	0.701

This table reports the estimation of groups of top and bottom provinces, respectively. The ranking of provinces is based on their annual per GDP Capita from 2015 to 2018. The group of top provinces includes top five bond issuers from each year based on their economics strength, while the group of bottom provinces includes bottom five bond issuers. Independent variables in Column 1 to Column 6 are same as Column 1 to Column 6 in Table 2.2 except the province effects. Robust standard errors are in parentheses, and p-values are denoted by asterisks according to the following scheme: *** p<0.01, ** p<0.05, * p<0.1

Chapter 3

Auction Mechanisms and Treasury Revenue: Evidence from the Chinese Experiment

3.1 Introduction

Researchers around the world have long been interested in understanding which multi-unit auction format generates a lower yield rate and a higher price for bond issuers (Back and Zender, 1993; Bikhchandani and Huang, 1993; Goswami et al., 1996; Kremer and Nyborg, 2003; Hortacsu and McAdams, 2010; Hortacsu and Kastl, 2011). The debate is also of public interest, as a well designed Treasury auction market could potentially generate larger revenues and reduce tax burdens. The two auction methods most frequently used to sell Treasury Bonds are discriminatory and uniform-price auctions. In discriminatory-price auctions, trades occur at different rates indicated in the bids while, in uniform-price auctions, all winning bidders obtain the same yield rate, equal to the highest winning bid rate.

Ausubel et al. (2014) in their seminal paper in the theoretical multi-unit auction literature, derive general revenue rankings of uniform and discriminatory auctions under several conditions. They find that, by changing model setups, such as bidder-information symmetry and risk-neutrality assumptions, researchers can derive different revenue rankings. An empirical identification of which assumptions in Ausubel et al. (2014) hold in multi-unit auctions is, however, a challenging task. Therefore, they emphasize that determining the revenue-enhancing pricing rule is an empirical question and encourage empirical researchers to further pursue by either direct or counterfactual comparison of auction rule outcomes.

In this study, we exploit an alternating-auction-rule market experiment (hereinafter `the experiment') conducted between 2012 and 2015 by two large Chinese government banks-the Chinese Development Bank (CDB) and the Export-Import Bank (EIB)-to investigate the revenue ranking of uniform and discriminatory auctions.[17] The experiment lasted for three years and the total value of the experiment was U 1.95 Trillion (approximately $ 291 Billion). Because the Treasury auction formats are alternated in the experiment, the CDB and EIB design their auction formats based neither on bond characteristics, nor on financial and economic market conditions. Our summary statistics and balance tests confirm that the auction format used by the CDB and EIB to sell government bonds was not correlated with observed bond features or market conditions. Consequently, the two auction rules were used in an otherwise similar environment that allows us to obtain unbiased estimates to assess the effect of a specific auction rule on yield rates and revenue of Treasury securities.

[17] These banks are government policy banks that finance economic policies and the securities issued by these institutions are `Chinese government bonds.' These institutions have the same short and long credit ratings awarded by Moody's, Standard & Poor's, and Fitch. Their credit ratings also coincide with the ones awarded by these rating agencies to other Chinese government bonds issued by the Ministry of Finance (MOF).

In the Treasury auction data from the CDB and EIB experiments, we see that the yield rates generated from the two auction formats are not statistically different. We also see no substantial economic difference between the two auction formats in terms of revenue. This study is the first to address this important empirical revenue-comparison question by directly comparing the outcomes of those two multi-unit auction rules using real market data in a large-scale market-based experiment.[18]

Our empirical analysis looks for any difference in the yield rate of securities sold through discriminatory and uniform auctions during the experiment. This direct empirical comparison of yield rates is important because the theoretical literature is inconclusive regarding revenue superiority between the two auction formats.[19] As in Hortacsu et al. (2018), our outcome is the normalized auction yield rate, constructed as the weighted-average auction winning rate minus the prior day's corresponding market yield of Chinese bonds based on maturity and institution.[20] Hereafter, this is the `normalized rate.' Using the normalized rate is advantageous because the market yield curve removes unobserved heterogeneity across auctions as it captures fluctuations of the economic environments. Additionally, the same security at different times may experience dissimilar demand-side factors and accounting for unobservable heterogeneity at the auction level becomes crucial.

[18] The debate over the revenue comparison is more than a half-century old, originally initiated by Milton Friedman (1959 and 1991). Friedman (1991) claims that, by switching from the discriminatory to the uniform format, the US Treasury would save 75 basis points.

[19] Bukhchandani and Huang (1989) show that uniform auctions yield higher revenue than discriminatory auctions in multi-unit common value Treasury auctions with resale opportunities. Back and Zender (1993) show that Treasury's one-shot switch from the discriminatory to the uniform auction format could reduce Treasury's revenue. Moreover, under a risk-neutral and symmetric information environment, Wang and Zender (2002) show a revenue advantage in discriminatory over uniform auctions.

[20] Simon (1994), Nyborg and Sundaresan (1996), and Malvey et al. (1998) name the normalized auction yield rate as the mark-up.

Analysing the market-based experiment, we control for bond characteristics and market conditions in all specifications. Results from a control-based estimation approach with relevant baseline variables perform better (improve efficiency and increase statistical power) and dominate the uncontrolled estimates even when observable characteristics in groups (e.g., auction format) are statistically not different (Bruhn and McKenzie, 2009).

Our ordinary least squares regression (OLS) results indicate that normalized rates are not statistically different between uniform and discriminatory auctions. In our OLS results, the point estimates range from 0.001 to 0.008 percent depending on the empirical specification. Additionally, we use the Bayesian regression technique in our empirical models. Results from Bayesian models indicate that our estimated coefficients of the dummy variable that captures the difference in the two auctions range from -0.006 to 0.002.

A series of additional tests ensures that our results are robust. First, we examine whether normalized rates differ between the auction formats due to high and low yield rates in discriminatory auctions. Second, we investigate whether bidders are potentially aware of the alternating-rule auction format during the experiment and behave strategically by choosing the most profitable auction mechanism. Third, we investigate whether our results hold for the full distributions of normalized rates by re-estimating the empirical models using the quantile regression method. Lastly, we look for any differences between uniform and discriminatory auction yield rates held by the CDB and EIB individually.[21] These additional tests show that our results qualitatively do not change. See the details of the robustness tests in the Supplementary Material.

However, a reader may question whether our point estimates on the difference in the normalized rates does correspond to the actual difference in revenues from bond issuance in the two auction formats. Therefore, we estimate the change in revenue if the CDB and EIB would have issued their bonds in uniform over discriminatory auctions. This exercise shows that the potential loss/gain from issuing all bonds through a uniform auction ranges from -0.00041 percent (worst case) to 0.00054 percent (best case) of Chinese government expenditure during the three-year experiment. These results prove that the use of uniform or discriminatory formats does not generate considerable economic gain.

Our research also refers to the recent empirical literature on Treasury auctions. Pioneered by Hortacsu (2002), recent studies build and estimate structural Treasury auction models and base the evaluation of different auction rules on counterfactual simulation (Hortacsu and McAdams, 2010; Hortacsu and Kastl, 2011). Nevertheless, the counterfactual results based on structural estimation do not provide clear-cut conclusions about which Treasury auction rule generates a lower yield rate and larger revenue. Some studies present results favoring uniform auctions, others support discriminatory auctions. Another set of studies reports that the two mechanisms would generate quantitatively similar revenues.[22] In addition, although revenue equivalence is

[21] Additionally, our results hold even for only non-floating bond auctions-the largest subset of bonds in our sample.

[22] The empirical literature presents mixed views on the revenue comparison. Tenorio (1993), Umlauf (1993), and Armantier and Sbai (2006) report a revenue advantage in the uniform format, while Simon (1994) and Fevrier et al. (2004) support the discriminatory format. However, the most popular _nding in the empirical literature|Nyborg and Sundaresan (1996); Malvey et al. (1998); Horta_csu (2002); Horta_csu and McAdams (2010); and Bonaldi et al. (2015)-is empirical revenue equivalence with

often reported in empirical studies, the ambiguous revenue ranking in the theoretical literature (Wang and Zender, 2002; Ausubel et. al., 2014) does not necessarily imply revenue equivalence, which warrants careful experimental investigation.

By analysing the one-shot auction-rule change (i.e., single time-point auction rule switching during an investigation period) introduced by the U.S. Treasury in 1973-76 and 1992-93, other studies have investigated whether the uniform or discriminatory format generates a lower yield rate and a higher price (Simon, 1994; Mester, 1995; Nyborg and Sundaresan, 1996; Malvey and Archibald, 1998).[23] However, these studies were unable to provide unbiased estimates for the revenue ranking as the bonds issued under the two auction formats were different in several dimensions (market conditions, maturity, duration, volume, etc.).[24] Conversely, the auction format used by the CDB and EIB to sell government bonds during the experimental period was not related to bond characteristics and market conditions, which allow our OLS and Bayesian regressions to provide unbiased estimates for the different in the yield rates of uniform and discriminatory auctions. Our findings also complement previous structural estimations and counterfactual results.

Lastly, besides providing evidence of no relevant economic different between the two auction formats, the experiment offers us a novel research design. Other Treasuries and banks worldwide could replicate it and assess other aspects of auction mechanisms such

statistically insignificant differences. Also, Brenner et al. (2009) investigate revealed preferences of auction mechanism choices among approximately 50 countries.

[23] Tenorio (1993) and Kang and Puller (2008) also investigate one-shot changes from one auction format to another in Zambian foreign exchange and Korean Treasury auctions, respectively.

[24] Using laboratory experimental data, Sade et al. (2006a), Sade et al. (2006b) and Morales Camargo et al. (2013) investigate revenue ranking, collusion, bidders' information asymmetry in multi-unit auctions.

as the effects of asymmetric bidding behaviour, set-asides, lot-size effect, uncertain supply, and tilted supply function with great potential to increase revenues.

In Section 3.2, we explain the market background and, in Section 3.3, we explain the experiment and the data. Section 3.4 presents the auction market. We discuss our results in Section 3.5 and, in Section 3.6, we assess the economic difference between the two auction formats. The conclusion is presented in Section 3.7.

3.2 Market background

In this section, we introduce two government policy-bank bond issuers-the CDB and the EIB-which conducted the alternating rule experiment in the People's Republic of China (henceforth, PRC). We then present the identical credit ratings of these two institutions. Lastly, we explain the yield curve of each institution's securities, publicly announced every business day.

3.2.1 Two government security issuers (CDB and EIB)

The CDB issues bonds to finance government-initiated national development projects (domestic and foreign), while the EIB auctions off_ bonds to raise funds for projects related to exports and high-tech industries. Barbosa et al. (2020) provide a detailed explanation of the historical background of these two institutions.

3.2.2 Credit ratings

The CDB's and EIB's short- and long-term ratings are listed in Table 3.A.1 in the supplementary material. The credit ratings are awarded by three foreign agencies: Moody's, Standard & Poor's, and Fitch. This table also lists the ratings of government securities issued by the Ministry of Finance (MOF) as a benchmark reference. All institutions have homogeneous credit ratings within each year indicating that, as per the rating agencies, all government securities are categorized equivalently.

The credit ratings of these government banks are homogenous because their bonds are administrated by the People's Bank of China (Chen, 2014). Further, bond market participants perceive that bonds issued by these institutions are fully backed by the Chinese government (Chen, 2010; Li, 2014).[25] [26] Thus, the CDB and EIB have historically had the same credit ratings, enabling us to compare auction outcomes across institutions. Finally, although institutional credit ratings were awarded to these bond-issuing institutions, each government security has no credit rating. These institutions do not appear to have solicited credit analyses from rating agencies prior to 2017.

3.2.3 Yield curves

We use the market yield curve to normalize the bond-level auction yield rates and control for market volatility. The market yield data are obtained from the China Central Depository & Clearing Co., Ltd. (CCDC), a State Council-approved agency (also authorized by the China Banking Regulatory Commission) that records all government bond-related transactions.[27]

Based on previous resale market transactions, the CCDC publicly announces the yield curves for securities issued by each institution and maturity on every business day.

[25] The People's Bank of China (the central bank), which governs the CDB and EIB, operates directly under the government. Additionally, the MOF operates directly under the State Council.
[26] See Chen (2014) for political-economic background on the CDB and EIB, indicating that they have Chinese government-guaranteed sovereign credit ratings. Also see Chen (2010), and Li (2014) for details on credit rating equivalence.
[27] The secondary market for government bonds in China is quite substantial, with nearly 14 trillion USD in bonds traded on a yearly basis.

These yield curves provide official benchmarks to general investors.[28] [29]Moreover, resale market yield rates, especially for short-term bonds, experience significant volatility and convey information about market conditions. Hence, in our regression analyses, we use the variance of the yield curve in the period from five business days before the auction date to control for the volatility in the Chinese bond market.[30]

3.3 The experiment

For the periods May 2012-July 2014 and July 2013-May 2015, the CDB and EIB alternated between discriminatory and uniform pricing auction formats. The CDB held their weekly (or bi-weekly) auctions on Tuesdays, while the EIB typically held their bi-weekly (often less frequent) auctions on Fridays. In any auction, both institutions usually held multiple auctions with bonds of varying maturities.[31] During these market-based experiment periods, the institutions controlled the auction formats (alternating between them) but the experiment was not publicly announced. Most importantly, the auction rule choices made by the CDB and EIB cannot conceivably be correlated with the observed and unobserved bond characteristics or with financial market variables in our regression models. As we show in Section 3.5, observable bond characteristics and financial and economic market conditions are not correlated with the auction format.

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[28] No other benchmark yield curves are publicly announced in China

[29] The CCDC constructs the official yield curve mainly using settlement prices of government bonds in the inter-bank market. When they are unavailable, the CCDC uses bilateral quotes in the inter-bank market, bilateral quotes in the OTC market, transaction prices in the exchange market, quotes and final prices in fixed income platform of the exchange market, quotes of money broking corporations, and the estimated value of yield rate from market members.

[30] The variance is separately derived for each institution by the corresponding maturity.

[31] For instance, on April 8th, 2014, the CDB auctioned o_ four types of securities-with one-, two-, three-, five-, and seven-year maturities-through separate auctions.

3.3.1 CDB experiment

During the experiment, the CDB held a total of 269 auctions. Out of these, 139 were uniform and 130 were discriminatory. Within each (bi-) week, the CDB auctioned off bonds of different maturities (two-, three-, five-, and seven-year) with varying auction rules.[32] Table 3.A.2, Panel A presents a stylized pattern of this experiment. The auction mechanism alternated between discriminatory and uniform auction rules (see discriminatory auctions on 22 January 2013 and uniform auctions on 29 January 2013). Additionally, for some weeks, the CDB set the discriminatory format for three- and seven-year maturity notes, and the uniform format for five-year notes. However, in the following (bi-) week, all maturities were sold through the uniform auction format.

3.3.2 EIB experiment

Similarly, the EIB also experimented with their security auction rules. From July 2013 to May 2015, the EIB held 79 auctions|49 using the uniform format and 30 using the discriminatory format. Although the alternating auction-rule pattern is not as stylized as that used by the CDB due to fewer and relatively infrequent auctions, the pattern of the EIB's auction rule experiment is as follows. The EIB conducted bi-weekly (often less frequent) auctions, held typically on Fridays. The EIB alternated the two different auction rules for different maturities (see Table 3.A.2, Panel B.1) and, in the latter half of the experimental period, the EIB used both auction rules for bonds of the same type when reissuing them (see Table 3.A.2, Panel B.2).[33]

[32] In addition to the two-, three-, five- and seven-year notes, the CDB also auctioned off one year bills and ten-year notes. These were always sold through the uniform-pricing format. Hence, one-year and 10-year securities are excluded from our regression analyses.
[33] When reissued, each bond received a new ID. As we know the old bond ID, we can identify the reissue of an old bond.

3.3.3 The timing of auction-rule announcements

During the experimental period of 2012-2015, the CDB and EIB were required to follow strict security issuance guidelines set by the People's Bank of China. [34]Accordingly, the CDB and EIB made auction-rule announcements three business days in advance. So the participants knew which format was going to be used for a given auction only three business days before the auction date. To illustrate what was known by auction participants at the auction, consider the following example. Suppose that auctions are held every Tuesday and we consider two auctions in two consecutive weeks. Once the first auction's transactions are settled, the outcome of the auction is made public on Wednesday. Then, institutions announce the specific details of the second auction (e.g. auction date, volume, mechanism, corresponding maturity, etc.) on Thursday.[35][36]Hence, ex-ante, bidders did not know the specific date, volume, and maturity of upcoming auctions nor associated future auction formats. Hence, based on the time of the announcement, bidders could not condition their current bids on future auction rules.[37]

3.4 Auction market data

We obtain data on Treasury auctions in the Chinese bond market from two data sources, the Wind Database and Chinabond.com.cn. The Wind Database is maintained by 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

[34] Source: Official Notice of People's Bank of China (2009). These guidelines explicitly state that the public notice of a new issuance auction has to be made at least three business days in advance.
[35]A small number of deviations from these stylized announcement patterns were made when there was a long interval between two consecutive auction dates or in the event of a public holiday.
[36] Specifically, the CDB made a public announcement of the auction rule on a Thursday and bids were submitted on the Tuesday of the following week. The EIB made a public announcement typically on a Tuesday and bids were submitted on the Friday of the same week.
[37] Our data confirm that the CDB and EIB followed the guidelines set by the People's Bank of China.

Co. Ltd., which is the only government bond depository authorized by the MOF and is responsible for the establishment and operation of the government bond depository system.

The Wind Database provides access to the details of the CDB and EIB bond auctions. Our data contain not only the information of auctioned bonds, such as maturity, auction method, size of auction, and tender subjects (e.g., price or yield), but also the auction outcomes of weighted-average winning yield rate (or price), total demand, number of bidders, number of bids, number of winning bids, number of winners, final coupon rate for each auction, the presence or absence of floating coupons, as well as the highest and the lowest winning rate in discriminatory auctions. We collect supplementary information from Chinabond.com such as bond types, subsidies, coupon payment, and the date of each bond issued by the CDB and EIB.

Our data provide information at the auction-level. Bid-level data with the identity of bidders are not available due to the restrictive nature of Chinese bond market data. Nevertheless, the data generated from the experiment contain information on Treasury security yield rates for the two auction formats that is used to directly answer the long-standing revenue-ranking question in the literature. The definitions of the variables used in this study are in Table 3.A.3 in the supplementary material.

3.4.1 Auction rules and market conditions

A potential concern about our empirical strategy would be the possible correlation between auction formats, bond features, and market conditions. If a specific auction rule is endogenously chosen when the financial market experiences a specific circumstance, then our estimates would be biased despite using experimental data. There are three important reasons why the auction formats are not correlated to unobserved bond and market characteristics. First, under the (bi-) weekly alternating nature of the auction rules, as well as the strictly regulated timing of the auction announcements, it is not plausible that the unobserved bond characteristics, nor present and future financial and economic market conditions, have room to influence the auction rule. Second, systematic changes in financial market conditions do not normally occur on a (bi-) weekly basis. Lastly, during the experimental period of the EIB (described above) two auction rules were used within the same week. Also, note that the differenced construction of the normalized yields prevents unobserved characteristics from entering into our regression models.

We find statistical evidence that the respective auction rules are not associated with any specific bond type, nor are they chosen to match specific financial conditions. Table 3.1 reports summary statistics for observables associated with uniform and discriminatory auctions. In this table, we show the mean of the prior day's yield curve, the maturity of the auctioned security, market volatility, and the value of maturing bonds by institution for a given month. Similarly to Park and Reinganum (1986) and Ogden (1987), we include an indicator variable that captures whether the auction date takes place seven days before or seven days after the end of the month. This control variable captures large financial transactions concentrated at the end of the month, as financial institutions prefer to keep a relatively large liquidity at that time. In Table 3.1, we also provide 95 percent confidence intervals and calculated t-values. The results show that these variables are not statistically different between uniform and discriminatory auctions, indicating that bond characteristics and financial market conditions were well-balanced during the experiment. For example, the average market yield rate of Chinese bonds one day before the auction date is 3.685 percent for uniform auctions, while it is 3.683 percent for discriminatory auctions. The 95 percent confidence intervals clearly overlap between uniform and discriminatory auctions and the calculated t-value is 0.044. Similar conclusions are derived for other variables presented in Table 3.1. These results hold for 95 percent confidence intervals as well.[38]

3.4.2 Auction rules and number of bidders

Another concern is the equality of the number of bidders in these two auction formats during the experiment. It is worth noting that, to bid in the primary market, bidders have to be prequalified. Primary market bidders have to go through a rigorous prequalification process and past performance influences the continuation as a primary dealer in the following year. On average, during the experimental period, the CDB had about 76 pre-qualified bidders while the EIB had about 66. Additionally, we observe that more than 90 percent of dealers continue from year to year during the experiment period at each institution. Considering new entrants, the CDB and EIB had, respectively, about six and five new entrants every year during this period. More importantly, on average, about 88 percent of primary dealers participate in the auctions of both institutions. We observe a similar pattern for the pre- and post-experimental period. More detailed information can be found in Barbosa et al. (2020). However, the CDB and EIB enforce neither mandatory participation nor purchasing volume requirement. Hence, we examine bidders' participation behavior during the experiment period. In this case, we estimate the following equation:

$$n_{ijt} = \gamma D_{ijt} + X'_{ijt}\varphi + \alpha_j + \tau_t + \mu_{ijt}, \qquad (3.1)$$

[38] In addition to the t-test, we perform a Kolmogorov-Smirnov (KS) test to evaluate the equality of distributions of each variable by auction type. In all cases, we fail to reject that distributions are equal by auction format.

where our dependent variable is the number of bidders in an auction i sold by an institution j at a given time t. The indicator variable, D, controls for the auction mechanism ($D = 1$ for discriminatory auctions). Other observable characteristics, such as time gap between auctions by institution, demand-to-supply ratio of bonds, duration of the bond sold, and market conditions, are represented by the vector X. Institution effects and time effects are denoted by α and τ respectively and μ is the error term.

Given that the number of bidders is a count, we estimate Equation (3.1) using the Poisson Pseudo Maximum Likelihood (PPML) method.[39] We also estimate the above model using OLS. Table 3.A.4 in the Supplementary Material reports these results with and without floating bonds. Our main interest is in the coefficient of the auction mechanism dummy. Our results show that there is no statistical difference in the number of bidders based on auction rule during the experimental period.

Hence, conditional on controls, this experimental environment enables us to conceivably interpret the auction rule variable as conditional mean-independent, treating it as exogenously assigned. Taken all together, the Treasury auction experimental environment in China is quite advantageous to directly comparing the revenues generated from uniform and discriminatory auctions. In the next section, we conduct our empirical analysis by investigating whether there is any difference in the yield rate of the CDB and EIB securities sold through discriminatory and uniform auctions.

[39] For PPML estimation, the only condition required for consistency is the correct specification of the conditional mean of the independent variable (see Santos Silva and Tenreyro, 2006, 2010; Wooldridge, 1999).

3.5 Estimation results

To assess the revenue ranking of uniform and discriminatory auctions, we consider the following empirical model:

$$y_{ijt} = \beta D_{ijt} + X'_{ijt}\emptyset + \alpha_j + \tau_t + \epsilon_{ijt,} \qquad (3.2)$$

where our dependent variable, y, is the normalized yield rate for a given auction i, from institution j, in period t. The variable D is a dummy variable which identifies the auction mechanism as described before. The coefficient β identifies the difference in normalized rates generated from uniform and discriminatory auctions. We also include other controls (X) as described before. The error term is denoted by ϵ while α and τ are institution and time effects.

We estimate the parameters in Equation (3.2) using two different estimation methods. First, we conduct our empirical analysis using the ordinary least squares (OLS) approach. Second, we use a Markov-Chain-Monte-Carlo (MCMC) technique based on a hybrid Metropolis-Hastings sampling scheme with Gibbs updates to estimate our posterior mean and posterior standard deviations of the parameters in Equation (3.2). OLS results are presented in the first three columns of Table 3.2, while Bayesian results are presented in the last three columns.

In all our Bayesian regressions, we use uniform priors for the regression coefficients and an inverse-gamma prior with shape and scale parameters of 0.1 for the error variance. Further, we implement 22,500 iterations and the first 2,500 are omitted to mitigate possible start-up effects.[40] This Bayesian approach offers several considerable

[40] Gelman et al. (2004) provide a detailed description of the Bayesian method, including conditional distributions and the uniform prior distributions used in this study.

advantages. First, the MCMC gives us the finite-sample properties of the resulting estimates rather than asymptotic approximations. Second, incorporating a non-parametric unobserved heterogeneity component makes the specification of the model more flexible and, hence, the results more robust (Li and Zheng, 2009). However, in practice, one must verify the convergence of MCMC before making any inferential conclusions about the obtained results. In our exercise, we see that the posterior distribution looks normal. The kernel density estimates based on the first and second halves of the sample are very similar to each other and are close to the overall density estimate. Both approaches provide an unbiased and consistent estimate for β when auction rule variable D is exogenously determined, as in our case.

In our base model, presented in Column 1 of Table 3.2, we regress the normalized yield rate on a parsimonious model with an indicator for discriminatory auctions, floating bonds, monthly effects, year effects, and market drift term. Controlling for monthly and year effects are suitable because the government objectives or budgets could change yearly and/or the promotion of high-tech industries may vary by season. For example, it is quite common to promote new television in November or December than in July or August. Given the well-balanced experiment conducted by the CDB and EIB, described in Section 3.4, the estimations from this simple OLS regression provide unbiased estimates. Our estimated coefficient from this regression indicates that normalized winning rates for uniform and discriminatory auctions are statistically not different and are close to zero. This shows that our results on the statistical indifference of the yield rate between the two auction mechanisms hold even without controlling for additional observable auction characteristics and market conditions.

Exploiting a market-based experiment, in our other specifications we control for bond characteristics and market conditions to examine the auction-rule effect. As Bruhn and McKenzie (2009) have pointed out, in such non-laboratory experiments, a control-based estimation approach with relevant baseline variables improves efficiency, increases statistical power, and dominates the uncontrolled estimates even when observable characteristics in groups (e.g., discriminatory vs. uniform auctions) are not statistically different.

Hence, in Column 2 of Table 3.2, we include additional controls for auction and financial market conditions. Specifically, we do so in Column 2 and in all subsequent models (excluding Column 4) as we pool the observations from the CDB and EIB auctions. We also include bond-issuer fixed effects to account for any difference between bonds of different issuers that goes beyond their credit risk. In Columns 3 and 6, we include the number of bidders in addition to other controls. Overall, our results indicate that there is no statistical difference between uniform and discriminatory auctions' normalized yield rates. From our estimations in Table 3.2, the coefficients of the discriminatory auction dummy are close to zero. They vary from -0.006 percent (-0.6 bps) to 0.008 percent (0.8 bps), which corresponds to -0.001 percent and 0.002 percent of the mean auction rate of the bonds in our sample (the mean auction rate is 4.394 percent, i.e., 439.4 bps). In general, regardless of the estimation method, our results indicate that the estimated yield rate difference generated between uniform and discriminatory auctions is close to zero and has no statistical significance.

3.6 Assessing economic difference

In the previous section, we have shown that the normalized yield rates are not statistically different across the two auction formats. However, the point estimates are not perfectly equal to zero and the large monetary value involved in Treasury auctions raise questions about the exact size of the revenue gap created by the different auction formats. Thus, we investigate whether the bond issuers would experience any economically relevant change in revenue if they switched from one auction format to the other.

We use the point-estimates of the difference in the normalized rates reported by the discriminatory auction dummy, β, in Table 3.2 to calculate the change in CDB and EIB revenue if they issued their bonds using a uniform auction rather than a discriminatory one. We then compute the percentage change in the total revenue and the total change in the revenue with respect to Chinese government expenditure during the three years of the experiment (2013-2015) for each column.

For each institution, we first derive its total bond revenue by calculating the summation of all bonds that were auctioned off using uniform or discriminatory auctions. Next, we compute the total revenue if all bonds were sold through uniform auctions by replacing the price (p_i) of each bond issued by discriminatory auctions with its counterfactual price (p_i^c), which is its equivalent price if that bond was auctioned off through a uniform format. Accordingly, the counterfactual total revenue, TR^c is then given by:

$$TR^c = \sum_{i \in ua} p_i q_i + \sum_{i \in da} p_i^c q_i \qquad (3.3)$$

where p_i and q_i are the observed prices and quantities for each bond in auction i, and *ua* and *da* respectively refer to the subsets of bonds which were auctioned off using uniform or discriminatory mechanisms.

To obtain TR^c, we need to compute p_i^c using the estimated difference in the normalized rates, β, reported in Table 3.2. Adopting fixed-income pricing theory to our setting, we can write the p_i^c of a bond that was hypothetically issued through a discriminatory auction as:

$$p_i^c = \sum_{i \in m} \frac{k \times V}{(1 + yield + spread - \beta)^m} + \frac{V}{(1 + yield + spread - \beta)^m}, \quad (3.4)$$

where *m* is the number of coupon periods of the bond (i.e., its maturity), k is the periodical coupon rate payment on the maturity value *V*, *yield* is the period market yield rate, and *spread* is the margin over the market yield curve for a bond issued in a discriminatory auction.[41] For the CDB and EIB, the maturity value, V, of every bond is equal to 100 RMB. Note that, at the time of issuance, the *yield* + *spread* corresponds to the coupon rate, which makes the issue price of each bond equal to 100 RMB. To compute the counterfactual price p_i^c, we calculate the present value of the expected cash ow by subtracting the estimated β from the *spread*.

Now, with p_i^c computed from Equation (3.4), we can use Equation (3.3) to obtain the change in total revenue. In Table 3.3, we present the results from this exercise. The first row shows the estimated difference in the normalized rates, β, reported in Table 3.2. In the second and third rows in each column, we respectively report the percentage change in the total revenue and the total change in revenue with respect to Chinese government expenditure during the three years of the experiment.

The results in Table 3.3 reveal that the percentage change in the total revenue, if the bond issuers have issued all their bonds using a uniform auction, ranges from -0.012

[41] For example, see Fabozzi (2015).

percent to 0.016 percent at the mean. Further, the potential loss or gain from issuing all the EIB and CDB bonds through a uniform auction ranges from -0.00041 percent (worst case) to 0.00054 percent (best case) of the Chinese government expenditure during the three years of the experiment, which is negligible. We have provided upper and lower bounds (at 95 percent confidence intervals) of these revenue changes in parentheses. They range from a worst case of approximately -0.006% to a best case of +0.007%.

3.7 Conclusion

We have exploited a large auction experiment conducted by two Chinese Government Treasury security issuers-the CDB and the EIB-to investigate whether treasury securities should be sold through uniform or discriminatory auction mechanisms. We find that outcome yield rates for both formats are not statistically different. These estimates also indicate that there is no relevant economic difference in terms of revenue between the two mechanisms. Further, our results suggest that bidders do not reveal any preference for any one format.

Our observed empirical results are connected to preceding influential works as recent developments in the structural Treasury auction literature provide insightful views on market design. For instance, Hortacsu and McAdams (2010) report that, in their counterfactual simulation of Turkish Treasury auctions, switching from the discriminatory to the uniform format does not significantly increase revenue. Their result is similar to our finding. In addition, Bonaldi, Hortacsu, and Song (2015) report that, in the Federal Reserve's Mortgage-Backed Security auctions, there is a “negligible” revenue difference between the discriminatory format and truthful bidding uniform price auction (which works as a benchmark in their study) with mixed directions of revenue change when they counterfactually simulate each auction. Our direct comparison with alternating auction rules complements these prominent counterfactual studies by adding market-based experimental support| empirically, there is no substantive economic difference in revenue between uniform and discriminatory auctions.

Although the Chinese experiment enables us to directly compare auction outcomes and provide inferences on which Treasury auction rule generates a lower yield rate (larger revenues), our study has some limitations. Specifically, the lack of bid-level data with information about bidder identity prevents us from studying some aspects of market design-asymmetric bidding behaviour with heterogeneous costs, informational advantage with primary dealership, and allocative efficiencies-which researchers actively investigate these days (e.g., Cassola, Hortacsu, and Kastl, 2013; Hortacsu, Kastl, and Zhang, 2018; Bonaldi, Hortacsu, and Song, 2015). However, one of the contributions of this study is that an alternating auction rule experiment has the legitimate potential to uncover underlying economic incentives. Thus, we leave an investigation of these advanced topics to future researchers who can exploit Treasury auction bid data with alternating auction rules.

3.8 Figures and Tables

Table 3.1: Results of the balance test for covariates

Variable	Uniform	Discriminatory	*t*-Value
Market yield of Chinese bonds one day before the auction date	3.685	3.683	0.044
	[3.617, 3.753]	[3.612, 3.753]	
Log of duration	1.391	1.417	0.703
	[1.347, 1.435]	[1.357, 1.477]	
Log of demand/supply	0.886	0.888	0.093
	[0.830, 0.941]	[0.858, 0.919]	
Volatility	0.026	0.029	1.604
	[0.023, 0.028]	[0.026, 0.032]	
Log value of maturing bonds by institution for a given month	14.505	14.672	1.030
	[14.265, 14.746]	[14.461, 14.883]	
First and last week of the month	0.824	0.838	-0.322
	[0.770, 0.879]	[0.780, 0.895]	

This table reports the mean, the 95% confidence intervals and the calculated t-values for prior day's yield curve, duration, market volatility, and value of maturing bonds by the institution for a given month of the CDB and the EIB government bonds sold through uniform and discriminatory auctions. The variable duration refers to Macaulay duration, which is the weighted average term to maturity of the cash flows from a bond.

Table 3.2: Regression results for normalized rate

Variable	Normalized rate					
	OLS			Bayesian		
	(1)	(2)	(3)	(4)	(5)	(6)
Discriminatory auction	0.006	0.008	0.001	-0.006	0.002	-0.005
	[-0.085, 0.096]	[-0.089, 0.106]	[-0.081, 0.082]	[-0.070, 0.057]	[-0.067, 0.077]	[-0.071, 0.052]
Floating bond	-0.578	-0.579	-0.495	-0.575	-0.612	-0.482
	[-0.819, -0.336]	[-0.834, -0.323]	[-0.732, -0.259]	[-0.672, -0.479]	[-0.729, -0.510]	[-0.577, -0.395]
Log of duration		-0.115	-0.073		-0.112	-0.075
		[-0.252, 0.022]	[-0.194, 0.047]		[-0.172, -0.055]	[-0.156, 0.006]
Log of demand/supply		-0.002	-0.389		-0.006	-0.377
		[-0.213, 0.209]	[-0.594, -0.184]		[-0.106, 0.091]	[-0.452, -0.304]
Volatility		2.269	2.044		2.220	2.022
		[0.344, 4.195]	[0.093, 3.995]		[2.128, 2.319]	[1.854, 2.208]
Log of time lag between auctions by institution		0.050	0.025		0.063	0.019
		[-0.072, 0.171]	[-0.087, 0.138]		[0.002, 0.126]	[-0.030, -0.073]
Log value of maturing bonds by institution for a given month		-0.018	-0.016		-0.022	-0.018
		[-0.041, 0.005]	[-0.042, 0.010]		[-0.037, -0.006]	[-0.035, 0.001]
Log number of bidders			1.472			1.480
			[0.837, 2.106]			[1.406, 1.547]
Institution effects		Yes	Yes		Yes	Yes
First and last week of the month	Yes	Yes	Yes	Yes	Yes	Yes
Month and year effects	Yes	Yes	Yes	Yes	Yes	Yes
Market drift	Yes	Yes	Yes	Yes	Yes	Yes
Observations	348	348	348	348	348	348
R^2	0.355	0.376	0.494			
Log marginal likelihood				-246.660	-301.338	-281.949

This table reports OLS and Bayesian regressions of the normalized rates. We use an indicator variable (Discriminatory auction) which takes the value of one when auction format is discriminatory and zero otherwise. In Column 1 and 4, we control for floating bonds, first and last week of the month, month effects, year effects, and market drift without any other controls. In Columns 2 and 5 we include all auction and market controls (without number of bidders), in additional to time effects. We add number of bidders in Columns 3 and 6. In Column 2, 3, 5, and 6 as we have pooled the date, we also include bond-issuer fixed effects to account for any difference between bonds of different issuers that goes beyond their credit risk. The variable duration refers to Macaulay duration, which is the weighted average term to maturity of the cash flows from a bond. In Columns 1-3, 95% confidence intervals calculated based on robust standard errors are in brackets while in Columns 4-6, 95% credible intervals are in brackets.

Table 3.3: Economic magnitude of the revenue equivalence

Variable	OLS			Bayesian		
	(1)	(2)	(3)	(4)	(5)	(6)
Discriminatory auction point estimate	0.006	0.008	0.001	-0.006	0.002	-0.005
Total Revenue (%)	0.012	0.016	0.002	-0.012	0.004	-0.010
	(-0.169, 0.192)	(-0.177, 0.212)	(-0.161, 0.164)	(-0.139, 0.114)	(-0.133, 0.154)	(-0.141, 0.104)
Change Total Revenue/Gvt of China Expenditure in 2012-2015 (%)	0.00041	0.00054	0.00007	-0.00041	0.00014	-0.00034
	(-0.00572, 0.00650)	(-0.00599, 0.00718)	(-0.00546, 0.00555)	(-0.00472, 0.00386)	(-0.00451, 0.00521)	(-0.00478, 0.00352)

This table reports the economic magnitude calculated based on Table 2 estimates. Upper and lower bounds at 95% confidence intervals are in parentheses.

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Appendix 3. A

3. A.1 Extra Tables

This is the supplementary material for \Auction Mechanisms and Treasury Revenue: Evidence from the Chinese Experiment." It contains additional tables and figures used in the study that are necessary to fully document the research contained in the study and to facilitate the readers' ability to understand the work.

Table 3.A.1: Chinese government and policy banks' security credit ratings

Year	Fitch			Moody's			Standard & Poor's		
	MOF	CDB	EIB	MOF	CDB	EIB	MOF	CDB	EIB
Panel A: Long-term									
2012	A+	A+	A+	Aa3	Aa3	Aa3	AA-	AA-	AA-
2013	A+	A+	A+	Aa3	Aa3	Aa3	AA-	AA-	AA-
2014	A+	A+	A+	Aa3	Aa3	Aa3	AA-	AA-	AA-
2015	A+	A+	A+	Aa3	Aa3	Aa3	AA-	AA-	AA-
Panel B: Short-term									
2012	F1	F1	F1	P-1	--	--	A-1+	A-1+	A-1+
2013	F1	F1	F1	P-1	--	--	A-1+	A-1+	A-1+
2014	F1	F1	F1	P-1	P-1	--	A-1+	A-1+	A-1+
2015	F1	F1	F1	P-1	P-1	--	A-1+	A-1+	A-1+

This table reports the long-term and short-term credit ratings awarded by Moody's, Standard Poor's, and Fitch to the Chinese government bonds issued by the Minister of Finance (MOF), the Chinese Development Bank (CDB) and the Export- Import Bank (EIB). If a rate was updated in the middle of a calendar year, the updated rate is listed. “--”denotes that no rate was given by a credit rating agency.

Table 3.A.2: Example of alternating pattern for the CDB and EIB

Panel A: CDB			Panel B: EIB		
Date	Maturity in years	Auction mechanism	Date	Maturity in years	Auction mechanism
Jan 08, 2013	3, 5, 7	Discriminatory	Panel B.1: Alternating rule by date		
Jan 15, 2013	3, 5, 7	Uniform	Jul 31, 2013	2 (t)	Discriminatory (Uniform)
Jan 22, 2013	5, 7	Discriminatory	Aug 15, 2013	2 (t)	Discriminatory (Uniform)
	3	Uniform	Sep 24, 2013	2 (t)	Discriminatory (Uniform)
Jan 29, 2013	3, 5, 7	Uniform	Oct 21, 2013	2 (t)	Uniform (Discriminatory)
Feb 05, 2013	3, 5, 7	Discriminatory	Nov 04, 2013	2 (t)	Uniform (Discriminatory)
Feb 19, 2013	3, 5, 7	Uniform	Apr 11, 2014	3 (t)	Discriminatory (Uniform)
Apr 09, 2013	3, 7	Discriminatory	May 15, 2014	3 (t)	Uniform (Discriminatory)
	5	Uniform	May 23, 2014	3 (t)	Discriminatory (Uniform)
Apr 16, 2013	3, 5, 7	Uniform	Jun 06, 2014	3 (t)	Uniform (Discriminatory)
Apr 23, 2013	3, 7	Discriminatory	Panel B.2: Alternating rule by bond		
	5	Uniform	Nov 28, 2014 14 EXIM 78 (initial)	2	Discriminatory
May 07, 2013	3, 5, 7	Uniform	Dec 04, 2014 14 EXIM 78 (reissue)	2	Uniform
May 14, 2013	3, 7	Discriminatory	Dec 17, 2014 14 EXIM 78 (reissue)	2	Discriminatory
	5	Uniform	Apr 15, 2015 15 EXIM 09 (initial)	3	Uniform
May 21, 2013	3, 5, 7	Uniform	Apr 24, 2015 15 EXIM 09 (reissue)	3	Uniform
May 28, 2013	3, 7	Discriminatory	Apr 30, 2015 15 EXIM 09 (reissue)	3	Uniform
	5	Uniform	May 06, 2015 15 EXIM 09 (reissue)	3	Discriminatory
Jun 04, 2013	3, 5, 7	Uniform	May 13, 2015 15 EXIM 09 (reissue)	3	Discriminatory
Jun 18, 2013	3, 5, 7	Discriminatory	May 21, 2015 15 EXIM 09 (reissue)	3	Discriminatory
Jul 02, 2013	3, 5, 7	Discriminatory			
Jul 09, 2013	3, 5, 7	Uniform			
Jul 16, 2013	3, 5, 7	Discriminatory			
Jul 23, 2013	3, 5, 7	Uniform			
Jul 30, 2013	3, 5, 7	Discriminatory			

This table reports the stylized pattern of this alternating auction-rule experiment conducted by the CDB and EIB. Panel A shows that the auction mechanism alternated between discriminatory and uniform auction rules for CDB. Note that all bills (maturity less or equal to one year) and bonds (maturity) equal or more than 10 years) were sold using uniform. The alternating auction-rule experiment period for CDB was from May 2012 {July 2014. Panel B reports the stylized pattern of this alternating auction-rule experiment conducted by the EIB. The EIB conducted bi-weekly (or often much longer interval) auctions, held typically on Fridays, usually with two to four different maturities. The EIB alternated the two different auction rules for different maturities (Panel B.1- Alternating auction rule by date) and, in the latter half of the experimental period, the institution used the two auction rules on the same type of bond when reissuing (Panel B.2-Alternating auction rule by bond type). The alternating auction-rule experiment period for CDB was from July 2013 {May 2015. The index t in the upper panel denotes other maturity in years that were auctioned off in the same day.

Table 3.A.3: Description of the variables

Variable	Description
Discriminatory auctions	This variable takes the value one when the auction format is discriminatory and zero when the auction mechanism is uniform.
Floating bonds	The floating bonds variable is a binary indicator, which is equal to one if an auction is for floating bond, zero otherwise. Note that all of the floating bonds are sold through the uniform-price format only.
Market yield of Chinese bonds one day before the auction date	This variable is the publicly announced yield curve rates by the CCDC. Each business day, the CCDC publicly announces the yield curves for bonds issued by the CDB and EIB by maturity, which are based on previous resale market transactions. These yield curves provide official benchmarks to general investors.
Duration	The duration variable refers to Macaulay duration, which is the weighted average term to maturity of the cash flows from a bond. A similar duration variable is used by Simon (1994).
Demand/supply	This variable is the ratio of the total amount of tenders divided by a supply volume. This variable controls the strength of demand and the degree of competitions in an auction. A similar measure is used by Cordy (1999) and Goldreich (2007). In our sample, total demand was always more than the supply.
Lag time between auctions	This variable measures the business days since the last auction held by an institution.
Value of maturing bonds by institution for a given month	This is the sum of face values, which the issuer has to pay in a specific month. This variable controls the possibility that financial institutions may recycle their liquidity obtained through matured securities to bid for new issuance.
Number of bidders	This is the number of bidders in an auction.
CDB	This variable is a binary indicator variable that takes the value of one when auctions are let by the CDB and zero otherwise.
First and last week of the month	This indicator variable is equal to one if the auction date takes place seven days before or seven days after the end of the month, and equal to zero otherwise.
Market drift	This variable is constructed by counting the number of weeks since the start of the experiment by dividing each week by the number of total weeks in which the CDB and EIB conducted their market experiment. Simon (1994) notes that a market-drift variable controls for gradual unobservable changes that bidders face during the market experiment period. Although a model of long-term relationships with dynamic trade-offs is beyond the scope of this study, other studies point out that a repeated auction environment can sustain a variety of strategies in equilibria (see e.g., Skrzypacz and Hopenhayn, 2004) , and this time-shifting variable parsimoniously controls for potential gradual changes in long-term interactions among bidders, regardless of the auction formats.

Table 3.A.4: Regression results for number of bidders

Variable	Number of bidders			
	PPML		OLS	
Discriminatory auctions	0.001	0.001	0.017	0.005
	(0.014)	(0.014)	(0.025)	(0.016)
Floating bond	-0.053		-0.051	
	(0.026)		(0.031)	
Market yield of Chinese bonds one day before the auction date	0.015	0.008	0.011	-0.001
	(0.025)	(0.025)	(0.028)	(0.029)
Log of duration	-0.030	-0.025	-0.032	-0.025
	(0.019)	(0.020)	(0.024)	(0.026)
Log of demand/supply	0.244	0.227	0.265	0.246
	(0.025)	(0.026)	(0.034)	(0.035)
Volatility	0.065	-0.106	0.339	-0.057
	(0.265)	(0.273)	(0.508)	(0.305)
Log of time lag between auctions by institution	0.016	-0.005	0.016	-0.007
	(0.011)	(0.015)	(0.013)	(0.017)
Log value of maturing bonds by institution for a given month	-0.000	-0.002	-0.001	-0.002
	(0.005)	(0.006)	(0.006)	(0.007)
Institution effects	Yes	Yes	Yes	Yes
First and last week of the month	Yes	Yes	Yes	Yes
Month and year effects	Yes	Yes	Yes	Yes
Market drift	Yes	Yes	Yes	Yes
Observations	348	301	348	301
R^2	0.570	0.593	0.541	0.557

This table presents the estimates for the number of bidders in an auction, controlling for auction type, institutions, market conditions, time gap between auctions by institutions, demand and supply ratio of bonds, institution effects, first and last week of the month, monthly effects, year effects, and market drift. The variable duration refers to Macaulay duration, which is the weighted average term to maturity of the cash flows from a bond. We estimate this using the Poisson Pseudo Maximum Likelihood (PPML) method and also using OLS. Robust standard errors are in parentheses.

Appendix 3. B

3. B.1 Robustness tests

In this section of the supplementary material we perform additional tests to ensure that our results are robust. First, we examine whether there is a difference in normalized rates between auction formats due to the high and low yield rates observed in discriminatory auctions. Second, we investigate whether bidders are potentially aware of the alternating-rule auction format during the experiment and behave strategically by choosing the most profitable auction mechanism. Third, we investigate whether our results hold for the full distributions of normalized rates by re-estimating the empirical models using the quantile regression method. Lastly, we examine whether there are any differences in the auction yield rates between uniform and discriminatory auctions held by the CDB and EIB individually. The tables and figures related to these robustness tests' results are presented in the end of this supplementary material.

3. B. 1. 1 High and low auction rates in discriminatory auctions

In the main estimation results presented in Table 3.2, we consider only the auction-specific normalized weighted average winning bids. One could argue that the difference between auction formats might differ when we measure outcomes with the highest or the lowest winning auction rates observed in discriminatory auctions. To address this concern, we re-estimate our models with the normalized highest and lowest winning primary bids for discriminatory auctions using the specification in Table 3.2, Column 3 for OLS regression and in Column 6 for Bayesian estimation. Note that, in discriminatory auctions, the average range between the normalized highest and lowest winning bids is 0.032 percent with a standard deviation of 0.026.

In Table 3.B.1, we report the results for normalized weighted-average auction winning rate-based uniform auctions and highest and lowest winning bids of discriminatory auctions. The first two columns in Table 3.B.1 report the OLS estimation results, and the last two columns report the results of the Bayesian estimation. The results indicate that our main finding that there is no statistical difference between uniform and discriminatory formats-holds true for the normalized highest and lowest bids of discriminatory auctions compared to uniform auctions as well.

3. B. 1. 2 Restricted sample: without floating bond

As mentioned before, we observed 47 floating bonds, auctioned off using only the uniform auction format. As a robustness check, we drop these 47 auctions and re-estimate our main empirical models. We report OLS results in the first three columns and Bayesian results in the last three columns of Table 3.B.2. The first and the fourth columns report results for normalized weighted-average normalized rates for uniform and discriminatory auctions. In Columns 2 and 5, we report results using the normalized highest bids while, in Columns 3 and 6, we report the normalized lowest bids of discriminatory auctions. In all columns, we estimate the full model described in Columns 3 and 6 in Table 3.2. As in our earlier estimations, results indicate that there is no statistical difference between normalized rates generated from uniform and discriminatory auctions.

3. B.1.3 Bidders' behaviour in alternating auctions

Next, given that the CDB and EIB alternated between the two auction formats with remarkable regularity for three years, one could argue that bidders (financial institutions that participate in the primary market) could have been aware of the upcoming auction formats and, therefore, waited for the auction format that was most profitable to them. To test this potential threat to our research design, we conduct a number of exercises.

First, one may note that, if bidders wait for the format that is most favourable to them, they will behave differently in the first half of the experiment (when they are unaware that the issuing banks are alternating the auction formats) compared to the second half (after realizing the pattern of the experiment). To test this, we divide the CDB and EIB data into two periods-the first and second half of the experiment. We again estimate similar empirical models presented in Table 3.2, Columns 2, 3, 5, and 6. Our results are presented in Table 3.B.3 and indicate that there is no statistical difference between uniform and discriminatory auction yields in the first or the second half of the experiment. This suggests that bidders did not change their bidding patterns throughout the experiment.

Next, we record bidder participation by examining the average number of bidders by auction type during the experiment. During the experiment, the uniform auctions attracted 34.30 (5.82) bidders on average per auction, while discriminatory auctions attracted 35.88 (4.88) bidders on average (standard deviations are in parentheses). When considering the average number of bidders by institution, the CDB averaged 33.99 (5.26) bidders per auction, while the EIB averaged 38.54(4.56).[42]

In Figure 3.B.1, we have plotted the weekly average of the number of bidders per auction for all Treasury notes by auction mechanism during the experiment. One can observe that both auction types have similar patterns for the average number of bidders per auction. If bidders were using a dynamic waiting strategy, the number of participants in discriminatory and uniform auctions would move in opposite directions throughout the auction series. The figure does not reveal such a counter-cyclical movement pattern. Instead, it shows that the number of bidders remains similar across auction formats during the experimental period, indicating that bidders did not wait for their preferred auction format.[43]

In addition to this, we formally test whether there is a difference in the number of bidders in the first and second half of the experiment depending on the auction format. We regress the number of bidders on the auction mechanism dummy, a variable that indicates that the auction is let during the second half (second half indicator) and also on another variable that captures the difference between uniform and discriminatory auctions in the second half (second half indicator × discriminatory auction indicator). We also control for observable auction and market characteristics. In Table 3.B.4, we report estimations using the Poisson Pseudo Maximum Likelihood (PPML) method in

[42] There were no Treasury instruments with maturities greater than one year or less than 10 years (Treasury notes) sold using the discriminatory auction format before or after the experiment by either institution. For this reason, we cannot compare the number of bidders per auction before, after, and during the experimental period.

[43] Kang and Puller (2008) conclude that, in Korean Treasury auctions, there is a slight revenue advantage for the discriminatory format, but the revenue difference between the two formats is quite small due to the competitiveness of the market. The average number of bidders in Korean auctions is smaller than in Chinese auctions and, hence, the Chinese market could be considered more competitive than the Korean market. Note that, on average, the Korean auctions have about seven and 10 less bidders in uniform and discriminatory auctions, respectively, compared to similar Chinese auctions.

Column 1, and the OLS method in Column 2. All our estimated results in Table 3.B.4 indicate that there is no statistical difference between the number of bidders in uniform and discriminatory auctions in the first and second period.

Another possible way to examine the robustness of bidder participation and normalized rates results is to investigate the differences of these outcomes just before and after the experiment. However, such a comprehensive investigation is not possible as the CDB and the EIB did not use discriminatory auctions prior to or following the experiment period. Alternatively, we compare the bidder participation and auction yield outcomes in uniform auctions during and 12 months after the experiment period. Our results indicate that the bidders did not behave differently during and after the experiment period (See Table 3.B.5 in the supplementary material).[44]

These exercises further support the notion that bidders (i) did not discriminate between auction formats as part of a static participation or dynamic waiting strategy, due to the rigidly framed non-overlapping auction announcement cycles, and (ii) did not behave differently during and after the experiment period. It is worth noting that, as the institutions neither officially nor publicly announced the end date of the experiment, the CDB and EIB could have stopped the experiment at any given time, making a potential forward-looking waiting strategy impossible for bidders.

[44] In principle, we could examine whether there were any differences in bidder entry and auction outcomes focusing only on uniform auctions. However, such a comparison faces challenges, as before the experiment period, auctions were much less frequent and had smaller volumes. As a natural consequence of less-frequent trading opportunities, the number of participating bidders and outcome yields were relatively higher before the experiment period, making the direct comparison challenging.

3. B.1.4 Effect on the distribution of bids

A potential concern is that our results may not hold for the full distribution of the normalized weighted average outcome of the yield. To address this issue, we re-estimate the empirical models using the quantile regression method for the 15^{th}, 25^{th}, 50^{th}, 75^{th}, and 85^{th} quantiles. We present these estimated results in Table 3.B.6.[45] Note that these empirical specifications are similar to the ones presented in Table 3.2, Column 3. The results are qualitatively similar to the ones shown in the OLS tables and indicate that there is no significant difference between outcomes generated from the two auction formats (Panel A). In Panel B, we report results using the normalized highest yield while, in Panel C, we report the normalized lowest yield of discriminatory auctions. We also estimate these specifications without floating bids, obtaining qualitatively similar results that indicate that there is no statistical difference between normalized rates based on auction formats. These results are not presented in this study, but can be provided upon request.[46][47]

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[45] Hahn (1995) shows that the asymptotic variance matrix of the quantile regression estimator depends on the density of the error. Hahn notes that, for regressors, the bootstrap distribution is shown to converge weakly to the limit distribution of the quantile regression estimator in probability. Therefore, the confidence intervals constructed by the bootstrap procedures have shown to provide asymptotically valid estimators. Hence, we obtain standard errors (reported in Table 3.B.6) via bootstrapping the variance-covariance matrix. Note that we implement the bootstrap procedure by repeating the regression 100 times on a randomly drawn new sample with replacement from the original data.

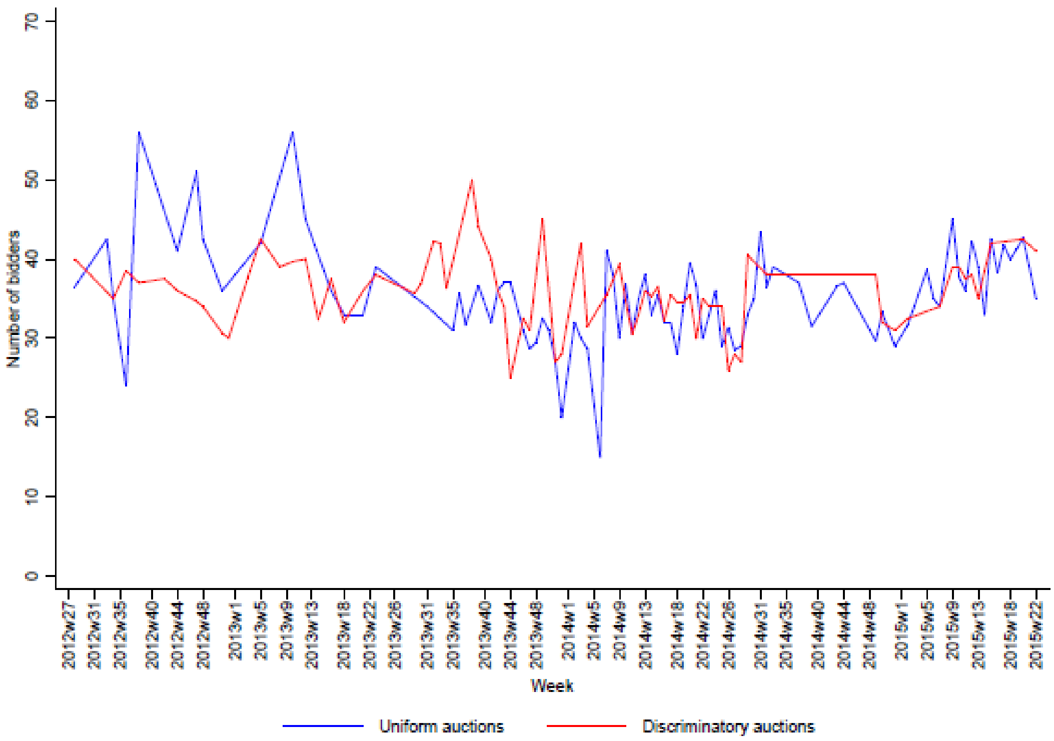
[46] A minor exception is that, in Panel C Table 3.B.6, when comparing the lowest normalized winning bids of discriminatory auctions with normalized uniform winning bid rates, we observe that the discriminatory auction rate is lower by -0.060% (-6.00 bps) compared to uniform auctions in the 85^{th} quantile.

[47] Note that here we are using the quantile method proposed by Koenker and Bassett (1978). This method essentially estimates a conditional Quantile Treatment Effect (QTE) under exogeneity (see Frolich and Melly, 2013). In our case, we have argued that the implementation of the two auction mechanism is random. Hence, our quantile regression results can also be treated as evidence from conditional QTE approach.

3. B.1.5 CDB vs. EIB

During our sample period, the experiments were conducted by the two institutions separately. Hence, we next examine whether there are any differences in the normalized rates between uniform and discriminatory auctions by institution. To do this, we re-estimate the models presented in Table 3.2, Columns 3 and 6, by institution. The results are presented in Table 3.B.7. Columns 1 and 2, present the OLS results for the CDB with and without floating bonds. In Column 3, we report the OLS results for the EIB. Columns 4-6, present the Bayesian results for the normalized rates. All columns indicate that, regardless of the institution, the revenues generated from the two auction mechanisms have no statistical difference.

Figure 3.B.1: Number of bidders by auction type



Notes: This figure plots the weekly average number of bidders per auction for all treasury notes by auction format during the experiment.

Table 3.B.1: Regression results for normalized rates with highest and lowest discriminatory auction rates

Variable	Normalized rate			
	OLS		Bayesian	
	Highest	Lowest	Highest	Lowest
	(1)	(2)	(3)	(4)
Discriminatory auction	0.028	-0.007	0.036	-0.012
	[-0.053, 0.110]	[-0.089, 0.074]	[-0.033, 0.101]	[-0.066, 0.042]
Floating bond	-0.491	-0.497	-0.488	-0.476
	[-0.727, -0.256]	[-0.733, -0.260]	[-0.565, -0.414]	[-0.571, -0.386]
Auction and market controls	Yes	Yes	Yes	Yes
Institution effects	Yes	Yes	Yes	Yes
First and last week of the month	Yes	Yes	Yes	Yes
Month and year effects	Yes	Yes	Yes	Yes
Market drift	Yes	Yes	Yes	Yes
Observations	348	348	348	348
R^2	0.499	0.492		
Log marginal likelihood			-279.097	-282.579

This table reports OLS and Bayesian regressions of normalized rates with highest and lowest discriminatory auction bids. Our dependent variables is the auction-specific normalized highest (Columns 1 and 3) and the lowest (Columns 2 and 4) winning rate on a given date. In all columns, we control for auction format, other auction, and market characteristics in addition to month effects, year effects, market drift, and bond-issuer fixed effects. In Columns 1-2, 95% confidence intervals calculated based on robust standard errors are in brackets while in 3-4, 95% credible intervals are in brackets.

Table 3.B.2: Regression results for normalized bids without floating bonds

Variable	Normalized rate					
	OLS			Bayesian		
	Average	Highest	Lowest	Average	Highest	Lowest
	(1)	(2)	(3)	(4)	(5)	(6)
Discriminatory auction	-0.006	0.022	-0.015	0.004	0.031	-0.007
	[-0.087, 0.074]	[-0.058, 0.102]	[-0.095, 0.066]	[-0.041, 0.055]	[-0.016, 0.079]	[-0.052, 0.036]
Auction and market controls	Yes	Yes	Yes	Yes	Yes	Yes
Institution effects	Yes	Yes	Yes	Yes	Yes	Yes
First and last week of the month	Yes	Yes	Yes	Yes	Yes	Yes
Month and year effects	Yes	Yes	Yes	Yes	Yes	Yes
Market drift	Yes	Yes	Yes	Yes	Yes	Yes
Observations	301	301	301	301	301	301
R^2	0.482	0.480	0.481			
Log marginal likelihood				-162.404	-162.473	-165.701

This table reports normalized rate regressions excluding floating bonds. In Columns 1-3 we present OLS results while in Columns 4-6 we present Bayesian results. Our dependent variables are the auction-specific normalized weighted-average, highest, and lowest normalized bids respectively. In all columns, we control for auction format, other auction, and market characteristics in addition to month effects, year effects, market drift, and bond-issuer fixed effects. In Columns 1-3, 95% confidence intervals calculated based on robust standard errors are in brackets and in Columns 4-6, 95% credible intervals are in brackets.

Table 3.B.3: Regression results for normalized rate in the first- and second-half of the experiment

Variable	Normalized rate			
	OLS		Bayesian	
	First-half	Second-half	First-half	Second-half
	(1)	(2)	(3)	(4)
Discriminatory auction	-0.021	0.009	-0.063	0.005
	[-0.184, 0.142]	[-0.090, 0.109]	[-0.150, 0.026]	[-0.072, 0.071]
Floating bond	-0.765***	0.160	-0.830	0.183
	[-1.055, -0.475]	[-0.342, 0.662]	[-0.961, -0.703]	[0.100, 0.268]
Auction and market controls	Yes	Yes	Yes	Yes
Institution effects	Yes	Yes	Yes	Yes
First and last week of the month	Yes	Yes	Yes	Yes
Month and year effects	Yes	Yes	Yes	Yes
Market drift	Yes	Yes	Yes	Yes
Observations	148	200	148	200
R^2	0.524	0.547		
Log marginal likelihood			-199.963	-169.182

This table reports OLS and Bayesian regressions for the normalized rates auctioned off in the first-and the second-half of the experiment. In all Columns, we control for all auction format, other auction, and market controls in addition to floating bonds, monthly effects, year effects, market drift, and bond-issuer fixed effects as in Table 2 Column 3 and 6. In Columns 1 and 2, 95% confidence intervals calculated based on robust standard errors are in brackets and in Columns 3 and 4, 95% credible intervals are in brackets.

Table 3.B.4: Results for number of bidders during the experiment

Variable	Number of bidders	
	PPML	OLS
	(1)	(2)
Discriminatory auction	-0.074	-2.194
	(0.053)	(1.854)
Second half	-0.008	-0.019
	(0.026)	(0.982)
Second half × Discriminatory auctions	0.011	0.114
	(0.030)	(1.114)
Auction and market controls	Yes	Yes
Institution effects	Yes	Yes
First and last week of the month	Yes	Yes
Month and year effects	Yes	Yes
Market drift	Yes	Yes
Observations	348	348
R^2	0.576	0.590

This table presents the estimates for the number of bidders in an auction, controlling auction type, institutions, market conditions, the time gap between auctions by institutions, demand, and supply ratio of bonds, and institution effects which are denoted by auction and market controls. Additionally, we have included month effects, year effects, and market drift. Robust standard errors are in parentheses.

Table 3.B.5: Bidder behaviour in uniform auctions during and after the experiment

Variable	Number of bidders	Normalized rate
After (12 months)	0.013	-0.061
	(0.024)	(0.071)
Floating bond	-0.044	-0.556
	(0.036)	(0.121)
Market yield of Chinese bonds one day before the auction date	-0.051	
	(0.023)	
Other controls	Yes	Yes
Observations	389	389
R^2	0.394	0.353

This table presents the estimates for the number of bidders and normalized rates in auctions controlling for after experiment period, institutions, market conditions, time gap between auctions by institutions, demand and supply ratio of bonds, institution effects, and all other market and time controls. The Column 1 is estimated using the Poisson Pseudo Maximum Likelihood (PPML) method and Column 2 is estimated using OLS. Robust standard errors are in parentheses.

Table 3.B.6: Quantile regression results for normalized rates

Variable	Normalized rate				
	Quantile				
	0.15	0.25	0.50	0.75	0.85
Panel A: with weighted averages of discriminatory auction winning bids					
Discriminatory auction	-0.008	-0.051	-0.037	-0.029	-0.030
	(0.060)	(0.053)	(0.032)	(0.030)	(0.035)
All controls	Yes	Yes	Yes	Yes	Yes
Observations	348	348	348	348	348
R^2	0.417	0.327	0.263	0.337	0.406
Panel B: with highest discriminatory auction winning bids					
Discriminatory auction	0.014	-0.016	-0.011	-0.014	-0.008
	(0.059)	(0.059)	(0.027)	(0.030)	(0.040)
All controls	Yes	Yes	Yes	Yes	Yes
Observations	348	348	348	348	348
R^2	0.418	0.328	0.265	0.340	0.407
Panel C: with lowest discriminatory auction winning bids					
Discriminatory auction	-0.027	-0.042	-0.036	-0.047	-0.060
	(0.059)	(0.045)	(0.033)	(0.039)	(0.033)
All controls	Yes	Yes	Yes	Yes	Yes
Observations	348	348	348	348	348
R^2	0.417	0.325	0.260	0.336	0.403

This table reports quantile regressions for the 15th, 25th, 50th, 75th and 85th quantiles of the normalized rates. In Panel A, our dependent variable is the normalized auction-specific weighted-average winning rate on a given date. In Panel B and Panel C, our dependent variables are the normalized auction-specific highest and lowest discriminatory auction winning bids respectively in addition to normalized uniform auction bids. All controls include auction format, other auction, and market controls in addition to floating bonds, monthly effects, year effects, market drift, and bond-issuer fixed effects as in Table 3.2, Column 3. Bootstrapped standard errors are in parentheses.

Table 3.B.7: Regression results for normalized rates by institution

Variable	Normalized rate					
	OLS			Bayesian		
	CDB		EIB	CDB		EIB
	(1)	(2)	(3)	(4)	(5)	(6)
Discriminatory auction	0.001 [-0.099, 0.100]	-0.020 [-0.111, 0.071]	-0.008 [-0.078, 0.061]	-0.001 [-0.097, 0.092]	-0.026 [-0.074, 0.027]	0.003 [-0.042, 0.047]
Floating bond	-0.451 [-0.700, -0.202]			-0.443 [-0.555, -0.337]		
Auction and market controls	Yes	Yes	Yes	Yes	Yes	Yes
Institution effects	Yes	Yes	Yes	Yes	Yes	Yes
First and last week of the month	Yes	Yes	Yes	Yes	Yes	Yes
Monthly and year effects	Yes	Yes	Yes	Yes	Yes	Yes
Market drift	Yes	Yes	Yes	Yes	Yes	Yes
Observations	269	222	79	269	222	79
R^2	0.511	0.545	0.880			
Log marginal likelihood				-267.600	-165.631	-75.411

This table reports results for normalized rates by institution. We estimate the models presented in Table 3.2, Columns 3 and 6, by institution. In Columns 1, 2, 4 and 5 we present the results for the CDB with and without floating bonds. In Column 3 and 6, we report the results for the EIB. Models in Column 1 and 3, we include floating bond dummy. In all columns, we control for auction format, auction, and market characteristics in addition to month effects, year effects, market drift, and bond-issuer fixed effects. In Columns 1-3, 95% confidence intervals calculated based on robust standard errors are in brackets and in Columns 4-6, 95% credible intervals are in brackets.

Chapter 4

Bond Losses and Systemic Risk

‘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 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)

4.1 Introduction

Recent studies have shown that the trading of bonds is a major part of banks' activities and accounts for a significant share of their revenues (King, Massoud, and Song, 2013; Begenau, Piazzesi, and Schneider, 2015). Hence, losses in this market can have significant consequences for banks as well as for the stability of the banking sector. The

2007-2008 global financial crisis, for instance, has shown how bank losses can cause instability in global financial systems and lead to severe macroeconomic fluctuations (De Bandt, Hartmann, and Peydro, 2010).

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

In this study, we show that banks make substantial losses in the process of buying (bidding for) on-the-run Treasury bonds in the primary markets and reselling them in the secondary market due to tight liquidity conditions. Using a novel dataset that tracks primary-to-secondary transactions in the Treasury bond market, we measure the loss or gain as the difference between primary and secondary market returns on the debut-day (the initial secondary market trading day for a given bond).[48] We show that, when this

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

inter-market margin is negative, the primary market dealer incurs a loss in their market value, which is a possible source of financial market instability.

This study has three objectives. First, we show that significant losses exist in the bond market even after controlling for bond and market characteristics. Using a unique data set from China, which contains trades of more than 2,350 Treasury bonds in primary and secondary markets from 2004-2017, we calculate the difference between primary and secondary market returns-the effective return for a bond.[49] We exploit the rare timing structure of the Chinese government bond issuance process where short trades are strictly prohibited. Due to the simple market structure and the no-short-trade regulation, we are able to investigate the channel and information structure of systemic risk observed in post-auction periods. Another advantage of our measurement is that it allows us to focus on an analysis of potential liquidity constraints rather than a combination of liquidity and short-position constraints. Differently, previous studies had to develop empirical strategies to measure bond losses (or gains) as it is required to disentangle speculative short trades under the intricate information revelation environment (Jordan and Jordan, 1997; Nyborg and Strebulaev, 2003).

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

[49] 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/ourinsights/ China-Bond-Market-Development-2017-in-Review.html.

informative for policymakers who are interested in understanding financial markets during a recession or who are interested in government security market (in)stability.

The second objective of this study is to explore the question: if financial losses are prevalent for primary market dealers, what is the possible market mechanism behind these losses? In line with the Reuters (2018) quote above, we hypothesize that, when facing high borrowing costs, primary market dealers are willing to liquidate their on-the-run bonds at a loss in order to minimize their financial distress. To test this possible explanation for bond market losses, we examine whether a change in the REPO rate can predict individual bond losses.[50] As suggested by Reuters, the REPO rate is considered the best indicator of general liquidity in China. Further, we investigate the volume of secondary market debut-day trades when the REPO rate is high. We expect the volume of bond trades to be higher when primary market dealers face high borrowing costs as they can generate cash using bond sales (meaning that the supply of bonds in the secondary market is higher). The results indicate that, when REPO rates are high, the probability of observing bond losses is higher and the secondary market volume is also higher.

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

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

To investigate this hypothesis further, we examine the movements of the Chinese FTSE Russel financial indexes on debut-days when Chinese primary market dealers suffer significant secondary market bond losses.[51] In this exercise, we first identify secondary market debut-days with significant bond losses using all secondary market debut-dates in which we observe only all positive or all negative margins. We then create a balanced panel for these secondary market transactions with FTSE banking and security sector indexes two days prior to and two days after the secondary market debut date. Using this data, we estimate a model in the difference-in-difference (DID) spirit to examine the impact of bond losses on the financial sector. We find that FTSE indexes fell significantly--by about 0.5-0.7 percent--following bond loss days compared to all positive days. This means that a negative return on an initial secondary market trading day transaction (which could have been caused by just one primary dealer) generates a disturbance in the entire Chinese financial sector's capitalization value. This finding further supports our hypothesis that bond losses can lead to financial market instability and also indicates that bond losses play a sizable informational role. Similarly, the fact that REPO rates remain the same after negative transaction days also suggests that bond losses can lead to financial market instability.

This study contributes to the literature on government security auctions and their market design. Preceding studies of Treasury auctions and related bond markets have concentrated on which auction format generates higher revenues (i.e., lower yields) for

[51] 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.

Treasuries.[52] However, yield (or price) gaps in financial assets, specifically between primary and secondary markets, have been called to attention by financial economists as well as scholars studying friction in financial markets. Among a few influential studies, Nyborg and Sundaresan (1996) investigate mark-ups and information ow before and after bid submissions.[53] We contribute to this literature by investigating the inter-market yield gap and its informational role in market stability.[54]

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

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

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

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

In addition, our study contributes to the literature on government security issuance market (in) stability. Preceding studies focus on instability related to short squeezes (e.g., Jegadeesh, 1993; Jordan and Jordan, 1996; and Nyborg and Strebulaev, 2003). In the spirit of this literature, our study investigates potential policy options that could curb abnormal market behaviour. Specifically, we investigate which auction mechanism-uniform or discriminatory-is better at reducing losses. As we show, negative margins in the bond market can have a significant effect on the capitalization value of the financial sector. Thus, a government interested in promoting financial stability would benefit from knowing which auction mechanism best mitigates bond losses. To the best of our knowledge, this study is the first to show a linkage between bond losses (a possible indicator of winner's curse), liquidity constraints, auction mechanisms, and financial sector-wide instability, as well as clarifying the information transmission channels behind them.[55]

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

[55] 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.

The remainder of the study proceeds as follows: The next section gives a background to the Chinese government bond-issuing institutions, and their primary and secondary markets. Section 4.3 describes the data, employing summary statistics. Section 4.4 defines the debut-day measure of returns in the Chinese bond market. Section 4.5 investigates borrowing cost-based liquidity constraints and bond losses. Section 4.6 reports results on the relationship between bond losses and financial stability. Section 4.7 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 4.8 concludes the analysis.

4.2 Institutional background

4.2.1 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).

4.2.1.1 The Chinese Ministry of Finance

Initiated by the MOF, the history of Chinese government securities was closely related to the establishment and economic development of the People's Republic of China (PRC). In 1949, the MOF launched their first bonds, called “People's Victory Bonds,” to fund large military expenditures and regenerate the national economy. In 1953, three years after the founding of the PRC, to rebuild the economy and complete “The Plan of the First Five Years,” the MOF decided to issue bonds to cover a large financial deficit. These securities were called “National Economic Construction Government Bonds,” and the bond issuance lasted until 1958. These two bonds were regarded as the precursors to today's Chinese government securities. However, between 1958 and 1980, China did not issue any bonds.

In 1979, the Chinese government implemented a profit-retention scheme among state-owned companies, which led to an increase in the discrepancy between fiscal revenue and expenditure.[56] Accordingly, in early 1980s, the Chinese government suffered from a fiscal deficit. In 1981, to solve this fiscal challenge, the Chinese government decided to resume issuing bonds.[57] Since the early 1980s, the contemporary Chinese bond market has developed rapidly, and the MOF began to use a system of primary dealers in 1993. In 1995, for the first time, the MOF used auctions as a mechanism to sell government securities. Subsequently, in 1996, auctions became the only method used to issue bonds in the primary market.

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

[56] Shen and Cao (2014. p4).
[57] 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.

limit.[58] However, since 2016, the MOF has discontinued using discriminatory auctions, and has started using only hybrid auctions to sell bonds with maturities of less than one year. Accordingly, the MOF currently only uses uniform and Spanish auctions to sell its bonds.

4.2.1.2 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.

4.2.1.3 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

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

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 4.7.

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.

4.2.2 Chinese bond issuers and credit ratings

In this subsection, we discuss the credit ratings associated with the four Chinese government and policy bank security-issuing institutions. There are three major institutional rating characteristics and they are: (i) credit ratings are homogeneous within each year during our period of analysis; (ii) bonds issued by the four institutions are all backed by the Chinese government; (iii) ratings for individual bonds are non-existent. Tables 4.A.1 and 4.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.[59] 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.[60] Thus until recently, each Government Security auction was held without an individual bond credit rating.

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[59] 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-gainsa-little-independence

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

4.2.2.1 The selection of primary dealers

In order to bid in Chinese government security auctions, primary dealers must be prequalified. The MOF's primary dealer groups were organized once a year from 2000 to 2008, and the frequency changed to once every three years since 2009. In order to identify qualified primary dealers, the MOF created a document of prequalification rules, known as Management Rules of Organizing Treasury Bond Underwriting Groups. The prequalification is based on each dealer's financial capacity, past performance, value, and volume of trading over the past three years. An independent committee of experts ranks primary dealers according to these criteria. Based on this ranking, the MOF chooses the primary dealers that can participate in the primary market. For the MOF, for instance, if the target number of primary bidders is 50. The top 45 primary dealers are allowed to continue for another year (or term), and other dealers compete for the remaining five seats.[61] 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.[62] In this study, we refer to all prequalified dealers as “primary” dealers.[63]

One of the most distinctive characteristics of primary dealers in China is their overlapping nature across the four bond-issuing institutions. As Figure 4.1 shows, during the period 2004-2017, more than 50 percent of primary dealers submitted bids

[61] 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.

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

[63] The number of registered bidders is plotted in Figure 4.A.1, while Figure 4. A.2 plots the year-to-year continuing incumbents. More than 90 percent of bidders continue from the previous year, and more than 50 percent of bidders who participated in 2004 are still in the market in 2017 (see Figure 4.A.3).

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.

4.2.2.2 Secondary market of government and policy bank bonds

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

Chinese government and policy bank bonds have a rigorous timeline regarding secondary market appearance. Specifically, primary market participants are prohibited from trading newly issued bonds at a secondary market for a certain period after an auction-typically five business days.[64] 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.[65] Thus, in China, financial

[64] 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.
[65] 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-

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

4.3 Data

4.3.1 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.[66]

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.[67] Further, our study use data only from bonds issued through auctions, as information about issue rates

issued transactions are not considered in this study. Visit the website for details: http://www.sse.com.cn/services/tradingservice/tbondp/home/.

[66] 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.

[67] 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.

(or prices) are only available for auctioned bonds. Note that since 2004 all institutions started relying only on auctions to sell their bonds.

The Wind Database provides access to details of primary market data on bond auctions held by the MOF, CDB, EIB and ADB from 1998 to 2017. Our data contains not only information of auctioned bonds, such as bond ID, maturity, auction method, size of each auction, and tender subjects (e.g., price or rate), but also the auction outcomes of weighted-average winning rate (or price), low and high winning rates, total demand, number of bidders, number of bids, number of winners, number of winning bids, and final coupon rate for each auction, as well as the presence or absence of floating coupons. We collected supplementary information from Chinabond.com, such as bond types, subsidies, coupon payment, and the frequency for each bond. These two datasets provide more than 2,900 primary market auctions. The Wind Database also provides relevant data of secondary re-sale 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.[68] This allows us to match each primary and secondary transaction by bond ID, which is a unique feature of our data.

The Wind Database also provides secondary market yield data. As in Keloharju et al., (2005), we use the secondary market yield curve to calculate resale market volatilities by maturity. On each business day, the CCDC announces yield curves for bonds issued by the MOF, CDB, EIB, and ADB. These yield curves are based on the previous period's resale market transactions and provide official bond market information to investors. Daily yield curve data for each institution is available, since 2002 for the MOF and

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

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.

4.3.2 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.[69]

Table 4.1 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%.[70] 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

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

[70] 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.

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 economic fundamentals) could change in the short time between the auction and the secondary market debut-days. We first show the average volatility of yield curves _ve 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.[71] 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.[72]

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

[72] 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.

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.

4.4 Returns in the Chinese bond market

4.4.1 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 4.2 shows the cumulative distribution (CDF) of this raw margin for our data. As we can see, many transactions are negative. However, we caution against the direct interpretation of this gap (or return) as bond losses, because this distribution is not controlled by any auction, bond, and financial market characteristics, which could vary between the primary auction day and the debut-day. Hence, our next step is to remove the observable effects of auction, bond, and market characteristics from this raw margin.

This removal will allow us to obtain a measure of the adjusted margin that is not driven by observables. Specifically, given the unique market and information structure, our measurement has a noisy public signal interpretation, which may reveal liquidity constraints within a primary market bidder (or bidders). The procedure to obtain this conditional measure is as follows. Specifically, we follow a bid homogenization introduced by Haile et al. (2006), which is widely used in empirical auction studies. First, we estimate the following regression, explaining the observed margin for a given bond (i) by institution (j) as a function of auction (x), bond (z), and market characteristics (m), as seen in Equation 4.1.

$$margin_{ijt} = \alpha + z'_{ij}\gamma + m'_{it}\omega + \theta_j + \tau_t + \epsilon_{ijt} \tag{4.1}$$

where τ is the time fixed-effects, θ is the institution effect, α is the constant, and

ϵ is the residual. First, in the right-hand side of Equation (4.1), x, z, m and fixed effect terms are known to the financial market participants. Thus, ϵ captures the unobservable variation of the return that is not explained by the observable variables, including the privately-possessed liquidity constraint information. Here, the term of "unobservable" means unobserved information to researchers and general financial market participants, except bidders who sell on-the-run issues on debut-days (and who know the reasons behind the debut-day reselling activities). Second, _ plays a role of a noisy public signal.[73] ϵ is noisy because financial market participants (except bidders who sell on-the-run issues) do not know the exact motive behind the trade. On the other hand, as the transacted secondary market yields are publicly posted on the

[73] 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.

interbank market and other websites with bond IDs (but without the identities of the traders), every financial market participant can monitor ϵ.[74] Third, the homogenized margin 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.

As the residuals in Equation 4.1 by construction have a mean of zero, we subtract the mean market rate of return from the residuals to obtain the adjusted margin (Equation 4.2).

$$margin_{ijt}^{*} = \widehat{\epsilon_{ijt}} - \overline{\widehat{margin}} \quad (4.2)$$

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

Table 4.2 presents the estimated parameters and explains the market gap (i.e. return), as in Equation 4.1. In Column 1, we present results from the model that are estimated while excluding our financial market volatility and trend measures. This is our baseline model, to which we compare the sensitivity of parameters when re-estimated with market controls. Results indicate that floating coupon bonds reduce the margin compared to bonds without any coupons. The log number of bidders in an auction

[74] 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.

tends to induce aggressive bidding and increase the market gap, which is consistent with auction theory. Results indicate that, if the time lag between the primary and secondary market debut-day is longer, primarily due to public holidays, then this time lag tends to increase the margin. Additionally, the coefficient of the previous month's trading volume indicates that, if the trading intensity is high, then the margin is low, which is consistent with liquidity premium theories. Finally, the volatility, constructed using the previous five days' yield curve information at a given maturity, indicates that, if the market is volatile, then the margin is high.

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

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

Note that not all of the on-the-run bonds are resold on their debut-days. A concern one might have with these margin regressions is selection bias after controlling for covariates, and bonds that were traded are not randomly selected. Given that we observe all primary and debut-day secondary market transactions, we address this concern by using a Heckman-based correction model. We specify the probability of selling on the first allowed trading day in the secondary market (the selection equation) using the same variables in the outcome equation given in Column 5 of Table 4.2, 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 4.2, using the quantile regression method proposed by Koenker and Bassett (1982). We report these results in Table 4.A.5 in Appendix 4.A. Qualitative interpretations of the coefficients are similar to what we observed in Table 4.4 and, hence, we do not discuss these results in detail. The main point is that the patterns discussed in the mean regression hold throughout the distribution of margins as well.

However, in all models, the controls explain some variation, but not all. In Figure 4.3, we plot the fitted margins (from Equation 4.1) and adjusted margins (from Equation 4.2). In the figure, we use predicted margins and residuals obtained after estimating the empirical model described in Column 5 in Table 4.2, and use them to construct the adjusted margins as described in Equation 4.2. Now, we compare the CDFs of fitted (un-adjusted) margins (Figure 4.2) with the adjusted margins (Figure 4.3). 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 4.3, we observe that, on average, the market generates positive returns (adjusted margins). However, about 20% of transactions suffer losses. In Table 4.3, we present the distributional statistics of the adjusted margins with 95% confidence intervals. We observe that, at the bottom part of the distribution, negative values indicate the losses with statistical significance.

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

Next, we re-estimate the market gap regressions (Equation 4.1), previously seen in Table 4.2, with the control for the secondary market volume. These regression results are reported in Table 4.4 and they are qualitatively similar to those reported in Table 4.2.[75] However, these data provide an opportunity to calculate the gains and losses for the volumes sold in the secondary market.

In Table 4.5, we report the summary statistics for the gains and losses (positive and negative adjusted margins) based on regression results presented in Column 5 of Table 4.4. 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

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

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).

4.4.2 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 4.2.[76] However, we now construct the adjusted margins before, during, and after the crisis. These results are presented in Table 4.6. We also draw the CDF of these homogenized margins, and they are presented in Figure 4.4.

The results indicate that, during the crisis years, the adjusted margins were negative and with higher magnitudes in the bottom half of the distribution, including the 50th percentile. This pattern was not observed before or after the financial crisis, indicating that bond losses were more prevalent during 2008-2009. However, after 2009, our results in Table 4.6 show that the adjusted profit margins have increased for primary dealers and this difference is statistically significant.

In Table 4.7, we breakdown the gains and losses by period. The basic interpretation is similar to Table 4.5. However, during the 2008-2009 period, the average losses were

[76] We also estimate these models using dummies to indicate the crash and after-crash periods. These OLS and quantile models are presented in Table A.6 and Table 4.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.

about 2.8 times larger than the average gains. To be specific, during the financial crisis, the average gains were about U 45.90 million, while the average losses were ¥ 128 million per transaction.

Next, as we noticed, in Table 4.2, 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 4.1, using only uniform bonds sold since 2007. Details of the analysis and regression results are presented in Appendix 4.B.

4.5 Liquidity constraints and bond losses

Having defined bond losses, in this section, we examine whether we can predict bond losses when the financial market faces high money market borrowing costs, i.e., when the costs of intertemporal substitutions for alleviating current liquidity shortage are high. First, we identify secondary market transactions and days in which all traded bonds generated negative adjusted margins, and at least one transaction generated a loss that fell below the bottom 10th of the distribution. This explains the observation of a negative adjusted margin of 15.7%.[77] We identify 52 days (out of 1,185 days) where all transactions incurred losses. This classification works as our most restrictive sample, and we later relax the cut-off threshold on these definitions of losses. We denote a transaction with a loss (loss = 1) and a day where all transaction incurred losses (all losses = 1).

As represented by the Reuters' report, the best indicator of general liquidity in China is the seven-day REPO rate. Hence, we use the REPO rate as a proxy for liquidity

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

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

First, at the transaction level, we use a simple probit to examine the probability of observing bond losses on trades given the REPO rate of the debut-day. We report these results in Table 4.8, Column 1 Panel A. Note that these losses are based on our adjusted margins, and hence they have been estimated after controlling for bond, auction, and market characteristics. The positive and significant coefficient of the REPO rate indicates that when the market observes a high REPO rate, there is a higher probability of observing bond losses in the secondary market. In Column 2, we report the results for auctions with available records of secondary market volumes. The results are similar to what we observe in Column 1. Next in Column 3, we examine a different construction of the dependent variable, which is equal to one on a debut-day when all adjusted margins are negative, and otherwise zero. Our probit results indicate that when the REPO rate is high on a given day, then there is a higher probability that all secondary market transactions are losses on that day.

Next we examine whether the traded volume is affected by the REPO rate, at both transaction and debut-day levels. Here our dependent variable is either (i) secondary market traded volume by bond (in logs), compared to its primary market auctioned volume (in logs), or (ii) the total secondary market volume of all bonds for a given trading day (in logs), compared to these bonds' total primary market volume (in logs).

In Columns 4 and 5 we report these results estimated using OLS. Both columns indicate that when liquidity constrains are tighter, secondary market trading volumes are higher, compared to low liquidation cost days. It is possible that our results from this analysis are driven by the market crash in 2008 and 2009. Hence, we re-estimate these models without bond transactions between 2008 and 2009. These results are presented in Panel B. The results indicate that our findings are not sensitive to the market crash, and are thus robust.

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

4.6 Bond losses and financial stability

Now we turn our attention to the effect of bond losses on financial instability by analysing what happened to the FTSE Russel Chinese financial indexes -consisting of representative bank, security, and insurance sector public companies –on the days when Chinese primary market dealers suffered substantial bond losses. As we mentioned earlier, the FTSE Chinese financial indexes provide broad coverage of the Chinese stock market and financial institutions. Hence, any movement on these indexes reveals information about the financial health of banks and insurance companies in China. We exploit the fact that more than 90 percent of financial institutions that represent the FTSE banking, security, and insurance indexes are also primary dealers. In Table 4.A.8, we present a breakdown of the number of primary banks that represent the FTSE indexes.

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

First, as above, we use secondary market debut-days with at least one transaction where the adjusted margins fall below the bottom 10th (-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 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

$$I_{it} = \beta_1 N_i + \beta_2 T_t + \beta_3 N_i \times T_t + \alpha_{it} + \varepsilon_{it} \quad (4.3)$$

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 4.9, Panel A. Note that all +/- day indexes values are normalized by the corresponding secondary market trading day value.

We estimate the above model with a plus-minus one day time span, as well as with a plus-minus two days span. Further, we estimate these models without years 2008 and 2009. The results indicate that banking index fell by about 0.6-0.8 percent following days with bond losses. These panel regression results support our hypothesis that bond losses could lead to financial market instability, at least in (but not limited to) the financial sectors' capitalization values. Similar patterns are observed for the security index (See Panel B in Table 4.9). Next, we estimate a similar model where the dependent variable is the REPO rate, normalized by the debut date value. The coefficient of interest, β_3, indicates that the REPO rate is not responsive to the observed bond losses (Panel C in Table 4.9). This result further support our hypotheses that financial indexes respond to bank losses, while money market rates do not.[78]

4.7 Auction mechanisms and bond losses

In the previous section, we demonstrated that bond losses are prevalent in bond markets, and that such losses generate a drop in the entire Chinese banking sector's stock capitalization value. A government that cares about financial stability may consider all available policy instruments to stabilize the market. In the context of the financial bond market, the government, as a bond issuer, can use different auction

[78] 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.

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.[79]

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

4.7.1 Alternating auction rule experiment

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

Each week, the CDB auctioned o_ bonds with maturity lengths of 3, 5, and 7 years. However, as shown in Table 4.A.9, each week they alternated the auction mechanism

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

between the discriminatory and uniform formats. The CDB repeated this pattern of alternating auction rules between May 2012 and July 2014.[80] The EIB also implemented a similar experiment design with the alternation of uniform- and discriminatory- auction formats. As shown in Table 4.A.10 Panel A, in the early part of their experiment, the EIB alternated between auction formats every two or three months. In the second half of the experiment, the EIB alternated the auction format for the same type of bond (identified by bond ID and initial and reissue status). We note this market experimentation for two bonds in Table 4.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 them were using discriminatory auction format while 139 were sold using uniform auctions 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).[81]

An important feature of experiment conducted by the CDB and EIB is that bidders know the format of a given auction only five days before it occurs. This means that, when they are participating in a typical auction, they do not know the format of the upcoming auctions. This is an important feature of the experiment, as bidders will not

[80] 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.

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

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 4.1 and 4.2) for this period. OLS and quantile results are presented in Tables 4.10 and 4.A.11.[82] 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 4.7, we plot these adjusted margins by uniform and discriminatory auction formats.

Figure 4.7 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.[83] Table 4.11 supports the evidence provided in Figure 4.7 and indicates that the margins generated from uniform auctions are larger than the margins generated from discriminatory auctions.[84]

Next, we also re-estimate the market gap (Equation 4.1) controlling for volume. We have only 74 observations (out of 348) with volume records during the experimental

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[82] 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.

[83] 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].

[84] 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 4.A.12 in the Appendix 4.A. Table 4.A.13 and Figure 4.A.5 present adjusted margins that have been constructed by using high, low, and weighted average winning primary

period. However, our results indicate that the basic findings are similar to the ones we find in Table 4.4.[85] 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).

4.7.2 Policy Implications

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

4.8 Conclusion

In this study, 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

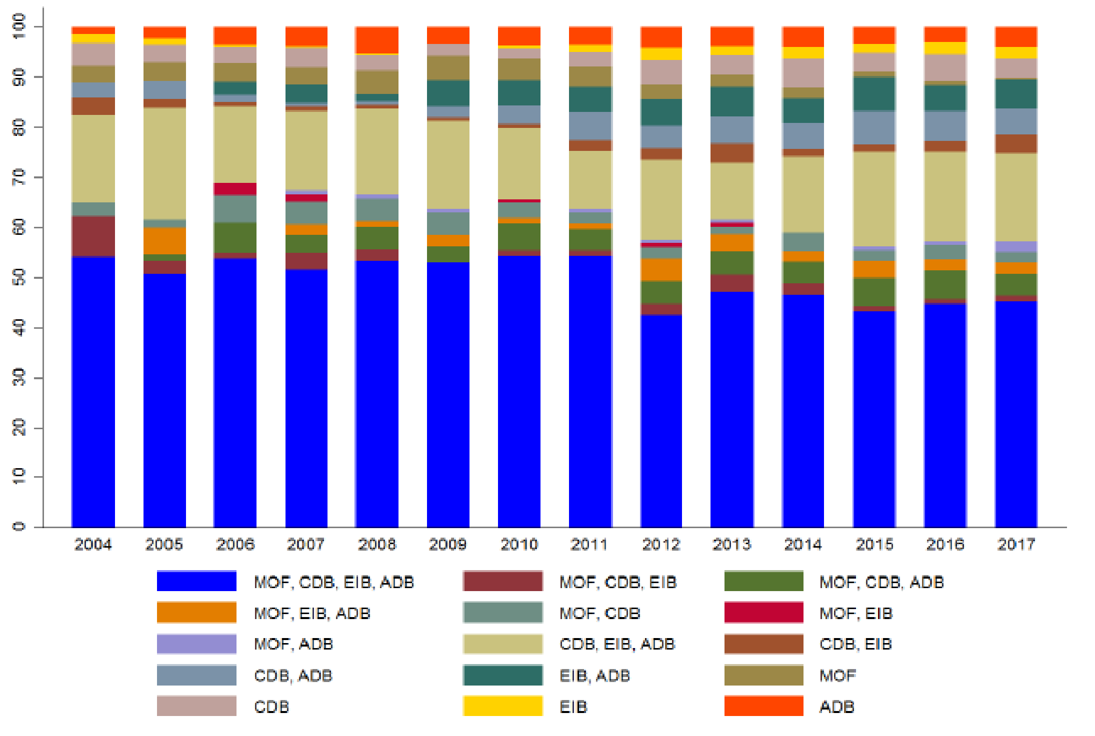
[85] We do not report these results but can provide upon request.

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

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

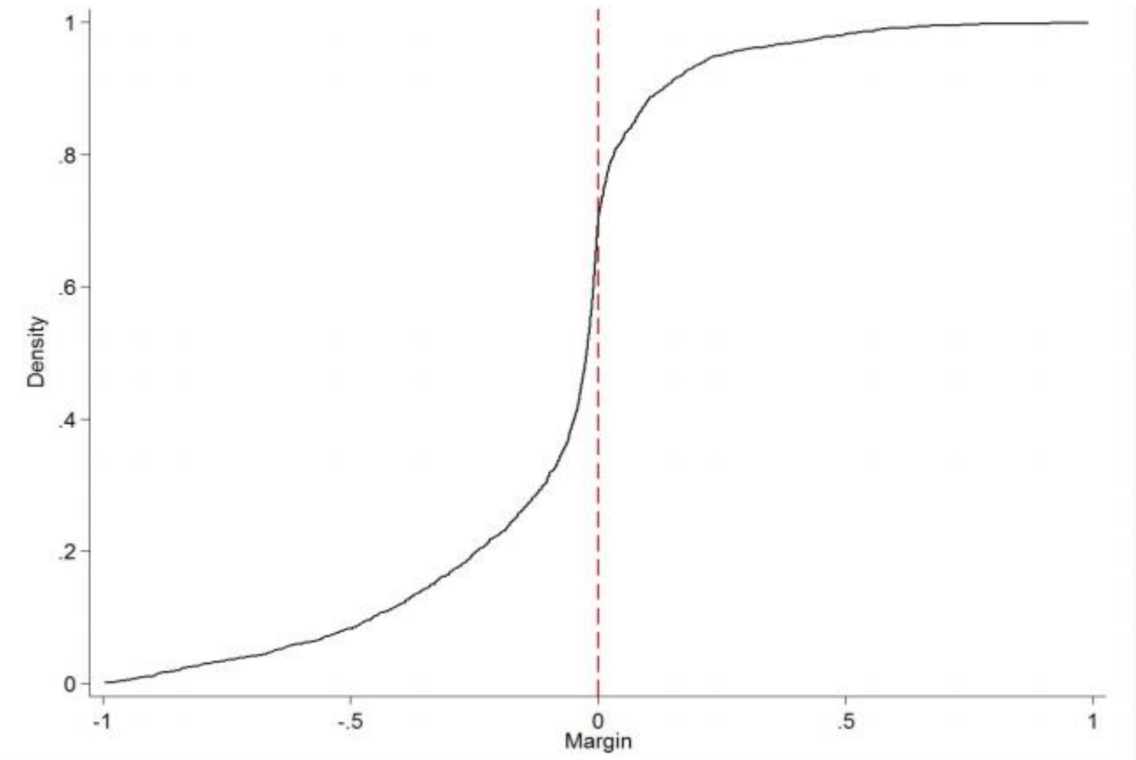
4.9 Figures and Tables

Figure 4.1: Primary dealer overlap



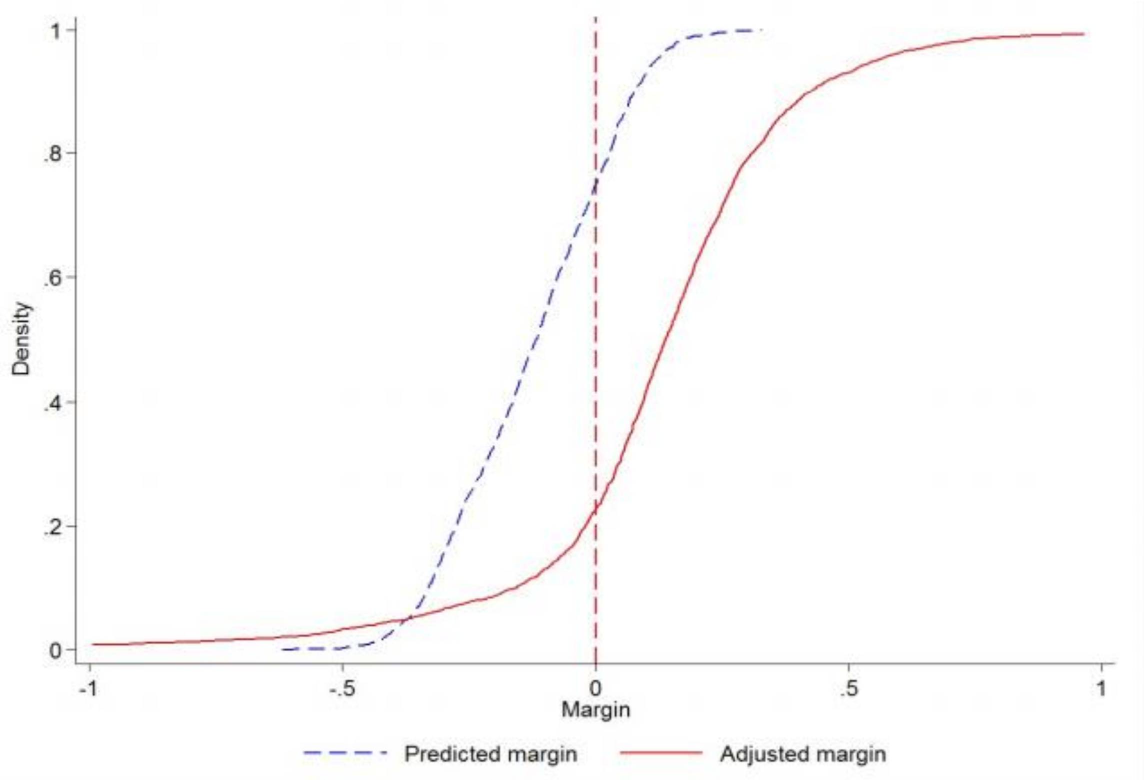
Notes: In this figure, we show the overlapping nature across the four bond-issuing institutions. During the period 2004- 2017, about 50 percent of primary dealers submitted their bids in all MOF, CDB, EIB, and ADB auctions. Moreover, around 25 percent of primary dealers submitted bids across three policy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

Figure 4.2: Raw margin



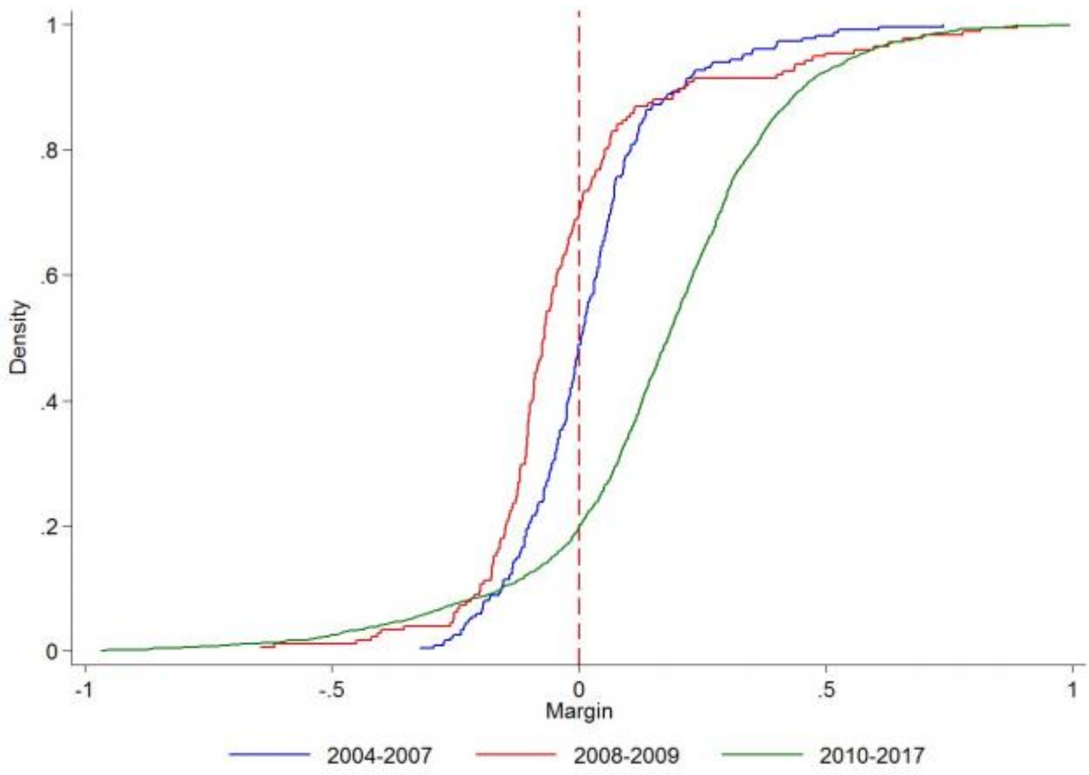
Notes: This figure shows the cumulative distribution (CDF) of the raw margin. We define the margin for a given bond as the primary minus secondary market rates. This distribution is not controlled by any auction, bond and financial market characteristics.

Figure 4.3: Adjusted margin



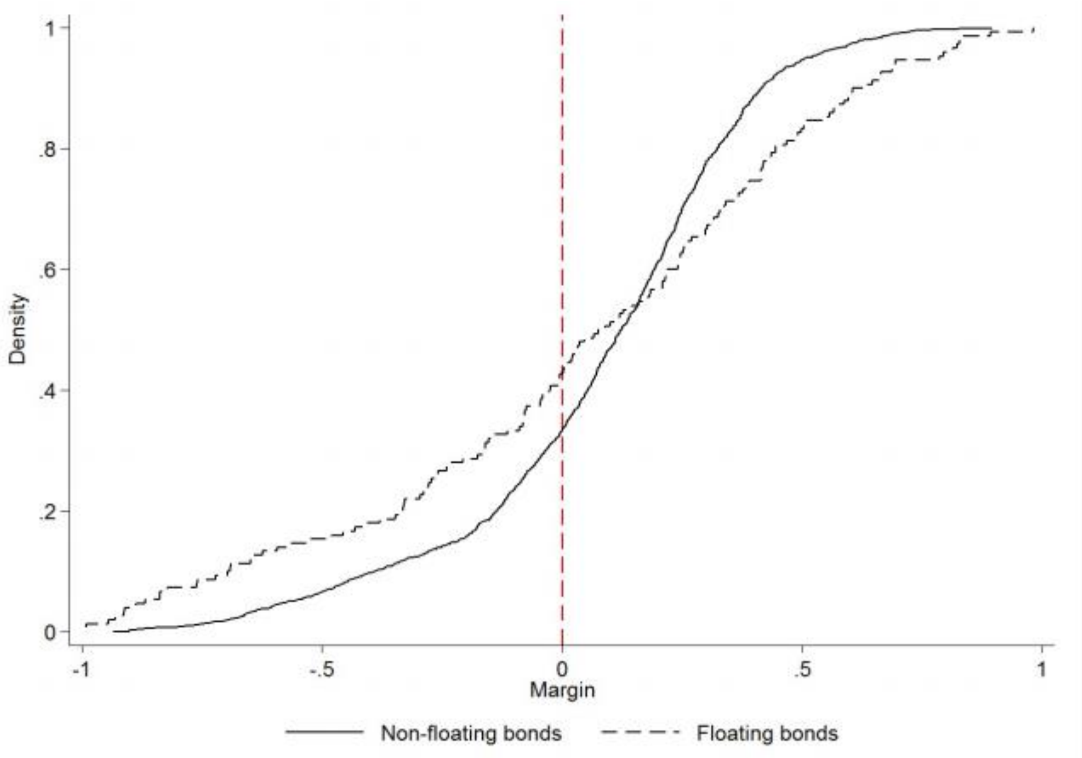
Notes: In this figure, we plot the CDF of fitted margins (From Equation 4.1) and adjusted margins (From Equation 4.2). Here, we use predicted margins and residuals obtained after estimating the empirical model described in Column 5 in Table 2. Then we use them to construct the adjusted margins as described in Equation 4.2.

Figure 4.4: Adjusted margins by period



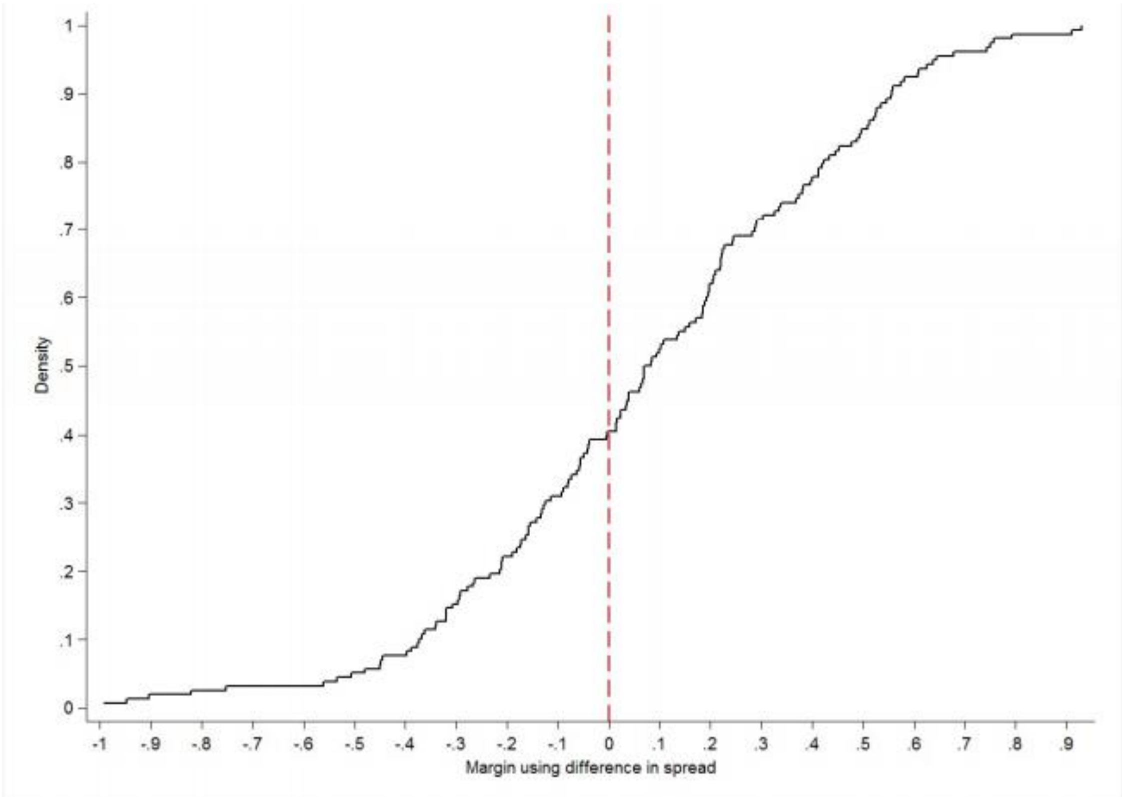
Notes: In this figure, we plot the CDF of adjusted margins before, during, and after the 2008-2009 crisis. We use predicted margins and residuals obtained after estimating the empirical model described in Column 5 in Table 2 to construct the adjusted margins by period.

Figure 4.5: Adjusted margins for floating and non-floating bonds



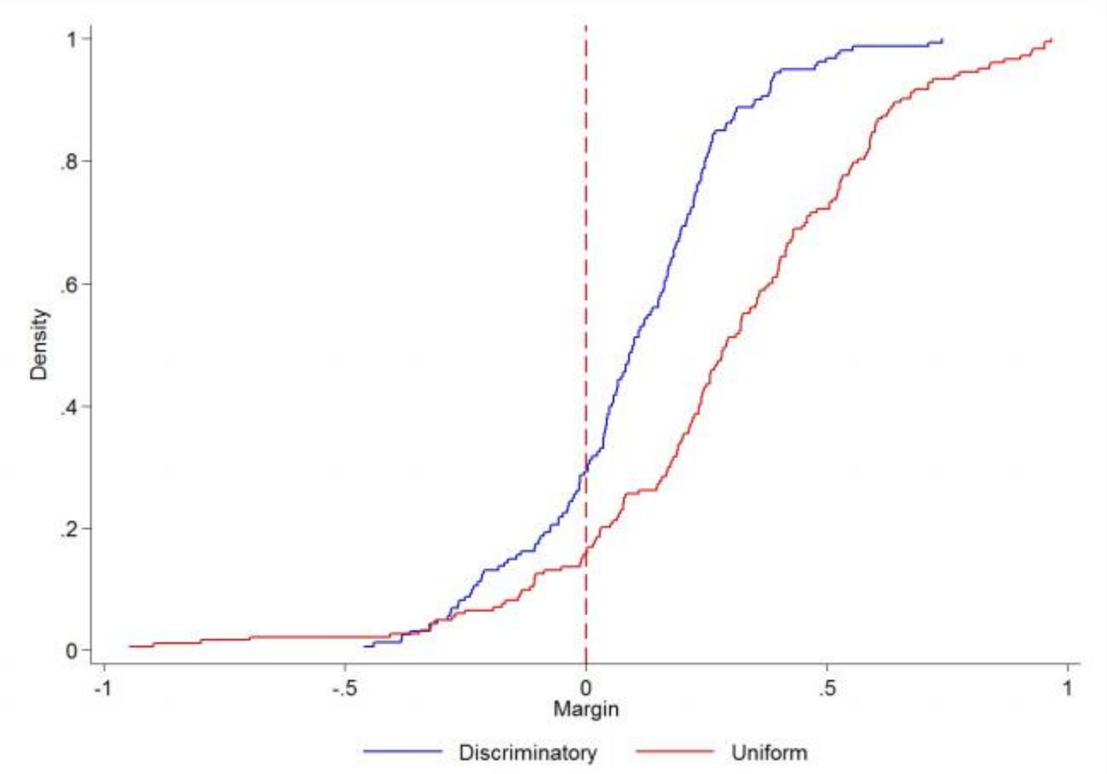
Notes: In this figure, we show the CDF of adjusted margins by bond type. Note that floating bonds were sold using only the uniform auction format since 2007.

Figure 4.6: 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 4.7: 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 4.1: Summary statistics

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 market debut day	0.017
	(0.011)
REPO rate (in percentage)	3.062
	(1.131)
Government yield gap between a primary auction date and a day before the	-0.003
secondary market (in percentage)	(0.093)
Value of maturing bonds by institution for a given month (in ¥ 100,000)	2,823,731.00
	(3,270,008.00)

This table reports summary statistics of data used in the analysis 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.

Table 4.2: Regression results for market gap

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

This table presents the estimated parameters and explains the market gap (margin), as in Equation 4.1. 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.

Table 4.3: Adjusted margins

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

This table presents the distributional statistics of the adjusted margins. 95% confidence intervals are in parentheses. For constructing the adjusted margins, as described in Equation 4.2, we use predicted margins and residuals obtained after estimating the empirical model described in Column 5 in Table 4.2

Table 4.4: Regression results for market gap with volume

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

This table presents the estimated parameters and explains the market gap (margin), as in Equation 4.1. 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.

Table 4.5: Gains and losses

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

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 4.4. Standard deviations are in parentheses.

Table 4.6: Adjusted margins during 2004–2007, 2008–2009, and 2010-2017

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

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.

Table 4.7: Gains and losses by period

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

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 4.4. All basic interpretation is similar to Table 4.5. Standard deviations are in parentheses.

Table 4.8: Effect of REPO rate on adjusted margins and volume

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

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 _rst 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.

Table 4.9: Bank and security index variation

Variables	All years		Without 2008-2009	
	+/- One day	+/- Two days	+/- One day	+/- Two days
	(1)	(2)	(3)	(4)
Panel A: Bank index				
Negative adjusted margin trades	0.003***	0.003**	0.003***	0.003**
	(0.001)	(0.001)	(0.001)	(0.001)
After the secondary market trades	0.000	0.001	0.000	0.001
	(0.001)	(0.000)	(0.000)	(0.000)
Negative adjusted margin trades × after the secondary market trades (*β3*)	-0.007**	-0.007***	-0.006**	-0.007***
	(0.003)	(0.002)	(0.003)	(0.002)
Observations	5,742	9,570	5,217	8,695
R-squared	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 × after the secondary market trades (*β3*)	-0.006**	-0.005**	-0.005*	-0.005**
	(0.003)	(0.002)	(0.003)	(0.002)
Observations	5,751	9,585	5,226	8,710
R-squared	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 × after the secondary market trades (*β3*)	0.000	0.000	-0.000	-0.000
	(0.149)	(0.111)	(0.152)	(0.113)
Observations	5,742	9,570	5,217	8,695
R-squared	0.002	0.002	0.001	0.001

This table reports results for the panel regression (event study) model to examine the impact of bond losses on the financial sector. The first two columns report results for all years, while the last two columns report results without 2008 and 2009. We are interested in the value of the coefficient of β_3, which measures the di_erence 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.

Table 4.10: Regression results for market gap during the alternating-rule experiment

Variable	Primary rate -secondary rate				
	(1)	(2)	(3)	(4)	(5)
DA	-0.043	-0.050	-0.042	-0.049	-0.050
	(0.033)	(0.034)	(0.033)	(0.034)	(0.034)
Floating coupon bond	-0.791***	-0.799***	-0.792***	-0.800***	-0.801***
	(0.089)	(0.087)	(0.089)	(0.087)	(0.087)
Log number of bidders	0.350**	0.341**	0.350**	0.341**	0.342**
	(0.169)	(0.164)	(0.170)	(0.165)	(0.166)
Lag of days between primary 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 secondary market		4.758**		4.908**	4.983**
		(2.212)		(2.218)	(2.229)
Government yield gap between primary auction date and day before the secondary market			0.092	0.135	0.142
			(0.153)	(0.154)	(0.155)
Log value of maturing bonds by institution for a given month					0.007
					(0.010)
Institution effects	Yes	Yes	Yes	Yes	Yes
Month & year effects	Yes	Yes	Yes	Yes	Yes
Observations	348	348	348	348	348
R_2	0.553	0.559	0.553	0.560	0.560

This table reports the OLS results for the market gap between uniform and discriminatory auction formats during the alternating experiment period. All explanatory variables are similar as Table 4.2. 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.

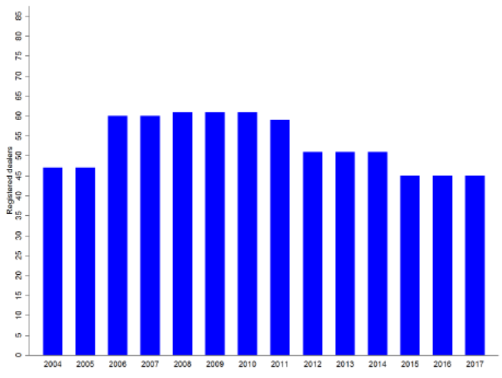
Table 4.11: Adjusted margins during the alternating-rule experiment by auction mechanism

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

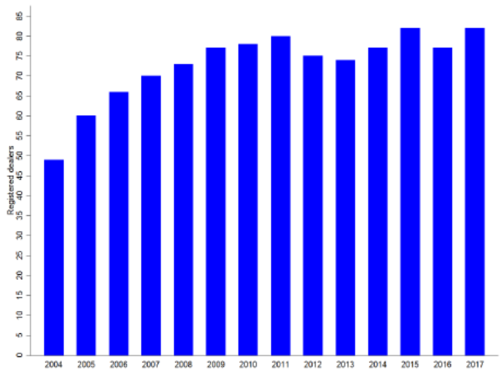
This table reports the distributional adjusted margins for discriminatory and uniform auctions for selected percentiles. In this exercise, we use the data from the alternating-rule market experiment period only. This experiment is conducted by CDB and EIB from 2012 to 2015. 95% confidence intervals are in parentheses.

Appendix 4.A Extra figures and tables

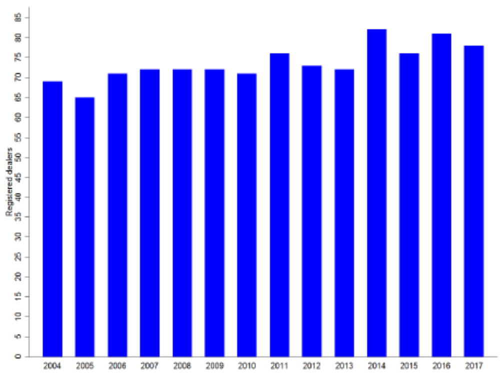
Figure 4.A.1: Registered primary dealers



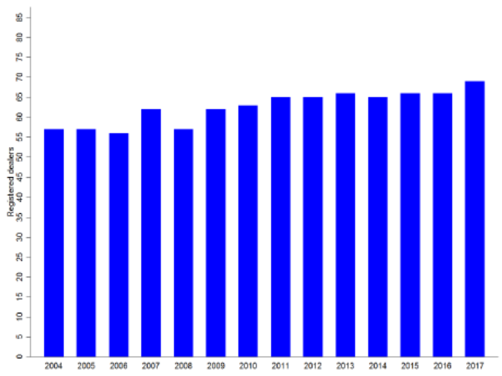
Panel A: MOF



Panel B: ABD



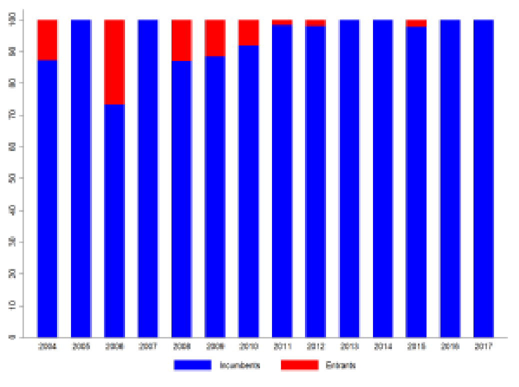
Panel C: CDB



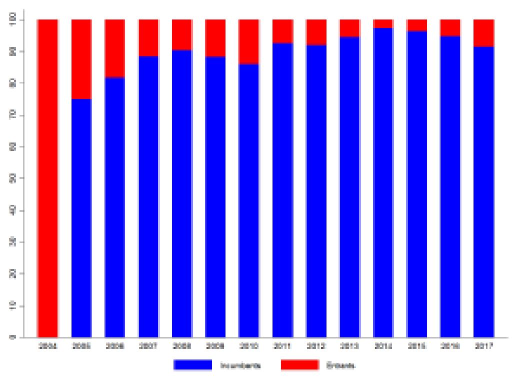
Panel D: EIB

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).

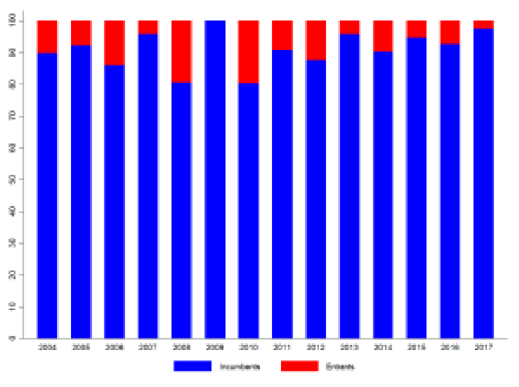
Figure 4.A.2: Ratios of incumbents and entrants



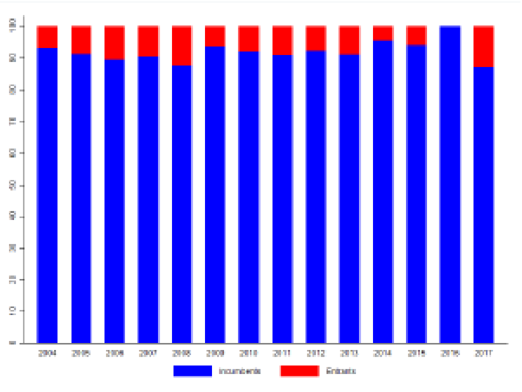
Panel A: MOF



Panel B: ADB



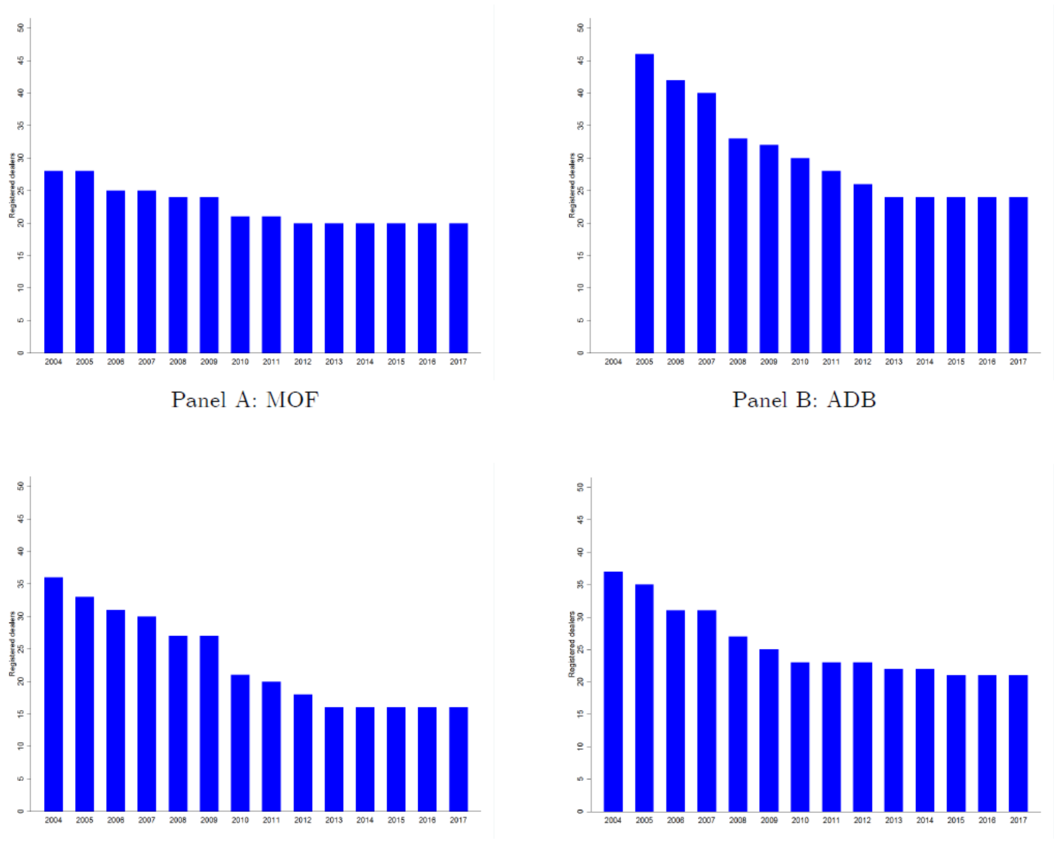
Panel C: CDB



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 4.A.3: The number of continuing primary dealers



Panel A: MOF

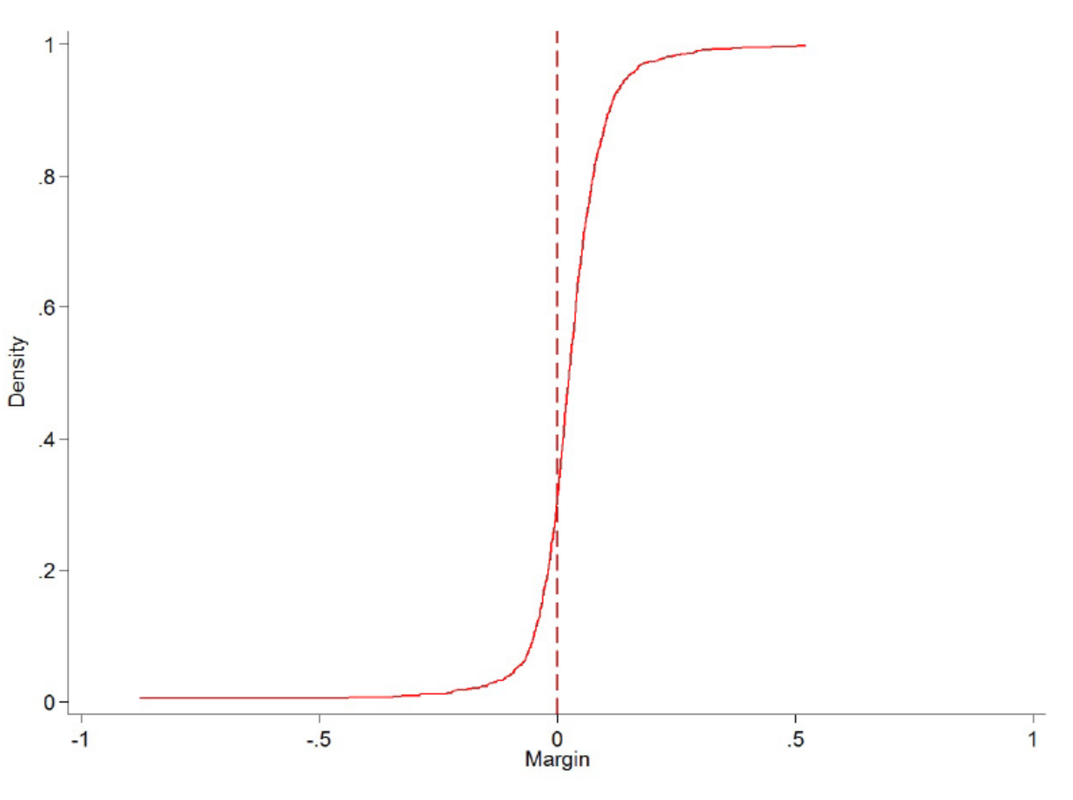
Panel B: ADB

Panel C: CDB

Panel D: EIB

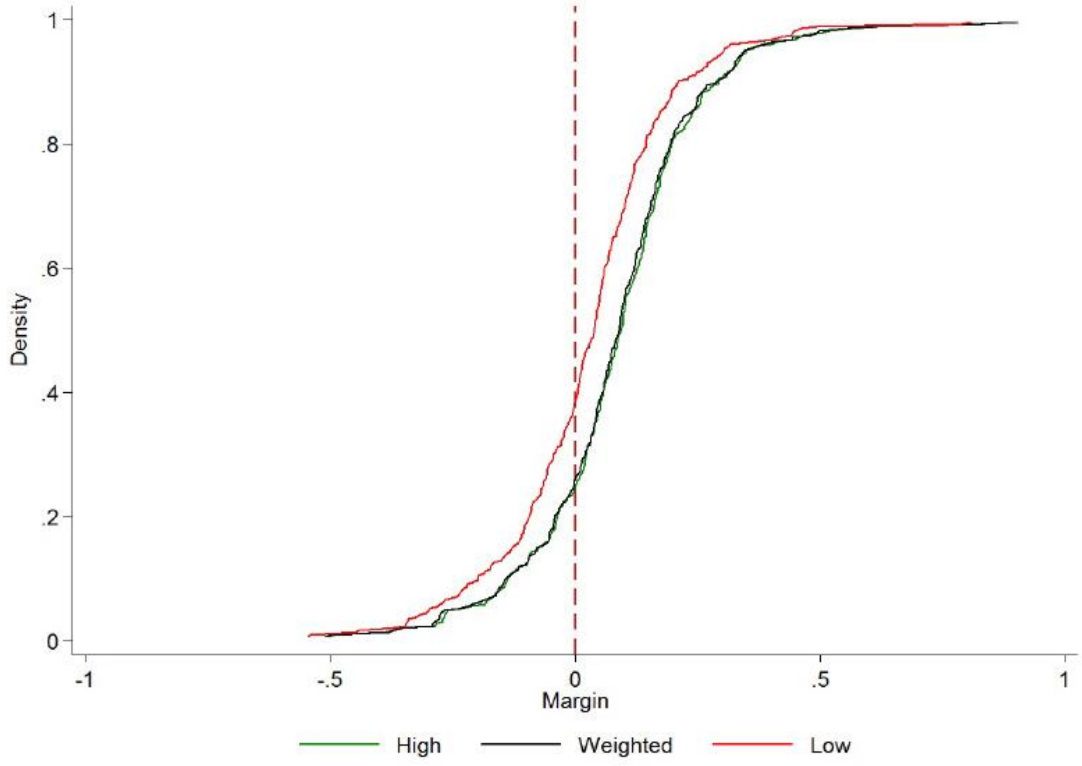
Notes: In this figure, we plot the year-to-year continuing incumbents for each institution from 2004 to 2017. Note that the continuing incumbents are primary dealers who are authorised by bond issuers as members to participate bond auctions every year during 2004 to 2017. Because ADB used auction since 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 4.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 4.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 4.A.12.

Table 4.A.1: Chinese government and policy banks' long term security credit ratings

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

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

Table 4.A.2: Chinese government and policy banks' short term security credit ratings

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

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.

Table 4.A.3: Secondary market T-bill distribution

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

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.

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

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

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

Table 4.A.5: Quantile regression results for market gap

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

This table presents results for margins using the quantile regression method proposed by Koenker and Bassett (1982) 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.

Table 4.A.6: Regression results for market gap by period

Variable	Primary rate -secondary rate					
	OLS					Heckman
	(1)	(2)	(3)	(4)	(5)	(6)
2008 - 2009	0.157***	0.159***	0.157***	0.159***	0.163***	0.146***
	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)	(0.040)
2010 - 2017	0.127***	0.121***	0.126***	0.120***	0.126***	0.109***
	(0.034)	(0.034)	(0.034)	(0.034)	(0.033)	(0.040)
HA (Spanish)	0.020	0.017	0.019	0.017	0.018	-0.011
	(0.026)	(0.027)	(0.026)	(0.027)	(0.027)	(0.042)
DA	0.027	0.027	0.026	0.026	0.027	0.049*
	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.028)
Fixed coupon bond	-0.098***	-0.094***	-0.098***	-0.094***	-0.096***	-0.005
	(0.024)	(0.023)	(0.024)	(0.023)	(0.023)	(0.022)
Floating coupon bond	-0.153**	-0.150**	-0.153**	-0.150**	-0.152**	
	(0.064)	(0.064)	(0.064)	(0.064)	(0.064)	
Notes	-0.011	-0.010	-0.010	-0.010	-0.010	-0.040*
	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.021)
Bonds	0.032	0.032	0.032	0.032	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 secondary market		-0.669		-0.680	-0.661	-0.862
		(0.777)		(0.779)	(0.780)	(0.697)
Government yield gap between primary auction date and the day before the secondary market			-0.041	-0.044	-0.044	-0.043
			(0.071)	(0.071)	(0.071)	(0.075)
Log value of maturing bonds by institution for a given month					-0.001	-0.001
					(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 X^2						292.47

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.

Table 4. A.7: Quantile regression results for market gap by period

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

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.

Table 4.A.8: FTSE index institutions and the primary market dealers

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

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.

Table 4.A.9: Example of alternating pattern for the CDB

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

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.

Table 4.A.10: Example of alternating pattern for the EIB

Date	Bond ID	Maturity (in years)	Auction mechanism
Panel A: Experimentation by date			
Jul 31, 2013		2(t)	Discriminatory
Aug 15, 2013		2(t)	Discriminatory
Sep 24, 2013		2(t)	Discriminatory
Oct 21, 2013		2(t)	Uniform
Nov 04, 2013		2(t)	Uniform
Apr 11, 2014		3(t)	Discriminatory
May 15, 2014		3(t)	Uniform
May 23, 2014		3(t)	Discriminatory
Jun 06, 2014		3(t)	Uniform
Panel B: Experimentation by bond			
Nov 28, 2014	14 EXIM 78 (initial)	2	Discriminatory
Dec 04, 2014	14 EXIM 78 (reissue)	2	Uniform
Dec 17, 2014	14 EXIM 78 (reissue)	2	Discriminatory
Apr 15, 2015	15 EXIM 09 (initial)	3	Uniform
Apr 24, 2015	15 EXIM 09 (reissue)	3	Uniform
Apr 30, 2015	15 EXIM 09 (reissue)	3	Uniform
May 06, 2015	15 EXIM 09 (reissue)	3	Discriminatory
May 13, 2015	15 EXIM 09 (reissue)	3	Discriminatory
May 21, 20	15 EXIM 09 (reissue)	3	Discriminatory

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.

Table 4.A.11: Quantile regression results for market gap during the alternating experiment

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

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

Table 4.A.12: Regression results for market gap using discriminatory auctions

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

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

Table 4.A.13: Adjusted margins for discriminatory auctions

Variable	Percentile				
	0.10	0.25	0.50	0.75	0.90
Highest primary market winning rate	-0.137	0.002	0.095	0.176	0.294
	[-0.164, -0.110]	[-0.025, 0.029]	[0.068, 0.122]	[0.149, 0.203]	[0.267, 0.321]
Weighted average of the primary market winning rate	-0.139	-0.001	0.092	0.171	0.292
	[-0.166, -0.112]	[-0.028, 0.026]	[0.065, 0.119]	[0.144, 0.198]	[0.265, 0.319]
Lowest primary market winning rate	-0.198	-0.063	0.040	0.120	0.212
	[-0.225, -0.171	[-0.090, -0.037]	[0.013, 0.067]	[0.093, 0.147]	[0.185, 0.239]

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

Appendix 4.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 analyse the models described in Equation 4.1 using only uniform bonds sold since 2007. The regression results are presented in Table B.1, and the general conclusions are qualitative the same.

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 4.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.[86] 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

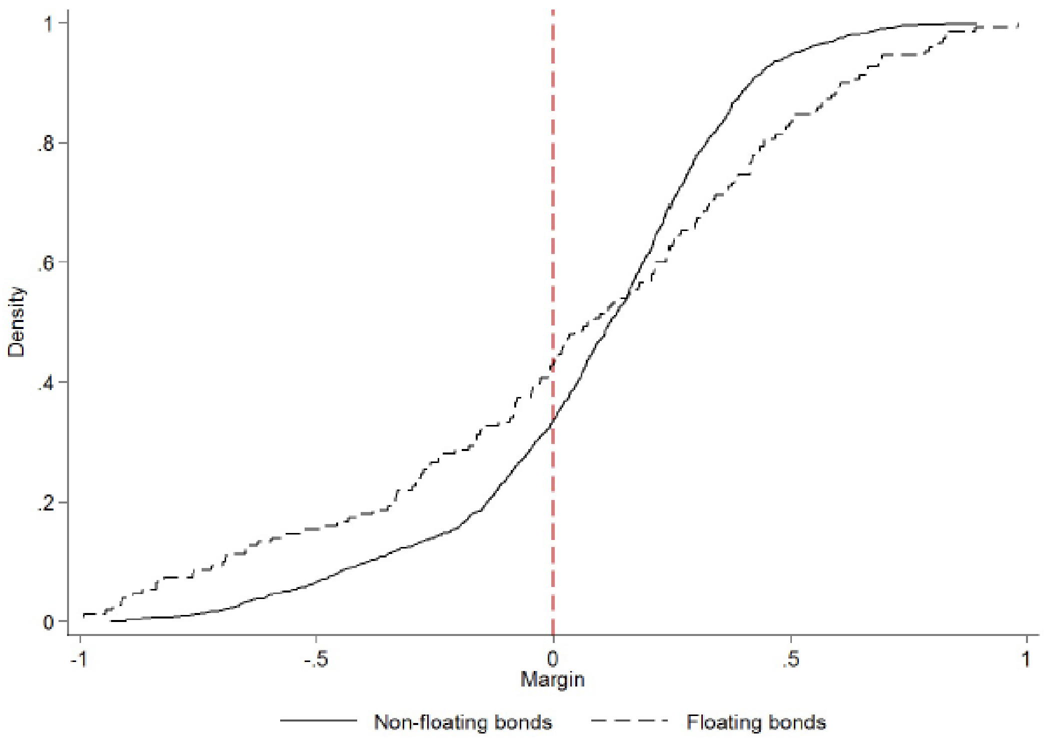
[86] Note that, in floating bonds, bidders bid for the spread. In these floating bonds, the effective return is the indexed interest rate - London Interbank Offered Rate (LIBOR) or Shanghai Interbank Offered Rate (SHIBOR) - plus the spread. Additionally, the spread already accounts for changes in the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

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 4.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 4.B.2, we construct the adjusted margins for the floating bonds.[87] In Figure 4.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 4.B.3, we show the distribution of the adjusted margins constructed by spread with 95% confidence intervals.[88]

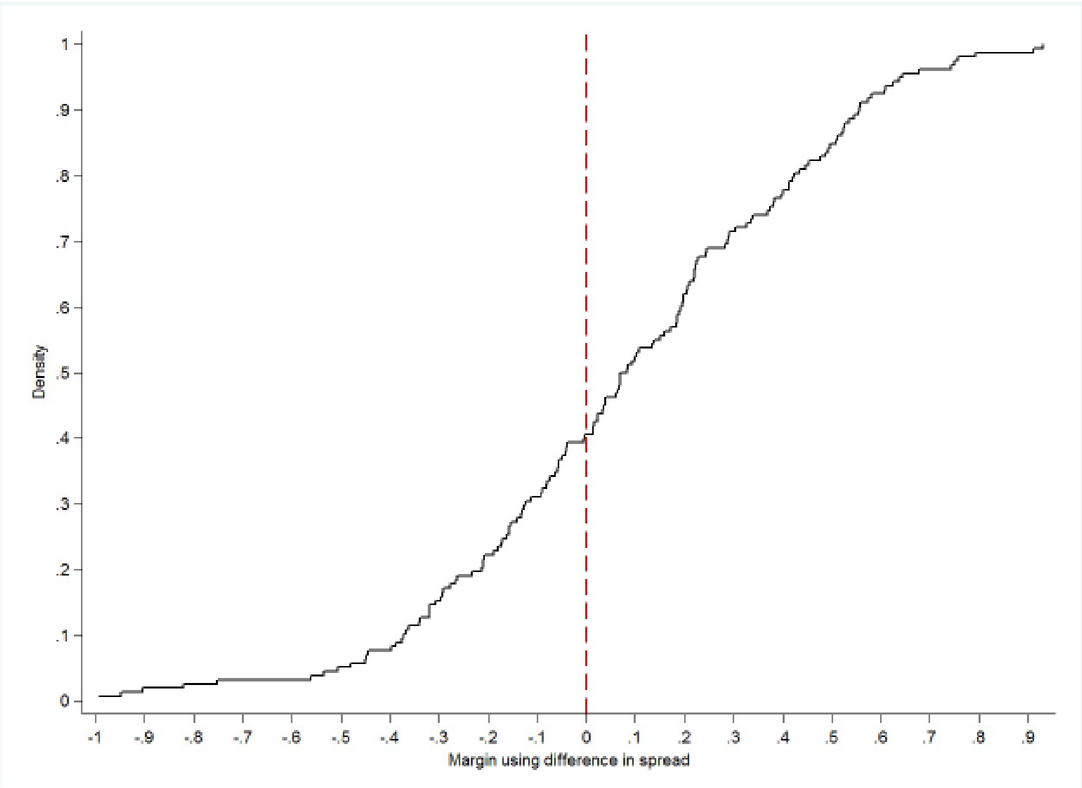
[87] All floating bonds were sold in the secondary market and, hence, no selection model is estimated.
[88] We do not compare the floating and non-floating bonds' gains and losses as we do not have the volume of the floating bonds.

Figure 4.B.1: Adjusted margins for floating and non-floating bonds



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



In this figure, we show the CDF of adjusted margins for 168 floating bonds, based on Column 5 in Table 4.B.2. The spread of floating bonds are constructed by expected cash-flow rates.

Table 4.B.1: Regression results for uniform floating and other bonds' market gap

Variable	Primary rate - secondary rate				
	(1)	(2)	(3)	(4)	(5)
Fixed coupon bond	-0.031	-0.031	-0.037	-0.037	-0.037
	(0.064)	(0.064)	(0.063)	(0.064)	(0.064)
Floating coupon bond	-0.199**	-0.198**	-0.207**	-0.207**	-0.206**
	(0.081)	(0.082)	(0.080)	(0.081)	(0.081)
Notes	0.022	0.022	0.022	0.022	0.022
	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)
Bonds	0.047	0.047	0.047	0.047	0.047
	(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***	-0.144***	-0.144***
	(0.028)	(0.028)	(0.028)	(0.028)	(0.028)
Volatility	0.698**	0.693*	0.753**	0.747**	0.747**
	(0.348)	(0.355)	(0.362)	(0.368)	(0.368)
Volatility of FTSE bank index at the day before secondary market		0.082		0.123	0.119
		(1.266)		(1.271)	(1.274)
Government yield gap between primary auction date and the day before the secondary market			0.158	0.159	0.158
			(0.113)	(0.113)	(0.115)
Log value of maturing bonds by institution for a given month					0.000
					(0.002)
Institution effects	Yes	Yes	Yes	Yes	Yes
Month & year effects	Yes	Yes	Yes	Yes	Yes
Observations	1,442	1,442	1,442	1,442	1,442
R^2	0.199	0.199	0.200	0.200	0.200

This table presents the OLS results for margins by bond types - floating and non-floating bonds, based on the empirical model described in Equation 4.1. 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.

Table 4.B.2: Regression results for floating bonds' difference in spread

Variable	Difference in primary and secondary market spread				
	(1)	(2)	(3)	(4)	(5)
Notes	-0.693**	-0.675**	-0.687**	-0.661**	-0.660**
	(0.302)	(0.291)	(0.304)	(0.293)	(0.295)
Bonds	-0.921**	-0.887***	-0.907**	-0.855**	-0.859**
	(0.353)	(0.338)	(0.360)	(0.345)	(0.348)
Log number of bidders	0.542**	0.538*	0.539*	0.531*	0.532*
	(0.272)	(0.274)	(0.274)	(0.277)	(0.280)
Log of days between primary and secondary market	0.054	0.087	0.041	0.061	0.062
	(0.120)	(0.127)	(0.119)	(0.127)	(0.126)
Log of trading volume in the previous month	-0.165*	-0.194**	-0.179*	-0.226*	-0.227**
	(0.091)	(0.094)	(0.097)	(0.100)	(0.101)
Volatility	2.090	1.427	2.073	1.346	1.352
	(1.558)	(1.586)	(1.555)	(1.574)	(1.583)
Volatility of FTSE bank index at the day before secondary market		15.138***		16.170***	16.236***
		(5.193)		(5.385)	(5.415)
Government yield gap between primary auction date and the day before the secondary market			-0.846	-1.802	-1.839
			(1.343)	(1.477)	(1.500)
Log value of maturing bonds by institution for a given month					-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	0.200

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-ow 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.

Table 4.B.3: Adjusted margins by bond type

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

This table reports the adjusted margins by bond type for selected percentiles. Note that, to obtain our adjusted measure of margin for floating and non-floating bonds, we estimate the models described in Equation 4.1 without the bond-type dummies for the selected sample. 95% confidence intervals are in parentheses.

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

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

In this table, we report the distributional statistics of the adjusted margins constructed by spread with 95% confidence intervals. The computation process of spread is similar with in Table 4.B.2.

Chapter 5

Conclusion

5.1 Conclusion Remark

The bond market is one of the main financial markets, which plays a significantly role in any national economy. In most market economy countries, government policy makers use bonds as an important macro-economic tool, to adjust domestic economy and privatise state owned assets. Both participants in bond markets may suffer losses and financial market instability if they do not adopt proper issuing formats. This highlights the importance of considering various issuance mechanisms.

In this dissertation, I analyse the Chinese bond market, which is the third largest in the world. In Chapter 2, I examine revenue ranking of bonds issued using uniform auctions and book building. I used data from Chinese local government bonds. Differences in revenue between uniform auctions and book buildings are considered across three revenue measurements: primary rates and two normalized yield rates. Results show that book building leads to a higher yield, which lowers the bond issuers' revenue. Furthermore, a Heckman model is used to address the potential selection bias and endogenous problems. Results from estimates support the conclusion from OLS approaches: uniform auctions generate more revenue than book building. Therefore, this study provides empirical evidence to policy makers in support of uniform auctions. Results suggest to bond issuers that adopting uniform auctions will generate higher revenue.

In Chapter 3, we compare revenue ranking of bonds issued using discriminatory and uniform auction formats. Here we use auction data from CDB and EIB where they conducted a market experiment between 2012 and 2015. Results show no statistical difference in revenue between discriminatory auctions and uniform auctions, based on more than 300 observations. Furthermore, results suggest that bidders do not have a preference for either type of auction. These findings are supporting by previous literature, using market experiment data.

In Chapter 4, this study addresses three objectives and analyses discriminatory auctions and uniform auctions from bond losses perspectives. Firstly, the prevalence of government bond losses in post-auction periods are analysed, by constructing gaps between the primary market rate and secondary market rate. There are about 20% bond losses exists in the bond market and this proportion rises during the financial crisis. Next, the market mechanism which leads to bond losses is explored. REPO rates in the money market are used as the proxy of liquidity constraint for banks. The probability of banks selling their bonds at a loss to release their liquidity pressure when they face the high borrowing cost in the money market is examined. Results show that liquidity constraint is one of the major leading causes of bond losses. Furthermore, the FTSE index falls after bond losses, suggesting a positive correlation between bond losses and financial market instability. Based on an alternating market-based experiment conducted by CDB and EIB, this study finds that uniform auctions can mitigates bond losses better than discriminatory auctions. This finding may help explain why Chinese bond issuers have stopped using discriminatory auctions since 2016. This finding also helps explain why discriminatory auctions are driven out by uniform auction in the global trend. This dissertation provides insights to policy makers regarding different issuing mechanisms for bond issuers. Uniform auctions generate more revenue to bond issuers compared with book building, while uniform auctions do not generate more revenue than discriminatory auctions. However, uniform auctions stabilize the financial market by reducing bond losses. Based on these finding, this thesis recommends that policy makers use uniform auctions as the issuing mechanism for bond issuers.

5.2 Further Study

In this thesis, the first study only focuses on the revenue difference between the book building and uniform auctions. Under the IPO setting, under-pricing under auctions and book building is the main concern by most researchers. Therefore, it is worthy to study the difference of under-pricing under the bond market condition. In the second study, the revenue comparison between discriminatory auctions and uniform auctions is using the bond level data. Specifically, the lack of individual bids from each dealers limits me to study further. I will leave these two advanced topics to future once I obtain the necessary data.

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