Auction Mechanisms and Treasury Revenue: Evidence from the Chinese Experiment

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Abstract

This paper exploits a large-size auction experiment conducted by two Chinese Government Treasury security 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, we find that 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 behavior.

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1 Introduction

Researchers have long tried to understand 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; Hortaçsu and McAdams, 2010; Hortaçsu and Kastl, 2011; 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 changing model setups, such as bidder-information symmetry and risk-neutrality assumptions, can produce different revenue rankings. An empirical identification of which assumptions hold in multi-unit auctions is, however, a challenge. Therefore, they argue that determining the revenue-enhancing pricing rule is an empirical question and encourage empirical researchers to pursue either direct or counterfactual comparison of multi-unit auction outcomes.

In this paper, 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.[1] The experiment lasted three years and the total value was ¥ 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 for unbiased estimates to assess the effect of a specific auction rule on yield rates and revenue.

In the Treasury auction data, we see that the yield rates generated from the two auction formats are not statistically different. We also see no substantial difference in revenue. In

[1] These banks are government policy banks that finance economic policies and the securities they issue are 'Chinese government bonds.' These institutions have the same short and long credit ratings awarded by Moody's, Standard & Poor's, and Fitch.

addition to these findings, this paper provides the first study on multi-unit auction revenue comparison using real market data in a large-scale market-based experiment.[2] Notably, this experiment offers us a novel research design that other Treasuries and banks worldwide could replicate to assess other revenue increasing strategies of auction mechanisms.[3]

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.[4] As in Hortaçsu et al. (2018), our variable of interest 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.[5] Hereafter, this is the 'normalized rate.' The normalized rate attempts to control for unobserved heterogeneity across auctions as it captures fluctuations of 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.

Analyzing 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.

We perform additional tests to ensure that our results are robust. First, we investigate

[2]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.

[3]They include the effects of asymmetric bidding behavior, set-asides, lot-size effect, uncertain supply, and tilted supply function to potentially increase revenues.

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

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

whether bidders are potentially aware of the alternating-rule auction format during the experiment and behave strategically by choosing the most profitable auction mechanism. Our findings suggest that bidders did not change their participation and bidding patterns throughout the experiment based on the auction format. Second, 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. To address this concern, we re-estimate our models with the highest and lowest normalized winning bids for discriminatory auctions. We find, again, that the absence of a statistical difference between uniform and discriminatory formats holds as well for the normalized highest and lowest bids of discriminatory auctions compared to uniform auctions.

Additionally, we investigate whether our results hold for the full distributions of normalized rates by re-estimating the empirical models using the quantile regression method. The results are qualitatively similar to the ones shown in the mean regressions indicating that there is no significant difference between normalized rate distributions generated by uniform and discriminatory auctions. Further, we examine whether there are any differences in the auction yield rates between uniform and discriminatory auctions held by the CDB and EIB individually. Our results indicate that, regardless of the institution, the revenues generated from uniform or discriminatory auctions have no statistical difference. Finally, we take advantage of within-day variation in format to control for unobserved heterogeneity. Our findings indicate that, after controlling for unobserved heterogeneity, the normalized rates from the two auction formats are not statistically different. Details of these robustness tests and results are presented in Section 7.

However, a reader may question whether our point estimates on the difference in the normalized rates does correspond to the actual difference in revenue in the two auction formats. Therefore, we estimate the change in revenue if the CDB and EIB had issued their bonds in uniform (discriminatory) over discriminatory (uniform) 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. The value in billions of ¥ ranges from -0.233 to 0.312. These results show that the use of uniform or discriminatory formats does not generate considerable revenue difference.

Our research also refers to the recent empirical literature on Treasury auctions. Pioneered by Hortaçsu (2002), recent studies build and estimate structural Treasury auction models and base the evaluation of different auction rules on counterfactual simulation (Hortaçsu

and McAdams, 2010; Hortaçsu 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. For instance, Kang and Puller (2008) analyzed a one-shot-auction-rule switch from discriminatory to uniform auctions at the Korean Treasury. They concluded that there is a slight revenue advantage for the discriminatory format. However, the revenue difference between the two formats is quite small due to the competitiveness of the market.[6]

Another set of studies reports that the two mechanisms would generate quantitatively similar revenues.[7] Although revenue equivalence is often reported in empirical studies, given the ambiguous revenue ranking in the theoretical literature (Wang and Zender, 2002; Ausubel et al., 2014), a close experimental investigation is required to further understand Treasury auction markets.

By analyzing 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 which format generates a lower yield rate and a higher price (Simon, 1994; Mester, 1995; Nyborg and Sundaresan, 1996; Malvey and Archibald, 1998).[8] However, these studies were unable to provide unbiased estimates for revenue ranking as the bonds issued under the two auction formats were different in several dimensions (market conditions, maturity, duration, volume, etc.).[9] 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 difference in the yield rates of uniform and discriminatory auctions. Our findings also complement previous structural estimations and counterfactual results.

The paper is organized in the following manner. Section 2 explains the market background and Section 3 presents the experiment and the data. Section 4 explains the auction market.

[6]Using bids from uniform and discriminatory auctions, Kang and Puller (2008) also compare the efficiency properties of the two formats. They find that the discriminatory auction better allocates treasury bills to the highest value financial institutions.

[7]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 finding—Nyborg and Sundaresan (1996), Malvey et al. (1998), Hortaçsu (2002); Hortaçsu and McAdams (2010), and Bonaldi et al. (2015)—is empirical revenue equivalence with statistically insignificant differences.

[8]Tenorio (1993) also investigates one-shot changes from one auction format to another in Zambian foreign exchange.

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

Section 5 presents the results and Section 6 assesses the revenue difference between the two auction formats. Section 7 presents robustness tests. Section 8 offers concluding remarks.

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.

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. The CDB and EIB do not mandate the number of times a dealer participates or the volume they purchase. Participating in these auctions is strictly voluntary. However, in these Treasury auctions, primary dealers are required (according to prequalification requirements) to bid frequently and win a substantial number of Treasury auctions to retain their primary dealership status in the future. According to the financial consultants and market practitioners we talked to and given the high stakes involved in the primary market for Treasuries, primary dealers avoid selecting themselves into specific auctions or auction formats in order to keep their dealer status. Barbosa et al. (2020) provide a detailed explanation of the historical background of these two institutions.

2.2 Credit ratings

The CDB's and EIB's short- and long-term ratings are listed in Table A.1 in the Appendix. 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 all government securities are categorized equivalently.

The credit ratings of these government banks are homogenous because their bonds are administered 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).[10,11] 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.

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.[12]

Based on previous resale market transactions, the CCDC publicly announces every business day the yield curves and maturity for securities issued by each institution to provide official benchmarks to general investors.[13,14] 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 from five business days before the auction date to control for volatility in the Chinese bond market.[15]

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. Both institutions usually held multiple auctions with bonds of varying maturities.[16] During these market-based experiment periods, the institutions controlled the auction formats (alternating between them) but did not announce the experiment

[10] The People's Bank of China, which governs the CDB and EIB, operates directly under the government.

[11] See Chen (2014) for the background on the CDB and EIB. Also see Chen (2010) and Li (2014) for details on credit rating equivalence.

[12] The secondary market for government bonds in China is quite substantial, with nearly 14 trillion USD in bonds traded on a yearly basis.

[13] In China, the CCDC's yield curves are the most representative benchmarks. Zhongzheng yield curves are the second-most recognized benchmarks. However, according to the Baidu search engine (a representative web search engine in China), the CCDC yield curves are nearly 18 times more popular than the Zhongzheng yield curves.

[14] Construction of the yield curve is described in Table A.3.

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

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

publicly. Also, at any time, the institutions could have stopped the experiment. Most importantly, the auction rule choices 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 5, observable bond characteristics and financial and economic market conditions are not correlated with the auction format.

3.1 CDB experiment

During the experiment, the CDB held a total of 269 auctions—139 uniform and 130 discriminatory. Within each (bi-)week, the CDB auctioned off bonds of different maturities (two-, three-, five-, and seven-year) with varying auction rules.[17] Table 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.

3.2 EIB experiment

Similarly, the EIB also experimented with their security auction rules. From July 2013 to May 2015, the EIB held 79 auctions—49 uniform and 30 discriminatory. 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 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 A.2, Panel B.2).[18]

[17] In addition to the two-, three-, five- and seven-year notes, the CDB also auctioned off one-year bills and ten-year notes, always through the uniform-pricing format. Hence, one-year and 10-year securities are excluded from our regression analyses.

[18] When reissued, each bond received a new ID. From the old bond ID we can identify the reissue of an old bond.

3.3 Auction rules

During the experimental period (2012-2015), the CDB and EIB were required to follow strict security issuance guidelines set by the People's Bank of China.[19] Accordingly, the participants in the CDB and EIB auctions knew which format was going to be used only three business days before each auction date. To illustrate what was known by auction participants, 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 is made public on Wednesday. Then, institutions announce the specific details of the second auction (e.g. date, volume, mechanism, corresponding maturity, etc.) on Thursday.[20,21] Our data confirm that the CDB and EIB followed the guidelines set by the People's Bank of China. Hence, ex-ante, bidders did not know the specific date, volume, and maturity of upcoming auctions nor associated future auction formats. Therefore, based on the timing of the announcement and published government documents, bidders face great uncertainty about future auction rules. Hence, we postulate that bidders could not condition their current bids on upcoming auction mechanisms.[22]

Further, according to the primary market rules set by the Peoples Bank of China (the Central Bank), issuers are prohibited from subscribing (and/or subscribing in disguised) financial bonds issued by themselves. Additionally, all potential bidders are required to submit both price (rate) and quantity when submitting bids and all tenders are treated as competitive bids.

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 CCDC, which is the only government bond depository authorized by the MOF and is responsible for the establishment and operation of the government bond

[19] These guidelines explicitly state that the public notice of a new issuance auction has to be made at least three business days in advance.

[20] A small number of deviations may occur when there are long intervals between two auction dates or during public holidays.

[21] Specifically, the CDB announced the auction rule on Thursday and bids were submitted on Tuesday of the following week. The EIB announced the auction rule typically on Tuesday and bids were submitted on Friday of the same week.

[22] Our conversations with market practitioners in the Shenzhen Exchange and PricewaterhouseCoopers China (PwC CN) also suggest that they agree with this view.

depository system.

The Wind Database provides access to 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 submitted bid quantities for securities, allotment per auction, 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, and the highest and the lowest winning and losing rates in both auction formats. 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 experimental data contain information on Treasury security yield rates for the two auction formats to directly answer the long-standing revenue-ranking question in the literature. The definitions of the variables used in this paper are in Table A.3 in the Appendix.

4.1 Auction rules and market conditions

A potential concern about our empirical strategy is 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 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 suppresses potential unobserved heterogeneity across auctions.

We find statistical evidence that the auction rules are not associated with any specific bond type, nor are they chosen to match specific financial conditions. Table 1 reports summary statistics for observables associated with uniform and discriminatory auctions, where 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. Similar 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 1, we also provide 95 percent confidence intervals and calculated t-values. The null hypothesis is the means (or proportions) reported in the first two columns are equal.

The results in Table 1 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 yield curve 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 1. These results also hold for 90 percent confidence intervals.[23] Considering other regression variables, the period between two auctions is about 8.5 days and the bid-to-cover ratio is about 2.5. We use the bid-to-coverage ratio as a measure of auction competitiveness as used by other researchers (for example, see Gordy, 1999 and Goldreich, 2007).

In Table 2, we provide summary statistics for all the dependent variables used in this study separately for uniform and discriminatory auctions. Given that our primary interest is in the gap of outcome variables between auction formats, we have shown the difference between the two auction mechanisms and the corresponding t-test statistics. The null hypothesis is the means reported in the columns two and three are equal. The results indicate that the differences in outcome variables are not statistically different between auction formats. However, given that these differences in outcome variables are not controlled for any market conditions, we advise a cautious interpretation of these t-values.[24]

In our sample, we observe 47 floating bond auctions that represent about 13.5 percent of all auctions. Note that these floating bonds were issued only by the CDB through uniform auctions. To preserve the integrity of the experiment, in our baseline estimates, we use all auctions, including the floating bonds. However, we report results without these 47 floating bond auctions 'side-by-side' and show that these results are qualitatively similar as the ones

[23] 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.

[24] In Figure A.1, we present the average normalized winning rates weighted by volume by auction format for a given day. We also draw a local polynomial mean smoothing plots with 95% confidence intervals for both auction formats.

using the full sample.

4.2 Auction rules and number of bidders

Another concern is the equality of the number of potential 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 continuation as a primary dealer. 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 continued 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 participated 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:

$$n_{ijt} = \gamma D_{ijt} + X'_{ijt}\varphi + \alpha_j + \tau_t + u_{ijt}, \tag{1}$$

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, bid-to-cover 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 u is the error term.

Given that the number of bidders is a count, we estimate Equation (1) using the Poisson Pseudo Maximum Likelihood (PPML) method.[25] We also estimate the above model using OLS. Table 3 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.

It is important to note that the absence of a statistical difference of the number of bidders in these two auction formats during the experiment is compatible with the result of no statistical

[25]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).

difference in terms of revenue between mechanisms presented in the next section, which is in line with Ausubel et al.'s (2014) findings. According to Ausubel et al. (Section 5.4), in an auction with endogenous entry (infinite pool of potential entrants that may join an auction after incurring a fixed cost), the ranking of entry corresponds to the inverse of the revenue rankings as higher revenue to the auctioneer relates to less expected surplus to the bidders, thereby encouraging less entry.

Note that, in the presence of no statistical difference in revenue between two auction mechanisms, both auction formats leave the same expected surplus to the pool of bidders (primary dealers). Consequently, following the standard auction entry equilibrium arguments, and consistent with Ausubel et al. (2014), these two auction formats should exhibit the same number of bidders, as reported in our entry regression results.

One may also note that participation in the auctions in our setup could potentially be endogenous, and, hence, an auction format could attract different types of bidders. If this is the case, the potential selection of bidder types into an auction format can be potentially confounding. An application of selection empirical methods, in the spirit of Heckman (1974, 1976, 1979), could deal with selection of bidders into the auction format. Nevertheless, those methods require bidder identities at each auction, which was not released by the CDB and EIB to preserve the confidentiality of the bidders. Given this data limitation, we perform alternative empirical tests to investigate whether there is selection into an auction format by analyzing the highest losing bid rate (the worst bid),[26] the average submitted bid quantities for securities, the average allotment per bidder, and the primary dealers' secondary-market debut-day return (see Appendix A.2). Although not fully suppressing selection from our estimates, these additional tests provide results that give us cautious confidence that our insignificant statistical revenue difference between uniform and discriminatory auctions is not driven by a selection of types in an auction format.[27]

Hence, conditional on controls, this experimental environment enables us to conceivably interpret the auction rule variable as conditional mean-independent, treating it as exogenously

[26]Samuelson (1985), Marmera et al. (2013), and Gentry and Li (2014) show that the marginal valuation (type) of the worst bidder conveys relevant information about the types of bidders that enter an auction. In this spirit, we examine whether the marginal valuation of the worst bidder is the same in both auction formats. Note that, in the context of Treasury auctions, the worst losing bid is the highest bid rate in an auction. Given that the pool of pre-qualified primary dealers (potential bidders) are the same in both auction formats, types of bidders in the two format auctions tend to be the same (no selection of bidders' type) if the marginal valuation of the worst bidder (lowest bidder type) is the same.

[27]We have spoken to officials in the Shenzhen Exchange and an official at PricewaterhouseCoopers China (PwC CN) and they say that primary dealers do not strategically pick the auctions and the auction format that suit them better. These views are in line with the outcomes of the statistical analyses that we present in Figure A.1, Section 7.1 and Appendix A.2.

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.

5 Estimation results

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

$$y_{ijt} = \beta D_{ijt} + X'_{ijt}\phi + \alpha_j + \tau_t + \epsilon_{ijt}, \tag{2}$$

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 (2) using two different estimation methods. First, we conduct our empirical analysis using the 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 (2). OLS results are presented in the first three columns of Table 4, 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.[28] This Bayesian approach offers several considerable 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

[28] Gelman et al. (2004) provide a detailed description of the Bayesian method used in this paper.

estimate. Given an experimental setting, both approaches enable econometricians to have unbiased and consistent estimators.

In our base model, presented in Column 1 of Table 4, 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 terms. 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 models in November or December than in July or August. 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 4, 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 the normalized yield rates of uniform and discriminatory auctions. From our estimations in Table 4, regardless of the empirical specification, 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 Table 5, we report the results for the sample without floating bonds. Overall, as in the full sample, our results indicate that there is no statistical difference between the normalized yield rates of uniform and discriminatory auctions. In our full specification, presented in Columns 3 and 6, the coefficients of the discriminatory auction dummy are -0.006 percent

(-0.6 bps) and 0.007 percent (0.7 bps) respectively. 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.

6 Assessing revenue 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 raises 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 in Table 4 to calculate the change in CDB and EIB revenue if they issued their bonds using a uniform (discriminatory) auction rather than a discriminatory (uniform) one. We then compute the percentage change in total revenue, the total change in revenue with respect to Chinese government expenditure, and the yearly cost of debt during the three-year experiment.

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:

$$TR^c = \sum_{i \in ua} p_i q_i + \sum_{i \in da} p_i^c q_i, \tag{3}$$

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 4. 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:

$$p_i^c = \sum_{i \in m} \frac{k \times V}{(1 + yield + spread - \beta)^m} + \frac{V}{(1 + yield + spread - \beta)^m}, \tag{4}$$

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.[29] 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 flow by subtracting the estimated β from the *spread*.[30]

Now, with p_i^c computed from Equation (4), we can use Equation (3) to obtain the change in total revenue. In Table 6, we present the results from this exercise. The first row shows the estimated difference in the normalized rates, β, reported in Table 4. 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 6 Panel A 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 to 0.016 percent at the mean (¥ -0.233 billion to ¥ 0.312 billion). Further, the potential loss or gain from issuing all the EIB and CDB bonds through a uniform auction ranges from -0.00041 to 0.00054 percent of the Chinese government expenditure during the three years of the experiment, which is negligible. Similarly, the cost of debt (interest rate paid extra) ranges from -0.263 to 0.350 percent.

A similar approach can be used to compute the total revenue if all bonds were sold through discriminatory auctions. Table 6 Panel B shows the results when the bond issuers have issued all their bonds using discriminatory auctions. In Panel C, we compare revenues when all auctions were uniform vs. all discriminatory auctions. The results indicate that the potential loss or gain from using all uniform or discriminatory auctions ranges from -0.00103 to 0.00137 percent of Chinese government expenditure. When considering the value in billions of ¥, it ranges from -0.593 to 0.790.

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

[30] For floating bonds, p_i^c was computed by considering the yield curve for each security benchmark rate at the issued date to obtain the expected future coupon payments.

7 Robustness tests

In this section, we present the details of the additional tests we performed to ensure that our results are robust. First, we examine whether bidders behave strategically by choosing the most profitable auction mechanism. Next, we analyze whether there is a difference in normalized rates between auction formats due to the high and low yield rates observed in discriminatory auctions. Third, we investigate whether our results hold for the full distributions of normalized rates. Fourth, we consider whether there are any differences in the auction yield rates between auction formats held by the institutions individually. Additionally, we take advantage of within-day variation in format to control for unobserved heterogeneity. Finally, we control for bonds which are re-issued.

7.1 Bidders' behavior in alternating auctions

Given that the CDB and EIB alternated between the two auction formats with remarkable regularity for three years, one could argue that primary dealers 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, if bidders wait for the format that is most favorable 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 4, Columns 2, 3, 5, and 6. Our results are presented in Table A.4 and indicate that there is no statistical difference between uniform and discriminatory auction yields in the first and 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. 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).[31]

[31] As no Treasury notes were sold using the discriminatory auction format before or after the experiment by either institution, we cannot compare the number of bidders per auction before, after, and during the experimental period.

In Figure 1, we have plotted a scatter plot to show the number of bidders by auction format and by day of auction. Then, we draw local polynomial mean smoothing plots with 95% confidence intervals. As one can see, these plots overlap each other. Even though these plots are not conditional upon any other observable characteristics such as maturity or institutions, one can observe that both auction types have a similar random pattern for the 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. Instead, this figure indicates that the number of bidders remains similar (random) across auction formats during the experimental period, indicating that bidders did not wait for their preferred auction format.

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 categorical variable that indicates that the auction is let during the second half (= 1), and also on another variable that captures the difference between uniform and discriminatory auctions in the second half (second half indicator $\times$ discriminatory auction indicator). We also control for observable auction and market characteristics. In Table A.5, we report estimations using the PPML method in Column 1 and the OLS method in Column 2. All our estimated results in Table A.5 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 the experiment period and 12 months later. Our results indicate that the bidders did not behave differently during and after the experiment period (See Table A.6).[32]

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

[32] 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. For example, from 2011:11 to 2012:04, the average number of auctions per month was about 5.5, while, during and six months after the experiment, the average frequency of auctions per month was 20 and 23, respectively. In Figure A.2 and A.3, we plot the monthly frequency and volumes for the CDB and the EIB from January 2004 to January 2016 respectively. Additionally, in Figure A.4, we draw the volumes for Treasury notes relevant to the experiment that were auctioned off by the CDB and the EIB. As one can see from these figures, even though there was an upward trend in overall value during the period, the value of notes related to the experiment stayed relatively constant.

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. In addition, as the experiments themselves are not publicly announced, these institutions could have also modified their alternating patterns at any time during their experiments. These uncertainties made a potential forward-looking waiting strategy quite challenging, if not impossible, for bidders.

7.2 High and low auction rates in discriminatory auctions

In the main estimation results presented in Table 4, 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 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 4, 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 A.7, 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 A.7 report the OLS estimation results, and the last two columns report the results of the Bayesian estimation. In Panel A, we report the results for all auctions while, in Panel B, we report for auctions without floating bonds. 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.

7.3 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 15th, 25th, 50th, 75th, and 85th quantiles. We present these estimated results in Table A.8.[33] Note that these empirical specifications are

[33]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

similar to the ones presented in Table 4, 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.1). In Panel A.2, we report results using the normalized highest yield while, in Panel A.3, 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 (See Panel B.1 - B.3). We do not present these results in this paper, but can provide them upon request.[34,35]

7.4 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 4, Columns 3 and 6, by institution. The results are presented in Table A.9. 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.

7.5 Within day auctions

In a recent paper, Allen et al. (2020) take advantage of within-day variation to control for unobserved auction heterogeneity. They note that their empirical strategy could identify dependencies in demand for Treasury Bills of different maturities on the same day. We also observed 168 auctions using both auction formats on the same date by the same institution. However, our sample size declined by more than 50% in this exercise as we use only the days

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 A.8) 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.

[34] A minor exception is that, in Panel C Table A.3, 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 85th quantile.

[35] 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 Frölich 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 a conditional QTE approach.

on which both types of auctions were held by an institution.[36] Hence, we advise caution in interpreting these results while presenting them in Table A.10. Results are robust and indicate that the normalized winning rate, worst rate, and the number of bidders are not statistically different between the auction formats.

7.6 Effect of reissue bonds

During the market experiment, both the CDB and EIB re-issued bonds. Reissued bonds can have two opposing effects on auction outcomes. As the liquidity of the reissued bonds increases, it could result in a higher liquidity premium in the primary auction outcome yields. On the other hand, as the supply volume increases, it shifts the supply function of that specific bond to the right, which could result in a lower price (or higher yield) in the primary auction market. These liquidity and supply effects are expected to have opposite directions. The bid-to-cover ratio could be considered a no-contradiction test for these two opposing effects. If the liquidity effect is stronger, the bid-to-cover will increase. On the other hand, if the supply effect is stronger, the bid-to-cover would decrease. We find that the bid-to-cover ratios are not statistically different across standard and reissued securities (see Table A.14 in Appendix A.2).

As for the relation between auction mechanism and reissuance, the crucial question is whether the potential unobserved variables are correlated with the auction rule indicator through the channel of reissuance. Hence, we have estimated an empirical model with a reissue indicator variable that takes the value of one for reissued bonds and zero otherwise. These results are presented in Table A.11. The auction type variable's coefficient indicates that the normalized rates from the two auction formats are not statistically different as in our main findings.

8 Conclusion

We have exploited a large auction experiment conducted by two Chinese Government Treasury security issuers 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. There is no relevant economic difference in terms of revenue between the two mechanisms. Our results also do not provide statistical support that the bidders

[36] Further, the control variable duration passes the balance test only at the 90 percent confidence interval for the same day sample.

prefer one format to the other.

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, Hortaçsu 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, Hortaçsu, 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 compare auction outcomes directly 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 behavior 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, this study demonstrates that an alternating auction rule experiment has the legitimate potential to uncover underlying revenue incentives. We leave an investigation of these advanced topics to future researchers who can exploit Treasury auction bid data with alternating auction rules.

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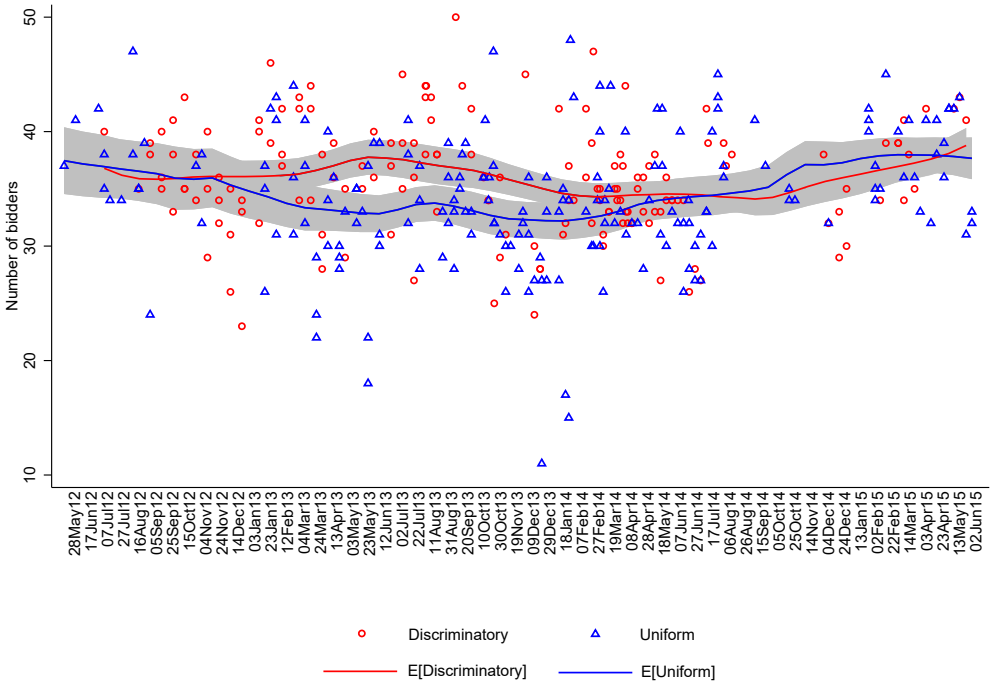
Figure 1: Number of bidders by auction type



Notes: This figure plots the number of bidders per auction for all treasury notes by auction format by date during the experiment. The lines represent the expected number of bidders per auction by auction format estimated by a local polynomial mean with 95% confidence intervals.

Table 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 bid-to-cover ratio	0.865	0.888	-0.813
	[0.818, 0.912]	[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	-1.013
	[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*, *bid-to-cover ratio*, *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 2: Summary statistics of dependent variables

Variable	All	Uniform	Discriminatory	Difference	t-Value
Normalized rate	0.801	0.795	0.806	-0.011	-0.267
	[0.761, 0.841]	[0.726, 0.863]	[0.760, 0.852]		
Normalized highest discriminatory	0.813	0.795	0.830	-0.035	-0.853
auction winning rates	[0.774, 0.853]	[0.726, 0.863]	[0.784, 0.876]		
Normalized lowest discriminatory	0.797	0.795	0.798	-0.003	-0.074
auction winning rates	[0.757, 0.836]	[0.726, 0.863]	[0.752, 0.844]		
Normalized worst rates	1.043	1.046	1.041	0.006	0.132
	[0.100, 1.087]	[0.971, 1.122]	[0.991, 1.090]		
Number of bidders	35.189	34.404	35.881	-1.477	-2.42
	[34.585, 35.794]	[33.452, 35.356]	[35.120, 36.643]		

This table reports the mean, the 95% confidence intervals and the calculated t-values for outcome variables used in this study. To be specific, they are *normalized 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, *normalized highest* and *lowest discriminatory auction winning bids*, *normalized worst bids*, and *number of bidders*.

Table 3: Regression results for number of bidders

Variable	Number of bidders			
	PPML		OLS	
	(1)	(2)	(3)	(4)
Discriminatory auction	0.001	0.001	0.006	0.005
	(0.014)	(0.014)	(0.016)	(0.016)
Floating bond	-0.053		-0.051	
	(0.026)		(0.031)	
Market yield of Chinese bonds	0.015	0.008	0.011	-0.001
one day before the auction date	(0.025)	(0.025)	(0.029)	(0.029)
Log of duration	-0.030	-0.025	-0.032	-0.025
	(0.019)	(0.020)	(0.024)	(0.026)
Log of bid-to-cover ratio	0.244	0.227	0.264	0.246
	(0.025)	(0.026)	(0.033)	(0.035)
Volatility	0.065	-0.106	0.113	-0.057
	(0.265)	(0.273)	(0.295)	(0.305)
Log of time lag between auctions	0.016	-0.005	0.016	-0.007
by institution	(0.011)	(0.015)	(0.013)	(0.017)
Log value of maturing bonds by	-0.000	-0.002	-0.001	-0.002
institution for a given month	(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, bid-to-cover ratio, 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. The regressions in Columns (1) and (3) include the full sample while the ones in Columns (2) and (4) include only non-floating bonds. Robust standard errors are in parentheses.

Table 4: 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 bid-to-cover ratio		-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		0.050	0.025		0.063	0.019
by institution		[-0.072, 0.171]	[-0.087, 0.138]		[0.002, 0.126]	[-0.030, -0.073]
Log value of maturing bonds by		-0.018	-0.016		-0.022	-0.018
institution for a given month		[-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 5: Regression results for normalized rate without floating bonds

Variable	Normalized rate					
	OLS			Bayesian		
	(1)	(2)	(3)	(4)	(5)	(6)
Discriminatory auction	-0.005	-0.00001	-0.006	-0.0007	0.005	0.004
	[-0.089, 0.079]	[-0.097, 0.097]	[-0.087 - 0.074]	[-0.066, 0.068]	[-0.069, 0.076]	[-0.042, 0.055]
Log of duration		-0.025	0.009		-0.010	0.0055
		[-0.140, 0.090]	[-0.089 - 0.107]		[-0.068, 0.046]	[-0.051, 0.066]
Log of bid-to-cover ratio		-0.034	-0.356***		-0.045	-0.339
		[-0.256, 0.188]	[-0.588 - -0.124]		[-0.130, 0.046]	[-0.383, -0.294]
Volatility		1.853	1.930**		1.841	1.934
		[0.336, 3.369]	[0.417 - 3.443]		[1.740, 1.952]	[1.866, 2.007]
Log of time lag between auctions		0.020	0.030		0.026	0.021
by institution		[-0.057, 0.097]	[-0.042 - 0.102]		[-0.034, 0.080]	[-0.014, 0.057]
Log value of maturing bonds by		-0.035	-0.032**		-0.037	-0.033
institution for a given month		[-0.058, -0.012]	[-0.058 - -0.005]		[-0.051, -0.022]	[-0.046, -0.021]
Log number of bidders			1.309***			1.315
			[0.522 - 2.096]			[1.262, 1.369]
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	301	301	301	301	301	301
R^2	0.308	0.304	0.482			
Log marginal likelihood				-130.621	-181.634	-162.404

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 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 6: Magnitude of the revenue equivalence

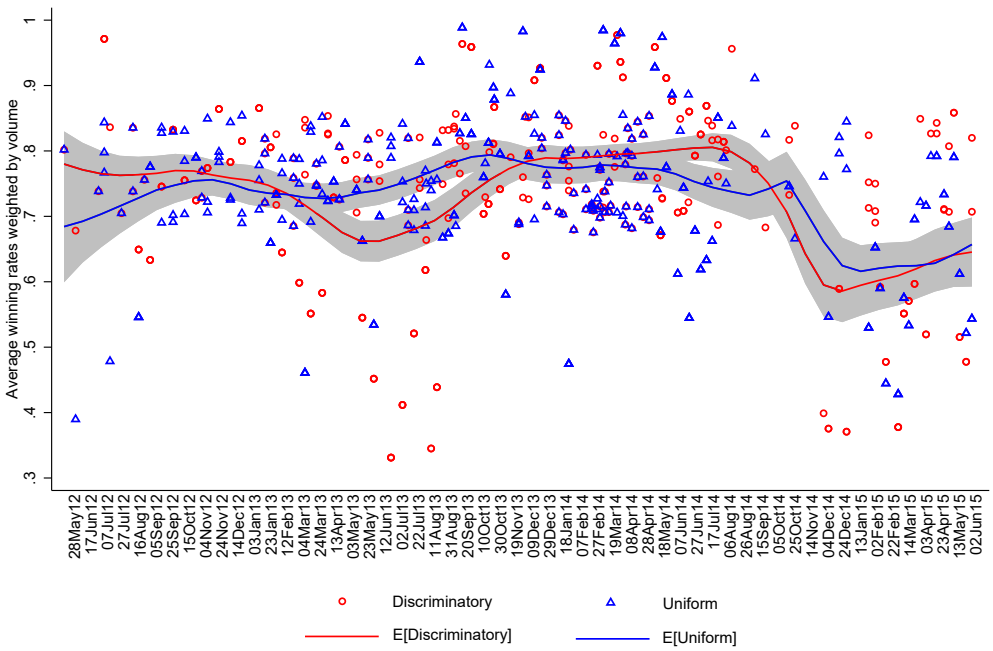
Variable	OLS			Bayesian		
	(1)	(2)	(3)	(4)	(5)	(6)
Discriminatory auction	0.006	0.008	0.001	-0.006	0.002	-0.005
Gvt expenditure (in billions of ¥)	57,677	57,677	57,677	57,677	57,677	57,677
Cost of bonds (in billions of ¥)	89	89	89	89	89	89
Panel A: Discriminatory auctions sold using uniform format						
Δ 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)
Δ Revenue (in billions of ¥)	0.234	0.312	0.039	-0.233	0.078	-0.194
	(-3.301, 3.744)	(-3.456, 4.141)	(-3.147, 3.202)	(-2.720, 2.224)	(-2.604, 3.006)	(-2.759, 2.028)
Δ Revenue / Gvt expenditure	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)
Δ Revenue / Yearly cost of bonds	0.263	0.350	0.044	-0.263	0.088	-0.219
(%)	(-3.710, 4.214)	(-3.884, 4.654)	(-3.536, 3.598)	(-3.057, 2.499)	(-2.926, 3.378)	(-3.100, 2.279)
Panel B: Uniform auctions sold using discriminatory format						
Δ Revenue (%)	-0.018	-0.025	-0.003	0.018	-0.006	0.015
	(-0.293, 0.262)	(-0.323, 0.274)	(-0.250, 0.249)	(-0.174, 0.215)	(-0.235, 0.206)	(-0.159, 0.218)
Δ Revenue (in billions of ¥)	-0.359	-0.478	-0.060	0.359	-0.120	0.299
	(-5.716, 5.110)	(-6.308, 5.351)	(-4.866, 4.868)	(-3.401, 4.208)	(-4.589, 4.024)	(-3.013, 4.265)
Δ Revenue / Gvt expenditure	-0.00062	-0.00083	-0.00010	0.00062	-0.00021	0.00052
(%)	(-0.00991, 0.00886)	(-0.01094, 0.00928)	(-0.00847, 0.00844)	(-0.00590, 0.00729)	(-0.00796, 0.00698)	(-0.00538, 0.00739)
Δ Revenue / Yearly cost of bonds	-0.403	-0.538	-0.067	0.404	-0.134	0.336
(%)	(-6.424, 5.742)	(-7.089, 6.014)	(-5.491, 5.471)	(-3.822, 4.725)	(-5.157, 4.522)	(-3.488, 4.793)
Panel C: The difference between uniform and discriminatory formats						
Δ Revenue (%)	0.030	0.040	0.005	-0.030	0.010	-0.025
	(-0.430, 0.486)	(-0.450, 0.537)	(-0.409, 0.415)	(-0.354, 0.289)	(-0.339, 0.390)	(-0.359, 0.263)
Δ Revenue (in billions of ¥)	0.593	0.790	0.099	-0.593	0.198	-0.494
	(-8.411, 9.465)	(-8.807, 10.449)	(-8.105, 8.087)	(-6.925, 5.624)	(-6.628, 7.595)	(-7.024, 5.132)
Δ Revenue / Gvt expenditure	0.00103	0.00137	0.00017	-0.00103	0.00034	-0.00086
(%)	(-0.01458, 0.01641)	(-0.01527, 0.01812)	(-0.01390, 0.01402)	(-0.01201, 0.00975)	(-0.01149, 0.01317)	(-0.01218, 0.00890)
Δ Revenue / Yearly cost of bonds	0.666	0.888	0.111	-0.666	0.222	-0.555
(%)	(-9.453, 10.637)	(-9.898, 11.743)	(-9.007, 9.088)	(-7.782, 6.321)	(-7.448, 8.535)	(-7.893, 5.767)

This table reports the magnitude of revenues calculated based on Table 4 estimates. Upper and lower bounds at 95% confidence intervals are in parentheses. China government expenditure during 2013-2015 was ¥ 57,677 billion (and it is approximately $ 9,228 billion). Yearly cost of EIB & CDB government bonds issued during 2013-2015 was ¥ 89 billion (and it is approximately $ 14 billion).

Appendix

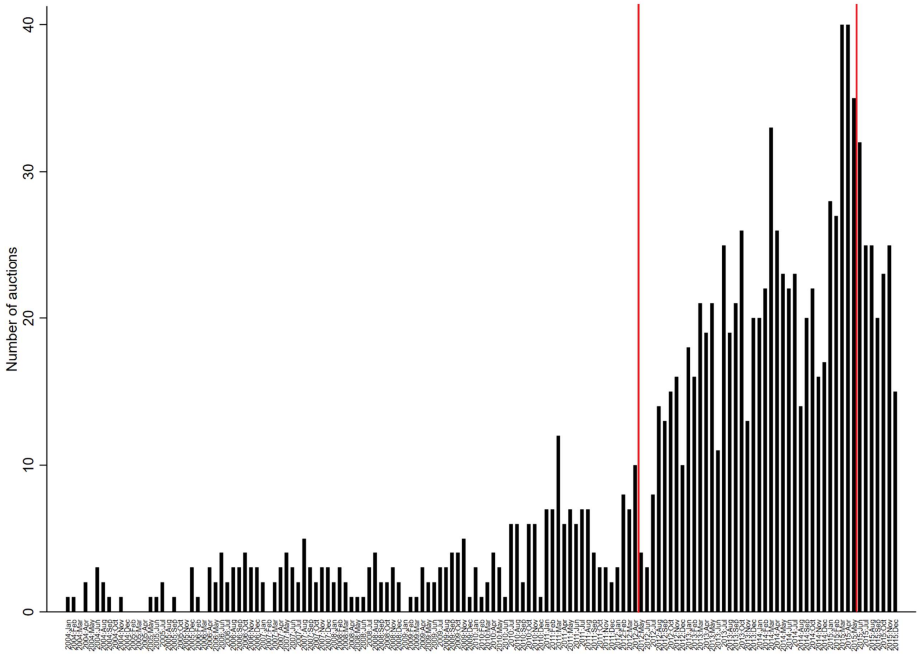
A.1 Extra Figures and Tables

Figure A.1: Normalized average winning rates by auction type



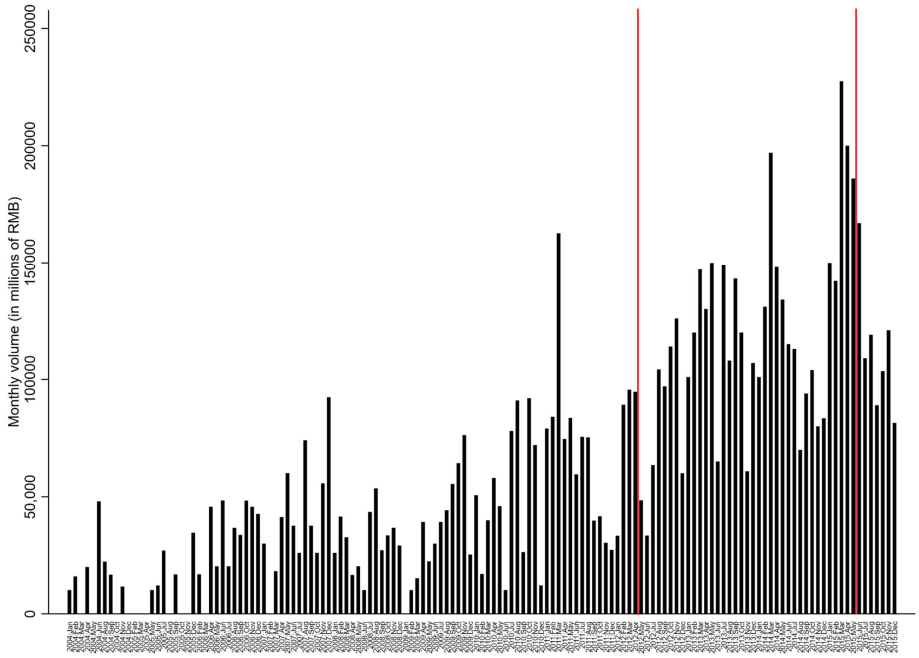
Notes: This figure plots the normalized volume-weighted average of winning rates by auction format by date during the experiment. The lines represent the expected winning rates by auction format estimated by a local polynomial mean with 95% confidence intervals.

Figure A.2: Frequency of auctions by month



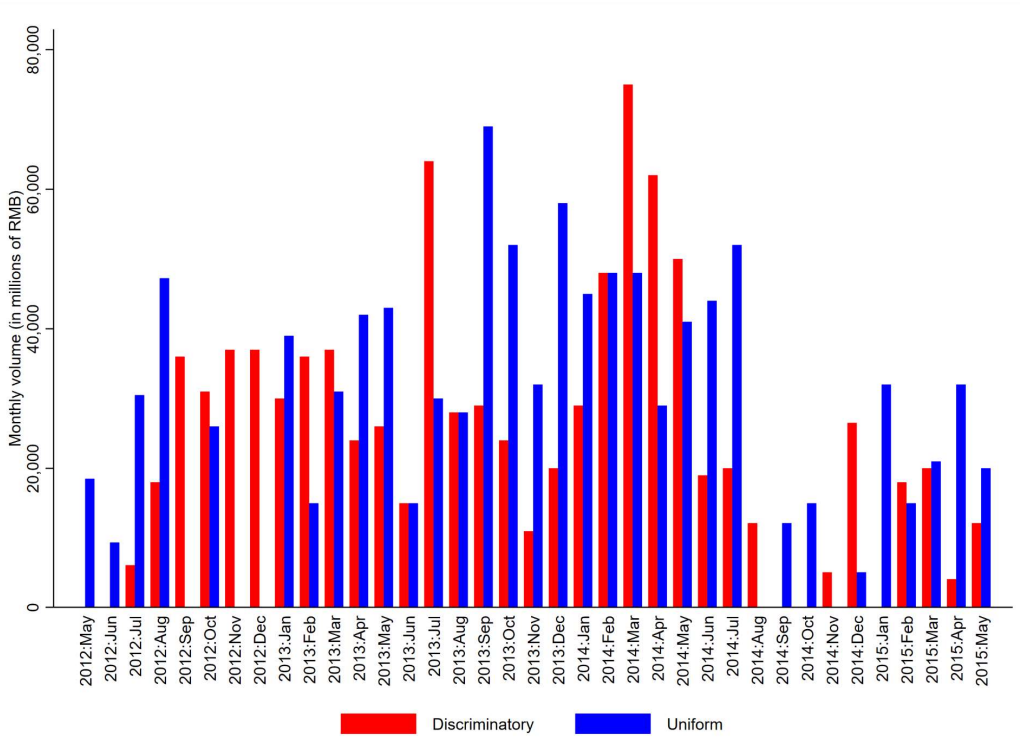
Notes: This figure plots monthly frequency of bonds issued from January 2004 to December 2015.

Figure A.3: Volume of bonds issued



Notes: This figure plots monthly volume of bonds issued from January 2004 to December 2015.

Figure A.4: Volume of bonds issued during the experiment



Notes: This figure plots monthly volume of bonds issued during the experiment (May 2012 - May 2015).

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

Panel A: 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
	3	Uniform
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
	5	Uniform
Apr 16, 2013	3, 5, 7	Uniform
Apr 23, 2013	3, 7	Discriminatory
	5	Uniform
May 07, 2013	3, 5, 7	Uniform
May 14, 2013	3, 7	Discriminatory
	5	Uniform
May 21, 2013	3, 5, 7	Uniform
May 28, 2013	3, 7	Discriminatory
	5	Uniform
Jun 04, 2013	3, 5, 7	Uniform
Jun 18, 2013	3, 5, 7	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

Panel B: EIB			
Date	Bond ID	Maturity in years	Auction mechanism
Panel B.1: Alternating rule by date			
Jul 31, 2013		2 (t)	Discriminatory (Uniform)
Aug 15, 2013		2 (t)	Discriminatory (Uniform)
Sep 24, 2013		2 (t)	Discriminatory (Uniform)
Oct 21, 2013		2 (t)	Uniform (Discriminatory)
Nov 04, 2013		2 (t)	Uniform (Discriminatory)
Apr 11, 2014		3 (t)	Discriminatory (Uniform)
May 15, 2014		3 (t)	Uniform (Discriminatory)
May 23, 2014		3 (t)	Discriminatory (Uniform)
Jun 06, 2014		3 (t)	Uniform (Discriminatory)
Panel B.2: Alternating rule by bond			
Nov 28, 2014	14 EXIM 78 (initial)	2	Discriminatory
Dec 04, 2014	14 EXIM 78 (reissue)	2	Uniform
Dec 17, 2014	14 EXIM 78 (reissue)	2	Discriminatory
Apr 15, 2015	15 EXIM 09 (initial)	3	Uniform
Apr 24, 2015	15 EXIM 09 (reissue)	3	Uniform
Apr 30, 2015	15 EXIM 09 (reissue)	3	Uniform
May 06, 2015	15 EXIM 09 (reissue)	3	Discriminatory
May 13, 2015	15 EXIM 09 (reissue)	3	Discriminatory
May 21, 2015	15 EXIM 09 (reissue)	3	Discriminatory

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 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. 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.
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).
Bid-to-cover ratio	This variable is the ratio of the total amount of submitted bid quantities for securities divided by supply (allotment) 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 submitted bid quantities was always more than the allotment.
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 A.4: 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)
Panel A: All auctions				
Discriminatory auction	-0.021	0.009	-0.021	0.002
	[-0.184, 0.142]	[-0.090, 0.109]	[-0.121, 0.084]	[-0.074, 0.075]
Floating bond	-0.765	0.160	-0.753	0.134
	[-1.055, -0.475]	[-0.342, 0.662]	[-0.864, -0.646]	[0.023, 0.243]
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			-201.260	-158.042
Panel B: Without floating bonds				
Discriminatory auction	-0.032	0.015	-0.018	-0.003
	[-0.102, 0.038]	[-0.085, 0.114]	[-0.057, 0.017]	[-0.075, 0.056]
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	104	197	104	197
R^2	0.879	0.567		
Log marginal likelihood			-37.590	-136.970

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 A.5: Results for number of bidders during the experiment

Variables	Number of bidders			
	All auctions		Without floating bonds	
	PPML	OLS	PPML	OLS
	(1)	(2)	(3)	(4)
Discriminatory auction	-0.008	-0.019	-0.024	-0.687
	(0.026)	(0.982)	(0.026)	(1.018)
Second half	-0.074	-2.194	-0.162***	-5.242**
	(0.053)	(1.854)	(0.055)	(2.036)
Second half × Discriminatory auctions	0.011	0.114	0.032	0.934
	(0.030)	(1.114)	(0.031)	(1.159)
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	301	301
R^2	0.576	0.590	0.606	0.616

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, bid-to-cover ratio, 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 A.6: Bidder behavior in uniform auctions during and after the experiment

Variable	All auctions		Without floating bonds	
	Number of bidders	Normalized	Number of bidders	Normalized
		Winning rate		Winning rate
	(1)	(2)	(3)	(4)
After (12 months)	-0.001	-0.111	0.054	-0.026
	(0.026)	(0.080)	(0.021)	(0.059)
Floating bond	-0.061	-0.549		
	(0.037)	(0.122)		
Market yield of Chinese bonds one day	-0.075		-0.040	
before the auction date	(0.024)		(0.024)	
Other controls	Yes	Yes	Yes	Yes
Observations	359	359	309	309
R^2	0.393	0.391	0.450	0.357

This table presents the estimates for the number of bidders and normalized winning in auctions controlling for after experiment period, institutions, market conditions, time gap between auctions by institutions, bid-to-cover ratio, institution effects, and all other market and time controls. The Columns 1 and 3 are estimated using the Poisson Pseudo Maximum Likelihood (PPML) method and Column 2 and 4 are estimated using OLS. Robust standard errors are in parentheses.

Table A.7: Results for normalized rates with highest and lowest discriminatory auction rates

Variable	Normalized rate			
	OLS		Bayesian	
	Highest	Lowest	Highest	Lowest
	(1)	(2)	(3)	(4)
Panel A: All auctions				
Discriminatory auction	0.028	-0.007	0.029	0.003
	[-0.053, 0.110]	[-0.089, 0.074]	[-0.035, 0.090]	[-0.050, 0.063]
Floating bond	-0.491	-0.497	-0.485	-0.483
	[-0.727, -0.256]	[-0.733, -0.260]	[-0.556, -0.416]	[-0.583, -0.385]
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			-269.235	-281.385
Panel B: Without floating bonds				
Discriminatory auction	0.022	-0.015	0.031	-0.007
	[-0.058, 0.102]	[-0.095, 0.066]	[-0.016, 0.079]	[-0.052, 0.036]
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	301	301	301	301
R^2	0.480	0.481		
Log marginal likelihood			-162.473	-165.701

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 A.8: Quantile regression results for normalized rates

Variable	Normalized rate				
	Quantile				
	0.15	0.25	0.50	0.75	0.85
Panel A: All auctions					
Panel A.1: With weighted averages of discriminatory auction winning rates					
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 A.2: With highest discriminatory auction winning rates					
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 A.3: With lowest discriminatory auction winning rates					
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
Panel B: Without floating bonds					
Panel B.1: With weighted averages of discriminatory auction winning rates					
Discriminatory auction	-0.046	-0.042	-0.038	-0.046	-0.039
	(0.054)	(0.040)	(0.033)	(0.029)	(0.034)
All controls	Yes	Yes	Yes	Yes	Yes
Observations	301	301	301	301	301
R^2	0.264	0.225	0.337	0.453	0.519
Panel B.2: With highest discriminatory auction winning rates					
Discriminatory auction	-0.013	-0.026	-0.022	-0.019	-0.014
	(0.055)	(0.045)	(0.032)	(0.028)	(0.029)
All controls	Yes	Yes	Yes	Yes	Yes
Observations	301	301	301	301	301
R^2	0.258	0.250	0.335	0.453	0.519
Panel B.3: With lowest discriminatory auction winning rates					
Discriminatory auction	-0.064	-0.045	-0.046	-0.048	-0.059
	(0.056)	(0.040)	(0.033)	(0.029)	(0.031)
All controls	Yes	Yes	Yes	Yes	Yes
Observations	301	301	301	301	301
R^2	0.264	0.254	0.333	0.453	0.518

This table reports quantile regressions for the 15th, 25th, 50th, 75th and 85th quantiles of the normalized rates. Panel A considers the full sample, an Panel B includes only the non-floating bonds. In Panel A.1 and B.1, the dependent variables are the normalized auction-specific weighted-average winning rate. In Panel A.2, A.3, B.1 and B.2, the 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 2, Column 3. Bootstraped standard errors are in parentheses.

Table A.9: 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	-0.020	-0.008	0.018	-0.012	-0.017
	[-0.099, 0.100]	[-0.111, 0.071]	[-0.078, 0.061]	[-0.062, 0.100]	[-0.075, 0.049]	[-0.057, 0.025]
Floating bond	-0.451			-0.417		
	[-0.700, -0.202]			[-0.504, -0.325]		
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				-237.193	-165.631	-56.380

This table reports results for normalized rates by institution. We estimate the models presented in Table 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.

Table A.10: Regression results controlling for within-day variation

Variable	OLS		Bayesian		PPML	OLS
	Normalized		Normalized		Number of bidders	
	Winning rate	Worst rate	Winning rate	Worst rate		
	(1)	(2)	(3)	(4)	(5)	(6)
Discriminatory auction	0.071	0.060	0.042	0.029	0.013	0.412
	[-0.025, 0.167]	[-0.070, 0.191]	[-0.020, 0.104]	[-0.036, 0.096]	(0.016)	(0.539)
Auction and market controls	Yes	Yes	Yes	Yes	Yes	Yes
Institution effects	Yes	Yes	Yes	Yes	Yes	Yes
Date effetcs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	168	168	168	168	168	168
R^2	0.757	0.758				0.774
Log marginal likelihood			85.275	77.182	-467.676	

This table reports results for normalized rates and the number of bidders for the within-day exercise. Models in Columns 1 and 3 provide the results winning rates, and Columns 2 and 4 reports the results for worst bids. In Columns 5 and 6, we report the results for the number of bidders. In Columns 1 through 4, we include date fixed effects. In all columns, we control for auction format, bond-issuer effects, volatility, bid-to-cover ratio, the time lag between auctions, number of bidders, and value of maturing bonds by the institution that vary with a day and/or by auction. 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. The regressions in Columns 4 and 5 report robust standard errors in parentheses.

Table A.11: Regression results for normalized rates: alternate specification

Variable	Normalized rate			
	OLS		Bayesian	
	(1)	(2)	(3)	(4)
Discriminatory auction	0.012	0.003	0.014	0.007
	[-0.071, 0.095]	[-0.078, 0.084]	[-0.052, 0.078]	[-0.040, 0.051]
Floating bond	-0.576		-0.548	
	[-0.808, -0.344]		[-0.591, -0.501]	
Reissued bond	-0.116	-0.096	-.0936	-0.099
	[-0.232, -0.001]	[-0.190, -0.002]	[-0.165, -0.029]	[-0.152, -0.049]
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
Monthly and year effects	Yes	Yes	Yes	Yes
Market drift	Yes	Yes	Yes	Yes
Observations	348	301	348	301
R^2	0.499	0.489		
Log marginal likelihood			-277.547	-169.586

This table reports results for normalized rates while controlling for reissue bonds (alternate specification). In Columns 1 and 3 we present the results with floating bonds. In Column 2 and 4, we report the results without floating bonds. 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 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.

A.2 Complementary analysis: Auction formats and bidder types

In this section of the Appendix, we perform a series of statistical tests to examine if there is statistical evidence of bidder types selecting into auction formats. These tests analyze the worst bidder type (marginal valuation), the average submitted bid quantities for securities, the average allotment per bidder, and the primary dealers' secondary-market debut-day return and examine whether they do or do not statistically vary with auction format. Together, as we show next, they indicate that an insignificant statistical revenue difference between uniform and discriminatory auctions is not driven by a selection of types in an auction format. However, as mentioned in Section 2.1 in the paper, note that there is an important institutional feature in the CDB and EIB Treasury auctions that restrain bidders from strategically picking the auctions and the auction format that suit them better.

Marginal valuation of the worst bidder type. Theoretical results from auction models with endogenous entry (Samuelson, 1985; Marmera et al., 2013; Gentry and Li, 2014) show that the marginal valuation (type) of the worst entering bidder in an auction characterizes the equilibrium entry behavior. These results indicate that the types of bidders in two different auctions are the same (no selection of bidders' type) if the pool of potential bidders and the marginal valuation of the worst bidders (lowest bidder type) are the same in both formats. In this spirit, we examine whether the marginal valuation of the worst bidder (lowest type) is the same in both auction mechanisms. The preceding analysis starts investigating whether bidder types select into an auction, given the pool of pre-qualified primary dealers–potential bidders–are the same in both auction formats.

To evaluate whether the marginal valuation of the lowest bidder types are the same in both auction formats, we rely on the theoretical results in Ausubel et al. (2014). Focusing on the modeling framework of their Proposition 1 and Theorem 1, Ausubel et al. (2014) describe the bidder's bidding strategy in the uniform auction. They precisely show that, if a bidder has a positive probability of influencing the price in a situation where the bidder wins a positive quantity, then the bidder has incentives to shade her/his bid. However, if a bidder cannot be pivotal for small quantities (which could happen with a large number of bidders), then s/he bids her/his expected values for them. If the same bidder is pivotal with positive probability for large quantities, then s/he shades her/his bid for such quantities. In a similar vein, Kastl (2011) and Hortacsu, Kastl and Zhang (2018) show that, whenever there is a positive probability of the market clearing price (rate) being below (above) her/his bid, a bidder's bid will be higher than her/his marginal valuation for the corresponding quantity.

Note that the market clearing price (rate) in a uniform auction will never be below (above) the worst losing bid. Therefore, based on Kastl (2011), Ausubel et al. (2014) and Hortacsu, Kastl and Zhang (2018), the bidder of a worst losing bid in a uniform auction optimally sets a bid that corresponds to her/his marginal valuation. From their results, one can conclude that the worst losing bid in a uniform auction for Treasury securities corresponds to the true marginal valuation of a bidder for the corresponding quantity.

Next, in Proposition 2 of the same paper, Ausubel et al. describe the bidder's bidding strategy in the discriminatory auction that is characterized in their Equation (6). From an inspection of Equation (6), one can also conclude that the worst losing bid in a discriminatory auction for Treasury securities corresponds to the true marginal valuation of a bidder as well. Therefore, based on Ausubel et al.'s (2014) results, one can conclude that the worst losing bids in both auction formats indicate the true marginal valuation of a bidder for the corresponding quantity.

Following these results, we empirically investigate whether the worst losing bid rates are not statistically different across auction formats. If the worst losing bid rates are not statistically different, it implies that the marginal valuation of worst losing bidder types are the same in uniform and discriminatory auctions. This is because the demand for a given bond (the submitted bid quantities) are statistically equal in both auction formats, as shown below in the section "*Submitted bid quantities for securities*". Note that, in the context of Treasury auctions, in which a bid consists of a step demand function represented by pairs composed by a bid rate and amount of securities, the worst losing bid is the highest bid rate in an auction.

To compare the worst losing bid rates in uniform and discriminatory auctions, we consider the empirical model described in equation (2) using the normalized worst losing bid rate as a dependent variable. Table A.12 reports the estimated parameters based on the sample containing only all bonds (Columns 1 and 2) and non-floating bonds (Columns 3 and 4) using OLS and Bayesian estimation methods and two different samples. (The table is presented below as well.) OLS results are presented in Columns 1 and 3 of Table A.12 while Bayesian results are presented in Columns 2 and 4. Our OLS results indicate that normalized worst losing bid rates are not statistically different between uniform and discriminatory auctions. In our OLS results, the point estimates range from 0.000 to 0.008 percent depending on the empirical specification. The results from Bayesian models indicate that our estimated coefficients of the dummy variable that capture the difference in the worst losing bid rates in the two auctions are not statistically significant, with point estimates ranging from 0.022 to 0.032. This empirical exercise reveals that the worst losing bidder's type is not statistically

different in uniform and discriminatory auctions. This empirical exercise on the worst losing bidder's type, combined with the fact that the pool of pre-qualified primary dealers are the same in both auction formats, and the statistical equality of number of bidders in both formats, provides our first set of results suggesting that there is no bidder type selection into auction formats.

Additionally, we examine the robustness of normalized worst rates results to investigate the differences of these outcomes just before and after the experiment using uniform auctions during the experiment period and 12 months later. Our results indicate that the normalized worst rates from uniform auctions were not statistically different during and after the experiment period (See Table A.13).

Although our results provide supporting evidence that bidders do not select into auction formats, they should be interpreted cautiously as the foundations of our empirical strategy were inspired by theoretical findings for single-unit auction models (Samuelson, 1985; Marmera et al., 2013; Gentry and Li, 2014). However, note that, to the best of our knowledge, bidder entry behavior is still a developing area in multi-unit auction models. Hence, the characterization of the equilibrium entry behavior in a multi-unit auction is still an open question in the auction literature. Given the relevance of this subject, we believe that it is an interesting path for future research on the topic.

Submitted bid quantities for securities. We also examine whether the total submitted bid quantities for securities normalized by supply (bid-to-cover ratio) and the total submitted bid quantities (total demand) varies with auction format. After controlling for market conditions, the submitted bid quantities for securities in an auction reveals information about bidders' appetite for these debt instruments, which turns out to unveil information about the type of bidders that are ultimately acquiring these securities in an auction. Hence, if the bid-to-cover ratio as well as the total submitted bid quantities for securities does not vary with the auction format, it also suggests that the bidder types are likely to be the same in both auction formats. Note that the total submitted bid quantities corresponds to the end-points of the demand schedule.

To compare the bid-to-cover ratio and the total submitted bid quantities in uniform and discriminatory auctions, we consider a similar empirical model described in equation (2). In Panel A of Table A.14, we show the estimated parameters for bid-to-cover ratio based on the sample containing all bonds (Columns 1-3) and only non-floating bonds (Columns 4-6) using OLS estimation methods. Our results indicate that the bid-to-cover ratio is not statistically different between uniform and discriminatory auctions in all specifications. In Panel B, we

report the findings for total submitted bid quantities. They are also not statistically different between the auction formats.[37] This shows that the end-points of the demand schedule are not statistically different between uniform and discriminatory auctions.

Average allotment per bidder. Further, we investigate the average submitted bid quantities for securities and allotment per bidder between auction formats. Here also, our results indicate that the average submitted bid quantities and average allotment per bidder are statistically not different between the two auction mechanisms.[38]

Primary dealers' secondary-market return. Finally, we examine whether the short-term returns of primary dealers, measured by the difference between primary and secondary market returns on the debut-day (the initial secondary market trading day in which a given security is allowed to be resold), vary with auction format.[39] In this analysis, the primary dealer's return is defined as the difference between the yield of a bond acquired in a primary market auction minus the yield of the same bond sold in a secondary market transaction.[40] That corresponds to the primary dealers' actual debut-day return in the secondary market, as it is based on primary-to-secondary transaction data. The primary-secondary market return is a matter of interest to primary dealers in China as primary dealers buy to make markets. During the market experiment period, we observe that they sold about 95% of the bonds they acquired in the primary auctions a few days later, on the debut-day. (See Barbosa et al., 2020 for more details on that.) Therefore, any statistical difference in the secondary-market debut-day return of primary dealers (that could be explained by the auction format) would also unveil a selection on bidder types in an auction format.

In Table A.15, we report the effect on auction format on the primary-to-secondary return of primary dealers. Our estimations indicate that the secondary-market debut-day measurement of primary dealers' short-term returns are statistically not different in uniform and discriminatory auctions in all specifications. This also indicates that primary bidders are indifferent between the two auction mechanisms as they yield the same returns, further supporting our

[37] These point-estimates are about 3 percent of the total submitted bid quantities.

[38] The average mean of submitted bid quantities for securities per bidder for uniform auctions was 39,302.85 [37,595.87, 41,009.83] while, for discriminatory auctions, it was 38,985.95 [37,707.27, 40,224.63]. Similarly, the average mean of the allotment per bidder for uniform auctions was 16,627.91 [15,915.53, 17,340.30] while, for discriminatory auctions, it was 38,985.95 [15,524.70, 16,611.93]. All values are in ¥ 10,000 and 95 percent confidence intervals are in parentheses.

[39] Dealers are strictly prohibited from having resale trades (of auctioned securities) before the bond's debut day, typically five days after an auction.

[40] A bond's yield is defined as the discount rate that makes the present value of all of the bond's cash flows equal to its agreed price.

main regression outcome.

Summary. In a nutshell, the above empirical tests show that the lowest type (marginal valuation), the average submitted bid quantities for securities, the average allotment per bidder, and the primary dealers' secondary-market debut-day return do not statistically vary with auction format. These statistical tests, to an extent, successfully eliminated possible type selection patterns.

We would also like to re-emphasize that these non-statistical differences in various exercises are in line with practitioners' views of the market. Regardless of no-profitability-difference or institutional background reason, the results did not reveal any statistical evidence of dealers selecting into different formats. Consequently, the market experiment we study is quite advantageous to measure the effects of the auction mechanism: in addition to the (bi-)weekly alternating rule advantage, we also have a similar pool of bidders in both auction formats, which further supports the otherwise equivalent market environment in our main regression analyses.

Table A.12: Results for worst losing rates

Variables	Normalized worst rate			
	All auctions		Without floating bonds	
	OLS	Bayesian	OLS	Bayesian
	(1)	(2)	(3)	(4)
Discriminatory auction	0.008	0.032	-0.0003	0.022
	[-0.080, 0.097]	[-0.045, 0.122]	[-0.089, 0.088]	[-0.023, 0.070]
Floating bond	-0.458	-0.397		
	[-0.691, -0.226]	[-0.453, -0.327]		
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	301	301
R^2	0.576	0.590	0.606	0.616
Log marginal likelihood		-311.033		-177.206

All regressions include log of duration, log of bid-to-cover ratio, volatility, log of time lag between auctions by institution, log value of maturing bonds by institution for a given month, and log number of bidders. In OLS estimates, 95% confidence intervals calculated based on robust standard errors are in brackets and in Bayesian estimates, 95% credible intervals are in brackets.

Table A.13: Bidder behavior in uniform auctions during and after the experiment

Variables	Normalized worst rate	
	All auctions	Without floating bonds
	(1)	(2)
After (12 months)	0.005	0.104
	(0.087)	(0.065)
Floating bond	-0.552	
	(0.123)	
Other controls	Yes	Yes
Observations	359	309
R^2	0.386	0.332

This table presents the estimates for the normalized worst rates in auctions controlling for after experiment period, institutions, market conditions, time gap between auctions by institutions, bid-to-cover ratio, institution effects, and all other market and time controls. All models are estimated using OLS. Robust standard errors are in parentheses.

Table A.14: Relation between bid-to-cover ratio, submitted bid quantities and auction format

Variables	All bonds			Without floating bonds		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Bid-to-cover ratio						
Discriminatory auction	-0.043	0.040	0.030	-0.105	0.048	0.041
	(0.079)	(0.093)	(0.096)	(0.095)	(0.094)	(0.097)
Floating bond		0.031	-0.175			
		(0.132)	(0.141)			
Bank effects	No	Yes	Yes	No	Yes	Yes
Year and month effects	No	Yes	Yes	No	Yes	Yes
Market drift	No	Yes	Yes	No	Yes	Yes
Other variables	No	No	Yes	No	No	Yes
Observations	348	348	348	301	301	301
R-squared	0.001	0.160	0.202	0.004	0.186	0.232
Panel B: Submitted total bid quantities						
Discriminatory auction	48,839.761	51,149.832	50,396.770	66,898.273	50,289.752	45,862.608
	(42,662.788)	(51,683.729)	(53,588.759)	(45,460.939)	(51,459.393)	(53,365.247)
Floating bond		44,754.909	-48,090.852			
		(84,721.548)	(86,290.515)			
Bank effects	No	Yes	Yes	No	Yes	Yes
Year and month effects	No	Yes	Yes	No	Yes	Yes
Market drift	No	Yes	Yes	No	Yes	Yes
Other variables	No	No	Yes	No	No	Yes
Observations	348	348	348	301	301	301
R-squared	0.004	0.155	0.193	0.007	0.171	0.219

This table reports OLS results for bid-to-cover ratio (Panel A) and submitted total bid quantities (Panel B). We use an indicator variable (Discriminatory auction) which takes the value of one when auction format is discriminatory and zero otherwise. In Column 1-3, we use all bonds while in Columns 4-6 we present results without floating bonds. Robust standard errors are in parentheses.

Table A.15: Regression results for market gap during the alternating-rule experiment

Variable	Primary rate – secondary rate				
	(1)	(2)	(3)	(4)	(5)
Panel A: All auctions					
Discriminatory auction	-0.043	-0.050	-0.042	-0.049	-0.050
	(0.033)	(0.034)	(0.033)	(0.034)	(0.034)
Floating bond	-0.791	-0.799	-0.792	-0.800	-0.801
	(0.089)	(0.087)	(0.089)	(0.087)	(0.087)
Log number of bidders	0.350	0.341	0.350	0.341	0.342
	(0.169)	(0.164)	(0.170)	(0.165)	(0.166)
Lag of days between primar market and	-0.036	-0.045	-0.034	-0.042	-0.038
secondary market	(0.045)	(0.046)	(0.044)	(0.046)	(0.047)
Log of trading volume on the previous month	-0.099	-0.122	-0.096	-0.119	-0.119
	(0.041)	(0.044)	(0.041)	(0.044)	(0.044)
Volatility	0.392	0.115	0.516	0.289	0.301
	(0.655)	(0.664)	(0.701)	(0.706)	(0.711)
Volatility of FTSE bank index at the day before		4.758		4.908	4.983
secondary market		(2.212)		(2.218)	(2.229)
Government yield gap between primary auction			0.092	0.135	0.142
date and day before the secondary market			(0.153)	(0.154)	(0.155)
Log value of maturing bonds by institution for a					0.007
given month					(0.010)
Institution effects	Yes	Yes	Yes	Yes	Yes
Month & year effects	Yes	Yes	Yes	Yes	Yes
Observations	348	348	348	348	348
R^2	0.553	0.559	0.553	0.560	0.560
Panel B: Without floating bonds					
Discriminatory auction	-0.042	-0.040	-0.041	-0.039	-0.038
	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)
Other controls as in Panel A	Yes	Yes	Yes	Yes	Yes
Observations	301	301	301	301	301
R^2	0.484	0.485	0.486	0.487	0.487

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