Entry and Exit in Treasury Auctions

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Abstract

Many financial markets are populated by dealers, who commit to regularly participate in the market, and non-dealers who do not commit. This market structure introduces a trade-off between competition and volatility, which we study using data on Canadian Treasury auctions. We document a consistent exit trend by dealers and increasing, but irregular participation by non-dealer hedge funds. Using a structural model, we evaluate the impact of dealer exit on hedge fund participation and its consequences on market competition and volatility. We find that hedge fund entry was partially driven by dealer exit, and that gains thanks to stronger competition associated with hedge fund entry are off-set by losses due to their irregular market participation. We propose an issuance policy that stabilizes hedge fund participation at a sufficiently high average level and achieves sizable revenue gains.

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1 Introduction

Governments worldwide have traditionally relied on regulated banks, known as primary dealers, to consistently purchase government debt and regularly facilitate trade between investors, such as firms, public entities, and individuals. More recently, other institutions have assumed an increasingly important role. For instance, in the U.S. hedge funds doubled their (gross) exposure to U.S. Treasuries between early 2018 and February 2020, reaching $2.39 trillion (Banegas et al. (2021)). Given that hedge funds and other non-dealer institutions, referred to as customers, are subject to less stringent regulations than dealers and have no obligation to participate in market-making activities, the implications of this observed trend on the functioning of Treasury markets remain uncertain.[1]

The goal of this paper is to better understand the trade-off between having committed dealers versus increased participation by customers in Treasury markets and evaluate the consequences for market functioning. Answering these questions is challenging because there is limited data that allows us to study how customers trade Treasuries. We overcome this challenge by focusing on the Canadian primary market in which the government issues bonds via regularly held auctions. We document dealer exit and increasing, yet irregular, customer participation. We then introduce and estimate a structural model to assess the role of dealer exit in explaining customer entry, and to quantify the benefits of greater customer competition against the costs of higher market volatility.

Our data combines bidding information of all Canadian Treasury auctions from 1999 until 2022 with price information from the secondary market, the futures market, and the repurchase (repo) market. Two types of bidders participate in the auctions: dealers and customers. Only dealers can submit bids directly to the auctioneer; customers must bid via a dealer—a common feature in Treasury auctions. For all securities, we observe bidder types, unique anonymized bidder identifiers, and all submitted bids. We also know via which dealer a customer submits bids and where the market cleared.

With these data, we document a series of facts, the first set of facts being related to entry and exit. We show that dealers have systematically exited the primary market since the very first auctions took place. In contrast, customers, in particular hedge funds, have entered.

[1] Unprecedented market turmoil in March 2020 triggered a policy debate on whether to reform Treasury market rules (e.g., Logan (2020), Ackerman and Hilsenrath (2022), Grossman and Goldfarb (2022)).

However, unlike dealers, who have an obligation to regularly attend auctions and buy sufficient amounts of debt, customer participation is irregular. This suggests that customers select specific auctions, depending on market conditions. In line with this idea, we show that customers participate at auction when secondary market (buy-sell) spreads in the days leading up to the auction are high. The second set of facts help us model bidding behavior, conditional on auction participation. We show that dealers who observe an aggressive customer bid systematically adjust their own bids in anticipation of greater competition in the auction. Sophisticated customers, such as hedge funds, should take this adjustment into account when bidding.

Motivated by the empirical evidence and institutional features of the market, we construct a model that mimics a fiscal year. At the start of each year, when the government announces its debt issuance plan, each dealer decides, at a cost, whether to commit to bidding in all auctions of the upcoming year, and the number of participating dealers is announced publicly. Then, before each auction, customers observe the market conditions, and decide whether or not to enter that specific auction, at an entry cost. Conditional on participation, all customers and dealers draw private signals about how much they value the bond—representing how much profit they expect to generate post-auction—, and place their bids. The auction clears at the price at which aggregate demand meets supply and each bidder pays their offered prices for each unit won.

To solve for equilibrium conditions of this game and estimate dealer and customer values and entry costs, we build on the empirical literature on multi-unit auctions, in particular Guerre et al. (2000), Hortaçsu (2002), Kastl (2011), and Hortaçsu and Kastl (2012). Unlike existing studies, we endogenize bidder participation, and we allow customers to behave strategically in that they anticipate dealer updating their own bids.

This contributes to the empirical auction literature that allows for endogenous entry, but has so far focused on single-object auctions (see Hortacsu and Perrigne (2021) for an overview). Estimation approaches for entry in single object auctions require knowledge of how the equilibrium bid function behaves. In multi-unit auctions this is a complicated object and so these tools are not directly transferable. Instead, we exploit estimated bounds on bidder-specific surpluses together with a matching procedure to estimate entry costs in multi-unit auctions. This approach could be used to endogenize bidder participation in other auction settings, including those for electricity, renewable energy, or carbon allowances.

We find that both dealers and customers have high participation costs, and that customers are willing to pay more for bonds than dealers. The latter suggests that (participating) customers expect to execute more profitable trading strategies with the bond post-auction than (participating) dealers. One reason for this may be that customers face less stringent regulation than dealers, especially post global financial crisis in 2007-2009. Consistent with this, we find that dealer values are not significantly different from customer values prior to 2007-2009, but differ significantly afterwards.

To disentangle whether the surge in customer engagement resulted from dealers leaving the market, potentially influenced by regulatory shifts, or from broader alterations in market conditions favoring customer bond purchases, we employ our structural model and conduct a counterfactual analysis. In this process, we calculate counterfactual bids without relying on the conventional assumption of truthful bidding, as typically employed in multi-unit auction studies. Instead, we utilize the empirical guess-and-verify method introduced by Richert (2021). By reintroducing the dealers who withdrew from the market since 2014 and simulating customer participation in these counterfactual auctions, we observe that an average customer would have been approximately 44% less likely to partake in an average auction if dealers had not exited. This substantial reduction in participation indicates that dealer exit is a significant economic driver of customer entry.

We next use our model to evaluate market consequences from the rise in customer participation. On the one hand, stronger participation may increase competition (as in Bulow and Klemperer (1996)). This would reduce debt funding costs and price distortions due to bid-shading. On the other hand, irregular bidder participation may increase volatility in market outcomes, such as the market price. For example, two auctions may clear at different prices only because one auction attracts more customers than the other, and not because the auctions offer bonds of different fundamental values. This introduces unnecessary volatility that might destabilize the financial system.

To build an intuition for these effects, we start with a simplified environment with one type of bidder (dealers) that bids directly to the auctioneer, and ask by how much (expected) auction outcomes vary in the number of competing bidders. We find that the (expected) price drops by 11% when removing one bidder, because of stronger shading, and because there is a non-zero risk of auction failure due to insufficient demand. In contrast, when the expected number of participating customers drops by one, there is no risk of auction failure. The expected price, however, decreases by 0.7%, and bid-shading increases by 7.9% due to weaker competition.

To compare the competition and volatility effect from increasing, yet irregular customer participation, we contrast the revenue gain from attracting one extra customer in expectation with the expected revenue loss coming from across auction variation in customer participation probabilities. Irregular participation results in revenue losses relative to consistent average participation, because expected auction revenues are concave in customer participation probabilities. The concavity implies that revenue improvements when participation is high are more than offset by losses under low participation. With our model estimates, revenue gains from attracting an additional customer are nearly perfectly off-set by volatility losses: both effects are equal in size (C$ 2.9M or 9 bps).

In light of the competition-volatility trade-off, we propose a simple issuance policy that aims at increasing competition while simultaneously decreasing volatility. Our idea is to strategically shift supply from auctions in which we predict strong customer participation to auctions with low predicted customer participation. The hope is that by doing so, we can stabilize customer participation and attract sufficiently many market participants to guarantee a high level of competition. Indeed, we find that the median revenue increases by about C$16 million per auction (or roughly 48 bps) when implementing our proposed rule.

The competition-volatility trade-off we highlight might be present in other settings. It is common in auctions for financial products to have a set of regular and irregular bidders (e.g., Hendricks et al. (2023) for mortgage securities; Richert (2022) for credit event auctions). Our framework can be easily adjusted to fit these applications. Furthermore, the economic insights generalize to non-auction markets which are populated by regular and irregular participants. Examples include market makers versus opportunistic traders in financial markets, global versus local firms in production markets, loyal versus non-loyal customers in consumption markets, and irregular versus stable energy generation in electricity markets (Petersen et al. (2022)).

2 Institutional details and data

In most countries, government bonds are issued in primary auctions to a small set of regulated banks, often called primary dealers, and to customers (see Appendix Figure A1).

Canadian primary market. Canada adopted this market structure to distribute its debt in November 1998. Since then, Treasury auctions are held according to an annual auction schedule. For instance, between 1999 and 2022 there have been about 28 government bond auctions per year, with an average (nominal) issuance size of C$3.24 billion given the bonds' face value is C$100. The auction schedule specifies the timing of auctions and the total debt to be issued. One week prior to the auction the precise issuance size is announced.

Anyone can participate in Treasury auctions, but only dealers can bid directly.[2] Other bidders, called customers, can only participate indirectly by placing their bids via a dealer, who can observe the customer's bid (see Appendix Figure A2). Indirect customer bidding is a common feature of Treasury auctions, e.g., in the U.S., and Japan.

Customers include different types of institutions, such as pension, mutual, and ETF funds, insurance companies, sovereigns, or bank treasuries. For over a decade, the biggest customer category are alternative investments companies, which include hedge funds. For simplicity, we use the term hedge fund to describe these investment companies throughout the paper.

A bidder may submit and update two types of bids from the time the tender call opens until the auction closing. The first type is a competitive bid. This is a step-function with at most 7 steps, which specifies how much a bidder offers to pay for specific amounts of the asset for sale.[3] During normal times, primary dealers can demand up to 25% of supply for their own account and 25% for their customers (with an aggregated cap of 40%) in form of competitive bids.

The second type of bidding is a non-competitive bid. This is a quantity order that the bidder will win for sure at the average price of all accepted competitive bid prices. The

[2]Strictly speaking, there are two types of dealers in Canada. Most dealers are primary dealers, but some are government security distributors. These are smaller dealers, who also place bids on behalf of customers, but face fewer market making requirements. For simplicity, we do not distinguish between the groups.

[3]Prices are expressed with three decimal places, e.g., C$ 99.999, and quantities must be stated in multiples of C$1,000. The minimum demand is C$100,000.

Bank of Canada actively utilizes non-competitive bids to reduce the announced auction supply (before observing submitted bids). For example, it buys Treasuries (assets) to match bank notes (liabilities). For dealers and customers, non-competitive bids are trivial since they cannot be larger than C$10 million for dealers and C$3-C$5 million for customers.

All submitted bids are aggregated and the market clears at the price at which aggregate demand equals auction supply. In case of excess demand, bidders are rationed pro-rata on-the-margin, which means that the auctioneer proportionally adjusts demand at the clearing price until supply equals demand (see Kastl (2012) for a formal definition). Every bidder wins the units demanded at bids weakly above the clearing price, and pays the bids for each unit won.[4]

Regulations. In Canada, as elsewhere, dealers have an obligation to actively buy bonds in the primary market. Concretely, primary dealers face minimal bidding requirements of roughly 10% of auction supply in normal times. The minimum level of bidding must be at reasonable prices, and accepted bids should be approximately equal to a dealer's secondary market share over a specified time period. Primary dealers are also expected to act as market-makers in the secondary cash and repo markets where they provide liquidity to investors who seek to exchange government bonds for cash. In exchange, primary dealers enjoy benefits. For instance, they have privileged access to liquidity facilities and overnight and term repurchase operations, and extract auction rents from observing customer bids.

Given the important role dealers play in the market, they are heavily regulated. In particular, in the aftermath of the 2007-2009 financial crisis, regulation tightened for dealers (and large banks more broadly). For instance, banks faced heightened capital requirements. A notable illustration of this is the Basel III leverage ratio, which was enforced at the close of 2014, and represents a significant limitation for bond trading (CGFS (2016); Allen and Wittwer (2022); Favara et al. (2022)). In addition, starting in 2016, dealers must report all trades to the Investment Industry Regulatory Organization of Canada, while customers are exempt.

Traditionally, customers, such as hedge funds, played a negligible role in Treasury mar-

[4]Shortly after the auction cleared, the clearing price, and some additional aggregate summary statistics about the auction, are announced publicly. This implies that no one has incentives to participate in the auction to learn about the market price, without wanting to win.

kets.[5] We know that this has changed in recent years, but we have a limited understanding of what customers are doing, given that there are only a handful of empirical studies. For example, Sandhu and Vala (2023) argue that hedge funds can act as market makers, engaging in trades that counter the positions of other investors. During times of distress, such as March 2020, hedge funds can contribute to market imbalances, reduced liquidity, and increased price volatility (e.g., Barth and Kahn (2020); Vissing-Jorgensen (2021)). Increased hedge fund trading may also have implications for systemic risk in the market, given that hedge funds are more likely to employ riskier trading strategies (e.g., Dixon et al. (2012))—an effect that we do not consider in our analysis.

Data. Understanding the activities and impact of customers on market functioning poses challenges due to limited data availability. For one, comprehensive long panels of trade-level data with unique identifiers for all traders are not readily accessible. For instance, the U.S. started collecting trade-level data through TRACE in mid-2017, but customer reporting with unique IDs is not mandatory. Similarly, while the Bank of England and Bank of Canada provide firm IDs, identifying all customers remains difficult (e.g., Kondor and Pintér (2022); Allen and Wittwer (2023); Pintér and Semih (2022); Barth et al. (2022)). Additionally, customers, unlike dealers, are not obliged to report their trades. Consequently, studies analyzing hedge fund trading behavior face limitations in examining trades between hedge funds and dealers, which could represent a biased sample of hedge fund trades.[6]

We overcome the data challenge by focusing on the primary market, where we can trace market participants over a long time horizon, thanks to unique identifiers. Bidder identifiers are created by Bank of Canada staff who observe bidder names, and therefore are able to account for mergers, acquisitions, and name changes. We observe all winning and losing bids in regular government bond auctions from the beginning of 1999 until the end of January, 2022. This represents the entire auction history with the exception of three auctions held in December of 1998. Table 1 provides summary statistics for our auction sample.

We augment the auction data with daily average prices of each security from the sec-

[5]In stock markets, hedge funds have long been active, and their role in these markets has been discussed in the academic literature (e.g., Stein (2009)).

[6]For instance, Banegas et al. (2021) acknowledge challenges in assessing the extent of hedge funds' Treasury selloff during March 2020, given the lack of detailed data on their cash and derivatives positions.

Table 1: Data summary of bond auctions

	Mean	SD	Min	Max
(Nominal) amount issued (in C$B)	3.24	1.04	1.00	7.00
Revenue (in C$B)	3.25	1.04	0.88	7.00
Number of dealers	14.46	2.61	11	23
Number of customers	6.74	2.56	1	15
Comp demand of a dealer (in %)	14.80	7.51	0.00	40
Comp demand of a customer (in %)	5.83	4.70	0.01	25
Non-comp demand of a dealer (in %)	0.09	0.04	0.00	0.30
Non-comp demand of a customer (in %)	0.19	0.16	0.00	0.76
Non-comp demand of the Bank of Canada (in %)	13.84	4.00	0.01	20
Number of submitted steps of a dealer	4.34	1.71	1	7
Number of submitted steps of a customer	1.86	1.02	1	7
Amount won by a dealer (in %)	4.79	5.85	0	35
Amount won by a customer (in %)	4.02	5.90	0	25

Table 1 displays summary statistics of our sample, which goes from February 10, 1999 until January 27, 2022. There are 645 auctions, none of which failed due to insufficient demand. The typical auction issues $3.2 billion worth of debt. Bonds have a face value of C$100. The total number of competitive bidding functions (including updates) is 62,813. Competitive bids are step functions with at most 7 steps. The total number of non-competitive bids is 10,552. Demand and amount won are in percentage of supply.

ondary market, the futures market, and the repo market from the Canadian Depository for Securities (CDS). These data range from the beginning of 2014 until the end of 2021.

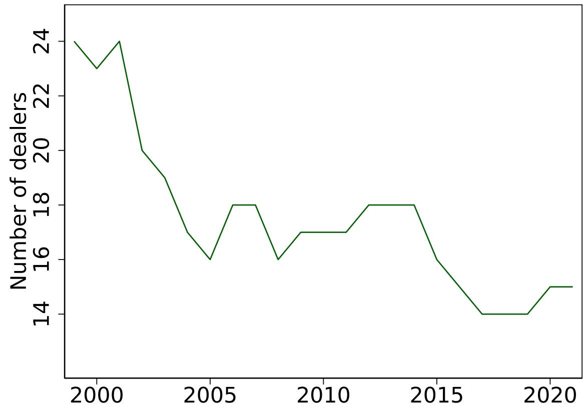
3 Empirical evidence: Exit, entry and bid updating

We document a series of stylized facts to motivate our structural model.

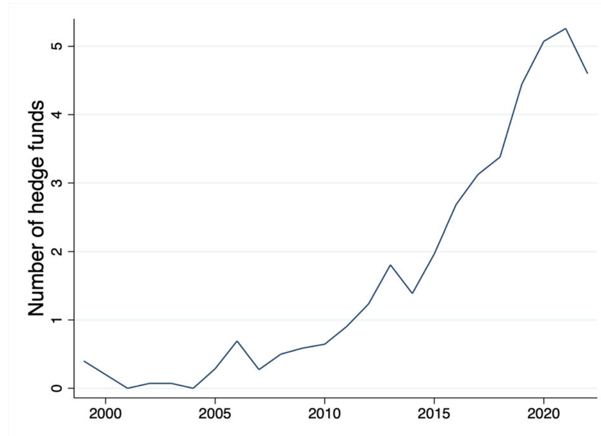
Exit and entry. We observe two striking time trends regarding entry and exit in the Canadian primary market. Appendix Figure A3 visualizes similar trends using public data of U.S. Treasury auctions to illustrate that these trends are not Canadian-specific.

On the one hand, dealers have exited the market since the first Treasury auctions took place. The total number of dealers declined from 24 in 1999 to 15 in 2021 (see Figure 1A). After an early round of exits, the number of dealers remained stable until 2014, when global players—such as Deutsche Bank and Morgan Stanley—exited the primary market for Canadian debt. Smaller broker-dealers—PI Financial Corporation and Ocean Securities—followed in 2015 (see Appendix Table A1). The exit of global banks from the Canadian bond

Figure 1: Dealer exit and hedge fund entry from 1999-2022



(A) Average number of dealers in a year



(B) Average number of hedge funds in a year

Figure 1A shows how many dealers have participated in primary auctions on average in a year since the first auction in 1999 until 2022. Figure 1B shows how many hedge funds participate on average each year.

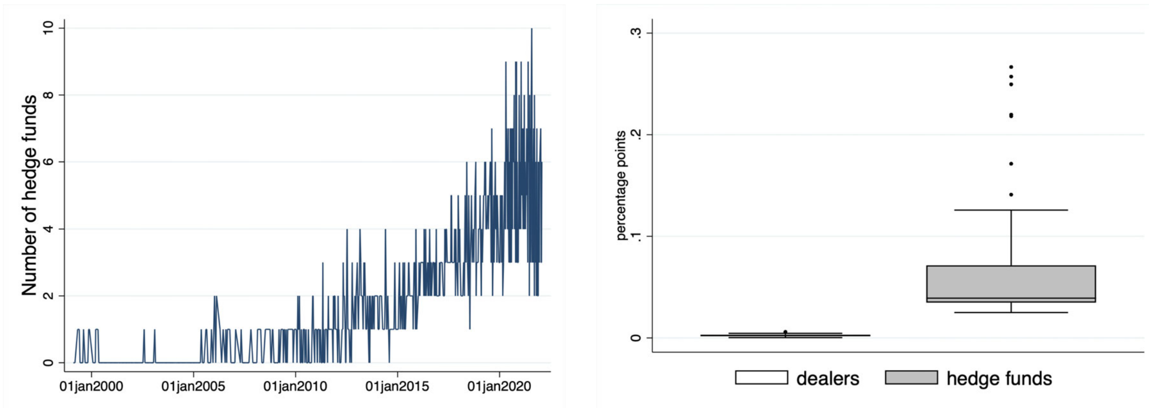
market around 2013-2015, during a period of tighter banking regulations and monitoring, suggests that stricter regulations may have pushed some banks out of the market.[7] More recently, two dealers sought buyers, which would mean exiting via acquisition: RBC (which is also a dealer) has, subject to government approval, purchased HSBC, and Laurentian Bank failed to find a buyer.

On the other hand, customers—in particular hedge funds—have become more active (see Figures 1B, and 2A). The total number of hedge funds has increased from zero to up to ten in 2021. Furthermore, they have been buying an increasingly larger share of the auction allotments relative to dealers and other customer groups (see Appendix Figures A4, and A5). However, since customers have no obligation to participate regularly, like dealers, their auction participation is highly volatile as shown in Figure 2.

Predicting customer participation. To better understand what predicts customer participation, we regress the number of participating customers on a set of explanatory variables, using data from 2014 onward (when customers are almost exclusively hedge funds). Appendix Table A2 predicts participation of customers at the bidder-level—results are simi-

[7]This would align with anecdotal evidence. For instance, according to research by Greenwich Associates—a leading financial consultancy—regulations implemented after the 2008 global financial crises caused general retreat from Canadian debt markets in 2014 (Altstedter (2014)).

Figure 2: Irregular hedge fund participation



(A) Number of hedge funds per auction (B) Variance in participation

2A shows the number of participating hedge funds in all auctions. The first box plot of Figure 2B, called dealers, shows the distribution of the variance in the percentage of dealers bidding across auctions in year out of all dealers active in. The second box plot, called hedge funds, shows the analogue for hedge funds. The distribution is similar when including all customers.

lar. Importantly, we do not try to estimate causal effects of customer participation. Instead, we focus on prediction, which we use in Section 7 to propose a policy rule that stabilizes customer participation at a sufficiently high average.

The first predictor of customer participation we include indicates the auction dates for which we estimate that a basis trade, which means buying a bond and shorting the future, could be profitable (inspired by Barth and Kahn (2020); Banegas et al. (2021)).[8] The second indicator variable tells us whether the bond-to-be-issued has benchmark status, which is the Canadian equivalent of being on-the-run (Berger-Soucy et al. (2018)). It could be, for example, that hedge funds buy more liquid on-the-run bonds because they are easier to sell.

The third and fourth predictors are indicator variables that capture the importance of monetary policy committee meetings (MPC) and quantitative easing (QE). Including an indicator for MPC meetings is inspired by the findings of Lou et al. (2023), who demonstrate that hedge funds tend to purchase bonds outside of the pre-MPC window to avoid interest

[8]We calculate the basis as in Hazelkorn et al. (2022). Specifically, to determine profitability of buying bonds at auction and shorting the corresponding futures contract, we approximate the bond's value as the quantity-weighted average price of winning bids (by customers) plus accrued interest between the auction date and the futures' expiration date. If this price is below the price of the future multiplied by a conversion rate that is determined by the Bank of Canada, we say that a basis trade is profitable. The conversion rates are published here: `https://www.m-x.ca/en/markets/interest-rate-derivatives/bond-futures-conversion-factor`, accessed on 08/23/2023.

rate uncertainty. Including an indicator for auction-days on which the central bank conducts a bond issuance in the morning and engages in quantitative easing by purchasing bonds in the afternoon, where hedge funds can sell the bonds they just bought (similar to An and Song (2018, 2023)). The fifth predictor is the rate at which Canadian dollars are exchanged to U.S. dollars on auction day, which matters for U.S.-Canadian arbitrage trades.

The sixth variable measures the buy-sell spread at which a to-be-issued bond is traded prior to the auction influence customer participation. We approximate this spread by the average difference between the highest and lowest price within a day at which a bond-to-be-issued is traded in the secondary market three days prior to the auction. The seventh and eight variables count the number of dealers who participate in the auction, and the number of customers who have participated in the previous auction.

In addition, we add controls that capture the interest rate environment and expectations about the stance of monetary policy, and therefore future bond prices. Specifically, we construct an overnight index swap (OIS) curve which captures the market expectations of the Bank of Canada's interest rate target for the overnight lending rate over 12 months; and include 1- and 3-month Canadian Dollar Offered Rates (CDOR), which is an important interest rate benchmark (e.g., McRae and Auger (2018)).[9]

Our estimation findings, reported in Table 2, indicate that customers are more likely to participate in auctions when the secondary-market spread is high. This suggests that they buy bonds at auction when they can (quickly) sell them at high prices. In addition, we find some support for Lou et al. (2023)'s idea that hedge funds avoid buying bonds prior to monetary policy announcements. The other explanatory variables are statistically insignificant, when including year-fixed effects. For the number of dealers, this is because there is little variation within a year—a feature we will incorporate in our model. For some of the other explanatory variables, this might be because of low statistical power. For example, between 2014 and 2021 there are only five cases in which we estimate that a basis trade could be profitable.

Low statistical power, in addition to a moderately sized R^2 indicates that there may be unobservable factors that play a significant role in driving customer participation—a feature

[9]Furthermore, even though transactions data only starts in 2016, we did experiment with including interdealer repo rates and repo spreads to capture the cost of overnight borrowing, but the coefficients are not statistically significant.

Table 2: Predictors of customer participation

Number of customers	(OLS1)		(OLS2)		(Year-FE)	
β_1: Basis trade	+0.984	(0.916)	+0.740	(0.915)	+0.908	(0.860)
β_2: Benchmark status	+0.238	(0.343)	+0.108	(0.350)	−0.060	(0.330)
β_3: MPC	-1.682^{*}	(0.834)	−0.685	(0.885)	-1.704^{*}	(0.848)
β_4: QE	+0.636	(0.387)	+0.405	(0.425)	−0.418	(0.437)
β_5: Exchange rate	−0.634	(1.927)	−0.050	(2.029)	−4.413	(3.326)
β_6: Spread	$+0.406^{***}$	(0.059)	$+0.420^{***}$	(0.059)	$+0.366^{***}$	(0.056)
β_7: Number of dealers	-0.319^{**}	(0.117)	−0.235	(0.128)	+0.067	(0.140)
β_8: Lagged number of customers	$+0.237^{***}$	(0.052)	$+0.187^{***}$	(0.054)	+0.025	(0.056)
Extra controls	–		✓		✓	
Adjusted R^2	0.256		0.277		0.370	
Observations	327		327		327	

Table 2 shows the estimation results of regressing the observed number of participating customers in an auction on a series of explanatory variables using data from the beginning of 2014 until the end of 2021 in column (OLS1). "Basis trade" is an indicator variable equal to 1 if buying a bond at auction and shorting the future is profitable (calculated as in Hazelkorn et al. (2022)). "Benchmark status" is an indicator equal to 1 if the issued bond is on-the-run and 0 otherwise. "MPC" and "QE"" capture conventional and unconventional monetary policy, respectively. "Exchange rate" is the CAD/USD exchange rate on auction date. "Spread" is the high minus low trading price for the bond being auctioned. "Number of dealers" and "Lagged number of customers" are the number of dealers who participate at auction and the number of customer who participated in the previous auction. In column (OLS2) we add additional controls that capture the interest rate environment and expectations about the stance of monetary policy, and therefore future bond prices: the OIS curve and 1- and 3-month CDOR. In column (Year-FE) we include year fixed effects, in addition. Standard errors are in parenthesis.

our model will incorporate.

Dealer updating. Our auction model, presented in Section 4, builds on Hortaçsu and Kastl (2012), who model the bidding process of Canadian Treasury auctions, in which customers must bid via dealers.

Intuitively, dealers who observe an aggressive customer bid should aggressively update their own bid, as they face more competition than expected. In theory, it could also be that after observing an aggressive customer bid, a dealer re-evaluates their own valuation for the bond upwards. However, this does not seem to be the case in our empirical application, which is consistent with Hortaçsu and Kastl (2012). To show this, we conduct a statistical test in Appendix Table A3, and reject the hypothesis that dealers learn about fundamentals (see Appendix B.1).

One complication when analyzing in which direction a dealer updates her bid in response

Table 3: Dealer updating

Change in qw-bid of dealer		
Customer's qw-bid	$+0.00074^{***}$	(0.00012)
Customer's number of steps	-0.00131	(0.02030)
Customer's total demand	$+0.00003$	(0.00011)
Observations	16,159	
Adjusted R^2	0.002	

Table 3 shows the results from regressing the change in a dealer's quantity-weighted average (qw) bid (conditional on updating after observing a customer bid) on the quantity-weighted average bid, the number of steps, and the total demand of the customer. We use bidding data from all regular Treasury auctions from 1999 until 2022. Bids are in bps, quantities are in million C$. Standard errors are in parentheses.

to observing a customer's bid arises from the fact that bids are step functions, and it is not obvious how to capture the shape and movement of that function. To get a sense of what matters most, we consider three moments of the customer's bidding step function: the quantity-weighted average bid, the number of steps, and the highest amount demanded, where the quantity-weighted average bid is the price a bidder is willing to pay per-unit of the bond.

Another complication comes from the fact that a dealer might observe multiple customer bids in a short window, before updating its bid or may update their own bid without observing a customer bid. To handle these rare cases, we collapse the raw data so that these multiple own bids are replaced by their average. Whenever a dealer doesn't update their bid, the change is zero.

In line with our conjecture, we find in Table 3 that a dealer bids more aggressively when observing a more aggressive customer bid. Of the moments in the customer's step function that we consider, only the quantity-weighted average is statistically significant—a detail that we will exploit in our estimation presented in Section 5. Appendix Figure A6 visualizes the positive correlation between change in the dealer's quantity-weighted and the customer's average bid.

4 Model of the Canadian primary market

Motivated by the empirical evidence, we construct a model with two main features, which are both novel relative to the existing literature. First, we endogenize the bidders' participation decision. Here we distinguish between the dealer's decision to exit the market at an annual frequency and the customer's decision to enter specific auctions. This allows us to highlight the benefit of greater competition versus the cost of higher market volatility when an increasing share of bidders participate irregularly. Second, we allow customers to be sophisticated and to anticipate that dealers will update their bids when observing the customer's bid. We show in Appendix B.2 and Figure 5 that this feature is empirically relevant, in that model estimates are biased if we assume that customers do not anticipate dealer updating.

4.1 Players, timing and preferences

In our model description we highlight four assumptions in particular, because they directly relate to the model primitives that we later estimate. We denote random variables in **bold**.

There are two groups (g) of market participants: dealers (d) and customers (h). The number of dealers who consider remaining as dealers, $\bar{N}^d$, and the number customers who are interested in bidding, N^h, are commonly known.[10] Similarly, all distributions and functional forms are commonly known.

At the beginning of a year, the debt issuance plan is announced, stating T auctions will be held. At this point, dealers decide whether they wish to continue being a dealer, i.e., committing to participate in all auctions in the upcoming year. Whether this is profitable depends on the private annual cost each dealer faces, γ_i^d. One may think of this as an opportunity cost that an institution that acts as a (primary) dealer suffers because it cannot do other things during the time it fulfills dealer-activities, such as bidding at auction and making markets.

Assumption 1. *At the beginning of the year, dealers' private commitment costs for all T auctions of the year, $\boldsymbol{\gamma_i^d}$, are drawn independently from a common atomless distribution G^d.*

After each dealer makes their decision, the market is informed about the number of bidders

[10]We could distinguish between different types of customers, for instance hedge funds versus other customers. Theoretically, such an extension would be straightforward. However, empirically, non-hedge fund customers play such a small role that the cost of complicating the model and increasing measurement error (due to more bidder groups in the resampling procedure described below) outweighs the benefit of separating non-hedge fund customers from other customers.

who will act as dealers in the upcoming year, N^d. In reality, this information is posted on the website of the auctioneer.

Before each auction t, customers observe how costly it is for them to enter the auction. Similar to dealers, one may think of these entry costs as opportunity costs, since it takes time monitor the market and compute competitive bids.[11]

Assumption 2. *Before each auction t, customers' entry costs for auction t, $\boldsymbol{\gamma^h_{ti}}$, are drawn independently from a common atomless distribution G^h.*

In addition, customers observe the distribution from which they will draw their (multi-dimensional) private signal, $\boldsymbol{s^h_{ti}}$,—which affects their willingness to pay—if they choose to bid at auction. The signal captures institution-specific knowledge, including information about the balance sheet or outstanding client orders, on auction day. The signal distribution is specified in Assumption 3. It captures current market conditions, which can be unobserved to the econometrician. For example, the expected willingness to pay may be high when secondary buy-sell spreads are high (as suggested by the evidence in Table 2), or when interest rates are expected to fall.

Observing the signal distribution, each customer decides whether to enter an auction, before learning their private signal. This timing reflects the idea that most customers are part of large institutions, who tend to allocate tasks (such as bidding at auction or trading other assets) some time in advance, before the bidding process starts. Similar timing assumptions are standard in the literature on endogenous bidder entry to single-object auctions.

Assumption 3. *Dealers' and customers' private signals $\boldsymbol{s^d_{ti}}$ and $\boldsymbol{s^h_{ti}}$ are for all bidders i independently drawn from common atomless distribution functions F^d_t and F^h_t with support $[0,1]$ and strictly positive densities f^d_t and f^h_t.*

Within an auction, a bidder's signal must be independent from all other signals, conditional on everything that bidders know when bidding, which includes a reference price-range provided by the auctioneer. To support this assumption, we follow Hortaçsu and Kastl (2012) and test whether dealers who observe customer's bid's only learn about the degree of com-

[11] In principle these costs could be constant over time or within customer. However both of these alternative assumptions imply entry patterns that are inconsistent with the data.

petition in the auction (and not about the fundamental value of the bond). Our findings, reported in Appendix Table A4, support the conditional independence assumption.

Assumptions 1-3 rule out that bidders have incentive to adopt strategies that connect multiple auctions. Thus, technically, our game consists of dealers' exit decisions plus T ex-ante identical, and separate auction sub-games. We think that this is reasonable in our setting, given that the typical dealer sells most of their auction-purchased bonds before the next auction takes place. Further, customer participation in two subsequent auctions is uncorrelated (once we control for the upward time-trend in customer participation in Appendix Table A2). In other settings, it can be important to take these inter-temporal strategic considerations into account (e.g., Rüdiger et al. (2023)).[12]

How bidders bid in a specific auction t depends on how much they value the bond at that time. This, in turn, is driven by their signals.

Assumption 4. *A bidder i of group $g \in \{d, h\}$ with signal s_{ti}^{g} values amount q of the bond by $v_t^g(q, s_{ti}^g)$. This value function is non-negative, measurable, bounded strictly increasing in s_{ti}^g for all q, weakly decreasing in q for all $s_{ti,}^g$.*

Given these values, bidders place bids. Each bid is a step function that characterizes the price the bidder would like to pay for each amount. Specifically, bidder i has the following action set to place a bid in auction t:

$$A_{ti} = \begin{cases} (b, q, K) : dim\,(b) = dim(q) = K \in \{1, ..., \overline{K}\} \\ b_k \in [0, \infty) \text{ and } q_k \in [0, 1] \\ b_k > b_{k+1} \text{ and } q_k > q_{k+1}\ \forall k < K. \end{cases} \tag{1}$$

Following Hortaçsu and Kastl (2012), bidding evolves in three rounds. First, dealers can place early bids directly to the auctioneer. Second, each participating customer is randomly matched to a dealer and places her bid with this dealer.[13] Third, each dealer observes these customer bids (if any), and may update their own bids.

[12]Rüdiger et al. (2023) analyze inter-temporal incentives of Argentinian primary dealers to forgo short-term auction gains to fulfill longer-term minimal bidding requirements necessary to maintain the dealer-status. Appendix Figure A7 provides evidence that Canadian primary dealers are above minimal bidding requirements, and therefore do not face the same inter-temporal trade-off as in Rüdiger et al. (2023).

[13]The assumption of random matches simplifies the equilibrium conditions and estimation procedure. In Appendix Figure A8 we provides some evidence that random matching is a reasonable approximation

To rationalize early bidding (which we observe in the data), we let one dimension of dealer i's signal $\boldsymbol{s_{ti}^{d}}$ be a random variable $\boldsymbol{\Psi_{ti}} \in [0,1]$ which is the mean of another Bernoulli random variable, $\boldsymbol{\Phi_{ti}}$, that determines whether the dealer's later bid will make it in time before the auction closes. The idea is that the dealer might not have sufficient time to re-compute her bid and enter it into the bidding interface when observing a customer's bid shortly before the auction deadline. Whether there is sufficient time or not is revealed only in the last stage. Formally, the dealer observes the realization $\omega_{ti} \in \{0,1\}$ of $\boldsymbol{\Phi_{ti}}$, where $\omega_{ti} = 1$ means that the late bid will make it in time in that stage. Further, the dealer observes her own signal, s_{ti}^{d}, in addition to Z_{ti}^{d}, which includes the bids of the customer(s) that was (were) matched to this dealer or the fact that no customer bid arrived.

A pure bidding strategy is a mapping from the information set of a bidder to the action space at each stage of the game. To capture everything that a bidder knows, we introduce a bidder's type, labeled $\theta_{i\tau}^{g}$, where time τ summarizes the auction date and the bidding stage, e.g., $t1$. The type is the private signal of the bidder in the first and second stage of the game, and it may include Z_{ti}^{d} at the final stage. With this, bidding strategies can be represented by bidding functions, labeled $b_{i\tau}^{g}(\cdot, \theta_{i\tau}^{g})$, for bidder i of group g with type $\theta_{i\tau}^{g}$ at time τ.

When choosing the bidding function, a customer anticipates that their dealer can update their own bid—which differs from Hortaçsu and Kastl (2012), who focus on dealers. However, since the customer doesn't know the dealers type, $\theta_{i\tau}^{d}$, she doesn't know whether and how the dealer will update their bid. As a result, a customer cannot be sure if the market-clearing price will increase or decrease when she marginally increases her own demand at step k—anything can happen.[14] This makes it complex for the customer to determine her optimal bid.

To render the customers' optimization problem solvable, we assume that dealers only pay attention to finite sets of L_t moments of the customers' bidding function when updating

of reality. Further, we provide evidence that since 2014 dealers have not been leaving the market because they systematically observe fewer customers than dealers who remain in the market, which would violate the random matching assumption. We find that the that on average the total number of customers that an exiting dealers observes in a year (because the customer bids via this dealers) is not statistically different from the average number of customers that remaining dealers observe. The test's p-value is 0.28 for auctions post-2014.

[14] As a comparison, when dealers don't update bids, the market clearing price will weakly increase in all states of the world if the customer increases her quantity q_k at price b_k by a little bit, assuming that all other participants play as in the equilibrium.

their own bid—motivated by the empirical evidence presented in Table 3.[15] Formally, a moment is a mapping μ_t^l that transforms the bidding function, $b_{i\tau}^h(\cdot, \theta_{i\tau}^h)$ for type $\theta_{i\tau}^h$, into a real number $\mathbb{R}$. We restrict attention to moments that are differentiable with respect to quantity at each price. This includes, for example, the intercept with the price or quantity axis, some smooth approximation of the slope, or the quantity-weight bid:

$$\mu_t^l(b_{i\tau}^h(\cdot, \theta_{i\tau}^h)) = \frac{b_1 q_1 + \sum_{k=2}^K b_k(q_k - q_{k-1})}{q_K} \tag{2}$$

when $\{b_k, q_k\}_{k=1}^K$ constitute bidding function $b_{i\tau}^h(\cdot, \theta_{i\tau}^h)$.

Once all bidders submit their step function, the market clears at the lowest price, P_t^*, at which the aggregated submitted demand satisfies total supply. The supply, $\boldsymbol{Q_t}$, is unknown to bidders when they place bids because a significant fraction of the total allotment goes to the Bank of Canada, who is the largest non-competitive bidder; $\boldsymbol{Q_t}$ is distributed on $[\underline{Q}_t, \overline{Q}_t]$ with strictly positive marginal density conditional on s_{ti}^g $\forall i, g = h, d$.

Given all bidding functions, $b_{i\tau}^g(\cdot, \theta_{i\tau}^g)$, bidder i of group g wins amount q_{ti}^{g*} at market clearing. She pays the amount she offered to win for each unit won. In case there is excess demand at the market clearing price, each bidder is rationed pro-rata on-the-margin.

4.2 Equilibrium conditions

We first characterize the equilibrium in auction t conditional on customer and dealer participation. Then, we determine the entry and exit decisions of customers and dealers, respectively.

Bidding. To find the optimal bidding strategy, a dealer maximizes her expected total surplus, taking the behavior of other bidders as given. For bidder i in group g of type $\theta_{i\tau}^g$ the expected total surplus at time τ is

$$TS_{\tau i}^g = \mathbb{E}_t \left[\int_0^{\boldsymbol{q_{ti}^{g*}}} [v_t^g(x, s_{ti}^g) - b_{i\tau}^g(x, \theta_{i\tau}^g)] dx \right]. \tag{3}$$

[15] Alternatively, we could assume that customers only think that this is the case, even though the dealer responds to the full curve.

Note that for customers who bid a single time, $TS^h_{\tau i}$ is equivalent to TS^h_{ti}. For dealers, we have two surpluses, one for each bidding round, TS^g_{t1i} and TS^g_{t2i}. In all cases, the expectation is taken over the amount the bidder will win at market clearing, $\boldsymbol{q^{g*}_{ti}}$, which depends on the strategies and types of all bidders, as well as the unknown supply.

We focus on group-symmetric Bayesian Nash equilibrium (BNE) in which all dealers and customers play the same bidding strategy if they are the same type. Formally, a pure strategy BNE of auction t is a collection of bidding functions $b^g_{i\tau}(\cdot, \theta^g_{i\tau})$ that each bidder i and almost every type $\theta^g_{i\tau}$, $b^g_{i\tau}(\cdot, \theta^g_{i\tau})$ maximizes the bidder's expected total surplus (3) at each time τ.

Since there is no cost of submitting steps, all bidders choose the maximal number of steps in equilibrium: $K = \overline{K}$. To rationalize variation in the number of steps in the data, we could follow Kastl (2011) and include a private cost of computing and submitting steps. We refrain from doing so since this doesn't add additional economic insights.

Proposition 1. *Fix a set of L_t moment functions that map a customer's bid function into a real number, $\mu^l_t : b^h_{i\tau}(\cdot, \theta^h_{i\tau}) \to \mathbb{R}$, and consider a group-symmetric BNE.*

(i) Every step k but the last step in the dealer's bid function $b^d_{i\tau}(\cdot, \theta^d_{i\tau})$ has to satisfy

$$\Pr(b_k > \boldsymbol{P^*_t} > b_{k+1} | \theta^d_{i\tau}) \left[v^d_t(q_k, s^d_{ti}) - b_k \right] = \Pr(b_{k+1} \geq \boldsymbol{P^*_t} | \theta^d_{i\tau})(b_k - b_{k+1}). \tag{4}$$

At the last step, $b_K = v^d_t(\bar{q}(\theta^d_{i\tau}), s^d_{ti})$, where $\bar{q}(\theta^d_{i\tau})$ is the maximal amount the dealer may be allocated in the auction equilibrium.

(ii) Every step k in a customer's bid function $b^h_{i\tau}(\cdot, \theta^h_{i\tau})$ that generates moments $m^l_t = \mu^l_t(b^h_{i\tau}(\cdot, \theta^h_{i\tau}))$ for all l has to satisfy:

$$\begin{aligned}
&\Pr(b_k > \boldsymbol{P^*_t} > b_{k+1} | \theta^h_{i\tau}) \left[v^h_t(q_k, s^h_{ti}) - b_k \right] = \\
&\Pr(b_{k+1} \geq \boldsymbol{P^*_t} | \theta^h_{i\tau})(b_k - b_{k+1}) - \sum_{l=1}^{L_t} \lambda^l_t \frac{\partial \mu^l_t(b^h_{i\tau}(\cdot, \theta^h_{i\tau}))}{\partial q_k} + Ties(b^h_{i\tau}(\cdot, \theta^h_{i\tau})),
\end{aligned} \tag{5}$$

with $Ties(b^h_{i\tau}(\cdot, \theta^h_{i\tau})) = \Pr(b_k = \boldsymbol{P^*_t})\mathbb{E}[v^h_t(\boldsymbol{q^{h*}_{ti}}, s^h_{ti}) \frac{\partial \boldsymbol{q^{h*}_{ti}})}{\partial q_k} | b_k = \boldsymbol{P^*_t}] - \Pr(b_{k+1} \geq \boldsymbol{P^*_t})\mathbb{E}[v^h_t(\boldsymbol{q^{h*}_{ti}}, s^h_{ti}) \frac{\partial \boldsymbol{q^{h*}_{ti}}}{\partial q_k} | b_{k+1} \geq \boldsymbol{P^*_t}] + \Pr(b_k = \boldsymbol{P^*_t})\mathbb{E}[\frac{\partial \boldsymbol{q^{h*}_{ti}}}{\partial q_k} | b_k = \boldsymbol{P^*_t}] + \Pr(b_{k+1} = \boldsymbol{P^*_t})\mathbb{E}[\frac{\partial \boldsymbol{q^{h*}_{ti}}}{\partial q_k} | b_{k+1} = \boldsymbol{P^*_t}] + \Pr(b_{k+1} < \boldsymbol{P^*_t})\mathbb{E}[\frac{\partial \boldsymbol{q^{h*}_{ti}}}{\partial q_k} | b_{k+1} < \boldsymbol{P^*_t}]$. *Here we have omitted the dependence on $\theta^h_{i\tau}$. In addition,*

$$\lambda^l_t [m^l_t - \mu^l_t(b^h_{i\tau}(\cdot, \theta^h_{i\tau}))] = 0 \text{ for all } l \text{ in auction } t, \tag{6}$$

with Lagrange multipliers $\lambda_t^l \in \mathbb{R}$ for all l.

(iii) The moments, $\{m_t^l\}_{l=1}^L$, are such that expected total surplus (3) is maximized, and $m_t^l = \mu^l(b_{i\tau}^h(\cdot, \theta_{i\tau}^h))$ for all l and all customers.

From the existing literature we know how the dealer determines her equilibrium bid. Essentially, in each stage, τ, she chooses her bid to maximize total surplus, $TS_{\tau i}^d$, defined in (3), subject to market clearing:

$$\max_{\{q_k, b_k\}_{k=1}^K} TS_{\tau i}^d \text{ subject to market clearing.} \tag{7}$$

She trades off the expected surplus on the marginal infinitesimal unit versus the probability of winning it, summarized in Proposition 1 (i) (see Kastl (2017), p. 237 for more details). Given that it is never optimal for a dealer to submit a bid above her true value, dealer demand is never rationed in equilibrium, except for the last step. At the last step the dealer submits her true value, because it is not possible to increase the winning probability of (non-existing) subsequent steps by shading the bid.

Our innovation is to characterize the equilibrium bidding of a customer. The key difference between the dealer and the customer comes from the fact that customers take into account the dealer's response to observing their bid. Since dealers only change their own bids in response to changes in the L_t moments of the observed customer bidding function, $\{m_t^l\}_{l=1}^L$, the customer's optimatlity conditions can be decomposed into two parts. This helps to draw the connection to the dealer's equilibrium condition. First, for each fixed set of moments, $\{m_t^l\}_{l=1}^L$, the customer's equilibrium bidding function must achieve highest expected surplus among all functions that induce the same dealer updating, i.e., have the $\{m_t^l\}_{l=1}^L$:

$$\max_{\{q_k, b_k\}_{k=1}^K} TS_{\tau i}^h \text{ subject to market clearing and } m_t^l = \mu_t^l(b_{i\tau}^h(\cdot, \theta_{i\tau}^h)) \text{ for all } l \in L_t. \tag{8}$$

The corresponding optimality conditions are summarized in Proposition 1 (ii). Second, among those partially optimal functions, the customer chooses the optimal one, by choosing moments $\{m_t^l\}_{l=1}^L$ so that the expected total surplus, $TS_{\tau i}^h$, is maximized—Proposition 1 (iii).

Dealer updating implies that it can be optimal for a customer to place a bid above her true value. As a consequence ties can occur at any step with positive probability. Formally, in Proposition 1 (ii) the term $Ties(b_{i\tau}^h(\cdot, \theta_{i\tau}^h))$ includes all the cases in which the customer ties with some other bid and must be rationed.

To illustrate why it can be optimal for customers to bid above their value and tie at non-final steps with positive probability, assume customer i places her bids via dealer j. She could submit a step-function with $b_k \leq v_k$ for all k. Alternatively, she could deviate and bid above her value, for example, at the fourth step, $b_4 > v_4$, as depicted in Figure 3A.[16] This would increase her quantity-weighted bid relative to bidding below her value at all steps, i.e., modify one moment, m_t^1. Observing a higher quantity-weighted average of the customer's bid, dealer j updates her own bid towards a more aggressive bid—shown Figure 3B.

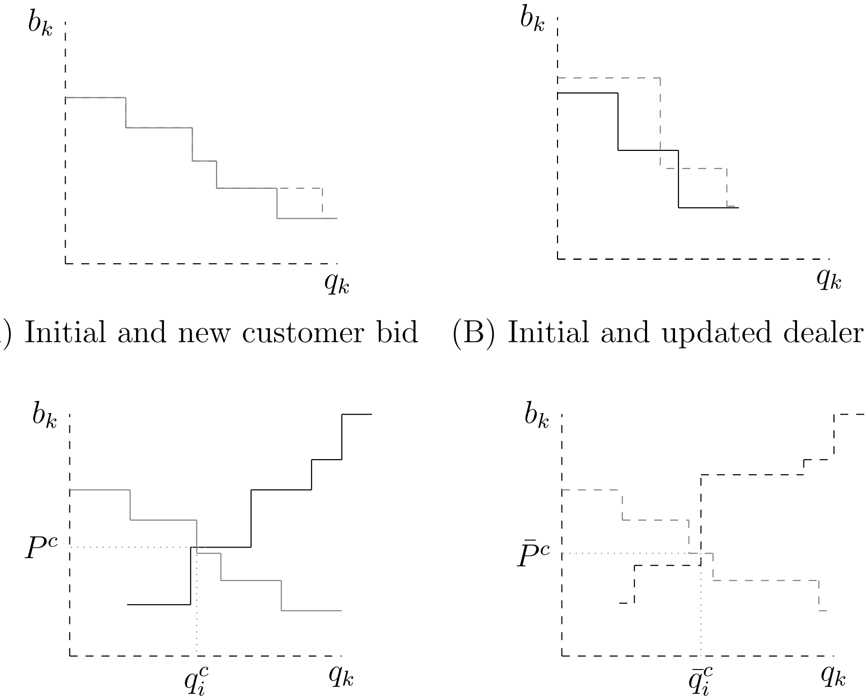
How the dealer updates her bid depends on her private beliefs about where the market will clear, which hinges on the dealer's private type, on the distributions of types, and the bidding strategies of all bidders that compete with the dealer. The customer does not know dealer j's private type, so she cannot perfectly predict how the dealer will update. However, she can predict the dealer's update probabilistically.

The customer constructs the distribution of residual supply curves against which she plays (which includes the dealer's update), to choose the bidding function that maximizes her expected auction surplus. Figures 3C–3D display one realization from the distribution of residual supply curves and the implied point of market clearing given the customer's bid for both scenarios. Given this realization, it is profitable for the customer to bid above her value. Rather than clearing at the second step of the customer's bidding function, the auction now clears at the third step, which implies that the customer wins more units at prices below her values when deviating to $b_4 > v_4$. Here, the customer does not tie. However, given another realization of the residual supply curve, the customer could tie at the fourth step. At this step she would be happy to be rationed and win fewer units at prices above value.

Entry and exit decisions. A customer i enters an auction t if her entry cost, γ_{ti}^h, is smaller than the total surplus she expects to earn from participating in the auction before she observes her private signal, but knowing the current market conditions, which are captured

[16] Note that it is never profitable to extend the last step in the customer's bidding function out. This can come at the benefit of inducing less aggressive dealer bidding, which can be beneficial for the customer. However, it also comes at the cost of surplus loss from winning additional units and having to pay prices above values for those units.

Figure 3: Bidding example



(A) Initial and new customer bid (B) Initial and updated dealer bid

(C) Initial market clearing (D) New market clearing

Figure 3 provides an example for why it can be optimal for a customer to deviate from a bidding function with $b_k \leq v_k$ (shown in solid lines) and bid above their value, here at step $b_4 > v_4$ (in the dashed lines in panel A). This is true even though this triggers a more aggressive dealer bid, as shown in the dashed line of panel B. Panels C and D display one realization of market clearing for both customer bids; the downward-sloping step-function is the customer's bid, and the upward-sloping function is one realization of the residual supply curve that the customer faces.

by the signal distributions, F_t^g, and the shape of the value functions, $v_t^g(\cdot,\cdot)$, for $g = \{h, d\}$.

Proposition 2. *Customer i with entry cost γ_{ti}^h enters auction t if*

$$\gamma_{ti}^h \leq \mathbb{E}_t[\boldsymbol{TS_{ti}^h}|N^d] \text{ with } TS_{ti}^h \text{ given by (3).} \tag{9}$$

Note that we have relabeled the time subscript τ to t to highlight that TS_{ti}^h is the surplus that customer i expects from participating in auction t. The expectation is taken over the customer's private signal $\boldsymbol{s_{ti}^h}$, and is conditional on N^d dealers bidding in the auction.

Anticipating all auctions, $t = 1, ..., T$ of the upcoming year, dealer i exits the market if her commitment cost is higher than the surplus she expects to earn from bidding in all T auctions of the upcoming year.

Proposition 3. *At the beginning of the year, dealer i with commitment cost γ_i^d exits the market if*

$$\gamma_i^d \geq \sum_{N^d=1}^{\bar{N}^d} \left(\sum_{t=1}^{T} \mathbb{E}_t \left[\boldsymbol{TS_{ti}^d} | N^d \right] \right) \Pr(\boldsymbol{N^d} = N^d) \tag{10}$$

where $TS_{ti}^d = [1 - \Psi_{ti} + \Psi_{ti} \Pr(\textit{no customer})] TS_{t1i}^d + \Pr(\textit{at least 1 customer}) TS_{t2i}^d$

with TS_{t1i}^d *and* TS_{t2i}^d *given by (3) for* $\tau = t1, t2$.

The dealer cares about the aggregate surplus she expects to earn over the entire year, and when taking her decision she doesn't know how many other dealer's will compete in the auctions, N^d. Therefore, the dealer considers all possible realizations of $\boldsymbol{N^d}$ and weights each by how likely it is to occur, $\Pr(\boldsymbol{N^d} = N^d)$. Furthermore, for each auction t, the dealer must take an expectation over bidding rounds, τ, to determine how much surplus she expects to earn in the auction, TS_{ti}^d. This is because ex-ante the dealer doesn't know whether she will place a final bid and earn a surplus of TS_{t2i}, or just an early bid which leaves her with a surplus of TS_{t1i}. This depends on the probability that the final bid will make it on time, Ψ_{ti}, and the probability that at least one customer is matched to the dealer.

5 Identification and estimation

The goal is to learn about the unobserved bidder values, $v_t^g(\cdot, s_{ti}^g)$, and the entry and exit cost distributions, G^h and G^d.

Identifying and estimating values. The idea behind identifying and estimating bidder values from bidding data is to infer how much each bidder is truly willing to pay from the equilibrium conditions under the assumption that everyone plays this equilibrium, here specified in Proposition 1. Other than our object of interest—bidder values—we either observe all of the elements in Proposition 1, or can estimate them.

For dealers it suffices to estimate the probabilities of where the market will clear to point-identify dealer values at all submitted steps, q_k (Kastl (2012)). We estimate these probabilities by extending Hortaçsu and Kastl (2012)'s resampling procedure so as to account for the fact that in the data bidders sometimes update their bids more often than predicted by our model (details in Appendix C). We account for differences across auctions (including differences that arise from different market conditions, such as secondary buy-sell spreads), by resampling within rather than across auctions. We can then leverage monotonicity of the value distribution to construct an upper and a lower bound for the marginal value at intermediate quantities where steps are not submitted.

Learning about customer values is more difficult, because the customer's equilibrium condition (5) involves ties, which implies that it depends on all quantity points on the bidding curve, and not only at submitted steps. This leaves us with K equations but infinitely many unknowns, so that customer values cannot be point-identified. However, we can construct sets of informative bounds on customer values that are consistent with the observed bids—a formal statement is provided in Proposition 4 in Appendix A. Specifically, we aim to recover K upper and K lower values for $v_t^h(q_k, s_{ti}^h)$ for a customer i in a fixed auction t. For this, we assume that dealers only pay attention to the quantity-weighted bid when updating their own bid—motivated by the empirical evidence in Table 3. Condition (5) then simplifies to an equation with a single moment, the quantity-weighted bid (2). For simplicity, we drop the super- and subscript $l = 1$.

To identify customer value bounds, we proceed in three steps. First, we guess a Lagrange multiplier, $\lambda_t \in \mathbb{R}$, and replace the system of equations from Proposition 1 (ii) with a system that eliminates the infinitely many unknown values due to rationing. To do this, we utilize boundedness and monotonicity to replace values at quantities where a step is not submitted, with a bound. For example, the upper bound on the value at quantity $q \in (q_k, q_{k+1})$ is $\overline{v}_t^h(q_k, s_{ti}^h)$, and the lower bound is $\underline{v}_t(q_{k+1}, s_{ti}^h)$. This results in a system of $2K$ equalities which are linear in the unobserved values, with $2K$ unknown.

Second, we simplify this system of equations by showing that at a subset of steps rationing never occurs in equilibrium, which implies that we can cancel out all of the terms involving rationing at these steps. We do this by constructing profitable deviations at these steps in Lemma 1. With these simplifications, it is straightforward to express the system of equations in matrix format and show that the matrix has full rank, which proves that the system is identified.

To provide an intuition for how Lemma 1 works, consider a customer with $\lambda > 0$. If the dealer did not update their bid ($\lambda = 0$), this customer would submit a bid with a lower quantity-weighted bid. With dealer updating, they cannot reach this optimum, but move as closely as possible to it. To do this, the customer starts at the unconstrained optimum and inflates the quantity-weighted bid in the cheapest way possible, meaning that the costs coming from dealer updating are minimized. At steps other than the last step, this may involve rationing, i.e., demanding larger quantities than in the unconstrained bid so as to inflate the quantity-weighted bid without winning all of the extra units. However, at the last step, demanding a larger amount causes the quantity-weighted bid to fall, and therefore the customer does not find it optimal to tie at the last step. Terms involving rationing at the last step therefore are zero. A similar logic applies when $\lambda < 0$. Now the customer would want to submit a bid with a higher quantity-weighted bid if the dealer didn't update. Ties may now only occur at the last step, so that the terms involving rationing drop out at all earlier steps.

Third, we check that the guessed Lagrange multiplier, λ_t, is valid in equilibrium by relying on Proposition 1 (*iii*). To do this we rely on the fact that we observe the distribution of dealers' post-updating bids following any customer order. This allows us to calculate what residual supply curves a customer would have faced had they chosen any other quantity-weighted bid. With this we can compute bounds on the expected surplus that the customer could have achieved at any alternative quantity-weighted bid (conditional on the customer value bounds that are consistent with the guessed λ_t). We then check whether the guessed λ_t is consistent with the changes in surplus between the submitted quantity-weighted bid and the alternative quantity-weighted bids. For example, if the guessed λ_t suggests that the customer is forgoing profitable changes in their bid in order to reduce their quantity-weighted bid, then the residual supply curves that they expect to face after submitting a larger quantity-weighted bid must imply large enough losses in surplus. However, these losses should not be so big that the customer would rather choose a bid function that resulted in an even lower quantity-weighted bid.

Identifying and estimating cost distributions. To learn about the cost distributions, G^h and G^d, we rely on Propositions 2 and 3, respectively. For this, we fix the maximal number of dealers to what we observe in our sample, i.e., $\bar{N}^d = 24$. We define the number of potential customers in a year, N^h, as the maximal number of customers we observe bidding in any auction of that year.

We first compute bounds on how much customers and dealers expect to gain from participating in the game, i.e., the RHS of (10) and (9), respectively. For customers, this is straightforward. We can compute each customer's auction surplus (3) at the upper and lower bound of the customer's values, $\overline{TS}^h_{ti}$, and $\underline{TS}^h_{ti}$, conditional on auction participation. For example, $\overline{TS}^h_{ti}$ is the area between the upper bound on the customer s value function and the submitted bid function, where each quantity is weighted by the probability that it is won at market clearance. We then average $\overline{TS}^h_{ti}$ across all participating customers in an auction to obtain the expected surplus prior to auction entry, $\mathbb{E}_t[\overline{\boldsymbol{TS}}^h_{ti}|N^d]$, and similarly for the lower bound. Here we rely on the assumption that customers signals are drawn iid from the same distribution.

For dealers, constructing bounds on the expected annual auction surplus, given in (9), is more difficult, since dealers make their entry decision before knowing how many other dealers will participate in the upcoming year. This implies that we need to compute two additional objects besides the expected total surplus given the observed number of dealers (which is constructed like for customers). First, we need to compute the expected total surpluses when a different number of dealers than observed participates in the market, for all potential numbers. Second, we compute how likely it is that N^d dealers participate when $\bar{N}^d$ is the maximal number of dealers from the empirical probability that a dealer participates in a fixed year.[17]

We could exactly compute the counterfactual surpluses at non-observed numbers of participating dealers following a similar approach presented in our counterfactual exercises. However, this is computationally intensive. Therefore, we approximate these surpluses by finding auctions that are similar (in that all bidders expect similar per-unit auction surpluses), but with different numbers of participating dealers. For example, to obtain the counterfactual surplus for an auction in which N^d dealers participate, we find a similar auction in which N^d_1 dealers participate. For that similar auction we compute the expected surplus for dealers: $\mathbb{E}_t[\overline{\boldsymbol{TS}}^{\boldsymbol{d}}_{\boldsymbol{ti}}|N^d_1]$. Repeating this exercise for other similar auctions with different numbers of participating dealers provides an estimate for each counterfactual surplus.

With the bounds on how much dealers and customers expect to gain from auction participation, we identify bounds on their cost distributions by matching the predicted participation

[17]Formally: $\Pr(\boldsymbol{N^d} = N^d) = \binom{\bar{N}^d}{N^d}(N^d/\bar{N}^d)^{N^d}(1-(N^d/\bar{N}^d)^{\bar{N}^d - N^d}$.

probability of a customer and a dealer (according to Propositions 2 and 3) to what we observe in the data. For example, the predicted probability of a customer entering an auction, $\Pr(\boldsymbol{\gamma^h_{ti}} \leq \mathbb{E}_t[\boldsymbol{TS^h_{ti}}|N^d])$, must equal the observed entry probability (the number of customers who bid in an auction, N^h_t, relative to the number of customers who consider bidding, N^h). Relying on the fact that

$$\Pr(\boldsymbol{\gamma^h_{ti}} \leq \mathbb{E}_t[\underline{\boldsymbol{TS}}^{\boldsymbol{h}}_{\boldsymbol{ti}}|N^d]) \leq \frac{N^h_t}{N^h} \leq \Pr(\boldsymbol{\gamma^h_{ti}} \leq \mathbb{E}_t[\overline{\boldsymbol{TS}}^{\boldsymbol{h}}_{\boldsymbol{ti}}|N^d]) \tag{11}$$

we could identify a lower and upper bound for the customer's cost distribution non-parametrically as long as we can construct sufficiently many different surpluses, $\mathbb{E}_t[\overline{\boldsymbol{TS}}^{\boldsymbol{h}}_{\boldsymbol{ti}}|N^d])$ and $\mathbb{E}_t[\underline{\boldsymbol{TS}}^{\boldsymbol{h}}_{\boldsymbol{ti}}|N^d])$, to cover the full support of the cost distribution. With our data, we impose an exponential distribution with parameter β^h for customers, and β^d for dealers.[18]

6 Estimated values and costs

For each auction t, we estimate dealer values, $\hat{v}_{itk}$, and bounds for customer values, $\underline{v}_{itk}$ and $\overline{v}_{itk}$, at each submitted quantity step k of final bids. In addition, we obtain upper and lower bounds for the (exponential) cost distributions of both bidder groups, G^h, G^d.

Customer and dealer values. Before interpreting the economic magnitudes of our value estimates, we show in Figure 5 that it is quantitatively important to account for the fact that sophisticated customers, such as hedge funds, anticipate that dealers might update their own bid after observing the customer's bid. An alternative assumption would be to neglect customer bidding incentives that are triggered by dealer updating. In that case, we could simply follow the estimation procedure of the existing literature, and back out customer values in the same way we back out dealer values. However, our results highlight that customer values would be significantly biased if we followed this simpler approach.

Independent of the assumption we make about the customer's degree of sophistication,

[18]Concretely, for customers we estimate a set of β^h, using the following criterion function: $Q'(\beta^h) = Q(\beta^h) - \inf_{\beta'} Q(\beta')$ with $Q(\beta^h) = (\frac{N^h_t}{N^h} - H(\mathbb{E}_t[\underline{\boldsymbol{TS}}^h_{ti}|N^d]; \beta^h))_+)^2 + (\frac{N^h_t}{N^h} - H(\mathbb{E}_t[\overline{\boldsymbol{TS}}^h_{ti}|N^d]; \beta^h))_-)^2$, where H is the CDF of an exponential distribution with parameter β^h. As the sample size grows, all points in the identified set produce criterion values of zero. To account for finite sample errors, we define a contour set of level c_n, and estimate the parameter set $\{\beta^h|Q'(\beta^h) \leq c_n\}$. We choose the cutoff c_n proportionally to the number of auctions in our sample $c_n = \log(645)/645$, inspired by Chernozhukov et al. (2007).

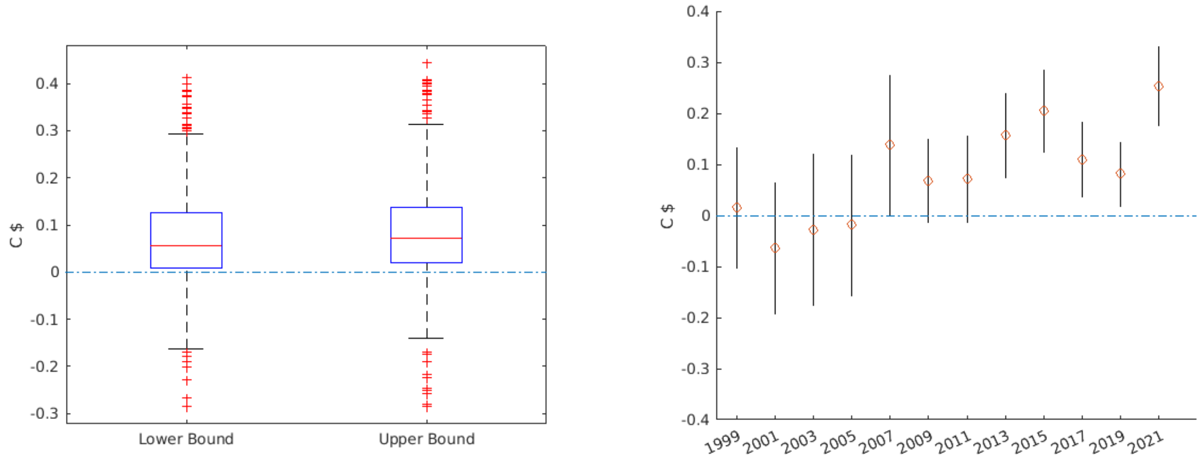
customers are typically willing to pay more than dealers (see Figure 4, Appendix Figure A9). In our benchmark where customers are fully sophisticated, we estimate that customers are willing to pay 6.9-7.7 bps more per unit of the bond than dealers in the median. This difference is economically meaningful compared to the median market yield-to-maturity of the bonds, which is 161 bps, and sizable compared to the median difference between the quantity-weighted average winning bid and the quantity-weighted average secondary market price on auction day (one day after the auction), which is 0.4 bps (2 bps). Further, the difference is statistically significant at the 5% level (as shown in Appendix Table A4), and it cannot be driven by customer selection into more profitable auctions given that we are considering value differences conditional on auction participation. This is true when using the lower and upper bound of customer values. To be conservative, we rely on the lower-bounded values for the remainder of the paper.

Over time customer values have increased relative to dealer values, as shown in Figure 4.[19] Since values reflect how much an auction participant expects to earn from trading bonds in the secondary market, this finding suggests that customers anticipate increasingly larger per-unit returns from buying bonds relative to dealers. This is in line with anecdotal evidence according to which more stringent regulations for dealers since the financial crisis in 2007-2009 have decreased profit margins for dealers relative to customers. The finding is also in agreement with evidence documented by Sandhu and Vala (2023), who argue that hedge funds, who enter the market after 2009, are able to obtain higher than average returns in the secondary market for Canadian government bonds, because they have more flexibility to employ complex and risky trading strategies (Ontario Securities Commission (2007)).

Finally, we test whether our estimated distribution of customer values correlates with the observed market conditions that predict customer participation (shown in Table 2). This provides a validity check for our value estimates since we have not used any information of these market conditions in our estimation. Specifically, we regress the average quantity-weighted customer value per auction, in addition to other moments of the customer value distribution, such as the standard deviation, on the explanatory variables that we used to predict customer participation in Table (2). Our findings, reported in Appendix Tables

[19] This trend could come from the same customers becoming more profitable over time. Alternatively, if different customer types (e.g., hedge funds vs. pension funds) have systematically different value distributions, it could come from a change in the composition of customer types over time.

Figure 4: Difference between customers and dealers values



(A) (B)

Figure 4A shows the distribution of the difference in quantity-weighted average values between participating customers and dealers, using customer lower bound values on the LHS, and upper bound values on the RHS. We remove outliers, defined as a value that is more than three scaled median absolute deviations from the median. Figure 4B plots the point estimates and 95% confidence intervals from regressing the difference between the average customer value and the average dealer value in each auction on a set of time indicator variables. The first indicator is 1 for 1999-2000, the second indicator is 1 for 2001-2002, and so forth, until 2021-2022. The confidence intervals are computed using the point-estimates of dealer and customer values at the lower bounds, and therefore do not account for noise in the estimation of these values. Prices are in C$ with a face value of 100.

A5 and A6, confirm our prior that customer values are higher (and more disperse) when secondary market spreads are wide.[20]

Participation costs. Participation costs capture the opportunity cost of profits that customers and dealers could generate outside the Treasury market. These costs differ from values in that they are independent of how much a bidder wins at auction; they must be payed when an institution spends time bidding at auction (and in the case of dealers, conduct other market making-activities), even if the institution doesn't buy any bonds.

On average, we estimate an annual cost of being a dealer between C$3.198 and C$4.310 million with (bootstrapped) confidence interval [C$2.837M, C$4.551M]. This is sizable compared to the average annual profit a bank generates from its market-making activities in

[20]Most coefficients that are statistically significant at a 10% level in Table 2 and Appendix Table A5 share the same sign with the exception of QE, the number of dealers and the lagged number of customers. While the latter two coefficients lose significance when including year-fixed effects, the QE coefficient remains statistically significant and positive. This is also the case when using observed bids as independent variables. Therefore it is unlikely that this stems from estimation error.

Figure 5: Customer bid-shading under different bidding assumptions

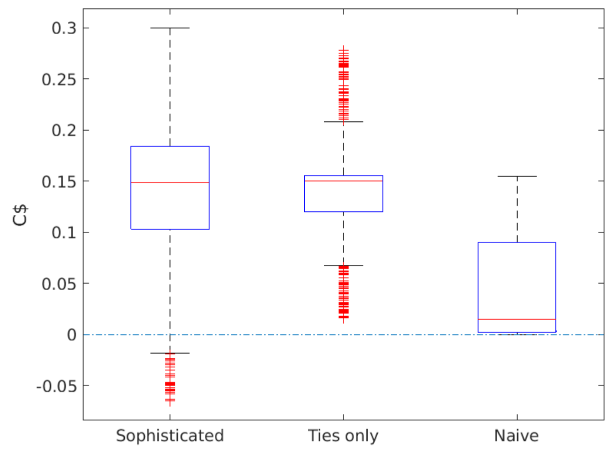


Figure 5 shows the distribution of the customers' average shading factors in C$, defined as the customer's quantity-weighted average value minus the quantity-weighted average bid, under different assumptions regarding the customer's degree of sophistication. The box plot called "Sophisticated" shows the distribution of the lower bound quantity-weighted customer value estimates according to our model. "Ties only" estimates the values under the assumption that customers bid according to Proposition 1 (ii) but setting $\lambda = 0$. The "Naive" box uses the dealers' optimality condition, i.e., forcing the customer to bid without accounting for the impact of the information their bid on the dealers' behavior.

all financial markets combined, which is roughly C$413 million (Allen and Wittwer (2023)). To get a sense of whether our cost estimate is sensible, we collect information on fees that a typical trading desk must pay in order to act as primary dealer for a year, for example, to access data-feeds and electronic platforms, such as Bloomberg. These fees sum to C$ 3.1 million, which is surprisingly close to our estimate, even though we have not used the information on fees in our estimation.

The average entry cost of a customer is between C$429,500 and C$459,300 per auction with a (bootstrapped) confidence interval [C$402,000, C$490,710]. Given that there are about 28 auctions per year, the customer cost is larger than the dealer's cost. This is in line with the idea that customers are better at executing profitable trading strategies—here outside of the Treasury market, driving up the opportunity participation cost.

Summarizing, our findings highlight systematic differences between dealers and customers, both in terms of values and entry costs.

7 Drivers and consequences of customer participation

With the estimated model, we conduct counterfactuals to understand why hedge funds entered the market, and evaluate the consequences for market functioning. For this, we assume that all model primitives, such as the distributions of values and costs, remain fixed when changing market rules. We use final bids only and the lower bound estimates of values and costs. Ideally, we would compute counterfactual outcomes for all auctions in our sample. However, this is computationally intense. We therefore only consider every third auction since 2014, i.e., the period when hedge funds became the dominating customer group.

Computing counterfactuals Conducting counterfactuals for multi-unit auctions in which bidders have multi-unit demand is challenging because it is impossible to solve for an equilibrium analytically. Since we can only characterize necessary equilibrium conditions, it is generally difficult to compute counterfactual bids. We proceed in two steps (explained in more details in Appendix D.1).

First, we allow each bidder to expand their auction-specific demand in responds to changes in the auction environment, for example, changes in the number of participating dealers. To account for unobservable constraints that restrict the amount bidders are able to buy, such as balance sheet constraints, we limit the amount of that expansion to the size of the quantity a bidder ever demanded (as percentage of supply) in an auction.[21] If the demanded percentage is above 25%, which happens in rare cases during the COVID pandemic, we replace it by 25% to incorporate the feature that, during normal times, bidders face a bidding limit of 25% of supply. This gives us an empirical distribution of maximal demand for dealers and customers, respectively.

Second, extending Richert (2021)'s empirical guess-and-verify approach, we solve for the counterfactual bid distributions such that two conditions are satisfied: (i) the distribution of values implied by these bids, and optimal bidding, are indistinguishable from the distribution of the estimated values; and (ii) the counterfactual distribution of maximal demand in an auction is first-order stochastically dominated by the empirical distribution of maximal

[21]For small changes in the number of dealers this approach may be conservative, given that dealers do not increase their maximum quantity demanded when a dealer exits the market, as shown in Appendix Table A3.

demand across all auctions. As robustness, we alternatively shift the empirical distribution of maximal demand by 5 percentage points to the right.

Our approach might not fully capture the size of demand in counterfactual auctions that are far from any observed auction. We therefore focus our discussion on local changes where our approach provides more reliable predictions. To avoid focusing on any particular draw from the cost or value distribution, we take the ex ante perspective, and compare expected market outcomes. For instance, we analyze the expected price at which an auction clears under current market rules, relative to counterfactual market rules.

Why did customers enter? We first aim at understanding whether customers entered the market because of dealer exit or because of changing market conditions. For this we compare the status quo, in which two dealers left in 2014, with a counterfactual with two additional dealers (fixing dealer participation but allowing customers to select into auctions).

Our findings suggest that customer participation was partially driven by dealer exit and partially due to changes in the market that made it more profitable for customers to buy bonds (as the time-trend in Figure 4B suggests). Adding two dealers reduces a customer's participation probability by roughly 17.5 percentage points, or 44.3%, on average. Furthermore, Figure 6 highlights that the probability of participating in some auctions drops to almost zero.[22]

Competition-volatility trade-off. Next, we illustrate the competition-volatility trade off that arises when adding market participants who don't participate with regularity.

For this, we first consider a hypothetical auction environment with only dealers. This eliminates effects coming from changes in bidder composition or from dealer bid-updating. In this simplified auction environment, we ask by how much the expected auction price and auction coverage varies in the number of competing dealers.

Consider a typical auction, shown in Figure 7: If 14 dealers compete, the market clears at a competitive price, which is similar to the observed one. If only 13 or 12 dealers compete, the expected price drops by close to 10%, and 20% respectively.[23] The expected price and

[22]Appendix Figure A10 shows by how much the expected revenue and expected price changes in the counterfactual relative to the status quo. Given that all auctions are relatively competitive given the observed number of bidders, these effects are relatively small.

[23]Appendix Figure A11 shows the analogous results for other auctions, specially the p5 and p95.

Figure 6: Why did customers enter?

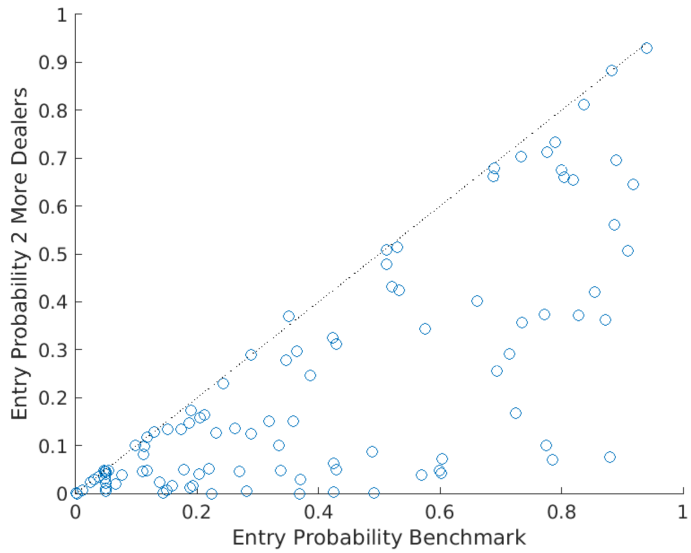


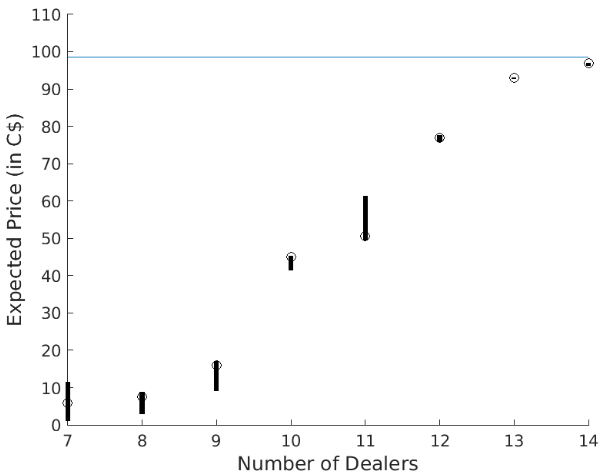
Figure 6 shows the probability for a customer to participate in every 3rd auction from 2014 onward in the status quo (on the x-axis) and the counterfactual in which we add back the two dealers who left (on the y-axis). Probability is in percentage points.

revenue drop for two reasons. First, with fewer bidders, the auction is less competitive, and therefore bidders increase the extent to which they shade their values. Second, auction failure, because total demand is insufficient, becomes more likely (as shown in Figure 7B). To disentangle these two effects, we re-compute expected auction outcomes under fixed bids but allowing for the increased probability of auction failures. For example, if only 13 dealers compete, the failure probability is 5%, which means that the total price drop of 10% is evenly split between the competition-effect and the auction-failure-effect.

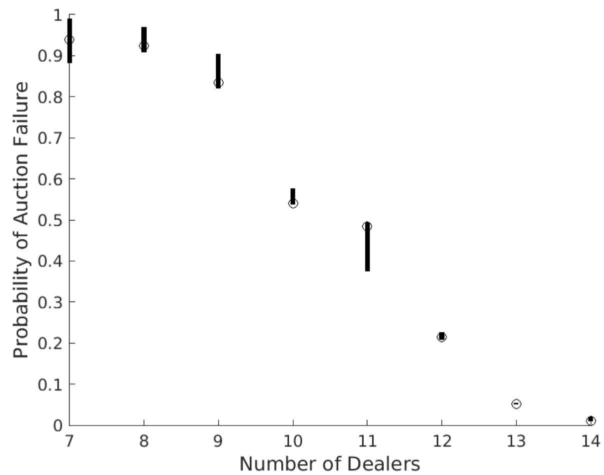
Next, we analyze the effect of varying the probability with which customers participate in a typical auction, fixing the number of dealers—see Figures 8 and A12. When the expected number of customers falls by one, there is no risk of auction failure. However, the expected price decreases by 0.7%, expected revenue decreases by 0.08% (or C$2.7 million) and bid-shading increases by 7.9%.

To compare the competition effect to the volatility effect from rising customer participation, we compute the expected revenue loss from a reduction in expected customer participation of one competitor on average, and the expected revenue loss from across auction

Figure 7: Typical auction: Varying number of dealers



(A) Expected price



(B) Auction failure

Figure 7 shows how the range of expected price (in C$) at which an auction clears varies as the number of dealers increases in an auction which issues the average supply with medium customer participation, i.e., 3 customers. In theory, there is one expected price for each fixed number of dealers. In practice, we determine a range of prices (marked in black) given that our numerical procedure to determine counterfactual bids allows for small differences between the value distribution that is implied by the counterfactual bids and the true value distribution (see Richert (2021)). The blue horizontal line shows the average observed bid, which is close to the observed market clearing price.

variation in customer entry rates.[24] For the median auction, the competition effect (C\$ 2.9M) is slightly larger than the loss from irregular participation (C\$ 2.85M). However, when the distribution of customer entry probabilities gives more weight to auctions with fewer customers than in our data, the volatility loss can out-weight the competition effect. This is because low auction revenues on bad days, on which few customers enter, dominates the smaller increases in auction revenues on good days.

Taken together, these findings highlight the potential risk of introducing volatility in auction coverage and clearing prices when bidder participation is irregular. Our results also indicate that losing additional dealers could have detrimental effects unless an adequate number of new customers enter the market. This is not a hypothetical concern, as one of the dealers (HSBC) has been acquired by another dealer (RBC).

Alternative policies. In the final part of the paper, we aim at determining a simple policy that both reduces volatility and increases competition relative to the status quo.

As a starting point, we consider modifications to commitment requirements. We first eliminate dealer commitment, meaning that we allow dealers to freely decide whether to enter each auction in the hope that this increases competition without harming volatility. Then, we require customers to commit to participating in the same way as dealers, in the hope that this decreases volatility without harming competition. Due to endogenous bidder participation, in both cases, it is theoretically possible to increase competition and decrease volatility relative to the status quo. Empirically, we find that neither of these two alternative policy regimes achieves that goal (see Appendix D.2 for details).

Instead, we propose to strategically reshuffle supply across auctions to incentivize and stabilize customer participation. The idea is that we can predict (with some noise) how many customers each auction would attract under the current supply schedule based on observable market conditions to then shift some of the supply from attractive auctions to unattractive auctions.

[24] Formally, let pr denote the probability that a customer participates, and $\text{pr\_data} = \frac{1}{T}\sum_t N_t^h/\bar{N}^h$. The competition effect $= \mathbb{E}\left[\boldsymbol{revenue}|pr = pr\_data\right] - \mathbb{E}\left[\boldsymbol{revenue}|pr = pr\_data - \frac{1}{\frac{1}{T}\sum_t N_t^h}\right]$ is the difference between the expected auction revenue with observed customer entry probabilities and the expected revenue when we remove one customer, in expectation. The volatility effect $= \mathbb{E}\left[\boldsymbol{revenue}|pr = pr\_data\right] - \mathbb{E}\left[\mathbb{E}[\boldsymbol{revenue}|pr]\right]$ is the expected revenue with observed entry probabilities minus the expectation of expected revenues over the distribution of customer entry probabilities.

Figure 8: Typical auction: Varying customer participation probability

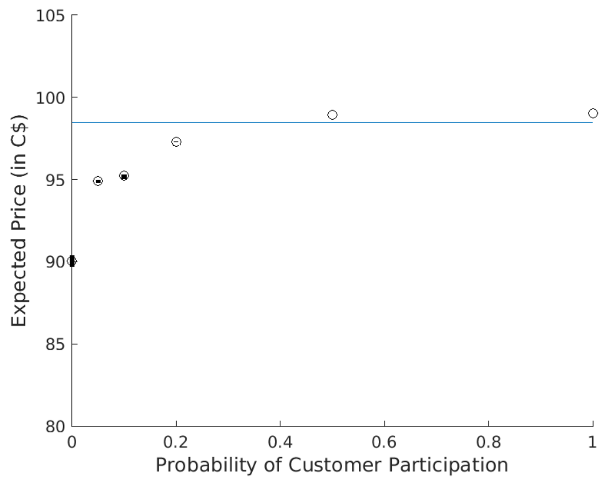
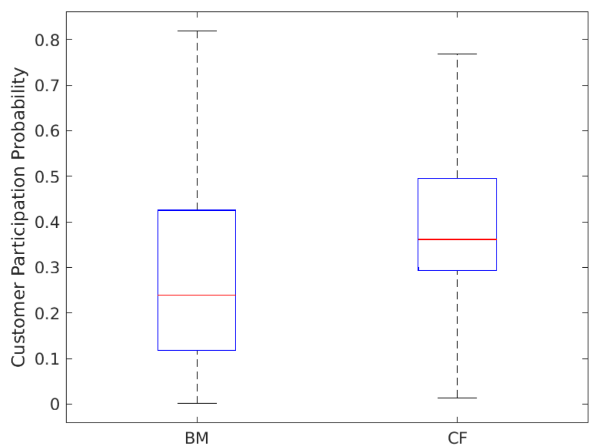


Figure 8 shows how the range of expected price (in C$) at which an auction clears varies as the participation probability of (all) customers varies between 0 and 1 computed at grid points (0, 0.05, 0.1, 0.2, 0.5, 1) in an auction which issues the average supply with medium customer participation, i.e., 3 customers. In theory, there is one expected price for each counterfactual. In practice, we determine a range of prices (marked in black) given that our numerical procedure to determine counterfactual bids allows for small differences between the value distribution that is implied by the counterfactual bids and the true value distribution (see Richert (2021)). The blue horizontal line shows the average observed bid, which is close to the observed market clearing price.

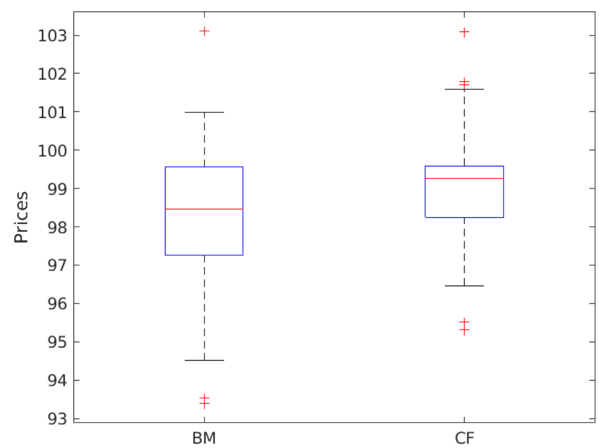
Concretely, we rely on the OLS regression from Table 2 to predict how many customers will want to participate under the current supply schedule, given observable market conditions. We exclude the lagged number of participating customers as explanatory variable, because this variable changes endogenously in the counterfactual. We think that it is reasonable to assume that all other predictors of customer participation, such as the secondary market spread, are not materially affected by the moderate supply changes we propose. We also exclude 2020 onward when debt issuance spiked in response to the unprecedented level of fiscal intervention during the COVID pandemic. We rank the predicted number of participating customers, $\hat{N}_t^c$, from smallest to highest, and obtain a quantile ranking, ranging from 0 (smallest $\hat{N}_t^c$) until 1 (highest $\hat{N}_t^c$) from the empirical distribution of $\hat{N}_t^c$. The quantile ranking is a single dimensional index, $s \in [0, 1]$, which captures the intensity of predicted customer participation.

Based on this participation index, we increase supply by 10% in the auction with lowest participation ($s = 0$) and decrease supply by 10% in the auction with highest participation

Figure 9: Reshuffling supply to incentivize customer participation



(A) Customer participation



(B) Expected price

Figure 9A shows the distribution of customer participation probabilities across auctions in the status quo and the counterfactual in which we strategically reshuffle supply to incentivize stable customer participation (in pp). Figure 9B displays the corresponding distributions of expected auction prices (in C$).

($s = 1$). We adjust supply linearly for all auctions in between. Formally, the new supply in an auction with index s is $Q_t + 0.2(0.5 - s)$ given the observed supply is Q_t. This rule implies that the supply in the auction with median participation ($s = 0.5$) is left unchanged. To avoid issuing too extreme amounts of debt in any counterfactual auction relative to the status quo, we normalize all initial supplies to one, i.e., $Q_t = 1$ for all t.[25]

We find that implementing such supply adjustments successfully increases competition while decreasing volatility (see Figure 9). Both, the median expected price and the median number of participating customers increase, suggesting enhanced competition relative to the status quo. In addition, customer participation probability per auction stabilizes around a median of 36%, and price volatility diminishes. As a result, the median revenue per auction increases by about C$16 M (or about 48 bps).

This simple rule does not account for all factors that influence the complicated decision on how to issue government debt. For example, it abstracts from the term-structure of

[25]To illustrate why normalizing supply reduces the supply changes we propose, consider one auction that supplies C$ 4 billion and one auction that supplies C$ 1 billion in the status quo. Assume that our rule would suggest shifting 10% of C$ 4 billion from the first to the second auction. This would mean increasing supply by C$ 400 million—a massive percentage increase of 40%.

bonds, and therefore ignores complications that arise from rolling over debt in the future.

However, the rule has at least three attractive features. First, it is easy to implement and politically feasible, given that the central bank already changes the supply issued to bidders by placing sizable non-competitive bids. Second, the rule is supply-neutral in relative terms in that we add the same percentages of supply in one auction that we subtract in another. Since the observed supplied quantity (in dollars) is uncorrelated with the quantity changes we make (in dollars) the rule is also supply-neutral in absolute terms, as long as we repeat our exercise with sufficiently many auctions. Third, the rule is essentially revenue-neutral. This is because there is no statistically significant correlation between the average (quantity-weighted) value for the auctioned bond of participating bidders and the predicted number of participating customers.[26] Therefore, our rule does not systematically shift supply from low-value auctions, that clear at low prices, to high-value auctions, or vice versa.

8 Conclusion

We study dealer exit and customer entry in the primary market for Canadian government debt, and analyze consequences for the functioning of the market. We show that customer participation has increased, but remains highly irregular. We introduce and estimate a structural model to trade-off the benefits of higher competition from customer entry with the costs of higher market volatility. Our framework could be used in other settings with regular and irregular market participants.

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[26]The point estimate from regressing the average quantity-weighted value of all bidders in an auction that issues a bond with C$ 100 face value on the predicted number of participating customers is -0.03. The confidence interval is $[-0.14, +0.07]$.

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ONLINE APPENDIX

Entry and Exit in Treasury Auctions

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Appendix **A** presents mathematical details, including formal proofs.

Appendix **B** presents additional empirical tests supporting our model.

Appendix **C** explains how we estimate dealer and customer values.

Appendix **D** provides details about counterfactuals, and presents additional findings.

A Mathematical appendix

In this appendix we prove Proposition 1. The proof relies on Lemma 1, stated and proved below. Finally, we prove that customer value bounds are identified, which is summarized in Proposition 4.

Proof of Proposition 1. The proof of statement (i) is analogous to the proof of Kastl (2011)'s Proposition 1.

To show statements (ii) take the perspective of customer i and assume all other bidders play an equilibrium. For ease of notation we drop the auction and time subscripts, t and τ. Fix L moment functions μ^l. Given that dealers only updates their own function when the customer submits a function with at least one different moment $\{m^l\}_{l=1}^L$, we can decompose the conditions that characterize the customer's best reply (and with that an equilibrium given that the other bidders play an equilibrium by assumption) into two parts.

First, we fix some set of moments $\{m^l\}_{l=1}^L$, and find $b_i^h(\cdot,\theta_i^h)$ that maximizes the customer's expected total surplus,

$$TS_i^h = \mathbb{E}_t\left[\int_0^{\boldsymbol{q_i^{h*}}} [v^h(x,s_i^h) - b_i^h(x,\theta_i^h)]dx\right] \text{ such that } \mu^l(b_i^h(\cdot,\theta_i^h)) = m^l \text{ for all } l. \quad (3)$$

Denoting Lagrange multipliers of the constraints by λ_l, the objective function is: $TS_i^h - \sum_{l=1}^L \lambda^l \left(m^l - \mu^l(b_i^h(\cdot,\theta_i^h)\right)$. Given this objective function, we can follow Kastl (2011)'s perturbation argument in the original proof in Appendix A.2. step by step with one difference.

There is an additional term that comes from the constraints that all moments l of chosen function, $\mu^l(b_i^h(\cdot, \theta_i^h)$ must equal the fixed moments m^l. This term doesn't create issues when taking derivatives since moment functions are differentiable w.r.t. quantity. Further, since dealers only update their own bids if a moment of the customer's bidding function changes, and we are keeping these moments fixed, no complications arise when predicting in which states of the world the market will clear relative to the original proof. Following Kastl (2011)'s steps, we obtain equations A.2 and A.3 in Kastl (2011) plus the additional term: $\sum_l^L -\lambda^l \frac{\partial \mu^l(b_i^h(\cdot,\theta_i^h)}{\partial q_k}$. Combining these equations gives condition (5) in Proposition 1. Unlike for dealers, these expressions do not simplify further because it may be optimal for customers to tie steps other than the last one. This is explained in Lemma 1 below.

Statement (iii) specifies that in equilibrium the customer must choose a bidding function that gives rise to moments $\{m^l\}_{l=1}^L$ so that the total expected surplus is maximized globally. Note that solving this maximization is challenging (even when we restrict attention to moments that are real numbers) because the objective function, i.e., the expected auction surplus, is not differentiable w.r.t. these moments. To see this consider a change in moment m^l. The dealer who observes the corresponding bid function updates her own bid because a change in m^l (weakly) changes the dealer's information set and with that its type, θ_i^d. Therefore, the dealer submits a different bid function, i.e., a step function with steps at different points. This changes the customer's beliefs about the price at which the auction will clear. Formally, the distribution of the clearing price, when fixing the customer's own bid function, changes, and since biding functions are step functions, a change in such a function easily leads to non-continuous jumps that render the objective function TS_i^h non-differentiable.

Lemma 1. *(i) For a customer ties occur with zero probability for a.e. s_i^h in any equilibrium, for either all steps except the last step, or at the last step. (ii) For a dealer Kastl (2011)'s Lemma 1 applies.*

Proof of Lemma 1 (i)**.** For ease of notation we eliminate the auction, and time subscripts, t and τ, as well as the customer superscript, h.

Case 1: $\lambda > 0$. Consider a step $k = K$. Suppose bidder i ties on a step $k = K$. Take some $q_m = sup\{q|v(q, s_i) \leq b_k\}$ and let $\bar{q} = max\{q_k - \delta, q_m\}$ with δ some strictly positive step size bounded above by $q_k - q_{k-1}$, i.e., the bidder either steps to where she gets positive surplus from the amount she purchases or she buys less units at a negative surplus. Take the deviation to bid $b'_{ik} = b_{ik} + \epsilon$, where $\epsilon > 0$ is sufficiently small, at $\bar{q}$ and the associated step. Bidder i gets less units than they would in a tie and no longer pays for those units. This doesn't come at a loss. In fact, the deviation is strictly profitable, because of dealer updating. To see this, let us abbreviate the moment, i.e., the quantity-weighted bid, of the deviated bidding function by $\mu(\bar{q}, b')$, and similarly for the original bidding function. Deviating to b'_{ik} comes at a constraint-penalty of $-\lambda(m - \mu(\bar{q}, b'))$ since the targeted moment, $m = \mu(q_k, b)$, is no longer met. Because $\mu(\bar{q}, b') > \mu(q_k, b) = m$, and $\lambda > 0$ by assumption, $-\lambda(m - \mu(\bar{q}, b')) > 0$, representing a strictly positive profit from deviating.

Case 2: $\lambda < 0$. Suppose bidder i ties on a step $k < K$. Take some $q_m = sup\{q|v(q, s_i) \leq b_k\}$ and let $\bar{q} = max\{q_k - \delta, q_m\}$ with δ some strictly positive step size bounded above by $q_k - q_{k-1}$, i.e., the bidder steps either to where she gets positive surplus from the amount she purchases if possible or if not at least she buys less negative. Take the deviation to bid $b'_{ik} = b_{ik} + \epsilon$, where $\epsilon > 0$ is sufficiently small, at $\bar{q}$ (and the associated step). Bidder i gets less units than they would in a tie and each one of these they longer have to pay for. There is no loss to them from not winning these units. Similar to the first case, there is a positive gain that arises due to dealer updating. The deviation comes at a "penalty" of $-\lambda(m - \mu(\bar{q}, b'))$. Because $\mu(\bar{q}, b') < \mu(q_k, b) = m$, the bracketed term is positive. λ is negative by assumption so that $-\lambda(m - \mu(\bar{q}, b')) > 0$.

Case 3: $\lambda = 0$. Kastl (2011)'s original proof applies. □

Proposition 4. *Given customer s^h_{ti} behaves according to Proposition 1 (ii) and (iii), and the dealer only pays attention to one moment of the customer's bidding function, i.e., $L = 1$, upper and lower bounds on customer values, $\overline{v}^h_t(\cdot, s^h_{ti})$ and $\underline{v}^h_t(\cdot, s^h_{ti})$, are identified.*

Proof of Proposition 4. We fix an auction t and a customer i, and drop the auction t, time τ, customer h, bidder i subscripts and superscripts for simplicity. Further, we assume that only one moment, m, matters, for instance, the quantity-weighted bid, consistent with our estimation, and drop the l-subscript.

The identification argument is complicated by the fact that condition (5)—here slightly rearranged—not only contains values at submitted steps, $v(q_k, s)$, but also values at some intermediate quantities between submitted steps, $v(\boldsymbol{q^*}, s)$:

$$
\begin{aligned}
0 = &\Pr(b_k > \boldsymbol{P^*} > b_{k+1}|\theta, m)v(q_k, s)+ \\
&\Pr(b_k = \boldsymbol{P^*}|\theta, m)\mathbb{E}\left[v(\boldsymbol{q^*}, s)\frac{\partial \boldsymbol{q^*}}{\partial q_k}\Big| b_k = \boldsymbol{P^*}, \theta, m\right] + \\
&\Pr(b_{k+1} \geq \boldsymbol{P^*}|\theta, m)\mathbb{E}\left[v(\boldsymbol{q^*}, s)\frac{\partial \boldsymbol{q^*}}{\partial q_k}\Big| b_{k+1} \geq \boldsymbol{P^*}, \theta, m\right] - \\
&\Pr(b_k > \boldsymbol{P^*} > b_{k+1}|\theta, m)b_k - \\
&\Pr(b_{k+1} \geq \boldsymbol{P^*}\Big|\theta, m)(b_k - b_{k+1}) - \\
&\Pr(b_k = \boldsymbol{P^*}|\theta, m)\mathbb{E}\left[\frac{\partial \boldsymbol{q^*}}{\partial q_k}\Big| b_k = \boldsymbol{P^*}, \theta, m\right] - \\
&\Pr(b_{k+1} = \boldsymbol{P^*}|\theta, m)\mathbb{E}\left[\frac{\partial \boldsymbol{q^*}}{\partial q_k}\Big| b_{k+1} = \boldsymbol{P^*}, \theta, m]\right] - \\
&\Pr(b_{k+1} < \boldsymbol{P^*}|\theta, m)\mathbb{E}\left[\frac{\partial \boldsymbol{q^*}}{\partial q_k}\Big| b_{k+1} < \boldsymbol{P^*}, \theta, m\right] + \lambda\frac{\partial \mu(b(\cdot, \theta))}{\partial q_k}.
\end{aligned}
\tag{12}
$$

Here, and for all other expressions in this section, we include the fixed moment, m, as a condition alongside the bidder's type. Dependence on intermediate quantities implies that customer values cannot be point-identified.

To identify customer value bounds, we first we guess a Lagrange multiplier, $\lambda \in \mathbb{R}$, and simplify the system of equations (12) to obtain conditions (13) for $\lambda > 0$ and (**??**) for $\lambda < 0$.

We start by relying on monotonicity and boundedness of the value function: for all $q_{k-1} \leq q \leq q_k$ we know that $v(q_{k-1}, s) \geq v(q, s) \geq v(q_k, s)$. In addition, we sign the derivatives of the rationed quantity: increasing the bid at step k increases the quantity rationed in the event of a tie at step k and decreases the quantity rationed in the event of a tie at step $k + 1$.

Next we eliminate terms in condition (12) to obtain a system of $2K$ linear equations with $2K$ unknowns to solve. For this, we obtain an upper bound on the value at step q_k (which is satisfied with non-zero probability) by making the terms involving the value and the derivative of the rationed quantity in the event of a tie as small as possible (and making them as big as possible for the lower bound). To do this, we plug in $\overline{v}(q_k, s)$, the max possible value at intermediate quantities along the next step, for terms involving rationed quantities at the next step (e.g. line 3 of equation (12)). In addition, we plug in $\underline{v}(q_k, s)$, the smallest possible value at intermediate quantities along the current step, for terms involving ties at the current step (e.g. line 2. of equation (12)). To obtain a lower bound, we instead substitute the maximum value at the current step, $\overline{v}(q_{k-1}, s)$ (in line 2. of equation (12)) and the minimum value at the next step, $\underline{v}(q_{k+1}, s)$ (in line 3 of equation (12)).

To simplify the system of equations further, we rely on Lemma 1 according to which ties never occur in equilibrium at a subset of steps. This allows us to cancel terms involving ties at these steps. There are two cases depending on the sign of λ. When the current λ is negative, at steps before the last step ties cannot be optimal, and the terms involving the derivative of the rationed quantity drop out except for at the second-to-last step. When the current λ is positive, the only simplification occurs at the last step, where the rationing terms all drop out. Furthermore, at the last step, all terms involving b_K drop out.

With these simplifications, we obtain the following system of equations for two cases $\lambda > 0$, and $\lambda < 0$. It can help to transform this system of equation into a single matrix, one for each case, to see that the system is indeed identified (conditional on knowing λ).

(i) When $\lambda < 0$:

$$
\begin{aligned}
A_1 &= \Pr(b_1 > \boldsymbol{P^*} > b_2|\theta, m)\overline{v}(q_1, s) \\
A_1 &= \Pr(b_1 > \boldsymbol{P^*} > b_2|\theta, m)\underline{v}(q_1, s), \text{ and analogously for } k = 2, ...K-2, \\
A_{K-1} &= \Pr(b_{K-1} > \boldsymbol{P^*} > b_K|\theta, m)\overline{v}(q_{K-1}, s) + \Pr(b_K \geq \boldsymbol{P^*}|\theta, m)\mathbb{E}\left[\frac{\partial \boldsymbol{q^*}}{\partial q_{K-1}}\Big| b_K \geq \boldsymbol{P^*}, \theta, m\right]\overline{v}(q_{K-1}, s) \\
A_{K-1} &= \Pr(b_{K-1} > \boldsymbol{P^*} > b_K|\theta, m)\underline{v}(q_{K-1}, s) + \Pr(b_K \geq \boldsymbol{P^*}|\theta, m)\mathbb{E}\left[\frac{\partial \boldsymbol{q^*}}{\partial q_{K-1}}\Big| b_K \geq \boldsymbol{P^*}, \theta, m\right]\underline{v}(q_K, s) \\
A_K &= \Pr(b_K > \boldsymbol{P^*} > 0|\theta, m)\overline{v}(q_K, s) + \Pr(b_K = \boldsymbol{P^*}|\theta, m)\mathbb{E}\left[\frac{\partial \boldsymbol{q^*}}{\partial q_K}\Big| b_K = \boldsymbol{P^*}, \theta, m\right]\underline{v}(q_K, s) \\
A_K &= \Pr(b_K = \boldsymbol{P^*}|\theta, m)\mathbb{E}\left[\frac{\partial \boldsymbol{q^*}}{\partial q_K}\Big| b_K = \boldsymbol{P^*}, \theta, m\right]\overline{v}(q_{K-1}, s) + \Pr(b_K > \boldsymbol{P^*} > 0|\theta, m)\underline{v}(q_K, s),
\end{aligned}
$$

$$
\begin{aligned}
\text{where } A_k = {} & \Pr(b_k > \boldsymbol{P^*} > b_{k+1}|\theta, m)b_k + \Pr(b_{k+1} \geq \boldsymbol{P^*}|\theta, m)(b_k - b_{k+1}) \\
& + \Pr(b_k = \boldsymbol{P^*}|\theta, m)\mathbb{E}\left[\frac{\partial \boldsymbol{q^*}}{\partial q_k}\Big| b_k = \boldsymbol{P^*}, \theta, m\right] + \Pr(b_{k+1} = \boldsymbol{P^*}|\theta, m)\mathbb{E}\left[\frac{\partial \boldsymbol{q^*}}{\partial q_k}\Big| b_{k+1} = \boldsymbol{P^*}, \theta, m]\right] \\
& + \Pr(b_{k+1} < \boldsymbol{P^*}|\theta, m)\mathbb{E}\left[\frac{\partial \boldsymbol{q^*}}{\partial q_k}\Big| b_{k+1} < \boldsymbol{P^*}, \theta, m\right] - \lambda\frac{\partial \mu(b(\cdot, \theta))}{\partial q_k} \text{ for all } k = 1, ..., K_1, \\
\text{and } A_K = {} & \Pr(\boldsymbol{P^*} > b_K|\theta, m)b_K + \Pr(b_K = \boldsymbol{P^*}|\theta, m)\mathbb{E}\left[\frac{\partial \boldsymbol{q^*}}{\partial q_K}\Big| b_K = \boldsymbol{P^*}, \theta, m\right] - \lambda\frac{\partial \mu(b(\cdot, \theta))}{\partial q_K}.
\end{aligned}
\tag{13}
$$

(ii) When $\lambda > 0$:

$$B_1 = \Pr(b_1 > \boldsymbol{P^*} > b_2|\theta, m)\overline{v}(q_1, s) + \Pr(b_2 \geq \boldsymbol{P^*}|\theta, m)\mathbb{E}\left[\frac{\partial \boldsymbol{q^*}}{\partial q_1}\Big| b_1 = \boldsymbol{P^*}, \theta, m\right]\underline{v}(q_1, s)$$

$$B_1 = \Pr(b_1 > \boldsymbol{P^*} > b_2|\theta, m)\underline{v}(q_1, s) + \Pr(b_2 \geq \boldsymbol{P}|\theta, m)\mathbb{E}\left[\frac{\partial \boldsymbol{q^*}}{\partial q_1}\Big| b_2 \geq \boldsymbol{P^*}, \theta, m\right]\underline{v}(q_2, s)$$

$$B_2 = \Pr(b_2 > \boldsymbol{P^*} > b_3|\theta, m)\overline{v}(q_2, s) + \Pr(b_3 \geq \boldsymbol{P^*}|\theta, m)\mathbb{E}\left[\frac{\partial \boldsymbol{q^*}}{\partial q_2}\Big| b_3 \geq \boldsymbol{P^*}, \theta, m\right]\overline{v}(q_2, s)$$

$$B_2 = \Pr(b_3 = \boldsymbol{P^*}|\theta, m)\mathbb{E}\left[\frac{\partial \boldsymbol{q^*}}{\partial q_2}\Big| b_2 = \boldsymbol{P^*}, \theta, m\right]\overline{v}(q_1, s) + \Pr(b_2 > \boldsymbol{P^*} > b_3|\theta, m)\underline{v}(q_2, s)$$

$$+ \Pr(b_3 \geq \boldsymbol{P}|\theta, m)\mathbb{E}\left[\frac{\partial \boldsymbol{q^*}}{\partial q_2}\Big| b_3 \geq \boldsymbol{P^*}, \theta, m\right]\overline{v}(q_4, s), \text{ and analogously for } k = 3, ...K-2,$$

$$B_{K-1} = \Pr(b_{K-1} > \boldsymbol{P^*} > b_K)\overline{v}(q_{K-1}, s) + \Pr(b_{K-1} = \boldsymbol{P^*})\underline{v}(q_{K-1}, s)\mathbb{E}\left[\frac{\partial \boldsymbol{q^*}}{\partial q_{K-1}}\Big| b_{K-1} = \boldsymbol{P^*}, \theta, m\right]$$

$$B_{K-1} = \Pr(b_{K-1} = \boldsymbol{P^*})\overline{v}(q_{K-1}, s)\mathbb{E}\left[\frac{\partial \boldsymbol{q^*}}{\partial q_{K-1}}\Big| b_{K-1} = \boldsymbol{P^*}, \theta, m\right] + \Pr(b_{K-1} > \boldsymbol{P^*} > b_K)\underline{v}(q_{K-1}, s)$$

$$B_K = \Pr(b_K > \boldsymbol{P^*} > 0)\overline{v}(q_K, s)$$

$$B_K = \Pr(b_K > \boldsymbol{P^*} > 0)\underline{v}(q_K, s)$$

$$\text{where } B_1 = A_1 - \overline{v}(q_1, s)\Pr(b_1 = \boldsymbol{P^*}|\theta, m))\mathbb{E}\left[\frac{\partial \boldsymbol{q^*}}{\partial q_1}\Big| b_1 = \boldsymbol{P^*}, \theta, m\right]$$

$$\text{and } B_k = A_k \text{ for } k = 2, ...K. \tag{14}$$

This system of equations would be identified if λ was known. Since this isn't the case, we rely on Proposition 1 (iii) to obtain identification of value bounds.

Specifically, we know that perturbing m cannot be optimal. Formally, total expected surplus must decrease when increasing and decreasing m by $\epsilon > 0$:

$$TS(b(\cdot, \theta), m) - TS(b(\cdot, \theta), m + \epsilon) \geq \lambda\epsilon \tag{15}$$

$$TS(b(\cdot, \theta), m - \epsilon) - TS(b(\cdot, \theta), m) \leq \lambda\epsilon, \tag{16}$$

where

$$TS(b(\cdot, \theta), m) = \sum_{k=1}^{K}\Big[\Pr(b_k > \boldsymbol{P^*} > b_{k+1}|\theta, m)V(q_k, s) - \Pr(b_k > \boldsymbol{P^*}\Big|\theta, m)b_k(q_k - q_{k-1})\Big]$$
$$+ \sum_{k=1}^{K}\Pr(b_k = \boldsymbol{P^*}|\theta, m)\mathbb{E}\Big[V(\boldsymbol{q^*}, s) - b_k(\boldsymbol{q^*} - q_{k-1})\Big| b_k = \boldsymbol{P^*}, \theta, m\Big]$$

with $q_0 = b_{K+1} = 0$. This expression is equivalent to equation (3) for $g = h$. $TS(b(\cdot, \theta), m+\epsilon)$ and $TS(b(\cdot, \theta), m - \epsilon)$ are defined analogously.

We can use (18) to find bounds for (15) and (16). Consider (15) first, and omit conditioning on θ for simplicity, and let $1(\cdot)$ denote the indicator function to obtain

$$
\begin{aligned}
&\sum_{k=1}^{K}\Bigg[\max\Big\{0, \Delta\Pr(b_k \geq \boldsymbol{P^*} \geq b_{k+1})\Big\}\Big(\sum_{j=1}^{k}\overline{v}(q_{j-1}, s)(q_j - q_{j-1})\Big)\\
&\quad + \min\Big\{0, \Delta\Pr(b_k \geq \boldsymbol{P^*} \geq b_{k+1})\Big\}\Big(\sum_{j=1}^{k}\underline{v}(q_j, s)(q_j - q_{j-1})\Big) + \Delta\Pr(b_k > \boldsymbol{P^*})b_k(q_k - q_{k-1})\Bigg] +\\
&\sum_{k=1}^{K}\Bigg[\max\Big\{0, \Delta\Pr(b_k = \boldsymbol{P^*})\Big\}\Big(\sum_{j=1}^{k-1}\overline{v}(q_{j-1}, s)(q_j - q_{j-1})\Big) + \min\Big\{0, \Delta\Pr(b_k = \boldsymbol{P^*})\Big\}\Big(\sum_{j=1}^{k-1}\underline{v}(q_j, s)(q_j - q_{j-1})\Big)\\
&\quad + \Big(\Pr(b_k = \boldsymbol{P^*}|m)\overline{v}(q_{j-1}, s)(\mathbb{E}[\boldsymbol{q^*}|b_k = \boldsymbol{P^*}, m] - q_{k-1})\\
&\quad - \Pr(b_k = \boldsymbol{P^*}|m+\epsilon)\overline{v}(q_{j-1}, s)(\mathbb{E}[\boldsymbol{q^*}|b_k = \boldsymbol{P^*}, m+\epsilon] - q_{k-1})\Big)\\
&\quad \times 1\Big(\Pr(b_k = \boldsymbol{P^*}|m)(\mathbb{E}[\boldsymbol{q^*}|b_k = \boldsymbol{P^*}, m] - q_{k-1}) - \Pr(b_k = \boldsymbol{P^*}|m+\epsilon)(\mathbb{E}[\boldsymbol{q^*}|b_k = \boldsymbol{P^*}, m+\epsilon] - q_{k-1}) > 0\Big)\\
&\quad + \Big(\Pr(b_k = \boldsymbol{P^*}|m)\underline{v}(q_j, s)(\mathbb{E}[\boldsymbol{q^*}|b_k = \boldsymbol{P^*}, m] - q_{k-1})\\
&\quad - \Pr(b_k = \boldsymbol{P^*}|m+\epsilon)\underline{v}(q_j, s)(\mathbb{E}[\boldsymbol{q^*}|b_k = \boldsymbol{P^*}, m+\epsilon] - q_{k-1})\Big)\\
&\quad \times 1\Big(\Pr(b_k = \boldsymbol{P^*}|m)(\mathbb{E}[\boldsymbol{q^*}|b_k = \boldsymbol{P^*}, m] - q_{k-1}) - \Pr(b_k = \boldsymbol{P^*}|m+\epsilon)(\mathbb{E}[\boldsymbol{q^*}|b_k = \boldsymbol{P^*}, m+\epsilon] - q_{k-1}) < 0\Big)\\
&\quad - b_k\Big(\mathbb{E}[\boldsymbol{q^*} - q_k|b_k = \boldsymbol{P^*}, m] - \mathbb{E}[\boldsymbol{q^*} - q_k|b_k = \boldsymbol{P^*}, m+\epsilon]\Big)\Bigg]\\
&\quad \geq \lambda\epsilon, \qquad (17)
\end{aligned}
$$

where $\Delta\Pr(\cdot)$ indicates taking a difference between $\Pr(\cdot|.., m)$ and $\Pr(\cdot|.., m+\epsilon)$ and $v(q_0, s) = \overline{v}(q_1, s)$.

Similarly for (16):

$$\sum_{k=1}^{K}\Big[\max\Big\{0,\Delta\Pr(b_k\geq \boldsymbol{P^*}\geq b_{k+1})\Big\}\Big(\sum_{j=1}^{k}\underline{v}(q_j,s)(q_j-q_{j-1})\Big)$$

$$+\min\Big\{0,\Delta\Pr(b_k\geq \boldsymbol{P^*}\geq b_{k+1})\Big\}\Big(\sum_{j=1}^{k}\overline{v}(q_{j-1},s)(q_j-q_{j-1})\Big)+\Delta\Pr(b_k>\boldsymbol{P^*})b_k(q_k-q_{k-1})\Big]+$$

$$\sum_{k=1}^{K}\Big[\max\Big\{0,\Delta\Pr(b_k=\boldsymbol{P^*})\Big\}\Big(\sum_{j=1}^{k-1}\underline{v}(q_j,s)(q_j-q_{j-1})\Big)+\min\Big\{0,\Delta\Pr(b_k=\boldsymbol{P^*})\Big\}\Big(\sum_{j=1}^{k-1}\overline{v}(q_{j-1},s)(q_j-q_{j-1})\Big)$$

$$+\Big(\Pr(b_k=\boldsymbol{P^*}|m-\epsilon)\underline{v}(q_j)(\mathbb{E}[\boldsymbol{q^*}|b_k=\boldsymbol{P^*},m-\epsilon]-q_{k-1})$$

$$-\Pr(b_k=\boldsymbol{P^*}|m)\underline{v}(q_j)(\mathbb{E}[\boldsymbol{q^*}|b_k=\boldsymbol{P^*},m]-q_{k-1})\Big)$$

$$\times 1\Big(\Pr(b_k=\boldsymbol{P^*}|m-\epsilon)(\mathbb{E}[\boldsymbol{q^*}|b_k=\boldsymbol{P^*},m-\epsilon]-q_{k-1})-\Pr(b_k=\boldsymbol{P^*}|m)(\mathbb{E}[\boldsymbol{q^*}|b_k=\boldsymbol{P^*},m]-q_{k-1})>0\Big)$$

$$+\Big(\Pr(b_k=\boldsymbol{P^*}|m-\epsilon)\overline{v}(q_{j-1})(\mathbb{E}[\boldsymbol{q^*}|b_k=\boldsymbol{P^*},m-\epsilon]-q_{k-1})$$

$$-\Pr(b_k=\boldsymbol{P^*}|m)\overline{v}(q_{j-1})(\mathbb{E}[\boldsymbol{q^*}|b_k=\boldsymbol{P^*},m]-q_{k-1})\Big)$$

$$\times 1\Big(\Pr(b_k=\boldsymbol{P^*}|m)(\mathbb{E}[\boldsymbol{q^*}|b_k=\boldsymbol{P^*},m-\epsilon]-q_{k-1})-\Pr(b_k=\boldsymbol{P^*}|m+\epsilon)(\mathbb{E}[\boldsymbol{q^*}|b_k=\boldsymbol{P^*},m]-q_{k-1})<0\Big)$$

$$-b_k\Big(\mathbb{E}[\boldsymbol{q^*}-q_k|b_k=\boldsymbol{P^*},m-\epsilon]-\mathbb{E}[\boldsymbol{q^*}-q_k|b_k=\boldsymbol{P^*},m]\Big)\Big],$$

$$\leq \lambda\epsilon \tag{18}$$

where $\Delta\Pr(\cdot)$ instead now indicates taking a difference between $\Pr(\cdot|..,m-\epsilon)$ and $\Pr(\cdot|..,m)$.

Summarizing, we now have a system of $2K$ linear equations, $2K+1$ unknowns, and 2 inequalities from the optimality of the K steps submitted by customer i. This proves that customer value bounds are identified. □

B Empirical tests

B.1 Testing independent private values

We perform a formal test for independent private values, introduced in Hortaçsu and Kastl (2012), for the auctions of bonds in our sample. The test checks for equality of the estimated marginal values of dealers before and after observing a customer bid. In a common values environment, a customers' bid would provide the dealer with information that changes their expected marginal values for acquiring the bond being sold. Under independent private values, this bid reveals information about the expected level of competition, but should not affect their marginal value. Similar to the findings of Hortaçsu and Kastl (2012) for bills, we fail to find evidence that dealer marginal values are shifted by the information learned through the customers bids in the bond market. We calculate a p-value of 0.384, and therefore do not reject the null (of no learning about fundamentals).

B.2 Testing bounds

Here we test whether customers take dealer updating into account when placing a bid. Formally, we want to know if $\lambda = 0$ in Proposition 1 (*ii*). To do this, we fix an auction (and therefore omit the auction t-subscript) We construct measures $T_i = |v^h(q, s_i^h; \lambda = 0) - v^h(q, s_i^h)|$ for each customer i. Here $v^h(q, s_i^h; \lambda = 0)$ denotes the customer's value for amount q assuming that $\lambda = 0$, and $v^h(q, s_i^h)$ is the value if $\lambda \neq 0$. With this we construct a test statistic analagous to SSQ_T from Hortaçsu and Kastl (2012). The test rejects the null hypothesis with p-value of 0.00, where the p-value is computed via bootstrap.

B.3 Testing value differences

Here we test whether customer values are significantly above dealer values. The null hypothesis is that customer values at the lower bound are weakly smaller than dealer values at the upper bound.

We compute three aggregate test statistics following Hortaçsu and Kastl (2012): the first test is in the spirit of a Chi-squared test, the second is based on the 95th percentile of across-auction differences, and the third is based on the maximum difference in values across auctions. Since we are interested in a one-sided null hypothesis (are customer values larger than dealer values), we drop the absolute value, which differs from Hortaçsu and Kastl (2012). In all cases we omit the subset of auctions where not a single customer participated. We compute these test statistics for the differences in average quantity-weighted value, the average maximum value, and the average minimum value of dealers/customers. In addition, we compute confidence intervals for a set-estimate of the mean difference.

Results are reported in Table A4. For all measures, the customer values appear to be above dealer values, however the differences in the average maximum value are less precise, with some of the test-statistics insignificant.

C Details regarding the estimation of values

To back out dealer values and bounds on customer values from the equilibrium conditions of Proposition 1, we need to estimate the probabilities that enter these conditions, which are determined by the distribution of the market clearing price, $\boldsymbol{P_t^*}$. For customers, we also need to estimate the Lagrange multiplier, λ, and the terms that captures ties in condition (5).

We estimate the market clearing price distributions by simulating market clearing. If all bidders were ex-ante symmetric and bid directly to the auctioneer, we would fix a bidder in an auction, and draw $N-1$ bid functions, with replacement, from all observed bids in that auction. This would simulate one possible market outcome for the fixed bidder. Repeating this many times, we could obtain the distribution of the market clearing price $\boldsymbol{P_t^*}$ for this bidder. Our setting is more complicated, because there are dealers and customers, and customers must bid via dealers. Hortaçsu and Kastl (2012) introduce a resampling procedure to estimate the price distribution from the dealer's perspective. We extend their method to learn about customers. Further, we allow signals within a bidder to be correlated over the course of an auction. This is to avoid estimation bias arising from the fact that we observe some bidders updating their bids without observing a customer bid.[27]

Specifically, we resample as follows: We first construct the residual supply curve that bidder i faces in auction t. For this, we start by randomly drawing a customer bid from the set of N^h potential customer bids. If the customer did not participate in the auction, her bid is 0; if she updated her bid, we randomly select one of her bids. Next, we find a dealer that observed a similar bid to that customers bid.[28] If the selected dealer made multiple bids, we select a random bid from the set of bids submitted by that dealer after they observed a bid similar to the current customer's bid. If the dealer did not update her bid after learning the customer's bid, we choose the last bid before learning it. Once a bid is selected, we drop all other bids from that dealer. We repeat this procedure N^h times if i is a dealer and N^h-1 times if i is a customer. Next, we resample the dealers who didn't observe customer bids.

[27]For simplicity, our model does not rationalize such updates, but an extended model based on Hortaçsu and Kastl (2012) could.

[28]Ideally, we would choose a dealer that observed an identical bid. Given our limited sample size, however, this event is extremely unlikely. To reflect customer uncertainty about the value of the dealer observing their bid, we set a bandwidth and define similar bids using the quantity-weighted average bids.

Starting with a list of "uninformed" dealers, we draw one such dealer.[29] If they submitted more than one bid, we randomly select one bid and drop the others. Continue drawing from the set of uninformed dealers so that there are $N^h + N^d - 1$ bidding curves. This is one realization of the residual supply curve that i expects to face. We repeat the process many times to estimate the distribution of the clearing price, each time starting with the full set of bids made in the auction.

As in Kastl (2011), consistency of the estimator requires that the probability of market clearing at each step is strictly bounded away from zero. However, in our finite sample this event may occur. For steps with win-probabilities close to or equal to zero, we mix the estimated clearing price distribution with a uniform distribution over the range of placed bids in order to give all bids a small win probability. In addition to reducing the sensitivity of the analysis to these small probabilities, we truncate the estimated marginal values by assuming that marginal values are below the maximum bid ever made in the auction year for a bond with the same maturity as the bond being sold plus C\$0.1 for 12M, C\$0.05 for 6M and 0.025 for 3M bills, which is roughly equivalent to 10 bps in terms of yield-to-maturity.

With the estimated price distributions, we can solve for the value that rationalizes a dealer's bid at each step, using condition (4). To obtain customer value bounds, we implement an estimation procedure that follows our identification argument presented in the main text, and formally explained in the proof of Proposition 4 in Appendix A.

To begin, we search over the (one-dimensional) set of λ. For each feasible λ, there is a unique set of lower and upper bounds for the value at each step, q_k, where that customer submitted a step that satisfy equation (5). Using these implied values, together with the definition of the total surplus allows us to obtain upper and lower bounds on the λ based on (18). This range of (λ_L, λ_U) are the set of feasible λ which are consistent with the observed choices and values. To obtain the maximum and minimum we find the value at each point that maximizes (minimizes) the change in the total surplus. Whether this is the upper or lower envelope of the set of marginal values consistent with the observed bids, depends only on the sign of the change in clearing probabilities under the increased moment m. If the initial λ is in the range (λ_L, λ_U), than the associated value curve is part of the identified set

[29] This includes sampling bids from dealers that later become informed and place a later bid but who were not selected in the simulated residual supply curve in the customer resampling step.

of values that can rationalize the behavior of the given customer. When it is outside the range, the bid is not consistent with equilibrium behavior for that set of values. To trace out the identified set, we repeat this exercise along a grid of possible λ.

D Details regarding counterfactuals

In Appendix D.1 we explain how we compute counterfactual equilibria. In Appendix D.2 we present what happens when we make changes to the rules of bidder commitment.

D.1 Computational details

We are interested in finding a set of bid distributions that imply a value distribution that is similar to the true (in our case estimated) value distribution. We therefore construct a criterion function that compares these distributions along several dimensions. The criterion has three components.

First, we evaluate the value distributions at quantiles of the quantity-bid distribution, corresponding to orders for 1.1, 1.7, 2.3, 3.4, 3.6, 4.5, 5.6 and 25% s of the total supply. For each auction and bidder group g, we construct bounds of the value distribution at each discrete level of quantity using an evenly spaced grid running from the 5^{th} percentile to the 95^{th} percentile. . At each point we compare the bounds on the implied values from the guess of the bid distribution to the true values and add to the criterion function $max(F_L^{IM} - F_U, 0)^2$ and $min(F_U^{IM} - F_L, 0)^2$, where F_L^{IM} denotes the implied value distribution at each of the quantity levels evaluated on the grid points and F_U denotes the corresponding upper bound on the distribution known from the data. F_U^{IM} and F_L are defined analogously.

The second component of the criterion measures the distribution of slopes across the same fixed grid of quantity levels described above. Given the bounds on bidders' values across these points, we calculate the largest and smallest slope that fits within these bounds, i.e., minimize the violations of the bounds. We then compare the distribution of the slopes, along an evenly spaced grid of slopes, again adding to the criterion function $max(F_L^{IM} - F_U, 0)^2$ and $min(F_U^{IM} - F_L, 0)^2$, where F now represents the distribution of the slopes (and the notation for bounds, and implied values is as above).

Third, we want the across-bidder distribution of the largest quantity bid (within each bidder group) to be smaller than the distribution of the largest quantities (within a bidder) ever purchased. The restriction is designed to capture the fact that some bidders might be capacity constrained below the regulatory 25%, and therefore even if the counterfactual price is low, they may not be interested in purchasing up to 25%. Therefore, we require the distribution of largest quantity bid by each bidder of group g in auction t to be first-order stochastically dominated by the distribution of max (across auctions) quantities ever bid. Evaluating this along a set of grid points (evenly spaced in quantity-space from 0 to 25%), results in an additional contribution to the criterion function of 0 if the counterfactual distribution of maximum quantities at a given grid point is above the max-quantity distribution in the data and the squared difference of the probabilities of quantities less than that grid point when the counterfactual distribution is below the distribution from the data.

In an alternative specification we increase the maximum quantities by 5 percentage points of supply. Our findings are similar, although with slightly smaller price effects and a smaller likelihood of auction failure (see Appendix Figures A13, and A14). If we allow each bidder to demand up to the bidding limit (25%), no auction would fail. However, assuming that all bidders have the capacity to buy Treasuries worth more than C$ 81 million in each auction is unrealistic. This would be possible only if a bidder receives an extraordinary amount of client orders, or has sufficient balance sheet space despite stringent regulatory constraints.

D.2 Evaluating the importance of commitment

In light of the competition-volatility trade-off presented in the main text, we evaluate two alternative policy regimes regarding bidder commitment. First, we make changes to assess the extent to which primary auctions run smoothly without forcing regular dealer participation. Second, we attempt to minimize volatility by requiring customers to commit to participating in the same way as dealers. In both cases it is theoretically ambiguous whether competition and volatility increase or decrease relative to the status quo, due to endogenous bidder participation.

To analyze the importance of dealer commitment, we compare two settings—the first has dealers commit as in the status quo but allows customers to place bids directly with the auctioneer; the second has both bidder groups bid directly with the auctioneer but doesn't impose obligatory participation on dealers. To compute the counterfactual without dealer commitment, we assume that a dealer's cost to enter one auction equals her estimated annual cost divided by the average number of auctions in a year.

We find that most auctions attract sufficiently many bidders to guarantee full auction coverage, even without obligating dealers to regularly participate (see Appendix Figure A15). However, both dealer and customer participation is highly irregular. Moreover, three out of one-hundred and one auctions risk failure without dealer commitment (where we define an auction to be at risk if it's chance of not clearing is above 5%). The expected price of these at-risk auctions drops by more than 5%. Further, even in fully covered auctions, expected revenue decreases by 0.04% in the median without dealer commitment.

To assess the impact of customer commitment, we force customers to decide at the beginning of each year whether or not to commit to participating in all auctions of the upcoming year. They enter the market if their annual participation cost (approximated by the estimated auction-specific cost scaled by the average number of auctions in a year) is larger than the total surplus they expect from participating in all auctions of that year. Dealer participation is fixed.

We find that between one and two fewer customers would participate if they had to commit (see Appendix Table A7). Nevertheless, auctions would remain relatively competitive since sufficiently many bidders would remain in the market. Expected revenue drops by C$ 3.6M, or about 0.11% on average.

Appendix Table A1: List of dealers that exited and entered auctions, and when

Dealer name	Bill auctions	Bond auctions
CT Securities	Entry 1999, exit 2000	Entry 1999, exit 1999
Salomon	Entry 1999 exit 2000	Entry 1999, exit 2001
Goldman Sachs	Entry 1999, exit 2001	Entry 1999, exit 2002
SG Valeurs	Entry 1999, exit 2004	Entry 1999, exit 2004
JP Morgan	Entry 1999, exit 2007	Entry 1999, exit 2007
Deutsche Bank	Entry 1999, exit 2014	Entry 1999, exit 2014
Morgan Stanley	Entry 1999, exit 2001	Entry 1999, exit 2014
PI Financial Corp	Entry 2009, exit 2015	Entry 2009, exit 2015
Ocean Securities	Entry 2006, exit 2008	Entry 1999, exit 2015
Sherbrooke SSC	Entry 2020	Entry 2020

Appendix Table A1 lists all entries and exits of dealers in bill and bond auctions from 1999 until 2022. We only list years, even though we do observe the exact dates of entry and exit.

Appendix Table A2: Predictors of customer participation—Individual level

Participation_i	(OLS)		(Bidder-FE)		(Bidder-Year-FE)	
β_1: Basis trade	+0.0356	(0.0398)	+0.0356	(0.0457)	+0.0569	(0.0464)
β_2: Benchmark status	−0.0121	(0.0138)	−0.0171	(0.0149)	−0.0138	(0.0146)
β_3: MPC	−0.0500	(0.0332)	−0.0525	(0.0349)	−0.0491	(0.0357)
β_4: QE	+0.0062	(0.0148)	−0.0198	(0.0218)	−0.0306	(0.0166)
β_5: Exchange rate	−0.0730	(0.0829)	−0.0132	(0.138)	−0.0478	(0.0946)
β_6: Spread	$+0.0229^{***}$	(0.0023)	$+0.0195^{***}$	(0.0055)	$+0.0179^{***}$	(0.0050)
β_7: Number of dealers	+0.0023	(0.0051)	+0.0131	(0.0102)	$+0.0151^{*}$	(0.0065)
β_8: $\text{Lagged-participation}_i$	$+0.532^{***}$	(0.0106)	$+0.228^{***}$	(0.0538)	+0.0317	(0.0309)
Extra controls	✓		✓		✓	
Adjusted R^2	0.282		0.422		0.506	
Observations	6,593		6,577		6,574	

Appendix Table A2 is analogue to Table 2, but zooms in on customer bidding participation at the individual level. We regress an indicator for whether customer i participated in an auction ("Participation") on the same explanatory variables as in Table 2 only that we replace the number of customers who participate in the previous auctions by whether customer i participated in the previous auction, called "Lagged-participation". To take time-variation in the set of potential customers into account, we use data from all auctions between the first and last time we observe the customer bidding at auction to construct all customer-specific participation and lagged participation indicators. In column (Bidder-FE) we include a bidder-fixed effect, and in column (Bidder-Year-FE) we include a year-bidder fixed effect. Standard errors are in parenthesis. They are clustered at the bidder-level in the columns (Bidder-FE) and (Bidder-Year-FE). Our preferred specification includes bidder-year fixed effects, analogues to column (Year-FE) in Table 2. As in Table 2 Spread is the only significant predictor among the market-level explanatory variables. The coefficient of Lagged-participation is positive without controlling for the upward time-trend in customer participation. However, when accounting for this trend, this coefficient becomes statistically insignificant, suggesting that customers are not more likely to participate in an auction based on their participation in the previous auction. The number of dealers is weakly statistically significant, which likely arises from the fact that a fiscal year does not start in January.

Appendix Table A3: Dealers do not demand more when a dealer exits the market

	Demand in C$		Demand in % of supply	
exit	-12.22	(28.28)	-0.288	(0.929)
Adjusted R^2	0.0221		0.0027	
Observations	286		286	

Appendix Table A3 provides evidence that (participating) dealers do not significantly adjust their auction-demands when a dealer exits the market. Concretely, we regress the maximal amount any participating dealer demands in the closest auctions around a dealer-exit (which we observe, but cannot display, in Appendix Table A1) on an indicator exit-variable that is one post-exit and exit-event-fixed effects. We report the estimated coefficients, and standard errors in parenthesis, with demands expressed in millions C$ and in percentages of supply. In both cases, the exit-coefficient is statistically insignificant at 10%. This is also the case when estimating separate regressions for each of the eight exit events.

Appendix Table A4: Differences in customer and dealer values

	P95	Sum	Max	CI
QWA-Value	0.00	0.00	0.00	[825, 2906]
Max-Value	0.06	0.00	0.93	[-836,2406]
Min-Value	0.00	0.00	0.00	[615, 1976]

Appendix Table A4 shows the results from testing whether customer values are above dealer values. Columns P95, Sum, and Max present p-values for the test-statistics which take the 95th percentile, the sum of squared standardized differences, and the maximum difference across auctions of the average values of dealers less the lower bound of customer values. P-values are computed using the bootstrap. The confidence intervals (CI) are for interval estimates of the mean difference. The QWA-value is the average (within customers and dealers) of the individual participants quantity-weighted average values. The Max-Value row compares the within group average values of the individual bidders' maximum value (at their first submitted step). The Min-Value row compares the within group average values of the individual bidders' minimum value (at their last submitted step).

Appendix Table A5: Predictors of customer participation, customer values and bids

	Values (OLS)		Bids (OLS)		Values (Year-FE)		Bids (Year-FE)	
β_1: Basis trade	-1.610	(1.905)	-1.493	(1.864)	-1.129	(1.858)	-0.945	(1.804)
β_2: Benchmark status	$+0.692$	(0.729)	$+0.500$	(0.713)	$+1.039$	(0.712)	$+0.839$	(0.692)
β_3: MPC	-2.822	(1.842)	-3.271	(1.803)	-2.015	(1.832)	-2.502	(1.779)
β_4: QE	$+3.945^{***}$	(0.886)	$+4.046^{***}$	(0.867)	$+3.298^{***}$	(0.944)	$+3.290^{***}$	(0.916)
β_5: Exchange rate	$+6.628$	(4.226)	$+8.236^{*}$	(4.135)	$+4.840$	(7.189)	$+6.934$	(6.979)
β_6: Spread	$+0.929^{***}$	(0.123)	$+0.912^{***}$	(0.120)	$+1.012^{***}$	(0.121)	$+0.995^{***}$	(0.118)
β_7: Number of dealers	$+0.378$	(0.266)	$+0.340$	(0.261)	-0.011	(0.303)	-0.054	(0.294)
β_8: Lagged number of customers	-0.099	(0.112)	-0.062	(0.110)	-0.001	(0.120)	$+0.019$	(0.116)
Extra controls	✓		✓		✓		✓	
Adjusted R^2	0.2933		0.3023		0.3354		0.3543	
Observations	327		327		327		327	

Appendix Table A5 is similar to Table 2. In the "Values" and (OLS) column, we regress our estimated quantity-weighted average values of customers on all explanatory variables we used in Table 2 to predict customer participation. We add a year-fixed effect in the (Year-FE) column. In the "Bids" columns, we replace the value estimates by the observed quantity-weighted bids of customers. The data ranges from the beginning of 2014 until the end of 2021. Standard errors are in parenthesis.

Appendix Table A6: Predictors of customer participation and moments of the customer value distribution

	(1) Average	(2) Median	(3) 5-Percentile	(4) 95-Percentile	(5) Std	(6) Range
Basis trade	−1.129	−1.073	−1.021	−1.119	+0.017	−0.098
	(1.858)	(1.859)	(2.672)	(1.903)	(0.846)	(2.352)
Benchmark status	+1.039	+0.947	+1.267	+0.999	−0.124	−0.269
	(0.712)	(0.713)	(1.024)	(0.729)	(0.324)	(0.902)
MPC	−2.015	−2.444	+0.074	−2.796	−1.090	−2.870
	(1.832)	(1.833)	(2.634)	(1.876)	(0.834)	(2.319)
QE	+3.298***	+3.335***	2.765*	+3.375***	+0.156	+0.610
	(0.944)	(0.944)	(1.357)	(0.966)	(0.429)	(1.195)
Exchange rate	+4.840	+7.242	−5.599	+7.258	+5.354	+12.86
	(7.189)	(7.192)	(10.34)	(7.360)	(3.271)	(9.099)
Spread	+1.012***	+1.073***	+0.553**	+1.173***	+0.217***	+0.619***
	(0.121)	(0.122)	(0.175)	(0.124)	(0.055)	(0.154)
Number of dealers	−0.0112	−0.0508	+0.109	−0.040	−0.089	−0.148
	(0.303)	(0.303)	(0.435)	(0.310)	(0.138)	(0.383)
Lagged number of customers	−0.001	+0.019	−0.082	+0.002	+0.040	+0.084
	(0.120)	(0.120)	(0.172)	(0.123)	(0.055)	(0.152)
Extra controls	✓	✓	✓	✓	✓	✓
Year fixed effect	✓	✓	✓	✓	✓	✓
Adjusted R^2	0.335	0.355	0.101	0.375	0.010	0.091
Observations	327	327	327	327	327	327

Appendix Table A6 regresses moments of the estimated customer value distribution (at the lower bound) on all explanatory variables that we include to predict customer participation in Table 2, plus year-fixed effects. "Average" stands for the quantity-weighted average value, which approximates the quantity-weighted expected value. "Median" considers the median value, "5-" and "95-Percentile" show the 5th and 95th percentile of the quantity-weighted average value, "Std" is its standard deviation, and "Range" is the difference between the 95th and 5th percentile. The data ranges from the beginning of 2014 until the end of 2021. Standard errors are in parenthesis.

Appendix Table A7: Customer commitment

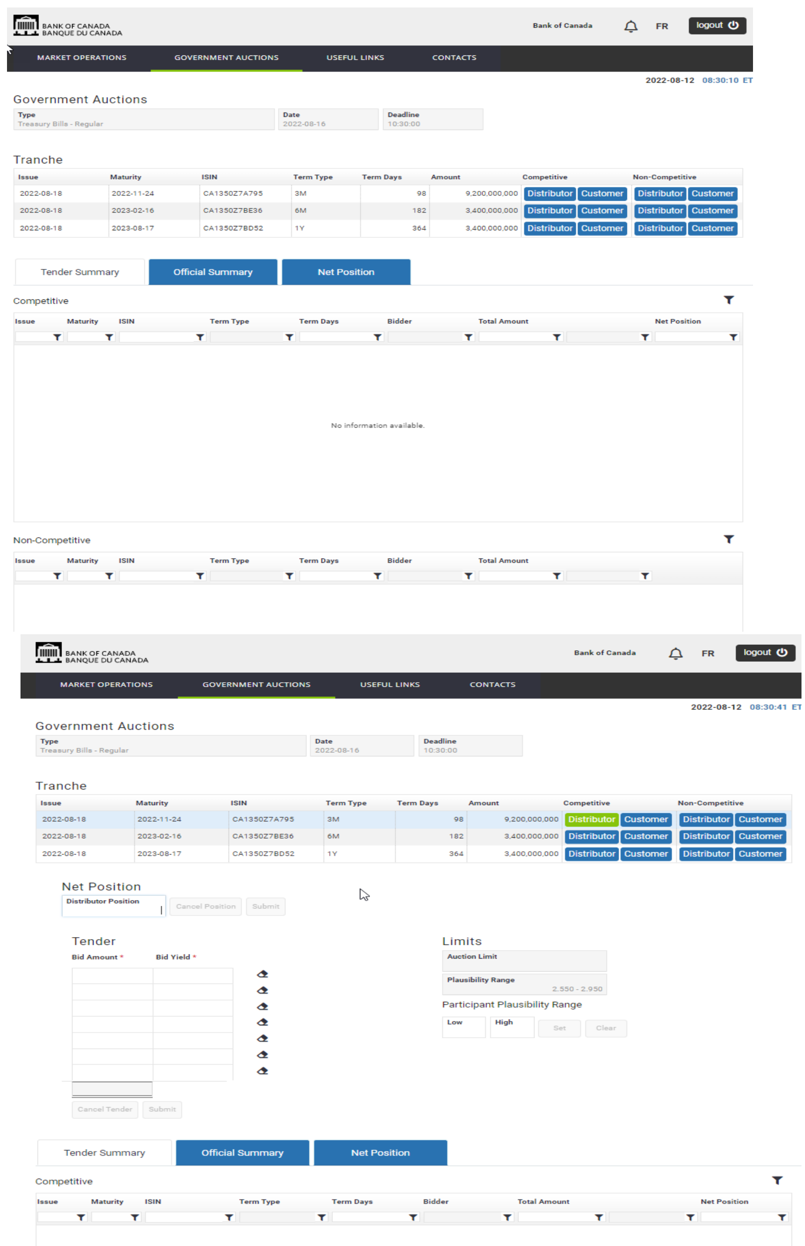
Year	No. of customers		Clearing Price		Revenue		Std of Revenue	
	Com	SQ	Com	SQ	Com	SQ	Com	SQ
2015	7	6.68	99.34	99.74	3.52	3.53	0.41	0.28
2016	7	8.94	100.18	100.30	3.46	3.47	0.28	0.26
2017	5	6.10	99.65	99.76	3.59	3.59	0.26	0.44
2018	6	6.44	98.59	98.56	3.82	3.82	0.43	0.50
2019	7	9.18	98.43	98.27	3.91	3.91	0.49	0.62
2020	7	11.52	98.03	97.95	4.25	4.25	0.61	0.60
2021	7	8.84	98.19	98.15	4.09	4.09	0.59	0.68
2022	7	9.39	98.51	98.60	4.14	4.15	0.68	0.68

Appendix Table A7 compares the counterfactual with customer commitment (Com) to the status quo (SQ), where customers make per-auction entry decisions. Dealer participation is fixed. Note that the equilibrium number of customer entrants depends on auction-specific profits for each of the 30 auctions per year across 8 years. To avoid computing the equilibrium in all of these auctions for each possible number of customers, we utilize a selected sample of five auctions. These auctions are strategically chosen to align the number of customers with percentiles (5th, 25th, 50th, 75th, and 95th) of the customer participation distribution since 2014, while the quantity sold approximates the average amount. When calculating profits, surpluses, and prices for each year, we re-weight the predictions from these five auctions to match the composition of auctions in that specific year. Expected revenues are in C$ billions.

Appendix Figure A1: Primary auctions in different countries

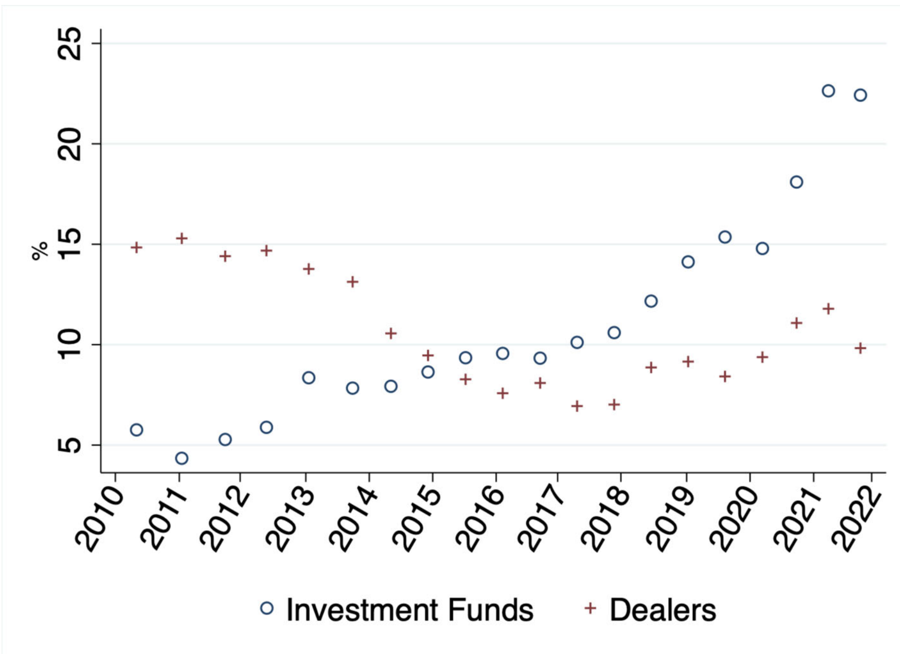
Appendix Figure A1, taken from Muller (2019), shows an overview of how different countries issue debt. Towards the left are countries like Canada who heavily rely on dealers to make markets. Towards the right are countries like the U.S. who let anyone participate in primary auctions.

Appendix Figure A2: What a dealer sees when bidding



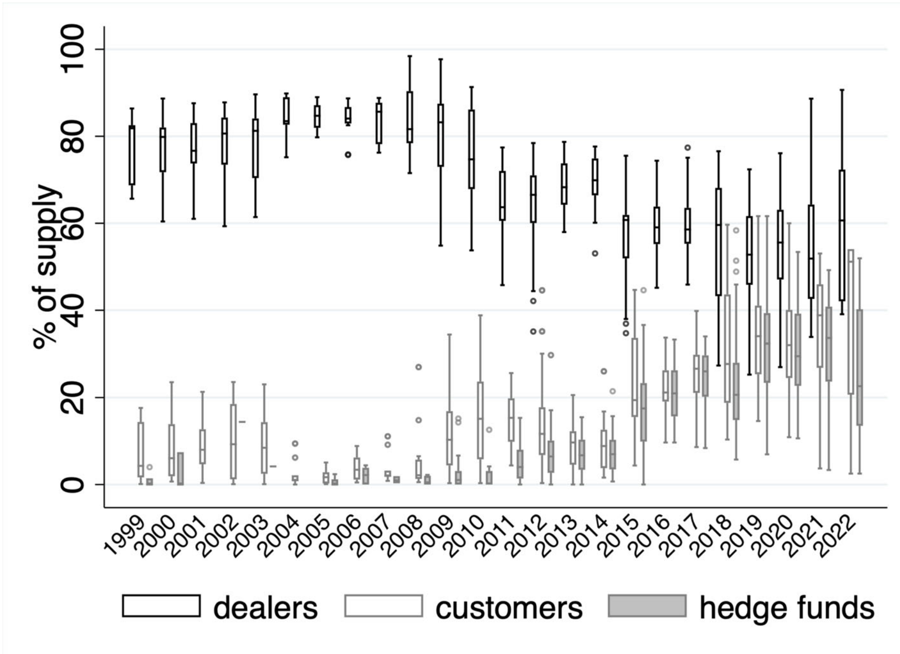
Appendix Figure A2 shows a screenshot of what a dealer sees when placing its bids, either for its own account or on behalf of a customer.

Appendix Figure A3: Auction allotment by investor class for U.S. government bond auctions



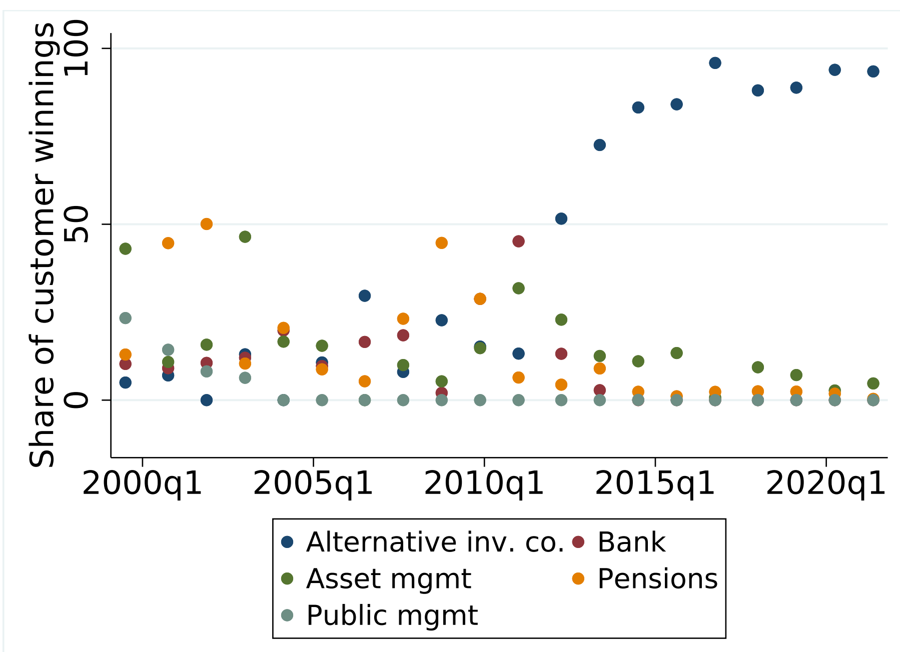
Appendix Figure A3 shows the auction allotment in percentage of supply in U.S. government bond auctions from the beginning of 2010 until the end of January 2022 for broker/dealers (plus) and for investment funds (circle). Broker/dealers include Includes primary dealers, other commercial bank dealer departments, and other non-bank dealers and brokers; Investment funds include mutual funds, money market funds, hedge funds, money managers, and investment advisors. To create this graph we use public data from TreasuryDirect.org, available at `https://home.treasury.gov/data/investor-class-auction-allotments`, accessed on July 19, 2023.

Appendix Figure A4: Purchased amount by dealers, customers, and hedge funds



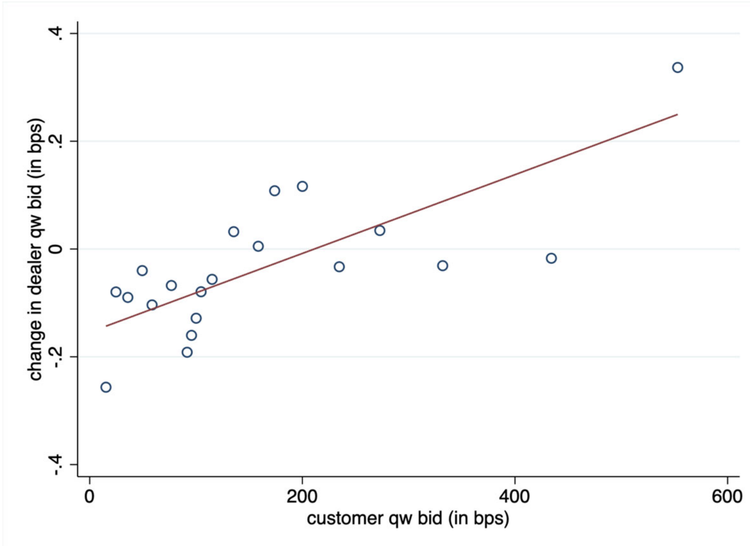
Appendix Figure A4 shows the distribution of how much dealers, customers, and hedge funds win (as a group) in percentage of the total amount issued across all bond auctions in our sample for each year from 1999 until 2022.

Appendix Figure A5: Purchased amount by investor groups



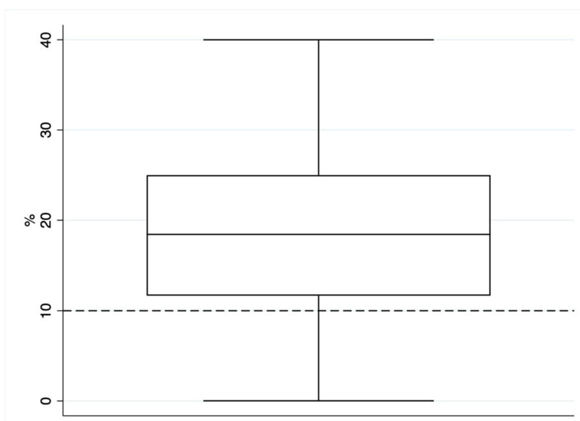
Appendix Figure A5 shows a binned scatter plot of how much each investor group wins in percentage of the total supply bought by non-dealers from 1999 until 2022.

Appendix Figure A6: Dealer adjustment and customer bid



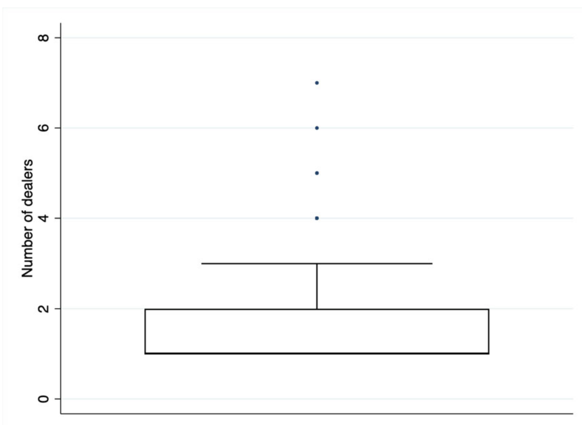
Appendix Figure A6 shows the correlation between the change in the dealer's quantity-weighted bid and the quantity-weighted bid of the customer. A quantity-weighted bid is the total amount a bidder bid divided by the total amount she demanded. A bid is measured in yields to maturity and expressed in bps.

Appendix Figure A7: Primary dealers are above minimal bidding requirements

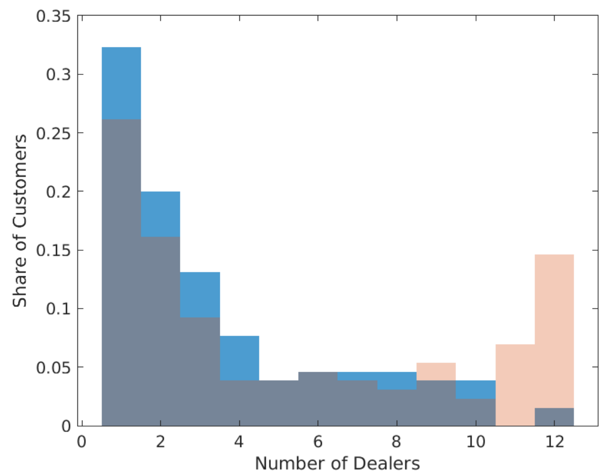


Appendix Figure A7 provides evidence that primary dealers are, with rare exception, above the minimal bidding limit of 10% that is required to maintain the primary dealer-status, conditional on market participation in a given year. In addition, supervisory data show that there have been extremely few violations in the past decade. This suggests that Canadian dealers do not face the dynamic trade-off by Rüdiger et al. (2023), according to which dealers forgo one-shot auction surpluses in order to fulfill minimal bidding requirements that must be met over a longer horizon. Concretely, the figure shows the distribution of the maximal amount an active primary dealer demands in an auction (as percentage of supply), where a primary dealer is active if it places at least one bid over the course of an entire year, and the maximal demand is zero if the dealer does not participate in an auction. The distribution is taken over auctions and primary dealers. Outliers are excluded.

Appendix Figure A8: Random matching of customers to dealers



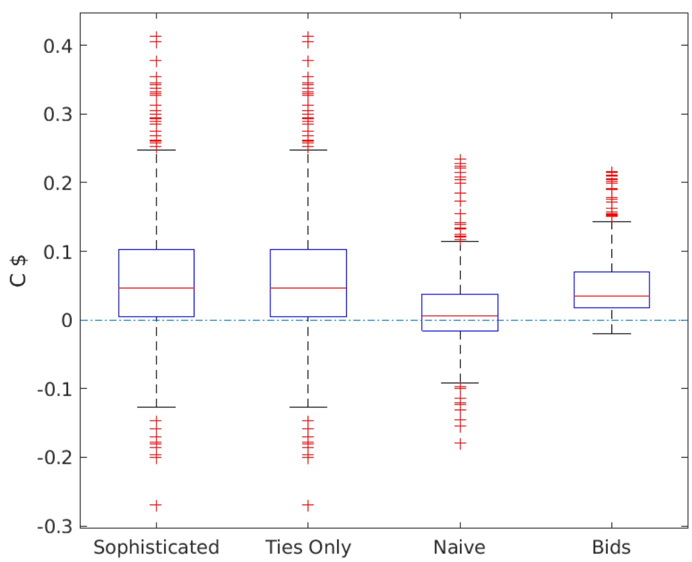
(A) within Auction



(B) Across auctions

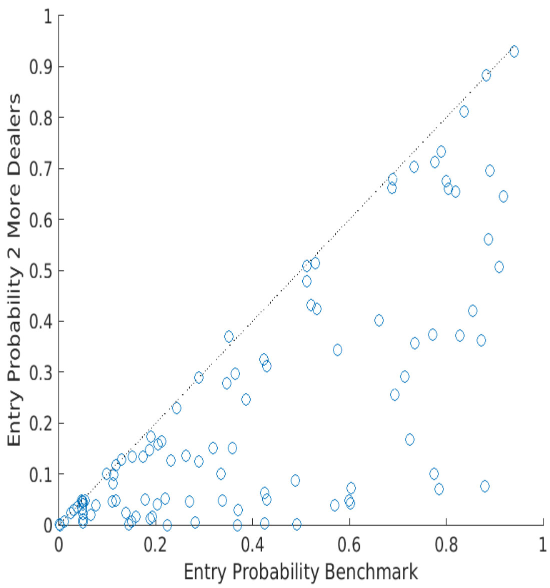
Appendix Figure A8A shows the distribution of how many dealers a customer places a bid through within an auction. The median is 1. Figure A8B plots the distribution of the number of unique dealers used by a customer in all auctions in the data (in pink) and the number of unique dealers that would be predicted for each customer under random matching (in blue). The model prediction fixes the maximum number of dealers at the median number of dealers across years (12). The distributions are broadly similar, but the model predicted distribution somewhat overestimates the probability that a customer sometimes uses all of the possible dealers.

Appendix Figure A9: Customer dealer value comparison under different bidding assumptions

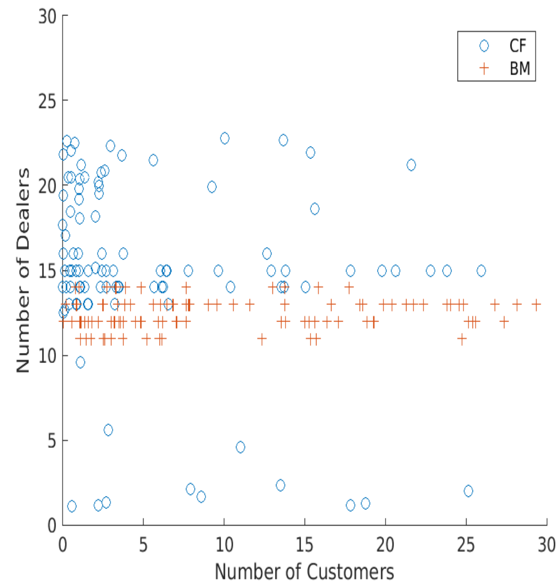


Appendix Figure A9 shows three distributions of the difference in quantity-weighted average values between participating customers (at the lower bound) and dealers for different assumptions on customer bidding behavior, in addition to the analogous distribution of the difference in "Bids". "Sophisticated" customers bid according to Proposition 1(ii). "Naive" customers do not take into account that dealers can update their own bids, and thus behave analogously to dealers whose equilibrium conditions are specified in Proposition 1(i). "Ties Only" customers account for ties in the equilibrium condition of Proposition 1(ii) but never bids above value because she sets $\lambda = 0$.

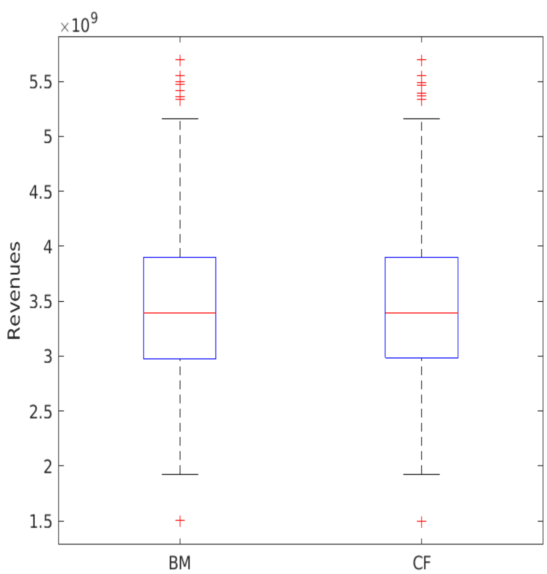
Appendix Figure A10: Revenue and price effect—adding back dealers



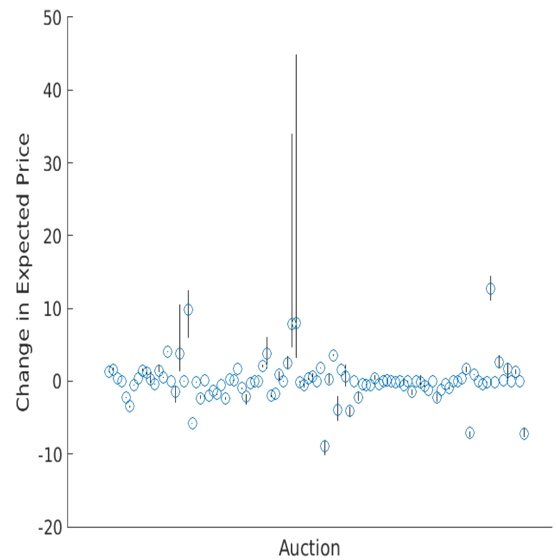
(A) Customer entry probability



(B) Exp. number of dealers/customers



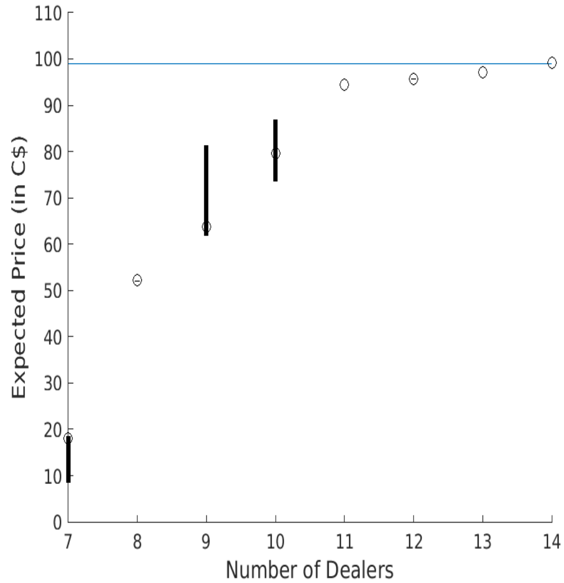
(C) Exp. revenues (in C$)



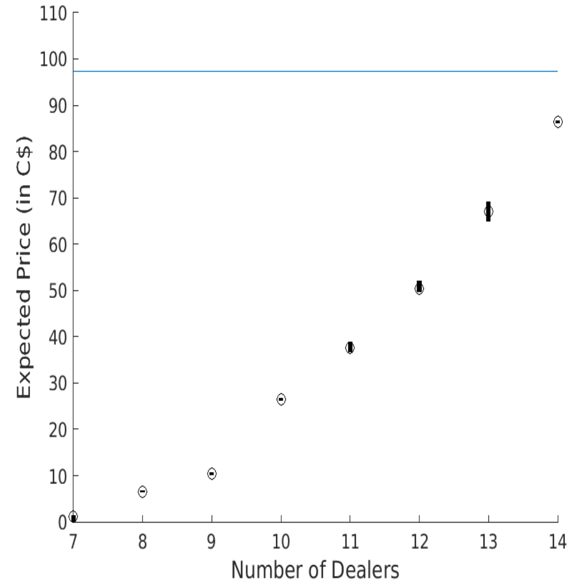
(D) Percentage change of expected price

Appendix Figure A10A shows hedge fund (HF) participation probabilities (in percentage points) in every 15th auction from 2014 onward in the status quo (on the x-axis) and the counterfactual in which we add back the two dealers who left (on the y-axis). Figure A10B shows the expected number of dealers and HFs that participate in each auction in the status quo and the counterfactual. Figure A10C shows the distribution of the expected auction revenues in million C$. Figure A10E is a time series of the percentage change in the expected price when going from the status quo to the counterfactual. Prices are in C$ with a face value of 100.

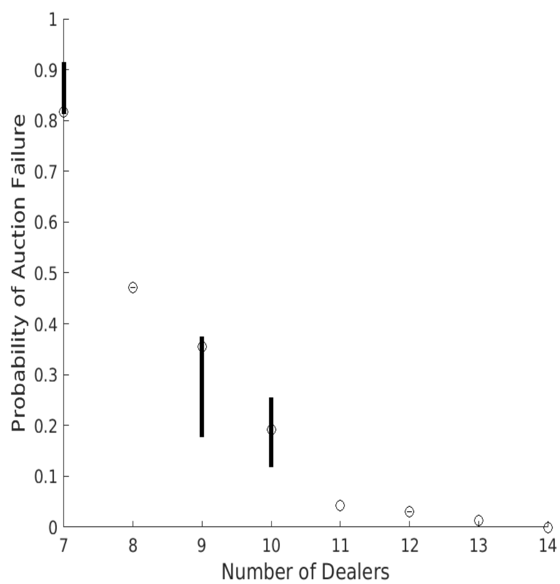
Appendix Figure A11: Expected price and number of dealers for auction p5, and p95



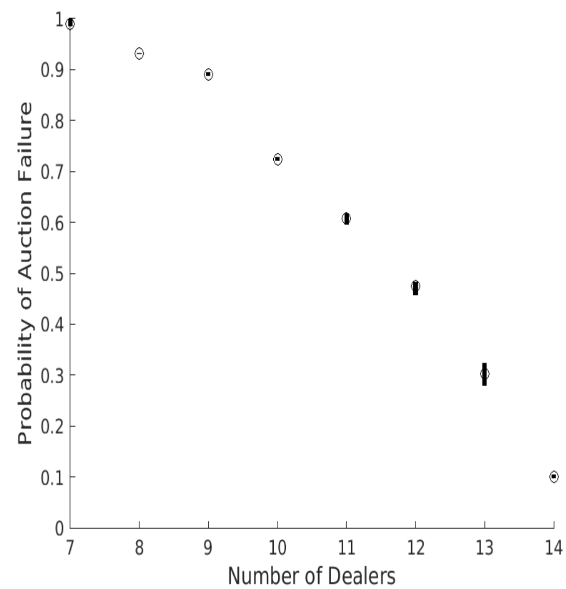
(A) Expected price



(B) Expected price



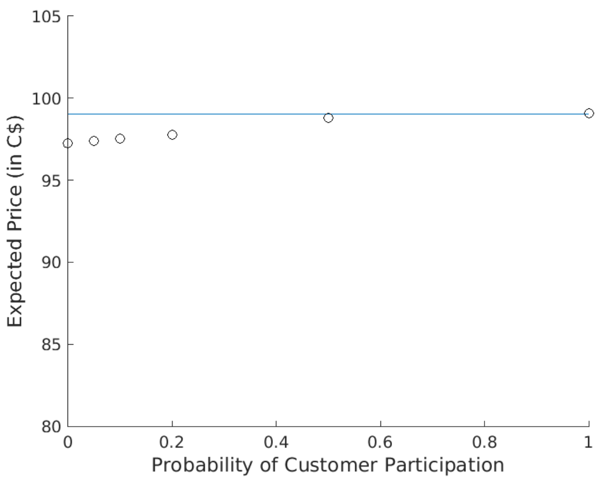
(C) Auction failure



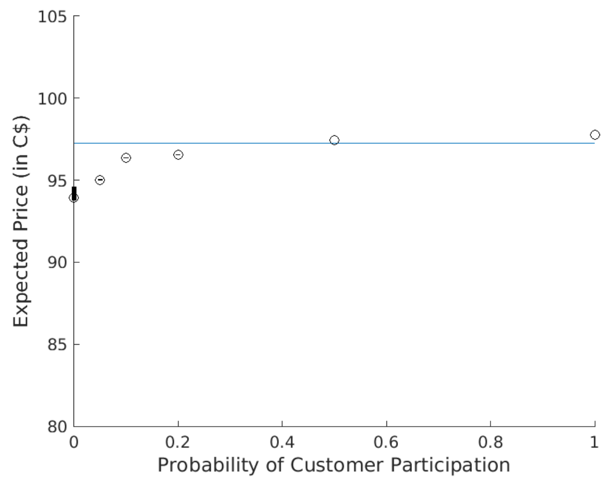
(D) Auction failure

Appendix Figure A11 is analogous to Figure 7. It shows how the range of expected price (in C$) at which an auction clears varies as the number of dealers increases from 7 to 14 in two representative auctions, which issue the average supply with 1 participating customer in A11A, and with 4 participating customers in A11B. Here, 1 and 4 are the 5th and 95th percentile of the observed distribution of the number of participating customers. In A11C and A11D we show the auction failure for these two auctions, respectively. In theory, there is one counterfactual equilibrium for each fixed number of dealers. In practice, we determine a range of prices (marked in black) given that our numerical procedure to determine counterfactual bids allows for small differences between the value distribution that is implied by the counterfactual bids and the true value distribution (see Richert (2021) for details). The blue horizontal line shows the average observed bid, which is close to the observed market clearing price.

Appendix Figure A12: Varying customer participation probability



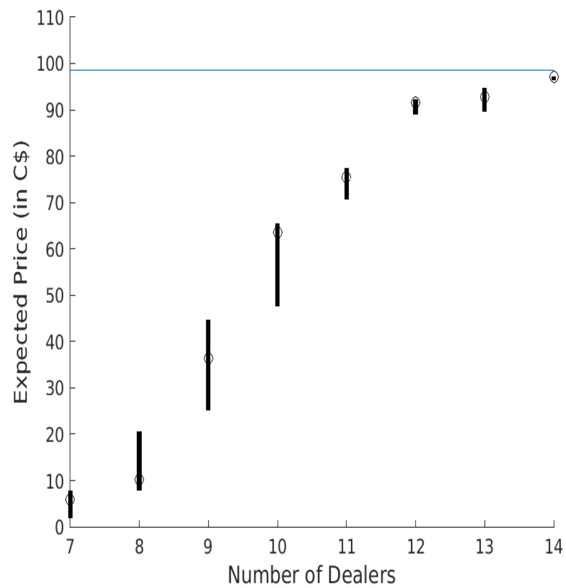
(A)



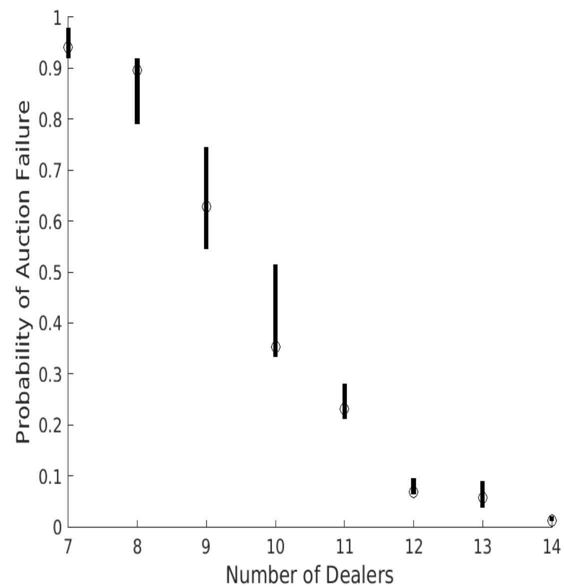
(B)

Appendix Figure A12 shows how the range of expected price (in C$) at which an auction clears varies as the customer participation probability varies between 0 and 1 in an auction in two representative auctions, which issue the average supply with 1 participating customer in A12A, and with 4 participating customers in A12B. Here, 1 and 4 are the 5th and 95th percentile of the observed distribution of the number of participating customers. In theory, there is one expected price for each counterfactual. In practice, we determine a range of prices (marked in black) given that our numerical procedure to determine counterfactual bids allows for small differences between the value distribution that is implied by the counterfactual bids and the true value distribution (see Richert (2021) for details). The blue horizontal line shows the average observed bid, which is close to the observed market clearing price.

Appendix Figure A13: Varying number of dealers under the alternative distribution of maximal quantities



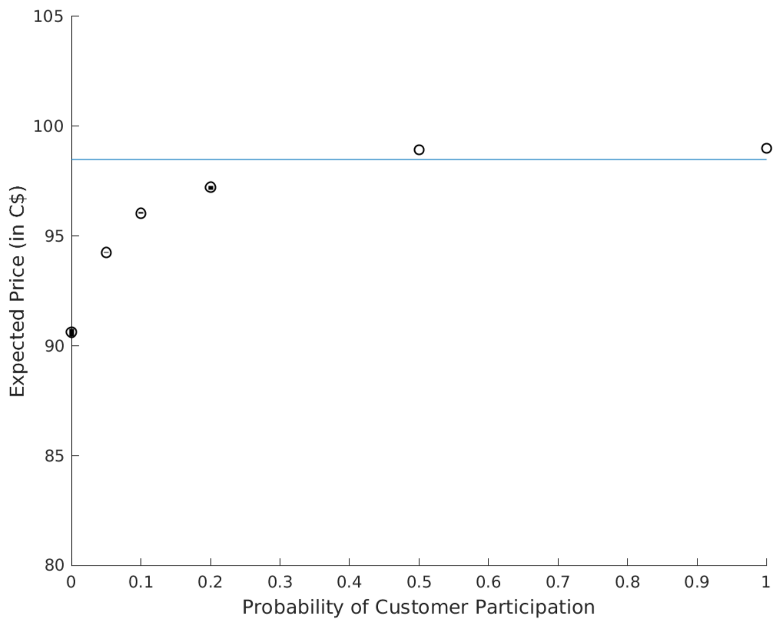
(A) Expected price



(B) Auction failure

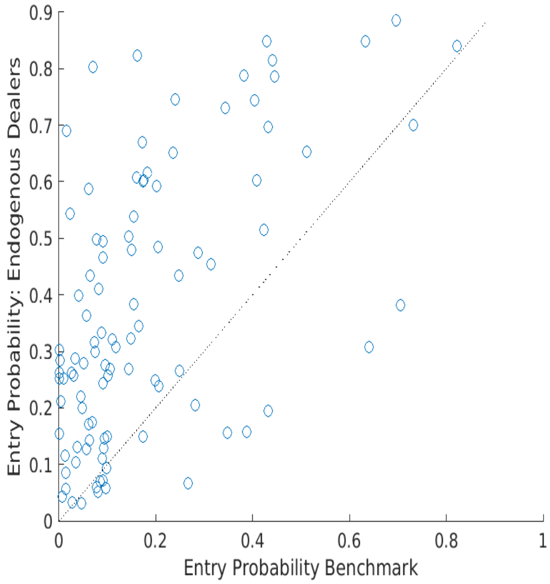
Appendix Figure A13 is analogous to Figure 7, but using the alternative distribution of maximal quantities of Appendix D.1. It shows how the range of expected price (in C$) at which an auction clears varies as the number of dealers increases from 7 to 14 in an auction which issues the average supply with medium customer participation—by which we mean 3 customers participate. In theory, there is one expected price for each fixed number of dealers. In practice, we determine a range of prices (marked in black) given that our numerical procedure to determine counterfactual bids allows for small differences between the value distribution that is implied by the counterfactual bids and the true value distribution (see Richert (2021) for details). The blue horizontal line shows the average observed bid, which is close to the observed market clearing price.

Appendix Figure A14: Varying customer participation probability under the alternative distribution of maximal quantities

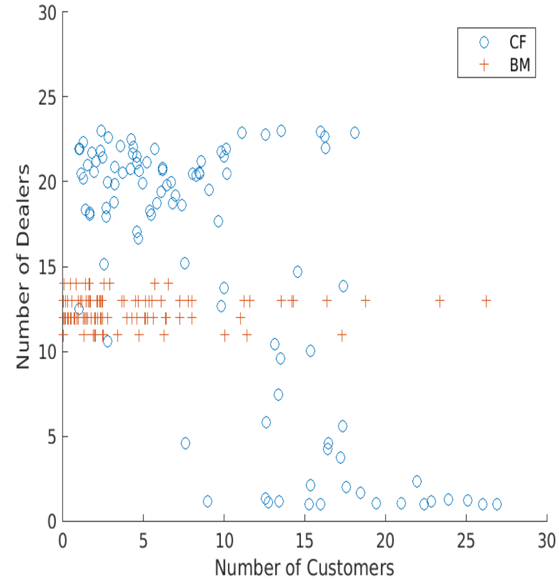


Appendix Figure A14 is analogous to Figure 8, but using the alternative distribution of maximal quantities of Appendix D.1. It shows how the range of expected price (in C$) at which an auction clears varies as the customer participation probability varies between 0 and 1 in an auction which issues the average supply with medium customer participation—by which we mean 3 customers participate. In theory, there is one expected price for each counterfactual. In practice, we determine a range of prices (marked in black) given that our numerical procedure to determine counterfactual bids allows for small differences between the value distribution that is implied by the counterfactual bids and the true value distribution (see Richert (2021) for details). The blue horizontal line shows the average observed bid, which is close to the observed market clearing price.

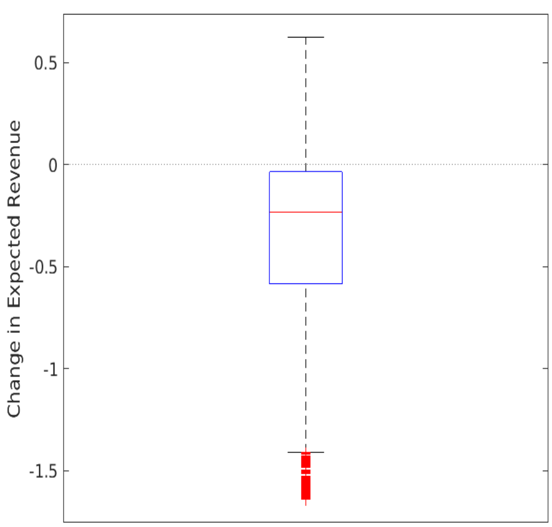
Appendix Figure A15: No dealer commitment



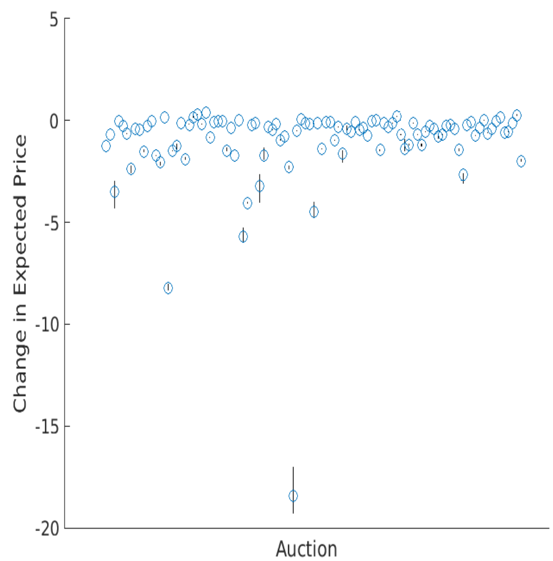
(A) Hedge entry probability (in %)



(B) Expected number of dealers/customers



(C) Percentage change in expected revenue



(D) Percentage change in expected revenue

For every third auction starting in 2014, Figure A15A shows the probability, in percentage points, that a customer participates in the status quo (on the x-axis) and the counterfactual in which we add back the two dealers who left (on the y-axis). Figure A15B shows the expected number of dealers and customers that participate in each auction in the status quo and the counterfactual. Figure A15C shows the distribution of the percentage change in the expected auction revenue. Figure A15D is the time series of the percentage change in the expected price when going from the status quo to the counterfactual. Prices are in C$ with a face value of 100.