Value of (Keeping) Primary Dealer Status in Treasury Auctions*

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February 14, 2020

Abstract

We use bid data from Argentinian Treasury bill auctions from 1996 to 2000 to study how banks' balance sheet and past performance affect bidding behavior. Exploiting variation in primary dealers' regulations we show that when banks lag behind their regulatory targets for primary market participation, they bid more aggressively. They also bid more aggressively for existing securities that are reissued when the regulation tightens the requirements for secondary market participation. Consistent with regulations which imply that auctioned securities are not a prime source of liquidity, we find that banks which face liquidity needs bid less aggressively for them. A novel implication of our results is that in institutional settings that feature dealer turnover, intertemporal considerations in bidding behavior should be introduced. We develop a dynamic model to quantify these effects on bidding, and to estimate how much primary dealers value their status.

JEL classification: D44; G12; G21; L10; L13

Keywords: Treasury Auctions; Multi-unit Auctions; Structural Estimation; Bidding Behavior; Balance-sheet Data; Market Making

*The authors would like to thank Helmut Elsinger, Philipp Schmidt-Dengler and seminar participants at Austrian National Bank and Universidad Torcuato Di Tella for helpful comments. All remaining errors are our own.

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1 Introduction

Every year trillions of dollars worth of public debt is sold by governments around the world to finance their budgets.[1] In most cases public debt is sold through auctions, with interested buyers potentially submitting multiple bids specifying quantities and unit prices offered for these quantities. Given the size of these markets, the question of the optimal auction design is one that has attracted attention both from researchers and policy-makers. Recent developments in non-parametric methods to estimate bidder valuations have been particularly helpful, as they have allowed the study of auction performance under a number of counterfactuals. But all existing research features a static framework that assumes bidder behavior is not influenced by past auction performance, and studies on how bidder behavior might be affected by the balance-sheet positions of participating banks have been of limited use due to the low frequency of available data. Using a unique data set which allows us to match auctions with monthly balance-sheet data, we are able to improve the understanding of factors that drive bidder behavior.

We use bid data from Argentinian Treasury bill auctions from 1996 to 2000, and focus the analysis on 3-month treasury bills. During this period there was at least one auction of 3-month treasury Treasury bills every month, and we are able to match auction data to banks' monthly balance-sheet data. Using the resampling methods developed in Guerre, Perrigne and Vuong (2000), Hortaçsu and McAdams (2010) and Kastl (2011) we estimate bidder valuations and shading for each auction. We use balance-sheet data to construct measures for the banks' asset and liability positions that are used to determine liquidity requirements, and we measure dealers' past auction performance to gauge whether they are meeting their regulatory obligations or not. We then analyze how their valuation, bid shading and the ultimate quantity of debt bought, depend on these variables as well as other balance-sheet variables. We identify two relevant subsamples based on regulatory variation and analyze these separately. In the first period, which lasted until July 1998, there were strong incentives for dealers to participate in primary markets, but less incentives to participate in secondary markets. Conversely, in the second period, from August 1998 onward, dealers must account for at least 1.5% of traded volume in secondary markets and, at the same time, the obligations in the primary markets were reduced.

Three main results emerge from the analysis. (i) Exploiting the variation in the regulation of market-making activities, we show that in the first period, when dealers fear losing their market maker status, they bid more aggressively.[2] (ii) dealers also bid more aggressively for existing securities that are reissued in the second period, where the regulation tightens the requirements to participate in secondary markets. (iii) When banks face an increase in deposits, and thus need to increase their holdings of liquid assets to meet liquidity requirements, their valuations are lower and they bid less aggressively.

Our first result highlights that it would be more accurate to model these auctions in a dynamic setting, as dealers not only value the securities they buy for their contribution to current profits, but also for their effect on future expected profits. We conjecture that a similar effect would be present in other institutional settings that feature dealer turnover for based on their performance in primary markets. We view our second result as indicative that more liquid secondary markets increase revenue for the auctioneer. Finally, our third result highlights a pecking order for securities' liquidity in this period. In December 1996 the Argentine Central

[1] The U.S. Treasury alone auctions more than eight trillion dollars of debt every year.

[2] By estimating market makers surplus, we find that losing market maker status would account to a loss of at least 12.5% of their profits.

Bank arranged an insurance contract against systemic risk with a consortium of private foreign banks. This was structured as a repo agreement, and short-term Treasury bills were not eligible. Thus, since short-term treasury bills were not a prime source of liquidity in this period, banks bid less aggressively for these bills when they face an increase in their liquidity needs.

Given our finding that dealers bid more aggressively when they are behind they primary market regulatory targets, we model bidding behavior in a dynamic setting. We introduce cumulative demand as a state variable that affects the probability of retaining dealer status in the future. Dealers' value function is increasing and concave in cumulative demand, and its curvature measures how much more aggressively they would bid relative to a static auction. We estimate the dynamic model separately for the periods in which primary market regulations are binding or not. We find that in the former the value function is significantly more concave than in the latter.

Related literature. Over the past twenty years a number of papers have applied structural econometric techniques to study bidder behavior in multi-unit auctions. These methods can be characterized as either parametric or non-parametric. Février, Préget and Visser (2004) is an example of the former. They use the Euler equation that characterizes optimal bidding in Wilson (1979) to simulate the French Treasury's revenue under a uniform instead of a discriminatory auction format. The main drawback of this approach is that it requires the modeller to impose structure on the mapping from signals into bid functions and finding explicitly the equilibrium strategies. In contrast, the non-parametric approach does not require any parametric specification nor an explicit solutions of equilibrium strategies.

Most non-parametric methods in multi-unit auction studies are extensions of Guerre *et al.* (2000) who use a two-step approach for estimating the distribution of private values in single-unit auctions. Equilibrium bids are characterized by linking values with each bid and the distribution of all bids. In a first step the distribution of bids is estimated. Using the equilibrium condition, this provides a pseudo sample of values. In a second step, a kernel is used on this sample to non-parametrically estimate the density of private values.

Hortaçsu (2002) and Hortaçsu and McAdams (2010) were the first to extend the approach of Guerre *et al.* (2000) to multi-unit auctions. They use bid data from Turkish Treasury auctions to estimate revenue under a uniform instead of a discriminatory auction format. Again, the equilibrium condition in Wilson (1979) is used. This links marginal values with the bid function and a shading term that depends on the distribution of clearing prices. Thus, to estimate marginal values one must first estimate this distribution. This is done by randomly drawing bid schedules from the actual bids observed in one or several auctions to determine the clearing price in a hypothetical auction. Repeating this procedure a large number of times generates a distribution of clearing prices.

Kastl (2011) extends the model of Wilson (1979) and estimation method of Hortaçsu (2002) and Hortaçsu and McAdams (2010) to account for the discreteness of bids. When there is a cost to make a bid, bid schedules are step functions and Kastl (2011) shows that in this case bidding above marginal value may be optimal.

Closest to our work is a group of papers which apply the aforementioened non-parametric structural estimation methods to analyze different aspects of treasury bill auctions. Hortaçsu and Kastl (2012) investigate dealers' information gain from observing customer orders in Canadian Treasury auctions. Cassola, Hortaçsu and Kastl (2013) study the 2007 subprime market crisis through bidding behavior in ECB auctions. Hortaçsu, Kastl and Zhang (2018) show that primary dealers consistently bid higher than direct and indirect bidders in US Treasury auctions, and relate this to their valuations and ability to shade bids. Elsinger, Schmidt-Dengler and Zulehner (2019) analyze competition in Austrian Treasury auctions using the EU Accession as a quasi-experiment. We differ from the aforementioned paper in that we are able to link monthly balance-sheet data to the participating banks in our dataset.[3] More importantly, we are the first to study Treasury auctions in a dynamic setting and show (and quantify) that when dealers fear losing their market making status they bid more aggressively.

The rest of the paper is organized as follows. Section 2 describes the regulation governing Argentinian treasury auctions and describes the bidding behavior in the period that is analyzed. Section 3 describes the structural estimation approach and outlines the resampling procedure, and section 4 relates bidding behavior to balance-sheet variables. In Section 5 we develop a dynamic model to study how primary market regulations affect dealers' behavior, and in section 6 we estimate this model to quantify how much dealers value their status. Section 7 concludes.

2 Argentinian Treasury auctions

In April 1996, Argentina implemented a market maker system to auction public debt with the objective of developing a domestic treasury market. A calendar with auctions dates, security types, and volumes was published at the beginning of each fiscal year. All auctions in this period use the uniform price format. Under this format, all winning bids are rewarded at the clearing price. Each auction consists of two rounds. The first round is competitive although it is possible to submit non-competitive bids. The second round on the other hand is purely non-competitive, where bidders can choose to acquire additional securities at the clearing price of the first round. In this round dealers are allowed to acquire up to 10% of the average amount won in the previous three auctions of the same type of instrument.[4]

When Argentina introduced Treasury auctions, it had maintained a currency board with the peso at parity with the dollar for more than five years. The country had secured price stability at the cost of being exposed to external shocks. This can be seen in Figure 1 that features the cut-off yields for auctions of short-term bills.[5] This shows that interest rates spiked during the Asian crisis in July 1997, when Russia defaulted on its sovereign debt in September 1998, and after Brazil devalued the real in January 1999. Besides those episodes, yields reveal a certain degree of political uncertainty when Domingo Cavallo was ousted as Finance Minister in July 1996 and during the presidential campaign in late 1999.

We focus exclusively on auctions of 3-month treasury bills. These auctions took place on a monthly basis until December 1999, and starting from January 2000 there were two auctions per month in several months.[6]

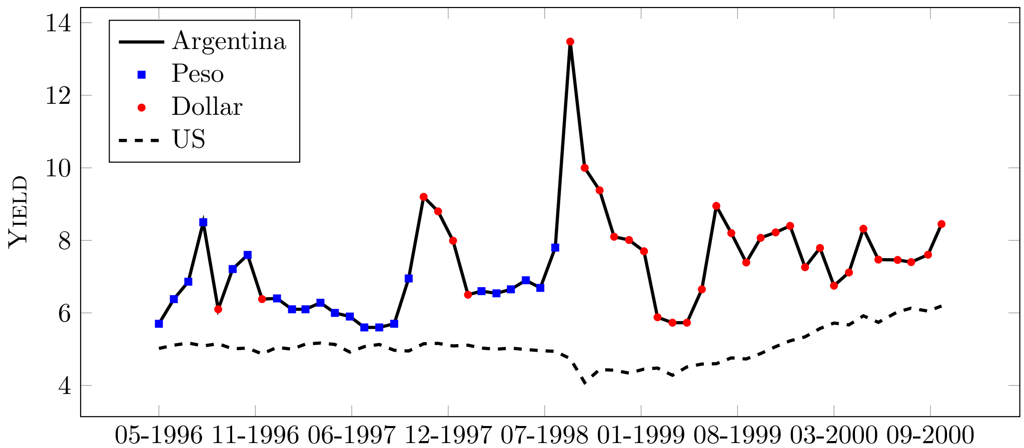
[3]Cassola *et al.* (2013) also use balance sheet data, but except for a smaller subsample of banks, this data was only available annually, and could therefore not be analyzed at the same frequency as the auctions. Furthermore, Cassola *et al.* (2013) is interested in how bidding behavior can be used as a proxy for bank health, while we seek the converse: how banks' balance sheet affects bidding behavior.

[4]During the first year the option was calculated using the last two auctions plus the current one.

[5]For Argentina, the yield is the monthly auction average. The United States yield is constructed as follows. From May 1996 to June 2000, it is the monthly auction average, and from July 2000 it is the secondary market rate of the last day of the month (since the auction average is not available in this period). Both series are taken from the Federal Reserve Economic Data.

[6]In the first period, auctions were held around the second week of the month. In the second period, auctions were held around the second and fourth week of the month.

Figure 1: 3-Month T-bill Yield



Initially the auction size was 250 million USD, and after January 2001 this was expanded to 350 million USD. These securities represented approximately 25% of the stock of Treasury bills of maturities of up to a year.

Dealers. Initially twelve banks, among the largest in the financial system, were chosen to be primary dealers: Banco de Galicia, J. P. Morgan, Banco de Santander, Chase Manhattan Bank, Deutsche Bank, Banco Río, Banco Francés, Banco de Crédito Argentino, HSBC, Bank of America, Citibank, and Bank Boston. Dealers acquired both rights and obligations. Within the latter, participating in primary issues, quoting prices and trading in secondary markets were the most important. Performance was evaluated on a yearly basis (at the end of March) and banks that underperformed could ultimately lose their dealer status. Dealers received fees that initially only depended on their participation in primary issues. Issues of 3-month bills paid 0.075% and fees for longer maturities were higher.

At the end of the year (in March 1997) dealers were evaluated and ING, that had been ranked fourth by treasuries bought during the year, replaced Banco de Crédito Argentino as a market maker. The following year (April 1998), ABN replaced Banco Santander as a market maker.[7]

Market making regulations. There were a number of regulatory changes made over the years that allow us to estimate the importance of market making incentives in valuation and bid shading. These changes are summarized in Table 1, and we here discuss each of them in turn. Resolution 238/96 of the Secretariat of the Treasury (Ministry of Economics and Public Finance) from April 1996 outlined the functioning rules for the primary market and established that twelve dealers will be recognized and their performance evaluated at the end of the year (March 31, 1997). Market makers had obligations to buy at least 4% of the total amount of each type of securities sold, and participate in secondary markets. Their performance was evaluated by an index, I_G, calculated as

$$I_G = 0.80 I_{MP} + 0.20 I_{MS},$$

[7] Banco de Santander had bought Banco Río, and therefore had to relinquish its market making activities.

where I_{MP} essentially measures volume bought in the primary market, and I_{MS} measures participation in secondary market trading. Dealers had the option to purchase additional securities at the cut-off price the day after each auction took place in a "second round". They could buy up to 10% of the average total securities bought in the previous two auctions and the current one (for the same maturities and currency).

Resolution 155/97 from March 1997 adjusted the primary market requirement such that dealers must buy at least 4% of the total securities sold, regardless of the type of security. It further established that the option to buy securities in the second round was calculated on the average of the past three auctions. Provision 9/97 of the Under Secretariat of Financing (Secretariat of the Treasury) from July 1997 recognized that the linear nature of index I_G led to some banks not to participate in secondary markets. Therefore, the index was henceforth calculated as the geometric average of I_{MP} and I_{MS}, with the former still given a weight of 0.8.

Resolution 323/97 from July 1997 eliminated the maximum number of dealers and increased their obligations in primary market to buying 5% of the total securities sold in the year. Resolution 370/98 from July 1998 reduced the obligation of market makers in primary markets back to 4% of the total securities sold. It further strengthened the requirement of secondary market participation such that each market maker must be responsible for at least 1.5% of the traded volume. Resolution 11/98 of August 1998 prioritized secondary market trading by giving more weight to operations made through the posting of bid and ask prices (relative to over-the-counter transactions). The weight on I_{MS} was increased to 0.3. Resolution 429/99 from August 1999 split the payment of commissions to dealers such that a part of it would be based on secondary market participation. To further strengthen secondary market participation, bid and ask prices' duration in electronic trading were audited up to sixty times each trading day.

As Table 1 shows, there are two marked periods in our sample. Between April 1996 and July 1998 regulations were aimed mostly at securing participation in primary markets. From August 1998 regulations sought the formation of liquid secondary markets for Treasury bills with market makers rewarded, and audited, for this. Thus, we expect that in our first period, dealers bidding should be influenced by their past performance in primary markets as falling short of the required purchased exposed them to the risk of losing their status since they were challenged by potential competitors. During the second period, bidding behavior should not be influenced by past performance as the restriction on a maximum number of dealers was lifted and the requirements on purchases lowered. Instead we expect to find bidding to be more aggressive on existing securities whose market is reopened since by being more liquid they allow to meet the requirements on secondary market participation at a lower cost.

Liquidity requirements. It should be noted that due to the Central Bank's limited capacity to act as a lender of last resort under the currency board, banks faced high liquidity requirements in the period we consider.[8] One way for banks to meet these liquidity requirements was through open market repurchase operations with the Central Bank. Short-term treasury bills were useful in this respect. However, these securities were not eligible for a contingent repurchase contract that the Central Bank arranged with a consortium of private foreign banks in December 1996 to insure against systemic risk.[9] Thus, we infer that short-term treasury bills

[8]See for example Argentine Central Bank Communications "A" 2422 from March 1996 and "A" 2787 from October 1998, that increased requirements from 15% to 20% of deposits.

[9]The securities that were admissible are detailed in Central Bank Communication "A" 2516 from March 1997. For a study of the effect of the contingent repurchase agreement on bank liquidity demand, see Gonzalez-Eiras (2003).

Table 1: Summary of Market Making Regulations

Date	Regulation	Primary market	Secondary market
1996 March	Res 238/96	(i) Buy at least 4% of securities sold, by type of instrument (ii) Maximum number of dealers (iii) Fees depend on participation in primary and secondary markets	(i) Trade in secondary markets not quantified (ii) Performance measured by arithmetic average of participation in primary and secondary markets
1997 March	Res 155/97	(i) Buy at least 4% of securities sold, regardless of type of instrument	
July	Prov 9/97		(i) Performance measured by geometric average of participation in primary and secondary markets
July	Res 323/97	(i) Eliminates maximum number of dealers (ii) Buying obligation raised to 5%	
1998 July	Res 370/98	(i) Buying obligation reduced to 4%	(i) Must account for at least 1.5% of traded volume
August	Prov 11/98		(i) Transactions made through posting of bid and ask prices are given more weight in performance measure
1999 August	Res 429/99		(i) Splits payment of fees, such that a part is contingent on secondary trading (ii) Quality of bid and ask prices posted is audited

were not a prime source of liquidity in this period.

3 Static model and estimation

We start with a static model to estimate bidder valuations following Kastl (2011), who builds on the uniform-price share-auction framework of Wilson (1979), and introduces an upper bound on the number of bids that can be submitted.[10] We first describe a static auction model which makes a minimum of assumptions on the distribution of bidder valuations, and which matches the characteristics of Argentinian treasury bill auctions. In particular, we model the non-competitive bids using distributional assumptions that match the observed data. We then state a first-order condition which allows us to identify the bidders' marginal valuations, and outline a resampling strategy that estimates the different components of this equation.

3.1 Model

Auctions. Each auction is for Q arbitrarily divisible units and uses the uniform price format. There are n bidders, each of which submits a non-increasing bid schedule $y_i(p)$ which specifies the quantity demanded at price p.[11] We assume that the bid schedules are step functions with K_i steps, and denote by b_{ik} the k'th step of bidder i's bid function, with corresponding quantity q_{ik}. Denote the market-clearing price by p_*. Whenever there is rationing at the market clearing price, we assume that the pro-rata rule is used.

Bidders. Bidders are risk neutral with independent private values. There are two types of bidders: type-L bidders are large, and participate with probability 1. Type-S bidders are small, and they have identical probability $w \in (0, 1)$ of participating. Let N_k denote the number of bidders of group k, and let n_k denote the number of type-k bidders active in the auction. Finally, let $n = n_L + n_S$ be the total number of participating bidders. Thus, $n_L = N_L$, whereas

$$n_S \sim \mathrm{B}(w, N_S),$$

where $\mathrm{B}(\cdot)$ is the binomial distribution, and N_S is the set of all small bidders participating in a given year (and thus w is the probability of a given small bidder participating in an auction in the year). [12]

Valuations. For each auction, each bidder i receives a private signal θ_i drawn from a distribution F. Bidder i's marginal valuation of unit q is given by $v(q, \theta_i)$, with v strictly increasing in θ_i and weakly decreasing in q. Bidder i's gross utility from acquiring q units is thus

$$V_i(q, \theta_i) := \int_0^q \left(v(s, \theta_i) + \mathbf{1}_{i \in MM} f\right) ds,$$

where $\mathbf{1}_{i \in MM}$ is an indicator for whether bidder i is a market maker for this auction and f is the market maker fee from primary market participation. Let $\overline{v}(s, \theta_i) = v(s, \theta_i) + \mathbf{1}_{i \in MM} f$ denote the total value of acquiring q units. This is the quantity we will estimate.

[10] This can be shown to be rationalizable by adding a small cost of submitting each bid step.

[11] Although the bids in the auction we consider were rate-offers, we have converted these to prices in the analysis, and will therefore also consider prices in the model section.

[12] To avoid cumbersome notation we do not distinguish auction year.

Non-competitive bids. We assume that the bidders can also make non-competitive bids, but that these bids are independent of their private value.[13] Inspecting the data, we observe that there is a large number of non-competitive bids by large bidders[14] at 2% of the total first-round supply (this is the maximum amount allowed for non-competitive bids). Furthermore, among small bidders in the first year, there are several bids at 0.2% of total first-round supply. The total of the remaining non-competitive bids is approximately exponentially distributed across auctions. Therefore, we model the total amount of non-competitive bids in an auction as $q_{NC} = q_{NC1} + q_{NC2} + q_{NC3}$, where q_{NC1} represents the large-bidder bids at 2% of supply, q_{NC2} represents the small-bidder bids at 0.2% of supply, and q_{NC3} represents the remaining non-competitive bids. Thus,

$$\begin{aligned} q_{NC1} &\sim \mathrm{B}(w_1, N_L) \times 0.02Q; \\ q_{NC2} &\sim \mathrm{B}(w_2, N_S) \times 0.002Q; \\ q_{NC3} &\sim \exp(\lambda), \end{aligned}$$

where w_1, w_2 and λ are assumed to be constant throughout the auction year.

Strategies and equilibrium. The equilibrium concept is Bayesian Nash equilibrium in pure strategies, such that bidder i's strategy is a function from his private signal to a K_i-step bid function: $\sigma_i(p|\theta_i) := \sum_{k=1}^{K_i} q_{ik} \cdot \mathbf{I}_{p\in(b_{ik+1},b_{ik}]}$, where, $\mathbf{I}$ is the indicator function. An equilibrium then requires that for each i, and θ_i, $\sigma_i(\cdot|\theta_i)$ maximizes i's expected utility conditional on θ_i and $\sigma_{-i}(\cdot|\cdot)$.

3.2 Equilibrium and estimation

We first present an equilibrium condition which identifies the marginal bidder valuations in terms of quantities whose empirical counterparts can be observed, and then outline the resampling procedure used to estimate the valuations.

Marginal valuations. First, we define the following equilibrium quantities:

$$\begin{aligned} \pi^T_{ik} &:= \mathbf{Pr}(b_{ik} = p_*; \text{tie}); \\ m_{ik} &:= q_{ik} - q_{ik+1}; \\ R_{ik} &:= \frac{Q - \lim_{p\downarrow p_*} \sum_{(j,k):b_{jk}\leq p} m_{jk}}{\sum_{(j,k):b_{jk}\leq p_*} m_{jk} - \lim_{p\downarrow p_*} \sum_{(j,k):b_{jk}\leq p} m_{jk}} \end{aligned}$$

Here, π^T_{ik} is i's probability of being tied at the k'th step, m_{ik} is the marginal quantity demanded at step k, and R_{ik} is the expected rationing coefficient at step k.

[13] This could be true, for instance, if non-competitive bids were bids from customers for which the bank only acted as a middleman. See for instance Hortaçsu *et al.* (2018).

[14] Large bidders comprise market makers and a few other banks who behave like market makers. See Appendix B for our definition of large bidders.

Kastl (2011) shows that rational bidders maximizing the following objective function

$$\mathbf{E}\left[V_i(q,\theta_i) - p_* \sum_k q_{ik}\mathbf{I}_{\{b_{ik}\geq p_*\}}\right],$$

under the assumptions made in the model section, for all steps $k = 1, ..., K_i - 1$, the marginal valuation satisfies[15]

$$\overline{v}(q_{ik},\theta_i) = \frac{\mathbf{E}[p_*; b_{ik} > p_* > b_{ik+1}] + q_{ik}\frac{\partial \mathbf{E}[p_*; b_{ik}\geq p_* \geq b_{ik+1}]}{\partial q_k} + \pi_{ik}^T b_{ik} R_{ik} + \pi_{ik+1}^T [v(q_{ik+1},\theta_i) - b_{ik+1}]R_{ik+1}}{\mathbf{Pr}(b_{ik} > p_* > b_{ik+1}) + \pi_{ik}^T R_{ik}}.$$

This expression depends on quantities that can all be estimated empirically, using a procedure proposed by Hortaçsu and McAdams (2010) and Kastl (2011). The procedure uses the observed bids to resample residual supply curves, which then allows for the estimation of the distribution of clearing prices given bidder i's bid. Taking this to be i's expectation of the distribution of clearing prices, the right-hand side components of the marginal valuation can then be estimated. Finally, the valuations can be recovered using the above expression.

Resampling procedure. We assume that the auctions can be grouped together, such that the distribution of private signals is the same within an auction group. We set the size of each auction group to be 3. In Appendix A we detail the construction of these groups. Bidders were designated as large if either (i) they were dealers, or (ii) their total demand in that period was comparable to that of the market makers. See Appendix B for details. Since the non-competitive demand was largely driven by dealers, and since these were designated for a year at the time, starting in April, we take non-competitive demand to follow the same distribution within the period April-March.

Denote by $g \in G$ an auction group, and denote by $m \in M$ a market-maker year, i.e. a year starting in April and finishing in March. Let $\hat{y}_i^t$, $\hat{q}_{NC}^t$, $\hat{n}_k^t$ and $\hat{N}_k^t$ denote the empirical equivalents of y_i, q_{NC}, n_k and N_k, for auction t and use superscript g to refer to the sum over $t \in g$. The resampling procedure is then as follows for bidder i in auction t.

1. Fix bidder i and his bid function $\hat{y}_i^t(\cdot)$.

2. Record the number of large bidders who participate in auctions in group g, and let this be denoted $\tilde{n}_L^t$, and notice that $\tilde{n}_L^t = N_L^t$. Calculate the probability that a small bidder participates in an auction in auction group g as $\hat{w}^g = \hat{n}_S^g/\hat{N}_S^g$. Then draw $\tilde{n}_S^t$ according to $\hat{w}^g$ for all $t \in g$.

3. Within each market-maker year m, calculate the probability of 2% bids by large bidders and denote this $\hat{w}_1^m$, and calculate the probability of 0.2% bids by small bidders and denote this $\hat{w}_2^m$. Finally, fit an exponential distribution to the total of the remaining bids for each m, and denote the estimated

[15] At step K_i it is

$$\overline{v}(q_{iK_i},\theta_i) = \frac{\mathbf{E}[p_*; b_{iK_i} > p_*] + q_{iK_i}\frac{\partial \mathbf{E}[p_*; b_{iK_i}\geq p_*]}{\partial q_{K_i}} + \pi_{iK_i}^T b_{iK_i} R_{iK_i}}{\mathbf{Pr}(b_{iK_i} > p_*) + \pi_{iK_i}^T R_{iK_i}}.$$

parameter by $\hat{\lambda}^m$.[16] Then, draw $\{\hat{q}^t_{NC}\}_{t\in m}$ from the distribution

$$\mathrm{B}(\hat{w}_1^m, N_L^t) \times 0.02Q^t \oplus \mathrm{B}(\hat{w}_2^m, N_S^t) \times 0.002Q^t \oplus \exp(\hat{\lambda}^m) \oplus y^t_{iNC},$$

where y^t_{iNC} is bidder i's own non-competitive demand at t.

4. For all $t \in g$, draw $\tilde{n}^t_L - \mathbf{I}_{\{i \text{ is large}\}}$ bid functions from large bidders in g, and $\tilde{n}^t_S - \mathbf{I}_{\{i \text{ is small}\}}$ bid functions from small bidders in g ($\tilde{n}^t_L$ and $\tilde{n}^t_S$ are explained in step 2). Denote this set of bid functions by S_i^g.

5. Calculate the residual supply as

$$RS_i^t(p) = Q^t - \hat{q}^t_{NC} - \sum_{(i,s)\in S_i^g} \hat{y}_i^s(p)$$

6. Compute the market clearing price p^t_* and rationing coefficient given RS^t_i and $\hat{y}^t_i$.

7. Repeat steps (3) to (6) S times. This gives a distribution of market clearing prices which can be used to estimate the probabilities and expectations of the right hand side of the marginal valuation, as well as an expected rationing coefficient at each b_{ik}.

8. Finally, the derivative $\frac{\partial \mathbf{E}[p^t_*; b^t_{ik} \geq p^t_* \geq b^t_{ik+1}]}{\partial q^t_k}$ is calculated by perturbing the demand schedule at step k by δ units such that the new demand is $q^t_k - \delta$, whereas demand at all other steps is constant.[17] The derivative is then estimated as

$$\frac{\hat{\mathbf{E}}[p^t_*; b^t_{ik} \geq p^t_* \geq b^t_{ik+1}, q^t_k] - \hat{\mathbf{E}}[p^t_*; b^t_{ik} \geq p^t_* \geq b^t_{ik+1}, q^t_k - \delta]}{\delta},$$

where $\hat{\mathbf{E}}[\cdot]$ is the empirical expectation.

We use $S = 3000$ and calculate the average valuations of 5 bootstrap draws.

In Figure 2 we show the bid function and 10 randomly drawn residual supply curves for bidder 1 in auction 12. We have reversed the order of the y-axis in order to facilitate the interpretation. As can be seen, the residual supply curves cross the bid function in an interval of size around 50 basis points. Notice also that there are crossings at most of the steps of the bid function. Thus, just looking at these 10 residual supply curves, the probabilities and expectations used to calculate the marginal valuations are well-defined at most steps.

Figure 3 represents the average marginal valuation for 100 bootstrap draws for bidder 1 in auction 12, as well as the 10th and 90th percentile valuations. As can be seen, at most steps the marginal valuation is very tightly distributed around the mean. Notice also that the marginal valuation is below the bid for the first 6 steps, and above the bid for the last two steps. The intuition for this might be that the incentive to shade increases along a bidder's demand curve.

[16] Whenever an auction group g is split over two market-maker years m and m', we calculate the coefficients using the pooled bids in the following sense. If g has two auctions in m and one in m', we construct a new group of bids m'' which consists of the bids from m repeated twice and the bids from m'. The coefficients are then estimated using m''.

[17] For δ we used 1% of total supply. We experimented with different values, and results were similar.

Figure 2: Bid Function and Random Residual Supplies: Auction 12, Bidder 1

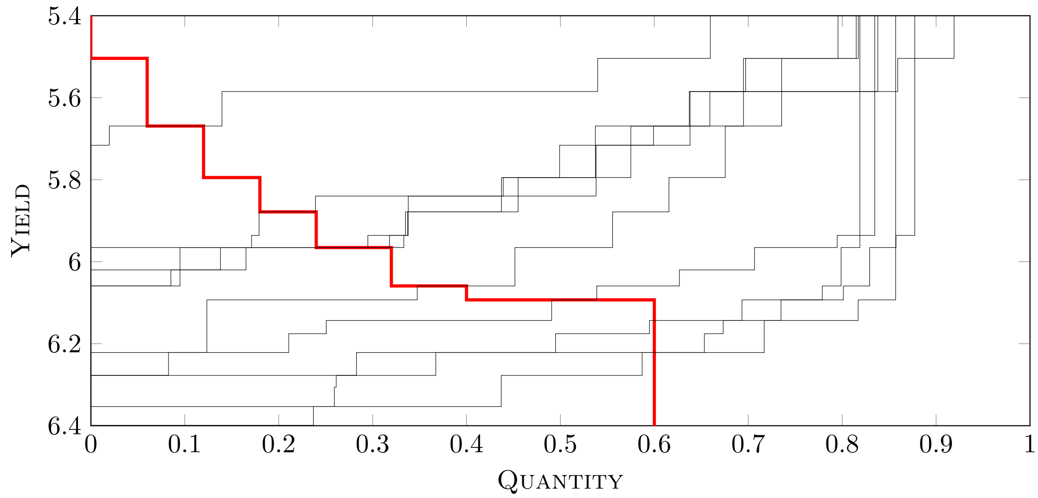
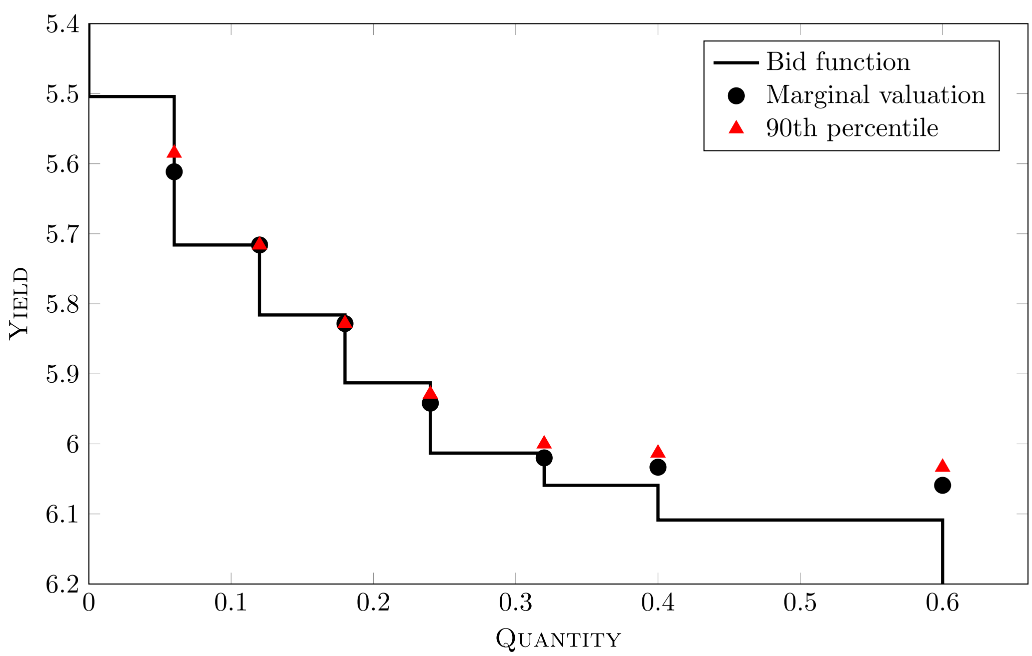


Figure 3: Bidder Valuations: Auction 12, Bidder 1



4 Valuations, shading and the balance sheet

4.1 Data

We use bid data from Argentinian Treasury bill auctions covering the period from May 1996 to October 2000.[18] All auctions in this period used the uniform price format. Under this format, all winning bids are rewarded at the clearing price. Each auction consists of two rounds. the first round is a competitive round although it is possible to submit non-competitive bids. The second round on the other hand is purely non-competitive, where dealers can choose to acquire additional securities at the clearing price of the first round.

For the analysis we focus exclusively on auctions of 3-months treasury bills. We excluded the auction of September 1998, which took place shortly after Russia defaulted on its sovereign debt, as it yielded a very high market clearing rate and presented irregular bidding behavior. This leaves us with 63 auctions comprising a total of 872 competitive bids. Securities were initially denominated either in pesos or dollars (in this period a currency board was in place with exchange rate at parity), while after the Russian crisis only dollar securities were sold. Initially auction size was 250 million USD, and after January 2000 this was expanded to 350 million. There was no supply uncertainty.

Table 2 summarizes the auction data. Looking at the full sample, we observe that between 14 and 15 bidders on average submit bids, and of these between 12 and 13 on average submit at least one winning bid. On average, each bidder submits between 4 and 5 bids (that is, their bid function has between 4 and 5 steps). There is significant use of the option of using non-competitive bids, with 72% of bidders resorting to this kind of bids. However, there are less than 2 bidders on average who make second-round bids, which suggests that this possibility does not play a large role in the bidders' strategy.[19] The bid-to-cover ratio is high, with bids on average covering more than 3.6 times the supply on offer. Finally, the average clearing rate in the auctions was around 7.25%.

The number of bidders per auction fell slightly from the early to the late period, whereas the number of winning bidders per auction increased slightly. The number of competitive bids per bidder and the number of bidders who submitted second-round bids fell slightly. A notable change between the two periods is that the number of bidders who submitted non-competitive bids increased by 2 bidders per auction in the late period. This suggests a relative decrease in the importance of private information as dealers buy bills to trade them in secondary markets relatively more often than they buy them with the intent to hold to maturity. The average bid-to-cover ratio fell slightly in the late period, whereas the average clearing rate rose slightly.

4.2 Valuations and shading

In this subsection we analyze how valuations and shading are correlated with different balance sheet items in order to better understand what might drive valuations and strategic behavior. First, we notice that a small change in valuations was observed between the early and the late period. As illustrated in Figure 4, there

[18] We are missing data on the first auctions that took place in April 1996, and we disregard auctions after October 2000, since in that month the Argentine vice-president resigned triggering a period of political and economic turmoil that would lead to the collapse of the government a year later, and shortly afterwards the default on sovereign debt and the abandonment of the currency board.

[19] Recall that only market makers can buy in the second round, and that the quantity they can buy depends on how much they have bought in previous auctions.

Table 2: Summary Statistics

	Full sample	May 96 - Jul 98	Aug 98 - Oct 00
# bidders	14.38	14.78	14.08
	(2.40)	(3.32)	(1.34)
# winning bidders	12.48	12.15	12.72
	(1.94)	(2.55)	(1.30)
# competitive bids/bidder	4.53	4.74	4.36
	(3.39)	(3.68)	(3.15)
# bidders with non-competitive bid	10.48	9.33	11.33
	(2.36)	(2.66)	(1.69)
# bidders with 2nd round bid	1.75	1.81	1.69
	(0.44)	(0.40)	(0.47)
Bid-to-cover 1st round	3.62	3.81	3.49
	(0.85)	(0.99)	(0.71)
Bid-to-cover both rounds	3.65	3.83	3.51
	(0.86)	(1.01)	(0.71)
Clearing rate	7.25	6.71	7.65
	(1.04)	(0.96)	(0.93)
Auctions	63	27	36

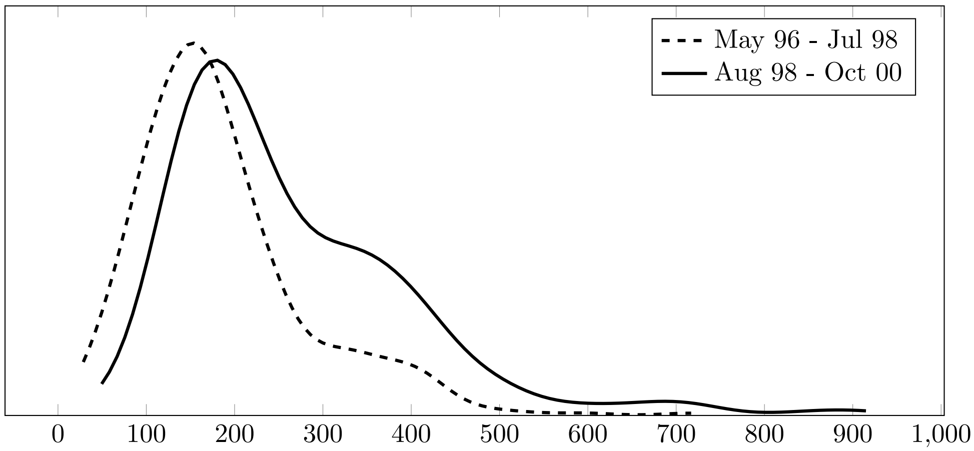
Note: The table report mean values (standard deviations in parenthesis below). The first column includes the full sample. The second column includes the period from May 1996 to July 1998. The third column includes the period from August 1998 to October 2000.

was a right-ward shift in the distribution of valuations (measured in yield relative to US bills), implying that valuations were lower (yields were higher) in the late period. This shift in valuations reflects the direct and indirect (through higher interest rates in the United States) deterioration of public finances in Argentina.

The dependent variables of the analysis are *Valuation* and *Shade*. These are calculated as follows. The valuation takes the estimated valuations measured in yield basis points at each bid step for bidder i in auction t, and calculates the quantity-weighted average valuation using the quantities that bidder i demand at each step. Since a higher yield implies a lower valuation, we invert the sign on the valuation variable, such that a positive (negative) coefficient estimate has the interpretation of a basis point reduction (increase) in yield, that is, an increase (decrease) in valuation. The shading variable is defined at each step as *valuation* less *bid*, both defined in terms of yield basis points, and the quantity-weighted average is calculated for each bidder i in auction t. Thus, the shading variable measures how much the bidder undercuts his valuation with his offer. Again, we invert the sign of the shading variable such that a positive (negative) coefficient estimate has the interpretation of a basis point reduction (increase) in yield, that is, an increase (decrease) in valuation.

The following balance sheet variables are used in the analysis. *Deposits* measures the lagged deposits (financial and non-financial) in pesos as well as dollars, normalized by the lagged total assets of the bank. The

Figure 4: Distribution of Bidder Valuations: Pre and Post Regulatory Change



variable *Liquid Assets* measures the lagged cash holdings (peso and dollar) of the bank as well as well as the lagged holdings of securities (peso and dollar).[20] Again, these are normalized by the lagged total assets of the bank. We also include the lagged total assets as a variable, and denote this by *Total Assets*.

The variable *MM* indicates if the bank is either a market maker or behaves like a market maker (see definition in Appendix B). *Existing Instrument* indicates whether the auction offers a previously used instrument which has been reopened. The *Below MM Target* variables are dummy variables indicating when the proportion of cumulative demand in the year to the required fraction of cumulative supply at the time of an auction is less than 1, i.e. when i has an incentive to buy more due to his market maker obligations. The *Slack MM Position* variables are dummy variables indicating when the proportion is greater than 1.8, i.e. a situation where i, by being far above the level of required purchases, is rather certain of not losing market maker status.[21] Since we expect that market maker behavior changed after regulations shifted their focus from primary to secondary markets, we estimate these variables before and after July 1998.

Table 3 presents the results of the analysis. All the models were estimated using OLS and standard errors indicated are robust. We use bank and month fixed effects in all the regressions to capture idiosyncratic bidder characteristics and common effects such as the macroeconomic environment. The first three columns present the results of the model with the bidder valuations as the dependent variable. The next three columns present the results of the model with bid shading as the dependent variable. Columns (1) and (4) are estimated for the period May 1996 to July 1998, when market maker incentives to participate in primary markets were strong (see discussion in Section 2). Column (2) and (5) are estimated for the period August 1998 to October 2000, when dealers' incentives to participate in primary markets were weak. Finally, columns (3) and (6) are estimated for the entire sample.

We now discuss the results of Table 3.

[20]Securities are both private and public, and have different degrees of liquidity. We proceed knowing that this is an imperfect proxy for liquid assets.

[21]The cutoff value 1.8 was chosen such that it roughly corresponds to bidders being certain of retaining their market maker status when above it (see section 5 for more details). We tried other cutoffs with similar results.

Table 3: Valuation and Shading

	(1) Valuation	(2) Valuation	(3) Valuation	(4) Shade	(5) Shade	(6) Shade
Deposits	-15.98	-66.70	-34.65*	10.90*	17.75	10.31*
	(-0.77)	(-1.14)	(-1.66)	(1.67)	(1.26)	(1.93)
Liquid Assets	24.84	-24.38	3.88	-3.47	-3.27	-4.06
	(0.83)	(-0.45)	(0.14)	(-0.56)	(-0.38)	(-0.92)
Total Assets	3.55	-10.78	1.26	0.35	-0.97	0.92
	(0.88)	(-1.00)	(0.59)	(0.17)	(-0.31)	(1.39)
MM	25.68	97.62*	60.24	6.63	32.07*	28.26**
	(1.23)	(1.78)	(1.56)	(0.32)	(1.81)	(2.00)
Below MM Target (May 96 - Jul 98)	7.97		4.94	-3.70*		-4.76*
	(0.85)		(0.50)	(-1.67)		(-1.87)
Slack MM Position (May 96 - Jul 98)	-5.49		-0.05	1.14		-1.22
	(-0.87)		(-0.01)	(0.93)		(-0.82)
Below MM Target (Aug 98 - Oct 00)		-2.07	-2.63		-1.48	-0.38
		(-0.15)	(-0.18)		(-0.58)	(-0.14)
Slack MM Position (Aug 98 - Oct 00)		-10.66	-12.42*		0.20	2.13
		(-1.33)	(-1.69)		(0.08)	(1.00)
Existing Instrument		29.20***	29.33***		-4.30*	-4.38*
		(5.36)	(5.36)		(-1.72)	(-1.76)
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N	387	485	872	387	485	872
Adj. R^2	0.86	0.73	0.82	0.27	0.37	0.35

Note: t-statistics in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Dealers' incentives. Our main interest is the effect of market maker incentives on valuations and shading. Notice that being a market maker by itself increases valuations, particular in the later period (the coefficient on *MM* is positive and significant in column (2)), and also increases shading (the coefficient on *MM* is positive and significant in columns (5) and (6)).

Consider first the effect on shading of being below the MM target. As can be seen, in the early period in which market maker incentives are expected to be binding, being below the MM target reduces shading (the coefficient on *Below MM Target (May 96 - Jul 98)* is negative and significant in columns (4) and (6)). The effect on valuation is not significant (the coefficient on *Below MM Target (May 96 - Jul 98)* is not significant in columns (1) and (3)). Thus, the MM target seems to influence the strategic behavior of bidders rather than affecting their actual valuations: a market maker who is below his target responds by reducing his bid shading. Furthermore, this effect is only present in the early period, and not in the later period where market maker incentives in the primary market are not binding (the coefficient on *Below MM Target (Aug 98 - Oct 00)* is not significant in columns (5) and (6)).

Conversely, we do not find an effect on valuations of being below the MM target (neither the coefficient on *Below MM Target (May 96 - Jul 98)* nor the coefficient on *Below MM Target (Aug 98 - Oct 00)* is significant for valuations anywhere). Nor do we find an effect on neither valuations nor shading of having a slack MM position in the early period (the coefficient on *Slack MM Position (May 96 - Jul 98)* is not significant anywhere), whereas we do find some indication that having a slack MM position reduces valuations in the later period (the coefficient on *Slack MM Position (Aug 98 - Oct 00)* is negative and significant in column (3), but not in column (2)).

Thus, the main take-away is that the results indicate that: (i) Dealers who were below their target did not increase their valuations but responded strategically by reducing their bid shading. (ii) This effect is present only in the early period (May 1996 to July 1998) when market maker incentives for primary market participation were present.

Existing assets. We now consider how the fact that the asset being auctioned is a preexisting instrument, whose primary market is being re-opened. However, since only one auction a month took place in the early period, the month fixed effects used for the regressions imply that we cannot estimate the effect of whether an asset already exists. Only in the later period do we have several auctions per month.[22]

When the asset is a previously used instrument, we observe that valuations are higher (the coefficient on *Existing Instrument* is positive and significant in columns (2) and (3)) whereas shading is reduced (the coefficient on *Existing Instrument* is negative and significant in columns (5) and (6)). Thus, although in principle an existing and a new asset offer the same payment profile, there is a clear indication that bidders treat them differently. We conjecture that the reason for this is that existing assets are already traded in the secondary markets, and therefore more liquid, reducing costs of later trading them. Therefore, bidders give these assets a higher valuation.

Other balance sheet variables. When interpreting the banks' balance sheet variables, one must take into account that the model includes bank fixed effects, and therefore the coefficients can be thought of as measuring the effect of a change in the variable rather than the effect of the level of the variable. There is some evidence that valuations are lower and shading higher when banks have more deposits (the coefficient on *Deposits* is negative and significant in column (3), and positive and significant in columns (4) and (6)). We believe the explanation for this is that an increase in deposits means that the bank needs to demand more liquid assets to meet their liquidity requirements. Since Argentinian treasury bills were not considered a primary source of liquidity (see section 2), it seems logical that in times of high liquidity needs, a bank diminishes its demand for Argentinian treasury bills, and therefore has a lower valuation and acts more strategically by shading its bids more.

Changes in the holdings of liquid assets do not seem to affect bidding (the coefficient on *Liquid Assets* is not significant anywhere) nor does the size of the bank, as measured by its assets (the coefficient on *Total Assets* is not significant anywhere).

4.3 Bidder Surplus and existing asset with year fixed effects

In this section we (i) consider bidder surplus, and (ii) run the regressions without month fixed effects to better estimate the effect of existing instruments, which in the model of the previous section could only be estimated from January 2000 onward, since before this date there was only one auction per month and therefore these variable was absorbed by the time fixed effect.

[22]In Section 4.3 we estimate the model for the early period with year fixed effects instead of month fixed effects.

Table 4: Surplus and Year Fixed Effects

	(1) Surplus	(2) % Surplus/Unit	(3) Valuation	(4) Shade
Deposits	-0.79	-0.80*	-105.88*	2.78
	(-0.14)	(-1.78)	(-1.83)	(0.55)
Liquid Assets	-20.54**	-0.57	-15.11	-2.62
	(-2.46)	(-1.20)	(-0.21)	(-0.46)
Total Assets	0.43	-0.01	-14.53	-2.21
	(0.41)	(-0.19)	(-1.34)	(-1.19)
MM	29.34*	0.60**	-1.06	-0.69
	(1.79)	(2.14)	(-0.03)	(-0.03)
Below MM Target (May 96 - Jul 98)	-2.84	-0.08	15.04	-3.55
	(-1.11)	(-1.03)	(1.01)	(-1.62)
Slack MM Position (May 96 - Jul 98)	-0.77	-0.50	-19.98	0.36
	(-0.30)	(-1.46)	(-1.20)	(0.32)
Below MM Target (Aug 98 - Oct 00)	0.01	0.06		
	(0.00)	(0.80)		
Slack MM Position (Aug 98 - Oct 00)	-3.50	-0.34		
	(-1.11)	(-1.30)		
Existing Instrument	1.45	-0.40	-48.16***	-0.71
	(0.46)	(-1.05)	(-2.89)	(-0.47)
Bank Fixed Effects	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	No	No
Year Fixed Effects	No	No	Yes	Yes
N	872	752	387	387
Adj. R^2	0.11	-0.017	0.038	0.19

Note: t-statistics in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

To analyze the effect of balance sheet variables on the bank's surplus, we introduce the variable *Surplus* which measures the maximum surplus of each bank in thousands of US dollars. This is calculated using the upper envelope of the estimated marginal valuations. Table 4 describes the results for valuation and shading. The variable *% Surplus/Unit* measures the percentage surplus obtained on each unit the bank buys. Columns (1) and (2) estimates bidder surplus. Apart from the dependent variable, everything is as in the analysis of Section 4.2. Columns (3) and (4) refer to the model without month fixed effects. This model is estimated with year fixed effects, and restricted to the period from May 1996 to July 1998, when dealers did not have binding commitments in the secondary market.

First, consider bidder surplus. The only variables that affect bidder surplus are deposits (for per unit surplus), liquid assets (for total surplus) and whether the bidder is a market maker (for both measures of surplus). The proportion of deposits and liquid assets are found to be negatively related to bidder surplus. We find that dealers have a higher surplus of almost 30,000 US dollars per auction and 60 basis points on each unit they buy. The driver of this may be that dealers have higher valuations (which also include market making fees) and they strategically shade their bids more, as seen in Table 3. Considering that fees were 0.075% per unit bought, and that our estimate for bidder surplus is an upper bound, market maker status accounted for at least 12.5% of their profits.

Table 5: Quantity Bought

	(1) Bought	(2) Bought	(3) Bought
Deposits	-0.02*	0.01	-0.01
	(-1.69)	(1.12)	(-1.07)
Liquid Assets	-0.01	-0.03**	-0.02***
	(-0.80)	(-2.31)	(-2.61)
Total Assets	0.01*	0.00	0.00**
	(1.93)	(0.85)	(2.09)
MM	0.01	0.02**	0.01**
	(1.53)	(2.32)	(2.49)
Below MM Target (May 96 - Jul 98)	0.00		0.00
	(0.37)		(0.42)
Slack MM Position (May 96 - Jul 98)	-0.00		0.00
	(-0.92)		(0.38)
Below MM Target (Aug 98 - Oct 00)		-0.00	0.00
		(-0.25)	(0.11)
Slack MM Position (Aug 98 - Oct 00)		-0.00	-0.00
		(-0.40)	(-0.84)
Existing Instrument		0.00	0.00
		(0.23)	(0.25)
Bank Fixed Effects	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes
N	398	507	905
Adj. R^2	0.22	0.28	0.23

Note: t-statistics in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Second, consider the model which omits month fixed effects, instead including year fixed effects and restricting the estimation to the early period. Focusing on the existing assets, we see that now the effect of an existing asset on the valuation is negative and significant, whereas the effect on shading is no longer significant. We believe the reason for this finding is that there are more reissues in the second part of this period, after the Asian crisis, than in the first. Thus, this is capturing time variation in average valuations. Notably, shade by construction is the difference between values and prices. Thus, the regression for shade is not affected by the time variation in valuations. The fact that existing assets are not significant in this regression thus reassures us in our interpretation of the regression with monthly fixed effects: dealers bid more aggressively for existing instruments when they are required to participate in secondary markets.

4.4 Quantities bought

In this subsection we analyze the relationship between quantities bought and the balance sheet variables. The dependent variable is *Bought*, which measures the proportion of the total supply bought by bidder i in auction t. We then regress this on the same variables as in the previous section. Table 5 presents the results of the analysis. All the models were estimated using OLS and standard errors indicated are robust.

Consider first the main variables from the analysis in the previous section. Notice that there is no effect of market maker incentives, neither of being below the MM target, nor having a slack MM position. There is still, however, a positive effect of being a market maker, in the sense that dealers buy more than other participants, even controlling for bank size. Whether the asset is an existing instrument that has been reopened is also insignificant in the analysis. Thus, quantities bought are *not informative* of strategic bidding incentives.

Looking at the other balance sheet variables, there is a weak negative effect from an increase in deposits that is seen only in the early period. An increase in liquid assets leads the bank to buy less, particularly in the late period. Finally, an increase in assets leads the bank to buy more, particularly in the first period.

5 A dynamic model

In this subsection we specify a dynamic model that takes into account intertemporal dealers' incentives and show how the interpretation of our results change when taking this into account.

Dynamic model. In a dynamic setting, participants consider not only the current effect of bidding on profits, but also their effect on future expected profits. When dealers compete for a fixed number of market making licenses, or there are high minimum purchase requirements, winning a larger share of an auction increases the likelihood of retaining dealer status. We introduce dynamic considerations by having a state variable, a_t, that captures cumulative demand, and making future dealer status a function of it.

Assumption 1. *We postulate that cumulative demand evolves as*

$$a_{t+1} = a_t(1-\rho) + q_t.$$

Once market maker status is lost it can never be regained. If this happens a bidder can only make static profits, which in expectations are given by V_i^0.[23]

Since dealers are evaluated on a yearly basis, $\rho = \frac{1}{12}$ before year 2000 (as short term bonds are auctioned monthly), and $\rho = \frac{1}{22}$ for year 2000. Note that when bidding in auction t, a_t is known. Denote by $\xi(a_{t+1})$ the probability of being a dealer in auction $t+1$. Given that dealers who fail to purchase a sufficient amount of auctioned securities lose their market maker status, we assume there exists a threshold $\bar{a}$ above which a dealer does not lose her condition, while for $a_t < \bar{a}$ market maker status is lost for sure.[24] Thus, $\xi(a_{t+1}) = 1_{a_{t+1} \geq \bar{a}}$.

Now a state is (Q, S_{-i}, a_{-i}) which we summarize by Z_i. All expectations that in Kastl (2011) are over S_{-i} now are over Z_{-i}.

Assumption 2. *We assume that the distribution of* S *is independent of the distribution of* a*, and bidder* i *observes her cumulative demand* a_i *but not that of other participants.*

With these assumptions we can characterize bidding through a Bellman equation, with value function $W^i(a_t, Z_i^t)$. Importantly, since signals Z_i^t are not observed and are assumed to be i.i.d., what we can estimate

[23]From our estimates we know the difference in expectations between V_i and V_i^0 is of at least 12.5% of profits.

[24]While performance also is measured for secondary market participation, the most important component in evaluating dealers is participation in primary markets.

is $\mathbf{E}_t[W^i]$. Hence:

$$\begin{aligned}\bar{W}^i(a_t) &= \mathbf{E}_t[W^i(a_t, Z_i^t)], \\ W^i(a_t, Z_i^t) &= \max_{q_i^t, b_i^t, a_{t+1}} \mathbf{E}_t\big[V_i^1(q, Z_i^t) - p_*^t \textstyle\sum_k q_{ik}^t 1_{\{b_{ik}^t \geq p_*^t\}} \\ &\quad +\beta\left(\xi(a_{t+1})\bar{W}^i(a_{t+1}) + (1-\xi(a_{t+1})\right)\frac{V_i^0}{1-\beta}\big], \\ \text{s.t.} &\quad a_{t+1} = a_t(1-\rho) + \mathbf{E}_t\left[\sum_k q_{ik}^t 1_{\{b_{ik}^t \geq p_*^t\}}\right].\end{aligned}$$

Let $v(q_{ik}^t, \theta_i^t)\Phi_{ik}^t - \Psi_{ik}^t = 0$ denote the static first-order condition (neglecting ties) with respect to q_{ik}^t of the static problem, where

$$\begin{aligned}\Phi_{ik}^t =& \mathbf{P}_t(b_{ik}^t > p_* > b_{ik+1}^t), \\ \Psi_{ik}^t =& \mathbf{E}_t[p_* | b_{ik}^t > p_* > b_{ik+1}^t] \cdot \mathbf{P}_t(b_{ik}^t > p_* > b_{ik+1}^t) \\ &+ q_{ik}^t \frac{\partial \mathbf{E}_t(p_*; b_{ik}^t \geq p_* \geq b_{ik+1}^t)}{\partial q_{ik}^t},\end{aligned}$$

do not depend on the valuation.

With dynamic considerations, new terms related to the discounted value function must be taken into consideration. We proceed to do this now by replicating the derivation of proposition 1 in Kastl (2011).[25] In table 3 we found that *Below MM Target* was significant and negative for shading in the period May 96 - July 98. The dynamic model tells us that this estimate is a lower bound for the reduction in shading due to fear of losing market making status.

6 Estimation

We do not have a standard stochastic dynamic programming problem. In these one chooses control sequence to maximize an objective, and the problem can be written recursively. For example,

$$V(x) = \max_c \pi(x, c) + \beta \mathbf{E}[V(x')],$$

where there is a law of motion that determines the distribution of x' given x and c. In our case we do not solve for policy function $c(x)$, but instead want to rationalize what valuations are behind bidders' behavior (i.e. we want to estimate the π given the observed c).

We begin by first noting that given our analysis in the previous section, the dynamic problem can be rewritten as

$$\bar{W}^i(a_t) = \max_{q_i^t, b_i^t} \mathbf{E}_t\left[V_i^1(q, Z_i^t) - p_*^t \textstyle\sum_k q_{ik}^t 1_{\{b_{ik}^t \geq p_*^t\}} + \beta \bar{W}^i(a_t(1-\rho) + \textstyle\sum_k q_{ik}^t 1_{\{b_{ik}^t \geq p_*^t\}})\right],$$

[25] See appendix D.

where additionally one has the constraint that $a_{t+1} = a_t(1-\rho) + \mathbf{E}_t\left[\sum_k q_{ik}^t 1_{\{b_{ik}^t \geq p_*^t\}}\right] \geq \bar{a}$. The first-order condition, neglecting ties, is given by

$$v(s,\theta_i^t)\Phi_{ik}^t - \Psi_{ik}^t + \Phi_{ik}^t \beta \frac{d\bar{W}(a_{t+1})}{da_{t+1}}|_{a_{t+1}=(1-\rho)a_t+q_k} = 0. \tag{1}$$

Denote by $\hat{a}_i^t$, $\hat{b}_{ik}^t$ and $\hat{q}_{ik}^t$ the amounts of a^t, b^t and q^t chosen in the data at time t by bidder i at step k. We will work with the *observed* distribution of a_{t+1} given a_t which is derived from the distribution of $\hat{q}_{ik}^t$. This we need to estimate the expectation in the value function above to apply value function iteration. Even though this will not be the distribution out of equilibrium for arbitrary policy functions, it will by construction be the equilibrium distribution if we correctly identify $\bar{W}$. Thus, we obtain the following recursive estimation equation:

$$\bar{W}_{(n)}^i(a_t) = \mathbf{E}_t\left[V_i^1(\hat{q}, Z_i^t) - p_*^t \sum_k \hat{q}_{ik}^t 1_{\{\hat{b}_{ik}^t \geq p_*^t\}} + \beta \bar{W}_{(n-1)}^i\left(a_t(1-\rho) + \sum_k \hat{q}_{ik}^t 1_{\{\hat{b}_{ik}^t \geq p_*^t\}}\right)\right], \tag{2}$$

where the bids are already, by assumption, optimal, and the expectation is over current Z_i (for first terms).

Assumption 3. *We assume that $\bar{W}_{(n)}^i(a_t)$ is a contraction and thus converges. Since all auctions with dynamic incentives take place monthly we calibrate $\beta = .95^{\frac{1}{12}} = 0.996$. When we calculate $V_{i,(k)}^1$ we only use dealers with $a_t > 2\bar{a}$.*[26]

We thus separate the problem in two.

1. The first-order condition in equation (1) gives the object of interest, valuations, as a function of the value function $\bar{W}$.
2. We estimate $\bar{W}$ by taking into account how current bids affect the distribution of a_{t+1}.

We proceed numerically with a candidate $\bar{W}$ and suggest the following iterative procedure. The problem can either be solved by discretizing the state space or by adopting a parametric approximation of the value function.

Assumption 4. *We use one of two strategies for estimation*

1. *Adopt a parametric approximation of the value function, such that $\hat{\bar{W}}(a)$ follows a logistic-type function:*

$$\hat{\bar{W}}(a) = \alpha + (\mathbf{E}[V_i^1] - \alpha)\frac{(a-\gamma)^\epsilon}{\xi + (a-\gamma)^\epsilon}. \tag{3}$$

2. *Adopt a non-parametric approach discretizing the state space, and use a simple initial guess such that $\hat{\bar{W}}(a)$ is linear increasing between $\bar{a}$ and $2\bar{a}$ (or $1.5\bar{a}$) and flat after upper bound such that $\bar{W}_{(0)}(\bar{a}) = \mathbf{E}[V_{i,(0)}^0]$ and $\bar{W}_{(0)}(2\bar{a}) = \mathbf{E}[V_{i,(0)}^1]$.*

Here, $0 < \epsilon < 1$ determines the curvature of the approximate value function, $0 \leq \gamma$ according to the theory should be zero, but since we probably cannot have an infinite derivative at $\bar{a}$ (particularly since some

[26]Or another multiple of $\bar{a}$, perhaps $1.5\bar{a}$, this depends on what threshold we use, see discussion below. We use this threshold to capture dealers that are 'far' from losing their status.

observations of our state variable will be below $\bar{a}$, and thus we account for the fact that our model is an approximation of actual bidding architecture), we introduce this parameter. Parameter $\xi > 0$ determines limit behavior for high a and parameter $\alpha > 0$ determines limit behavior for $\bar{a}$. Our initial guess will be $\alpha_{(0)} = \mathbf{E}[V^0_{i,(0)}]$.

Assumption 5. *We either condition $\hat{\bar{W}}$ on Z_i or take the expectation over Z_i. While the former would be preferred (such that we estimate a value function for each bidder), the latter might be more realistic due to data limitations, and perhaps consistent with model in assuming group of bidders are ex ante homogeneous.*

Importantly, if we take $\bar{a}$ to be the actual regulatory fraction of cumulative demand that must be bought by the end of the year we will have a large fraction of bidders/auctions below $\bar{a}$. Thus, we set $\bar{a}$ as, say, 75% of this regulatory level. And those bidders that still are below $\bar{a}$ we estimate their bidding as if $a_t = \bar{a}$.

1. Iteration 0. Set starting values.
   (a) Calculate V^0_i by using the static formula to estimate $v(\hat{q}, s)$ and Φ for all non-dealers regardless of a_t, then take the mean of this.[27] This value is not iterated as it does not depend on dynamic concerns.
   (b) Calculate $V^1_{i,(0)}$ by using the static formula to estimate $v(\hat{q}, s_i)$ and Φ_i for all dealers.[28]
   (c) Fit $\hat{\bar{W}}_{(0)}(a)$ using V^0_i and $V^1_{i,(0)}$, and using one of the specifications in Assumption 4.
2. Iteration $n \geq 1$.
   (a) Retrieve $v_{(n)}$ by solving (1) using $\hat{\bar{W}}_{(n-1)}$ to calculate $\frac{d\bar{W}(a_{t+1})}{da_{t+1}}|_{a_{t+1}=(1-\rho)a_t+q_k}$.
   (b) Calculate $V^1_{i,(n)}$ from $v_{(n)}$. Estimate $E[V^1_{i,(n)}]$ (this should not change much since these are valuations for bidders for which dynamic considerations are not important), and update this in parameterized value function if using this approach.
   (c) Obtain $\bar{W}_{(n)}$ (or $\bar{W}^i_{(n)}$) by evaluating $\bar{W}$ in (2) using $v_{(n)}$ and the sample distribution of a_{t+1} given a_t (which is not updated), and using one of the parametrics specifications in Assumption 4. We call this evaluation $\tilde{W}_{(n)}$.

   Note that if we use discretization approach then we have to smooth the estimate of $\tilde{W}_{(n)}$ to be able to take derivatives in the next iteration. The smooth estimate is our $\bar{W}_{(n)}$.

   If we use the parametric approximation of the value function, then we need to update the parameters $(\alpha, \epsilon, \gamma, \xi)$, by fitting the observed values of $\tilde{W}_{(n)}$ to the assumed parametric equation (3). This can be done by unweighted nonlinear least squares (choosing the parameters that minimize the sum of squared differences between $\tilde{W}_{(n)}$ and $\hat{\bar{W}}$ when evaluated at our observed a's). The $\hat{\bar{W}}$ for the optimal parameters is our $\bar{W}_{(n)}$.

[27] a_t should not matter as they are not MM. Use data from before July 1998. Perhaps we should exclude those banks that exert effort to become dealer the following year.

[28] We should exclude Banco de Galicia, which we treat differently in estimation due to its significantly larger share, i.e. we have to see if larger market share implied higher profits *beyond* having a higher a. As Banco de Galicia is always well above the regulatory requirement is should not be concerned by cumulative demand.

Iterate until convergence. Note that to speed up convergence we might do steps a, b, and c several times without updating $v_{(n)}$. Then update $v_{(n)}$ and repeat. Once converged, then estimate v from (1) and report the difference with static estimation for several values of a. Finally, redo the estimation for the period in which dynamic considerations are lower (after July 1998). We expect to find smaller deviations relative to static estimation.

TO BE DONE

7 Conclusion

Using recently developed structural estimation techniques on a unique data set on Argentinian Treasury bill auctions, we analyze the effect of balance-sheet variables on bidding behavior. Exploiting variation in the regulation of market making activities we show that when banks fear losing their market maker status, they bid more aggressively. They also bid more aggressively for existing securities that are reissued when the regulation tightens the requirements to participate in secondary markets.

We develop a dynamic model to take into account that the threat of losing dealer status introduces intertemporal considerations in bidding behavior. We find that a dealer's value function is an increasing an concave function of its cumulative demand. The curvature of the value function measures how much more aggressively they bid when their cumulative demand is below primary market regulatory requirements. It also allows us to estimate how much dealers value their status. We believe our findings generalize to institutional environments with dealer turnover, and should be taken into account in the design of Treasury auctions.

Appendix

A Auction groups

The auction groups were constructed as follows. All groups were of size 3, and were chosen to be consecutive auctions, *except* in instances where the 3 consecutive auctions in question were clearly different, either because they were not denominated in the same currency or if the clearing rate was abnormally different. To evaluate whether auctions of the same currency were similar, the clearing rate as well as the interbank rates and fixed term interest rates for Pesos and Dollars were used. Decisions on how to group the auctions were then made by inspecting these variables. The groups which did not consist of consecutive auctions of the same currency were the following.

- Group 3 consisted of September and December 1996, and February 1998 (dollar securities, clearing rates of 6.10%, 6.38% and 6.50%, respectively).
- Group 10 consisted of October and November of 1998, and July of 1999 (clearing rates of 10.00%, 9.38% and 8.95%, respectively).
- Group 13 consisted of May, June and August of 1999 (clearing rates of 5.73%, 6.65% and 8.20%, respectively).
- Group 22 consisted of September and October of 1997, and of March of 1998 (clearing rates of 5.70%, 6.95% and 6.60%, respectively).
- Group 23 consisted of May and both October auctions of 2000 (clearing rates of 8.68%, 7.65% and 9.25%, respectively).

In order to construct these groups, auctions were occasionally used in more than one group for resampling purposes, but these duplicate auctions were subsequently deleted when analyzing the data. We conducted robustness checks with groups chosen of consecutive auctions.

B Bidder groups

We allocated bidders into two groups. First, we consider large bidders which are dealers and banks competing for a market maker slot (there are three of these that succeed). Second, there are small bidders. Size is determined yearly based on the share of the total securities sold that banks buy. It is important to note that some banks start being small bidders and become large ones later on. Initially the twelve dealers were: Banco de Galicia, J. P. Morgan, Banco de Santander, Chase Manhattan Bank, Deutsche Bank, Banco Río, Banco Francés, Banco de Crédito Argentino, HSBC, Bank of America, Citibank, and Bank Boston.

C Robustness check: Truncated regression

As a robustness check on the OLS regressions presented in the paper, we also estimated the model using truncated regression to take into account limited dependent variable. We use the same definition of *Valuation* and *Shade* as above. The upper and lower bounds were chosen by inspecting the data. For the valuation model, the lower bound for the truncation was chosen to be -1,400 and the upper bound (recall that the valuation variable has inverted sign in order to facilitate the interpretation). For the shading model, the lower bound for the truncation was chosen to be -200 and the upper bound 50. Apart from the truncation, the models are estimated as in Table 3 and the standard errors are robust.

Table 6: Valuation and Shading – Truncated Regression

	(1) Valuation	(2) Valuation	(3) Valuation	(4) Shade	(5) Shade	(6) Shade
Deposits	-15.98	-66.70	-34.65*	10.90*	17.96	10.33**
	(-0.84)	(-1.20)	(-1.76)	(1.83)	(1.33)	(2.04)
Liquid Assets	24.84	-24.38	3.88	-3.47	-3.25	-4.09
	(0.91)	(-0.47)	(0.15)	(-0.62)	(-0.40)	(-0.97)
Total Assets	3.55	-10.78	1.26	0.35	-1.00	0.92
	(0.96)	(-1.06)	(0.63)	(0.19)	(-0.33)	(1.47)
MM	25.68	97.62*	60.24*	6.63	32.13*	28.28**
	(1.35)	(1.88)	(1.65)	(0.34)	(1.92)	(2.12)
Below MM Target (May 96 - Jul 98)	7.97		4.94	-3.70*		-4.78**
	(0.93)		(0.53)	(-1.83)		(-1.98)
Slack MM Position (May 96 - Jul 98)	-5.49		-0.05	1.14		-1.23
	(-0.95)		(-0.01)	(1.02)		(-0.87)
Below MM Target (Aug 98 - Oct 00)		-2.07	-2.63		-1.52	-0.39
		(-0.16)	(-0.19)		(-0.63)	(-0.16)
Slack MM Position (Aug 98 - Oct 00)		-10.66	-12.42*		0.21	2.12
		(-1.40)	(-1.79)		(0.08)	(1.05)
Existing Instrument		29.20***	29.33***		-4.36*	-4.39*
		(5.67)	(5.68)		(-1.81)	(-1.86)
Bank Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
N	387	485	872	387	485	872

Note: t-statistics in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 6 presents the results. Comparing with the results of Table 3 we see that there is no change in the coefficients that are significant except *MM* which loses a few decimal points in the t-value (sufficient to make it insignificant), merely a few changes in the level of significance exhibited. Furthermore, the coefficient sizes are similar. In total, this indicates that the results of the main section are robust with respect to whether the regression is truncated or not.

D Proof of Proposition 1 in Kastl (2011) for dynamic model

Define $\theta_{jk}(q_k)$ as in appendix A in Kastl (2011). Now sets are a partition of Z_{-i}. Equation A1 holds, since now distributions are over pairs of s, a but intuition is the same. Same for idea that a local perturbation of q_k has no effect on states θ_{4k} and θ_{5k}. Definition of $\omega_{jk}(q')$ is unaffected, as is that of $Pr(\theta_{jk}(q'))$ for $j = 1, 2, 3$.

Lemma A1 seems to hold as the reasoning of a positive gain and an infinitesimal loss do not seem to depend on the nature or distribution of states (it depends on prices and quantities). Same goes for limit at end of lemma A1 (note how important it is that things are defined in terms of prices and quantities and these absorb the underlying states). Importantly, later we make an assumption that imposes more structure than lemma A1. We need to check this and subsequent lemmas. Lemmas A2, A3, A4 hold for same reasons.

Now we have three terms in $\mathrm{E}_{Z_{-i}}[\cdot]$, the first two as in Kastl (2011), plus the discounted value function, which depends on a_{t+1}. For the new term related to discounted value function, we now must note that what matters when we perturb q_k is the effect on a_{t+1}. Note that for θ_{1k} we have $\frac{da_{t+1}}{dq_k} = 1$ while for θ_{2k} and θ_{3k} we have rationing, as in original paper.

We proceed under the assumption that if $a_t > \bar{a}$ then $a_{t+1} \geq \bar{a}$ a.s. (we validate this assumption after the derivation of the envelope condition). The reason for caring about values for a_{t+1} is that the FOC in principle holds terms $\frac{d1_{a_{t+1}\geq\bar{a}}}{da_{t+1}}$ which are zero everywhere but diverge for $a_{t+1} = \bar{a}$. Thus, if a_{t+1} crosses $\bar{a}$ from below there is a jump in the objective due to the indicator function. And note that it is not sufficent to make an assumption like lemma A1 to rule out terms that have $\frac{d1_{a_{t+1}\geq\bar{a}}}{da_{t+1}}$ as it is not a priori certain that the likelihood of having such a crossing is infinitesimal.

We would start with something like (omitting the β)

$$\lim_{q'\to q_k} \quad \frac{\sum_{j=1}^{3}\left[\mathrm{E}_{Z_{-i}}[1_{(1-\rho)a_t+Q^c(Z_{-i}|q')\geq\bar{a}}\bar{W}((1-\rho)a_t+Q^c(Z_{-i}|q'));\theta_{jk}(q')]\right.}{q'-q_k}$$
$$-\frac{\left.\mathrm{E}_{Z_{-i}}[1_{(1-\rho)a_t+Q^c(Z_{-i}|q_k)\geq\bar{a}}\bar{W}((1-\rho)a_t+Q^c(Z_{-i}|q_k));\theta_{jk}(q_k)]\right]}{q'-q_k}$$

where we have replaced a_{t+1} and have left some arguments of expectations out for notation simplicity.

Taking care of the terms in the derivative gives:

$$\begin{aligned}
&Pr(\theta_{1k}(q_k))Pr(1_{(1-\rho)a_t+q_k\geq\bar{a}})\frac{d\bar{W}(a_{t+1})}{da_{t+1}}|_{a_{t+1}=(1-\rho)a_t+q_k}\\
&+Pr(\theta_{2k})\mathrm{E}_{Z_{-i}}[1_{(1-\rho)a_t+Q^{RAT}(Z_{-i},q_k-q_{k-1})\geq\bar{a}}\frac{d\bar{W}(a_{t+1})}{da_{t+1}}|_{a_{t+1}=(1-\rho)a_t+Q^{RAT}}\frac{dQ^{RAT}(Z_{-i},q_k-q_{k-1})}{dq_k}|\theta_{2k}]\\
&+Pr(\theta_{3k})\mathrm{E}_{Z_{-i}}[1_{(1-\rho)a_t+Q^{RAT}(Z_{-i},q_{k+1}-q_k)\geq\bar{a}}\frac{d\bar{W}(a_{t+1})}{da_{t+1}}|_{a_{t+1}=(1-\rho)a_t+Q^{RAT}}\frac{dQ^{RAT}(Z_{-i},q_{k+1}-q_k)}{dq_k}|\theta_{3k}]
\end{aligned}$$

Note that this is all we need to do the estimation.

We can also derive the envelope condition (again under the assumption that if $a_t > \bar{a}$, then a.s. $a_{t+1} \geq \bar{a}$ such that we can neglect term $\frac{d1_{a_{t+1}\geq\bar{a}}}{da_{t+1}}$), which should be simpler as changes in a_t have no effect on partition θ.

$$\frac{d\bar{W}(a_t)}{da_t} = E\left[\frac{dW^i(a_t,Z_i^t)}{da_t}\right] = \beta(1-\rho)\mathrm{E}_{Z_{-i}}[1_{(1-\rho)a_t+Q^C(Z_{-i})\geq\bar{a}}\frac{d\bar{W}(a_{t+1})}{da_{t+1}}|_{a_{t+1}=(1-\rho)a_t+Q^C(Z_{-i})}],$$

where in the last step we assume that the marginal effect of a_t on W^i is independent of Z_i^t (i.e. that the signal only affects current valuations). Note that the value function is independent of a when $a < \bar{a}$ and equal to $\frac{V^0}{1-\beta}$. This tells us that those bidders that lose market maker status behave as in a static setting (also note that if a.s. $a_{t+1} \geq \bar{a}$, then we can discard a.s. $a_{t+1} \geq \bar{a}$ in envelope). The envelope condition can be written, for $a_t > \bar{a}$, as

$$\frac{d\bar{W}(a_t)}{da_t} = \beta(1-\rho)\mathrm{E}_{Z_{-i}}[\frac{d\bar{W}(a_{t+1})}{da_{t+1}}|_{a_{t+1}=(1-\rho)a_t+Q^C(Z_{-i})}].$$

So, $\frac{d\bar{W}(a_t)}{da_t}$ is a submartingale.

Note that there is an upper bound for $\bar{W}$ as $a \to \infty$. In this limit a market maker is certain of never losing her status. Thus, it must be the case that

$$\lim_{a_t \to \infty} \bar{W}^i(a_t) = \frac{V_i^1}{1-\beta} \equiv \bar{W}_i^1,$$

where V_i^1 is the expected per period profit in a static setting from being a market maker (remember that market makers profit both from fees from primary auctions and, presumably, fees from clients).[29]

If we conjecture that $\bar{W}$ is constant at this level for all a then derivatives are always zero (except at $\bar{a}$) and the envelope condition is trivially satisfied. For this case the new terms derived above are all zero so the problem's solution coincides with the static one in Kastl (2011). This hints that $\bar{W}$ should not be constant. Then it must be the case that either $\bar{W}$ is increasing and concave or decreasing and convex. But economic intuition rules out the latter case. Finally, for the envelope condition to hold everywhere it must be the case that

$$\lim_{a_t \to \bar{a}} \frac{d\bar{W}(a_t)}{da_t} = \infty. \tag{4}$$

We interpret the envelope condition as telling us that the optimal behavior for a bidder that is close to $\bar{a}$ is to place a first bid of magnitude $\bar{a} - (1-\rho)a_t$ at a very high price such that with probability almost surely $a_{t+1} \geq \bar{a}$. Note that for (4) to hold when $a_t = \bar{a}$ this implies that $a_{t+1} = \bar{a}$ with positive probability.

With this insight we can simplify the new terms in the FOC as now $1_{(1-\rho)a_t+q_k \geq \bar{a}} = 1$ a.s. (note how this validates our assumption that $\frac{d1_{a_{t+1}\geq \bar{a}}}{da_{t+1}}$ could be neglected). We have:

$$\begin{aligned} &Pr(\theta_{1k}(q_k))\frac{d\bar{W}(a_{t+1})}{da_{t+1}}|_{a_{t+1}=(1-\rho)a_t+q_k} \\ &+Pr(\theta_{2k})\mathrm{E}_{Z_{-i}}[\frac{d\bar{W}(a_{t+1})}{da_{t+1}}|_{a_{t+1}=(1-\rho)a_t+Q^{RAT}}\frac{dQ^{RAT}(Z_{-i}, q_k - q_{k-1})}{dq_k}|\theta_{2k}] \\ &+Pr(\theta_{3k})\mathrm{E}_{Z_{-i}}[\frac{d\bar{W}(a_{t+1})}{da_{t+1}}|_{a_{t+1}=(1-\rho)a_t+Q^{RAT}}\frac{dQ^{RAT}(Z_{-i}, q_{k+1} - q_k)}{dq_k}|\theta_{3k}] \end{aligned}$$

Thus, the FOC neglecting ties is given by

$$\overline{v}(s, \theta_i^t)\Phi_{ik}^t - \Psi_{ik}^t + \Phi_{ik}^t\beta\frac{d\bar{W}(a_{t+1})}{da_{t+1}}|_{a_{t+1}=(1-\rho)a_t+q_k} = 0. \tag{5}$$

[29] Recall that regulations on primary market participation cease to be binding in July 1998. Thus, after this date we can think of dealers bidding as in a static setting as their status is unaffected by cumulative demand.

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