# Hedging Winner's Curse with Multiple Bids: Evidence from the Portuguese Treasury Bill Auction

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**Abstract**

Auctions of government securities typically permit bidders to enter multiple price-quantity bids. Despite the widespread adoption of this institutional feature and its use by bidders, the motivations behind its use and its effects on auction outcomes are not well understood theoretically and have been little explored empirically. Using bidding data from treasury bill auctions in Portugal, this paper examines how bidders use multiple bids to hedge against winner's curse. The data show that, *ceteris paribus*, a bidder submits a greater number of bids and disperses prices on these bids more widely when there is a greater potential for winner's curse. In particular, both these measures of bid-spreading increase with the volatility of market interest rates and the expected number of participating well-informed bidders.

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## Non-technical Summary

In Portugal, as in the United States and other countries, bidders at auctions of treasury securities are permitted to submit multiple bids. That is, a bidder is permitted to enter one *or more* bids, each of which specifies an interest rate and a quantity. The auctioneer allocates the bids, starting with the bid with the lowest rate, until the issue has been fully exhausted. A bidder might, for example, submit bids for bills with a face value of one million escudos at 7.5%, two million escudos at 8.0%, and another one million escudos at 8.5%. If the available bills are sold out at 8.25%, then the bidder wins the first two bids and loses the third. Furthermore, the bidder pays different prices for the two winning bids, in accordance with their different rates.

This paper is an empirical investigation of how bidders use the right to submit multiple bids. I examine whether bidders use multiple bids to limit exposure to winner's curse. Winner's curse arises when, after having won, a bidder realizes that the other bidders valued the bills less than she did, i.e., that she paid too much. The potential for winner's curse increases with the volatility of market rates, which makes the value of the bills more uncertain. It also increases with the number of competing bidders, especially well-informed bidders, because winning becomes worse "news" for a bidder's estimate of the value of a good when she has outbid a larger group of competitors.

Consistent with this conjecture, I find that bidders use multiple bids more intensively as the volatility of market rates and the expected number of competing well-informed bidders increase. This finding holds for both the number of bids submitted by a bidder and the price dispersion among the bidder's bids. Also consistent with this conjecture, treasury borrowing costs fall when a larger number of bids per bidder is submitted. This suggests that bidders are willing to pay for insurance against a negative outcome, and that insurance can take the form of multiple bids.

In the simple sealed-bid auction model most studied, bidders compete to purchase a single indivisible item. Each bidder submits a single bid, and the item is awarded to the highest bidder. Auctions of government treasury securities are necessarily more complex than the single item case because it is generally infeasible, and often deemed undesirable, to sell an entire issue to a single bidder. A bid in a treasury security auction specifies not only an interest rate at which the bidder is willing to buy, but also the quantity the bidder is willing to acquire at that rate. The government collects these rate–quantity bids from participating bidders, sorts them from lowest rate to highest, and then allocates securities to bids in this order until the issue is fully sold.

An apparently ubiquitous feature of treasury auctions, observed in both OECD and developing countries, is that bidders are *not* restricted to a single rate–quantity bid each.[1] A bidder may, for example, submit bids for bills with a face value of $1 million at 7%, $2 million at 7 1/8% and another $1 million at 7 1/2%. If the available bills are sold out at 7 3/8%, then the bidder wins the first two bids and loses the third. Bidders do make use of the right to enter multiple bids: in the auctions studied in this paper, the median number of bids per bidder is three. Despite the widespread adoption of this institutional feature and its use by bidders, the motivations behind its use and its effects on auction outcomes are not well understood theoretically and have been little explored empirically.

This paper investigates two intuitively plausible and theoretically supported motivations for submitting multiple bids. First, multiple bids offer a way to express a downward sloping demand for the securities, which could be due to risk aversion or to high transaction costs in the secondary market. As bidders in treasury auctions tend to be large firms, it has generally been argued that they are risk neutral (see, e.g., Branco 1992). However, the manager who chooses the firm's bids may face a concave payoff function, due either to his own risk aversion or to the design of the firm's managerial incentive scheme, and thus the firm might behave as if risk averse. Second, and more interesting from a theoretical viewpoint, multiple bids may offer a natural way to hedge winner's curse. If a bidder spreads her bids over a range of interest rates, then when demand is weaker than

[1] Department of the Treasury, Securities and Exchange Commission and the Board of Governors of the Federal Reserve System (1992, Appendix B), henceforth cited as *Joint Report*, explicitly mentions that Australia, Belgium, Italy and the United States permit bidders to submit multiple bids; no country is reported to prohibit multiple bids. Umlauf (1993) reports that the Mexican treasury securities auction permits multiple bids. I have confirmed the same for Portugal and Brazil.

she expects (i.e., when she overvalues the securities relative to her peers), she will win at a higher average rate than she expected; when demand is stronger than she expects, she will win at a lower average rate than expected.

These conjectured motivations for multiple bids have testable implications. The main hypotheses tested in this paper are:

(H1) Bidders' use of multiple bids, whether measured by the number of bids per bidder or by the price dispersion within a bidder's set of bids, increases with the degree of uncertainty in the market.

(H2) Bidders' use of multiple bids, measured as in H1, increases with the expected number of competing bidders and especially with the expected number of well-informed competing bidders.

H1 is implied by both the risk aversion and winner's curse conjectures. The greater the degree of uncertainty over the value of the securities, the riskier it is to buy them and the greater the potential for winner's curse. If the conjectured motivations are important, then the use of multiple bids should increase correspondingly. H2 is implied only by the winner's curse conjecture. The potential for winner's curse increases with the number of competing bidders, and thus so should the need to hedge. I test the hypotheses using bidding data from a sample of treasury bill auctions in Portugal, and find that both are strongly supported. Thus, there is specific evidence (i.e., from H2) for the winner's curse conjecture, but the additional contribution of risk aversion and transaction costs cannot be ruled out.

The following section discusses theoretical results pertaining to the use of multiple bids and reviews previous empirical evidence. Winner's curse is defined and empirical and experimental evidence of bidders' awareness of it is surveyed. Details of Portugal's treasury bill auction rules are given in Section 2, and the data are introduced in Section 3. Section 4 investigates the effect of multiple bidding on auction outcomes. Consistent with prediction, I find that, *ceteris paribus*, dispersion in winning bid rates increases with the number of bids per bidder. I also find that treasury borrowing costs decrease with the number of bids per bidder, which suggests that the hedging implicit in multiple bidding is not costless to bidders. Thus, the use of multiple bids is not immaterial from the seller's perspective. Finally, regression analyses of how bidders make use of multiple bids are presented in Section 5. Both the number of bids submitted by each bidder and the dispersion of each bidder's bids are analyzed as dependent variables. Implications are discussed in the conclusion.

# 1 Theoretical motivation and empirical literature

Auctions of government treasury securities (hereafter referred to as "treasury auctions") are often cited as examples of common-value auctions. In a common-value auction, bidders know they will place the same value on the good ex-post (say, because it can be resold on a secondary market), but ex-ante do not know what that value will be. For bidders (and theorists), common-value auctions are complex because the private information of competing bidders is relevant to the bidder not only for strategic purposes, but also for her own estimation of the value of the good.[2] It is the existence of private information on common valuation that gives rise to the winner's curse problem. If each bidder obtains an unbiased estimate of the value of the good, then the winners are the ones who happen to draw the most optimistic signals. That is, *conditional on winning*, the estimate is upward biased, so a winning bidder will on average be disappointed when the true value is revealed. The greater the number of competing bidders, the more upwardly biased is the winning signal, so the greater the potential for winner's curse.

This does not imply that bidders will make negative expected profit. As in any adverse selection model, bidders in equilibrium will adjust ex-ante for winner's curse in their strategies. In a single-unit auction, bidders do this by "shading downward" by an extra margin from their estimates, where the size of this margin increases with the number of bidders.[3] In a divisible-good, multiple-bid auction, I conjecture that bidders have an additional strategic dimension. Instead of simply making level shifts up or down in her demand schedule, a bidder can also change the slope of the schedule.[4] If the hedging metaphor is correct, I predict the bidder will steepen her inverse demand

[2]Under independent-private-values, by contrast, knowledge of others' valuations is useful for strategic purposes but has no effect on the bidder's own valuation. This greatly simplifies the bidder's decision problem. See McAfee and McMillan (1987a) and Milgrom (1989) for general introductions to auction theory.

[3]Technically, risk neutral bidders form bids as a function of the expected value of the good conditional on the private signal *and* on winning. As the number of competing bidders increases, the gap between the "winning adjusted" expectation and unadjusted expectation gets larger, so the bid is shaded down by a larger margin.

[4]Note that a bid in a multiple-unit auction represents a complete demand schedule, not a one-dimensional price. In single-unit auctions, the "slope of the bidding schedule" typically refers to the change in bid price with respect to changes in the bidder's private signal. In this paper, the slope of interest is the change in bid price with respect to

schedule when the potential for winner's curse increases.

Two approaches have been taken to modeling treasury auctions under the common-value assumption.[5] First, the prototypical single-unit framework of Milgrom and Weber (1982) can be generalized to multiple-units. This generalization is straightforward *if* one assumes that each bidder demands no more than a single unit of the good (see Bikhchandani and Huang 1989). Such an approach, of course, removes multiple bids from consideration, so is unsuited for present purposes. If bidders are permitted to demand multiple units and to submit separate bids for each unit, the problem becomes analytically intractable.[6] In Gordy (1996), I model a multiple-bid discriminatory price auction of two units to $m$ bidders in which the sets of possible signals and of permitted bids are restricted to be finite.[7] The set of possible symmetric, pure-strategy solutions for the equilibrium bidding strategy is then finite as well, so the model can easily be investigated numerically. I find that as the precision of publicly observable information decreases or the number of competing bidders increases, a risk averse bidder will spread her bids more widely. These results provide formal theoretical support for hypotheses H1 and H2.[8]

The second family of treasury auction models is based on the "auctions of shares" model of Wilson (1979). The good is assumed to be perfectly divisible, and bidders are assumed to submit continuous demand schedules. In a share auction model with risk averse bidders, uncertain supply and no private information, Wang and Zender (1996) solve for the unique linear equilibrium bidding schedule under discriminatory pricing. It is straightforward to show that the slope of this schedule (expressed as an inverse demand curve) strictly increases with the number of bidders, with the uncertainty in the value, and with the degree of bidder risk aversion. This result supports both the

bid quantity, *holding fixed the bidder's signal.*

[5]A richer literature exists for independent-private-values multiple-bid auctions. Under IPV, multiple bids can result directly from standard utility theory (i.e., declining marginal utility for consumption of the good for sale). See, for example, Noussair (1995), Nautz (1995), and Tenorio (1993b, 1993a).

[6]The problem, briefly stated, is that the first order conditions of the bidder's maximization program give rise to terms of the form $S_i^{-1'}(S_j(x))$, where $S_i$ is the equilibrium strategy for the $i$th bid as a function of the bidder's private signal $x$.

[7]In a *discriminatory price* auction, each winning bidder pays the price on her bid. Portuguese and most U.S. treasury auctions, among many others, use this rule. Danish and Swiss treasury securities and recent U.S. two year and five year notes are sold in *uniform price* auctions, in which all winning bids are sold at the stopout price. For discussion of the long-standing policy debate on the choice between uniform and discriminatory pricing, see Simon (1994b), Back and Zender (1993), and the Joint Report.

[8]In the risk neutral case, it appears that bidders will not make use of multiple bids, but the results are ambiguous. For a small subset of the parameter space explored, I find equilibria in which a risk neutral bidder might submit two different prices for the two items. Everywhere else in the parameter space, each bidder submits two identically priced bids.

risk aversion and winner's curse conjectures, as a steeper inverse demand curve implies that the price difference between bids on the $q^{\text{th}}$ and $q+1^{\text{th}}$ dollars is strictly increasing for any $q$. Similar results are obtained by Viswanathan and Wang (1996) for an extension of this model to include pre- and post-auction trading.[9]

A potential but unlikely alternative motivation for multiple bids is bidder collusion. Back and Zender (1993) show that under uniform pricing there exist self-enforcing collusive equilibria which require that demand schedules steepen with the number of bidders. These equilibria appear not to exist under the discriminatory price rules used in Portugal, and furthermore I find in Section 4 that seller revenue increases with the number of bids per bidder. Therefore, collusion cannot plausibly explain H2.

As a general caveat to this theoretical discussion, treasury auctions in practice may not be purely common-value. For example, if there are significant transaction costs in the secondary market, which is certainly the case in Portugal, then there will be a private component to bidder valuations. In Milgrom and Weber's (1982) terminology, the bidders would have *affiliated* values. Even under risk neutrality, bidders would then in general have downward sloping demand for treasury securities, which could be expressed using multiple bids. However, as there is no reason for the slope of private components in valuation to be negatively correlated with the number of competing bidders, the possibility of private components does not compete with the winner's curse conjecture in explaining the evidence for hypothesis H2.

As far as I am aware, there is only one previous empirical study of multiple bids in the literature. Scott and Wolf (1979) propose a non-equilibrium model in which each bidder forms probability distributions over the auction stopout rate (i.e., the highest winning rate) and post-auction market rate.[10] The bidder, who is assumed risk averse, selects a portfolio of multiple bids much as a risk averse investor forms a portfolio of risky securities. This idea is clearly similar to my risk aversion conjecture, but also is consistent with the winner's curse conjecture, because the risk of winner's curse affects the correlations of returns across the set of possible bids. Scott and Wolf use bidding

[9] Wilson (1979) provides two examples under uniform pricing which also appear to support my conjectures. In an example with $m$ risk neutral bidders, the slope of the inverse demand schedule steepens with $m$. In the other example, with two risk averse bidders, inverse demand curves steepen everywhere as the precision of public information falls.

[10] Their model differs from standard auction analyses in that bidders ignore the effect of their own strategies on the stopout rate.

data and pre-auction forecasts of the stopout rate from two primary dealers in the U.S. treasury markets to show that the dealers' bids approximate a mean-variance efficient portfolio reasonably well.

There is a rich but inconclusive empirical literature on bidders' adjustment for winner's curse. Capen, Clapp and Campbell (1971) introduced the concept of winner's curse in a study of auctions of offshore oil and gas leases. They cite early industry analyses finding winning bidders in these auctions consistently earn subnormal returns. Using a longer data series, however, Hendricks, Porter and Boudreau (1987) find that winning bidders earn positive expected profit under a 5% real discount rate and real oil and gas prices held constant at the levels prevailing during the sample period. Nonetheless, they also find that some firms would have earned significantly higher profits if they had reduced their own bids by some constant factor, even if all competing bids were held constant. It appears that at least some of the firms regularly underestimated the upward bias in winners' valuations. Gilley and Karels (1981) use the same data set to examine whether bidders are aware that the potential for winner's curse increases with the number of bidders. Using a Heckman correction for endogeneity in participation, they find that bid levels do decrease with the number of competing bidders, as predicted. Brannman, Klein and Weiss (1987) examine the effect of the number of bidders on the distribution of winning bids. If bidders understand and adjust for winner's curse, winning bids should increase in inverse proportion to the number of bidders. If bidders fail to appreciate the winner's curse, winning bids should increase in proportion to a maximum order statistic. Assuming normally distributed valuation errors, Brannman et al. find the maximum order statistic model gives a better fit in most cases in samples from five different auction settings.

Experimental studies have produced somewhat more consistent results, perhaps because it is easier in a controlled setting to eliminate endogeneity in participation and to measure the true value of the good. Bidders in Bazerman and Samuelson's (1983) experiment earn negative average profit. Consistent with a failure to understand the winner's curse, they become more aggressive as the number of competing bidders increases and the precision of public information decreases. Kagel and Levin (1986) find that bidders learn to avoid winner's curse after repeated auctions with a fixed number of competitors. When the number of competing bidders is increased, however, the bidders earn negative average profit. The bidders do adjust in the correct direction, but not sufficiently to avoid winner's curse. See Thaler (1988) for a broader survey of both field and experimental studies of the winner's curse.

## 2 Auction rules

The primary market for Portuguese treasury bills is a discriminatory price auction in which bidders are permitted to submit multiple bids. The auction rules are similar to those used in the better-known U.S. treasury auctions, with a few important differences:

- Only financial institutions registered in Portugal and subject to a reserve requirement may purchase Portuguese treasury bills. I will refer to these institutions as "banks," although technically they need not be. The only authorized bidders are these banks and brokers acting as agents of these banks.

- A small bidder in the U.S. auction may submit a "non-competitive" bid, which is a quantity bid that always wins and is sold at the average rate of winning "competitive" (rate–quantity) bids. The Portuguese auction allows only competitive bids.

- In the U.S., a bidder cannot bid to acquire more than 35% of the issue. This rule is intended to prevent an aggressive bidder from engineering a squeeze on dealers who sell long in the when-issued market.[11] This issue does not arise in Portugal, which does not have a when-issued market, so no quantity limit is imposed.

- In Portugal, a reservation rate is set by the Ministry of Finance. Bids above this rate will not be allocated even if the issue is not fully sold. Bidders are aware that a reservation rate is imposed, but the rate itself is unannounced.[12]

At least four working days before the issue date, the Banco de Portugal (central bank) announces the maturity and issue ceiling of the bills to be auctioned. The maturity is either 91, 182 or 364

[11] The Salomon scandal in 1991 was an attempt by Salomon Brothers to circumvent this rule by falsely submitting bids beyond this limit under customer names (see Jordan and Jordan 1996).

[12] It appears that the Ministry of Finance set the reservation rate *before* the auction during my sample period, so bidders could take the reservation rate as exogenous. The rules, however, do not prohibit the Ministry from choosing the reservation rate after observing the bids.

days. Bids are due at the Banco de Portugal in sealed envelopes by 4:30 PM of the third working day before issue. Each bid consists of an interest rate and a desired quantity, in integer multiples of one million escudos (roughly US$8,000 at the time). Bidders are permitted to submit as many as six bids each, although this limit does not appear to have been enforced.

Placement takes place the morning of the second working day before issue. The bids are ordered by interest rate. Allotment starts with the lowest rate bid, and stops when the issue ceiling is reached (in which case any tie for claims to allotment are settled pro rata) or when the reservation rate is reached. On the same day, bidders are informed privately of the face value and discount price on the treasury bills allocated to them, and the total quantity and weighted average interest rate of treasury bills sold are announced publicly.

At the discretion of the Banco de Portugal, placement may be followed immediately by an "additional session," in which the Banco de Portugal accepts quantity bids for treasury bills at the weighted average rate determined in the first session. Bids submitted by bidders who obtained bills in the first session are given preference.

On the issue date, the Banco de Portugal issues the alloted treasury bills, and debits the bidders' demand deposit accounts at the Banco de Portugal. Banks are permitted to buy and sell treasury bills after issue, but transactions must be individually negotiated as there is no liquid secondary market. At least during the sample period, trades are rare, so bills are typically held until maturity.

## 3 Data

The data contain a complete record of bids for every Portuguese treasury bill auction between June 1988 and April 1993, and a complete record of transactions on the Portuguese interbank money market (IMM) for the same period. Treasury bills have been auctioned in Portugal since August 1985, so it can be assumed that participants were well familiar with bidding strategy by the start of the sample period. For each auction, the data include the date of auction, the maturity of bills for auction (91, 182 or 364 days), the issue ceiling (i.e., the quantity on offer), the unannounced reservation rate, and whether the auction was followed by an additional session. For each bid at each auction, the quantity, rate, and bidder identity are recorded, as well as the outcome of the bid.

After elimination of auctions for which the auction record is incomplete, there remain 474 auctions in the sample.[13] A total of 66 institutions are eligible as bidders. As the bidders may be quite diverse in sophistication and size, I divide them into three types. Type 1 bidders appear in at least half of the auctions and generally bid for large quantities. Type 2 bidders participate less often and typically bid for somewhat smaller quantities. Type 3 bidders are minor players who bid rarely and for small quantities. There are 13, 14 and 39 bidders of each type, respectively.[14] In Figure 1, the number of auctions in which each bidder appears is plotted against the log of the bidder's mean total bid quantity (i.e., the average across the auctions in which the bidder appears of the total quantity of the bidder's bids); the plotted symbol is the bidder's type.[15] Together, the Type 1 bidders account for 80% by volume of the bids in the sample, and the Type 2 bidders account for 17%.

As there is no secondary market, the main source of public information on market interest rates is the interbank money market. The IMM is primarily used by the banks to loan and borrow overnight money for the purpose of reserve management. Turnover is on the order of 1,500 billion escudos (US$12 billion) per month for overnight loans. There is also trading in longer maturities up to one year, but turnover is not heavy enough to permit construction of direct measures of rate volatility for maturities comparable to treasury bills.[16] Therefore, I take the volatility of overnight rates as proxy for the uncertainty in market interest rates. Let IMMVOL be defined as the standard deviation of overnight rates in the seven trading days prior to auction. Because this index of market volatility may be more informative for auctions of shorter maturity bills than for longer maturity bills, in the regressions of Sections 4 and 5 IMMVOL is interacted with dummies for the three bill

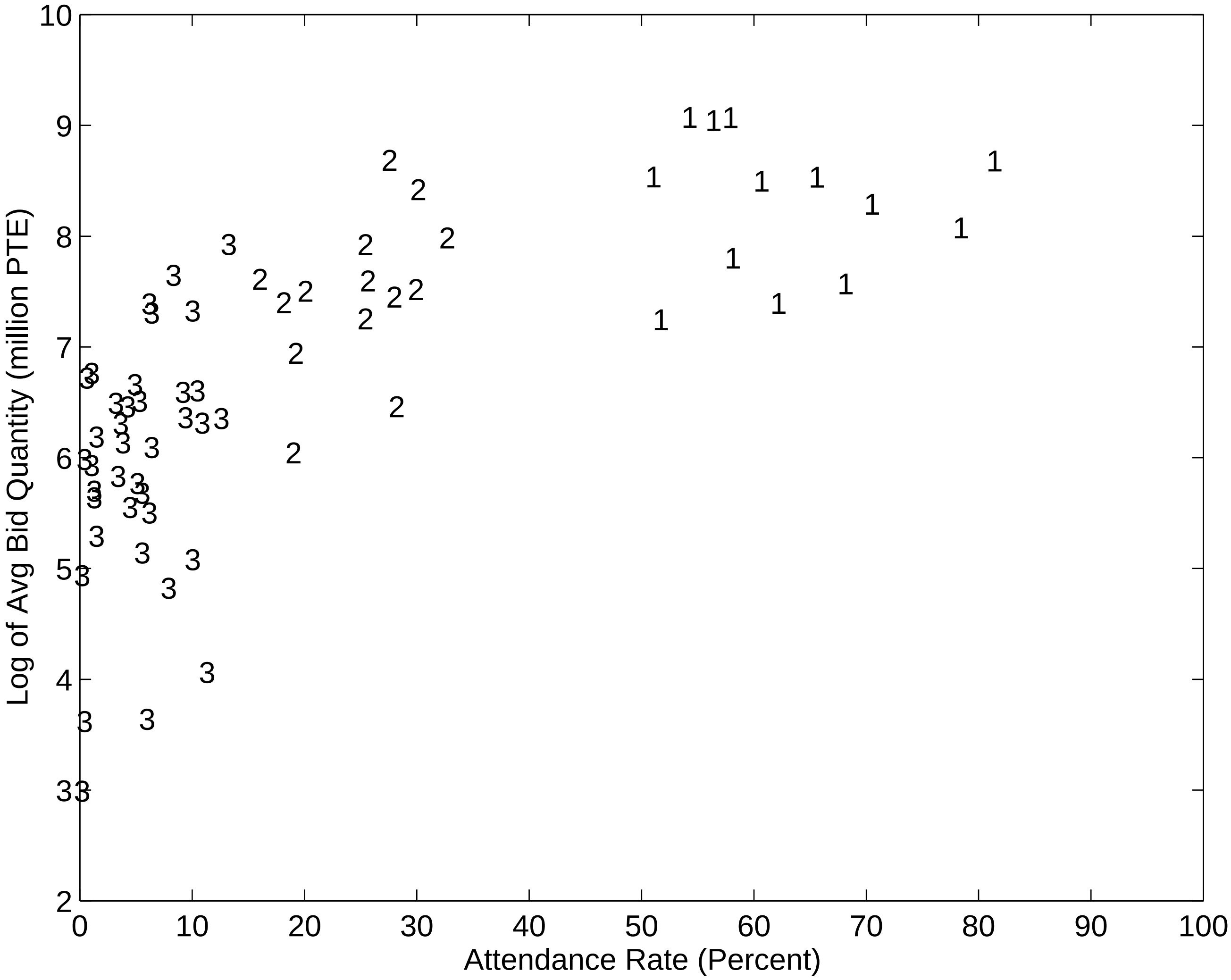
[13] All auctions in the first six weeks of 1990 were eliminated because contemporaneous IMM data was unavailable. In another handful of cases, the bidding record was inconsistent with published summary statistics, probably due to data entry errors.

[14] My taxonomy is based entirely on bidding frequency. Type 1 bidders are defined as those bidding in over half the auctions, Type 3 as those bidding in less than 15% of the auctions, and Type 2 as the remainder. Although the divide between Types 2 and 3 may be arbitrary, the distinction between Types 1 and 2 in Figure 1 appears quite clear. Three of the Type 3 bidders never actually bid in my sample.

[15] Note that no bidder participates in more than 80% of the auctions. In contrast, primary dealers in the U.S. are expected to bid in every auction. In the US, primary dealers make a business of bidding for bills at auction and selling them in the when-issued market; consequently, it is reasonable for the government to expect their regular participation. In Portugal, bills are purchased to hold in portfolio, not for resale, so participation is limited by the bidders' portfolio needs.

[16] In the 86 to 96 day maturity range, monthly IMM turnover is on the order of 5 to 30 billion escudos. Turnover in the 175 to 189 day range is typically one-third to one-half of that. In the over 350 day range, turnover is negligible. It *is* feasible to measure volatility using 28–32 day IMM loans, for which turnover is roughly 60 billion escudos per month, and there are almost always several trades per day; I try this in Section 5.4.

Figure 1: Auction Participation



maturities. In Figure 2, I plot the overnight IMM rate and IMMVOL over the sample period.

In a fully developed and liquid capital market, it would clearly make little sense to measure the uncertainly in longer rates by the volatility of overnight rates, which is driven in large part by the micro-mechanics of banks' reserve period maintenance. In the Portuguese context, however, it is plausibly the index of volatility most relevant to the bidders. As overnight funds are by far the most liquid financial instrument in Portugal, the overnight rate acts as an anchor for the IMM market, and volatility in this market makes it more difficult for the market to price longer term loans.[17] Volatility in the overnight rate is also readily observable to all of the bidders, which assures a degree of symmetry in the bidders' prior distributions on the value of the bills. Furthermore, losing bidders place their excess cash in the overnight market until the next auction of bills, so the overnight rate is an important component of the bidder's opportunity cost.

In addition to IMM volatility and the number of bidders of each type (M_TYPE1, M_TYPE2, M_TYPE3), several other factors in the bidding environment may affect the use of multiple bids. These control variables are listed and described in Appendix A.

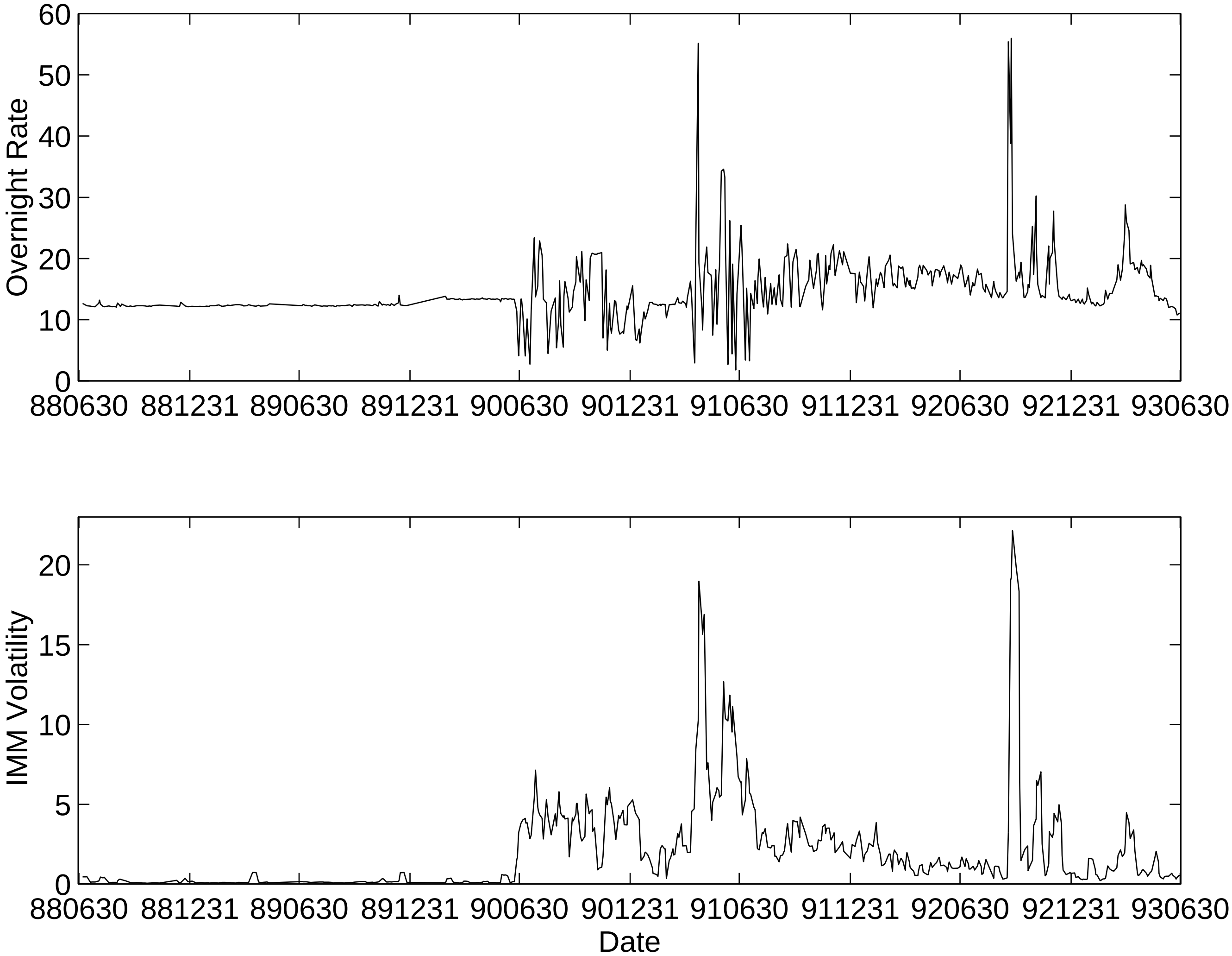
## 4 Auction outcomes under multiple bidding

The success of a treasury auction from the seller's point of view depends on both the average winning rate, relative to alternative sources of government funding, and the quantity sold. For simplicity, I take the reservation rate to be the government's alternative cost of funds and I assume the government wants to sell as much as possible, up to the issue size.[18] Bidders' use of multiple bidding could affect auction outcomes in a number of ways. If multiple bidding is a hedging mechanism, we would expect it would be costly to the bidders; i.e., it would increase expected

[17]The covered interest parity relationship was useless for this purpose until the final months of the sample period. Until the end of 1992, capital controls were in place to allow the Banco de Portugal to maintain high real interest rates without causing large inflows of foreign exchange; the arbitrage needed to enforce the covered interest parity relationship was thus prevented. The head of treasury security operations at one of the largest bidders confirmed to me that foreign rates were not a consideration in bidding during this period. It is reassuring to observe that when the capital controls were lifted, IMM rates immediately aligned with the covered interest parity rate on British pounds.

[18]Both of these assumptions may be imperfect, but we have no other observable indicators of the government's objectives. An optimal reservation price is higher than the seller's valuation, so I am assuming that, if the Ministry of Finance set the reservation rate strategically, its "markup" rule was constant. For much of the sample, reservation rate policy was passive, so indeed may represent neither a strategic choice nor a valuation. Furthermore, the government may not always have been concerned with quantity sold. Treasury bills were sold partly to absorb excess liquidity from a banking system that had previously been subject to lending ceilings and controlled interest rates. If liquidity were less than expected, and the issue then failed to sell out, the government would not necessarily have been disappointed.

Figure 2: IMM Overnight Rate and Volatility




Note: IMM volatility was negligible until financial market liberalization in mid-1990. For most of 1991 and the first half of 1992, the Banco de Portugal followed a policy of nonintervention in the IMM except on the first day of each reserve period; consequently, rates tended to be highly volatile, especially towards the end of each reserve period. When the central bank relaxed this policy in the summer of 1992, the volatility on the IMM subsided. The final spike in rates occurs in September 1992 during the ERM crises.

revenue per unit sold. On the other hand, if it were used to support collusion, multiple bidding would be associated with lower revenue per unit. We would also expect multiple bidding to increase the range of bids rates, and therefore the "tail" of winning bid rates. This may be of interest in itself, because a longer winning tail may reduce the information value of the auction in price discovery. However, the effect of bid-spreading on quantity sold depends on whether the distribution of bids is centered above or below the reservation rate, and thus is ambiguous.

I define REVENUE as the reservation rate less the average winning rate in the auction. A higher value implies higher seller revenue per unit sold, relative to the seller's reservation price. Q_SOLD is the quantity sold as a fraction of the issue size. Dispersion in the winning rates is measured by WINTAIL, defined as the difference in percentage points between the lowest bid rate and the stopout rate. In the regressions below, the dependent variables are treated as censored. REVENUE and WINTAIL are non-negative by construction, and each are equal to zero in 26% of the auctions. The rules of the auction bind Q_SOLD from below at zero and from above at one; in the sample, it is never zero but equals one 63% of the time. For each of these variables, censoring should be thought of in a metaphoric rather than literal sense. For example, we can think of the latent variable for REVENUE as an unobserved index of the strength of demand for the issue. Above a certain threshold, increased demand will be revealed in increased REVENUE. Anywhere below that threshold, REVENUE is bound at zero.

The explanatory variable of main interest is BIDS/BIDDER, defined as the number of bids submitted in the auction divided by the number of participating bidders. The effect of the number of bidders of each type (M_TYPE1, M_TYPE2, M_TYPE3) is of direct interest as well. As a measure of the tightness of the reservation rate, I include IMMBENCH, defined as the difference between the reservation rate and the IMM rate on 28–32 day loans. The higher is IMMBENCH, the less likely is the reservation rate to bind, so the higher REVENUE and WINTAIL should be. The variable COVERAGE is defined as the total quantity of bids submitted divided by the issue size; the higher the COVERAGE, the more competitive the auction, so the higher the REVENUE and the smaller the WINTAIL. I also include most of the auction-level independent variables listed in Appendix A.[19]

[19] In the regressions reported below, I exclude the variable LOG(SUPPLY), which should not be relevant conditional on COVERAGE. Including LOG(SUPPLY) does not change the results.

Table 1 shows regression results using Powell's (1986) symmetrically censored least squares (SCLS) Tobit model.[20] The first column shows that an additional bid per bidder is associated with a decrease in the average winning rate of 84 basis points when the reservation rate is not binding. This evidence is consistent with the hedging conjecture and does not support the collusion hypothesis. Coefficients on IMMBENCH and COVERAGE are large and positive, as expected. Coefficients on the M_TYPE variables are of opposing signs, small and statistically insignificant, which indicates that the competitive effect of a greater number of bidders is roughly balanced by the opposing winner's curse effect. Theory is itself ambiguous on which will dominate, so the result is unsurprising. The negative coefficients on the IMMVOL variables, one of which is significant, are consistent with both theory and previous empirical evidence from the U.S. treasury auction which show that seller revenue decreases with uncertainty.[21] The negative coefficient on CAP_BOUND is likely to reflect stickiness in the reservation rate, which induces serial correlation in how tightly the reservation rate binds. Finally, the large positive coefficient on WILL_REOPEN is as expected, because additional sessions were intended for use when demand was exceptionally high; it also is consistent with a reduction in winner's curse (see Appendix A).

Estimated coefficients in the WINTAIL regression are also consistent with prediction. Dispersion increases with BIDS/BIDDER and with the number of bidders (especially with the number of larger bidders). Dispersion decreases with COVERAGE because, all else equal, a higher quantity volume of bids pushes the stopout rate closer to the lowest rate. Dispersion increases with IMMBENCH simply because the reservation rate is less likely to bind, and thereby truncate the distribution of winning bids, when IMMBENCH is high; dispersion decreases with CAP_BOUND for a similar reason. I have tried two alternatives to WINTAIL as measures of dispersion and obtained very similar results.[22] Regression results for Q_SOLD are reported in the second column

[20]SCLS is a semi-parametric generalization of the standard Tobit. Where the Tobit model assumes that the error term in the latent equation has normal distribution, the SCLS assumes only that it is symmetric and has heteroscedasticity bounded away from zero and from infinity.

[21]Milgrom and Weber (1982) show for the single-unit common-value model that seller revenue increases with the precision of public information. Numerical results show similarly for the multiple-bid model in Gordy (1996). In the U.S. treasury auction, Simon (1994a) finds the markup of the average winning rate over the when-issued rate is positively related to pre-auction volatility in the bond yield. Cammack (1991) finds the markup is positively related to the dispersion of winning bid rates. Bikhchandani, Edsparr and Huang (1994) provide somewhat inconclusive evidence that bidders' expected profit increases with the dispersion of winning bid rates, which in turn is positively related to two proxies for uncertainty.

[22]One is the quantity-weighed standard deviation of winning bid rates. For robustness to outlier bids, I also try the difference between the rate on the 20th percentile of winning bids (by quantity, sorted from lowest rate to the

Table 1: SCLS Regression Models for Auction Outcomes

| | REVENUE | Q_SOLD | WINTAIL |
|---|---|---|---|
| CONSTANT | −4.394** | 0.162 | −34.702** |
| | (0.782) | (0.090) | (8.147) |
| BIDS/BIDDER | 0.838** | −0.130** | 12.261** |
| | (0.131) | (0.023) | (1.715) |
| COVERAGE | 0.231** | 0.722** | −3.447** |
| | (0.060) | (0.098) | (0.952) |
| M_TYPE1 | −0.011 | −0.011 | 2.677** |
| | (0.037) | (0.016) | (0.743) |
| M_TYPE2 | −0.001 | 0.014 | 1.622** |
| | (0.031) | (0.013) | (0.549) |
| M_TYPE3 | 0.019 | 0.022 | 0.178 |
| | (0.034) | (0.019) | (0.511) |
| IMMBENCH | 0.658** | 0.042* | 2.713* |
| | (0.087) | (0.016) | (1.090) |
| IMMVOL*MATURITY091 | −0.122 | 0.026* | 2.106** |
| | (0.074) | (0.010) | (0.773) |
| IMMVOL*MATURITY182 | −0.096 | 0.020* | 2.600** |
| | (0.056) | (0.010) | (0.846) |
| IMMVOL*MATURITY364 | −0.492** | 0.021 | −0.685 |
| | (0.130) | (0.019) | (1.251) |
| RESERVE_DAYS | 0.025 | −0.008 | 0.577 |
| | (0.035) | (0.011) | (0.567) |
| WILL_REOPEN | 1.720** | 0.002 | −5.155 |
| | (0.183) | (0.040) | (3.340) |
| MATURITY182 | −0.278 | 0.027 | −7.048* |
| | (0.248) | (0.062) | (3.021) |
| MATURITY364 | −0.316 | 0.022 | −5.037 |
| | (0.308) | (0.103) | (3.496) |
| REGIME1 | −0.788* | −0.085 | −12.802** |
| | (0.341) | (0.065) | (3.247) |
| REGIME2 | −0.050 | 0.044 | −4.220 |
| | (0.244) | (0.065) | (3.321) |
| CAP_BOUND | −0.774** | 0.008 | −9.000** |
| | (0.210) | (0.046) | (2.983) |
| $T = 473$ auctions | | | |

Dependent variables measured in percentage points. Standard errors in parenthesis. Symbols * and ** indicate statistical significance at 5% and 1% levels, respectively. One observation from the full sample of 474 auctions is lost because the IMM 28–32 day benchmark could not be constructed for that date.

for completeness. Positive coefficients on IMMBENCH and COVERAGE are as expected.

The main results are robust to model specification. Ordinary least squares and standard Tobit estimators place the same signs and similar levels of significance on BIDS/BIDDER, COVERAGE, IMMBENCH, and CAP_BOUND, although the coefficients are smaller in magnitude. As the reservation rate may not always be a meaningful measure of value, I have regressed via OLS the average winning rate on the reservation rate, the IMM benchmark, and the other variables used above. Conclusions are unchanged.

# 5 Evidence on the Use of Multiple Bids

In this section, I present evidence from Portugal's treasury bill auctions that, *ceteris paribus*, a bidder submits a greater number of bids and disperses prices on these bids more widely when there is greater risk of winner's curse. In particular, I find that the use of multiple bids increases with the expected number of competing well-informed bidders and with the volatility of market interest rates. Before presenting the main regression results, two econometric issues need to be resolved. First, we do not observe how bidders form expectations of others' participation. It is possible that bidders learn ex-ante from pre-auction communication which bidders will be participating. In this case, ex-ante expectations equal ex-post realizations. Otherwise, we must either find suitable instruments for the measurement error induced by using ex-post realizations, or impose a structural model of bidder participation decisions. This problem will be addressed in section 5.1. The second econometric issue concerns the possible endogeneity of bid quantities. This problem also requires either suitable instruments or a structural model, and will be addressed in section 5.2. Section 5.3 presents the main regression results. To check the robustness of these results, I have tried a number of alternative definitions of the dependent and main independent variables and several different alternative model specifications. These are summarized in section 5.4.

## 5.1 Bidder expectations of others' participation

Let MCOMPETE1$(t, i)$ be the expected number of Type 1 bidders competing against bidder $i$ at auction $t$, and define MCOMPETE2$(t, i)$ and MCOMPETE3$(t, i)$ correspondingly. As these ex-

stopout) and the stopout rate.

ante expectations are not directly observable, the analyses are conducted under three alternative sets of assumptions.

The simplest approach is to assume that the bidders know with certainty beforehand who will be participating in the auction. In this case, MCOMPETE1$(t,i)$ = M_TYPE1$(t) - \mathcal{I}(1,i)$ where $\mathcal{I}(1,i)$ equals one if bidder $i$ is of Type 1 and equals zero otherwise. MCOMPETE2 and MCOMPETE3 are given similarly. Because expectations are assumed to equal observed realizations, I will refer to this as the "Realized" model for MCOMPETE. As potential bidders are all institutions which interact with each other regularly, e.g., on the IMM, this is not an entirely implausible assumption, but it is preferable to make the weaker assumption that others' participation is not known with certainty and that each bidder forms her own expectations rationally using all information ex-ante available to her.[23] Given suitable instruments, consistent estimates can be obtained when instrumental variable (IV) techniques are applicable. I will refer to this approach as "Realized-IV."

In most of the regression specifications used in section 5.3, direct IV methods are unavailable. The alternative, then, is to take predicted values from a structural model of participation. I assume that the bidder takes her own participation decision as given, and models the participation of other bidders as independent Bernoulli$(p_{tj})$ draws, where $t$ indexes auctions and $j$ indexes bidder types, so that

$$\begin{aligned}\text{MCOMPETE1}(t,i) &= (N_1 - \mathcal{I}(1,i)) \cdot p_{t,1}\\ \text{MCOMPETE2}(t,i) &= (N_2 - \mathcal{I}(2,i)) \cdot p_{t,2}\\ \text{MCOMPETE3}(t,i) &= (N_3 - \mathcal{I}(3,i)) \cdot p_{t,3}\end{aligned}$$

where $N_j$ is the total number of potential bidders of Type $j$. The probabilities $p_{tj}$ are assumed to be given as a Logistic function $\Lambda(w_t\delta_j)$, where the $w_t$ are publicly observed auction-level variables and $\delta_j$ is a vector of commonly known coefficients.[24] I will refer below to this as the "Predicted"

[23]If others' participation is stochastic, then the degree of uncertainty in the bidder's estimate may itself affect her bidding strategy. McAfee and McMillan (1987b) show this to be the case in an independent-private-values auction with risk averse bidders. As this form of uncertainty in not directly observable, and is likely to have only a second-order effect, I do not address this possibility in the analyses below.

[24]Under the maintained assumption that the Logit model is correctly specified, the generated $\hat{p}_{tj}$ can be used in place of $p_{tj}$ because $\text{plim}_{T\to\infty}\hat{p}_{tj} = p_{tj}$; i.e., the measurement error disappears asymptotically. Although use of these generated regressors does not affect consistency, conventional standard errors are no longer correct. Newey (1984) shows in a general setting how to correct the variance-covariance matrix for generated regressors, but the method

model for MCOMPETE.

The vector of explanatory variables $w_t$ includes auction-level variables already introduced. The effect of IMM volatility (interacted here with maturity dummies) is of primary interest, because volatility increases the potential for winner's curse in the auction and the risk that borrowing overnight could become expensive around the issue date. If bidders are risk averse, they may be less inclined to participate in the auction when IMMVOL is high. I also include in $w_t$ four predictors of excess liquidity in the banking system, as treasury bills were used by Portuguese banks during the sample period mainly as a means of storing excess cash. These instruments are described in Appendix B.

Estimated coefficients, given in Table 2, are consistent with prediction. The probability of participation decreases with IMMVOL for each bidder type, with smaller bidders more sensitive to volatility than larger bidders. Participation increases with LOG(SUPPLY), perhaps because a larger issue size increases the probability of winning a bid at any given rate. Participation is reduced when the reservation rate policy is tight, as proxied here by CAP_BOUND. Significant coefficients on DAYS:ANY and PRORATA indicate that participation increases with excess cash in the banking system.

### 5.2 Potential endogeneity in bid quantities

In absolute terms, any gains to using multiple bids increase with the escudo quantity at stake. As long as there is some penalty to submitting many small bids (e.g., the risk of annoying the central bank), small bidders will submit fewer bids, so bid quantity should be an explanatory variable in a model of bid-spreading. In a fully developed and liquid financial market, in which positions in treasury bills can be readily financed and closed, however, quantity bid would be jointly determined with other aspects of bidding strategy, and thus possibly endogenous. In the case of Portugal, endogeneity is less likely to be a problem. Because treasury bills were difficult to sell and less profitable than commercial loans, the total quantity demanded by a bidder would likely be limited by cash on hand, the level of which was mostly outside the short-run control of the banks

is quite tedious to implement for the models used below. Fortunately, as noted by Wooldridge (1996, §6.1), the consensus in the literature is that the correction is typically small. Comparison of the uncorrected standard errors in Table 5 with those of comparable IV regressions, which need no correction, suggests that the correction would make little difference in this case as well.

Table 2: Logit Regression Models for Bidder Participation

| | Type 1 | Type 2 | Type 3 |
|---|---|---|---|
| CONSTANT | $-4.261^{**}$ | $-6.086^{**}$ | $-7.104^{**}$ |
| | (0.757) | (0.733) | (0.797) |
| IMMVOL*MATURITY091 | $-0.146^{**}$ | $-0.182^{**}$ | $-0.225^{**}$ |
| | (0.024) | (0.030) | (0.032) |
| IMMVOL*MATURITY182 | $-0.115^{**}$ | $-0.131^{**}$ | $-0.251^{**}$ |
| | (0.015) | (0.027) | (0.039) |
| IMMVOL*MATURITY364 | $-0.162^{**}$ | $-0.171^{**}$ | $-0.202^{**}$ |
| | (0.025) | (0.039) | (0.048) |
| LOG(SUPPLY) | $0.574^{**}$ | $0.583^{**}$ | $0.461^{**}$ |
| | (0.077) | (0.074) | (0.080) |
| RESERVE_DAYS | −0.023 | −0.012 | −0.012 |
| | (0.019) | (0.019) | (0.021) |
| WILL_REOPEN | −0.057 | −0.127 | 0.099 |
| | (0.082) | (0.099) | (0.106) |
| MATURITY182 | $0.336^{**}$ | $-0.565^{**}$ | $-0.468^{**}$ |
| | (0.082) | (0.084) | (0.095) |
| MATURITY364 | $0.742^{**}$ | −0.221 | $-0.700^{**}$ |
| | (0.128) | (0.129) | (0.148) |
| REGIME1 | 0.167 | $0.496^{**}$ | $0.284^{*}$ |
| | (0.102) | (0.101) | (0.127) |
| REGIME2 | $-0.290^{**}$ | $0.337^{**}$ | $0.898^{**}$ |
| | (0.085) | (0.089) | (0.112) |
| CAP_BOUND | $-0.771^{**}$ | $-0.846^{**}$ | −0.117 |
| | (0.092) | (0.094) | (0.105) |
| PRORATA | $-0.690^{**}$ | $-0.467^{**}$ | $-0.409^{*}$ |
| | (0.156) | (0.140) | (0.162) |
| SAMEDAY | 0.158 | 0.046 | $-0.663^{**}$ |
| | (0.165) | (0.148) | (0.213) |
| DAYS:ANY | $0.042^{**}$ | $0.037^{**}$ | 0.007 |
| | (0.014) | (0.010) | (0.009) |
| DAYS:OWN | 0.004 | −0.004 | 0.005 |
| | (0.003) | (0.003) | (0.003) |
| $T = 474$ | | | |

Standard errors in parenthesis. Superscripts * and ** indicate statistical significance at 5% and 1% levels, respectively.

(e.g., due to shifts in account balances and lines of credit). It may be supposed that a quantity is chosen by senior managers as a function of exogenous conditions, and then given to the treasury securities manager as a fixed and exogenous limit. Nonetheless, it is desirable to weaken that assumption. I will maintain the assumption that the decision to participate is taken as exogenous by the treasury securities manager, but allow for some flexibility (and thus endogeneity) in bid quantity.

Let LOGQ$(t, i)$ be the log of the total quantity (in millions of Portuguese escudos) on the bids submitted by bidder $i$ at auction $t$. In the regressions of section 5.3, two approaches are taken to the problem of endogeneity of this variable. When IV techniques are applicable, I instrument for LOGQ directly. Otherwise, it is necessary to introduce a linear reduced form equation for LOGQ, which I specify as

$$\text{LOGQ}(t, i) = z_{ti}\theta + \xi_i + v_{ti} \tag{1}$$

where $\xi_i$ is a bidder fixed effect and the vector $z_{ti}$ includes the other independent variables used in the main regressions below and a set of instruments. Because LOGQ is presumed to be strongly influenced by the bidder's cash on hand, I use as instruments the four systemic liquidity variables introduced in section 5.1, and three additional bidder and time varying liquidity proxies (see Appendix B).

Fixed effect regression results are shown in Table 3. Coefficients on the IMMVOL variables are generally negative and sometimes significant, which suggests that bidders reduce quantity demands when the market is volatile. Coefficients on the MCOMPETE variables are positive and typically significant, which may simply be due to positive correlation across the bidders in excess cash levels. Coefficients on the liquidity instruments are mostly significant at the 1% level, and all but DAYS:ANY and DAYS:OWN (which are numerically small) are of the predicted signs.

## 5.3 Main regression models for BIDCOUNT and BIDSPREAD

The dependent variables in this section are measures of bidders' use of multiple bids. The first, BIDCOUNT$(t, i)$, is a count of bids submitted by bidder $i$ at auction $t$.[25] The second measures

[25]In my sample, in no case does a bidder submit two or more bids at a single rate; that is, the bidder's multiple bids are all distinct. In the U.S., by contrast, primary dealers bid for customers as well as for their own accounts, and often do not consolidate several bids at the same rate into a single bid.

Table 3: Reduced Form Regression Model for LOGQ

| MCOMPETE Model: | Predicted | Realized |
|---|---|---|
| MCOMPETE1 | 0.018 | 0.024** |
| | (0.018) | (0.005) |
| MCOMPETE2 | 0.037* | 0.036** |
| | (0.017) | (0.005) |
| MCOMPETE3 | 0.195** | 0.030** |
| | (0.057) | (0.005) |
| IMMVOL*MATURITY091 | 0.005 | −0.021* |
| | (0.019) | (0.010) |
| IMMVOL*MATURITY182 | −0.007 | −0.006 |
| | (0.010) | (0.006) |
| IMMVOL*MATURITY364 | −0.021 | −0.029** |
| | (0.016) | (0.011) |
| LOG(SUPPLY) | 0.071 | 0.105** |
| | (0.056) | (0.025) |
| RESERVE_DAYS | 0.006 | 0.005 |
| | (0.006) | (0.006) |
| WILL_REOPEN | 0.012 | −0.005 |
| | (0.032) | (0.031) |
| MATURITY182 | 0.087* | 0.041 |
| | (0.040) | (0.028) |
| MATURITY364 | 0.085 | 0.052 |
| | (0.057) | (0.042) |
| REGIME1 | −0.301** | −0.277** |
| | (0.051) | (0.033) |
| REGIME2 | −0.096** | −0.071* |
| | (0.035) | (0.029) |
| CAP_BOUND | −0.012 | −0.046 |
| | (0.081) | (0.031) |
| PRORATA | 0.010 | −0.057 |
| | (0.068) | (0.045) |
| SAMEDAY | −0.226** | −0.249** |
| | (0.050) | (0.046) |
| DAYS:ANY | −0.010* | −0.006* |
| | (0.004) | (0.003) |
| DAYS:OWN | −0.003** | −0.003** |
| | (0.001) | (0.001) |
| DAYSINCE | 0.001* | 0.001* |
| | (0.000) | (0.000) |
| LAGLOGQ | 0.347** | 0.333** |
| | (0.012) | (0.011) |
| UNFILLED | 0.224** | 0.185** |
| | (0.027) | (0.026) |
| 6353 Observations ($T = 474$, $N = 66$) | | |

Non-participants at each auction are excluded from these regressions. Standard errors in parenthesis. Superscripts * and ** indicate statistical significance at 5% and 1% levels, respectively.

the dispersion of a bidder's bids. I order by rate the bids submitted by the bidder, and define BIDSPREAD$(t,i)$ as the difference between the rates on the 85th and 15th percentiles of quantity submitted.[26] A maintained assumption in this section is that the decision to participate (though not necessarily the quantity submitted) is exogenous, so non-participants at each auction are excluded from the sample. Descriptive statistics for the two dependent variables are given in Table 4, and a histogram for BIDCOUNT in Figure 3.

Table 4: Dependent Variables

| | Min | Max | Mean | StdDev | Mode | (Pct at Mode) |
|---|---|---|---|---|---|---|
| BIDCOUNT | 1 | 12 | 2.839 | 1.624 | 1 | (27.4%) |
| BIDSPREAD | 0 | 300 | 13.214 | 14.697 | 0 | (29.7%) |
| 6353 Observations ($T = 474$, $N = 61$) | | | | | | |

Non-participants at each auction are excluded. Bidders who participated at only a single auction also are excluded because fixed effects cannot be identified.

In the first set of regressions, BIDCOUNT is modeled as

$$\text{BIDCOUNT}_{ti} = 1 + \exp(\alpha_i + x_{ti}\beta + \text{LOGQ}_{ti}\gamma)\epsilon_{ti} \tag{2}$$

where $\alpha_i$ is a fixed effect, $x_{ti}$ is a vector of independent exogenous variables, and $\epsilon_{ti}$ is a non-negative multiplicative error with mean one. This is consistent with a standard fixed effect Poisson specification for BIDCOUNT-1 (i.e., with a Poisson model for the number of "multiple" bids submitted beyond one), but imposes weaker distributional assumptions.

Following Wooldridge (1996, §6.1), the potential endogeneity of LOGQ is modeled as dependence in the errors term of the form $\ln(\epsilon_{ti}) = v_{ti}\rho + u_{ti}$, where $v$ is the residual in equation (1) and $u_{ti}$ is independent of $v_{ti}$ and $z_{ti}$. Equation (2) then can be re-written as a conditional expectation

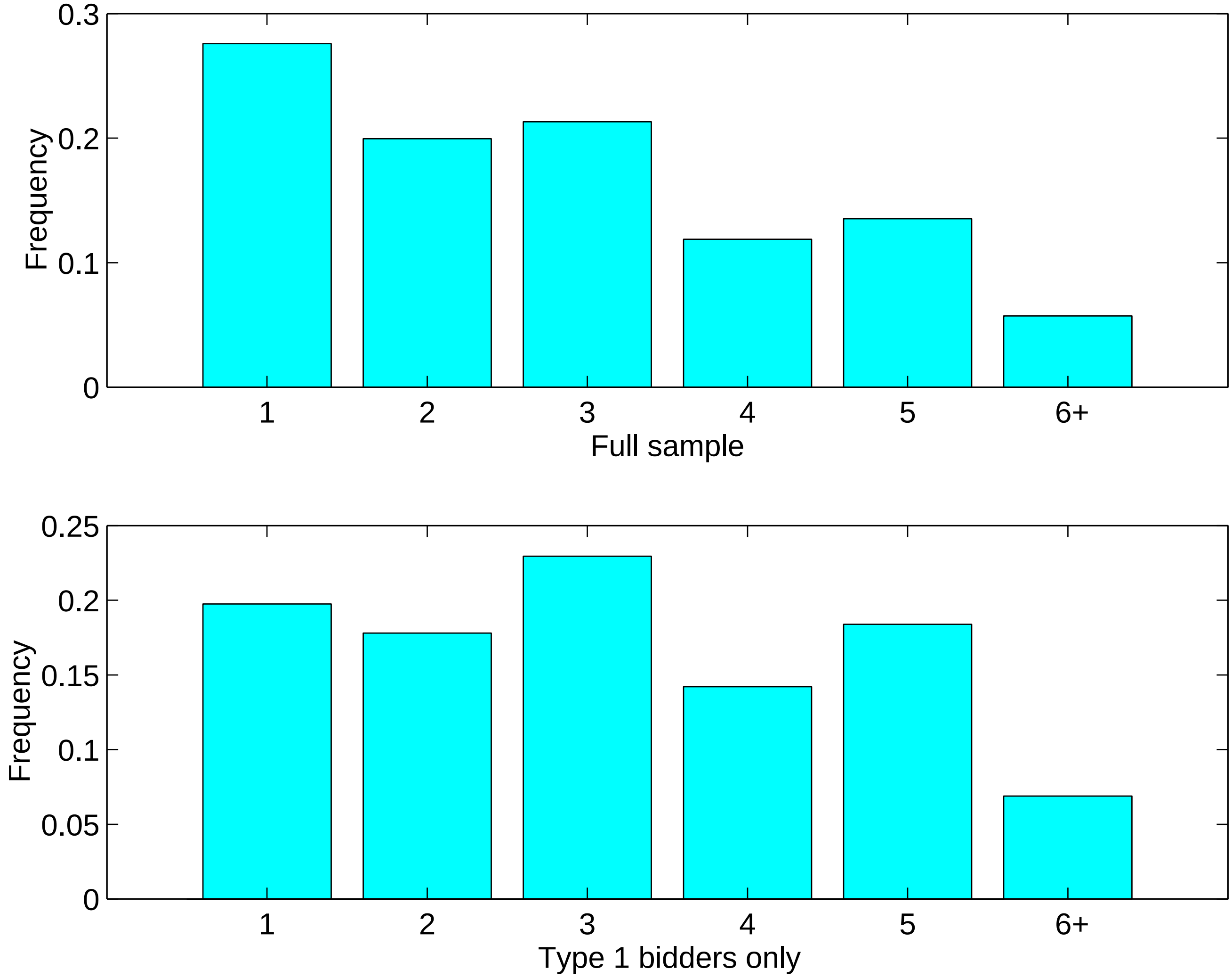
$$E[y_{ti}|\phi_i, x_{ti}, \text{LOGQ}_{ti}, v_{ti}] = \phi_i \exp(x_{ti}\beta + \text{LOGQ}_{ti}\gamma + v_{ti}\rho) \tag{3}$$

where $\phi_i$ is a multiplicative fixed effect.[27] Wooldridge (1990) shows that equations of this form

[26] The upper and lower 15% are cut off to avoid overweighting small extreme bids which may be unrepresentative of the bidder's strategy.

[27] Note that $\phi_i \neq \exp(\alpha_i)$ because the expectation of the remaining multiplicative residual $\exp(u_{ti})$ need not equal

Figure 3: Histogram: Number of Bids Per Bidder




Note: Non-participating bidders at each auction are excluded.

can be estimated consistently by the standard fixed effect Poisson of Hausman, Hall and Griliches (1984) ("HHG"), and provides a method for calculating standard errors robust to distribution and conditional heteroscedasticity in the errors. $v_{ti}$ is not observed, but can be replaced by predicted values $\hat{v}_{ti}$ from equation (1).[28] Note that LOGQ is exogenous if and only if $\rho = 0$.

I report results for the HHG fixed effect Poisson estimator in the first two columns of Table 5. Whether realized or generated values are used for MCOMPETE, the coefficient on MCOMPETE1 is positive, significant at the 1% level, and larger than the coefficients on MCOMPETE2 and MCOMPETE3. This result supports the conjecture that multiple bids are used to hedge the winner's curse associated with competition against well-informed bidders. The coefficient on IMMVOL*MATURITY091 is positive and significant at the 1% level, and the coefficients on IMMVOL*MATURITY182 and IMMVOL*MATURITY364 also are positive, if not always significant. The larger magnitude on IMMVOL*MATURITY091 is consistent with the intuition that the volatility of overnight rates is more indicative of uncertainty in shorter rates than longer rates. The coefficient on LOGQ is positive and significant at the 1% level, consistent with the idea that the absolute gains to multiple bidding increase with quantity bid. Significant coefficients on VHAT indicate that LOGQ is endogenous.[29] Also as expected (see Appendix A), the coefficients on WILL_REOPEN and RESERVE_DAYS are negative, and the coefficient on CAP_BOUND is positive. All other coefficients are insignificant or sensitive to specification.

A disadvantage to the HHG specification is that it does not allow consistent IV estimation using nonlinear two-stage least squares (NL2SLS).[30] However, under fixed $N$, large $T$ asymptotics, a NL2SLS Poisson specification with dummies for each bidder can be estimated consistently.[31] To instrument for both LOGQ and the MCOMPETE variables, I include in the set of instruments the

one.

[28] Under the maintained assumption that equation (1) is correctly specified, $\text{plim}_{T\to\infty}\hat{v}_{ti} = v_{ti}$, so consistency is unaffected. However, standard errors need to be corrected for the generated nature of the $\hat{v}_{ti}$. As discussed in footnote 24, the correction is complicated and typically small in magnitude, so is omitted.

[29] Regardless, results (not reported) do not change qualitatively if VHAT is omitted from the regression.

[30] In brief, both the derivative of the first moment and the score of the likelihood have endogenous errors in a denominator term. Even given suitable instruments, orthogonality cannot be guaranteed.

[31] The Portuguese auction series has a fixed set of potential bidders and potentially boundless number of auctions, which stands in contrast to the usual fixed $T$, large $N$ panel situation. Corresponding to the problem of consistent estimation of unit fixed effects in fixed $T$, large $N$ nonlinear panel contexts, in my situation time-specific fixed effects cannot be estimated consistently. In theory, dummies REGIME1 and REGIME2 should be subject to this problem. In practice, however, simulation studies (e.g., Heckman 1980) have shown that the inconsistency becomes very small after, say, 20 observations per unit. For both REGIME1 and REGIME2, I have well in excess of that number.

Table 5: Regressions Models for BIDCOUNT and BIDSPREAD[a]

| Dependent variable: | BIDCOUNT | | | | BIDSPREAD | |
|---|---|---|---|---|---|---|
| Specification: | HHG[b] | | NL2SLS Poisson[c] | | Honoré Panel Tobit | |
| MCOMPETE model: | Predicted | Realized | Realized-IV | | Predicted | Realized |
| LOGQ | 0.246** | 0.213** | 0.199** | 0.178** | 3.619** | 3.213** |
| | (0.058) | (0.060) | (0.033) | (0.017) | (1.059) | (1.087) |
| VHAT | 0.118* | 0.132* | · | · | −0.080 | 0.345 |
| | (0.051) | (0.053) | · | · | (0.865) | (0.902) |
| MCOMPETE1 | 0.064** | 0.037** | 0.081** | 0.090** | 2.273** | 0.634** |
| | (0.017) | (0.009) | (0.014) | (0.015) | (0.512) | (0.154) |
| MCOMPETE2 | 0.011 | 0.005 | 0.014 | 0.018 | 0.167 | −0.300* |
| | (0.015) | (0.007) | (0.011) | (0.011) | (0.547) | (0.150) |
| MCOMPETE3 | −0.187** | 0.012* | 0.025* | 0.028* | −2.436* | −0.065 |
| | (0.066) | (0.006) | (0.010) | (0.011) | (1.205) | (0.092) |
| IMMVOL*MATURITY091 | 0.071** | 0.053** | 0.058** | 0.080** | 2.767** | 1.297** |
| | (0.016) | (0.010) | (0.011) | (0.010) | (0.697) | (0.225) |
| IMMVOL*MATURITY182 | 0.023* | 0.010 | 0.021** | 0.025** | 1.554** | 0.751** |
| | (0.010) | (0.007) | (0.006) | (0.006) | (0.310) | (0.168) |
| IMMVOL*MATURITY364 | 0.020 | 0.004 | 0.015 | 0.023 | 0.950* | −0.061 |
| | (0.015) | (0.015) | (0.013) | (0.014) | (0.378) | (0.320) |
| LOG(SUPPLY) | −0.011 | 0.007 | −0.056* | −0.086** | 0.468 | 3.476** |
| | (0.040) | (0.033) | (0.028) | (0.030) | (1.657) | (0.869) |
| RESERVE_DAYS | −0.016** | −0.016** | −0.012 | −0.010 | −0.219* | −0.348** |
| | (0.005) | (0.005) | (0.007) | (0.007) | (0.086) | (0.096) |
| WILL_REOPEN | −0.142** | −0.135** | −0.112** | −0.106** | −6.335** | −6.615** |
| | (0.040) | (0.041) | (0.035) | (0.036) | (1.381) | (1.318) |
| MATURITY182 | −0.081 | 0.022 | 0.018 | 0.020 | −3.557** | −1.869* |
| | (0.042) | (0.028) | (0.040) | (0.043) | (1.243) | (0.735) |
| MATURITY364 | −0.126* | 0.042 | 0.000 | 0.037 | −4.725** | −0.792 |
| | (0.053) | (0.046) | (0.047) | (0.050) | (1.721) | (1.558) |
| REGIME1 | −0.155 | −0.111 | −0.166** | −0.163** | −1.563 | 0.425 |
| | (0.108) | (0.100) | (0.035) | (0.035) | (2.238) | (1.835) |
| REGIME2 | −0.030 | −0.133 | −0.154** | −0.129** | 0.887 | −0.982 |
| | (0.066) | (0.072) | (0.034) | (0.036) | (1.449) | (1.432) |
| CAP_BOUND | 0.179** | 0.017 | 0.140** | 0.149** | 11.193** | 3.291** |
| | (0.063) | (0.030) | (0.031) | (0.033) | (2.820) | (0.805) |
| Observations | 6353 | 6353 | 5005 | 6355 | 6353 | 6353 |
| Number of bidders | 61 | 61 | 22 | 63 | 61 | 61 |

a: Standard errors are in parenthesis. Symbols * and ** indicate statistical significance at 5% and 1% levels, respectively.

b: Standard errors are Wooldridge (1990) distribution and heteroscedasticity-robust.

c: Third column estimated with fixed effects. Fourth column estimated with dummies for bidder type.

variables listed in Appendix B as well as the number of bidders of each type that participated in the previous auction of the same maturity and the squares of these three lagged M_TYPE variables. To maintain the spirit of "large $T$," as well as for computational ease, I restrict the sample to the 22 bidders who appear in at least 100 auctions. An alternative is to replace the bidder fixed effects with bidder type dummies and run a NL2SLS Poisson estimator on the full sample of participating bidders. Results, shown in the third and fourth columns of Table 5, are similar to the HHG results, except that the coefficients on MCOMPETE3 are now positive and significant, though still much smaller than the MCOMPETE1 coefficients.

In the second set of regressions, the dependent variable is BIDSPREAD. This variable is non-negative by construction, and equal to zero in 30% of the observations. If the underlying "interest" in spreading one's bids is thought of as a latent index, linear in the regressors, then BIDSPREAD (which cannot be made negative when the latent index is negative) can be viewed as a censored observation of an unobserved $y^*$, specified as

$$y^*_{ti} = \alpha_i + x_{ti}\beta + \text{LOGQ}_{ti}\gamma_i + \epsilon_{ti} \tag{4}$$

where $x_{ti}$ is a row vector of independent variables. The $\epsilon_{it}$ are independently and symmetrically distributed random variables with mean zero, and independent of all regressors, except possibly LOGQ. As in the Poisson regressions, the endogeneity of LOGQ is due to dependence in the errors of the form $\epsilon_{ti} = v_{ti}\rho + u_{ti}$ and is eliminated by inclusion of $\hat{v}_{ti}$ from equation (1).[32] I estimate this panel SCLS specification using Honoré (1992) and report the results in the last two columns of Table 5.[33] Estimated coefficients are qualitatively consistent with each other and the coefficients for the BIDCOUNT regressions.

[32] Indeed, this technique was first developed for use in the Tobit estimator by Smith and Blundell (1986). Newey (1985) extends the method to a wide class of semi-parametric limited dependent variable models, which includes the SCLS Tobit.

[33] I gratefully acknowledge the use of FORTRAN routines for the panel Tobit estimator by Bo Honoré, which he has made available in the public domain. The reported coefficients are for the quadratic loss function estimator, denoted $\beta_4$ in his paper, optimized for unbalanced panels.

### 5.4 Robustness checks

A maintained assumption thus far is that the decision to participate in the auction is taken as exogenous by the manager setting the bids, even if the total quantity bid is not. To test the robustness of the coefficients to this assumption, I run a fixed effect Poisson model for BIDCOUNT which includes non-participants as BIDCOUNT=0; that is, I assume that the decision to submit any bids at all is governed by the same statistical process which determines the use of multiple bids.[34] Overall, the coefficients and standard errors for these regressions are numerically quite similar to those reported in Table 5.

BIDSPREAD can be measured in different ways. Instead of excluding the upper and lower 15% of quantity submitted, we can exclude the upper and lower 25%. Another alternative is the quantity-weighted standard deviation of the bid rates. Both yield qualitatively similar results. Results also are robust to the choice of specification. I have run Tobit and SCLS estimators with bidder dummies on the restricted sample used in the third column of Table 5. As the SCLS cannot be estimated with instruments, I have also tried linear IV fixed effects specifications.

Results are also robust to the measurement of market volatility. I have varied the length of the measurement window from three to ten days before auction, and have tried an index of volatility based on rates on 28–32 day IMM loans instead of overnight loans.[35] I have also run regressions on a subsample which excludes days for which IMMVOL is greater than five percentage points.

Bidders may sometimes enter "throw-away" bids, i.e., very high rate bids not expected to have a significant chance of winning. As these bids are unlikely to alter the bidder's expected payoff by very much, it is desirable to construct versions of BIDCOUNT and BIDSPREAD which exclude throw-aways. I have tried this using several criteria, e.g., bids over one percentage point higher than the IMM 28–32 day benchmark, or bids over one percentage point higher than the ex-post realized stopout rate. Coefficients are robust in all cases, and indeed often larger and statistically stronger. However, if I form the dependent variables using only *winning* bids, results become very weak and unstable across specifications. This is perhaps unsurprising, as this selection criterion is

[34] Technically, the specification is as in equation (2), except that 1 is no longer added to the right hand side. The coefficients for the first stage regression for LOGQ (now redefined as the log of 1 plus the total quantity submitted) are qualitatively similar to those in Table 3.

[35] This maturity is short enough to provide sufficient liquidity for the construction of an index of volatility, but long enough that it should not be affected greatly by the micro-mechanics of the eight day reserve periods; the correlation of this index with IMMVOL is 0.61.

inseparable from the risk that multiple bids are intended to hedge.

## Conclusion

Bidding data from Portugal's treasury bill auctions are used to examine bidders' use of multiple bids. Evidence is provided for the hypothesis that multiple bids are used to hedge the risk of winner's curse. Both the number of bids per bidder and the dispersion among a bidder's bids increase with the volatility of market rates (hypothesis H1) and with the expected number of competing well-informed bidders (hypothesis H2). Contrary to some previous findings in the empirical and experimental literature, these bidders appear at least to be aware that the potential for winner's curse increases with the number of competing bidders.[36] Results are robust to model specification and definitions of both dependent and independent variables.

Bidders in these auctions, although mainly large banks, appear to be risk averse. They are less likely to participate and, if they do participate, demand smaller quantities when market rates are volatile. This finding is contrary to the usual assumption of risk neutrality in theoretical studies of treasury auctions. Furthermore, a larger number of bids per bidder is found to be associated with higher per-unit revenue for the seller, which suggests that bidders use multiple bids to shift to a lower variance, lower return bidding strategy when the risk of winner's curse is greater.

The intuition of multiple bidding as a hedging mechanism has empirical support, but remains underdeveloped as a theoretical conjecture. Theoretical analysis of multiple-bid auctions is formidably complex, though it is now an area of increasingly active research. These empirical results may provide a useful direction for further progress.

[36] Unfortunately, without prices from a liquid secondary market, I cannot test whether bidding strategies adjust fully, or whether winner's curse is indeed observed when the number of bidders is large.

## A Explanatory variables

Variables of primary interest:

| | | |
|---|---|---|
| M_TYPE1<br>M_TYPE2<br>M_TYPE3 | $(t)$ | Number of bidders of each type at auction $t$. Type 1 are the largest, most regular bidders. Type 3 are the smallest, least regular bidders. |
| MCOMPETE1<br>MCOMPETE2<br>MCOMPETE3 | $(t, i)$ | Expected number of bidders of each type competing against bidder $i$ at auction $t$. Depending on beliefs on bidders' ex-ante knowledge, these are formed using either ex-post realized values or predicted values from Logit regressions for bidder participation. |
| IMMVOL | $(t)$ | Interbank money market volatility. Standard deviation of overnight rates in the seven trading days prior to auction. |

Controls for bid quantity:

| | | |
|---|---|---|
| LOGQ | $(t, i)$ | Log of total quantity, in millions of escudos, on bids by bidder $i$ at auction $t$. |
| VHAT | $(t, i)$ | Estimated residual in equation (1). Included to eliminate endogeneity of LOGQ. |

Other control variables (* indicates a note following the table):

| | | |
|---|---|---|
| LOG(SUPPLY) | $(t)$ | Log of the issue ceiling (in millions of escudos). |
| WILL_REOPEN* | $(t)$ | Dummy indicates auction followed by an additional session. |
| RESERVE_DAYS* | $(t)$ | Number of trading days remaining in the banks' reserve cycle on the issue date. |
| MATURITY091<br>MATURITY182<br>MATURITY364 | $(t)$ | Dummies for maturity of bills for auction. Excluded category is 91 day bills. |
| REGIME1*<br>REGIME2<br>REGIME3 | $(t)$ | Dummies for reservation rate policy regimes. In REGIME1 (pre-1990), reservation rate is fairly volatile and changes have little correlation with changes in the IMM rate. In REGIME2 (1990/1/1–1992/4/6), reservation rate rarely changes at all, despite high volatility on IMM. In excluded category REGIME3 (1992/4/6 onward), reservation rate changes frequently and in tandem with IMM rates. |
| CAP_BOUND* | $(t)$ | Dummy indicates reservation rate strictly binding at previous auction of same maturity bills. |

**Notes:**

**Issue size:** All else equal, a larger issue size reduces the severity of the winner's curse. For a given set of bid quantities, an increase in LOG(SUPPLY) increases the number of winning bids, so winning contains weaker negative information on the accuracy of one's signal. This effect may be offset if bidder quantity demand is endogenous.

**Bank reserve cycle:** IMM volatility tends to increase towards the end of a reserve cycle, so an obligation to purchase bills at that time carries greater risk.

**Additional sessions:** It is not clear whether the bidders knew before an auction whether an additional session would be held. However, this feature was used almost exclusively in a thirteen month subperiod of the sample, and most auctions in that subperiod were followed by an additional session; therefore, I assume that bidders regard WILL_REOPEN as known and exogenous. WILL_REOPEN is likely to affect bidding in two ways. The ability to obtain some desired quantity at the additional session (which sells bills at a rate that incorporates information from all the bidders) reduces the risk of winner's curse. However, it may facilitate bidder collusion in the primary auction.

**Reservation rate policy regimes:** The predictability of the reservation rate varied considerably over the sample period. I include REGIME dummies because uncertainty over the reservation rate might affect multiple bidding for a variety of possible reasons. If bidders attempt to use the reservation rate as a focal point for collusion, then predictability in the reservation rate facilitates coordination, which reduces the desirability of submitting multiple rates. If the reservation rate is indicative of government interest rate targets, then uncertainty over the reservation rate will coincide with greater uncertainty regarding future interest rates. See Gordy (1994) for more detailed discussion.

I have no specific information on formal reservation rate policy changes during the sample period. Somewhat arbitrarily, I divide the first and second regimes by the seven week period in 1990 for which I have no IMM data. The division between the second and third regimes is naturally made at the date on which Portugal joined the ERM (April 6, 1992). This was an unexpected and extremely important macroeconomic event, and it is reasonable to expect that a variety of policy changes may have been made by the Ministry of Finance at the same time.

**Reservation rate tightness:** Bidding strategies may be affected by how tightly the reservation rate is expected to bind. Bidder use of multiple bids could increase with CAP_BOUND for a number of reasons, e.g., to place bounds on the new reservation rate if it is loosened, or to signal with high rate bids to the Ministry of Finance that the reservation rate is too low. Quantity sold is announced after each auction, and will be less than the issue size only if the reservation rate was strictly binding, so CAP_BOUND is public knowledge.

Table 6: Auction Level Independent Variables

| | Min | Max | Mean | StdDev |
|---|---|---|---|---|
| IMMVOL | 0.057 | 22.150 | 2.060 | 2.854 |
| M_TYPE1 | 0 | 13 | 8.065 | 3.463 |
| M_TYPE2 | 0 | 12 | 3.414 | 2.895 |
| M_TYPE3 | 0 | 10 | 2.013 | 2.062 |
| LOG(SUPPLY) | 9.105 | 12.073 | 9.942 | 0.431 |
| WILL_REOPEN | 0 | 1 | 0.167 | 0.373 |
| RESERVE_DAYS | 0 | 6 | 2.173 | 1.566 |
| MATURITY182 | 0 | 1 | 0.422 | 0.494 |
| MATURITY364 | 0 | 1 | 0.186 | 0.389 |
| REGIME1 | 0 | 1 | 0.283 | 0.451 |
| REGIME2 | 0 | 1 | 0.546 | 0.498 |
| CAP_BOUND | 0 | 1 | 0.485 | 0.500 |
| Number of auctions: 474 | | | | |

Table 7: Means by Maturity

| | Maturity | | |
|---|---|---|---|
| | 91 | 182 | 364 |
| M_TYPE1 | 7.15 | 8.57 | 8.85 |
| M_TYPE2 | 3.93 | 3.01 | 3.24 |
| M_TYPE3 | 2.52 | 1.70 | 1.66 |
| SUPPLY[a] | 20.7 | 23.2 | 28.4 |
| WILL_REOPEN=1 | 0.10 | 0.17 | 0.30 |
| CAP_BOUND=1 | 0.49 | 0.46 | 0.53 |
| Number of Auctions | 186 | 200 | 88 |

a: In billions of Portuguese escudos, where one billion escudos is approximately $7.75 million. Logged value used in regressions.

## B Instruments for MCOMPETE and LOGQ

Proxies for excess cash in the banking system:

| | | |
|---|---|---|
| PRORATA | $(t)$ | Pro rated share allocated to bids made at the stopout rate in the last auction of bills of the same maturity. A higher share, all else equal, implies that bidders will have less excess cash for use at the present auction. Note that PRORATA is known to any bidder who had a bid at the stopout in the last auction, but I assume it is learned by the other bidders as well. |
| SAMEDAY | $(t)$ | Dummy indicating there will be an auction for bills of another maturity later on the same day. As bills of different maturities are only partial substitutes, bidders may wish to reserve cash for the later auction. |
| DAYS:ANY<br>DAYS:OWN | $(t)$ | Number of trading days since the previous auction of treasury bills of any and of the same maturity, respectively. *Ceteris paribus*, the greater the elapsed time since previous auctions, the greater the excess cash in the system. |

Proxies for a bidder's liquidity position:

| | | |
|---|---|---|
| DAYSINCE | $(t, i)$ | Let LAG$(t, i)$ index the most recent auction before $t$ at which bidder $i$ participated. Then DAYSINCE is the number of calendar days between $t$ and LAG$(t, i)$. All else equal, the longer the gap since a bidder's last participation, the greater the excess cash available for use in this auction. |
| LAGLOGQ | $(t, i)$ | LOGQ(LAG$(t, i), i)$. As excess liquidity is likely to be serially correlated, LAGLOGQ is likely to be positively correlated with the cash amount currently available for bidding. |
| UNFILLED | $(t, i)$ | Proportion of LAGBIDQ$(t, i)$ which was not won. The higher this portion, the more cash remaining for use at this auction. |

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