Bidding and Performance in Repo Auctions: Evidence from ECB Open Market Operations[1]

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Abstract

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Repo auctions are used to inject central bank funds against collateral into the banking sector. The ECB uses standard discriminatory auctions and hundreds of banks participate. The amount auctioned over the monthly reserve maintenance period is in principle exactly what banks collectively need to fulfill reserve requirements. We study bidder-level data and find: (i) Bidder behavior is different from what is documented for treasury auctions. Private information and the winner's curse seem to be relatively unimportant. (ii) Underpricing is positively related to the difference between the interbank rate and the auction minimum bid rate, with the latter appearing to be a binding constraint. (iii) Bidders are more aggressive when the imbalance of awards in the previous auction is larger. (iv) Large bidders do better than small bidders. Some of our findings suggests that bidders are concerned with the loser's nightmare and have limited amounts of the cheapest eligible collateral.
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1 Introduction

In central bank repo auctions, banks submit bids for borrowing central bank funds on a collateralized basis. These are among the most economically significant multiunit auctions in practice. They are widely used to conduct open market operations and are at the heart of the money markets in many countries or currency areas. For example, the Federal Reserve Bank holds daily repo auctions for several billion dollars each and the European Central Bank (ECB) holds weekly repo auctions with an average size of almost 300 billion euros where hundreds of banks participate. The primary concerns for central banks in repo auctions are to inject the right amount of central bank money to ensure that the short term interbank rate stays around the target level and that banks can cover their liquidity needs, including satisfying reserve requirements. An important reason that banks participate in the auctions is that the funds are needed to satisfy reserve requirements. In this paper, we study repo auctions empirically using bidder level data from the ECB. Our aim is to map out the key economic features of repo auctions with respect to bidding and auction performance. Our findings should provide useful inputs to theorists aiming to build realistic models of these auctions and to the policy makers who design them. The paper also provides an overview of the role repo auctions play in the implementation of monetary policy in the euro area.

Our dataset includes each individual bidder's set of bids in 53 consecutive ECB repo auctions, starting in June 2000 when the ECB switched from fixed rate tenders to discriminatory (pay your bid) auctions.[1] All bids are for two-week money and specify a quantity and a borrowing rate. Unique bidder codes allow us to follow each bidder over time. There are no "customer bids." This allows a potentially less noisy inferences on bidder behavior than what has been possible in the treasury auction literature (see, e.g, Nyborg, Rydqvist, and Sundaresan, 2002). The auctions follow a regular cycle; there is one every Tuesday morning. Thus there are up to five regularly scheduled repo auctions within each monthly reserve maintenance period and at any time there are two sets of repos outstanding. Each auction is timed to coincide with the repayment of loans from a previous auction, providing banks with the opportunity to refinance when loans fall due. Indeed, the repo auctions we

[1] The ECB's fixed rate tenders are studied empirically by Breitung and Nautz (2001). Nyborg and Strebulaev (2001) develop a theoretical model.

study are officially known as the ECB's *main refinancing operations.*

There are four broad themes to our analysis. First, we compare and contrast bidder behavior and auction performance in repo auctions with what has been documented in treasury auctions [e.g. Nyborg, Rydqvist, and Sundaresan (2002)]. These important multi-unit auctions are similar in terms of design and in having active secondary markets for the auctioned assets. Nevertheless, the dominant economic issues are potentially quite different. In treasury auctions, primary dealers buy to resell. The empirical evidence shows that bidders are less aggressive and underpricing is larger as volatility increases, suggesting that bidders have private information about the resale value and adjust rationally for the winner's curse [Cammack (1991), Nyborg, Rydqvist and Sundaresan (2002)].[2] In repo auctions, bidding banks may be more concerned with covering their liquidity needs than turning a profit; they may be more concerned with the loser's nightmare than the winner's curse (Nyborg and Strebulaev, 2004). Furthermore, the wide range of eligible collateral may lead bidders to be willing to pay a larger rate for the first units they win, if the cheapest eligible collateral is scarce.

We find that as volatility increases, bidders shade their bids less and underpricing falls. This is the opposite of the treasury auction finding. It suggests that private information and the winner's curse are not so important in repo auctions. Other tests we carry out support this view. The negative effect of volatility on discounts (bid shading) and underpricing may reflect that bidders *need* the funds from the auction to satisfy reserve requirements and are risk averse with respect to the alternative of borrowing in the interbank market. Such risk aversion could arise because of limited depth in the interbank market or because short banks fear being squeezed (the loser's nightmare). Another contrast with treasury auctions [Nyborg, Rydqvist, and Sundaresan (2002)] is that auction size matters; discounts and underpricing are increasing in auction size. This is consistent with there being a shortage of the cheapest eligible collateral.

Second, we examine the impact on bidding and performance of other exogenous variables that seem particularly pertinent to the ECB's repo auctions. The variable that has the most significant explanatory power is the level of the two week interbank rate relative to the auction's minimum bid rate. As the spread between these two rates fall, bidders

[2]See also Bjønnes (2001) and Keloharju, Nyborg, and Rydqvist (2005).

shade less, disperse less, and submit fewer bids. Bidders also start dropping out of the auction. These findings suggest that the minimum bid rate is a binding constraint. This may reflect collateral considerations, but can also reflect expectations that the ECB will lower the minimum bid rate in time for the next auction. We also find evidence that bidders become more aggressive when award ratios (award as a percentage of demand) in the previous auction were more dispersed across bidders. This is consistent with the loser's nightmare being important; a theoretical model by Nyborg and Strebulaev (2004) shows that bidders are more aggressive when short positions are more pronounced, because the costs of being squeezed and the benefits from squeezing are larger. That awards from the previous week's auction affect bidding in the current auction suggests not only that positions matter, but that borrowing in the interbank market is not a perfect substitute for borrowing in the auction. The interbank market does not appear to be sufficiently frictionless so as to iron out any imbalances with respect to reserves that may have originated from the previous auction.

Third, we examine the intertemporal behavior of bidders. Since there are up to five auctions within each reserve maintenance period, bidders have a choice as to which auctions to bid in. We find that banks "cycle"; that is, they participate more heavily every second auction. This could be consistent with a loser's nightmare story. The idea is that if a bank borrowed heavily two auctions ago, it will have a large refinancing need in the current auction (unless it has taken countervailing trades in the meantime) and therefore bids aggressively. Supporting this, we find some evidence that bidders' are relatively more aggressive when they received relatively large awards two auctions ago. Cycling could also be consistent with bidders being collateral constrained since collateral that was used in last week's auction may not be available for this week's auction.

Fourth, we study differences in bidding behavior and performance among differently sized bidders. An important feature of the ECB's repo auctions is that there are hundreds of bidders, from large international banks to small local cooperatives. We document that large bidders systematically borrow at lower rates in the auctions than small bidders. The explanation for this is twofold; large bidders submit bids at lower rates and, as a group, their bids are less dispersed than small bidders. These findings are consistent with the view that small bidders have poorer access to the interbank market, but could also be driven by differences in the collateral held by small and large bidders.

We also examine large and small bidders' role in the phenomenon known as underbidding, where banks demand less in aggregate than what they collectively need to satisfy reserve requirements.[3] Underbidding is viewed as a problem from the ECB's perspective because it disrupts the implementation of monetary policy and leads to an increase in the volatility of interbank rates. It is also costly for the banking sector since the liquidity shortfall must be made up by borrowing at the ECB's lending facility, which is 100 basis points above the minimum bid rate in the auction. Banks that borrow more in the auction than what they need to satisfy reserve requirements provide a positive externality to other banks, since this reduces the collective recourse to the use of the lending facility. So underbidding is fundamentally a free-riding problem; when rates are expected to fall, each bank is relying on other banks to borrow sufficiently much in the auction to allow the bank to obtain the reserves it needs in the interbank market at a reduced rate once the ECB announces lower rates for the future. Standard externality arguments [Olsen and Zeckhauser (1966), Bergstrom, Blume, and Varian (1986)], would suggest the underbidding problem to be driven by smaller banks free-riding on larger banks. Instead, we find something of a reverse free-rider problem; in the underbid auctions, the largest bidders cut back demand more than the smallest ones. This supports the view that small bidders are more fearful of getting a smaller allocation in the auctions than large bidders because they have poorer access to the interbank market.

The rest of this paper is organized as follows. Section 2 describes the data and the role of the auctions in the ECB's operational framework. Section 3 raises some theoretical considerations. Section 4 contains the main empirical analysis, and Section 5 studies differences in behavior between large and small bidders. Section 6 concludes. An appendix contains the estimation of the conditional volatility of the two-week rate.

[3]ECB (2003, p.42) defines underbidding as "...the submission by credit institutions of aggregate bids which fall short of the amount needed to allow for a smooth fulfillment of reserve requirements in the period until the next MRO [main refinancing operation] is conducted." To try to deal with the underbidding problem, in November 2001 the ECB switched from a bi-monthly to a monthly review of the minimum bid rate. This did not help; since then, several more auctions were underbid. In March 2004, the ECB implemented more substantial changes (see Section 5.2).

2 Data and Markets

2.1 Background

The repo auctions we study in this paper are the ECB's main open market operations and are used to inject liquidity into the banking sector. Besides the repo auctions, there are two additional core features of the ECB's operational framework.[4] First, the ECB requires banks in the euro area to hold minimum reserves as an average over the reserve maintenance period.[5] These requirements are announced at the beginning of each maintenance period and the bulk of the reserves are then supplied through the repo auctions (ECB, 2002a). Second, at any time, banks can obtain overnight credit (against collateral) through the marginal lending facility and they can make deposits at the deposit facility. These rates are 100 basis points above and below, respectively, the minimum bid rate in the auction, making the auctions a more attractive source of liquidity for banks. Because the auctions are the main source of reserves for banks and because they *must* satisfy reserve requirements, banks have a need to participate in the auctions. Banks that do not obtain sufficient reserves in the auctions and cannot find what they need in the interbank market, *must* make up the shortfall at the end of the reserve maintenance period by borrowing at the lending facility or pay a penalty of 250 basis points relative to the lending rate.

Short term interbank rates are influenced by the size of the auctions relative to reserve requirements. If the auctions are "small" so that at the end of the maintenance period liquidity is in short supply, banks will have to use the marginal lending facility and the overnight rate will rise. On the other hand, if the auctions are "large" so that liquidity is abundant, banks will have to use the deposit facility and the overnight rate will fall. The ECB's policy is to steer liquidity conditions in a neutral way; that is, to adjust auction volumes so that banks can be expected to precisely fulfill their reserve requirements over the monthly period and so that aggregate reserve surpluses and deficits are equally likely (ECB, 2002b). There is some residual uncertainty, however, because it is difficult to exactly forecast exogenous flows to and from the banking sector, for example due to the collection of taxes or changes in the circulation of banknotes, and because the last auction in each maintenance period is usually held a few days before the end of the period. As

[4]For a more detailed account, see ECB (2002a) or Bindseil (2004).

[5]During the sample period, a new reserve maintenance period starts on the 24th of each month.

a result, at the end of the maintenance period the overnight rate typically either spikes up or down, as documented by Hartmann, Manna, and Manzanares (2001) or Figure 1. Under a liquidity neutral policy, fluctuations in the overnight rate can occur because of expectations of changes to the minimum bid rate and the standing facilities or because of changes in the relative market power between banks that are short and long reserves relative to their average requirements.

2.2 The Auctions

For this study, the ECB compiled a file with individual bidding data and summary statistics for its main repo auctions over a one year period, starting with the auction held on 27 June 2000 and ending with the auction held on 26 June 2001. The dataset contains the complete set of bids, broken down by bidder, in all 53 main repo auctions (main refinancing operations) held during this period. The auctions are scheduled well in advance; the intended timing of all regular operations in a year are announced three months before the start of the year. There is a main refinancing operation every week, each with a tenor of two weeks.[6] The terms are typically announced on Mondays, 3.30 pm through wire services, and the deadline for submitting bids is typically on Tuesdays, 9:30 am. Results are announced the same day at 11:20 am. Winning bids are settled the following business day. In each auction, each bidder can submit up to 10 bids which are rate-quantity pairs for two week money. The tick size is 1 basis point and the quantity multiple is 100,000 euros. Unlike US Treasury auctions, for example, there are no non-competitive bids. In total, our sample contains 29,833 individual demand schedules from 1,199 different bidders, coming from all twelve euro area countries. The auctions are all discriminatory. The data covers 12 complete reserve maintenance periods. The last auction in the dataset is the first auction in the 13th period.

Bidders' ability and willingness to participate in the auctions depend on the collateral that they hold. There are two tiers of eligible collateral (ECB, 2002a). Tier one consists of marketable debt instruments fulfilling uniform euro area-wide eligibility criteria (mainly

[6] Once a month, the ECB also holds *longer-term refinancing operations* with a maturity of three months. We do not study these auctions. The ECB may also hold non-regular, fine-tuning operations with non-standard maturities, for example overnight, but none occurred during the sample period.

Government bonds and covered bonds issued by banks). Tier two consists of other "marketable" securities, predominantly debt instruments such as CD's, but equity has also been used, and "non-marketable" assets such as bank loans. Tier two eligibility criteria are established by each national central bank, subject to approval by the ECB. The range of eligible collateral for the auctions is thus much wider than for interbank repos, where essentially only government bonds can be used. The eligible collateral that cannot be used in interbank repos may have a relatively low opportunity cost and may thus be preferred by bidders. As an example, in December 2000, government bonds comprised 58% of eligible collateral, with bank bonds making up 31%; but government bonds only comprised 39% of the collateral that was pledged in the auctions, with bank bonds constituting 50% (ECB, 2001b). Different eligible collateral may also have different opportunity costs since it is difficult for the central banks to make haircuts perfectly equilibrating. Collateralisation techniques vary across the euro area. In a majority of countries, national central banks operate a pooling system whereby counterparties open a pool account to deposit assets, the total value of which collateralises all their borrowing from the central bank. A minority of national central banks operate an earmarking system whereby collateral is individually earmarked to each ECB repo operation.

An important feature of the auctions is the minimum bid rate, which is strictly enforced and announced in advance. This reservation rate was changed only three times during the sample period. It started out at 4.25%, changed to 4.5% in time for the 5 September 2000 auction, then increased to 4.75% in time for the 11 October 2000 auction, and finally fell back to 4.50% for the auctions held on and after 14 May 2001. The minimum bid rate and the standing facilities in force throughout the sample period are illustrated in Figure 1. Although the standing facilities and the minimum bid rates were stable for long periods, they were in principle subject to change at the meetings of the ECB's Governing Council, normally held on the first and third Thursday of each month during the sample period.

The auctions are subject to relatively little supply uncertainty. With the auction announcement, the ECB also publishes an estimate of liquidity needs for the entire banking sector for the following week. Given the ECB's neutral allotment policy, this provides bidders with an unbiased estimate of the auction size. We refer to this liquidity neutral amount as the expected auction size. However, the ECB does not commit itself to a particular auction size, and it happens that the realized auction size differs from the expected size (see Figure 2). The mean expected size is 89.6 billion euros and the mean realized size is 88.9 billion euros. Some of the difference reflects updates in the ECB's liquidity forecasts after the auction announcement. But the largest differences are caused by the two underbid auctions (numbers 34 and 42). The standard deviation of the size surprise is 5.8 billion euros (1.7 billion if excluding the two underbid auctions). The absolute value of the difference is 1 billion euros or less in 29 auctions. Thus deviations from the expected auction size tend to be relatively small.

The number of bidders in each auction varies from 240 to 800. Figure 3 provides a histogram of the frequency of participation across bidders. 29 bidders participate in all 53 auctions and 101 bidders participate in only one auction. Table 1 provides participation statistics on a per maintenance period basis. Panel (a) shows, for example, that 2,938 individual bidder demand schedules are submitted in the first maintenance period and 2,441 of these include winning bids. In the 12th maintenance period, these numbers fall to 1,814 and 1,524, respectively. The number of bidders in the first period is 949, but only 623 in the 12th period. Panel (b) shows that slightly more than a third of the banks in the sample bid in an auction in every maintenance period and slightly more than a fourth receive a positive auction allotment every maintenance period. The averages are 7.861 and 7.279 periods, respectively. Panel (c) shows that across banks the average number of auctions where they bid is 24.9 and the average number of auctions where they win some units is 20.2. Finally, the downward time trend in the number of bidders during the sample period is illustrated on an auction by auction basis in Figure 4. In the first auction, there are 800 bidders and in the last auction, there are only 452.

The bidders in the auction are small compared with the auction size. The average bidder demands only .37% of the expected auction size. Bidders are also very heterogeneous. On average, the largest bidder receives 6.8% of awards, with a maximum of 26.6%. On average, 64.6% of bidders in a given auction submit multiple bids. The distribution of the number of bids within individual bidder demand schedules is in Figure 5. The mode is 1, the median is 2, and the mean is 2.4.

2.3 The Secondary Market

Secondary market rates provide a measure of the opportunity cost of borrowing in the auction. We use them to calculate discounts (bid-shading) and underpricing. The level of secondary market rates relative to the minimum bid rate may also affect bidder behavior. Since the funds obtained in the auctions have a two week tenor, we are particularly interested in two week rates. We are also interested in longer term rates in order to compute forward rates, from which we can gauge rate expectations.

We use the two week Eonia swap rate to benchmark the auctions. The Eonia (euro overnight index average) is an overnight rate computed as a weighted average of all overnight unsecured lending transactions in the interbank market initiated within the euro area by a set of panel banks. The Eonia is calculated on a daily basis by the ECB on behalf of the European Banking Federation. It is a widely used reference rate and is the euro equivalent to the federal funds rate in the US. Like the fed funds rate, the Eonia is highly volatile compared with other short term rates (see Figure 1). The two week Eonia swap provides banks with a way to hedge the risk from borrowing overnight over a two week period. The counterparty that pays the fixed leg receives the Eonia rate. Cash flows are nominally exchanged every day, but money does not physically exchange hands before the two weeks are up. By going short (paying fixed) the swap, a bank creates a nearly perfect hedge against borrowing on a daily basis in the interbank market. Thus an alternative to borrowing in the auction is to short the swap and borrow on an overnight basis over two weeks. The Eonia swap market is one of the most liquid segments of the euro area money markets.[7] The other two main two week contracts, deposits and interbank repos, are less liquid. Furthermore, the deposit rate is for unsecured loans and is therefore not directly comparable with borrowing in the auction, which is collateralized. The interbank repo rate is also not comparable, since it is possible to use considerably cheaper collateral in the auction than in an interbank repo, for example mortgage bonds and bank loans. Due to the low credit risk, high liquidity, and good hedging properties of the Eonia swap contract, the two week swap rate is arguably the most appropriate two week rate in terms of benchmarking the auction. This is consistent with the views expressed by traders we

[7] See ECB (2001a), which also documents that the one week to one month maturity range is the one with the highest turnover in the Eonia swap market.

have interviewed. But no interbank contract is a perfect match to the loans in the auction.[8] So we will also provide some statistics on how bidding in the auction compares to the deposit and repo rates.

Bid and ask quotations for the three two week rates were recorded from Reuters pages at 9:15 am every day throughout the auction sample period. The swap series, which we also use to compute secondary market conditional volatility, runs from 4 January 1999 to 2 July 2001. The bid-ask spread for the swap rate tends to vary between 2 and 3 basis points. Deposit and repo rate spreads are around 5 to 6 basis points. The mid-point of the bid and ask quotes is taken to be the best estimate of actual transaction rates.

Finally, we use Euribor (Euro Interbank Offered Rates) to compute forward rates. Euribor are important reference rates for interbank term deposits and is computed using the average rates quoted at 10:45 am every day by the same panel banks as for the Eonia. To gauge rate expectations, we use the one and two month rates to calculate the one month forward rate (the one month rate one month from today to two months from today). This forward rate is chosen because it is the shortest one we can calculate that avoids overlap with the current reserve maintenance period. Thus it reflects rate expectations rather than current liquidity conditions.

Figure 1 depicts the swap, deposit, 1 month forward, and the Eonia rates during the auction sample period.[9] The spikes and troughs in the Eonia are related to the end of the reserve maintenance period (see above). The figure shows that our sample period covers a period of rising as well as falling rates and rate expectations. This is fortuitous, since it allows us to examine the extent to which bidder behavior and performance is affected by the direction of rate expectations. One might expect this to matter, perhaps because of the presence of the minimum bid rate.

3 Theoretical Considerations

In this section, we discuss the theoretical ideas that have motivated the empirical analysis below or have influenced how we interpret our results.

[8] Although the Eonia swap itself has very low credit risk, the Eonia is an unsecured overnight rate and therefore contains credit risk, albeit less than a two week deposit contract.

[9] The repo rate tracks the swap and deposit rates. It is therefore omitted from the figure.

Winner's Curse

There is a strong common values element to the ECB's repo auctions since there is a very active and competitive secondary market for two week funds. If players have private information about post-auction secondary market rates, they face the winner's curse. We would expect rational bidders to adjust for the winner's curse by bidding more cautiously when uncertainty increases [Wilson (1977), Milgrom and Weber (1982)]. We would therefore expect to see bidders respond to an increase in volatility by decreasing the rates at which they bid and perhaps also the quantity they demand, as discussed by Nyborg, Rydqvist, and Sundaresan (2002) in the context of treasury auctions. Thus, under the hypothesis that bidders have private information about post-auction rates and adjust rationally for the winner's curse, discounts and underpricing should be increasing in volatility.[10]

Collateral: Private Values and Downward Sloping Demand

The requirement to provide eligible collateral may introduce a private values component to the auctions. There is a wide range of eligible collateral and different banks may hold different types having different opportunity costs. Additionally, banks may face collateral constraints in the sense that they have to use increasingly expensive collateral as the auction size grows. Thus the collateral requirement may induce downward sloping demand curves at the individual bank level and in the aggregate. If banks are collateral constrained, we would expect to see an increase in auction size to lead to more bid-shading, more bid dispersion, less quantity demanded, and more underpricing.

The Loser's Nightmare

The liquidity neutral policy of the ECB means that at any given point in time, some banks are running reserve deficits relative to their average daily reserve requirements, while others are running surpluses. Whether a bank is short or long reserves is to a large extent subject to exogenous shocks. For example, a bank may suddenly find itself short of liquidity because of large withdrawals. Short banks that do not obtain adequate funds in the auction may risk being squeezed in the interbank market; they may be charged an above fair market borrowing rate. That is, they face the loser's nightmare [Simon (1994), Nyborg and Sundaresan (1996)]. Since banks can always borrow (against collateral) at the

[10] An exception (with respect to underpricing) could occur if the seller reduces the auction size when bidding is weaker, something which the ECB does not do.

ECB's marginal lending facility, the loser's nightmare costs a bank at most 100 basis points per unit it is short. Banks may therefore have target amounts in the auction in order to reduce their reliance on the secondary market and exposure to the loser's nightmare.[11] In a theoretical model that captures this idea, Nyborg and Strebulaev (2004) show that when there is a bigger dispersion in bidders' pre-auction positions, i.e., when short positions are more extreme, bidding is more aggressive; shorts have more to lose from winning nothing and longs have more to gain from winning a lot.

4 Empirical Analysis of Bidding and Performance

This section examines how bidder behavior and auction performance is influenced by various exogenous variables such as volatility and auction size. We compare and contrast our findings with those in the treasury auctions literature.

4.1 Descriptive Statistics

Table 2 provides three panels with summary statistics of the exogenous and endogenous variables. The exogenous variables capture interest rate volatility, levels, and expectations as well as auction size and the projected number of bidders. The endogenous variables include bid-shading, intra-bidder dispersion, and underpricing measures. We also include a number of participation and award concentration measures.

4.1.1 Exogenous Variables

The exogenous variables are summarized in Panel (a). The daily conditional volatility of the swap rate is computed from a GARCH(1,1) model with dummies to capture key events within the reserve maintenance period (see the Appendix for details). On auction days, the volatility averages to 4.273 basis points (bp), which is roughly the same as for non-auction days, and varies from 1.176 bp to 8.538 bp. By way of comparison, during the sample period the average daily volatilities of 1 and 12 month EURIBOR is 2.7 bp

[11]A trader told us that in his bank they usually operate with a target amount. They are concerned about being substantially short, because other banks are likely to ask very high rates if and when they find out.

and 3.6 bp, respectively.[12] The relatively large volatility of the swap rate reflects the high volatility of the underlying Eonia, which has an average daily volatility of around 14 bp.

The expected auction size is the liquidity neutral amount as announced before the auction by the ECB (see Section 2). It averages to 89.585 billion euros and ranges from 5 to 177 billion euros.

The swap spread is the two week Eonia swap rate less the minimum bid rate. Bidders' abilities to shade and spread out their bids may be compromised when the swap rate is close to the minimum bid rate, something which we will examine in the regression analysis below. The average swap spread is 8.132 bp and the range is from -5.500 to 48.250 bp. It is unusual for the swap spread to be nonpositive. The four cases where we have a negative swap spread reflect strong views held by some players that the ECB would decrease the minimum bid rate for the next auction. Two of the auctions with a negative swap spread are underbid (bid-to-cover below 1).

The forward spread is the one month forward rate (from one month in the future to two months) minus the minimum bid rate. This captures interest rate expectations. When rates are expected to fall (rise), banks have a preference for doing the bulk of their borrowings of central banks funds late (early) in the maintenance month. In the regressions below, we will examine to what extent this affects bidding. Under the old fixed rate tender procedure, the bid-to-cover ratio rose as rates were rising. It became increasingly attractive to use collateral to borrow at the fixed rate tender rate and then turn around in the interbank market and lend at a much higher rate. The forward spread has an average of around 15.53 bp and varies from -26.65 bp to 62.66 bp. It is consistently positive throughout the first six maintenance periods and mixed thereafter. The smallest forward spread occurs on the auction held on 10 April 2001, which also has a negative swap spread and is underbid. The forward and swap spreads tend to move together; they have a correlation coefficient of .69.

The projected number of bidders is included in order to control for the falling time trend discussed in Section 2. This variable is computed by regressing the number of bidders in the current auction on the numbers in the two previous auctions. This is not meant to be the best model for forecasting the number of bidders, but is a simple solution for dealing

[12] Computed as standard deviations of the first differenced time series.

with the time trend. Letting N_j denote the number of bidders, the estimated regression equation is

$$\begin{array}{ccccccc} N_j & = & 127.67 & + & 0.22N_{j-1} & + & 0.53N_{j-2} \\ & & (1.96) & & (1.85) & & (4.59), \end{array} \quad (1)$$

where t-statistics are reported in brackets below the regression coefficients. The regression is adjusted for first order autocorrelation using the Cochrane-Orcutt transformation. Comparing the summary statistics for the projected number of bidders to the statistics for the actual number of bidders [Panel (c)], we see that the projection captures the mean (as it should) but underestimates the actual variability.

4.1.2 Endogenous Variables: Bidding

Panel (b) describes the bidding variables. All of these are calculated on an intra-bidder level; each variable is computed for each of the 29,833 individual demand schedules. Our approach follows Nyborg, Rydqvist, and Sundaresan (2002); we view a bidder's collection of bids in an auction as a distribution and then use the moments to measure bidder behavior. In particular, denote the set of bids (rate, quantity pairs) submitted by bidder i in auction j by $\{(r_{ijk}, q_{ijk})\}_{k=1}^{m_{ij}}$, where m_{ij} is his number of bids. The quantity weighted average rate of these bids is $r_{ij} = \sum_k w_{ijk} r_{ijk}$, where $w_{ijk} = q_{ijk} / \sum_k q_{ijk}$. The discount is then defined as:

$$discount_{ij} = R_j - r_{ij}, \quad (2)$$

where R_j is the secondary market rate (deposit, swap, or repo) right before the auction deadline (see Section 2). The discount is positive for all three two-week rates. The discount relative to the deposit rate is the highest (4.657 bp) , followed by that of the swap rate, (3.333 bp), and finally the repo rate (.040 bp). This reflects that deposit rates tend to be higher than swap rates which in turn are higher than repo rates, due to differences in collateral requirements and credit risk.

The higher order moments are defined along similar lines as the discount:

$$Standard\ deviation_{ij} = STD_{ij} = \sqrt{\sum_{k=1}^{m_{ij}} w_{ijk} \left(r_{ijk} - r_{ij}\right)^2}. \quad (3)$$

$$Skewness_{ij} = \frac{1}{STD_{ij}^3} \left[\sum_{k=1}^{m_{ij}} w_{ijk} \left(r_{ijk} - r_{ij}\right)^3\right], \quad (4)$$

and

$$Kurtosis_{ij} = \frac{1}{STD_{ij}^4}\left[\sum_{k=1}^{m_{ij}} w_{ijk}\left(r_{ijk} - r_{ij}\right)^4\right]. \tag{5}$$

In cases where a bidder submits only 1 bid, we define the skewness to be 0 and kurtosis to be 1.[13] The average standard deviation, skewness, and kurtosis are 0.704 bp, -0.018, and 1.529, respectively. However, there is a considerable variation across individual demand schedules.

The relative bid quantity of bidder i in auction j is $\frac{\sum_k q_{ijk}}{Q_j}$, where Q_j is the expected auction size. The average is .367%. It goes as low as .001% and as high as 80%. The maximum occurs in the smallest auction. The number of bids, m_{ij}, has an average of 2.397 and ranges from 1 up to the admissible maximum of 10.

4.1.3 Endogenous Variables: Performance and Participation

Panel (c) contains variables measuring auction performance and participation. Except for the award ratio, these measures are all on an auction by auction basis.

Award ratio is defined for individual demand schedule and is the quantity awarded as a fraction of quantity demanded. A bidder's award ratio in a given auction will be high if his bids are high relative to those of other bidders. In that sense, award ratio captures the relative aggressiveness of the bidder. Award ratios range from 0 to 1, with an average of .610. A large dispersion of award ratios in a given auction suggest that there are large surprises in the allocations to bidders and that some bidders may emerge from the auction with "large" short positions and others with "large" long positions, relative to average daily reserve requirements. We therefore call the standard deviation of award ratios within auctions *imbalance*. Under the hypothesis that short squeezing is an important feature of these markets, we would expect that the risk of short squeezing is increasing in the imbalance. Our imbalance measure ranges from 0 to .442 with an average of .302.

Underpricing is defined as the two week rate minus the quantity weighted average winning rate. Like the discount, underpricing is measured relative to the three two-week

[13] The rationale is as follows: A single bid can be regarded as the limit as c goes to zero of two bids of identical sizes at prices $b+c$ and $b-c$. The standard deviation is c, the third moment is 0, and the fourth moment c^4. Hence, skewness is zero and kurtosis one. In the limit, as c goes to zero, skewness remains zero and kurtosis one.

rates. Underpricing is 2.959 bp relative to the deposit rate and 1.643 bp and -1.347 bp relative to the Eonia swap and repo rates, respectively. In other words, the average winning bidder pays a rate which is between the swap and repo rates. That underpricing is negative with respect to the repo rate probably reflects that banks use cheaper collateral in the auction than what they can use in the interbank repo market. Using the swap rate as a benchmark, the evidence is that it is cheaper to borrow in the auction than in the interbank market. Since the typical bid-ask spread of the swap rate is around 2-3 bp and underpricing is measured relative to the midpoint of the spread, we see that bidders in the auctions are, roughly speaking, obtaining the funds at the swap bid rate. This confirms interviews we have had with traders who told us that banks do not view bidding in the auctions as a profit-making activity. Nevertheless, they participate because they need the funds. In our discussions below, we will normally take underpricing to be measured relative to the swap rate unless otherwise specified.

The stopout spread is defined as the stop-out rate minus the minimum bid rate and averages to 4.849 bp. The relatively large magnitude of the stopout spread reflects that the secondary market rates were considerably above the minimum bid rates for long periods over the sample period, as seen in the swap spread statistics.

Since, in a given reserve maintenance period, banks earn interest on their reserves equal to the average stop-out rate, it is interesting to see how winning rates compare with stop-out rates. From the variable winrate-stopout, we see that the banking sector tends to pay around 1.640 bp more for their reservable funds than they earn from the ECB. Together, the winrate-stopout and stopout spread variables inform us that the typical rate paid in the auction is approximately 6.5 bp above the minimum bid rate.

The average number of bidders across auctions is 563 and 459 typically win some units. The variation in participants as well as winners is large, going from 240 to 800 and 154 to 705, respectively. The variable manybids measures the percentage of bidders in an auction who submits multiple bids. We see that 64.574% typically do so.

Award concentration is measured by the Herfindahl index on a scale from 1 to 100 and averages to 2.124. This is approximately what it would be if we had 50 equal bidders. Comparing this to the average number of bidders illustrates the considerable size variation that exists across bidders. Award/demand concentration is the Herfindahl index based on award divided by the Herfindahl index based on demand. The average of this ratio is 1.368, showing that award tends to be more concentrated than demand. The average bid-to-cover ratio is 2.064, but varies from 0.471 to 16.661. The highest bid-to-cover occurred in the smallest auction. Finally, the largest (by award) 1, 10, and 50 bidders typically receive 6.819%, 34.340%, and 72.201% of the auction. Keeping in mind that more than 500 banks typically participate in each auction and the average bank demands less than 0.4% of the auction, this is further illustration of the large variation in size among participating banks.

4.2 Regression Analysis

In this section, we run a number of regressions to examine how bidder behavior and auction performance varies with exogenous factors. To allow for the possibility that bidders behave differently when rates are expected to rise as compared to when rates are expected to fall, we create two new exogenous variables. To capture falling rate expectations, we define the forward spread(-) to be equal to the forward spread if this is negative, and 0 otherwise. To capture rising rate expectations, we define forward-swap(+) to be the forward rate less the swap rate if this is positive, and 0 otherwise.[14]

To examine the loser's nightmare hypothesis, we include last auction's imbalance measure as a regressor. Under the hypothesis that the loser's nightmare and short squeezing is a consideration for bidders, we would expect to see bidding being more aggressive when last auction's imbalance is high. On the other hand, if the interbank market is perfect, we should not see lagged imbalance affect bidding in the current auction.

The regression results are reported in Table 3. We have selected those endogenous variables from Table 2 that we think are the most important and interesting. Panel (a) contains the bidder level regressions and Panel (b) contains the auction level regressions. Panel (a) regressions are weighted least squares run on individual demand schedules with bidder fixed effects. The weight on each demand schedule in auction j is $1/N_j$, where N_j is the number of bidders. To correct for correlations in errors within auctions, standard errors are computed using Rogers' (1983, 1993) method. A recent finance application and further discussion of this approach can be found in Vuolteenaho (2002). Bidder dependent

[14] Analogously to the forward spread(-), we could also define the variable forward spread(+) as being the forward spread if this is positive, and zero otherwise. A problem with this variable is that it would give rise to a potential multicollinearity problem in our regressions since it has a correlation of .68 with the swap spread.

variables are included in order to examine how past behavior and awards influence current bidding.[15] The variable AR1 is the bidder's award ratio in the last auction and AR2 is his award ratio two auctions ago. NOTBID1 and NOTBID2 are dummy variables which are 1 if the bidder submitted a bid one or two auctions ago, respectively, and zero otherwise. Panel (b) regressions are run using the Cochrane-Orcutt procedure.

We discuss the regression results by focusing on one exogenous variable at a time, starting with volatility and moving from left to right in the table. The last four regressors are discussed in the next subsection which addresses the intertemporal behavior of bidders.

The volatility of the swap rate impacts negatively on underpricing and discounts. A one basis point increase in volatility leads to a decrease in the discount by a significant .374 bp and a decrease in underpricing by a significant .526 bp. In other words, banks bid more aggressively when volatility is high. This is the opposite of what previous research has documented for treasury auctions [Nyborg, Rydqvist, Sundaresan (2002), Bjønnes (2001), Keloharju, Nyborg, and Rydqvist (2005)] and is the opposite of what one would expect from winner's curse based arguments. Also unlike the evidence from treasury auctions, there is no evidence that bidders cut back demand when volatility is high. Volatility is also statistically significant in the standard deviation regression; a one basis point increase in volatility increases standard deviation by .043 bp.[16]

These findings on volatility suggest that private information about secondary market rates and the winner's curse are not important considerations in the ECB's repo auctions. However, they do not prove it. One hypothesis is that while banks have private valuations for the bulk of central bank funds they need, and therefore do not face a winner's curse for those units, they may also bid for units that they intend to lend in the interbank market. If so, banks may face a winner's curse for those marginal units. To investigate this, we

[15]To deal with cross-correlation, we have also run Panel (a) regressions by first taking averages of the independent variables for each auction and then run the regressions using these. This averaging procedure precludes using bidder-level exogenous variables. We have done this using the Cochrane-Orcutt procedure to deal with any possible autocorrelation. The results are practically identical to those in Panel (a). Because of the presence of a minimum bid rate, the discount and underpricing regressions should arguably be run as Tobit regressions. Using the auction average approach, we find that Tobit regressions yield results which are qualitatively the same as, and quantitatively very close to, the non-Tobit regressions.

[16]We have run the regressions using different models for the volatility, but always with the same qualitative results.

rerun the regressions in Table 3 without the highest bids (chosen several ways). Whether we throw out the highest bid from each demand schedule with two or more bids, throw out the highest 10% to 50% of all bids, we continue to find that the volatility coefficient in the discount regression is statistically significantly negative. The coefficient ranges from −.181 (throwing out the highest 50% bids) to −.356 (throwing out the highest bid from each multi-bid demand schedule).[17] This supports the view that private information and the winner's curse is not a major concern in these auctions, even for marginal units.

As another examination of the private information/winner's curse hypothesis, we rerun the Table 3 regressions with a variable intended to proxy for the precision of private information, under the null hypothesis that bidders possess such. Under the private information/winner's curse hypothesis, the dispersion of bids across bidders would be expected to be larger when the precision of their signals is poor, as discussed for example by Nyborg, Rydqvist, and Sundaresan (2002). We therefore calculate the inter-bidder dispersion for each auction by first computing the quantity weighted average rate of each bidder's bids and then taking the standard deviation of these average rates. Then we run the Table 3 regressions with the inter-bidder dispersion as an additional explanatory variable. The coefficient on inter-bidder dispersion (which is measured in basis points) for selected regressions are as follows (t-statistics in brackets): discount (swap), −.501 (−1.568); relative bid quantity, .225 (1.673); underpricing, −.723 (2.779).[18] Contrary to the private information/winner's curse hypothesis, bidders are slightly more aggressive and underpricing is smaller when there is more dispersion across bidders. This suggests that inter-bidder dispersion is determined by something other than private information about secondary market rates. It is possible that a large dispersion across bidders reflect a larger variability in collateral or in the value of collateral, but it is unclear how this would translate into more aggressive bidding. Perhaps a more plausible explanation is that a high dispersion across bidders arises from aggressive bidding by shorts who attempt to cover.

[17]The complete regression results are available from the authors upon request.

[18]These regressions have a potential endogeneity problem (inter-bidder dispersion is endogenous). We have examined the robustness of the bidder-level regressions by calculating inter-bidder dispersion by randomly selecting 50% of the demand schedules in each auction and then run the regressions on the remaining sample. This procedure has been run 100 times. The coefficients are close to those where inter-bidder dispersion is calculated from all demand schedules per auction. Details of the regression results and the endogeneity robustness check are available from the authors upon request.

That private information and the winner's curse appear to be relatively unimportant in the ECB's repo auctions is not necessarily surprising. It is consistent with the ECB providing information on liquidity conditions and its monetary policy stance on an equal access basis. It is also consistent with the views expressed by traders we have interviewed. Although individual banks possess private information with respect to the fulfillment of their own reserve requirements and their collateral, each bank may simply be too small for this to yield significant insight into the movement of short term rates. A potential puzzle, however, is why bidders are more aggressive when volatility is high. One possibility is that a high volatility is associated with less liquid interbank markets, thus making the auctions relatively more attractive as a source of central bank funds. Another possibility is risk aversion; banks may be willing to pay more for funds obtained in the auction when the interbank rate is more uncertain.

Moving on, we see that the expected auction size impacts positively on the discount, standard deviation, underpricing, and award ratio. For example, a 10 billion increase in auction size leads to a statistically and economically significant .19 bp increase in underpricing. This supports the hypothesis that there is a scarcity of the cheapest eligible collateral. The idea is that as the auction size increases banks start to use more expensive collateral, thus submitting more bids at lower rates with the added result that their bids are more spread out. The negative coefficients on the relative bid quantity and bid-to-cover ratio are supportive of the view that collateral is limited. These also explain the positive coefficient on the award ratio.

The swap spread is highly significant in most regressions and is also the main reason the R^2's are so high. For each basis point increase in the swap spread, the discount increases by .262 basis points. Put differently, for each basis point the swap rate moves away from the minimum bid rate, bidders' average bids move up by only approximately .738 bp. A basis point increase in the swap spread increases underpricing by .106 bp. The swap spread also has a significant impact on dispersion: standard deviation increases by .032 bp per basis point increase in the swap spread and skewness changes by -.003 bp. Kurtosis increases by .005 bp. The swap spread also impacts positively on the number of bids per bidder. These findings suggest that the minimum bid rate is a binding constraint. When the swap spread is large, bidders have more room to spread out and shade their bids. We also see that more banks participate as the swap spread increases. This may be because of an expectation of a larger underpricing, or it may be because players with relatively expensive collateral find it worthwhile to participate. Finally, the swap spread has no notable effect on the quantity variables, including award concentration and bid-to-cover. This is not surprising because the expected auction size is equal to the amount of reserves that banks need.

Next, we discuss rate expectations. Note as a first "result" here that the regressions in Table 3 are reported without the forward-swap(+) variable as a regressor because in almost all cases it has no effect.[19] That rising rate expectations are not important for discounts and underpricing may at first glance appear surprising, since one might expect banks to be more eager to get reserves early when rates are expected to rise. However, a bank's alternative to borrowing in the auction is to obtain reserves in the interbank market. The insignificance of the forward-swap(+) points to that banks adjust their bids according to the swap rate rather than the forward rate.

In contrast, it appears that falling rate expectations matter. Looking down the forward spread(-) column in Table 3, we see that as the forward spread gets more negative, bidders shade less and underpricing is smaller. A one basis point decline in the forward spread(-) translates into a .163 bp decrease in the discount and a .179 bp decrease in underpricing. It seems that the stronger are the expectations that rates will fall, the smaller are discounts and underpricing. This is counterintuitive. We believe this is an artifact of the minimum bid rate. When the market expects rates to fall and the forward spread becomes negative, the swap spread also falls towards the minimum bid rate and in some cases below it. This creates a positive regression coefficient on the forward spread(-) in the discount and underpricing regressions since bids cannot be submitted below the minimum bid rate. To examine this interpretation, we create a dummy variable which is 1 if the swap spread is non-negative and 0 if it is negative and interact this with the forward spread(-). We then run the regressions with this interaction variable in place of the forward spread(-). The regression coefficients on the discount and underpricing are now insignificant, supporting our hypothesis that the apparent effects of falling rate expectations are an artifact of the minimum bid rate.[20]

[19]Including the forward-swap(+), we find that it is significant in only two cases. It has a significantly positive effect on the number of bids per bidder and on the variable manybids.

[20]The detailed regression results with the interaction term are not reported in the paper, but are

The projected number of bidders has no effect on the discount or underpricing and a negative effect on award concentration and bid-to-cover. We have also run the regressions without the projected number of bidders, with no notable changes.

The imbalance (standard deviation of award ratios) from the last auction has a statistically significantly negative effect on both discounts and underpricing. This is consistent with the loser's nightmare hypothesis. We also see that when last auction's imbalance is higher, skewness in the current auction falls. This would be consistent with bidders shifting the bulk of their bids up to relatively higher rates while leaving an opportunistic bid at a relatively low rate. The fact that the results from the previous auction affects bidding in the current auction also suggests that there are frictions in the interbank market, particularly for large trades. It seems that bidders prefer waiting until the next auction with smoothing out some of the allocation imbalances from the most recently held auction rather than relying completely on the interbank market to do so.

4.3 Intertemporal Behavior

In this section we investigate whether banks "cycle"; that is, whether they participate more heavily in every other auction. Related to that, we also look at to what extent a bidder's past awards affects his bidding in the current auction.

Since the repos in the auctions are for two weeks, a bank could in principle cover its liquidity needs by borrowing only in every other weekly auction. Nevertheless, to decrease its reliance on a particular cycle of auctions, a bank may wish to participate evenly in every auction; that is, aim to borrow 50% of its daily average reserve requirement in each auction. A bank that starts out with the objective of equal participation in each auction, however, may find itself deviating from that objective because of liquidity shocks, for example due to unexpectedly large customer withdrawals, or because of an unexpectedly large or small award ratio in an auction. Such a bank may find itself cycling if it deals with the shock predominantly by adjusting its demand in the auctions rather than through transactions in the interbank market.

We first examine the frequency with which bidders participate. This is measured by the *run*, which is the time between the current auction the bidder is participating in and

available from the authors upon request. We thank an anonymous referee for the interaction term idea.

the last. For example, if a bidder participates in auction numbers 1, 2, and 7, there is one run of 1 and one of 5. We measure runs based on bids and awards and find that bidders overwhelmingly tend to participate in adjacent auctions. Out of 28,633 bid runs, 22,477 are runs of 1 and 4,206 are runs of 2. Out of 23,158 award runs, 15,766 are runs of 1 and 4,892 are runs of 2. This suggests that bidders attempt to smooth their auction participation.

Next, we calculate the autocorrelation of bid and award sizes for bidders who participate in every maintenance period. This reduces the number of bidders to 407. For each bidder we first calculate the relative bid size (relative to expected auction size) and relative award size (relative to realized auction size) for each auction. Then we compute the two first autocorrelations of these two measures. Finally, we average across all 407 bidders. The results are in Table 4. We see that both bidding and award have negative first order autocorrelation but positive second order autocorrelation. Furthermore, the number of bidders with negative autocorrelation outweigh those with positive autocorrelation. This is reversed for the second order autocorrelation. Thus banks cycle.[21]

This is consistent with banks viewing the auctions as the main arena for obtaining their reserves, with the interbank market serving more of a fine-tuning role. This apparent preference for borrowing in the auctions, for many banks, supports the view that the loser's nightmare is an issue in the market for central bank funds.

The regressions in Table 3 look more formally at how a bidder's past awards impact on his bidding in the current auction. AR1 and AR2 in Table 3 are a bidder's award ratios in the previous auction and the one before that, respectively. The regressions control for the event that a bidder did not participate in either of the last two auctions by including the dummies NOTBID1 and NOTBID2. While last week's award ratio, AR1, and the award ratio two weeks ago, AR2, do not affect discounts, they have significant impact on other variables. The coefficients on AR1 are statistically significantly negative for the number of bids, the standard deviation of bids, and the relative bid quantity. In contrast, AR2

[21] The maturities of loans for the penultimate and ultimate auctions in a reserve maintenance period falls in the next maintenance period. We have also examined cycling within maintenance periods by regressing current demand and award on those two (or one) auctions ago, conditional on the auctions being in the same maintenance period. The results, which are available from the authors upon request, are along the same lines, though slightly weaker, as in Table 4.

has significantly positive impact on the relative bid quantity and this week's award ratio. Thus, the regression results are in line with the evidence we have just seen on cycling. A bidder who had a relatively large award ratio in last week's auction, tends to be less aggressive in the current week's auction in terms of his bid quantity. A bidder who had a large award ratio two weeks ago, and therefore faces large refinancing needs, increases his demand in the current auction and also submits his bids at high rates relative to other bidders, as evidenced by his current award ratio turning out to be relatively large.

5 Bidder Heterogeneity and Underbidding

5.1 Large versus Small Bidders

We start by examining the overall performance of large versus small bidders. One might expect large bidders to do better, since by virtue of being large, they have more to gain from investing time, effort, and resources in the bidding process. We break the sample up into 12 fixed groups of 100 banks each (99 in the group of smallest bidders) based upon the average relative bid size for each bank across all auctions that the bank participated in. The groups are ordered from smallest (group 1) to largest (group 12). An advantage of working with fixed rather than auction-dependent size groups is that any differences that we find in terms of performance, for example, can be attributed to systematic differences among specific groups of banks rather than differences in private information, refinancing needs, collateral portfolios, etc at given points in time. Another advantage is that by working with fixed groups, we can also examine whether differently sized banks are able to time their purchases to coincide with high underpricing.[22]

Table 5 provides means and standard errors of nine bidder level variables for each of the 12 groups as well as two group level variables (group standard deviation and stopout deviation). For each group, g, the means of the bidder level variables, with the exception of number of auctions, are computed by first averaging across bidders in the group for

[22]Our categorization of "large" and "small" banks is based on bid sizes rather than on balance sheets. What one normally would think of as a large bank, may well be a small bank in terms of bid size, and vice versa. We have constructed a similar table to Table 5 also for auction-dependent size groups, with similar results.

each auction and then averaging across auctions.[23] This is equivalent to taking a weighted average across all demand schedules with a weighting of $\frac{1}{53N_{jg}}$ for each schedule submitted in auction j, where N_{jg} is the number of bidding banks from group g in auction j (and 53 is the number of auctions). So the standard errors are calculated by weighing individual demand schedules submitted in auction j by $53N_{jg}$. This puts an equal weight on each auction and thus corrects for the decreasing time trend in the number of bidders. The number of auctions is the number that a bank participated in, averaged across bidders in the group.

The first row in Table 5 is the average relative bid quantity across bidders in each group, conditioned on participation. There is substantial variation across groups. The average participating bank in the largest group typically bids for 1.983% of expected auction size and receives 60.3% of that. Banks in the smallest group typically bid for 0.003% and receive 64.1% of that. So in terms of amounts bid for and amounts awarded, banks in the largest size group are several hundred times larger than banks in the smallest size group.

The table reveals a substantial difference in the performance of large and small bidders; larger bidders achieve a higher underpricing than smaller bidders. Comparing groups 12 and 1 we see that the larger group has an underpricing of 2.016 bp, while the underpricing for the smaller group is -.040 bp. In other words, across auctions, group 12 bidders obtain funds at 2.056 bp less than group 1 bidders.

In Table 6, we test the hypothesis that differently sized bidders perform differently. The table reports the pairwise differences in mean underpricing between groups, with p-values in brackets. We can see that group 12 has a significantly bigger underpricing than all other groups, with the exception of groups 11 and 10. Group 1 has a significantly smaller underpricing than all other groups. The table confirms that larger bidders borrow cheaper on average than smaller bidders.

The higher underpricing of the larger bidders is in part caused by their higher discounts. For example, the discount for Group 12 is 3.010, while for Group 1 it is 2.148.[24] Another

[23]Using underpricing as an example, the formula for the reported mean for group g consisting of 100 bidders is as follows:

$$\text{underpricing group } g = \sum_{j=1}^{53} \frac{1}{53} \frac{\sum_{i=1}^{100} \mathit{underpricing}_{ij}}{N_{jg}},$$

where $\mathit{underpricing}_{ij}$ is bidder i's achieved underpricing in auction j.

[24]In a previous version of this paper, we reported the statistics in Table 5 using equally weighted averages

important reason for the higher underpricing of larger bidders can be seen by looking at the dispersion of bids across bidders within groups. We have two measures of this. The group standard deviation is calculated by taking the standard deviation of bidders' discounts for each auction and then averaging across auctions. The stopout deviation measure represents the typical deviation of bids around the stop-out rate for each group. It is calculated as follows: First, for each bidder and for each auction, we calculate the deviation from the stop-out rate by subtracting from it the quantity weighted average rate bid. Second, for each bidder, we calculate the square root of the average squared deviation from step 1. Third and finally, for each group, we take the average from step 2 across bidders. These measures show that larger bidders have bids that are more clustered and also more tightly distributed around the stop-out rate than smaller bidders. For example, the group standard deviations for groups 12 and 1 are, respectively, 1.624 and 3.879. The stopout deviations are, respectively, .047 and .253. As a result, smaller bidders tend to win with higher bids than larger bidders, thus leading to less underpricing for the smaller bidders.

The clustering of bids and lower stopout deviation of larger bidders could be consistent with their having more precise information than smaller bidders.[25] But it could also be consistent with several other hypotheses. First, large bidders may have better access to the Eonia swap market; for example, they may run a smaller risk of being squeezed or they are able to negotiate better trades. If so, they can afford being less aggressive than smaller bidders. Although the Eonia swap market is in principle equally open to all banks, smaller banks often lack the resources, sophistication, and will (at board level) to make use of derivative contracts. A high group dispersion may be the result of aggressive bidding by banks that are running large reserve deficits and fear the interbank market. Second, large bidders may be more homogeneous in terms of the collateral they possess; there may be more small bidders with either very cheap or very expensive collateral. Third, large bidders may be more strategic and perhaps smarter in how they submit their bids.

across all demand schedules for each group. Calculated this way, there is no difference in discounts across groups – because smaller bidders participated more heavily in the early auctions when the swap spread and discounts tended to be relatively large – but there is still less underpricing for the larger groups.

[25] Such an interpretation is offered by Hortacsu and Sareen (2004), who introduce the stopout deviation measure in their study of Canadian treasury auctions.

There is some anecdotal evidence that some small banks submit their bids well before the deadline, thus giving themselves a competitive disadvantage since their bids do not fully incorporate market conditions (e.g. the swap rate) at the time of the auction. Table 5 also shows that large bidders tend to use more bids. This might suggest that they have a wider range of collateral, but it might also be that using more bids is strategically advantageous. Without more detailed data regarding reserve positions, trades in the interbank market, and collateral as well as a formal model of these auctions, it is difficult to say which of these hypotheses comes closest to explaining the superior performance of large bidders.

If large bidders have more precise information than small bidders, we might expect large bidders to obtain larger awards in auctions that are more heavily underpriced. To examine this, we regress each size group's relative bid quantity, b_{jg} and the group's relative award quantity, a_{jg} on a constant and underpricing, u_j, where j denotes the auction and g the group. Note that u_j is the underpricing for the auction as a whole (as defined in Table 2); it is not dependent on the group. We thus obtain two underpricing "betas" for each size group. If large bidders can time their purchases, we should see their beta being positive and that of small bidders being negative. The findings are reported in Table 7. For the "bid betas", only the one for group 2 is significant. For the "award betas", only the one for group 11 is significant, and it is negative. We conclude that there is no evidence that large bidders borrow more in more heavily underpriced auctions, suggesting that large bidders are not better informed than small bidders.

5.2 Underbidding

We now turn to studying the two underbid auctions, where banks demanded less in aggregate than the liquidity neutral amount. Several auctions held after the end of our dataset have also been underbid. Thus, from time to time, there is a breakdown in the ability of the auctions to bring to the banking sector the liquidity it needs to maintain reserve requirements. Understanding this breakdown is important. From the banking sector's perspective, it is costly. After the two underbid auctions in our dataset, banks borrowed more than 60 billion euros at the marginal lending facility, paying a 100 bp premium over the minimum bid rate. From the ECB's perspective, underbidding is undesirable because it disturbs the implementation of monetary policy. Indeed, to combat underbidding, in

March 2004 the ECB changed the tenors of their auctions from two to one week and also changed reserve maintenance periods to match the time between the meetings of the ECB's Governing Council where the minimum bid rate in the auctions are set (ECB, 2003). These are the most significant changes to the ECB's operational framework since the launch of the euro in 1999.

Table 8 provides summary statistics from the two underbid auctions. These were held on 13 February 2001 and 10 April 2001 and are the 34th and 42nd auctions, respectively, in our dataset. Demands in these two auctions are only 74.2% and 47.1%, respectively, of the liquidity neutral amounts which are 88 and 53 billion euros, respectively, and banks receive their demands in full. The realized auction sizes equal quantity demanded. An interesting aspect of these auctions is that the contemporaneous swap rate is below the minimum bid rate in the auction; the swaps spreads are -.5 bp for auction 34 and -5.5 bp for auction 42. Hence a bank could get cheaper funding by shorting the swap (paying fixed) and borrowing on an overnight basis for two weeks as compared with borrowing in the auction.

Given the negative swap spreads, one may ask why bid in the auction at all? Of course, if no banks bid, banks would have to pay the 100 bp penalty of the marginal lending facility for the entire amount they need to satisfy reserve requirements. In this case, the swap rate would certainly move up and it would be desirable to bid in the auction after all. Those that actually stay in the auction when the swap spread is negative may be banks that have particularly large liquidity needs and are more concerned about the loser's nightmare. Furthermore, the depth of the below minimum bid rate quotes were not sufficient to cover the entire auction.

As discussed in the Introduction, a plausible hypothesis is that underbidding is driven by small banks who rely on large banks to get the collectively required funds into the banking system. To examine this free-rider hypothesis, we break the bidders up into fixed size groups. To get a finer picture than before, we use different groups than in the previous section; namely, the largest 20, 21-50, 51-100, 101-200, and 201-1199. Table 9 Panel (a) reports the average amount bid for, amount awarded, and number of bidders for these size groups, excluding auctions 34 and 42. We see that normally 16.8 of the top 20 banks participate and bid for a total of 75.3% of the auction. Of the bottom 999 banks, 415.6 normally participate and as a group they bid for 30.0%. Panel (b) reports on the same variables for the two underbid auctions. The comparisons between the underbid and the normal auctions are striking. While the top 20 banks normally buy 34.7%, in the two underbid auctions they buy only 25.3% percent. In contrast, the bottom 999 banks normally buy 14.5%, but in the two underbid auctions they buy 18.7%. Similarly, the 101-200 largest banks normally buy 12.7%, but in the two underbid auctions they buy 16.3%. In other words, the top 20 banks normally buy about 7.6 percentage points *more* than the bottom 1099 banks. In the two underbid auctions, the top 20 buy 9.7 percentage points *less* than the bottom 1099. Panel (c) confirms the statistical significance of these differences between normal and underbid auctions.

As a robustness check on our finding that large bidders cut back more in the two underbid auctions, in Table 10 we examine the eight auctions that straddle each of the underbid auctions. We see that the fractional amount borrowed by the top 20 banks is reduced in both of the underbid auctions relative to the straddling auctions.

The fact that large bidders act as free-riders suggests that they consider themselves fairly small in the big picture. This is perhaps not surprising given that the largest bank in an average auctions gets only around 6% of the auction. But that large banks underbid more than small banks *is* surprising. Our finding may be driven by larger banks having better access to the swap market. Other possibilities are that small bidders happened to be more short than large bidders at the time of the underbid auctions or that they are less strategic than the large bidders.

6 Conclusion

This paper documents several empirical regularities with respect to bidding and performance in the ECB's repo auctions. The auctions we study are characterized by hundreds of bidders seeking to borrow central bank funds on a collateralized basis and are the source of the majority of central bank money in the euro area. The amount auctioned is in principle exactly what banks collectively need to fulfill reserve requirements. However, an individual bank has the choice between obtaining reservable funds in the auction, in the interbank market, or from the standing facility of the ECB at 100 basis points above the auction minimum bid rate.

We first examine how bidders react to exogenous factors and compare this to what has been documented in the treasury auctions literature. Among other things, we find (i) an increase in volatility leads to more aggressive bidding and less underpricing, perhaps because bidders are risk adverse relative to the alternative of obtaining funds in the interbank market; and (ii) an increase in auction size leads to less aggressive bidding and more underpricing, perhaps because bidders have to use increasingly expensive collateral as the auction size grows. These findings differ from those in treasury auctions (Nyborg, Rydqvist, and Sundaresan, 2002) and suggests that the economics of repo auctions may be different. For example, our findings suggests that private information about post-auction rates and the winner's curse are less important in repo auctions than in treasury auctions.

Second, we find that the interest rates at which banks bid tend to fall between the auction minimum bid rate and the two-week Eonia swap rate. Relative to this benchmark, auction underpricing averages to 1.64 basis points. Underpricing increases in the difference between the swap rate and the auction minimum bid rate. We find evidence consistent with the view that the minimum bid rate is a binding constraint, particularly when the market expects the central bank to lower it in upcoming auctions.

Third, we study the intertemporal behavior of bidders. We find that past auction results influence bidding. For example, a larger imbalance across bidders of awards relative to demands in the previous auction leads to more aggressive bidding, with underpricing falling. This is consistent with the view that the loser's nightmare is a concern for bidders in these auctions (Nyborg and Strebulaev, 2002). The auctions follow an overlapping cycle; there is one every week for two week money. We find that individual banks cycle; that is, they tend to participate more heavily every other auction. Our findings suggest that banks view the auctions as the main arena for obtaining reservable funds, with the interbank market serving more of a fine tuning role, perhaps because of limited depth in the interbank market.

Fourth, we examine the performance of large versus small bidders and find that large bidders do better in the sense of having a lower underpricing. This is driven by large bidders shading their bids more as well as having more concentrated bids. We also find that in the two underbid auctions in our sample, large bidders cut back demand more than small bidders. These findings suggest that large bidders may be less adverse to using the interbank market than small bidders.

Much of our evidence points towards considerations regarding the fulfillment of reserve requirements and collateral being important, with the loser's nightmare appearing to be a concern for bidders. Investigating this in more detail would be an important avenue for future research. A challenge here is obtaining data on the fulfillment of reserve requirements, the use and holdings of collateral, and details on interbank trades. From a policy perspective, it may be important to investigate the extent to which banks in different regions may have an advantage in terms of collateral. Anecdotal evidence suggests this may be the case. For example, the availability of government bonds varies across countries and is particularly high in countries such as Italy and Greece with high government debt levels. Also, the market for bank bonds, such as pfandbriefe, which are eligible collateral in the ECB's repo auctions and have a long history in Germany, have only recently started to spring up elsewhere in Europe.[26]

From a theoretical perspective, our findings suggest that an important line of future research on multiunit auctions would be to embed the auctions in a richer setting where players are concerned about their positions in the underlying asset both before and after the auction, perhaps because they may be squeezed if they are short. Some efforts along these lines have already been made by Chatterjea and Jarrow (1998) and Nyborg and Strebulaev (2004). However, we are not familiar with models that consider the sequential feature of repo auctions within the reserve maintenance period. Thinking about the interaction between the auctions and the secondary market is clearly also important from a policy perspective. For example, Nyborg and Strebulaev (2004) show that if the policy objective is to minimize short squeezes and market distortions, then a uniform price auction may be better than a discriminatory auction. However, if the policy objective is to maximize revenue, then a discriminatory auction may be better. Of course, neither of these mechanisms may be optimal in the rich setting of the real world. Our findings, however, suggest that when it comes to optimal auction design, inventory issues and the interaction between the auctions and the secondary market may be as important as information issues in some settings. Although our setting is very different, this is reminiscent of a conjecture made by Engelbrecht-Wiggans and Weber (1979, p.1275) that "some of the variance in bids observed in off-shore oil lease auctions may be due to strategic, rather than informational, factors."

[26] See, e.g., Association of German Mortgage Banks (2004).

7 Appendix: Conditional Volatility Estimation

To estimate the conditional volatility of the two week swap rate, we apply a modified GARCH(1,1) model (Bollerslev, 1986) to daily rate changes. As in Hamilton's (1996) study of the fed funds rate, we use calendar effects to capture the effect of fixed events such as the end and beginning of the maintenance period, ECB Governing Council meetings, the end and beginning of the month, and main and longer term refinancing operations. Not all of these events are in the final specification. Since interest rates tend to be mean-reverting and since conditional volatilities sometimes react asymmetrically to increases and decreases in rates, we also introduce stochastic variables to capture this. In particular, we use a dummy variable which takes the value 1 when the swap rate fell the previous day and 0 otherwise. We also use the "short-end" slope of the term structure of interest rates.

The final model specification and our results are in Table 11. The final specification has been chosen based upon a variety of diagnostic tests. We have examined closely the joint distributions of standardized residuals and standardized squared residuals [see, e.g., Engle and Ng (1993)]. We reject the hypothesis that the residuals or squared residuals could be autocorrelated. It should be noted that our empirical results are robust to many other model specifications for the process of conditional volatility.

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Table 1

Participation

Panel (a) presents the following statistics for each of the 13 maintenance periods for which we have data: the number of demand schedules submitted in all auctions within the maintenance period, the number of bidders who participated in at least one auction, the number of demand schedules that won some award, and the number of bidders who won some award. Panel (b) tabulates the number of banks that participated and won some award in from 1 to 12 maintenance periods. (This panel excludes the 53rd auction in our sample, since this is the only auction we have data for in the 13th maintenance period). Panel (c) tabulates the number of banks that participated in and won some award in from 1 to 53 auctions. N is the total number of banks who bid and won in our sample.

Panel (a): Demand schedules and bidders per maintenance period

	1	2	3	4	5	6	7	8	9	10	11	12	13
Demand schedules	2938	3608	2606	2362	2954	2302	2033	2601	2190	1620	2353	1814	452
Bidding	949	919	850	822	796	841	779	774	738	680	662	623	452
Winning schedules	2441	2427	1957	1906	2482	2084	1986	2407	1724	1423	1687	1524	262
Winning	865	843	767	746	758	812	772	737	678	604	576	577	262

Panel (b): Number of maintenance periods per bank

	mean	std	1	2	3	4	5	6	7	8	9	10	11	12
Bidding	7.861	4.068	120	85	64	55	50	68	63	72	59	75	81	407
Winning	7.279	4.202	125	78	62	66	52	70	62	69	79	79	83	327

Panel (c): Number of auctions per bank

	mean	std	1-5	6-10	11-15	16-20	21-25	26-30	31-35	36-40	41-45	46-53	N
Bidding	24.861	17.557	254	89	114	81	100	87	69	86	94	225	1199
Winning	20.258	16.034	268	120	122	106	98	87	72	87	84	108	1152

Table 2

Descriptive Statistics

Descriptive statistics on the exogenous variables (Panel (a)), the bidding variables (Panel (b)), and the participation and performance variables (Panel (c)). s.e. denotes the standard error of the mean, and N is the number of observations. Volatility of swap rate is the conditional volatility of the two week swap rate on auction days (see the Appendix). Expected auction size is the liquidity neutral amount, which is computed from the liquidity figures announced by the ECB prior to each auction. Swap spread is the difference between the two week swap rate and the minimum bid rate. Forward spread is the difference between the Euribor forward rate from 1 month to 2 months and the minimum bid rate. Projected number of bidders is obtained by a regression as described in the text. Discount and underpricing are the differences between the secondary market rates (deposit, swap, and repo) and the quantity-weighted average bid rate within each demand schedule and the quantity-weighted average winning rate, respectively. Standard deviation, skewness, and kurtosis are all quantity-weighted intra-bidder measures. Relative bid quantity is the quantity demanded by a single bidder relative to the expected auction size. Relative auction size is the quantity allotted in a given auction relative to the expected auction size. Largest 1, 10 and 50 is the alloted share of the 1, 10 and 50 largest (by award) bidders in a given auction. Manybids is the percentage of bidders who submit more than 1 bid in a given auction. Stopout spread is the difference between the stopout rate and the minimum bid rate. Winrate-stopout is the difference between the quantity-weighted average winning rate and the stopout rate. Award concentration is the Herfindahl index. Award/demand concentration is the Herfindahl index based on awards divided by the Herfindahl index based on demand. Imbalance is the standard deviation of award ratios, which are quantity awarded as a fraction of quantity demanded at the individual demand schedule level. Bid-to-cover is the quantity demanded in a given auction divided by the expected auction size. Units of measurement are in the second column.

	units	mean	std	s.e.	min	max	N
Panel (a): Exogenous Variables							
Volatility of swap rate	bp	4.273	1.217	0.167	1.176	8.538	53
Expected auction size	bln	89.585	31.669	4.350	5	177	53
Swap spread	bp	8.132	8.775	1.205	-5.500	48.250	53
Forward spread	bp	15.530	22.077	3.032	-26.652	62.657	53
Projected number of bidders		555.588	78.848	11.041	391.241	711.357	50
Panel (b): Bidding Variables							
Discount (deposit)	bp	4.657	4.369	0.025	-60.500	51.500	29833
Discount (swap)	bp	3.333	4.478	0.026	-59.500	48.250	29833
Discount (repo)	bp	0.040	4.122	0.024	-67	42	29833
Standard deviation	bp	0.704	0.901	0.005	0	28.284	29833
Skewness		-0.018	0.482	0.003	-4.984	13.712	29833
Kurtosis		1.529	1.709	0.010	1	189.005	29833
Relative bid quantity	%	0.367	1.491	0.009	0.001	80	29833
Number of bids		2.397	1.434	0.008	1	10	29833
Panel (c): Performance and Participation							
Underpricing (deposit)	bp	2.959	2.545	0.350	-4.645	10.064	53
Underpricing (swap)	bp	1.643	2.492	0.342	-5.645	6.762	53
Underpricing (repo)	bp	-1.347	3.096	0.425	-10.488	5.564	53
Stopout spread	bp	4.849	6.951	0.955	0	43	53
Winrate-stopout	bp	1.640	1.404	0.193	0.145	6.468	53
Number of bidders		562.925	116.188	15.960	240	800	53
Manybids	%	64.574	14.325	1.968	13.750	80.571	53
Number of winners		458.679	115.100	15.810	154	705	53
Award concentration		2.124	1.424	0.196	1.122	8.875	53
Award/demand concentration		1.368	0.627	0.086	0.928	4.615	53
Imbalance		0.302	0.134	0.018	0	0.442	53
Bid-to-cover		2.064	2.178	0.299	0.471	16.661	53
Largest 1	%	6.819	4.302	0.591	3.131	26.598	53
Largest 10	%	34.340	9.312	1.279	23.848	64.763	53
Largest 50	%	72.201	7.409	1.018	61.973	94.450	53
Relative auction size	%	99.410	8.698	1.195	47.073	109.434	53
Award Ratio		0.610	0.400	0.002	0	1	29833

Table 3

Regression Analysis

Regressions of the following dependent variables: discount (swap), standard deviation, skewness, kurtosis, relative bid quantity, award ratio, number of bids per bidder, underpricing (swap), number of bidders, manybids, largest10, bid-to-cover. The explanatory variables are, from left to right: volatility of swap rate, expected auction size, swap spread, forward spread(-) (forward spread if negative, 0 otherwise), projected number of bidders and imbalance. For Panel (a) there are four more variables: AR1 and AR2 (the bidder's award ratio in the last auction and two auctions ago, respectively), NOTBID1 and NOTBID2 (dummy variables which are 1 if the bidder submitted a bid one or two auctions ago, respectively, and zero otherwise). Panel (a) regressions are weighted least squares regressions (where weight is proportional to the number of bidders in each auction) run on individual demand schedules with fixed bidder effects. Standard errors are computed using Rogers' (1983, 1993) robust standard error method to calculate cross-correlation consistent estimates as discussed in Vuolteenaho (2002). Panel (b) regressions are run with the Cochrane-Orcutt procedure to correct for autocorrelation. For panel (a), N is the number of demand schedules across all auctions 4 to 53. In both panels we do not use the first three auctions because we do not have the projected number of bidders for them. t-statistics are reported in brackets.

	units	C	volatility swap bp	expected size bln	swap spread bp	forward spread (-) bp	proj # bidders 100's	imbalance	NOTBID1	AR1	NOTBID2	AR2	Adj R^2	N
Panel (a): Bidding variables														
Discount (swap)	bp	-0.060	-0.374	0.008	0.262	0.163	0.048	-5.541	0.035	0.036	0.114	-0.197	0.496	27594
		(-0.249)	(-2.259)	(1.032)	(4.051)	(3.609)	(0.186)	(-3.198)	(0.167)	(0.141)	(0.426)	(-0.608)		
Std	bp	-0.003	0.043	0.001	0.032	0.007	-0.022	-0.084	-0.037	-0.147	-0.011	0.061	0.183	27594
		(-0.144)	(2.338)	(1.936)	(12.334)	(2.291)	(-0.929)	(-0.515)	(-1.415)	(-4.119)	(-0.520)	(2.181)		
Skewness		0.001	-0.005	-0	-0.003	-0.003	0.009	-0.089	-0.002	-0.004	0.002	-0.062	0.010	27594
		(0.148)	(-1.015)	(-2.721)	(-2.867)	(-3.628)	(1.721)	(-1.911)	(-0.174)	(-0.382)	(0.190)	(-5.304)		
Kurtosis		-0.004	0.013	0	0.005	-0	0.053	0.046	-0.088	-0.138	0.025	0.061	0.003	27594
		(-0.326)	(1.383)	(0.904)	(1.890)	(-0.085)	(3.415)	(0.264)	(-3.364)	(-3.282)	(0.311)	(1.937)		
Relative bid quantity	%	-0.009	-0.028	-0.009	0.009	0.013	-0.197	0.352	-0.096	-0.198	0.205	0.239	0.056	27594
		(-0.207)	(-0.620)	(-2.168)	(1.268)	(1.397)	(-1.430)	(0.989)	(-2.093)	(-2.349)	(1.480)	(1.713)		
Award Ratio		0.007	-0.011	0.003	-0.009	-0.009	0.033	-0.006	0.014	0.047	0.050	0.112	0.166	27594
		(0.345)	(-0.684)	(4.273)	(-1.705)	(-2.302)	(1.166)	(-0.030)	(0.624)	(1.664)	(1.935)	(3.446)		
Number bids per bidder		-0.009	0.038	0.003	0.032	0.026	0.036	-0.043	-0.127	-0.339	-0.076	0.142	0.170	27594
		(-0.251)	(1.210)	(2.043)	(3.834)	(5.120)	(1.003)	(-0.115)	(-3.198)	(-7.044)	(-1.608)	(2.290)		
Panel (b): Performance and participation variables														
Underpricing (swap)	bp	0.656	-0.526	0.019	0.106	0.179	0.346	-4.708					0.700	50
		(0.444)	(-3.524)	(3.008)	(3.002)	(5.380)	(1.606)	(-3.316)						
Manybids	%	51.538	0.542	0.085	0.500	1.413	0.183	0.805					0.686	50
		(4.620)	(0.821)	(3.619)	(2.583)	(5.812)	(0.124)	(0.088)						
Largest 10	%	74.468	0.975	-0.156	0.108	-0.138	-4.993	13.947					0.475	50
		(6.787)	(1.810)	(-4.336)	(0.634)	(-0.955)	(-3.030)	(1.974)						
Number of bidders	100's	1.124	0.029	0.010	0.037	0.055	0.476	-0.635					0.722	50
		(1.469)	(0.485)	(4.550)	(2.829)	(5.384)	(4.182)	(-0.916)						
Bid-to-cover		11.159	-0.143	-0.038	0.044	0.074	-0.850	2.338					0.328	50
		(1.667)	(-0.721)	(-2.331)	(1.278)	(1.847)	(-1.177)	(1.281)						

Table 4

Autocorrelation of Quantity Demanded and Awarded

First and second autocorrelation coefficients for bids (quantity demanded) and awards (quantity awarded) (relative to the expected auction size and allotted quantity, respectively) for bidders who participated in each maintenance period in our sample. The reported mean across bidders is equally weighted. % positive is the percentage of bidders with positive autocorrelations. N is the number of bidders.

	mean	t-stat	% positive	min	max	N
bids, 1st	-0.028	-3.843	31.695	-0.644	0.561	407
bids, 2nd	0.126	12.765	68.796	-0.144	0.846	407
award, 1st	-0.114	-10.106	27.273	-0.721	0.804	407
award, 2nd	0.300	26.278	91.155	-0.432	0.842	407

Table 5

Small versus Large Bidders: Fixed Groups

Each bidder is placed in a group from 1 to 12 based upon his average relative bid quantity throughout the total sample for auctions he participates in. Group 1 consists of the 99 smallest bidders, Group 2 consists of the next 100 smallest bidders, ..., Group 12 consists of the 100 largest bidders. For each group, Panel (a) reports the means of: relative bid quantity, award ratio, discount (swap), underpricing (swap), standard deviation, skewness, kurtosis, number of bids, and number of auctions participated in. Standard errors (reported in brackets) are calculated by weighting individual demand schedules by the number of bids submitted in each auction by each group. Panel (b) reports the means of two group-level variables: group standard deviation and stopout deviation.

	1	2	3	4	5	6	7	8	9	10	11	12
Panel (a): Bidder-level variables												
Rel bid quant	0.003	0.006	0.010	0.017	0.026	0.038	0.055	0.080	0.123	0.214	0.432	1.983
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.004)	(0.007)	(0.010)	(0.060)
Award ratio	0.641	0.696	0.681	0.681	0.636	0.625	0.637	0.595	0.646	0.608	0.595	0.603
	(0.020)	(0.014)	(0.012)	(0.010)	(0.010)	(0.009)	(0.009)	(0.010)	(0.008)	(0.009)	(0.008)	(0.007)
Underpricing (swap)	-0.040	0.680	1.090	1.271	1.568	1.566	1.687	1.838	1.669	1.905	1.964	2.016
	(0.425)	(0.109)	(0.117)	(0.094)	(0.082)	(0.075)	(0.072)	(0.070)	(0.066)	(0.060)	(0.059)	(0.049)
Standard deviation	0.360	0.685	0.648	0.656	0.733	0.660	0.583	0.679	0.690	0.633	0.641	0.696
	(0.027)	(0.026)	(0.022)	(0.020)	(0.019)	(0.015)	(0.013)	(0.014)	(0.015)	(0.013)	(0.013)	(0.012)
Discount (swap)	2.148	2.215	2.449	2.422	2.773	2.797	2.787	3.059	2.761	3.006	3.085	3.010
	(0.250)	(0.127)	(0.126)	(0.096)	(0.089)	(0.082)	(0.077)	(0.075)	(0.074)	(0.070)	(0.066)	(0.056)
Skewness	-0.020	-0.047	-0.021	-0.031	0.008	0.011	-0.027	0	-0.044	-0.041	0.008	-0.009
	(0.005)	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)	(0.009)	(0.010)	(0.008)	(0.010)	(0.011)
Kurtosis	1.055	1.269	1.329	1.394	1.439	1.460	1.402	1.486	1.652	1.506	1.634	1.802
	(0.018)	(0.016)	(0.018)	(0.019)	(0.015)	(0.016)	(0.013)	(0.019)	(0.038)	(0.016)	(0.074)	(0.046)
Number of bids	1.372	1.954	2.128	2.236	2.430	2.346	2.194	2.451	2.496	2.318	2.378	2.554
	(0.029)	(0.032)	(0.037)	(0.030)	(0.031)	(0.024)	(0.024)	(0.027)	(0.026)	(0.023)	(0.022)	(0.023)
Auctions participation	9.090	16.570	15.680	21.890	22.280	26.150	26.540	27.300	29.270	30.260	33.500	39.800
	(1.111)	(1.440)	(1.392)	(1.601)	(1.743)	(1.637)	(1.643)	(1.661)	(1.776)	(1.740)	(1.506)	(1.442)
Panel (a): Group-level variables												
Group standard deviation	3.879	2.865	2.571	2.363	2.084	2.213	1.975	1.936	2.092	1.838	1.819	1.624
	(0.485)	(0.269)	(0.281)	(0.259)	(0.214)	(0.212)	(0.206)	(0.202)	(0.231)	(0.212)	(0.185)	(0.168)
Stopout deviation	0.253	0.190	0.186	0.164	0.137	0.110	0.109	0.092	0.084	0.094	0.052	0.047
	(0.025)	(0.027)	(0.024)	(0.045)	(0.019)	(0.016)	(0.020)	(0.011)	(0.010)	(0.022)	(0.003)	(0.006)

Table 6

Pairwise Tests of Differences in Mean Underpricing Between Groups.

Tests for differences in mean underpricing (swap) between the 12 groups in Table 5. The (i, j)th cell is the difference in underpricing (swap) between groups i and j, where i represents rows and j columns. Differences are in basis points. P-values are in brackets. Group 12 are the 100 largest bidders and Group 1 consists of the 99 smallest.

	1	2	3	4	5	6	7	8	9	10	11	12
1	0.00	-0.72	-1.13	-1.31	-1.61	-1.61	-1.73	-1.88	-1.71	-1.95	-2.00	-2.06
	(1.00)	(0.03)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
2	0.72	0.00	-0.41	-0.59	-0.89	-0.89	-1.01	-1.16	-0.99	-1.23	-1.28	-1.34
	(0.03)	(1.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
3	1.13	0.41	0.00	-0.18	-0.48	-0.48	-0.60	-0.75	-0.58	-0.82	-0.87	-0.93
	(0.00)	(0.01)	(1.00)	(0.22)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
4	1.31	0.59	0.18	0.00	-0.30	-0.29	-0.42	-0.57	-0.40	-0.63	-0.69	-0.74
	(0.00)	(0.00)	(0.22)	(1.00)	(0.02)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
5	1.61	0.89	0.48	0.30	0.00	0.00	-0.12	-0.27	-0.10	-0.34	-0.40	-0.45
	(0.00)	(0.00)	(0.00)	(0.02)	(1.00)	(0.98)	(0.28)	(0.01)	(0.33)	(0.00)	(0.00)	(0.00)
6	1.61	0.89	0.48	0.29	-0.00	0.00	-0.12	-0.27	-0.10	-0.34	-0.40	-0.45
	(0.00)	(0.00)	(0.00)	(0.01)	(0.98)	(1.00)	(0.24)	(0.01)	(0.30)	(0.00)	(0.00)	(0.00)
7	1.73	1.01	0.60	0.42	0.12	0.12	0.00	-0.15	0.02	-0.22	-0.28	-0.33
	(0.00)	(0.00)	(0.00)	(0.00)	(0.28)	(0.24)	(1.00)	(0.13)	(0.86)	(0.02)	(0.00)	(0.00)
8	1.88	1.16	0.75	0.57	0.27	0.27	0.15	0.00	0.17	-0.07	-0.13	-0.18
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)	(0.13)	(1.00)	(0.08)	(0.46)	(0.16)	(0.03)
9	1.71	0.99	0.58	0.40	0.10	0.10	-0.02	-0.17	0.00	-0.24	-0.30	-0.35
	(0.00)	(0.00)	(0.00)	(0.00)	(0.33)	(0.30)	(0.86)	(0.08)	(1.00)	(0.01)	(0.00)	(0.00)
10	1.95	1.23	0.82	0.63	0.34	0.34	0.22	0.07	0.24	0.00	-0.06	-0.11
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.46)	(0.01)	(1.00)	(0.48)	(0.15)
11	2.00	1.28	0.87	0.69	0.40	0.40	0.28	0.13	0.30	0.06	0.00	-0.05
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.16)	(0.00)	(0.48)	(1.00)	(0.50)
12	2.06	1.34	0.93	0.74	0.45	0.45	0.33	0.18	0.35	0.11	0.05	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.03)	(0.00)	(0.15)	(0.50)	(1.00)

Table 7

Regressions of Bid Quantity and Award by Group on Underpricing

Ordinary least squares regressions of (i) relative bid quantity and (ii) relative award on a constant and underpricing (swap). Both regressions are run for each of the 12 fixed groups in Table 5. Bid and award are relative to the expected auction size and allotted quantity, respectively. Constants are not reported. t-stats are given in brackets. Group 12 consists of the 100 largest bidders and Group 1 of the 99 smallest.

	bid	Adj. R^2	award	Adj. R^2	N
1	0.003	0.049	-0	0	53
	(1.624)		(-0.065)		
2	0.015	0.081	-0.001	0.002	53
	(2.113)		(-0.278)		
3	0.010	0.005	-0.007	0.011	53
	(0.524)		(-0.750)		
4	0.018	0.005	-0.017	0.044	53
	(0.501)		(-1.528)		
5	0.039	0.011	-0.011	0.018	53
	(0.762)		(-0.975)		
6	0.069	0.007	-0.021	0.015	53
	(0.599)		(-0.889)		
7	0.137	0.022	-0.002	0	53
	(1.083)		(-0.072)		
8	0.297	0.051	0.063	0.037	53
	(1.651)		(1.399)		
9	0.132	0.002	-0.043	0.014	53
	(0.327)		(-0.857)		
10	0.384	0.007	0.003	0	53
	(0.583)		(0.039)		
11	0.042	0	-0.396	0.135	53
	(0.024)		(-2.822)		
12	-0.303	0	0.430	0.028	53
	(-0.034)		(1.207)		

Table 8

Underbidding Case Study: Summary Statistics

Means of various statistics for the two underbid auctions, 34 and 42, in our sample.

	units	Auction 34	Auction 42
Date		13 Feb 2001	10 Apr 2001
Tender id		20010007	20010018
Maintenance period		8	10
Auction position		4 of 5	3 of 4
Expected size	bln	88	53
Bid-to-cover		0.742	0.471
Number of bidders		401	240
Relative bid quantity	%	0.185	0.196
Discount (swap)	bp	-0.944	-5.743
Underpricing (swap)	bp	-0.700	-5.645
Standard deviation	bp	0.138	0.070
Skewness		0.043	0.054
Kurtosis		1.150	1.371
Stopout spread		0	0
Winrate-stopout	bp	0.200	0.145
Volatility of swap rate	bp	4.425	4.536
Swap spread	bp	-0.500	-5.500
Forward spread	bp	-3.476	-26.652

Table 9

Underbidding Case Study: Summary Statistics for Five Fixed Groups

Panels (a) and (b): For each of five fixed bid-size based groups, we report means of relative bid quantity (based on expected auction size), award ratio (based on realized auction size), number of bidders, number of winners, average number of bids. The groups have been constructed analogously to those in Table 5. Group 1-20 consists of the 20 largest bidders (by average relative bid quantity), etc. Panel (a) excludes auctions 34 and 42. Panel (b) is for auctions 34 and 42 only.
Panel (c): For each group, tests for differences in mean relative award quantity between the two underbid auctions and all other auctions and the eight straddling auctions (four auctions before and four auctions after). P-values in brackets.

	1-20	21-50	51-100	101-200	201-1199
Panel (a): All auctions, excluding 34 and 42					
Rel. bid quantity: group	75.286	46.205	32.352	28.240	30.047
Award (realized): group	34.692	23.497	14.659	12.682	14.471
Number bidders	16.824	23.824	35.667	64.196	431.863
Number winners	14.804	20.216	29.059	51.235	348.765
Number of bids	2.963	2.524	2.601	2.480	2.373
Panel (b): Auctions 34 and 42					
Rel. bid quantity: group	14.948	15.304	9.092	10.018	11.280
Award (realized): group	25.311	25.289	14.415	16.285	18.700
Number bidders	9	14.500	20.500	38	238.500
Number winners	9	14.500	20.500	38	238.500
Number of bids	1.111	1.103	1.073	1.118	1.289
Panel (c): Tests of differences in mean award ratios					
not underbid vs 34	-7.352	2.038	-1.583	2.811	4.086
	(0)	(0.003)	(0)	(0)	(0)
8 straddling vs 34	-7.602	3.607	-1.433	1.992	3.436
	(0.003)	(0.025)	(0.165)	(0.003)	(0.008)
not underbid vs 42	-13.275	1.570	3.590	4.917	3.198
	(0)	(0.019)	(0)	(0)	(0)
8 straddling vs 42	-16.680	4.914	3.636	3.317	4.812
	(0.010)	(0.013)	(0.006)	(0.051)	(0.036)

Table 10

Underbidding Case Study: The Straddling Auctions

This table provides some descriptive statistics for auctions 34 and 42 and the four auctions preceding and succeeding these auctions. Top 20 refers to the 20 largest bidders and Bottom 999 refers to the smallest 999 bidders (see Table 9). Panel (a) covers auction 34 and panel (b) covers auction 42.

	-4	-3	-2	-1	34	+1	+2	+3	+4
Panel (a): Auction 34									
Expected size	101	104	85	101	88	169	25	153	49
Swap spread	4.500	2	4	0	-0.500	14	2.500	3.500	4.500
Bid-to-cover	1.363	1.140	1.619	1.034	0.742	1.187	4.385	1.241	2.658
Rel. bid quantity: top 20	44.581	41.954	57.950	36.840	19.999	41.193	176.528	44.794	111.445
Award (realized): top 20	28.859	36.566	30.600	35.305	26.948	34.673	33.855	32.114	44.426
Rel. bid quantity: bottom 999	21.889	16.919	22.610	15.318	14.060	15.626	62.076	15.660	35.856
Award (realized): bottom 999	16.748	14.971	15.417	15.009	18.946	13.272	21.307	12.985	14.367
	-4	-3	-2	-1	42	+1	+2	+3	+4
Panel (b): Auction 42									
Expected size	49	135	49	118	53	177	5	80	79
Swap spread	4.500	6	-4.500	0.500	-5.500	17.500	5.500	3.500	5.500
Bid-to-cover	2.658	1.349	1.174	1.094	0.471	1.456	16.661	1.842	2.088
Rel. bid quantity: top 20	111.445	47.956	35.546	50.517	9.897	65.484	611.664	90.232	86.603
Award (realized): top 20	44.426	36.049	28.577	45.528	21.026	49.037	8.755	48.320	40.948
Rel. bid quantity: bottom 999	35.856	18.855	13.779	11.479	8.500	17.433	210.864	19.061	19.793
Award (realized): bottom 999	14.367	13.230	12.124	10.604	18.057	10.114	25.541	11.102	8.881

Table 11

Conditional Volatility of Swap Rate

This table reports the results of the conditional volatility estimation of the two-week swap rate, using a modified GARCH(1,1) model. Panel (a) gives the coefficients of the mean equation, while panel (b) gives the coefficients of the variance equation. Slope is the difference between 12 and 1 month Euribor. Downswap takes the value 1 if the swap rate fell the previous day and 0 otherwise. Endmonth takes the value 1 if the day is the last business day of a month and 0 otherwise, Endres takes the value 1 if the day is the last business day of a reserve maintenance period and 0 otherwise. Mainrepo takes the value 1 if the day is an auction day (main refinancing operation) and 0 otherwise. (-1) stands for the preceding day's observation. For example, endres(-1) is a dummy variable for the first business day in a maintenance period.

	Coefficient	z-statistics
Panel (a): Mean equation		
Constant	-0.003	-1.790
Slope(-1)	0.012	3.592
Downswap(-1)	0.004	2.065
Panel (b): Variance equation		
C	0.0009	4.892
ARCH(1)	0.147	3.326
GARCH(1)	0.594	7.028
Endmonth	-0.002	-6.283
Endres(-1)	-0.001	-5.758
Endres	-0.002	-5.192
Mainrepo	-0.0004	-5.080

Figure 1: Standing Facilities, Minimum Bid Rate, and Secondary Market Rates

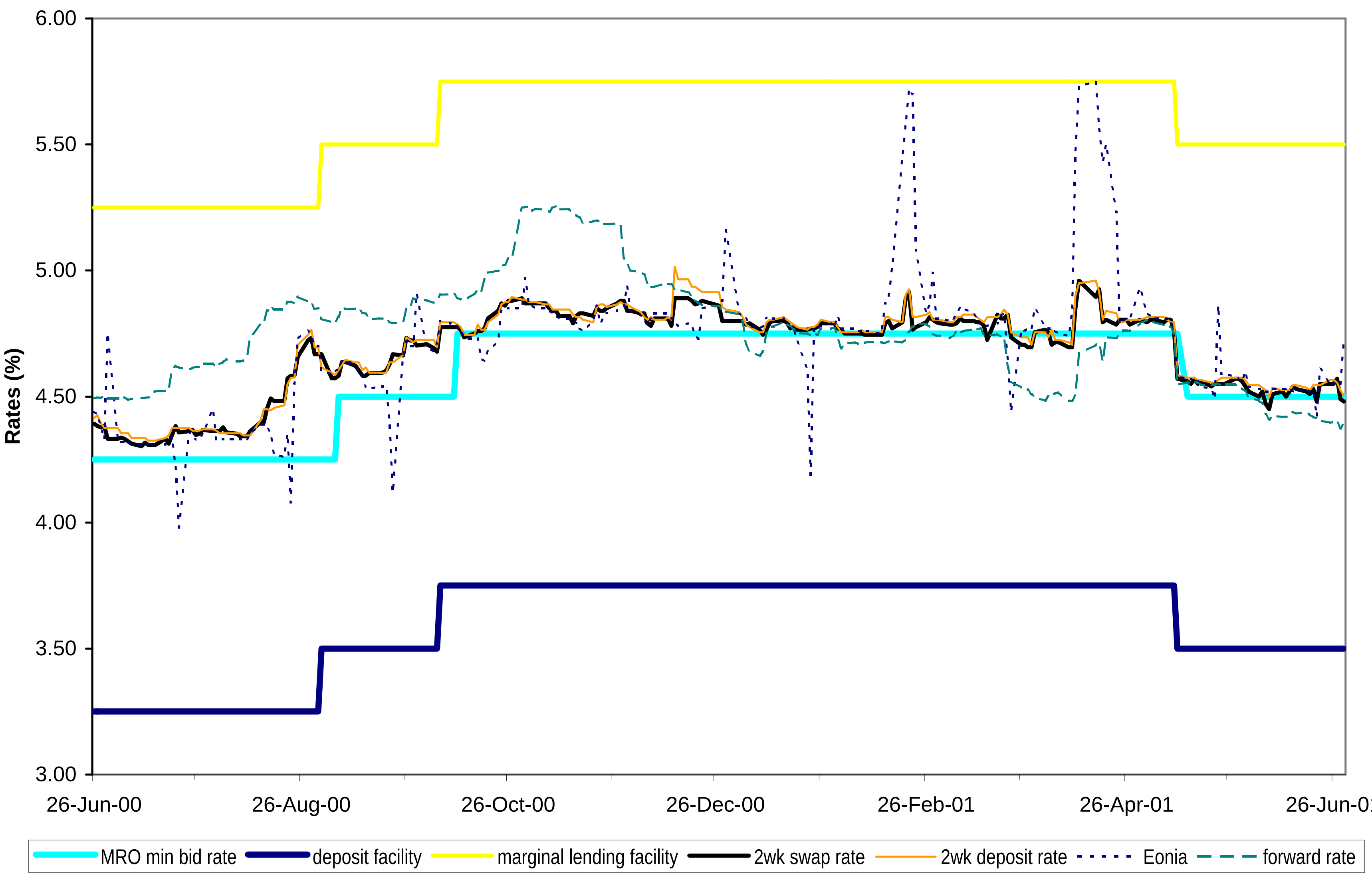

Figure 2: Expected Auction Sizes and Differences between Expected and Realized Auction Sizes (in bn euro)

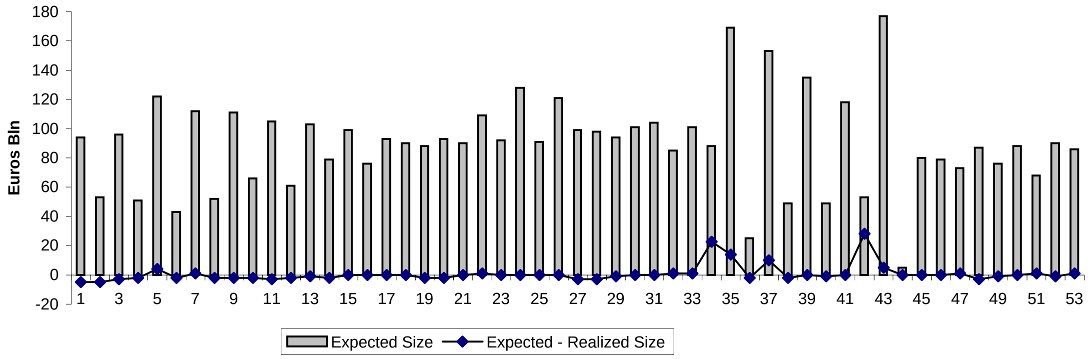

Figure 3: Frequency of Participation

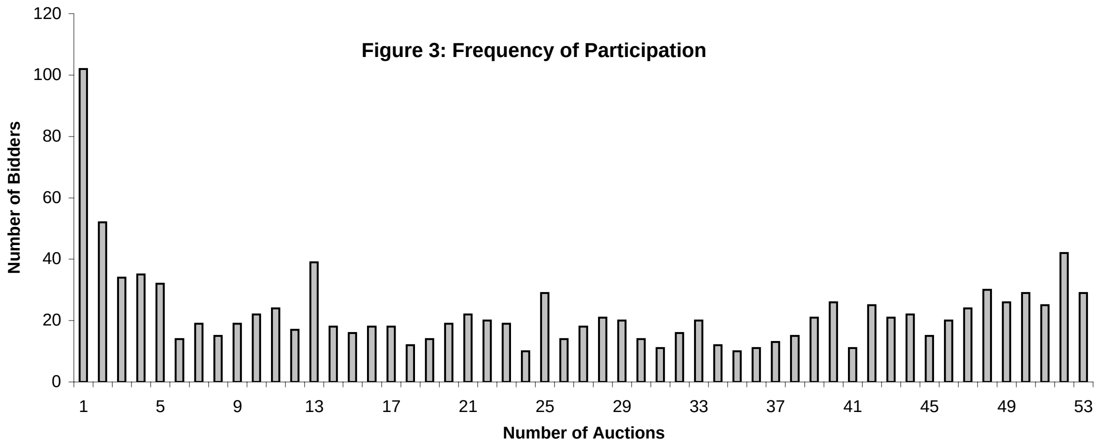

Figure 4: Time Trend of Number of Bidders

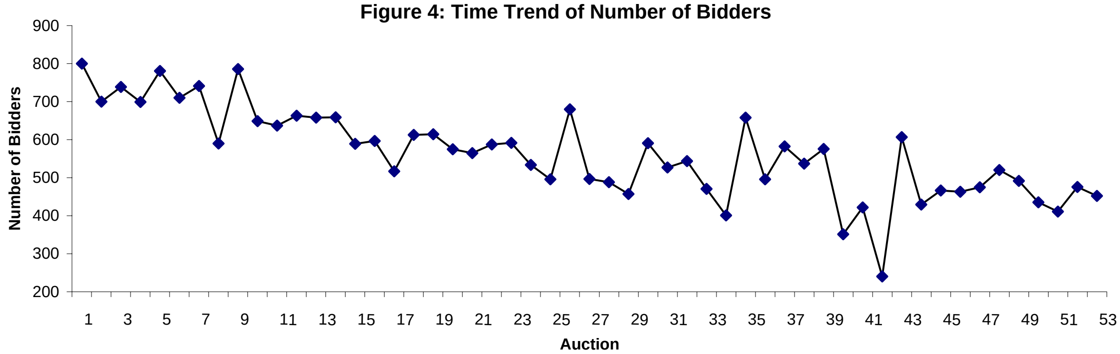

Figure 5: Distribution of Number of Bids