An Empirical Study of Auction Revenue Rankings: The Case of Municipal Bonds

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Abstract

Using a novel dataset of 386 first-price municipal bond auctions held in California, I perform counterfactual revenue comparisons, based on the theoretical result of Milgrom and Weber (1982). I show that the revenue in the second-price auction is non-parametrically identified, and the counterfactual revenue in the English auction can be bounded in an informative way. These results form a basis for nonparametric estimation of counterfactual revenue differences. I find that the revenue gain from using the English auction would be in the range 11 - 19 percent of the gross underwriting spread, and that most of it would already be captured by using the second-price auction. The recent explosive growth of internet English auctions, administered by Grant Street Group, provides external support to the claim that auction design matters in this market.

1 Introduction

This paper considers the estimation of counterfactual revenues in municipal bond auctions. The traditional design adopted by this industry is the first-price, sealed-bid auction, in which bids are delivered to the issuer of the bond by hand, phone or fax, without the involvement of any intermediaries. Auction theory, however, tells us that, under certain conditions, ascending auction formats may be revenue superior to the first-price auction. Establishing useful notation, let R_F be the expected revenue from the first-price auction, R_S - the expected revenue from the second-price auction and R_E - that from the ascending (English) auction.[1] The result of

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[1]In this paper, the English auction means the ascending bid button auction model of Milgrom and Weber. Both the second-price and the button English auctions can be viewed as different forms

Milgrom and Weber (1982) states that the revenues from these three formats are ranked: $R_F \leq R_S \leq R_E$.

Despite the fact that this revenue ranking result has received a great deal of attention in the theoretical literature, I am not aware of any previous empirical studies of the magnitudes of these effects.[2] Municipal bond auctions are a natural setting to explore this question. First, this is a large and important market, and understanding how alternative auction forms can improve revenues for the issuers is of obvious practical interest. Second, unlike many other financial markets, the secondary market for municipal bonds lacks liquidity (Downing and Zhang (2004), Harris and Piwowar (2004) and Green, Hollifield and Schürhoff (2004)). This means that private information about re-sale prices may be important.

A likely channel through which this information is conveyed to the bidders is the pre-sale of bonds before the auction.[3] If all bonds are pre-sold, then the bidders would know their valuations perfectly (because they would know their re-sale prices), and the environment would be with private values. As we know from Milgrom and Weber (1982), in this environment $R_S > R_F$ provided that these private values are affiliated (roughly, affiliation can be understood as positive correlation), and the theory also predicts that there will be no additional revenue gain from the English auction. On the other hand, to the extent that pre-sale is only partial, and to the extent that the market price is common across bidders (not implausible assumptions), one would expect a common value component in bidders' valuations. In this case the theory predicts the English auction to perform even better than the second-price.

I estimate a model of bidding that allows for common as well as for private components in bidders' valuations. Several other papers in the literature have proposed methods to estimate similar models - these include Paarsch (1992), Hong and Shum (2002), Hendricks, Pinkse and Porter (2003) and Bajari and Hortacsu (2003). Most of these papers use a parametric approach, with the exception of Hendricks, Pinkse and Porter (2003).[4] Parametric estimation can suffer from misspecification, so a nonparametric approach would have obvious advantages. Unfortunately, full nonparametric identification fails in a common values environment (Laffont and Vuong (1996)).[5]

of an ascending bid button auction, depending on how much information is revealed in the course of the auction (Milrgom (2004), pages 187 - 188).

[2]See, for example, the discussion of these effects in Klemperer (2004) and the references given there.

[3]See also Hortacsu and Sareen (2005) who explore the effects of pre-sales on bidding for Canadian treasury securities. There is a substantial related literature focusing on revenue comparisons in uniform and discriminatory treasury auctions (Cammack (1991), Umlauf (1993), Nyborg and Sundaresan (1996), Hamao and Jagadeesh (1998), Nyborg, Rydqvist and Sundaresan (2002), and, with a focus similar to mine, Hortacsu (2002)), but these auctions are divisible-good and their economics and econometrics are quite different.

[4]They assume that the econometrician can also observe ex-post values of the object, and their focus is on testing equilibrium bidding behavior.

[5]See also Athey and Haile (2002, 2005).

The identification result in this paper shows that counterfactual revenue in the second-price auction is identified and can be estimated non-parametrically, regardless of the general failure of identification. The argument can be summarized as follows. We know from Guerre, Perrigne and Vuong (GPV; 2000) and Li, Perrigne and Vuong (LPV; 2002) (see also Perrigne and Vuong (1999)) that, in a private values environment, the econometrician can recover consistent estimates of bidders' valuations from the first-order conditions of the Bayesian-Nash equilibrium of the bidding game. These estimates have been named "pseudo-values" by GPV and LPV, and this notion was extended to common-value environments by Hendricks, Pinkse and Porter (2003).[6] In a private values environment, pseudo-values can be interpreted as the estimates of counterfactual bids that would be submitted in the second-price auction. I show that the same interpretation continues to apply even in the environment with common values, and this allows me to estimate the counterfactual revenue R_S non-parametrically.

The revenue in the English auction, however, cannot be non-parametrically identified.[7] To make inferences about it, I use a bounding approach. I show that the expected value of the *highest* bid in the counterfactual second-price auction, which is identified, is an upper bound for R_E.[8] Consistent estimation of R_S and this bound on R_E presents no difficulties since it can be performed by following LPV.

Turning to the empirical implementation, my dataset consists of 386 municipal bond sealed-bid auctions held in the state of California in the period from May 1998 to July 2001. It includes the bids, bidder identities and various bond-specific covariates. No data on bidders' profits from selling the bonds are available, so the estimation must rely on the information contained in the bids. Estimation results are presented and discussed in Section 6, where several specifications are considered. Performing counterfactual comparisons, I find that $R_S - R_F$ are in the range 0.10 - 0.16 percent of the par value of the bond and 9 - 13 percent of the gross underwriting spread, (the difference between the initial resale price of the bond and the winning bid). I find that $\bar{R}_E - R_F$ are in the range 0.14 - 0.23 percent of the par value of the bond and 11 - 19 percent of the gross spread. It follows that the second-price auction would capture a significant fraction of the potential gains - 66 - 81 percent, depending on the specification.

[6] Pseudo-values are also used by Haile, Hong and Shum (2003) in their tests for common values

[7] To see why, suppose that the environment has common values, so that $R_E - R_S > 0$. By the observational equivalence result of Laffont and Vuong (1996), there is an observationally equivalent environment with private values in which the bidders have a dominant strategy to bid their values, so that $R_E - R_S = 0$.

[8] This bounding approach is in the spirit of Hortacsu (2002) who studies the Turkish treasury auction (an auction for a divisible good) and estimates an upper bound for the bids in the counterfactual Vickrey auction.

2 Institutional details of municipal bond auctions

The US municipal bond market is one of the world's largest security markets. Municipal bonds are issued by more than $50,000$ state and local governments and their agencies to build, repair or improve schools, streets and highways, as well as for many other kinds of public works. US households own municipal bonds either through direct ownership of individual bonds or through investment in institutional portfolios, including mutual funds, unit investment trusts, and bank trust accounts. Commercial banks and insurance companies are the major institutional holders.

Municipal bonds are typically issued either by a negotiated sale or by a sealed-bid, first-price auction, also known as a competitive sale in the industry. Although the focus of this paper is on auctions, it is useful to briefly discuss and compare these two most common selling mechanisms.[9] In a negotiated sale, the investment bank serves both as the originator and the distributor of the issue.[10] In a competitive sale, the issuer hires a financial advisor for origination services, and solicit bids by posting a notice of sale in the major industry publication, The Bond Buyer. Issuers typically put series of bonds for auction simultaneously, and the winning bidder receives the entire series (bids for partial quantities are not allowed). The reserve prices are rarely binding and auction cancellations are also very rare. The bidders are mainly investment and commercial banks; the prime motive for acquiring the bonds is resale to final investors. For a few days, the bonds are priced at a uniform price - at par or close to par - by all the dealers in the winning syndicate. They remain for sale at that price until the bonds "break syndicate" and are allowed to trade at what the market will bear.

The advantages of a competitive sale should be clear to an economist: we often expect that, if a seller is able to attract more buyers, the price will be higher.[11] But this intuition is firmly rooted in the private values assumption, and may not hold if common values are present.[12] If common values are important, the bids in a competitive sale may include a discount to allow for the winner's curse, while there is no similar effect in negotiated sales. Auction theory predicts that the strength of the winner's curse effect may be related to market uncertainty.[13] Ederington (1976) provides some supporting evidence for this hypothesis. Without making an explicit reference to a strategic model of bidding, he finds that the underwriting spread is more sensitive to market uncertainty in competitive sales than in negotiated sales.

[9] The internet ascending-bid auctions have also become popular recently. See more on this in the concluding section.

[10] Origination services consist of advising the issuer about the most appropriate terms of the issue and preparing the prospectus that describes the issue. Distribution services consist of placing the bonds with final investors.

[11] See, for example, Bulow and Klemperer (2002) who show that, when values are private and independent, the seller gains more by attracting a single additional bidder in the auction without a reserve price than from negotiating with existing bidders. See also the discussion in Klemperer (2004; page 91).

[12] See Bulow and Klemperer (2002).

[13] See, for example, the discussion of the diffuse prior model in Wilson (1992).

Dyl and Joehnk (1976) find that the distribution of bond ratings is skewed towards riskier bonds in negotiated sales, a behavior by the issuers that is consistent with the "winner's curse" effect at auction.[14] These studies suggest that both banks and issuers appear to respond to their strategic incentives in a manner consistent with predictions of auction theory.[15]

Why is private information important in this market and how is it obtained? Approximately $1.7 trillion worth of municipal bonds are currently in the hands of investors.[16] While some of these bonds are actively traded, others may not trade for months. The liquidity of the secondary market in municipal bonds is manifestly low: the bonds are often held by investors until maturity. The Municipal Securities Rulemaking Board (MSRB) has recently begun to disclose transaction data in the secondary market. Following this event, several very recent studies have explored liquidity and pricing using the MSRB data. A study by Chris Downing and Frank Zhang (2004) finds that only about a third of the bonds traded more than once over the entire period, and that most bonds only traded two or three times. Harris and Piwowar (2004) find that municipal bond trades are significantly more expensive than equivalently sized equity trades.

This low liquidity of the secondary market can make private information about re-sale values significant. Robinson (1960) describes the bidding process for municipal bonds in detail and concludes that prior to sale, bidders frequently pre-sell the bonds to their clients. Since the pre-sale price is likely to be correlated with the market value of the bond, it may be an important source of private information. If the entire issue of bonds is pre-sold, then the bidders would know their valuations perfectly (because they would know their re-sale prices), the environment would be with private values, and the theory predicts that the second-price auction would yield more revenue than the first-price auction.[17] The theory also predicts no additional gain from using the English auction. On the other hand, to the extent that pre-sale is only partial, the bidders are likely to be uncertain about the price they will receive in the secondary market, so that their valuations have both a known private and an unknown common component. In this case the theory predicts that the English auction would yield even more than the second-price auction. The goal of the following sections is to estimate predicted magnitudes of these counterfactual revenues.

[14] One explanation for why both selling formats can coexist may be that negotiated sales can have other advantages, such as origination of the issue by the underwriter, and savings on potentially costly preparation of bids (e.g., Dyl and Joehnk (1976)).

[15] There is also evidence of strategic behavior in markets for treasury securities. For example, Nyborg, Rydqvist and Sundaresan and Sundaresan (2002) study Swedish treasury auctions and find that the potential for the winner's curse is a factor that can explain bid shading in these auctions.

[16] The website of the Municipal Securities Rulemaking Board (MSRB), *www.msrb.org*, is a good source of various summary statistics on municipal bonds.

[17] To the extent that private values are affiliated.

3 The dataset and preliminary results

My dataset consists of 386 municipal bond auctions rated A and higher held in California in the period from May 1998 to July 2001. The sample was obtained from auction worksheets at Thomson Financial website (*www.tm3.com*, accessed on 8/9/2001). Similar data are publicly available from The Bond Buyer, the main municipal bond industry daily periodical. I opted for the Thomson Financial data since it contains more detailed information. Each worksheet contains the following information: (1) the name of the issuer, (2) the state, (3) par amount, (4) the sale date, (5) the date of first coupon, (6) the type of bond (general obligation or revenue), (7) credit rating (by Moody, S&P and Fitch), (8) the maturity of each bond, (9) par amount of each bond, (10) the coupon rate of each bond, (11) the identity of the lead underwriter, (12) dollar bid (not always reported), (13) the bid in terms of *total interest cost* (TIC), (14) the re-offer yield for the winner. A sample auction worksheet is reproduced in the Appendix.

The issue is awarded to the bidder whose bid has the lowest TIC, and the TIC's are always reported on the worksheets for every bidder. For my purposes, it will be more convenient to work with dollar bids (per \$1000 par value of the bond), which were computed from the TIC's according to the formula:

$$B = (1 + TIC)^{-t_f} \times \frac{\sum_{q=1}^{Q}(\sum_{t=0}^{T_q+1} \frac{C_q/2}{(1+\frac{TIC}{2})^t} + \frac{P_q}{(1+\frac{TIC}{2})^t})}{\sum_{q=1}^{Q} P_q} \times \$1000, \tag{1}$$

where q indexes the bonds in the issue (there are Q bonds), T_q is the number of semi-annual periods from the date of first coupon until maturity, C_q and P_q are coupon and principal payments, t_f is the time until the first coupon payment, and B is the dollar bid per \$1000 of face value.[18] Figure 1 shows the densities of bids and winning bids, estimated by the kernel method.

Table 1 reports summary statistics on bids, prices and spreads, broken down by the number of bidders. The number of bidders per auction varies from 2 to 8, and the average is 5 bidders. For the dataset as a whole, the average price is \$992.9, and the average bid is \$988.1. The minimum bid in the sample is \$933.6 and the maximum bid is \$1038. The standard deviations of the bids vary from \$7.21 (in auctions with 8 bidders) to \$12.3 (in auctions with 2 bidders), and there appears to be a decreasing pattern: auctions with higher number of bidders tend to have less dispersed bids. An interesting empirical regularity, revealed by a closer inspection of Table 1, is that the mean bid is inversely related to the number of bidders, but the mean price does not exhibit a clear pattern. The pattern in the bids is suggestive of interdependent values, but is not a conclusive evidence of their presence, since the same declining pattern can also occur when values are private (Pinkse and Tan (2005)). Moreover, there may be confounding effects due to interactions between the number of bidders and bond characteristics.

[18] This calculation of the bond price is based on the Municipal Securities Rulemaking Board rule G-33.

The average spread, the difference between the initial re-offer price and the price, is \$12.47.[19] Gross underwriting spreads typically exceed bidders' expected profits, since they are gross of a variety of costs that underwriters must incur, such as the costs of marketing and registering the bonds. Moreover, since the re-offer price typically exceeds the expected market value for the bond, it puts a natural (although possibly quite crude) upper bound on the revenue from using any selling mechanism.[20] In particular, one should not expect any of the counterfactual auctions considered in this paper to yield a revenue gain of more than \$12.47 over the first-price auction (per \$1000 of par value of the bond). This bound provides a useful benchmark to judge the results from a structural model estimated in this paper.

3.1 Can the bidders be treated symmetrically?

The revenue ranking result of Milgrom and Weber (1982), the basis for revenue comparisons in this paper, depends crucially on bidder symmetry, the assumption that many datasets are likely to violate at least to some degree. One would certainly want to be careful about assuming symmetry in auctions where is it likely that a group of bidders may have a clear advantage, either because their valuations tend to be larger (for example, if they are more cost efficient) or because they tend to be better informed.[21]

Among the various dimensions along which the bidders-banks may differ, the previous literature identified local presence as a potentially important factor. Butler (2002) studied negotiated underwriting of municipal bonds and found that "local underwriters charge lower fees on average than their non-local counterparts and place municipal bonds at lower yields". To my knowledge, these location effects have not been studied in the context of auctions.

To uncover local presence, I followed the methodology of Butler and used an Internet business directory and banks' own websites to determine whether they have offices in California. Banks with offices in California will be referred to as "in-

[19] It is interesting to compare this figure with those reported in Temel (2001), where some aggregate data on gross spreads obtained from Thomson Financial Securities Data are given. Over the period from 1989 to 1999, the gross underwriting spread for auctions varied within the range \$6.16 - \$10.53 (for the US in aggregate). My estimate, \$12.47, is above the upper bound of this range, but the standard error (1.82) is large enough to attribute this to sampling variation.

[20] I am grateful to Dolores Hamilton at Stone & Youngberg's San Francisco office for pointing this out to me.

[21] Take for example Wilson's drainage tract model (Wilson (1969)). In it, there is an informed bidder who knows the value of the tract, and an uninformed bidder who does not have any information about it. Wilson showed that in the first-price auction there is a unique equilibrium, in which the seller's expected revenue is positive. By contrast, in the unique equilibrium of the second-price auction, the uninformed bidder bids zero, and the seller earns zero revenue. Bidding for off-shore oil and gas leases was empirically studied by Hendricks and Porter (1988) and Porter (1995). For auctions with payoff asymmetries, Li and Riley (1999) constructed examples with independent signals in which the revenue ranking of Milgrom and Weber is also reversed. Also, a thorny feature of asymmetric auctions is that there may be multiple equilibria whose presence impedes revenue comparisons.

state", and the banks without such - as "out-of-state". Since most of the bidding is syndicated, and the syndicates may include both in- and out-of-state banks, it is necessary to decide how to assign location status to the syndicates. Here again I followed Butler and used the status of the syndicate manger for the entire syndicate: of the 41 banks that were managers, 32 were in-state and 9 were out-of-state.

The winning probabilities for in-state and out-of-state bidders are shown in Table 2. The following two empirical regularities stand out. First, the out-of-state banks have a very small presence: of all bids submitted, they account for as little as 1.7 percent (this figure is significantly smaller than the 9 percent obtained by Butler for negotiated underwriting in California). Second, the out-of-state banks have a significantly smaller probability of winning: 0.031 (0.022) versus 0.203 (0.018) for the in-state banks, and the difference is statistically significant at the 5 percent level.[22] But since the out-of-state banks have submitted relatively few bids (89 out of 2024), it is quite unlikely that their presence can have a substantial impact on average counterfactual revenue differences.

Another dimension along which the bidders are asymmetric is their syndication status.[23] In my sample, about 79 percent of the bids are submitted by syndicates (21 percent are submitted by the banks that bid solo). For the syndicates, the probability of winning an auction is 0.215 (0.009), while for the solo bidders, the probability is 0.160 (0.016). The difference between these winning probabilities is statistically significant at the 5 percent level, although clearly is not as drastic as the difference between the in-state and out-of-state banks. A plausible reason for syndicates to win with higher probability is their higher efficiency, comprised both of informational efficiency (banks sharing information about the market price of the bond) and cost efficiency (due to banks' specialization in selling the bonds to particular segments of the market). Since there is a substantial number of auctions with both solo and out-of-state bidders, this kind of asymmetry may have some impact, although it may also be limited in view of the fact that the winning probabilities of syndicates and solo bidders are not very far apart.

Since my dataset includes information on the identities of solo bidders and syndicate managers, a reasonable question to ask is whether these individual bank effects matter. To address this questions, I grouped the banks as major or fringe: the first group included those that submitted at least 10 bids, either solo or as syndicate managers, while the rest is included in the second group (see Table 3). I then estimated a logit regression (with auction fixed-effects) of the "winning" dummy on the location and syndication dummies as well as individual bank dummies. The results of this regression are reported in Table 4. The location and syndication effects are statistically significant, but individual bank dummies are not, with the only exception of Tucker Anthony Sutro, a Boston-based investment bank recently acquired

[22] Here and below, the standard errors are reported in parentheses immediately after the estimates.

[23] Syndication has also been found to affect bidding in offshore oil and gas lease auctions (Hendricks, Porter and Tan (2003)).

by the Royal Bank of Canada. In the logit specification, this bank has the odds of winning of only about 0.14 percent of the reference odds. However, it submitted only 36 bids, a relatively small fraction of 2024 bids in the sample. So it is quite plausible that the overall impact of this type of asymmetry is small.

My strategy of assessing the impact of all these asymmetries on the revenues is empirical. I form a subset that included only the auctions with no out-of-state or solo bidders, and only those in which Tucker Anthony Sutro was neither a solo bidder nor a syndicate manager. I then estimate the revenue effects for this subset and compare them with the original estimates; robustness in this sense will provide more confidence in the empirical analysis.

4 The model

A bond is auctioned to $n \geq 2$ risk-neutral bidders.[24] Every bidder i receives a private signal $S_i \in [\underline{s}, \bar{s}]$; the value for the bond for bidder i is given by $V(S_i, U)$, where U is a common component of bidders' valuations, and the function V is increasing in its first argument and non-decreasing in the second. This symmetric specification is sufficiently rich to incorporate private values, pure common values and the mixed case. The density of $(U, S_1, ..., S_n)$ is symmetric and satisfies the affiliation property. The model is thus a version of the general symmetric model of Milgrom and Weber (1986). This section briefly describes some of their results on ranking the revenues, mainly to provide a continuous transition to the next section that contains novel identification results.

In all the standard auctions considered in this paper, the first-price, the second-price and the English, the seller is allowed to set a reserve price $r \geq 0$. Following Milgrom and Weber, define the screening level s^* by

$$s^* = \inf\left\{s : E\left[V|S_1 = s, \max_{i\neq 1} S_i < s\right] \geq r\right\}.$$

Milgrom and Weber showed that in all standard auctions, only the bidders for whom $S_i \geq s^*$ submit serious bids. Those bidders for whom $S_i < s^*$ either submit non-serious bids (with values below r) or do not bid - in this paper, the latter is assumed. The potential bidders who choose to bid will be called active bidders.

In the first-price auction, the unique symmetric equilibrium bidding strategy $B(\cdot)$ is given by the solution to the differential equation

$$B'(s) = (v(s,s) - B(s))\frac{f(s|s)}{F(s|s)} \quad (s \geq s^*), \tag{2}$$

[24] In this paper, I assume that the bidders know the number of other bidders in the auction. As observed in Temel (2001, page 95), "traditionally, underwriters stay with the group with which their firms bid on the last occasion that the issuer came to the market". So one would expect syndicates to be stable for the same issue. There may be variation, due to exit, entry, and mergers of banks, but it seems plausible to assume that the number of actual bidders is known.

subject to the boundary condition $B(s^*) = r$, where

$$v(x,y) = E\left[V|S_1 = x, \max_{i\neq 1} S_i = y\right],$$

and $F(s|s)$ is the conditional distribution of the maximal rival signal ($f(s|s)$ denotes its density). The expected revenue is

$$R_F = EB\left(S_{(1)}\right),$$

where $S_{(1)}$ is the highest signal (the convention adopted here is that, if all signals are below s^*, i.e. there are no active bidders, then $B\left(S_{(1)}\right) = 0$).

In the second-price auction, the bidding strategy is

$$B^*(s) = v(s,s) \quad (s \geq s^*), \tag{3}$$

and the expected revenue is

$$R_S = EB^*\left(S_{(2)}\right),$$

where $S_{(2)}$ is the second-highest signal. To make this formula work in all situations, set $B^*\left(S_{(2)}\right) = r$ if there is a single active bidder, and set $B^*\left(S_{(2)}\right) = 0$ if there are no active bidders.

The English auction was introduced by Milgrom and Weber as a model of the ascending-bid auction, a format that is popular in practice. In the English auction, the auction clock starts at the price equal to r, and those potential bidders for whom the $S_i \geq s^*$ start out by indicating that they are active (e.g., by pressing a button). As the price is continuously rising, the bidders may decide that the price has become unacceptably high for them, and drop out (if they do, they cannot re-enter). The selling price is fixed when only one active bidder remains in the auction, at the level of the last drop-out price.

To derive the expected revenue in the English auction, focus on the event when there are at least two active bidders, so the price is formed at the stage when two remaining bidders in effect engage in a second-price auction. The expected price $w(t,s)$ paid by the winning bidder of type t when the second-highest type is s is given by[25]

$$w(t,s) = E\left[V(s,U)\,|S_1 = t, S_{(2)} = s\right]. \tag{4}$$

The expected revenue is the expected value of $w\left(S_{(1)}, S_{(2)}\right)$:

$$R_E = E\left[w\left(S_{(1)}, S_{(2)}\right)\right], \tag{5}$$

using the convention that $w\left(S_{(1)}, S_{(2)}\right) = r$ if there is a single active bidder, and $= 0$ if there are no active bidders.

The fundamental result of Milgrom and Weber is that the revenues are ranked across the three auctions, as follows:

$$R_E \geq R_S \geq R_F,$$

[25] The notation $S_{(i)}$ is used for ith highest signal.

where the first inequality is strict if and only if the values are strictly interdependent, and the second - if and only if the signals are affiliated but not independent.[26]

5 Identification of R_S and an upper bound for R_E

For empirical purposes, it turns out to be much easier to work with inverted bidding strategies. Following GPV and LPV, the differential equation (2) implies that

$$E\left[V|B(S_1)=b,\max_{j\neq 1} B(S_j)=b\right]=b+\frac{G(b|b)}{g(b|b)} \quad \left(b\in\left[r,\bar{b}\right]\right), \tag{6}$$

where $G(\cdot|b)$ is the equilibrium distribution of the highest bid among i's rivals conditional on the value of i's equilibrium bid being b, $g(\cdot|b)$ is its density, and $\left[r,\bar{b}\right]$ is the support of the bids.[27] I will use the notation $\xi(b)$ for the right-hand side of (6) as a function of the bid level b. In a private values environment, $\xi(b)$ can be interpreted as the inverse bidding strategy: $\xi(b)$ equals the value that corresponds to bid b. Also, since bidders bid their values when values are private, $\xi(b)$ can be interpreted as the counterfactual bid in the second-price auction that corresponds to bid b.

The identification of the counterfactual revenue in the second-price auction is based on the observation that the same interpretation of $\xi(b)$ as the counterfactual bid in the second-price auction carries over to a common values environment. To see why, notice that since the bidding strategy $B(\cdot)$ is increasing, the left-hand side of (6) can be written as

$$E\left[V|S_1=s,\max_{j\neq 1} S_j=s\right],$$

where s is the signal of the bidder who submits a bid $b=B(s)$. Consequently,

$$\xi(B(s))=E\left[V|S_1=s,\max_{j\neq 1} S_j=s\right].$$

But the right-hand side of this equation can be recognized as the bidding strategy in the second-price auction (recall (3)). This allows us to interpret the pseudo-values $\xi(b)$ as counterfactual bids in the second-price auction:

$$\xi(B(s))=B^*(s).$$

Note also that, since the screening levels are equal to s^* in both auctions, the distributions of the numbers of active bidders must be the same. These observations imply that the counterfactual revenue in the second-price auction is identified.

[26] The values are strictly interdependent if the function $V(S_i,S_{-i})$ is strictly increasing in at least one component of S_{-i}. The signals are strictly affiliated if the monotone likelihood ratio property holds with strict inequality.

[27] The basic reference here is GPV. See also Elyakime *et al.* (1994). LPV is also very relevant for my purposes since it explicitly treats the case of affiliated signals.

Proposition 1 *The counterfactual revenue R_S in the second-price auction is identified by the formula*[28]

$$R_S = E\xi\left(B_{(2)}\right) \tag{7}$$

The revenue R_E in the English auction not identified. This would be a serious obstacle for revenue comparisons, but certain inferences about R_E are nevertheless possible regardless of this. To see why, first notice, trivially, that the ranking result itself implies R_E is bounded from below by R_S. Second, an upper bound $\bar{R}_E$ can also be derived, as follows. The function $w(t,s)$, the expected price paid by the winning bidder of type t when the second-highest type is s, is non-decreasing in s by the affiliation of $(U, S_1, ..., S_n)$ and monotonicity of $V(\cdot,\cdot)$. Therefore for $t \geq s$,

$$\begin{aligned} w(t,s) &\leq w(t,t) \\ &= v(t,t). \end{aligned}$$

The function $v(t,t)$ in the last line is equal to $B^*(t)$, the bid that would be submitted by the bidder who had the same signal t in the *second-price* auction. Substituting this bound into equation (5) in Section 4 we get $R_E \leq EB^*\left(S_{(1)}\right)$ $\left(= E\xi\left(B_{(1)}\right) \text{ by Proposition 1}\right)$, so that the expected revenue in the English auction never exceeds the expected highest bid in the second-price auction; for convenience, this result is stated in a separate Proposition:

Proposition 2 *The counterfactual revenue in the English auction is bounded by* $\bar{R}_E = E\xi\left(B_{(1)}\right)$.

The bound $\bar{R}_E$ is identified from the data on all bids in the auction.

6 The estimation method and empirical results

6.1 The estimation method

I specify the econometric model of the underlying bidder valuations of the bonds as

$$V_{i\ell} = \alpha_0 + Z_\ell'\beta + v_{i\ell}, \tag{8}$$

where $\ell = 1, ..., L$ indexes auctions and i indexes bids within each auction. In this specification, the error term $v_{i\ell}$ has zero mean, is independent of the vector of covariates Z_ℓ, and has the same distribution across all values of Z_ℓ. The vector Z will include various bond characteristics such as credit rating, maturity etc.

We must specify an econometric model of the bids (a bids regression) that is consistent with the assumed specification (8). The term $Z_\ell'\beta$ will appear in the bids regression, but we also have to include the covariates that affect bidding strategies directly, such as the number of bidders $n \in \{2, ..., N\}$ and the level of market

[28] In this formula, set $\xi\left(B_{(2)}\right) = r$ if there is only one active bidder and $= 0$ if there are none.

uncertainty $\mathcal{U}$.[29] However, a latent model of valuations like (8) does not tell us how the number of bidders $n \in \{2, ..., N\}$ and market uncertainty $\mathcal{U}$ should enter into the bids regression; in particular, there are no theoretical grounds to assume linearity. We can, without loss of generality, capture the effect of the number of bidders through a vector of dummies. To be able to use the same approach for $\mathcal{U}$ (initially a continuous variable), its range is partitioned into M non-overlapping intervals $I_1, ..., I_M$ the level of uncertainty is modelled as a discrete variable $u = \{m : \mathcal{U} \in \mathcal{I}_m\}$ that indicates the interval for $\mathcal{U}$. This leads to the following baseline econometric model of the bids:

$$B_{i\ell} = Z_\ell' \beta + D\left(n_\ell, u_\ell\right)' \gamma + b_{i\ell}, \tag{9}$$

where $D\left(n_\ell, u_\ell\right) \in \{0,1\}^{(N-1)M}$ is the vector of dummies describing the categorical variables n_ℓ and u_ℓ for auction ℓ. Similarly to the error term $v_{i\ell}$ in (8), the error term $b_{i\ell}$ has zero mean, is independent of Z_ℓ and $D\left(n_\ell, u_\ell\right)$ and has the same distribution for all values of Z conditional on (n, u), but is now allowed to have different distributions across (n, u).[30]

In this paper, the average revenue differences are estimated. The estimation method consists of three steps. In the first step, the linear model (9) is estimated by OLS and the estimated coefficients $\widehat{\beta}$ are used to remove the effect of covariates, by computing the bids $\widehat{B}_{i\ell}$ that would be submitted if all auctions shared the same vector of covariates $Z = 0$:

$$\widehat{B}_{i\ell} = B_{i\ell} - Z_\ell' \widehat{\beta}.$$

In the second step, $\widehat{B}_{i\ell}$ are used to estimate counterfactual second-price auction bids $\xi\left(\widehat{B}_{i\ell}; n, u\right)$ in the environment with $Z = 0$. To perform this step, the dataset is split into subsets according to n and u, and an estimate $\xi_L\left(b; n, u\right)$ is derived for each subset following the "recipe" in LPV:

$$\xi_L\left(b, n, u\right) = b + \frac{\frac{1}{h_G} \sum_\ell \sum_{i=1}^n \mathbf{1}\left\{\widehat{Y}_{i\ell} \leq b\right\} K\left(\frac{\widehat{B}_{i\ell} - b}{h_G}\right)}{\frac{1}{h_g^2} \sum_\ell \sum_{i=1}^n K\left(\frac{\widehat{Y}_{i\ell} - b}{h_g}\right) K\left(\frac{\widehat{B}_{i\ell} - b}{h_g}\right)},$$

where $\widehat{Y}_{i\ell} = \max_{j \neq i} \widehat{B}_{j\ell}$ is the maximal rival bid, $\mathbf{1}$ is the indicator function of the event in the braces, $K(\cdot)$ is a suitable kernel, and h_G, h_g are the bandwidths. In this formula, the summation across $\ell = 1, ..., L_{n,u}$ runs over auctions having the same number of bidders $n_\ell = n$ and same market uncertainty cell $u_\ell = u$.

In the third and final step, a counterfactual sample of bids in the second-price auction is formed by exploiting the linearity of the model:

$$B_{i\ell}^* = Z_\ell' \widehat{\beta} + \xi_L\left(\widehat{B}_{i\ell}; n_\ell, u_\ell\right),$$

[29] The level of market uncertainty has been shown to matter in bond auctions by, for example, Ederington (1975,76). The next subsection will explain how $\mathcal{U}$ is measured.

[30] Lemma 4 in Haile, Hong and Shum (2003) shows that the specification (9) is implied by the latent valuations model (8). Apart from the effect of market uncertainty, the baseline specification is essentially the one considered in Haile, Hong and Shum (2003).

and then the average revenues R_S and $\overline{R}_E$ are estimated, the latter using Proposition 2:

$$R_{SL} = E^* B^*_{(2)\ell},\ \overline{R}_{EL} = E^* B^*_{(1)\ell},$$

where E^* denotes the sample average.[31]

As a robustness check, I also estimate the model for a log specification[32]

$$\log B_{i\ell} = Z'_\ell \beta + D\left(n_\ell, u_\ell\right)' \gamma + b_{i\ell}. \tag{10}$$

The only change here is that the effect of covariates is now removed by

$$\widehat{B}_{i\ell} = B_{i\ell} / \exp\left(Z'_\ell \widehat{\beta}\right),$$

and the counterfactual bids $B^*_{i\ell}$ are formed as

$$B^*_{i\ell} = \exp\left(Z'_\ell \widehat{\beta}\right) \xi_L \left(\widehat{B}_{i\ell}; n_\ell, u_\ell\right).$$

The rest of the estimation proceeds in parallel to the linear case.

6.2 Empirical implementation and results

The estimation results are contained in Tables 6 and 7. Specification I and II correspond to the linear and log specifications estimated using the entire dataset. Specifications III and IV correspond to the linear and log specifications estimated using the subset without the auctions with solo and out-of-state bidders as well as the auctions in which Tucker Anthony Sutro participated either as a solo bidder or as a syndicate manager.

The following covariates were used: the previous day's price of a comparable bond in the secondary market, a measure of market uncertainty, the issue's credit rating, (average) maturity, size, type (general obligation or revenue),[33] whether the

[31] To obtain consistent estimators, trimming is necessary; it was performed following the "recipe" in LPV. For the nonparametric estimation of function $\xi(\cdot)$ I again follow LPV and use the triweight kernel $K(x) = (35/32)(1-x^2)^3$ $(|x| \leq 1)$. The bandwidths were chosen as $h_G = c_G \left(nL_{n,u}\right)^{-\frac{1}{5}}$, $h_H = c_g \left(nL_{n,u}\right)^{-\frac{1}{6}}$; the constants c_g and c_G were chosen by the so-called rule of thumb: $c_g = c_G = 2,987 \times 1.06\sigma_b$, where σ_b is the standard deviation of the bids $\widehat{B}_{i\ell}$. The consistency of the method follows straightforwardly from the arguments in LPV; the proof is available on request. To compute confidence intervals, the block bootstrap was used. In resampling, each auction was treated as a separate block, and 2,000 bootstrap samples were drawn. The procedure is similar to the one used in Hendricks, Pinkse and Porter (2003). A basic reference for the statistical properties of the block bootstrap is Kunsch (1989).

[32] Lemma 4 of Haile, Hong and Shum (2003) can be straightforwardly extended to support the log specification (10), by specifying the corresponding log model for the valuations: $\log V_{i\ell} = \alpha_0 + Z'_\ell \beta + v_{i\ell}$.

[33] Revenue bonds are secured by the revenues of a project that they are financing. General obligation bonds are secured by the taxing and borrowing ability the municipality issuing it.

bonds were issued by a school district and the issuer's county. The covariates' descriptions and summary statistics are given in Table 5. The choice of covariates was guided by previous studies (West (1967), Kessel (1971), Ederington (1975,1976)).[34]

To construct the previous day's secondary market price of a comparable bond, I used California average market yields at market close of the day before each auction. These data are available from Thomson Financial in the form of the Municipal Market Data (MMD) database. The interface to this database allows a user to enter the date, the state issuing the bond, the bond's rating and whether it is a revenue or general obligation bond. Each record of the database contains the corresponding yield curve. This yield curve was used to price the auctioned series of bonds to obtain the hypothetical market price of a comparable bond at the previous day's market close.

To measure market uncertainty, I adopt the approach of Ederington (1975,1976) and use the average dispersion of the bids in the auctions that occurred within time period T before a given auction ℓ, as follows:

$$\mathcal{U}_\ell = \left(\frac{\sum_t \sum_{i=1}^{n_t} \left(B_{it} - \overline{B}_t\right)^2}{\sum_t n_t} \right)^{\frac{1}{2}},$$

where $\overline{B}_t$ denotes the average bid in auction t and the summation over t runs over all auctions that occurred within T days before auction ℓ; I use a two-week period for T. The variable $\mathcal{U}_\ell$ is then discretized into two cells, depending on whether $\mathcal{U}_\ell$ is above or below its sample mean.[35]

The results of the first-step regressions are given in Table 6. All continuous covariates are centered around their mean values. For the log specifications, the secondary market price is entered in logs. As measured by R^2, the variation in covariates accounts for about 0.45 of the total variation in the bids in specifications I and II and about 0.55 in specifications III and IV.

The secondary market price of the bond is significant at 1 percent level in all specifications. Of all factors, the secondary market price appears to be the most salient: it alone can explain about 0.28 of the variation in bids. Higher market uncertainty leads to lower bids (the dummy for high market uncertainty is negative and significant at 1 percent level in all specifications); as mentioned before, this effect is consistent with predictions of auction theory.[36] However, the effect is tiny

[34] My dataset allows me to use some new covariates: the secondary market price of a comparable bond as opposed to, arguably, less precise measures such as White's index used in previous studies (e.g., Kessel (1971)), and county dummies. But at the same time, I couldn't use all covariates used in previous studies (e.g., call provisions) because data on them were often missing in Thomson's worksheets.

[35] This might appear as a rather crude way to model market uncertainty. Why not to consider more cells for $\mathcal{U}_\ell$? Doing so would allow for a more precise measure of market uncertainty, but at the same time may lead to practical difficulties in the non-parametric step, because there may be too few observations in each cell. The estimations will show that the effect of market uncertainty is weak, so it is unlikely that the results would be sensitive to the modelling of market uncertainty.

[36] For example, the diffuse prior model of Wilson (1990, page 11) leads to this effect of market

- in specification I, for instance, high as opposed to low market uncertainty leads to about 0.018 percent reduction in the mean bid.

The effect of bond ratings appears to follow a robust pattern across the specifications: bonds having lower ratings, i.e. riskier bonds, tend to attract higher bids. A possible explanation is that riskier bonds have fewer substituted in the market and therefore convey larger monopoly rents. This is roughly consistent with the findings in a recent study by Harris and Piwowar (2004), who report that the spreads in the secondary market are higher for bonds with lower credit rating. This effect also shows up in the linear regression of re-offer prices on bond and market characteristics (the last two columns of Table 6) - riskier bonds tend to be re-sold at higher prices.

Revenue bonds tend to attract lower bids, as can be seen from the signs of the regression coefficients of the Revenue dummy in Table 6. The effect of the Revenue dummy on the re-offer price is also negative.[37] Bonds of longer maturities also tend to attract lower bids,[38] as do smaller issues and the issues of school districts, although for the latter two groups the effect is only significant for the entire dataset (specifications I and II). Several county dummies are significant, but as a group, they contribute relatively little - estimating the regressions without county dummies gave just slightly smaller R^2, about 0.43 for the full sample and about 0.53 for the subset.

Turning to counterfactual revenue comparisons, the two rows of Table 7 exhibit average counterfactual revenue differences. All estimates are per \$1000 of the bond's par value. The point estimates for $R_S - R_F$ are in the range from \$1.03 (in specification II) to \$1.62 (in specification IV). Importantly, the hypothesis $H_0 : R_S = R_F$ is rejected at the 95 percent confidence level in all specifications. To check whether these estimates are realistic, it is useful to compare them to the gross underwriting spread (the difference between the initial resale price and the winning bid; see the discussion in Section 3). From Table 1, the average spread is \$12.47 per \$1000 of the bond's par value, well above \$2.67, the most optimistic estimate for $R_S - R_F$ in the table (the 97.5th percentile for $R_S - R_F$ in specification IV). The point estimates $R_S - R_F$ account for about 9 - 13 percent of the gross underwriting spread. This is reassuring, since the gross spread should exceed $R_S - R_F$, as explained in Section 3.

The point estimates for $\bar{R}_E - R_F$ range from \$1.38 (in specification I) to \$2.34 (in specification IV); they are in the range 11 - 19 percent of the gross spread. These estimates are also below the average gross underwriting spread. It is evident that the second-price auction would already capture a significant fraction of the gains that the English auction could deliver: $(R_S - R_F) / \left(\bar{R}_E - R_F\right)$ is 66 - 81 percent,

uncertainty, and it was observed empirically for competitive sales of corporate bonds by Ederington (1975,1976).

[37] This is roughly consistent with the notion that revenue bonds are more liquid than general obligation bonds, as follows from the regression results of Downing and Zhang (2004). Controlling for a number of other factors, they find that revenue bonds tend to have smaller weekly price ranges than general obligation bonds.

[38] Again, this is consistent with the findings in Downing and Zhang (2004).

depending on the specification. It is interesting to see how large these revenue effects may be if issue sizes are also considered. In the dataset, the average size is about \$52 million, so $R_S - R_F$ per issue would be in the range \$52,000 - 84,000. This puts potential savings for issuers in California in the range \$22 - 33 million over the period covered by the dataset.

7 Conclusions

The novelty of this paper is to estimate counterfactual revenues in municipal bond auctions under alternative formats, and to develop identification and estimation methods that are needed for such revenue comparison in general. While I believe that my estimates are realistic, they obviously rely on a particular theoretical model that abstracts from some aspects of municipal bond auctions that may be relevant. Several additional considerations come to mind.

Is the multiplicity of equilibria in ascending auction an issue? In both second-price and English auctions, there are also asymmetric equilibria. If these equilibria are considered, estimating the revenue effects would clearly require some way of selecting among them, which may not be easy. On the other hand, the multiplicity of equilibria in a symmetric English auction (Bikchandani, Haile and Riley (2002)) does not interfere with revenue comparisons since all these equilibria are revenue equivalent.

Would different patterns of bidder entry affect revenue ranking? If the environment is symmetric, Levin and Smith (1994) have shown that the revenue ranking of any two common value auction mechanisms is preserved with entry, provided that both mechanisms induce excessive entry and we restrict attention to symmetric equilibria. When the asymmetries are present in the form of almost common values, Bulow and Klemperer (2002) and Avery and Kagel (1997) construct examples in which the advantaged bidder almost always wins the second-price auction, and where the first-price auction is revenue superior. This effect may be amplified if endogenous entry is added to the model, since the weaker bidders may prefer to stay out rather then enter and win with small probability. Athey, Levin and Seira (2004) explore these effects empirically for timber auctions. However, the examples constructed in those papers do not allow for affiliation of bidders' signals (which is a likely case in municipal bond auctions); Bulow and Klemperer mention that affiliation would make this sort of reverse ranking results harder to obtain. Also, in municipal bond auctions, the weaker bidders may choose to enter as part of a cartel rather than to stay out, which may mitigate the effect described above.

The possibility of legal cartels is also relevant when addressing the question: Is the fear of collusion (which might be easier to sustain in second-price or ascending auctions) an issue? The earlier literature (Robinson (1985)) suggested that collusion should be easier to sustain in second-price auctions because they make cartels self-enforcing. Robinson's paper provides an informal analysis of this issue, maintaining an implicit assumption that the cartel can costlessly illicit its members' private information. But this assumption is very strong; as has been theoretically shown by Hendricks, Porter and Tan (2003, Proposition 11 and the discussion thereafter), cartels may be unable to resolve their internal information revelation problems and fail to form, even in second-price auctions.

A likely resolution to these three issues will be empirical, using the data on internet auctions. The ascending auctions for municipal bonds, run by Grant Street Group over the Internet, have recently experienced explosive growth. The first-ever internet auction was conducted for the City of Pittsburgh in 1997 (the home city of Grant Street Group), followed by 25 auctions in 1998, 60 in 1999, 102 in 2000, 355 in 2002, 430 in 2003, and 451 in 2004.[39] Using data from these auctions would allow us to see if theory can account for the observed quantitative differences in revenues. This is left for future research.

[39] In January 2001, Grant Street Group was granted a US patent #6,161,099 for its auction technologies. Today, it is a large diversified house running auctions for various fixed-income products: municipal bonds, bills, guaranteed investment certificates and certificates of deposits, swaps, leases and tax liens. The information about Grant Street Group can be found on its website https://www.grantstreet.com. I accessed this website most recently on November 9, 2005.

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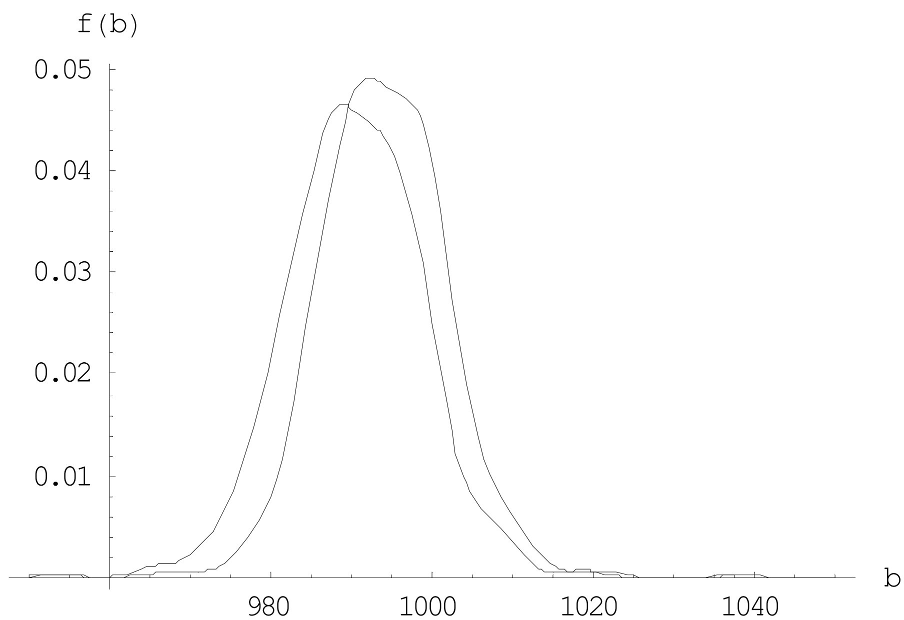

Figure 1: Densities of bids and winning bids

Table 1: Descriptive statistics

	number of bidders							
	2	3	4	5	6	7	8	total
Number of auctions	17	46	83	98	76	44	22	386
Average issue size (mil $)	66.59	142.6	73.54	27.22	27.15	27.78	17.06	52.13
Average price	998	994.9	993.7	994.2	992.5	993.8	992.9	993.89
Average spread	19.8	16.83	8.86	14.51	11.71	9.61	10.56	12.47
Average bid	996.3	992.2	990.7	990.7	989.5	990.3	988.1	990.7
Bid std. dev.	12.3	8.77	11.37	7.53	8.75	7.92	7.21	8.68
Min bid	981.8	964.9	933.6	965.2	954.7	968.8	959.9	933.6
Max bid	1038	1009	1018	1009	1022	1008	1005	1038

Table 2: Probabilities of bidding and winning

Bidder group	Probability of bidding	s.e.	Probability of winning	s.e.
In-state	0.821	0.031	0.203	0.018
Out-of-state	0.179	0.031	0.031	0.022
Syndicates	0.79	0.0092	0.215	0.009
Solo	0.21	0.0092	0.16	0.016

*probability of bidding is the probability that a randomly chosen bid is submitted by a bidder in the group

Table 3: The number of bids submitted by the banks

Major banks	# of bids	# of wins	win freq.	Fringe banks	# of bids	# of wins	win freq.
In-state				In-state			
A.G. Edwards	27	5	0.19	Banc One	2	1	0.50
Banc of America	236	40	0.20	Dain Rauscher	2	0	0.00
Bear Stearns	31	5	0.16	Edward D. Jones	1	0	0.00
Ebondtrade	14	2	0.14	First Albany	1	0	0.00
Everen Securities	30	4	0.13	Hutchinson Shockey	1	0	0.00
Fidelity	53	12	0.23	Miller & Schroder	4	0	0.00
Goldman Sachs	20	6	0.30	M.L. Stern	1	0	0.00
J.P. Morgan	21	3	0.14	O'Connor & Co	2	0	0.00
Legg Mason	16	1	0.06	Raymond James	2	0	0.00
Lehman Brothers	36	10	0.28	Stephens Inc	1	0	0.00
Merrill Lynch	147	21	0.16	Union Bank of CA	9	2	0.22
Morgan Stanley	159	48	0.30	Wells Fargo Brokerag	2	0	0.00
Morgan Stanley Dean	136	21	0.15				
Prudential Sec	73	13	0.18	Out-of-state			
Salomon Smith Barney	297	83	0.28	Carolina Capital	1	0	0.00
Stone & Youngberg	159	37	0.23	Craigie	1	0	0.00
Tucker Anthony Sutro	36	1	0.03	Griffin Kubik	1	0	0.00
UBS PaineWebber	62	15	0.24	IBIS Securities	1	1	1.00
US Bancorp Piper	241	30	0.12	Morgan Keegan	1	0	0.00
Wedbush Morgan	23	5	0.22	William R. Hough	6	1	0.17
				Zions FNB	5	1	0.2
Out-of-state							
First Security	53	12	0.23				
First Union	58	6	0.10				

Notes: For syndicates, the bank is the identity of the manager. Major banks are those that submitted 10 bids or more; the others are fringe banks.

Table 4: Fixed-effects logit regression

Estimated coefficients from a logit regression with auction fixed-effects. The dependent variable is the winning probability. Only major banks are included.

	Logit fixed-effects		
	Coefficient	Odds ratio	s.e.
Location effect			
(In-state)^			
Out-of-state	-2.5273*	0.0799	0.8775
Syndication effect			
(Syndicate)			
Solo	-0.0981*	0.9065	0.0121
In-state banks			
(Stone & Youngberg)^			
A.G. Edwards	-0.0033	0.9967	0.5291
Banc of America	-0.0384	0.9623	0.2478
Bear Stearns	-0.4082	0.6649	0.5394
Ebondtrade	-0.1345	0.8741	0.8037
Everen Securities	-0.5713	0.5648	0.5702
Fidelity	0.2034	1.2256	0.3748
Goldman Sachs	0.2888	1.3348	0.5388
J.P. Morgan	-0.4890	0.6133	0.6622
Legg Mason	-1.1772	0.3082	1.0517
Lehman Brothers	0.1608	1.1745	0.4356
Merrill Lynch	-0.2629	0.7689	0.3019
Morgan Stanley	0.4338	1.5431	0.2569
Prudential Securities	-0.3044	0.7376	0.2953
Salomon Smith Barney	-0.2218	0.8010	0.3585
Stone & Youngberg	0.2591	1.2957	0.2120
Tucker Anthony Sutro	-2.0012*	0.1352	0.5030
UBS PaineWebber	0.1666	1.1812	0.3474
US Bancorp Piper	-0.5197	0.5947	0.2612
Wedbush Morgan	0.0614	1.0633	0.5445
Fringe	0.3263	1.3859	0.5090
Out-of-state banks			
First Security	-0.5775	0.5613	0.4688
First Union	0.9862	2.6811	1.5175

Notes: N = 2042. Log-likelihood = -578.56
*p<0.05
^reference case in parentheses

Table 5: Description of covariates

Covariate	Description	Mean	St. Dev.	Min	Max
Secondary market price	secondary market price of a comparable bond at market close of previous day	1005.63	13.788	954.57	1079.02
High market uncertainty	dummy=1 if U is above its sample mean	0.44	0.5		
AAA insured	dummy=1 if issue is rated aaa insured	0.44	0.5		
AA	dummy=1 if issue is rated aa insured	0.15	0.36		
A	dummy=1 if issue is rated aa insured	0.11	0.32		
Revenue	dummy=1 if issue is revenue	0.3	0.46		
Maturity	maturity of the issue in years	14.61	5.21	0	36
Size	size of the issue in millions	43.25	109.09	1.1	1000
School district	dummy=1 if issued by a school district	0.72	0.45		
County dummies	dummy=1 if the issuer is located in the county				

Table 6: Regressions of bids and re-offer prices

Specifications I and II correspond to the entire dataset; I for bids and II for log bids. Specifications III and IV correspond to the subset; III for bids and IV for log bids. The regression of the re-offer price was estimated for the entire dataset.

	Specification I		Specification II		Specification III		Specification IV		Re-offer price	
	coefficient	s.e.	coefficient	s.e.	coefficient	s.e.	coefficient	s.e.	coefficient	s.e.
Intercept	989.6808**	0.5709	6.8974**	0.0006	989.2748**	1.0146	6.8969**	0.0010	1001.779**	0.4156
Secondary market price	0.4065**	0.0138	0.4163**	0.014	0.5698**	0.0255	0.5833**	0.0257	0.5472**	0.0130
(Low market uncertainty)^										
High market uncertainty	-0.1775**	0.0173	-0.0002**	0.0001	-0.2874**	0.0412	-0.0007**	0.0002	0.4752**	0.1663
Issue covariates										
(AAA)										
A	6.7172**	0.5895	0.0069**	0.0006	8.1210**	0.9690	0.0083**	0.0010	9.3975**	0.5538
AA	5.3292**	0.5544	0.0054**	0.0006	5.3376**	1.1938	0.0055**	0.0012	3.9603**	0.5326
AAA insured	1.4897**	0.3806	0.0015**	0.0004	3.4758**	0.6719	0.0035**	0.0007	1.5059**	0.368
(General obligation)										
Revenue	-3.1003**	0.4163	-0.0031**	0.0004	-2.9485**	0.8209	-0.0030**	0.0008	-1.9354**	0.4092
Maturity	-0.0661*	0.0329	-0.0001**	0.0000	-0.3338**	0.0604	-0.0003**	0.0001	0.2215**	0.0316
Size	0.0118**	0.0017	0.0000	0.0000	-0.0004	0.0031	0.0000	0.0000	0.0018	0.0016
School district	-1.7834**	0.4435	-0.0018**	0.0004	-1.5223	0.8347	-0.0042	-0.0002	-0.7484	0.4050
Number of bidders										
n=2	1.6394	1.2084	0.0016	0.0012	1.7841	1.6575	0.0017	0.0017	-2.8601*	1.1761
n=3	-1.9570**	0.6909	-0.0020**	0.0007	-4.0642**	1.0693	-0.0041**	0.0011	-0.4955	0.6634
n=4	0.5700	0.5013	0.0006	0.0005	-2.3688**	0.7774	-0.0024**	0.0008	0.6831	0.4843
(n=5)										
n=6	0.7854	0.4515	0.0008	0.0005	-0.5177	0.9172	-0.0006	0.0009	-0.6679	0.4343
n=7	1.8084**	0.5302	0.0018**	0.0005	2.5697*	1.1613	0.0026*	0.0012	2.4553**	0.4867
n=8	-1.9217**	0.6187	-0.0019**	0.0006	-2.4794	1.9440	-0.0025	0.0067	-1.8399	1.6187
…	…	…	…	…	…	…	…	…	…	…
R^2	0.4546		0.4552		0.5509		0.5544		0.5723	

Notes: The number of observation is 2006 for the bids regression and 386 for the re-offer price regression. Standard errors for the bids regression were computed by block-bootstrap. Additional regressors are the county dummies and the dummies for the number of bidders when the market uncertainty is high. The reference county is Los Angeles. The following county dummies were significant: in specifications I and II, Alameda, Humbolt, Marin, Sacramento, Santa Cruz, Stanislaus, Tulare, and Ventura; in specifications III and IV, Humbolt, Imperial, Riverside, Sacramento, San Bernardino, Santa Barbara, Solano, Stanislaus and Ventura.

*p<0.05,**p<0.01
^reference case in parentheses

Table 7: Comparison of counterfactual revenues

Average revenue differences per $1000 par value of the bond

	I	II	III	IV
R_S-R_F	1.12 [0.15, 2.09]	1.03 [0.06, 2.00]	1.34 [0.29, 2.39]	1.62 [0.57, 2.67]
$\bar{R}_E$-R_F	1.38 [2.53]	1.56 [2.68]	1.91 [3.32]	2.34 [3.82]

Figures in brackets indicate: for R_F and R_S-R_F, 95% bootstrap confidence intervals; for R_E-R_F, 95%