Forward Looking Strategies in Sequential Auctions: An Application to Highway Procurement*

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Abstract

This paper investigates the participation and bidding strategies of capacity constrained bidders in a repeated auction environment in which bidders receive information about future period auctions during the current auction cycle. Using Michigan highway procurement auction data from 2002 to 2010, I demonstrate that informing bidders of an upcoming auction of a substitute results in less aggressive bids and reduces the participation rate, which provides strong evidence that bidders are forward looking. I develop a dynamic model of participation and bidding for capacity constrained bidders that allows for multiple auctions being held in a period and for advertisements about future period auctions. I develop an estimation strategy that leverages that the expected sum of future profits is a function of the distribution of bids and use it to recover the bidder costs using the Michigan data. Based on these estimates, I quantify bidders' valuation of the advertisements, their effect on the bids, and efficiency-price trade-off of various advertisement policies.

1 Introduction

In many auction environments, the auctioneer procures (or sells) similar objects over time and the bidders have some information about future items up for auction. When bidders are capacity constrained, this knowledge about future auctions should affect participation decisions and bidding strategies. The reasons for these effects include the fact that a losing bidder has the opportunity to bid again in the following period and that a bidder may prefer an object in a future auction. The

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advertisements' dynamic effects result in an efficiency-price trade-off that is driven by a matching effect and a competition effect. Information about projects at future auctions leads to more efficient matching of bidders to object: firms will choose to participate in auctions in which they are likely to have lower costs. However, better matching is likely to reduce competition: bidders bid in fewer auctions because they are more likely to win those in which they participate – and increase prices. This motivates the primary research question: should the auctioneer advertise objects sold in future auctions during the current auction cycle?

I answer this question in the context of Michigan highway procurement auctions. The Michigan Department of Transportation (MDOT) procures 50 to 80 projects once per month using first-price sealed bid (FPSB) auctions. These projects are advertised up to six weeks prior to the letting date, so bidders are aware of a subset of the auctions held the following month while bidding on the present month's auctions. Figure 1 shows an example of this situation with two letting dates with three projects being auctioned off on each date. Prior to letting date 1, bidders are aware of two of the three contracts being auctioned off on letting date 2. In addition, the Michigan auction setting has capacity constrained bidders because MDOT sets the maximum amount of work (in dollar terms) that a firm is authorized to work on. For these reasons, the MDOT auctions are a good economic environment to study the effects of advertisements about future period auctions on the bidders' strategies and the efficiency-price trade-off.

[Figure 1 about here.]

Using the firm participation, bidding, and backlog data, I demonstrate that firms are capacity constrained. In particular, if a firm's backlog is larger than average, it is less likely to participate and bids less aggressively conditional on entry. Using the exogenous variation in the timing of the advertisements, I use regression analysis show that firms incorporate information about future auctions in their participation and bidding decisions. Announcements of following period auctions for projects near a firm reduces the probability of participation and results in less aggressive bids. These effects are more pronounced for smaller firms, for whom capacity constraints are more likely to bind.

Based on the reduced-form results, I develop a dynamic auction model for heterogeneous (in distance) projects with endogenous participation in which capacity constrained firms account for advertisements. This model contributes to the literature by accounting for the non-trivial participation decision when multiple projects are being simultaneously auctioned off in a dynamic setting.

The structural model estimates for the small (single-plant) firms demonstrate that cost is increasing in backlog and distance. The estimates further show that advertisements about future lettings results in less aggressive bids and that this effect is small relative to the effect of backlog. Further, the value function estimates show that the firms' valuation of the advertisements is increasing in the amount of additional information they provide over the firms' prior beliefs. The estimates for the large (multi-plant) firms and the counterfactual simulation to answer whether the government should advertise future auctions is in progress.

While this research focuses on highway procurement in Michigan, the insights from this research are applicable to other markets as well. Many states, such as California and New York, use similar highway procurement mechanisms. Considering that U.S. state and local governments spent $291 billion on transportation projects and maintenance in fiscal year 2017, even a small percentage improvement can result in substantial savings. In addition, the research can speak to other types of markets where agents are capacity constrained and they can get information about items available in the future. For example, consider the smartphone market where consumers typically want one phone. Advertisements about new models being released in the future can affect the replacement decision and the willingness to pay for a new phone.

The rest of the paper is organized as follows: Section 2 discusses the related literature. Section 3 provides an overview of the Michigan procurement market and the data. Section 4 presents reduced form evidence of forward looking strategies. Section 5 develops the dynamic model and Section 6 outlines the estimation strategy. Section 7 discuss the structural estimates. Section 8 discusses future work and concludes.

2 Literature Review

My research is most closely related to the structural dynamic auction literature. In their seminal paper, Jofre-Bonet & Pesendorfer (2003) (henceforth JP) developed a dynamic auction model to investigate how capacity constraints affect bidding behavior in the California highway construction market. Although my model is based on JP, I extend it in three ways. First, participation is endogenous and costly; in JP there is no entry cost and firms always bid. Second, the choice set consists of multiple auctions; in JP it consists of one auction. Third, the government advertises projects from future lettings in the current auction cycle: in JP bidders do not know about projects in future lettings. Other related papers in this literature are Groeger (2014), which estimated a dynamic model with endogenous participation to investigate synergies that result from participation in similar types of auctions, and Balat (2017), which extended JP to incorporate endogenous participation as well as observed and unobserved auction heterogeneity to measure the impact of accelerated procurement processes on government expenditure.

Other related works in the dynamic auction literature are Engelbrecht-Wiggans (1994) and Budish & Zeithammer (2016), both of which derive bidding strategies in second-price sealed bid (SPSB) sequential auctions. Zeithammer (2006) developed a model of forward looking bidding that generated predictions regarding bidding strategies and found some evidence that bidders were forward looking in Ebay data. While my research will also test if bidders are forward looking, my results should be more convincing because the MDOT auction environment allows me to determine exactly what information about future auctions is known to the bidders. This is because MDOT auction advertisements are centrally located, easy to find, and not too numerous, which means the search costs are minimal, especially in contrast to Ebay auctions. Furthermore, my research investigates forward looking behavior in participation decisions. Backus & Lewis (2016) develop an estimator to estimate demand in a large SPSB auction market of a finite set of differentiated products with capacity constrained bidders. Hendricks & Sorensen (2018) develop a dynamic model to study efficiency in an overlapping, sequential auction environment. Jofre-Bonet & Pesendorfer (2014) compare the expected procurement cost from FPSB auctions against Dutch auctions in sequential auctions and find the FPSB have lower procurement costs when the objects are substitutable. Saini (2012) develops a dynamic model of procurement auctions and demonstrates how to numerically solve for the Markov perfect equilibrium when there are two forward looking bidders.

This work utilizes methods from the literature on nonparametric estimation of valuation distributions in a private value setting. Guerre et al. (2000) investigates identification and estimation in a FPSB auctions in a independent private value setting. Li et al. (2002) extends these results to the affiliated private value setting.

My estimation approach uses methods from the dynamic optimization and games literature. In the seminal work, Rust (1987) demonstrated how to solve a discrete choice optimization problem using a nested fixed point algorithm. To overcome computation contraints of this estimator, Hotz & Miller (1993) developed a conditional choice probability estimator. Estimators based on this idea include Hotz et al. (1994) and Aguirregabiria & Mira (2002). This idea has been extended to dynamic games with a discrete action space in Aguirregabiria & Mira (2007), Bajari et al. (2007), and Pesendorfer & Schmidt-Dengler (2008). My estimation makes extensive use of the latter's estimator.

Finally, my paper is related to work on the analysis of highway contracts. In addition to papers discussed above, these include Porter & Zona (1993) and Bajari & Ye (2003), which investigate bidder collusion. Bajari et al. (2014) and Lewis & Bajari (2011) study how contract structures and incentives affect bids. Einav & Esponda (2008) and Li & Zheng (2009) study the effects of endogenous participation. Krasnokutskaya (2011) demonstrates how to estimate costs with unobserved heterogeneity. Somaini (2018) investigates identification of costs when bidders' signals are interdependent.

3 Empirical Setting

The Michigan Department of Transportation (MDOT) uses first-price sealed-bid (FPSB) auctions to award 50–80 highway construction and maintenance contracts once per month. On each monthly letting date, 110–145 firms submit a sealed bid for one or more of the contracts available. The contractors may participate in as many auctions as permitted by their work prequalification and financial rating status. The work prequalification status is a list of the types of work, such as bridge repair, that a firm has the capability and equipment to perform. The financial rating status, which is confidential, dictates the maximum amount of work in dollars that a firm is authorized to work on. The reason for this requirement is that MDOT makes payments after the work is performed so they want to ensure that the contractor can afford to cover its operating costs (cost of materials, wages, etc.). The financial rating status needs to be renewed periodically; the renewal rate is firm specific and is typically every 16–28 months. The financial rating requirements results in firms having capacity constraints.

Contracts are advertised on MDOT's website up to six weeks prior to the letting date. The ads contain detailed information regarding the projects including the location, work prequalification requirements, the engineer's estimate, and links to the project plans. Since auctions are typically held one month (four weeks) apart, the timing of the advertisements means that bidders have information about a subset of the contracts available in the following month's letting date while they are bidding on the present month's auctions (see Figure 1 for an example). MDOT does provide some information about contracts it plans to put up for auction after the following month's letting date, but this information is far less detailed and subject to frequent changes and updates.

Each contract consists of a list of tasks and materials ("line items") that a contractor is expected to provide and their associated, MDOT estimated, quantities. An example task would be milling (tearing up) a road and the associated quantity would be 10,000 square meters. Firms submit a vector of bids for one unit of each line item and the total bid is the inner product of these line item unit bids and their associated estimated quantities. The firm with the lowest total bid is awarded the contract. MDOT solicits unit price bids so that it can adjust the price it pays if the actual quantities differ from the planned quantities; if there are no changes to the plans then MDOT pays the total bid amount. I will be abstracting away from the unit price bids and modeling firms as simply deciding on the total bid.[1]

In order to submit a bid, the contractor must submit a form to become eligible to bid and be put on the plan holder list. This form can be submitted as late as 5:00 PM the day prior to the letting date. MDOT maintains a public list of plan holders and this list is updated daily. Firms are not certain about the identities of all plan holders because a contractor who submits eligibility forms near the deadline may not placed on the plan holder list until after the letting. Bidders also are not certain about the identities of their rivals because plan holders often choose not to bid and there are many potential entrants. While there is no formal reserve price, MDOT has the right to reject all bids if the lowest bid is greater than 110% of the engineer's estimate. From 2002–2010, the lowest bid exceeded 110% of the engineer's estimate in 8.2% of the auctions and in 14.6% of these cases all bids were rejected.

This research will focus on contracts in which firms must be prequalified to work with hot mix asphalt (HMA), a material commonly used in road paving work, and that have an engineer's estimate no greater than $10 million. These contracts account for a large subset of the MDOT auctions with a typical letting date having 20–44 HMA projects being offered. HMA auctions attracts bids from 51–88 firms on a typical letting date. The reason for focusing on HMA projects is that they involve similar types of work so they should be substitutable. Moreover, temperature is a key factor in the quality of HMA. HMA needs to be heated and mixed at a plant, so distance will be an important variable since the mix cools during transport. A firm's distance to a project will be a natural way to determine the auctions a firm considers in its participation decision.

Going forward, when I refer to an auction/project, it refers to one that has the HMA prequalification.

[1] Bidding strategies in unit price auctions where the actual quantities are not known at the time of bidding are studied in Athey & Levin (2001) and Bajari et al. (2014).

3.1 Data

I will be using data from all MDOT HMA auctions from 2002–2010 that includes in 4,233 auctions and 21,840 bids. For each contract, I have a complete list of the line items and their associated quantities. For each of these line items, I have the engineer's estimate of the unit price as well as all the submitted unit price bids and bidder identities, which allows me to compute the total bids. I do not see the bids for contracts in which all bids were rejected ($< 5\%$ of the auctions). In addition, the contract characteristics data includes the project progress and backlog in dollar amounts on a biweekly level. I use the project backlog data to construct a backlog variable for each firm. Following JP and Balat (2017), I construct a firm specific normalized backlog by taking the backlog in dollars less the firm's mean backlog divided by the standard deviation of the firm's backlog.

I collected the planholder lists (potential bidders) and contract advertising data. Since bidders can place themselves on the planholder list up to one day prior to the auction, these lists contain a subset of potential bidders. I supplement the list of potential bidders by deeming any firm that bid on an HMA auction in that year a potential bidder. The contract advertising data includes the ad date, location, work prequalification requirements (e.g. HMA work), and the percentage of the work to be subcontracted to a disadvantaged business enterprise (DBE).

I complement the MDOT contract and bid data with the locations of the bidders and projects at the street-level. The bidder locations were obtained from MDOT (this includes all the HMA plants certified to provide asphalt to MDOT as of November 2018), firm websites, and Somaini (2018). Project location data was also provided by the latter source; for the few contracts I did not have street-level location data for, I used the project county's centroid as the location. I construct a bidder distance variable by computing the haversine distance between the firm and project location. For firms with multiple plants, the distance variable is the minimum distance between each of their plants and the project.

3.2 Descriptive Statistics

Table 1 provides summary statistics of the data. The median project has a engineer's estimate of \$626K and attracts 4 bidders. The winners leave quite a bit of money on the table: the runner up bid is typically 4.6% larger than the lowest bid. On average the winning bid is 6.4% below the engineer's estimate. The winning bidder is about 10km (6.2mi) closer to the project and has a lower normalized backlog (i.e. is less constrained) than a typical bidder.

[Table 1 about here.]

Figure 2 shows a histogram of the number of letting dates by the percentage of the following period auctions that were announced before the current auction cycle ended. There is considerable variation in how many of the period $t + 1$ HMA auctions are announced in period t. Figure 3 shows a scatterplot of the number of announced $t+1$ auctions by the number of unannounced $t+1$ auctions on letting date t. To determine if the number of announced following period auctions gives bidders information about the number of unannounced auctions, I ran a Fischer test of the null hypothesis that the correlation between the variables is 0 against the two sided alternative. For the full sample, the correlation for the two variables is -0.401 and the test rejects the null with a P-value of 8×10^{-6}. This result is expected because not announcing any auctions implies that there is a positive number of unannounced auctions (there are HMA auctions every period). However, when I condition on the event that there is at least 1 announced auction and test the null hypothesis again, I get the correlation is -0.150 and the Fisher test cannot reject the null with a P-value of 0.152. The latter result provides evidence that announcements do not provide information about the unannounced auctions.

[Figure 2 about here.]

[Figure 3 about here.]

Small and Large Firms

There are two types of firms in the data: small and large. Small firms mainly bid on contracts in a single region of the state. These firms mainly have a single plant (or multiple plants in a local area) and mainly bid on one HMA auction conditional on submitting at least 1 bid. I will refer to small firms as single plant firms and define them to be firms that submitted between 10 and 99 bids in the sample. There are approximately 100 small firms in the data.

[Table 2 about here.]

The small firms typically do not submit bids. Their participation decision is strongly dependent on the availability of nearby auctions. Table 2 breaks auctions into three categories: (i) between 0 and 25km of the firm, (ii) between 25km and 50km of the firm, and (iii) more than 50km from the firm. A firm can only bid in an auction in one of the distance bins if one exists. The table clearly shows that not bidding is the most common action. However, the non-participation rate falls substantially when there is a nearby auction available. Moreover, notice that small firms still participate in auctions that are far away, even if a closer one is available.

The large firms bid on contracts in multiple regions and have multiple plants to service these regions. The large firms typically bid on multiple contracts on a letting date conditional on submitting at least one bid. I will often refer to large firms as multi-plant firms and define them to be firms that submitted at least 100 bids in the sample. There are approximately 45 large firms in the data.

4 Evidence of Dynamics

In a repeated auction environment where capacity constrained bidders are competing for substitutable objects, information about future objects up for auction will affect bids and the participation decision. Consider the case where bidders have a capacity constraint of one object. If bidders are informed that a substitutable object will be auctioned off in the following period, bids will be less aggressive because there is an opportunity cost of winning (equivalently there is option value in losing). If participation is costly then bidders are less likely to participate because the expected payoff from the auction decreases. This occurs because, in addition to the opportunity cost of winning, the rivals who do enter will be stronger, which reduces the probability of winning. To demonstrate that firms in the empirical setting satisfy these predictions, I utilize regression analysis. This analysis will exploit the exogenous variation in the amount of information that is revealed by MDOT about future auctions and the data on normalized backlog, which is a measure of capacity utilization.

Before detailing the regression specifications, I introduce some notation. Let i index the bidders and t index the periods. In each period t, there are $j = 1, \ldots, J_t$ contracts up for auction. A specific auction is denoted by the pair (j, t). A subset of these contracts, denoted $\mathcal{K}_{t-1}^{(P)}$, were announced (known) at least seven days prior to the period $t-1$ letting date (i.e. in the participation stage). Similarly, $\mathcal{K}_{t-1}^{(B)}$ denotes the period t auctions were announced at least two days prior to the period $t-1$ letting date (i.e. in the bidding stage). By construction, $\mathcal{K}_{t-1}^{(P)} \subseteq \mathcal{K}_{t-1}^{(B)}$. These two sets capture the differing information about following period auctions at the time of the participation and bidding decisions.

4.1 Auction Participation Regressions

The logit specification to determine if the advertisements affect the probability of bidding in an auction is:

$$\begin{aligned}\mathbf{1}(\text{Bid}_{i,j,t} > 0) &= \beta_0 + \boldsymbol{\beta}_1 \text{Dist}_{i,j,t} + \beta_2 \text{NormBacklog}_{i,t} + \beta_3 J_t + \boldsymbol{\alpha x}_{j,t} \\ &\quad + \beta_4 \sum_{(j',t+1)\in\mathcal{K}_t^{(P)}} \mathbf{1}(\text{Dist}_{i,j',t+1} \leq \text{Dist90}_{i,t}) + \varepsilon_{i,j,t},\end{aligned} \tag{4.1}$$

with year-month and firm fixed effects.[2] $\text{Dist}_{i,j,t}$ is the distance in kilometers between firm i and auction (j,t) and is binned in estimation. $\text{NormBacklog}_{i,t}$ refers to a firm's backlog in period t less its mean backlog divided by the standard deviation of its backlog. J_t is the number of HMA auctions in period t. $\boldsymbol{x}_{j,t}$ includes the auction-level covariates: the number of line items in the contract, the natural logarithm of the engineer's estimate, and the required percentage of DBE subcontracting. j' indexes contracts in period $t+1$. $\sum_{(j',t+1)\in\mathcal{K}_t^{(P)}} \mathbf{1}(\text{Dist}_{i,j',t+1} \leq \text{Dist90}_{i,t})$ is the number of announced HMA auctions in the period $t+1$ participation stage whose distance to i is less than $\text{Dist90}_{i,t}$, which is the 90th percentile of the distances between firm i and the contracts they bid on in the year that includes period t. The reason for including $\sum_{(j',t+1)\in\mathcal{K}_t^{(P)}} \mathbf{1}(\text{Dist}_{i,j',t+1} \leq \text{Dist90}_{i,t})$ in the regression is that when there are many future projects nearby, the more likely it is that one of these auctions is a close substitute of the current period auction; this means the option value of not bidding is higher. I use $\text{Dist90}_{i,t}$ as the definition of nearby because the firm has revealed that these are the distance to projects it will consider and it is resistant to outliers. The regressions are estimated separately for the small and large bidders because the raw data suggests their participation behavior is quite different.

[Table 3 about here.]

Table 3 columns (1) and (3) report the logit estimates for the small and large firms, respectively. The main drivers of participation are the distance to the auction, the engineer's estimate, and the normalized backlog. Normalized backlog is negative which implies that more capacity constrained firms are less likely to participate; this effect is more pronounced for the small firms than the large firms. The effect of advertisements is close to zero and is not significant in this specification. An alternative measure of the amount of information advertised about future period auctions are dummy variables that indicate if there is at least one announced auction within 25km of the firm

[2] A firm is deemed a potential bidder if it submitted at least one bid on an HMA auction in the year that includes period t.

and if there is at least one announced auction between 25km and 50km of the firm. These results are reported in columns (2) and (4) and show that firms being aware of nearby $t+1$ auctions reduces the participation probability as expected. For the one case where the sign is not as expected for the large firms, the estimate is close to zero and not significant.

Additional specifications that vary the covariate used capture the effect of advertisements on participation suggests that the information reduces the bidding rate. In robustness checks against capturing spurious correlations, I ran regressions where I used the number of auctions that were not announced during the participation stage; the unannounced auctions effect on the probability of participation were not significant. These estimates are reported in the Appendix A. I interpret the logit regression results as largely providing evidence that advertisements about period $t+1$ auctions reduce participation.

4.2 Bid Regressions

The specification used to test that bids are affected by information about future auctions is:

$$\begin{aligned}\frac{\text{Bid}_{i,j,t}}{\text{EngEst}_{j,t}/100} &= \beta_0 + \boldsymbol{\beta}_1 \text{Dist}_{i,j,t} + \beta_2 \text{NormBacklog}_{i,t} + \boldsymbol{\alpha x}_{j,t} \\ &+ \beta_3 \sum_{(j',t+1)\in\mathcal{K}_t^{(B)}} \mathbf{1}(\text{Dist}_{i,j',t+1} \leq \text{Dist90}_{i,t}) + \varepsilon_{i,j,t},\end{aligned} \tag{4.2}$$

with year-month, number of bidders, and firm fixed effects. The dependent variable represents bids as a percentage of the engineer's estimate. The covariates are the same as in (4.1) except $\boldsymbol{x}_t$ does not include the engineer's estimate and $\sum_{(j',t+1)\in\mathcal{K}_t^{(B)}} \mathbf{1}(\text{Dist}_{i,j',t+1} \leq \text{Dist90}_{i,t})$ is counting the number of period $t+1$ that were announced as of the bidding stage.

The regression results are reported in Table 4 columns (1). The coefficient on the number of announced period $t+1$ auctions near a firm, β_3, has the expected positive sign and is significant at conventional levels. These results provide strong evidence that bidders are taking into account the opportunity cost of winning. Firms that have more restrictive capacity constraints should be more sensitive to information about future auctions because the opportunity cost of winning is higher. I test this by interacting the backlog and advertisement covariates with a small bidder dummy variable and report this in column (2). These estimates show that small bidders are more responsive to the advertisements than the large firms. Columns (3) and (4) repeat the exercise using dummy variables that indicate if there is at least one announced auction within 25km of the firm and if there is at least one announced auction between 25km and 50km of the firm in lieu of the number of announced auctions. These results are consistent with the base specification.

[Table 4 about here.]

The other estimated coefficients have the expected signs: the bids are increasing in distance and number of line items (tasks). The bids are also increasing in normalized backlog as JP and Balat (2017) had found, which provides further evidence that firms are capacity constrained. The effect of backlog is more pronounced for small bidders. This result contrasts with Groeger (2014) and Somaini (2018), who found that backlog does not have a significant impact on bids in MDOT auctions. A reason for the difference in results is that I use observed backlogs and do not impute it using the planned start and end dates of projects.

Additional regression specifications that vary the covariate used to capture the effect of advertisements on bids also suggest that the information results in less aggressive bids. I repeated logit regression the robustness check against spurious correlations by inserting unannounced auctions as covariates; the unannounced auctions did not have a significant effect on bids. See the Appendix A for these regression results. I view the bid regressions as providing strong evidence that advertisements of nearby period $t+1$ auctions makes bids less aggressive and that this effect is more pronounced for small bidders.

5 Model

This section details the model that will be taken to the data. It is based on JP with modifications to handle the simultaneity of auctions on a letting date, a non-trivial participation decision, and incorporate advertisements about future auctions. The model involves capacity constrained firms choosing up to one auction in which to participate and deciding the bid level. As discussed in the data section, this is a reasonable approximation of how the small firms behave. Large firms will be treated as a collection of independent small firms. The notation will follow the convention that random variables are capital letters, their realizations are lowercase letters, and that vectors are in bold.

Time, denoted t, is discrete with an infinite horizon. In each period t, the government puts $\mathcal{J}_t = \{(1,t), \ldots, (J_t,t)\}$ contracts up for auction. Each project (j,t) has an engineer's estimate of ζ and a location $l_{j,t}$, which is observed by all the firms and the econometrician.[3]

[3] This model can be extended to allow for heterogeneity in the engineer's estimate.

There are two types of risk-neutral bidders: small (denoted $\mathbb{S}$) and large (denoted $\mathbb{L}$). Small firms are single plant firms that bid in at most one auction per period. Large firms have multiple plants and its profit is additive across plants. Each plant of the large firm can bid in at most one auction and makes this decision independently; the only restriction is that a large firm never has its own plants competing against another. Going forward, I will refer to the bidders as plants.

Plant i of type τ in period t is characterized by its location, backlog ($s_{i,t}$), a mean backlog ($\bar{s}_i$), and a standard deviation backlog ($sd(s)_i$). Define the plant's normalized backlog to be $\tilde{s}_{i,t} := \frac{s_{i,t}-\bar{s}_i}{sd(s)_i}$ and its distance to project (j,t) to be $d_{i,j,t}$. The plant's cost for auction (j,t) is an independent draw from $F_\tau(\cdot;\tilde{s}_{i,t}, d_{i,j,t}, \zeta)$. This specification of the cost distribution assumes that plants of type τ are symmetric after controlling for their normalized backlog, distance to an auction, and engineer's estimate; this implies an independent private value (IPV) setting. Since the engineer's estimate is assumed to be constant across all auctions, I will suppress the cost distribution's dependence on ζ.

Assume that there are a finite number of distance categories and that the cost distribution is invariant for distances within each category. This invariance within distance bins means that the plant views all the auctions in a bin as identical before costs are drawn. Therefore, the plant's participation decision is over which distance category auction to submit a bid; it randomly selects an auction in the distance category in which it decides to bid. Naturally, the plant's entry decision is restricted to distance bins that have an available auction. This means a plant only needs to track whether each distance category has an available auction in period t instead of tracking all the project locations.

In the model that is estimated, there are three distance categories: near (n), medium (m), and far (f). Following the data, I assume that there is always an available auction in the far distance bin. So the plant only needs to track if there is an available near or medium distance auction. Let $\boldsymbol{y}_{i,t} := (y_{i,t,n}, y_{i,t,m})$, where $y_{i,t,d}$ is 1 if there is period t auction in distance category d and 0 otherwise, denote the set of available distance categories in period t. The action space given the state is

$$\mathcal{A}(\boldsymbol{y}_{i,t}) = \begin{cases} \{0, f\} & \text{if } \boldsymbol{y}_{i,t} = (0,0); \\ \{0, m, f\} & \text{if } \boldsymbol{y}_{i,t} = (0,1); \\ \{0, n, f\} & \text{if } \boldsymbol{y}_{i,t} = (1,0); \\ \{0, n, m, f\} & \text{if } \boldsymbol{y}_{i,t} = (1,1); \end{cases}$$

where 0 corresponds to not participating.

For simplicity of exposition, the remainder of the section will assume that there are two distance categories, near (n) and far (f) and that there is always a far auction available. To ensure that it is clear where the medium distance bin variables will enter, I bold the state variables that become vectors when the third bin is introduced. For example, below $\boldsymbol{y}_{i,t}$ will be equivalent to $y_{i,t,n}$ but when the medium bin is introduced, $\boldsymbol{y}_{i,t} := (y_{i,t,n}, y_{i,t,m})$.

5.1 The Model Timing

The timing for plant i of type τ in period t is as follows:

1. Plant i observes $\boldsymbol{y}_{i,t}$ which is equal to 1 if there is a period t auction in the near distance bin and 0 otherwise.

2. The auctioneer reveals (advertises) the locations of a subset of period $t+1$ auctions. Let $\boldsymbol{w}_{i,t}$ be the state variable that indicates if there is an announced period $t+1$ auction in the near distance category.

3. The plant receives i.i.d. shocks for entering an auction in each distance bin with an auction and for not participating.

4. Based on the shocks, the plant decides whether to participate in a distance bin with an auction. If the plant participates in an auction in distance bin d, then it pays a bid preparation cost κ_d and obtains an i.i.d. cost signal from $F_\tau(\cdot; \tilde{s}_{i,t}, d)$.

5. The auctioneer reveals the locations of another subset of period $t+1$ auctions. Let $\boldsymbol{x}_{i,t}$ indicate if there is a period $t+1$ in the near distance bin based on all the advertisements released in period t.

6. The plant submits a bid to the auction for which it obtained a cost draw.

7. The plant wins the auction if it submitted the lowest bid at the price equal to its bid.

8. The plant's backlog evolves according to a stochastic transition function which takes into account whether the firm won the an auction in period t. I.e. its current backlog either stays the same or falls; the project magnitude ζ gets added to the evolved backlog if i wins.

Notice that there are two advertising rounds in a period: before the participation decision and before the bidding decision. This assumption is driven by the reduced form results which suggest that ads affect both participation and bidding as well as the institutional fact that ads issued at different times in period t. Both of these advertisements inform the plant about $\boldsymbol{Y}_{t+1}$, which indicates if there is a nearby auction in period $t+1$, in period t. The model also assumes that receiving a cost signal implies a bid will be submitted; this is made to avoid a selection issue with the bids.

There are two stages in a period: the participation stage and the bidding stage. In order to solve the model, I will work backwards, solving the bidding decision then using those results to solve the participation decision.

5.2 The Bidding Decision

When the plant has decided to bid in a distance d auction, its state variables are: (i) the cost draw c; (ii) a dummy that indicates if there is a near auction in period t, $\boldsymbol{y}_t$; (iii) a dummy that indicates if a near distance auction for period $t+1$ has been announced, $\boldsymbol{x}_t$; (iv) its backlog, s_t. Plant i maximizes (suppressing the i subscript):

$$\begin{aligned}\max_b \Big\{ &(b-c)\tilde{G}_M(b|d) \\ &+ \delta \mathbb{E}_{S_{t+1},\boldsymbol{Y}_{t+1},\boldsymbol{W}_{t+1}}[V(S_{t+1},\boldsymbol{Y}_{t+1},\boldsymbol{W}_{t+1})|s_t,\boldsymbol{y}_t,\boldsymbol{x}_t]G_M(b|d) \\ &+ \delta \mathbb{E}_{S_{t+1},\boldsymbol{Y}_{t+1},\boldsymbol{W}_{t+1}}[V(S_{t+1}+\zeta,\boldsymbol{Y}_{t+1},\boldsymbol{W}_{t+1})|s_t,\boldsymbol{y}_t,\boldsymbol{x}_t]\tilde{G}_M(b|d)\Big\},\end{aligned} \tag{5.1}$$

where $G_M(\cdot|d)$ is the cumulative distribution function of the minimum rival bid and $\tilde{G}_M(\cdot|d) := 1 - G_M(\cdot|d)$. The entry cost and epsilon shock do not enter because they are sunk. The first line gives the expected auction payoff for the risk-neutral bidder. The second line gives the continuation value if the plant loses the auction: it enters the period $t+1$ participation stage with backlog S_{t+1}, available auction distances $\boldsymbol{Y}_{t+1}$, and advertisements about period $t+2$ auctions $\boldsymbol{W}_{t+1}$. The third line gives the continuation value if the plant wins the auction. Winning affects the continuation value by adding the project's magnitude ζ to the plant's backlog.

Equation (5.1) implies that two plants with identical states will have different bids most circumstances. First, if the plants are at different locations, the transition laws for $\boldsymbol{Y}_{t+1}$ and $\boldsymbol{W}_{t+1}$ are different. This means the value functions will differ across the two plants so the optimal bid will as well. Second, if the plants have a different mean backlog and/or standard deviation of backlog, the value functions will differ as well. This is because the same backlog level s_t, can be a high normalized backlog $\tilde{s}_t$ for one plant and a low normalized backlog for another; normalized backlog directly impacts the cost distribution which affects the discounted future sum of payoffs. This means that in estimation, special care will be taken to account for this when pooling data across plants of a given type.

The first order condition of (5.1) is

$$c = b - \frac{\tilde{G}_M(b|d)}{g_M(b|d)} - \delta\Big(\mathbb{E}_{S_{t+1},\boldsymbol{Y}_{t+1},\boldsymbol{W}_{t+1}}[V(S_{t+1},\boldsymbol{Y}_{t+1},\boldsymbol{W}_{t+1})|s_t,\boldsymbol{y}_t,\boldsymbol{x}_t] \\ - \mathbb{E}_{S_{t+1},\boldsymbol{Y}_{t+1},\boldsymbol{W}_{t+1}}[V(S_{t+1}+\zeta,\boldsymbol{Y}_{t+1},\boldsymbol{W}_{t+1})|s_t,\boldsymbol{y}_t,\boldsymbol{x}_t]\Big), \tag{5.2}$$

where $g_M(\cdot|d)$ is the density function of the minimum rival bid. This first order condition is similar to that derived in JP: the cost is equal to the bid less two markup terms. The first markup term accounts for the level of competition the plant faces in period t. The second markup term accounts for the opportunity cost of winning (costs are increasing in backlog) on future profits. If the bidder is myopic ($\delta = 0$), this opportunity cost of winning is no longer part of the bid.

In order to return to the participation stage, when both the cost draw and the bidding stage advertisements are unknown, it remains to integrate out those variables. To simplify these expectations, I make the natural assumption that the advertisements are independent of the cost draw; this allows the two variables to be integrated out separately.

I begin with integrating out the cost draw. Let $\beta(c|d,s_t,\boldsymbol{y}_t,\boldsymbol{x}_t)$ denote the equilibrium bidding function and $\eta(b|d,s_t,\boldsymbol{y}_t,\boldsymbol{x}_t)$ be the inverse bid function. Then using the first order condition, the bidding stage objective function given a cost is:

$$\frac{\tilde{G}_M(\beta(c|d,s_t,\boldsymbol{y}_t,\boldsymbol{X}_t)|d)^2}{g_M(\beta(c|d,s_t,\boldsymbol{y}_t,\boldsymbol{X}_t)|d)} + \delta\mathbb{E}_{S_{t+1},\boldsymbol{Y}_{t+1},\boldsymbol{W}_{t+1}}[V(S_{t+1},\boldsymbol{Y}_{t+1},\boldsymbol{W}_{t+1})|s_t,\boldsymbol{y}_t,\boldsymbol{X}_t]. \tag{5.3}$$

Integrating this expression with respect to cost yields

$$\int_{\underline{c}}^{\infty}\left(\frac{\tilde{G}_M(\beta(c|d,s_t,\boldsymbol{y}_t,\boldsymbol{X}_t)|d)^2}{g_M(\beta(c|d,s_t,\boldsymbol{y}_t,\boldsymbol{X}_t)|d)} + \delta\mathbb{E}_{S_{t+1},\boldsymbol{Y}_{t+1},\boldsymbol{W}_{t+1}}[V(S_{t+1},\boldsymbol{Y}_{t+1},\boldsymbol{W}_{t+1})|s_t,\boldsymbol{y}_t,\boldsymbol{X}_t]\right) f(c|d,s_t)dc. \tag{5.4}$$

Under the equilibrium bidding assumption, $F(c|d,s) = G_B(\beta(c|d,s_t,\boldsymbol{y}_t,\boldsymbol{X}_t)|d,s_t,\boldsymbol{y}_t,\boldsymbol{X}_t)$ implies that $f(c|d,s) = g_B(\beta(c|d,s_t,\boldsymbol{y}_t,\boldsymbol{X}_t)|d,s_t,\boldsymbol{y}_t,\boldsymbol{X}_t)\frac{d\beta(c|d,s_t,\boldsymbol{y}_t,\boldsymbol{X}_t)}{dc}$. So the variable of integration can be changed from costs to bids:

$$\int_{\underline{b}}^{\infty}\frac{\tilde{G}_M(b|d)^2}{g_M(b|d)}g_B(b|d,s_t,\boldsymbol{y}_t,\boldsymbol{X}_t)db + \delta\mathbb{E}_{S_{t+1},\boldsymbol{Y}_{t+1},\boldsymbol{W}_{t+1}}[V(S_{t+1},\boldsymbol{Y}_{t+1},\boldsymbol{W}_{t+1})|s_t,\boldsymbol{y}_t,\boldsymbol{X}_t]. \tag{5.5}$$

Taking expectations of (5.5) over $\boldsymbol{X}_t$ yields:

$$\mathbb{E}_{\boldsymbol{X}_t}\left[\int_{\underline{b}}^{\infty}\frac{\tilde{G}_M(b|d)^2}{g_M(b|d)}g_B(b|d,s_t,\boldsymbol{y}_t,\boldsymbol{X}_t)db\Big|s_t,\boldsymbol{y}_t,\boldsymbol{w}_t\right]+\delta\mathbb{E}_{S_{t+1},\boldsymbol{Y}_{t+1},\boldsymbol{W}_{t+1}}[V(S_{t+1},\boldsymbol{Y}_{t+1},\boldsymbol{W}_{t+1})|s_t,\boldsymbol{y}_t,\boldsymbol{w}_t], \tag{5.6}$$

where the second term is obtained through an application of the law of iterated expectations. Thus, equation (5.6) represents the expected auction payoff in the participation stage without the entry cost and epsilon shock.

5.3 The Participation Decision

In the participation stage, the plant decides which (if any) auction in the available distance categories to bid in. Using the earlier derivation of the auction payoff, the participation value function can be written as:

$$\begin{aligned} V(s_t,\boldsymbol{y}_t,\boldsymbol{w}_t) = \mathbb{E}_{\boldsymbol{\varepsilon}}\Bigg[\max_{a\in\mathcal{A}(\boldsymbol{y}_t)}\Big\{&\mathbb{E}_{\boldsymbol{X}_t}[r(d=a,s_t,\boldsymbol{y}_t,\boldsymbol{X}_t)|s_t,\boldsymbol{y}_t,\boldsymbol{w}_t]-\kappa_a+\varepsilon(a) \\ &+\delta\mathbb{E}_{S_{t+1},\boldsymbol{Y}_{t+1},\boldsymbol{W}_{t+1}}[V(S_{t+1},\boldsymbol{Y}_{t+1},\boldsymbol{W}_{t+1})|s_t,\boldsymbol{y}_t,\boldsymbol{w}_t]\Big\}\Bigg], \end{aligned} \tag{5.7}$$

where $\kappa.$ is the entry cost,

$$r(d,s_t,\boldsymbol{y}_t,\boldsymbol{x}_t) := \int_{\underline{b}}^{\infty}\frac{\tilde{G}_M(b|d)^2}{g_M(b|d)}g_B(b|d,s_t,\boldsymbol{y}_t,\boldsymbol{x}_t)db,$$

$\kappa_0 = 0$, and $r(d=0,s_t,\boldsymbol{y}_t,\boldsymbol{x}_t)=0$. The latter two equalities state that not participating has neither an expected revenue nor entry cost. Notice that the participation decision has no impact on the continuation value. The reason for this is that plant accounts for the opportunity cost of winning in its bids so the continuation value is exactly the same as choosing not to participate.

6 Estimation

The model primitives to recover are the cost distribution $F(\cdot|\tilde{s},d)$ and the entry costs $\kappa.$. The solved model suggests the following multi-step estimator:

1. Estimate the conditional choice probabilities (CCP's) and transition functions off the data.
2. Estimate $G_B(\cdot|d,\tilde{s}_t,\boldsymbol{y}_t,\boldsymbol{x}_t)$ and $G_M(\cdot|d)$ from the bid data.

3. Recover the entry costs and value function by matching the estimated CCP's from step 1 with model predicted CCP's.

4. Use $\hat{G}_B(\cdot)$, $\hat{G}_M(\cdot)$, and $\hat{V}(\cdot)$ with the bid first order condition to recover the cost distribution.

The estimator detailed below is written for the model with the three distance categories near (n), medium (m), and far (f) because this is what is brought to the data. This means that $\boldsymbol{y}_{i,t} := (y_{i,t,n}, y_{i,t,m})$, $\boldsymbol{x}_{i,t} := (x_{i,t,n}, x_{i,t,m})$, and $\boldsymbol{w}_{i,t} := (w_{i,t,n}, w_{i,t,m})$.

6.1 Estimating Transition Probabilities and CCP's

The transition probabilities that need to be estimated are $\Pr(S_{i,t+1}|S_{i,t})$, $\Pr(\boldsymbol{X}_{i,t}|\boldsymbol{W}_{i,t})$, $\Pr(\boldsymbol{Y}_{i,t+1}|\boldsymbol{X}_{i,t})$, and $\Pr(\boldsymbol{W}_{i,t+1}|\boldsymbol{X}_{i,t})$. Note that $\Pr(S_{i,t+1}|S_{i,t})$ only needs to be estimated for the case in which the plant does not bid because the bid function accounts for the opportunity cost of winning as shown in (5.3). The pattern of dependence in the plant's evolution of state variables if it does not bid is shown graphically in Table 5.

[Table 5 about here.]

To estimate the backlog transition $\Pr(S_{i,t+1}|S_{i,t})$, I assume that backlog $S_{i,t}$ either stays the same or falls by 1 discrete amount (due to projects being worked off) for all plants; the work schedule is determined by the government. Since I observe the backlog independent of whether a firm won a project or not, I can estimate the probability that the backlog falls by one notch, which gives me $\widehat{\Pr}(S_{i,t+1}|S_{i,t})$.

The transition probabilities $\Pr(\boldsymbol{X}_{i,t}|\boldsymbol{W}_{i,t})$, $\Pr(\boldsymbol{Y}_{i,t+1}|\boldsymbol{X}_{i,t})$, and $\Pr(\boldsymbol{W}_{i,t+1}|\boldsymbol{X}_{i,t})$ are estimated separately for each firm using a frequency estimator. Notice that I assume that $\boldsymbol{Y}_{i,t}$ does not affect the transition law; adding this conditioning variable would require more data than I have available for each firm. Finally, I assume that $\boldsymbol{W}_{i,t+1}$ and $\boldsymbol{Y}_{i,t+1}$ are independent conditional on $\boldsymbol{X}_{i,t}$. These estimate allow me to compute $\Pr(\boldsymbol{W}_{i,t+1}|\boldsymbol{W}_{i,t})$ and $\Pr(\boldsymbol{Y}_{i,t+1}|\boldsymbol{W}_{i,t})$ using the standard conditional probability rules. Taken together, these estimates allow me to compute the transition matrices required for the dynamic model.

Recall that the state $\boldsymbol{y}_{i,t} = (y_{i,t,n}, y_{i,t,m})$ controls the action space $\mathcal{A}(\boldsymbol{y}_{i,t})$. The CCP's are estimated using a multinomial logit model after conditioning on the action space.[4] The linear

[4] In principle, the CCP's could be estimated nonparametrically. However, given the richness of the state space, the data requirement for such an estimator is impractical.

payoff, excluding the T1EV shock, of i of choosing action a in $\mathcal{A}(\boldsymbol{y}_t) - \{0\}$ is specified to be:

$$
\begin{aligned}
u(a) = \gamma_0^{(a)} + \gamma_1 \tilde{s}_{i,t} + \gamma_2 sd(s)_i + \gamma_4 \Pr(Y_{i,t+1,n} = 1|\boldsymbol{w}_{i,t}) + \gamma_5 \Pr(Y_{i,t+1,m} = 1|\boldsymbol{w}_{i,t}) \\
+ \gamma_6 \Pr(W_{i,t+1,n} = 1|\boldsymbol{w}_{i,t}) + \gamma_7 \Pr(W_{i,t+1,m} = 1|\boldsymbol{w}_{i,t}),
\end{aligned}
\tag{6.1}
$$

with year and month fixed effects and $u(0)$ is normalized to equal 0. Normalized backlog is included because this affects the cost distribution. The plant's standard deviation of backlog enters because plant's with smaller standard deviations have their normalized backlog impacted more by changes in backlog; this captures the idea that plants with the same state can have differing value functions. The advertisements about period $t+1$ auctions enter through the $\Pr(Y_{i,t+1,n} = 1|\boldsymbol{w}_{i,t})$ and $\Pr(Y_{i,t+1,m} = 1|\boldsymbol{w}_{i,t})$ covariates. Notice that if $w_{i,t,n} = 1$ then $\Pr(Y_{i,t+1,n} = 1|\boldsymbol{w}_{i,t}) = 1$. This specification captures how different plants have different probabilities of a nearby auction in the following period *even if none are announced in the participation stage.* The intuition is that a plant that is very likely to have a nearby project in the following period responds less to the advertisement than one that is unlikely to have a nearby project. Finally, I include $\Pr(W_{i,t+1,n} = 1|\boldsymbol{w}_{i,t})$ and $\Pr(W_{i,t+1,m} = 1|\boldsymbol{w}_{i,t})$ as covariates to account for the differences in plant transition probabilities.

6.2 Estimating Bid Distributions

The bid distribution is estimated separately separately for the big and small bidders. In order to pool data across auctions with different engineer's estimates, I work with normalized bids: $\tilde{b}_{i,t} := \frac{b_{it}}{\zeta_t}$. I specify a three parameter Weibull distribution, as utilized in JP and Athey et al. (2011), on the normalized bids. The bid distribution is

$$
G_{\tilde{B}}(\tilde{b}|Z,d) = 1 - \exp\left(-\left(\frac{\tilde{b}-\xi}{\lambda(Z,d)}\right)^k\right), \tag{6.2}
$$

where ξ is the support, k is the shape, and $\lambda(\cdot)$ is the scale parameter. The scale is parameterized according to $\ln\lambda(Z,d) = Z\alpha_Z + \alpha_d$. The Z includes similar covariates as in the multinomial logit estimator (conditioning on the advertisement state in the bidding stage), observable auction characteristics, and year and month fixed effects. While the dynamic model assumes that all auctions are identical (apart from distance) and that time doesn't matter after conditioning on the state, I include these in the bid distribution estimates in order to get the most precise estimates possible. When I incorporate these estimates in the dynamic model, I enforce the assumption that all auctions are identical apart from location and zero out the time fixed effects.

The distribution of the minimum rival bid is specified similarly except the scale parameter, which does not include any state variables. Further, I impose the restriction that the shape parameter is at least 1. This restriction is to ensure that bids are increasing in costs; the restriction is not binding.

Finally, notice that the normalized bid and minimum rival bid distribution estimates can be used to compute the expected auction revenue integral:

$$\int_{\underline{b}}^{\infty} \frac{\tilde{G}_M(b|d)^2}{g_M(b|d)} g_B(b|d, s_t, \boldsymbol{y}_t, \boldsymbol{x}_t) db = \zeta \int_{\underline{b}/\zeta}^{\infty} \frac{\tilde{G}_{\tilde{M}}(\tilde{b}|d)^2}{g_{\tilde{M}}(\tilde{b}|d)} g_{\tilde{B}}(\tilde{b}|d, s_t, \boldsymbol{y}_t, \boldsymbol{x}_t) d\tilde{b}.$$

I estimate the distributions using a two step estimator as in JP. In the first step, I estimate the support parameter by taking the lowest normalized bid observed in the data. Then, the shape and scale parameters are estimated via maximum likelihood.

6.3 Estimating the Entry Costs

To recover the entry costs I use the least squares estimator of Pesendorfer & Schmidt-Dengler (2008), which utilizes the insight that in equilibrium, the conditional choice probabilities (CCP) implied by the model should be consistent with the observed CCP's. The estimator involves searching for the flow profit parameters that minimize the distances between the CCP's. The flow revenue[5] from the auction that enters the participation decision (5.7) is

$$\mathbb{E}_{\boldsymbol{X}_t} \left[\int_{\underline{b}}^{\infty} \frac{\tilde{G}_M(b|d)^2}{g_M(b|d)} g_B(b|d, s_t, \boldsymbol{y}_t, \boldsymbol{X}_t) db \middle| \boldsymbol{w}_t \right],$$

and can be computed directly using the bid distribution and $\Pr(\boldsymbol{X}_{i,t}|\boldsymbol{W}_{i,t})$ estimates. So it remains to search over the entry cost parameters.

Given a set of entry cost parameters $\boldsymbol{\kappa}$, the flow profit $\boldsymbol{\Pi}_i(\boldsymbol{\kappa})$ can be computed for all M_s states

[5] Strictly speaking, the flow revenue from the auction includes the value function because it enters the bid as part of the markup. Through algebraic manipulation, the flow revenue that includes the value function is added to the continuation value.

for each plant i. Then the pseudo-value function is

$$\begin{aligned}\underbrace{V_i}_{M_s\times 1} &= \sum_a \Big[\underbrace{\boldsymbol{\sigma}_i(a)}_{M_s\times 1} * \underbrace{\boldsymbol{\Pi}_i(\boldsymbol{\kappa})}_{M_s\times 1}\Big] + \underbrace{\boldsymbol{D}_i}_{M_s\times 1} + \delta\Big[\sum_a \boldsymbol{\sigma}_i(a) * \underbrace{\boldsymbol{T}_i(a)}_{M_s\times M_s}\Big]V_i \\ &= \Big[\boldsymbol{I}_{M_s} - \delta\sum_a \boldsymbol{\sigma}_i(a) * \boldsymbol{T}_i(a)\Big]^{-1}\Big[\sum_a \big[\boldsymbol{\sigma}_i(a) * \boldsymbol{\Pi}_i(\boldsymbol{\kappa})\big] + \boldsymbol{D}_i\Big], \end{aligned} \tag{6.3}$$

where $*$ is the Hadamard (element-by-element) product[6], $\boldsymbol{\sigma}_i(a)$ is the stacked CCP of choice a for all states, $\boldsymbol{T}_i(a)$ is the transition matrix given action a, and $\boldsymbol{D}_i$ is the expected value of the epsilon shock. Note that when an action is not available in a given state $\sigma_i(a; s_{i,t}, \boldsymbol{y}_{i,t}, \boldsymbol{w}_{i,t}) = 0$ and that $D_i(s_{i,t}, \boldsymbol{y}_{i,t}, \boldsymbol{w}_{i,t}) = \sum_{a' \in \mathcal{A}(\boldsymbol{y}_{i,t})} \mathbb{E}[\varepsilon(a) | a = a', s_{i,t}, \boldsymbol{y}_{i,t}, \boldsymbol{w}_{i,t}] \sigma_i(a'; s_{i,t}, \boldsymbol{y}_{i,t}, \boldsymbol{w}_{i,t})$. If the true flow profit parameters and CCP values were plugged into (6.3), the pseudo-value function equals the value function. To reiterate, the i subscripts exist because firms have different mean and standard deviation of backlogs, so a backlog s results in a different normalized backlog $\tilde{s}$. Moreover, the conditional transition matrices are plant specific because their differing locations means the probability of an auction in a distance bin is plant specific.

Under an i.i.d. type 1 extreme value (T1EV) assumption on the epsilon shocks, the probability of action a in state $(s_{i,t}, \boldsymbol{y}_{i,t}, \boldsymbol{w}_{i,t})$ with entry cost $\boldsymbol{\kappa}$ is

$$p_i(a, s_{i,t}, \boldsymbol{y}_{i,t}, \boldsymbol{w}_{i,t}; \boldsymbol{\kappa}) := \frac{\exp\left[\Pi_i(a, s_{i,t}, \boldsymbol{y}_{i,t}, \boldsymbol{w}_{i,t}; \boldsymbol{\kappa}) + \delta \boldsymbol{T}_i(a; s_{i,t}, \boldsymbol{y}_{i,t}, \boldsymbol{w}_{i,t}) V_i(\boldsymbol{\kappa})\right]}{\sum_{a' \in \mathcal{A}(\boldsymbol{y}_{i,t})} \exp\left[\Pi_i(a', s_{i,t}, \boldsymbol{y}_{i,t}, \boldsymbol{w}_{i,t}; \boldsymbol{\kappa}) + \delta \boldsymbol{T}_i(a'; s_{i,t}, \boldsymbol{y}_{i,t}, \boldsymbol{w}_{i,t}; \boldsymbol{\kappa}) V_i(\boldsymbol{\kappa})\right]}, \tag{6.4}$$

where $\Pi(a, s_{i,t}, \boldsymbol{y}_{i,t}, \boldsymbol{w}_{i,t}; \boldsymbol{\kappa})$ is the flow profit of action a given the state and entry cost parameters and $\boldsymbol{T}_i(a; s_{i,t}, \boldsymbol{y}_{i,t}, \boldsymbol{w}_{i,t})$ is the row of the conditional transition matrix that corresponds to the state. Estimating $\boldsymbol{\kappa}$ is a matter of minimizing the objective function

$$\sum_{a' \neq 0} [\boldsymbol{p}_i(a'; \boldsymbol{\kappa}) - \boldsymbol{\sigma}_i(a')]' \boldsymbol{W}_{a'} [\boldsymbol{p}_i(a'; \boldsymbol{\kappa}) - \boldsymbol{\sigma}_i(a')], \tag{6.5}$$

where $\boldsymbol{W}_{a'}$ is a positive definite weight matrix, $\boldsymbol{p}_i(a'; \boldsymbol{\alpha})$ is the stacked model predicted probability of action a', and $\boldsymbol{\sigma}_i(a')$ is the stacked observed CCP. The probability of not bidding ($a' = 0$) is excluded because it is uniquely determined by the CCP of all other actions. The weight matrix differs across actions because not all actions are available in all states; this allows me to ensure that the estimator does not overweight states with more actions. A diagonal weight matrix is used in

[6]When Hadamard multiplying a vector and a matrix, the vector is broadcast into a matrix where each column equals the vector.

estimation with each state being weighted according to the number of data points used to obtain the offline CCP estimates for that state. Note that in estimation, I will estimate a parameter that scales the flow profit $\Pi(\cdot)$. This is equivalent to estimating a scale parameter on the epsilon shock. This scale parameter is so that the units of the T1EV shock do not improperly affect the results.

The identification of entry costs follows immediately from Propositions 2 and 3 in Pesendorfer & Schmidt-Dengler (2008). The propositions imply that if the discount factor and transition probabilities are known, then I can identify as many entry costs up to a location normalization (i.e. not participating has zero entry cost) as I have offline CCP estimates to match with the model.

6.4 Estimating the Cost Distribution

To infer the distribution of costs, notice that

$$F_i(c|d,s) = G_B(\beta_i(c|d,s,\boldsymbol{y}_t,\boldsymbol{x}_t)|d,s,\boldsymbol{y}_t,\boldsymbol{x}_t) \Leftrightarrow F_i(\eta_i(b|d,s_t,\boldsymbol{y}_t,\boldsymbol{x}_t)|d,s) = G_B(b|d,s,\boldsymbol{y}_t,\boldsymbol{x}_t)$$

and that $\eta_i(b|d,s,\boldsymbol{y},\boldsymbol{x})$ was derived in (5.2). $\eta_i(\cdot)$ requires estimates of the value function, which can be obtained by forward simulation (i.e. value function iteration) because the flow profit function is known (through the bid distribution and entry cost estimates). Under this procedure, standard errors are calculated via the delta method.

7 Structural Estimates

This section discusses the estimates of the structural model for the small (single plant) firms. I begin by presenting the offline CCP estimates along with the bid distribution estimates. Then I discuss the entry cost and value function estimates. The cost distribution and large firm estimates are in progress and are not presented here.

In estimation, the monthly discount factor is fixed at $\delta = 0.99$, which is approximately the 0.9 annual discount factor assumed by JP. Backlog, $s_{i,t}$, is a discrete variable that takes on values between \$0 and \$5 million in \$250 thousand increments. An auction in the near (n) distance bin is defined to be within 25km of the firm; the medium (m) distance bin is defined to be between 25km and 50km of the firm; the far bin includes auctions more than 50km from the firm.

The multinomial logit estimates used to compute the offline CCP's for each plant are presented in Table 6. There are four sets of estimates that correspond to the four different action spaces (e.g. bidding on a nearby auction is only possible if it is available as denoted by $y_{t,n} = 1$). The estimates show that plants are more inclined to participate in auctions that are closer, which is consistent with the data. Participation in any auction is decreasing in normalized backlog and increasing in the plant's standard deviation of backlog. Participation is falling in normalized backlog because the more constrained the plant is, the cost draw is higher in expectation which results in lower expected auction revenue. Participation is increasing in the standard deviation of backlog because relative to a plant with a small standard deviation: (i) winning the auction has less of an impact on its normalized backlog and (ii) the gain from not participating and having the backlog decrease is smaller. The participation stage advertisements affect on entry is presented in the $\Pr(Y_{i,t+1,n} = 1|\boldsymbol{w}_{i,t})$ and $\Pr(Y_{i,t+1,m} = 1|\boldsymbol{w}_{i,t})$ rows. If a nearby auction $t+1$ auction is announced then the probability of it occurring is 1. The probability is utilized (instead of a dummy indicating the announcement) because an auction being available in a distance bin have different likelihoods of occuring accross plants if not announced. The estimates largely have the expected sign: if a nearby or medium distance $t+1$ auction is announced, the probability of participating is reduced and this effect is smaller for plants that are likely to have nearby or medium distance $t+1$ auctions in the absence of an advertisement. The economic interpretation is that the opportunity cost of forgoing an auction today is smaller if there is a comparable auction available in the following period. For the two cases where the estimated sign is not as expected, the estimates are not significant at conventional levels. The last of these estimates to discuss is the probability a $t+2$ auction is announced in the participation stage of period $t+1$. While these estimates are mostly not significant, they have the expected sign: the higher the probability of a nearby or medium distance $t+2$ auction, the less likely a plant is to participate.

[Table 6 about here.]

The bid distribution is estimated as a three parameter Weibull distribution with mean $\xi + \lambda\Gamma(1+\frac{1}{k})$, where ξ, λ, and k are the support, scale, and shape parameters respectively and $\Gamma(\cdot)$ is the gamma function. Recall that the natural logarithm of the scale parameter is a linear function of the covariates so a positive sign on a scale parameter coefficient corresponds to a larger mean bid. The parameter estimates in Table 7 are largely as expected. The mean value of the bid is increasing in distance and normalized backlog. The mean of the bid is falling in the standard deviation of backlog because plants with a higher standard deviation have a smaller opportunity cost of winning because their normalized backlog does not increase as much. As with the participation decision, an advertised nearby auction results in $\Pr(Y_{i,t+1,n} = 1|\boldsymbol{x}_{i,t})$ being one. These advertisements result in less aggressive bids. The bids are also less aggressive if a medium distance auction is announced but this estimate is not statistically significant. The parametrization shows that the advertisements have more of an impact on plants that are unlikely to have a nearby auction if one is not announced. The likelihood of a $t+2$ auction announced in the period $t+1$ entry stage significantly affects the bids; the sign for nearby auctions is as expected but is not for medium distance auctions. Finally, the bid distribution controls for certain auction characteristics. While normalized bid is decreasing in the engineer's estimate, it should be noted that the number of line items (which has a positive coefficient) is positively correlated with the engineer's estimate.

[Table 7 about here.]

The minimum rival bid distributions were estimated separately for each plant and I do not report those estimates here. It is worth noting that the level of competition varied across distance bins and that the parametric restriction to ensure bids are increasing in costs was never binding.

The entry cost estimates are reported in Table 8. A separate entry cost was estimated for each distance bin and is reported as a percentage of the engineer's estimate ($750K). The entry costs are similar across bins and around 36% of the project's size; these estimates are implausibly large.[7] The reason for the high entry costs is that under the estimated bid distributions, the expected revenue from entering the auction is high so the relative low participation rates can only be explained by commensurately high entry costs. Another reason for these high estimates is that the payoff of not participating is zero plus the epsilon shock. In practice, firm's that don't participate can perform private jobs or even take subcontracts of the MDOT projects. So the entry cost estimates include the expected flow payoff of not participating.

[Table 8 about here.]

Finally, I present value function plots for a synthetic plant. I utilize a synthetic plant so I can easily vary the transition probabilities and firm characteristics. Figure 4 shows the value functions for a synthetic plant with a mean backlog of $0.5MM, a standard deviation of backlog of $0.25MM and transition functions computed using the following probabilities: (i) the probability of a near and/or medium distance $t+1$ auction being announced in the participation stage is 0.25; (ii) the probability that the bidding stage advertisements reveal additional information about the $t+1$ state is 0.3. (iii) the probability that there is a $t+1$ auction in a distance category not advertised in

[7] Groeger (2014) had a stochastic entry cost and found they were were about 15% conditional on entry.

period t is 0.3. The figure shows that a plant's value function is decreasing in backlog as expected. Going from zero backlog to $5MM backlog reduced the value function by about $750K, or a 10% decrease in the value function. Moreover, the value functions for are increasing in the availability of nearby (within 25km) and medium (between 25km and 50km) distance period t auctions. Finally, the plots show that advertising period $t+1$ auctions in the entry stage results in a higher value function. The gain in the value function going from $\boldsymbol{w}_{i,t} = (0,0)$ to $\boldsymbol{w}_{i,t} = (1,1)$ is modest and ranges between $6,300 to $18,300, which is approximately 0.8–2.4% of the engineer's estimate for a project. These estimates appear reasonable since the reduced form results suggested the ads had a 1-2% impact on participation and bidding. The gain from the advertisements gets smaller when backlog is large. This occurs because when a firm is constrained, the gain from knowing there are nearby auctions is limited because it is unlikely to participate anyway.

[Figure 4 about here.]

The value of the advertisements depends on how much additional information they provide over the plant's beliefs. To demonstrate this with the model, I adjust the transition functions to reduce the amount of information provided by shutting down any advertising in the bidding stage. Figure 5 shows these estimates and the gain in the value function going from $\boldsymbol{w}_{i,t} = (0,0)$ to $\boldsymbol{w}_{i,t} = (1,1)$ ranges from $8,250 to $24,400, which is approximately 1.1–3.2% of the engineer's estimate for a project. I further increase the value of advertisements by making the probability that a nearby or medium distance auction occurring 0 if it is not advertised in the participation stage. Figure 6 shows these estimates and the gain in the value function going from $\boldsymbol{w}_{i,t} = (0,0)$ to $\boldsymbol{w}_{i,t} = (1,1)$ ranges from $10,700 to $32,300, which is approximately 1.4–4.3% of the engineer's estimate for a project.

[Figure 5 about here.]

[Figure 6 about here.]

8 Conclusion

This paper investigates the participation and bidding strategies of capacity constrained bidders in repeated Michigan HMA highway procurement auctions. These projects up for auction are substitutable so bidders should account for information about future period auctions in their strategies.

Using regression analysis, I provide evidence that bidders are capacity constrained and that informing bidders of a close substitute up for auction in the following period marginally reduces the participation probability and results in less aggressive bids. These effects are more pronounced for small bidders.

Based on these data patterns, I develop a dynamic optimization model of participation and bidding. The model accounts for the simultaneity of auctions in a period as well as the advertisements about following period auctions. The model is estimated for the small firms and shows that the value function is decreasing in backlog. The value function estimates show that the advertisements have a modest impact (1-2% of a typical project's engineer's estimate) on the value function. Moreover, the model shows that the effect of the advertisements on the value function is increasing in how much information they convey in addition to the firm's beliefs in the absence of advertisements.

This paper is actively being worked on. Future work will involve estimating the cost distributions for the small firms and estimating the model on large firms. I plan to extend the model beyond a single agent optimization problem by introducing strategic interactions between the firms. Finally, I will simulate the counterfactual policies in which the government either announces all or none of the future period auctions during the current auction cycle. This will quantify the efficiency-price trade-off and allow me to answer whether the government should advertise future period auctions.

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A Additional Regression Results

Section 4 demonstrates that firms are less inclined to participate if there are announced nearby auctions in the following period and bid less aggressively when they do. This section reports the regressions that demonstrate the findings are robust to the definition of nearby. I do a further robustness check by included the number of unannounced auctions as covariates and find that they are not significant.

The participation logit regressions are reported in Tables 9 to 13. The bid regressions are reported in Tables 14 to 18.

[Table 9 about here.]

[Table 10 about here.]

[Table 11 about here.]

[Table 12 about here.]

[Table 13 about here.]

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[Table 15 about here.]

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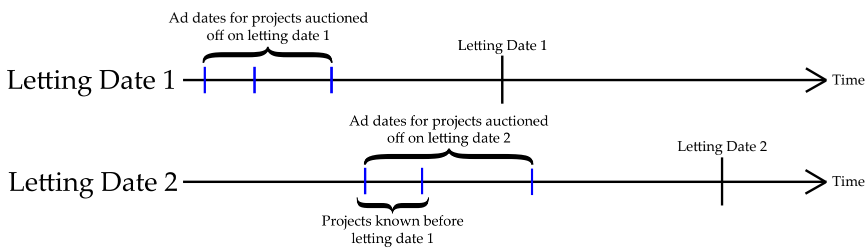


Figure 1: This figure shows an example of how information about future period auctions are known in the current period. There are three projects being auctioned off in each of two letting dates (black vertical lines) that are in separate periods. The advertisement dates for each project are shown by the blue vertical lines. Two of the projects auctioned off on letting date 2 are known prior to letting date 1 since they were advertised before the first letting; one of the projects on letting date 2 was advertised after the first letting date and is unknown to bidders prior to the advertisement.

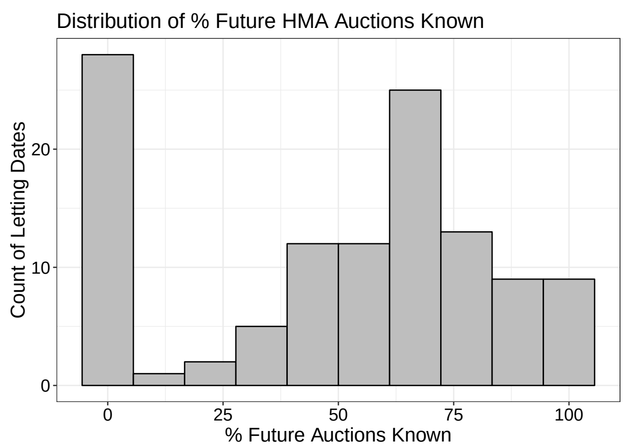


Figure 2: This figure shows the frequency count of letting dates by the percentage of the following period auctions that were announced in the current period.

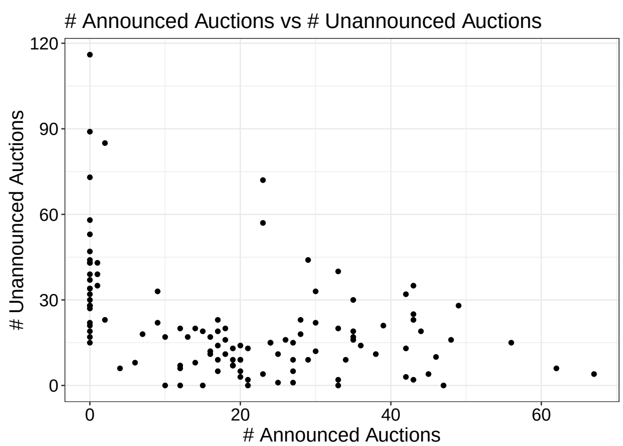


Figure 3: Each point represents the number of announced and unannounced $t+1$ auctions on letting date t.

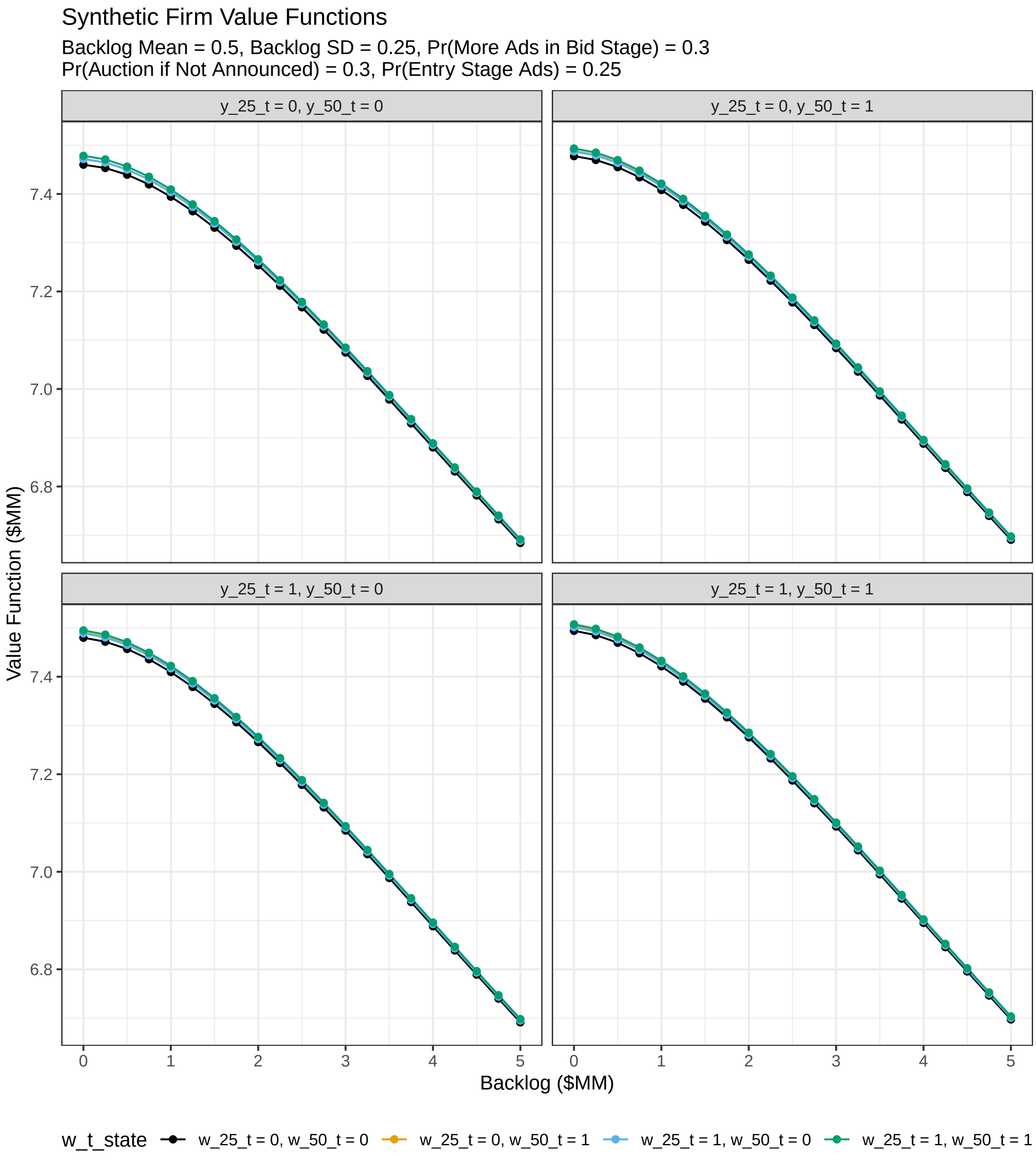


Figure 4: Presents the value functions for a synthetic firm with a mean backlog of \$0.5MM and standard deviation of backlog of \$0.25MM. See text for a description of how the transition probabilities were generated. Each panel shows the value functions given the availability of auction distance categories. $y\_d\_t = 1$ if there is a period t auction in distance category d. The different lines correspond to the advertisement state in the participation stage. $w\_d\_t = 1$ if a period $t + 1$ auction in distance bin d was announced. $d = 25$ corresponds to a near auction (0-25km) and $d = 50$ corresponds to a medium distance auction (25-50km). The value function is increasing in period t auction availability and in the number of advertisements. The gain in the value function from when $\boldsymbol{w}_{i,t} = (0, 0)$ to $\boldsymbol{w}_{i,t} = (1, 1)$ ranges from \$6,300 to \$18,300.

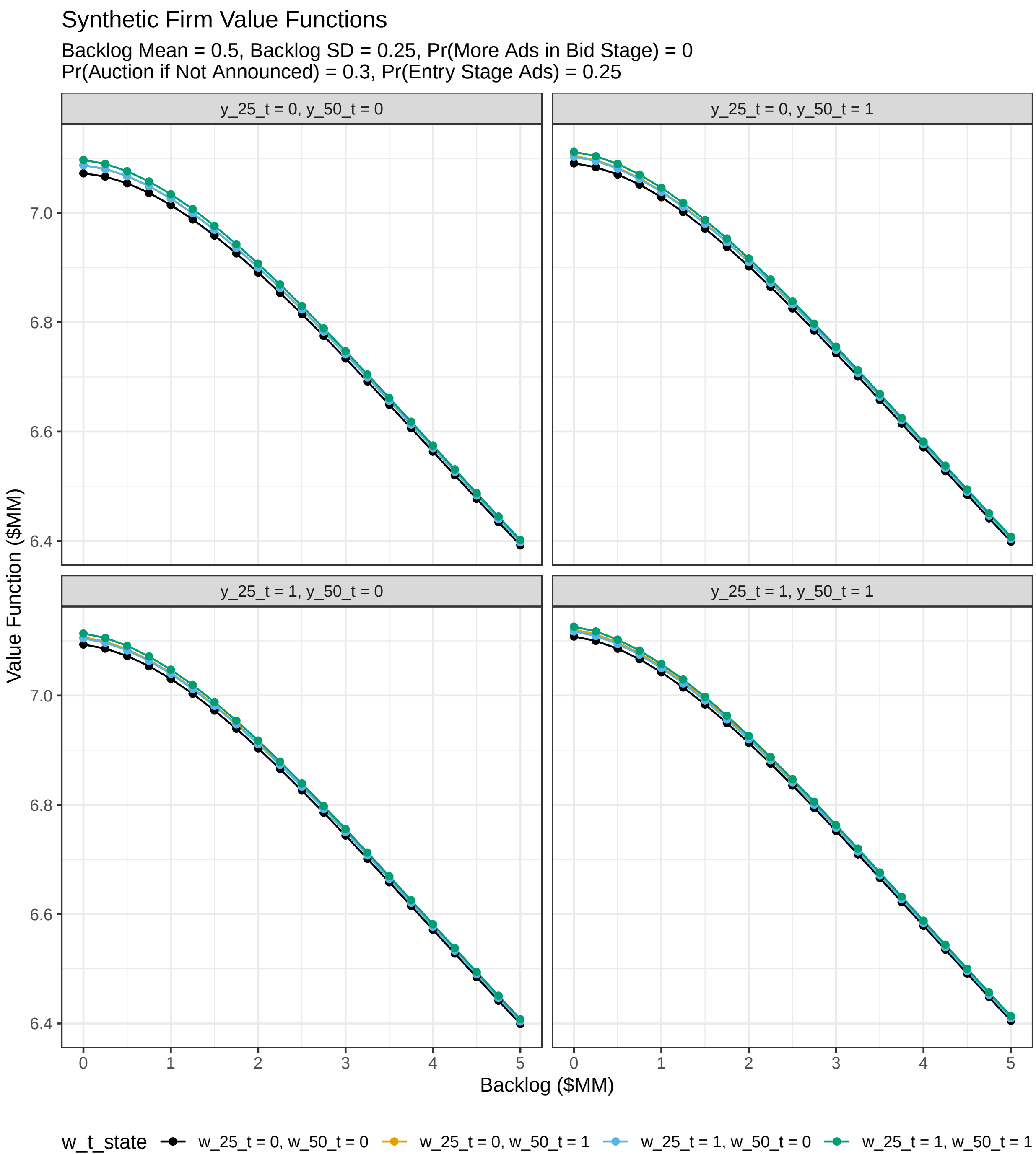


Figure 5: Presents the value functions for a synthetic firm with a mean backlog of $0.5MM and standard deviation of backlog of $0.25MM. This figure shows the value function when there are no advertisements in the bidding stage. Each panel shows the value functions given the availability of auction distance categories. $y\_d\_t = 1$ if there is a period t auction in distance category d. The different lines correspond to the advertisement state in the participation stage. $w\_d\_t = 1$ if a period $t+1$ auction in distance bin d was announced. $d = 25$ corresponds to a near auction (0-25km) and $d = 50$ corresponds to a medium distance auction (25-50km). The value function is increasing in period t auction availability and in the number of advertisements. The gain in the value function from when $\boldsymbol{w}_{i,t} = (0,0)$ to $\boldsymbol{w}_{i,t} = (1,1)$ ranges from $8,250 to $24,400.

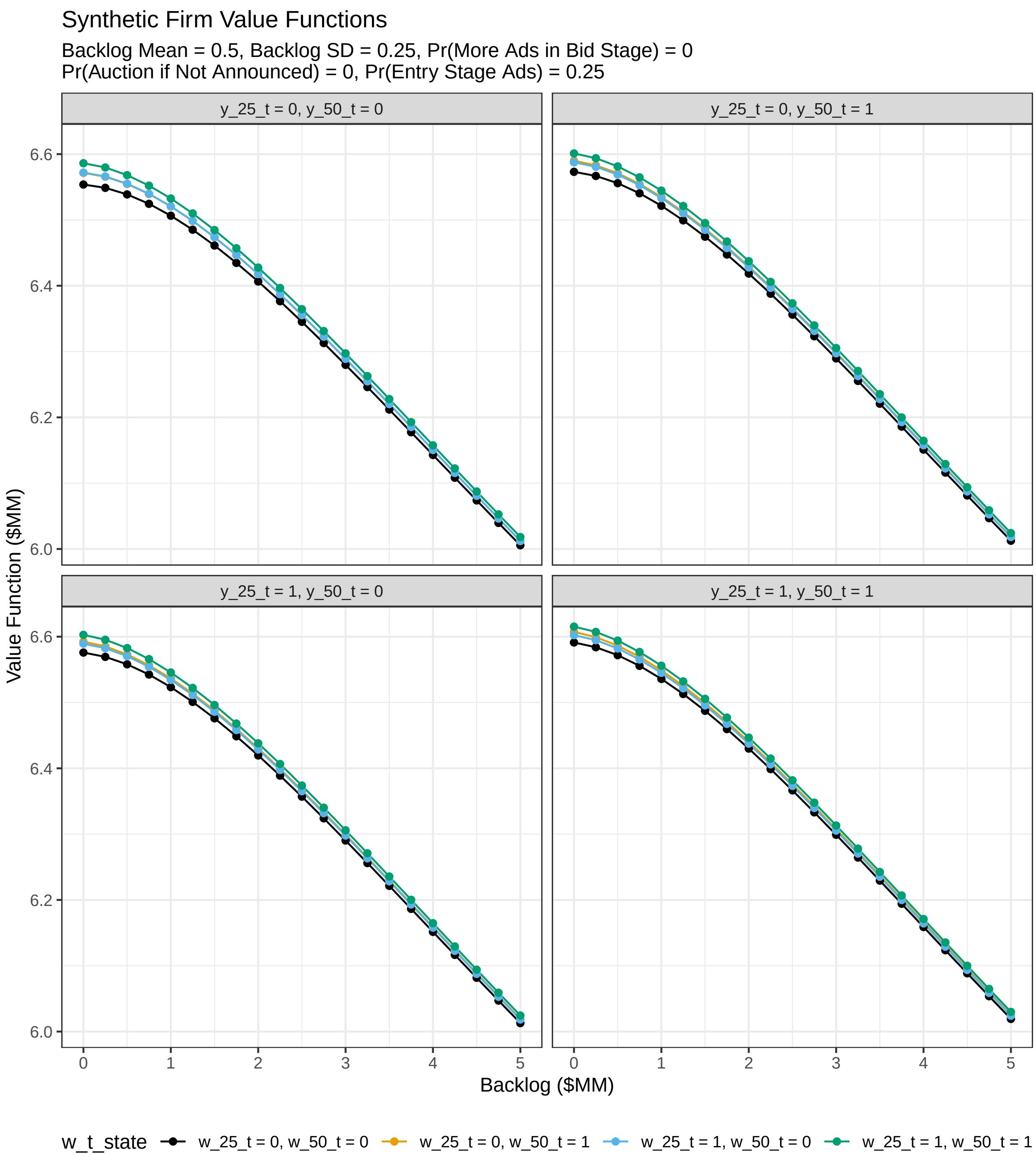


Figure 6: Presents the value functions for a synthetic firm with a mean backlog of $0.5MM and standard deviation of backlog of $0.25MM. This figure shows the value function when there are no advertisements in the bidding stage and the participation stage ads perfectly predict the availability of period t+1 auctions. Each panel shows the value functions given the availability of auction distance categories. $y\_d\_t = 1$ if there is a period t auction in distance category d. The different lines correspond to the advertisement state in the participation stage. $w\_d\_t = 1$ if a period $t+1$ auction in distance bin d was announced. $d = 25$ corresponds to a near auction (0-25km) and $d = 50$ corresponds to a medium distance auction (25-50km). The value function is increasing in period t auction availability and in the number of advertisements. The gain in the value function from when $\boldsymbol{w}_{i,t} = (0, 0)$ to $\boldsymbol{w}_{i,t} = (1, 1)$ ranges from $10,700 to $32,300.

Table 1: Auction Summary Statistics

Variable	N	Mean	SD	Pctl10	Pctl25	Pctl50	Pctl75	Pctl90
Eng Est ($000)	4,233	1,094	1,323	165	319	626	1,317	2,519
Lowest Bid ($000)	4,233	1,026	1,285	158	287	572	1,223	2,380
Participants	4,233	5.159	3.532	2	3	4	7	10
(Runner Up Bid/Lowest Bid-1)∗100	4,168	6.842	7.737	0.733	2.033	4.619	9.008	15.347
(Lowest Bid/Eng Est-1)∗100	4, 233	−6.374	12.963	−21.229	−14.386	−7.032	0.466	8.893
Distance of Winner (km)	4,233	44.186	57.494	4.917	12.064	30.168	53.917	92.068
Distance of Bidders (km)	21,840	54.183	56.265	7.921	19.361	40.856	70.823	109.450
Normalized Backlog of Winner	4,233	−0.161	0.974	−1.373	−0.891	−0.192	0.578	1.137
Normalized Backlog of Bidders	21,840	−0.029	0.908	−1.142	−0.715	−0.026	0.644	1.190

Reports the summary statistics of the HMA auctions from 2002-2010. PctlXX reports the percentile XX of the variable. The (Runner Up Bid/Lowest Bid-1)∗100 variable is summarized for the auctions with ≥ 2 bids.

Table 2: Small Firms' Participation Decision

1(Auction within $[0, 25]$km)	**1**(Auction within $(25, 50]$km)	Action	N	% Total Given Auction Availability
0	0	00	2,224	85.540
		50+	376	14.460
0	1	00	2,315	74.890
		50	484	15.660
		50+	292	9.450
1	0	00	885	61.800
		25	414	28.910
		50+	133	9.290
1	1	00	2,900	59.990
		25	1,053	21.780
		50	502	10.380
		50+	379	7.840

This table shows the small firms' action given the set of available auction distance categories. The distance categories are [0, 25]km, (25, 50]km, and (50, ∞)km. **1**(Auction within $[\underline{d}, \overline{d}]$km) is 1 if on a letting date there is at least one HMA auction between $[\underline{d}, \overline{d}]$km from the firm and zero otherwise. There is always an auction at least 50km away from the firm. The actions '00', '25', '50', '50+' correspond to not participating, bidding in a [0, 25]km auction, bidding in a (25, 50]km auction, and bidding in a (50, ∞)km auction respectively. N refers to the number of times a firm was observed with the set of available auctions and chose the action listed in that row.

Table 3: Auction Participation Logit Regressions

	Dependent variable: $\mathbf{1}(B_{i,j,t} > 0)$			
	Small Bidders		Large Bidders	
	(1)	(2)	(3)	(4)
Dist $\in (25, 50]$km	-0.797^{***}	-0.797^{***}	-0.585^{***}	-0.584^{***}
	(0.040)	(0.040)	(0.029)	(0.029)
Dist $\in (50, 100]$km	-2.175^{***}	-2.176^{***}	-1.754^{***}	-1.754^{***}
	(0.041)	(0.041)	(0.028)	(0.028)
Dist $\in (100, 150]$km	-3.781^{***}	-3.781^{***}	-3.318^{***}	-3.318^{***}
	(0.062)	(0.062)	(0.038)	(0.038)
Dist $\in (150, 200]$km	-4.673^{***}	-4.673^{***}	-4.811^{***}	-4.812^{***}
	(0.089)	(0.089)	(0.063)	(0.063)
Dist $\in (200, \infty)$km	-6.141^{***}	-6.142^{***}	-6.826^{***}	-6.828^{***}
	(0.090)	(0.090)	(0.092)	(0.092)
ln(Eng Est)	-0.359^{***}	-0.359^{***}	-0.051^{***}	-0.051^{***}
	(0.021)	(0.021)	(0.014)	(0.014)
# Period t Auctions	-0.003	-0.003	-0.004^{**}	-0.004^{***}
	(0.003)	(0.002)	(0.002)	(0.002)
Line Items	0.008^{***}	0.008^{***}	0.003^{***}	0.003^{***}
	(0.0004)	(0.0004)	(0.0003)	(0.0003)
% Subcont. to Disadvantaged Firm	-0.0004	-0.001	-0.006^{**}	-0.006^{**}
	(0.005)	(0.005)	(0.003)	(0.003)
Norm Backlog	-0.184^{***}	-0.183^{***}	-0.073^{***}	-0.073^{***}
	(0.020)	(0.020)	(0.012)	(0.012)
# Announced t+1 Auctions $\leq$ Dist90$_{i,t}$	0.004		-0.0004	
	(0.003)		(0.002)	
$\mathbf{1}(\geq$ 1 Announced t+1 Auction $\in$ [0, 25]km)		-0.095^{**}		0.016
		(0.042)		(0.029)
$\mathbf{1}(\geq$ 1 Announced t+1 Auction $\in$ (25, 50]km)		-0.016		-0.102^{***}
		(0.044)		(0.032)
Constant	2.369^{***}	2.479^{***}	3.328^{***}	3.377^{***}
	(0.436)	(0.438)	(0.256)	(0.257)
Observations	436,271	436,271	217,299	217,299
Log Likelihood	-20,186.340	-20,184.400	-35,710.540	-35,705.310

*p<0.1; **p<0.05; ***p<0.01.

• Reports the logit estimates of the regression of auction participation specified in (4.1). The regression includes year-month and firm fixed effects (not reported). Distance is in kilometers. The results show that more capacity constrained (i.e. higher backlog) firms are less likely to participate and provide some evidence that firms are less likely to participate if a nearby period $t+1$ auction is announced.

• "# Announced t+1 Auctions $\leq$ Dist90$_{i,t}$" corresponds to $\sum_{(j',t+1)\in\mathcal{K}_t^{(P)}} \mathbf{1}(\text{Dist}_{i,j',t+1} \leq \text{Dist90}_{i,t})$. This is the number of period t+1 auctions announced (known) at least seven days prior to the period t letting date and are near ($\leq$ Dist90$_{i,t}$) firm i. Dist90$_{i,t}$ is defined to be the 90th percentile of the distances to auctions that firm i bid on in the year that includes period t.

• "$\mathbf{1}(\geq$ 1 Announced t+1 Auction $\in$ [0, 25]km)" is one if at least one period t+1 auction within 25km of the firm was advertised at least seven days prior to the period t letting date; it is zero otherwise. "$\mathbf{1}(\geq$ 1 Announced t+1 Auction $\in$ (25, 50]km)" is defined analogously.

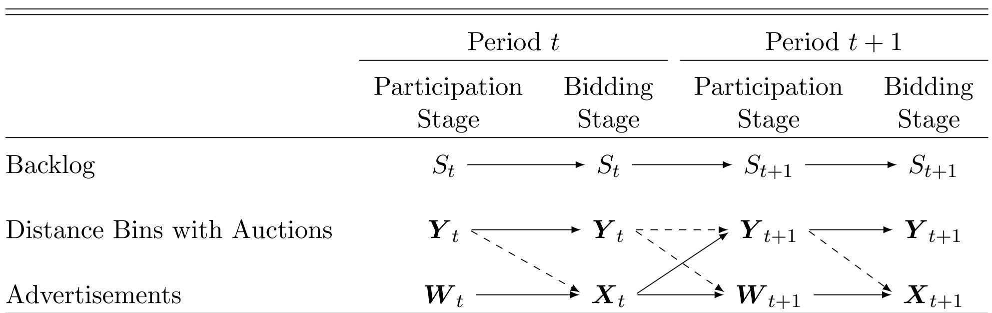
Table 4: Normalized Bid Regressions

	Dependent variable: Normalized Bid (Bid / EngEst × 100)			
	(1)	(2)	(3)	(4)
Dist $\in (25, 50]$km	2.700***	2.326***	2.709***	2.386***
	(0.383)	(0.343)	(0.385)	(0.339)
Dist $\in (50, 100]$km	4.737***	4.212***	4.754***	4.395***
	(0.369)	(0.657)	(0.367)	(0.549)
Dist $\in (100, 150]$km	6.011***	5.531***	6.056***	5.841***
	(0.616)	(0.936)	(0.613)	(0.769)
Dist $\in (150, 200]$km	6.541***	6.024***	6.635***	6.576***
	(0.797)	(0.682)	(0.800)	(0.621)
Dist $\in (200, \infty)$km	8.001***	4.776***	8.208***	5.680***
	(1.241)	(0.965)	(1.343)	(0.644)
Line Items	0.026***	0.030***	0.026***	0.029***
	(0.005)	(0.004)	(0.005)	(0.004)
% Subcont. to Disadvantaged Firm	−0.434***	−0.434***	−0.436***	−0.437***
	(0.031)	(0.026)	(0.031)	(0.026)
Norm Backlog	0.960***	0.882***	0.979***	0.904***
	(0.172)	(0.200)	(0.172)	(0.203)
# Announced t+1 Auctions $\leq$ Dist90$_{i,t}$	0.053**	0.047**		
	(0.023)	(0.023)		
1(small bidder)		−2.505***		−2.757***
		(0.147)		(0.173)
# Announced t+1 Auctions $\leq$ Dist90$_{i,t}$ × **1**(small bidder)		0.094***		
		(0.015)		
Norm Backlog × **1**(small bidder)		0.540***		0.533***
		(0.168)		(0.171)
1($\geq$ 1 Announced t+1 Auction $\in$ [0, 25]km)			0.684**	0.770***
			(0.279)	(0.292)
1($\geq$ 1 Announced t+1 Auction $\in$ (25, 50]km)			0.489	0.398
			(0.324)	(0.345)
1($\geq$ 1 Announced t+1 Auction $\in$ [0, 25]km) × **1**(small bidder)				1.004***
				(0.277)
1($\geq$ 1 Announced t+1 Auction $\in$ (25, 50]km) × **1**(small bidder)				1.012***
				(0.288)
Observations	21,840	21,840	21,840	21,840
R^2	0.192	0.166	0.192	0.166
Adjusted R^2	0.179	0.159	0.179	0.159

*p<0.1; **p<0.05; ***p<0.01. White standard errors are reported and clustered at the firm level.

- Reports the estimates of the OLS regression on normalized bids as described in (4.2). The regression includes year-month, firm, and number of bidders fixed effects (not reported). Columns (2) and (4) exclude the small firms' fixed effects in lieu of a small bidder dummy variable; the large firm fixed effects remain. Distance is in kilometers. The bids become less aggressive as Norm Backlog increases, which suggests that firms are capacity constrained. The "# Announced" rows and "≥ 1 Announced" rows capture the effects of advertisements. These estimates are positive and significant, which provides strong evidence that firms are forward looking and accounting for the opportunity cost of winning. This effect is more pronounced for the small firms.
- "# Announced t+1 Auctions $\leq$ Dist90$_{i,t}$" corresponds to $\sum_{(j',t+1)\in\mathcal{K}_t^{(B)}} \mathbf{1}(\text{Dist}_{i,j',t+1} \leq \text{Dist90}_{i,t})$. This is the number of period t+1 auctions announced (known) at least two days prior to the period t letting date and are near ($\leq$ Dist90$_{i,t}$) firm i. Dist90$_{i,t}$ is defined to be the 90th percentile of the distances to auctions that firm i bid on in the year that includes period t.
- "**1**($\geq$ 1 Announced t+1 Auction $\in$ [0, 25]km)" is one if at least one period t+1 auction within 25km of the firm was advertised at least two days prior to the period t letting date; it is zero otherwise. "**1**($\geq$ 1 Announced t+1 Auction $\in$ (25, 50]km)" is defined analogously.

Table 5: Pattern of Dependence in Transitions When The Plant Does Not Participate



This table shows the pattern of dependence in the states evolution if the plant does not participate in any auctions in period t. The solid arrows show the dependent relationships that are included in estimation. The dashed arrows show the dependent relationships that are excluded in estimation due to data limitations. Backlog transitions independently of the other states because when the plant does not bid, it cannot win an auction that would result in backlog increasing.

Table 6: Small Firm Multinomial Logit Estimates

	$(y_{i,t,n}, y_{i,t,m}) =$			
	(0, 0)	(0, 1)	(1, 0)	(1, 1)
(Intercept):$a = n$ (bid on near auction)			-0.168	-0.273
			(0.310)	(0.178)
(Intercept):$a = m$ (bid on medium distance auction)		-0.733^{***}		-1.014^{***}
		(0.244)		(0.181)
(Intercept):$a = f$ (bid on far auction)	-1.432^{***}	-1.238^{***}	-1.304^{***}	-1.295^{***}
	(0.300)	(0.246)	(0.318)	(0.183)
$\tilde{s}_{i,t}$ (Norm. Backlog)	-0.299^{***}	-0.243^{***}	-0.201^{**}	-0.165^{***}
	(0.084)	(0.063)	(0.079)	(0.044)
$sd(s)_i$ (Backlog Std. Dev.)	1.164^{***}	1.130^{***}	0.784^{***}	0.757^{***}
	(0.159)	(0.161)	(0.208)	(0.107)
$\Pr(Y_{i,t+1,n} = 1 \vert \boldsymbol{w}_{i,t})$ (Prob. of near t+1 auction)	-0.525^{**}	-0.340^{**}	0.222	-0.279^{**}
	(0.246)	(0.160)	(0.219)	(0.120)
$\Pr(Y_{i,t+1,m} = 1 \vert \boldsymbol{w}_{i,t})$ (Prob. of medium t+1 auction)	-0.118	0.035	-0.507^{**}	-0.429^{***}
	(0.227)	(0.179)	(0.203)	(0.145)
$\Pr(W_{i,t+1,n} = 1 \vert \boldsymbol{w}_{i,t})$ (Prob. of near t+2 auction advertised in t+1)	-0.627	-0.086	0.096	-0.009
	(0.744)	(0.430)	(0.559)	(0.261)
$\Pr(W_{i,t+1,m} = 1 \vert \boldsymbol{w}_{i,t})$ (Prob. of medium t+2 auction advertised in t+1)	-0.357	-0.339	-1.243^{***}	-0.624^{***}
	(0.601)	(0.324)	(0.469)	(0.233)
Observations	2,600	3,091	1,432	4,834
Log Likelihood	-977.122	-2,162.641	-1,186.282	-5,081.869

*p<0.1; **p<0.05; ***p<0.01.

• Reports the multinomial logit estimates specified in (6.1). The specification includes year and month fixed effects (not reported). Estimation was via maximum likelihood.

• $y_{i,t,n} = 1$ means there is a nearby auction available to bid on. $y_{i,t,m} = 1$ means there is a medium distance auction available to bid on. A near auction is defined to be one that is within 25km of the plant. A medium distance auction is defined to be one that is between 25km and 50km from the plant.

Table 7: $G_{\tilde{B}}$ Estimates

	Estimates
Shape: $\ln(k)$	1.185^{***}
	(0.010)
Scale: (Constant)	-0.944^{***}
	(0.048)
Scale: $d = n$ (bid on near auction)	-0.097^{***}
	(0.011)
Scale: $d = m$ (bid on medium distance auction)	-0.051^{***}
	(0.011)
Scale: $\tilde{s}_{i,t}$ (norm. backlog)	0.024^{***}
	(0.006)
Scale: $sd(s)_i$ (backlog std. dev.)	-0.043^{***}
	(0.012)
Scale: $\Pr(Y_{i,t+1,n} = 1 \mid \boldsymbol{x}_{i,t})$ (prob. of near t+1 auction given ads)	0.042^{***}
	(0.015)
Scale: $\Pr(Y_{i,t+1,m} = 1 \mid \boldsymbol{x}_{i,t})$ (prob. of medium t+1 auction given ads)	0.009
	(0.016)
Scale: $\Pr(W_{i,t+1,n} = 1 \mid \boldsymbol{x}_{i,t})$ (prob. of near t+2 auction advertised in t+1)	0.086^{**}
	(0.040)
Scale: $\Pr(W_{i,t+1,m} = 1 \mid \boldsymbol{x}_{i,t})$ (prob. of medium t+2 auction advertised in t+1)	-0.096^{***}
	(0.034)
Scale: $\mathbf{1}(y_{i,t,n} = 1)$ (near auction in period t)	0.015
	(0.011)
Scale: $\mathbf{1}(y_{i,t,m} = 1)$ (medium auction in period t)	-0.012
	(0.012)
Scale: ln(Line Items)	0.091^{***}
	(0.010)
Scale: % Subcont. to Disadvantaged Firm	-0.002
	(0.001)
Scale: ln(Eng Est)	-0.087^{***}
	(0.006)
Log Likelihood	$2,285.018$
Observations	5,311

*p<0.1; **p<0.05; ***p<0.01.

• Reports the three parameter Weibull distribution estimates of the normalized bid distribution (i.e. $\frac{B}{\zeta}$ where ζ is the engineer's estimate) as described in (6.2). The support parameter was taken to be the lowest normalized bid observed in the data. The shape and scale parameters were estimated via maximum likelihood.

• The support parameter was estimated to be 0.525.

• The scale parameter is parameterized as $\ln(\lambda) = Z\alpha$. Includes year and month fixed effects (not reported). The alpha estimates are reported in the table.

• A near auction is defined to be one that is within 25km of the plant. A medium distance auction is defined to be one that is between 25km and 50km from the plant.

Table 8: Entry Cost Estimates

Parameter	Estimate
κ_n (entry cost for near auction)	0.361
κ_m (entry cost for medium distance auction)	0.357
κ_f (entry cost for far auction)	0.365
ε Scale Parameter	0.078
Least Squares Objective	3.120

• Reports the entry cost estimates from the dynamic least squares estimator. States were weighted according to the number of observations entering offline estimates.
• Entry costs are reported as a percentage (in decimal form) of the engineer's estimate.
• "ε Scale Parameter" is the scale parameter of the Gumbel distribution with location parameter 0. Note that a T1EV distribution is a Gumbel distribution with a location parameter 0 and a scale parameter of 1.
• Least squares objective is the average across all small firms.

Table 9: Auction Participation Logit Regressions - Nearby if Distance $\leq$ Dist90

	Dependent variable: $\mathbf{1}(B_{i,j,t} > 0)$			
	Small Bidders		Large Bidders	
	(1)	(2)	(3)	(4)
Dist $\in (25, 50]$km	-0.797^{***}	-0.798^{***}	-0.585^{***}	-0.584^{***}
	(0.040)	(0.040)	(0.029)	(0.029)
Dist $\in (50, 100]$km	-2.175^{***}	-2.175^{***}	-1.754^{***}	-1.754^{***}
	(0.041)	(0.041)	(0.028)	(0.028)
Dist $\in (100, 150]$km	-3.781^{***}	-3.782^{***}	-3.318^{***}	-3.318^{***}
	(0.062)	(0.062)	(0.038)	(0.038)
Dist $\in (150, 200]$km	-4.673^{***}	-4.674^{***}	-4.811^{***}	-4.811^{***}
	(0.089)	(0.089)	(0.063)	(0.063)
Dist $\in (200, \infty)$km	-6.141^{***}	-6.142^{***}	-6.826^{***}	-6.826^{***}
	(0.090)	(0.090)	(0.092)	(0.092)
ln(Eng Est)	-0.359^{***}	-0.359^{***}	-0.051^{***}	-0.051^{***}
	(0.021)	(0.021)	(0.014)	(0.014)
# Period t Auctions	-0.003	-0.004	-0.004^{**}	-0.004^{**}
	(0.003)	(0.003)	(0.002)	(0.002)
Line Items	0.008^{***}	0.008^{***}	0.003^{***}	0.003^{***}
	(0.0004)	(0.0004)	(0.0003)	(0.0003)
% Subcont. to Disadvantaged Firm	-0.0004	-0.0003	-0.006^{**}	-0.006^{**}
	(0.005)	(0.005)	(0.003)	(0.003)
Norm Backlog	-0.184^{***}	-0.183^{***}	-0.073^{***}	-0.073^{***}
	(0.020)	(0.020)	(0.012)	(0.012)
# Announced t+1 Auctions $\leq$ Dist90$_{i,t}$	0.004	0.006^{*}	-0.0004	-0.001
	(0.003)	(0.003)	(0.002)	(0.002)
# Unannounced t+1 Auctions $\leq$ Dist90$_{i,t}$		0.006^{***}		-0.002
		(0.002)		(0.002)
Constant	2.369^{***}	2.427^{***}	3.328^{***}	3.307^{***}
	(0.436)	(0.436)	(0.256)	(0.256)
Observations	436,271	436,271	217,299	217,299
Log Likelihood	-20,186.340	-20,181.930	-35,710.540	-35,709.720

*p<0.1; **p<0.05; ***p<0.01.

• Reports the logit estimates of the regression of auction participation specified in (4.1). The regression includes year-month and firm fixed effects (not reported). Distance is in kilometers.

• "# Announced t+1 Auctions $\leq$ Dist90$_{i,t}$" corresponds to $\sum_{(j',t+1)\in\mathcal{K}_t^{(P)}} \mathbf{1}(\text{Dist}_{i,j',t+1} \leq \text{Dist90}_{i,t})$. This is the number of period t+1 auctions announced (known) at least seven days prior to the period t letting date and are near ($\leq$ Dist90$_{i,t}$) firm i. Dist90$_{i,t}$ is defined to be the 90th percentile of the distances to auctions that firm i bid on in the year that includes period t.

• The "Unannounced" covariates refer to t+1 auctions that were not announced at least seven days before the period t letting date.

Table 10: Auction Participation Logit Regressions - Nearby if Distance $\leq$ 25km

	Dependent variable: $\mathbf{1}(B_{i,j,t} > 0)$			
	Small Bidders		Large Bidders	
	(1)	(2)	(3)	(4)
Dist $\in$ (25, 50]km	-0.797^{***}	-0.797^{***}	-0.584^{***}	-0.584^{***}
	(0.040)	(0.040)	(0.029)	(0.029)
Dist $\in$ (50, 100]km	-2.175^{***}	-2.175^{***}	-1.754^{***}	-1.754^{***}
	(0.041)	(0.041)	(0.028)	(0.028)
Dist $\in$ (100, 150]km	-3.781^{***}	-3.781^{***}	-3.318^{***}	-3.318^{***}
	(0.062)	(0.062)	(0.038)	(0.038)
Dist $\in$ (150, 200]km	-4.674^{***}	-4.673^{***}	-4.811^{***}	-4.811^{***}
	(0.089)	(0.089)	(0.063)	(0.063)
Dist $\in$ (200, ∞)km	-6.142^{***}	-6.142^{***}	-6.826^{***}	-6.826^{***}
	(0.090)	(0.090)	(0.092)	(0.092)
ln(Eng Est)	-0.359^{***}	-0.359^{***}	-0.051^{***}	-0.051^{***}
	(0.021)	(0.021)	(0.014)	(0.014)
# Period t Auctions	-0.004	-0.004	-0.004^{**}	-0.004^{***}
	(0.002)	(0.003)	(0.002)	(0.002)
Line Items	0.008^{***}	0.008^{***}	0.003^{***}	0.003^{***}
	(0.0004)	(0.0004)	(0.0003)	(0.0003)
% Subcont. to Disadvantaged Firm	-0.001	-0.001	-0.006^{**}	-0.006^{**}
	(0.005)	(0.005)	(0.003)	(0.003)
Norm Backlog	-0.185^{***}	-0.185^{***}	-0.073^{***}	-0.073^{***}
	(0.020)	(0.020)	(0.012)	(0.012)
# Announced t+1 Auctions $\leq$ 25km	-0.062^{***}	-0.063^{***}	0.003	0.005
	(0.018)	(0.018)	(0.005)	(0.005)
# Unannounced t+1 Auctions $\leq$ 25km		-0.010		0.005
		(0.012)		(0.004)
Constant	2.480^{***}	2.483^{***}	3.317^{***}	3.329^{***}
	(0.436)	(0.436)	(0.255)	(0.255)
Observations	436,271	436,271	217,299	217,299
Log Likelihood	-20,181.320	-20,180.970	-35,710.380	-35,709.350

*p<0.1; **p<0.05; ***p<0.01.

• Reports the logit estimates of the regression of auction participation specified in (4.1). The regression includes year-month and firm fixed effects (not reported). Distance is in kilometers.

• "# Announced t+1 Auctions $\leq$ 25km" corresponds to $\sum_{(j',t+1)\in\mathcal{K}_t^{(P)}} \mathbf{1}(\text{Dist}_{i,j',t+1} \leq 25\text{km})$. This is the number of period t+1 auctions announced (known) at least seven days prior to the period t letting date and are near ($\leq$ 25km) firm i.

• The "Unannounced" covariates refer to t+1 auctions that were not announced at least seven days before the period t letting date.

Table 11: Auction Participation Logit Regressions - Nearby if Distance $\leq$ 50km

	Dependent variable: $\mathbf{1}(B_{i,j,t} > 0)$			
	Small Bidders		Large Bidders	
	(1)	(2)	(3)	(4)
Dist $\in (25, 50]$km	-0.798^{***}	-0.798^{***}	-0.585^{***}	-0.585^{***}
	(0.040)	(0.040)	(0.029)	(0.029)
Dist $\in (50, 100]$km	-2.176^{***}	-2.177^{***}	-1.754^{***}	-1.754^{***}
	(0.041)	(0.041)	(0.028)	(0.028)
Dist $\in (100, 150]$km	-3.782^{***}	-3.782^{***}	-3.318^{***}	-3.318^{***}
	(0.062)	(0.062)	(0.038)	(0.038)
Dist $\in (150, 200]$km	-4.674^{***}	-4.674^{***}	-4.811^{***}	-4.812^{***}
	(0.089)	(0.089)	(0.063)	(0.063)
Dist $\in (200, \infty)$km	-6.144^{***}	-6.143^{***}	-6.827^{***}	-6.827^{***}
	(0.090)	(0.090)	(0.092)	(0.092)
ln(Eng Est)	-0.359^{***}	-0.359^{***}	-0.052^{***}	-0.052^{***}
	(0.021)	(0.021)	(0.014)	(0.014)
# Period t Auctions	-0.004^{*}	-0.004	-0.004^{***}	-0.004^{***}
	(0.002)	(0.003)	(0.002)	(0.002)
Line Items	0.008^{***}	0.008^{***}	0.003^{***}	0.003^{***}
	(0.0004)	(0.0004)	(0.0003)	(0.0003)
% Subcont. to Disadvantaged Firm	-0.001	-0.001	-0.006^{**}	-0.006^{**}
	(0.005)	(0.005)	(0.003)	(0.003)
Norm Backlog	-0.185^{***}	-0.186^{***}	-0.072^{***}	-0.073^{***}
	(0.020)	(0.020)	(0.012)	(0.012)
# Announced t+1 Auctions $\leq$ 50km	-0.038^{***}	-0.039^{***}	-0.003	-0.002
	(0.010)	(0.010)	(0.003)	(0.003)
# Unannounced t+1 Auctions $\leq$ 50km		-0.009		0.002
		(0.007)		(0.002)
Constant	2.528^{***}	2.527^{***}	3.335^{***}	3.343^{***}
	(0.437)	(0.437)	(0.255)	(0.256)
Observations	436,271	436,271	217,299	217,299
Log Likelihood	-20,180.000	-20,179.220	-35,710.240	-35,710.040

*p<0.1; **p<0.05; ***p<0.01.

• Reports the logit estimates of the regression of auction participation specified in (4.1). The regression includes year-month and firm fixed effects (not reported). Distance is in kilometers.

• "# Announced t+1 Auctions $\leq$ 50km" corresponds to $\sum_{(j',t+1)\in\mathcal{K}_t^{(P)}} \mathbf{1}(\text{Dist}_{i,j',t+1} \leq 50\text{km})$. This is the number of period t+1 auctions announced (known) at least seven days prior to the period t letting date and are near ($\leq$ 50km) firm i.

• The "Unannounced" covariates refer to t+1 auctions that were not announced at least seven days before the period t letting date.

Table 12: Auction Participation Logit Regressions - Nearby if Distance $\leq$ 75km

	Dependent variable: $\mathbf{1}(B_{i,j,t} > 0)$			
	Small Bidders		Large Bidders	
	(1)	(2)	(3)	(4)
Dist $\in (25, 50]$km	-0.798^{***}	-0.798^{***}	-0.585^{***}	-0.585^{***}
	(0.040)	(0.040)	(0.029)	(0.029)
Dist $\in (50, 100]$km	-2.176^{***}	-2.176^{***}	-1.754^{***}	-1.754^{***}
	(0.041)	(0.041)	(0.028)	(0.028)
Dist $\in (100, 150]$km	-3.782^{***}	-3.782^{***}	-3.318^{***}	-3.318^{***}
	(0.062)	(0.062)	(0.038)	(0.038)
Dist $\in (150, 200]$km	-4.675^{***}	-4.675^{***}	-4.811^{***}	-4.811^{***}
	(0.089)	(0.089)	(0.063)	(0.063)
Dist $\in (200, \infty)$km	-6.144^{***}	-6.144^{***}	-6.827^{***}	-6.827^{***}
	(0.090)	(0.090)	(0.092)	(0.092)
ln(Eng Est)	-0.360^{***}	-0.360^{***}	-0.052^{***}	-0.052^{***}
	(0.021)	(0.021)	(0.014)	(0.014)
# Period t Auctions	-0.005^{*}	-0.004^{*}	-0.004^{***}	-0.004^{***}
	(0.002)	(0.003)	(0.002)	(0.002)
Line Items	0.008^{***}	0.008^{***}	0.003^{***}	0.003^{***}
	(0.0004)	(0.0004)	(0.0003)	(0.0003)
% Subcont. to Disadvantaged Firm	-0.001	-0.001	-0.006^{**}	-0.006^{**}
	(0.005)	(0.005)	(0.003)	(0.003)
Norm Backlog	-0.184^{***}	-0.184^{***}	-0.072^{***}	-0.072^{***}
	(0.020)	(0.020)	(0.012)	(0.012)
# Announced t+1 Auctions $\leq$ 75km	-0.026^{***}	-0.026^{***}	-0.003	-0.003
	(0.007)	(0.007)	(0.003)	(0.003)
# Unannounced t+1 Auctions $\leq$ 75km		-0.001		-0.0003
		(0.005)		(0.002)
Constant	2.575^{***}	2.576^{***}	3.345^{***}	3.343^{***}
	(0.438)	(0.438)	(0.256)	(0.256)
Observations	436,271	436,271	217,299	217,299
Log Likelihood	-20,180.300	-20,180.270	-35,709.960	-35,709.960

*p<0.1; **p<0.05; ***p<0.01.

• Reports the logit estimates of the regression of auction participation specified in (4.1). The regression includes year-month and firm fixed effects (not reported). Distance is in kilometers.

• "# Announced t+1 Auctions $\leq$ 75km" corresponds to $\sum_{(j',t+1)\in\mathcal{K}_t^{(P)}} \mathbf{1}(\text{Dist}_{i,j',t+1} \leq 75\text{km})$. This is the number of period t+1 auctions announced (known) at least seven days prior to the period t letting date and are near ($\leq$ 75km) firm i.

• The "Unannounced" covariates refer to t+1 auctions that were not announced at least seven days before the period t letting date.

Table 13: Auction Participation Logit Regressions - Nearby if Distance $\leq$ 100km

	Dependent variable: $\mathbf{1}(B_{i,j,t} > 0)$			
	Small Bidders		Large Bidders	
	(1)	(2)	(3)	(4)
Dist $\in (25, 50]$km	-0.797^{***}	-0.797^{***}	-0.585^{***}	-0.585^{***}
	(0.040)	(0.040)	(0.029)	(0.029)
Dist $\in (50, 100]$km	-2.175^{***}	-2.175^{***}	-1.754^{***}	-1.754^{***}
	(0.041)	(0.041)	(0.028)	(0.028)
Dist $\in (100, 150]$km	-3.781^{***}	-3.781^{***}	-3.318^{***}	-3.318^{***}
	(0.062)	(0.062)	(0.038)	(0.038)
Dist $\in (150, 200]$km	-4.674^{***}	-4.674^{***}	-4.811^{***}	-4.811^{***}
	(0.089)	(0.089)	(0.063)	(0.063)
Dist $\in (200, \infty)$km	-6.142^{***}	-6.142^{***}	-6.826^{***}	-6.826^{***}
	(0.090)	(0.090)	(0.092)	(0.092)
ln(Eng Est)	-0.360^{***}	-0.360^{***}	-0.051^{***}	-0.051^{***}
	(0.021)	(0.021)	(0.014)	(0.014)
# Period t Auctions	-0.004^{*}	-0.004	-0.004^{**}	-0.004^{**}
	(0.003)	(0.003)	(0.002)	(0.002)
Line Items	0.008^{***}	0.008^{***}	0.003^{***}	0.003^{***}
	(0.0004)	(0.0004)	(0.0003)	(0.0003)
% Subcont. to Disadvantaged Firm	-0.001	-0.001	-0.006^{**}	-0.006^{**}
	(0.005)	(0.005)	(0.003)	(0.003)
Norm Backlog	-0.183^{***}	-0.183^{***}	-0.073^{***}	-0.073^{***}
	(0.020)	(0.020)	(0.012)	(0.012)
# Announced t+1 Auctions $\leq$ 100km	-0.012^{**}	-0.012^{**}	-0.001	-0.001
	(0.005)	(0.005)	(0.003)	(0.003)
# Unannounced t+1 Auctions $\leq$ 100km		-0.002		-0.0003
		(0.004)		(0.002)
Constant	2.519^{***}	2.520^{***}	3.332^{***}	3.329^{***}
	(0.439)	(0.439)	(0.256)	(0.257)
Observations	436,271	436,271	217,299	217,299
Log Likelihood	-20,184.670	-20,184.560	-35,710.500	-35,710.490

*p<0.1; **p<0.05; ***p<0.01.

• Reports the logit estimates of the regression of auction participation specified in (4.1). The regression includes year-month and firm fixed effects (not reported). Distance is in kilometers.

• "# Announced t+1 Auctions $\leq$ 100km" corresponds to $\sum_{(j',t+1)\in\mathcal{K}_t^{(P)}} \mathbf{1}(\text{Dist}_{i,j',t+1} \leq 100\text{km})$. This is the number of period t+1 auctions announced (known) at least seven days prior to the period t letting date and are near ($\leq$ 100km) firm i.

• The "Unannounced" covariates refer to t+1 auctions that were not announced at least seven days before the period t letting date.

Table 14: Normalized Bid Regressions - Nearby if Distance $\leq$ Dist90

	Dependent variable: Normalized Bid (Bid / EngEst × 100)			
	(1)	(2)	(3)	(4)
Dist $\in (25, 50]$km	2.700***	2.326***	2.700***	2.324***
	(0.383)	(0.343)	(0.382)	(0.343)
Dist $\in (50, 100]$km	4.737***	4.212***	4.736***	4.203***
	(0.369)	(0.657)	(0.368)	(0.669)
Dist $\in (100, 150]$km	6.011***	5.531***	6.008***	5.507***
	(0.616)	(0.936)	(0.627)	(0.965)
Dist $\in (150, 200]$km	6.541***	6.024***	6.538***	5.999***
	(0.797)	(0.682)	(0.804)	(0.704)
Dist $\in (200, \infty)$km	8.001***	4.776***	7.991***	4.703***
	(1.241)	(0.965)	(1.228)	(1.028)
Line Items	0.026***	0.030***	0.026***	0.030***
	(0.005)	(0.004)	(0.005)	(0.004)
% Subcont. to Disadvantaged Firm	−0.434***	−0.434***	−0.434***	−0.433***
	(0.031)	(0.026)	(0.031)	(0.026)
Norm Backlog	0.960***	0.882***	0.960***	0.878***
	(0.172)	(0.200)	(0.172)	(0.199)
# Announced t+1 Auctions $\leq \text{Dist90}_{i,t}$	0.053**	0.047**	0.053**	0.051**
	(0.023)	(0.023)	(0.024)	(0.024)
$\mathbf{1}$(small bidder)		−2.505***		−2.393***
		(0.147)		(0.229)
# Announced t+1 Auctions $\leq \text{Dist90}_{i,t} \times \mathbf{1}$(small bidder)		0.094***		0.088***
		(0.015)		(0.017)
Norm Backlog × $\mathbf{1}$(small bidder)		0.540***		0.554***
		(0.168)		(0.169)
# Unannounced t+1 Auctions $\leq \text{Dist90}_{i,t} \times \mathbf{1}$(small bidder)				−0.010
				(0.015)
# Unannounced t+1 Auctions $\leq \text{Dist90}_{i,t}$			0.002	0.017
			(0.020)	(0.022)
Observations	21,840	21,840	21,840	21,840
R^2	0.192	0.166	0.192	0.166
Adjusted R^2	0.179	0.159	0.179	0.159

*p<0.1; **p<0.05; ***p<0.01. White standard errors are reported and clustered at the firm level.

- Reports the estimates of the OLS regression on normalized bids as described in (4.2). The regression includes year-month, firm, and number of bidders fixed effects (not reported). Columns (2) and (4) exclude the small firms' fixed effects in lieu of a small bidder dummy variable; the large firm fixed effects remain. Distance is in kilometers.
- "# Announced t+1 Auctions $\leq \text{Dist90}_{i,t}$" corresponds to $\sum_{(j',t+1)\in\mathcal{K}_t^{(B)}} \mathbf{1}(\text{Dist}_{i,j',t+1} \leq \text{Dist90}_{i,t})$. This is the number of period t+1 auctions announced (known) at least two days prior to the period t letting date and are near ($\leq \text{Dist90}_{i,t}$) firm i. $\text{Dist90}_{i,t}$ is defined to be the 90th percentile of the distances to auctions that firm i bid on in the year that includes period t.
- "$\mathbf{1}$($\geq$ 1 Announced t+1 Auction $\in$ [0, 25]km)" is one if at least one period t+1 auction within 25km of the firm was advertised at least two days prior to the period t letting date; it is zero otherwise. "$\mathbf{1}$($\geq$ 1 Announced t+1 Auction $\in$ (25, 50]km)" is defined analogously.
- The "Unannounced" covariates refer to t+1 auctions that were not announced at least two days before the period t letting date.

Table 15: Normalized Bid Regressions - Nearby if Distance $\leq$ 25km

	Dependent variable: Normalized Bid (Bid / EngEst × 100)			
	(1)	(2)	(3)	(4)
Dist $\in (25, 50]$km	2.706***	2.399***	2.706***	2.400***
	(0.385)	(0.336)	(0.385)	(0.336)
Dist $\in (50, 100]$km	4.747***	4.385***	4.747***	4.392***
	(0.368)	(0.554)	(0.368)	(0.550)
Dist $\in (100, 150]$km	6.044***	5.826***	6.044***	5.834***
	(0.612)	(0.768)	(0.612)	(0.764)
Dist $\in (150, 200]$km	6.608***	6.523***	6.608***	6.541***
	(0.796)	(0.611)	(0.797)	(0.614)
Dist $\in (200, \infty)$km	8.174***	5.553***	8.174***	5.589***
	(1.326)	(0.682)	(1.326)	(0.668)
Line Items	0.026***	0.029***	0.026***	0.029***
	(0.005)	(0.004)	(0.005)	(0.004)
% Subcont. to Disadvantaged Firm	−0.435***	−0.435***	−0.435***	−0.436***
	(0.031)	(0.026)	(0.031)	(0.025)
Norm Backlog	0.966***	0.894***	0.966***	0.895***
	(0.173)	(0.207)	(0.174)	(0.210)
# Announced t+1 Auctions $\leq$ 25km	0.034	0.035	0.034	0.040
	(0.045)	(0.037)	(0.048)	(0.041)
$\mathbf{1}$(small bidder)		−2.589***		−2.690***
		(0.133)		(0.156)
# Announced t+1 Auctions $\leq$ 25km × $\mathbf{1}$(small bidder)		1.037***		1.021***
		(0.053)		(0.068)
Norm Backlog × $\mathbf{1}$(small bidder)		0.521***		0.516***
		(0.172)		(0.180)
# Unannounced t+1 Auctions $\leq$ 25km × $\mathbf{1}$(small bidder)				0.129**
				(0.063)
# Unannounced t+1 Auctions $\leq$ 25km			−0.0004	0.025
			(0.081)	(0.080)
Observations	21,840	21,840	21,840	21,840
R^2	0.192	0.166	0.192	0.166
Adjusted R^2	0.179	0.159	0.179	0.159

*p<0.1; **p<0.05; ***p<0.01. White standard errors are reported and clustered at the firm level.

• Reports the estimates of the OLS regression on normalized bids as described in (4.2). The regression includes year-month, firm, and number of bidders fixed effects (not reported). Columns (2) and (4) exclude the small firms' fixed effects in lieu of a small bidder dummy variable; the large firm fixed effects remain. Distance is in kilometers.

• "# Announced t+1 Auctions $\leq$ 25km" corresponds to $\sum_{(j',t+1)\in\mathcal{K}_t^{(B)}} \mathbf{1}(\text{Dist}_{i,j',t+1} \leq 25\text{km})$. This is the number of period t+1 auctions announced (known) at least two days prior to the period t letting date and are near ($\leq$ 25km) firm i.

• The "Unannounced" covariates refer to t+1 auctions that were not announced at least two days before the period t letting date.

Table 16: Normalized Bid Regressions - Nearby if Distance $\leq$ 50km

	Dependent variable: Normalized Bid (Bid / EngEst $\times$ 100)			
	(1)	(2)	(3)	(4)
Dist $\in (25, 50]$km	2.708***	2.364***	2.707***	2.364***
	(0.384)	(0.340)	(0.385)	(0.340)
Dist $\in (50, 100]$km	4.751***	4.372***	4.750***	4.372***
	(0.367)	(0.561)	(0.367)	(0.560)
Dist $\in (100, 150]$km	6.050***	5.824***	6.050***	5.824***
	(0.613)	(0.772)	(0.613)	(0.772)
Dist $\in (150, 200]$km	6.610***	6.479***	6.611***	6.480***
	(0.797)	(0.611)	(0.797)	(0.612)
Dist $\in (200, \infty)$km	8.178***	5.543***	8.176***	5.543***
	(1.326)	(0.691)	(1.323)	(0.689)
Line Items	0.026***	0.030***	0.026***	0.030***
	(0.005)	(0.004)	(0.005)	(0.004)
% Subcont. to Disadvantaged Firm	−0.435***	−0.434***	−0.435***	−0.434***
	(0.031)	(0.026)	(0.031)	(0.026)
Norm Backlog	0.960***	0.894***	0.962***	0.895***
	(0.172)	(0.205)	(0.173)	(0.208)
# Announced t+1 Auctions $\leq$ 50km	0.044	0.048	0.036	0.047
	(0.040)	(0.033)	(0.036)	(0.028)
$\mathbf{1}$(small bidder)		−2.692***		−2.701***
		(0.155)		(0.190)
# Announced t+1 Auctions $\leq$ 50km $\times$ $\mathbf{1}$(small bidder)		0.431***		0.432***
		(0.032)		(0.036)
Norm Backlog $\times$ $\mathbf{1}$(small bidder)		0.536***		0.534***
		(0.170)		(0.178)
# Unannounced t+1 Auctions $\leq$ 50km $\times$ $\mathbf{1}$(small bidder)				0.003
				(0.032)
# Unannounced t+1 Auctions $\leq$ 50km			−0.019	−0.003
			(0.049)	(0.047)
Observations	21,840	21,840	21,840	21,840
R^2	0.192	0.166	0.192	0.166
Adjusted R^2	0.179	0.159	0.179	0.159

*p<0.1; **p<0.05; ***p<0.01. White standard errors are reported and clustered at the firm level.

• Reports the estimates of the OLS regression on normalized bids as described in (4.2). The regression includes year-month, firm, and number of bidders fixed effects (not reported). Columns (2) and (4) exclude the small firms' fixed effects in lieu of a small bidder dummy variable; the large firm fixed effects remain. Distance is in kilometers.

• "# Announced t+1 Auctions $\leq$ 50km" corresponds to $\sum_{(j',t+1)\in\mathcal{K}_t^{(B)}} \mathbf{1}(\text{Dist}_{i,j',t+1} \leq 50\text{km})$. This is the number of period t+1 auctions announced (known) at least two days prior to the period t letting date and are near ($\leq$ 50km) firm i.

• The "Unannounced" covariates refer to t+1 auctions that were not announced at least two days before the period t letting date.

Table 17: Normalized Bid Regressions - Nearby if Distance $\leq$ 75km

	Dependent variable: Normalized Bid (Bid / EngEst $\times$ 100)			
	(1)	(2)	(3)	(4)
Dist $\in (25, 50]$km	2.711***	2.371***	2.711***	2.363***
	(0.383)	(0.339)	(0.383)	(0.340)
Dist $\in (50, 100]$km	4.756***	4.379***	4.756***	4.380***
	(0.367)	(0.561)	(0.367)	(0.560)
Dist $\in (100, 150]$km	6.055***	5.835***	6.055***	5.840***
	(0.614)	(0.772)	(0.613)	(0.768)
Dist $\in (150, 200]$km	6.608***	6.501***	6.608***	6.522***
	(0.796)	(0.613)	(0.795)	(0.613)
Dist $\in (200, \infty)$km	8.184***	5.599***	8.184***	5.644***
	(1.330)	(0.681)	(1.333)	(0.659)
Line Items	0.026***	0.030***	0.026***	0.030***
	(0.005)	(0.004)	(0.005)	(0.004)
% Subcont. to Disadvantaged Firm	−0.434***	−0.434***	−0.434***	−0.434***
	(0.031)	(0.026)	(0.031)	(0.025)
Norm Backlog	0.955***	0.886***	0.955***	0.891***
	(0.171)	(0.203)	(0.171)	(0.206)
# Announced t+1 Auctions $\leq$ 75km	0.070**	0.075**	0.070**	0.078***
	(0.035)	(0.030)	(0.035)	(0.028)
1(small bidder)		−2.714***		−2.833***
		(0.173)		(0.238)
# Announced t+1 Auctions $\leq$ 75km $\times$ **1**(small bidder)		0.242***		0.239***
		(0.027)		(0.032)
Norm Backlog $\times$ **1**(small bidder)		0.526***		0.509***
		(0.169)		(0.175)
# Unannounced t+1 Auctions $\leq$ 75km $\times$ **1**(small bidder)				0.031
				(0.021)
# Unannounced t+1 Auctions $\leq$ 75km			0.0003	0.015
			(0.040)	(0.039)
Observations	21,840	21,840	21,840	21,840
R^2	0.192	0.166	0.192	0.166
Adjusted R^2	0.179	0.159	0.179	0.159

*p<0.1; **p<0.05; ***p<0.01. White standard errors are reported and clustered at the firm level.

- Reports the estimates of the OLS regression on normalized bids as described in (4.2). The regression includes year-month, firm, and number of bidders fixed effects (not reported). Columns (2) and (4) exclude the small firms' fixed effects in lieu of a small bidder dummy variable; the large firm fixed effects remain. Distance is in kilometers.
- "# Announced t+1 Auctions $\leq$ 75km" corresponds to $\sum_{(j',t+1)\in\mathcal{K}_t^{(B)}} \mathbf{1}(\text{Dist}_{i,j',t+1} \leq 75\text{km})$. This is the number of period t+1 auctions announced (known) at least two days prior to the period t letting date and are near ($\leq$ 75km) firm i.
- The "Unannounced" covariates refer to t+1 auctions that were not announced at least two days before the period t letting date.

Table 18: Normalized Bid Regressions - Nearby if Distance $\leq$ 100km

	Dependent variable: Normalized Bid (Bid / EngEst × 100)			
	(1)	(2)	(3)	(4)
Dist $\in (25, 50]$km	2.711***	2.382***	2.711***	2.379***
	(0.383)	(0.338)	(0.383)	(0.338)
Dist $\in (50, 100]$km	4.756***	4.387***	4.756***	4.388***
	(0.367)	(0.556)	(0.367)	(0.556)
Dist $\in (100, 150]$km	6.057***	5.845***	6.057***	5.847***
	(0.614)	(0.769)	(0.614)	(0.766)
Dist $\in (150, 200]$km	6.603***	6.496***	6.602***	6.506***
	(0.796)	(0.612)	(0.795)	(0.610)
Dist $\in (200, \infty)$km	8.189***	5.634***	8.184***	5.661***
	(1.333)	(0.673)	(1.334)	(0.659)
Line Items	0.026***	0.030***	0.026***	0.030***
	(0.005)	(0.004)	(0.005)	(0.004)
% Subcont. to Disadvantaged Firm	−0.433***	−0.434***	−0.434***	−0.434***
	(0.030)	(0.026)	(0.031)	(0.025)
Norm Backlog	0.959***	0.890***	0.959***	0.892***
	(0.171)	(0.203)	(0.171)	(0.205)
# Announced t+1 Auctions $\leq$ 100km	0.067**	0.070**	0.064*	0.072**
	(0.031)	(0.027)	(0.033)	(0.028)
$\mathbf{1}$(small bidder)		−2.751***		−2.789***
		(0.185)		(0.282)
# Announced t+1 Auctions $\leq$ 100km × $\mathbf{1}$(small bidder)		0.159***		0.158***
		(0.020)		(0.025)
Norm Backlog × $\mathbf{1}$(small bidder)		0.525***		0.518***
		(0.169)		(0.174)
# Unannounced t+1 Auctions $\leq$ 100km × $\mathbf{1}$(small bidder)				0.007
				(0.017)
# Unannounced t+1 Auctions $\leq$ 100km			−0.005	0.008
			(0.031)	(0.029)
Observations	21,840	21,840	21,840	21,840
R^2	0.192	0.166	0.192	0.166
Adjusted R^2	0.179	0.159	0.179	0.159

*p<0.1; **p<0.05; ***p<0.01. White standard errors are reported and clustered at the firm level.

• Reports the estimates of the OLS regression on normalized bids as described in (4.2). The regression includes year-month, firm, and number of bidders fixed effects (not reported). Columns (2) and (4) exclude the small firms' fixed effects in lieu of a small bidder dummy variable; the large firm fixed effects remain. Distance is in kilometers.

• "# Announced t+1 Auctions $\leq$ 100km" corresponds to $\sum_{(j',t+1)\in\mathcal{K}_t^{(B)}} \mathbf{1}(\text{Dist}_{i,j',t+1} \leq 100\text{km})$. This is the number of period t+1 auctions announced (known) at least two days prior to the period t letting date and are near ($\leq$ 100km) firm i.

• The "Unannounced" covariates refer to t+1 auctions that were not announced at least two days before the period t letting date.