The Effect of Pre-announcements on Participation and Bidding in Dynamic Auctions*

Diwakar Raisingh†

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Abstract

This paper studies the participation and bidding strategies of capacity constrained bidders in a repeated auction game in which the auctioneer pre-announces information about future auctions. When bidders are forward looking, pre-announcing upcoming auctions will impact their current period strategies. I use data from Michigan highway procurement auctions to demonstrate that participation and bidding are responsive to pre-announcements, which provides strong evidence that bidders are forward looking. To quantify the effect of pre-announcements on participation and bidding strategies, I develop and estimate a dynamic auction model. I show that bidders observing pre-announcements of low expected cost contracts have significantly lower participation probabilities and modestly less aggressive bids. Based on the model estimates of costs, I quantify the impact of pre-announcements on efficiency and government expenditures. Counterfactual simulations show that when the government ceases pre-announcing future auctions, efficiency falls because the reduction in information weakens the bidders' ability to match to contracts for which they are likely to have lower costs. This less efficient matching of bidders to contracts leads to increased participation, which reduces government expenditures.

1   Introduction

In many auction environments, the auctioneer procures (or sells) objects over time and the bidders have some information about future items up for auction while bidding in current period auctions. When bidders are capacity constrained, this knowledge about future auctions should affect participation decisions and bidding strategies, both because losing bidders can bid again in a subsequent period and because bidders may prefer an object in a future auction. From the auctioneer's perspective, pre-announcing future auctions thus induces a trade-off between efficiency and price via a matching effect and a participation effect. Knowledge of future auctions may help bidders match more efficiently to the objects they prefer – for instance, in a procurement setting, contractors can more easily plan to bid for projects for which their expected costs are low. However, enabling bidders to participate more selectively leads to fewer participants per auction, and this reduced competition will lower a seller's revenues or raise a procurer's costs. This raises two questions. The positive question is: How much does information from auction pre-announcements affect efficiency and procurer costs? The normative question is: Should the auctioneer disclose information about future auctions?

This paper answers these questions empirically in the context of Michigan highway procurement auctions from 2002-2010. The Michigan Department of Transportation (MDOT) procures multiple construction contracts once per month (called a letting) using first-price sealed bid (FPSB) auctions. Capacity constrained bidders need to decide which, if any, of the auctions to bid on in a period and what their bid level will be if they decide to participate. MDOT discloses information about the contracts up for auction up to six weeks prior to the letting date through announcements, so bidders are aware of a subset of the auctions held in the following month. I define pre-announcements to be the announcements of following month auctions made prior to the current month's letting date. Figure 1 shows an example of this information disclosure policy.

The pre-announcements, which are exogenous, permit a novel test of whether bidders are forward looking. Pre-announcements are only informative about the future, so if all bidders are myopic then the information disclosure will not affect their participation decisions or bid levels. I find that the data do not support this hypothesis: pre-announcements of nearby contracts reduces a bidder's participation rate and they bid less aggressively when they do participate. This evidence strongly suggests that bidders are forward looking.

Motivated by this evidence, I develop a dynamic model that captures the salient features of
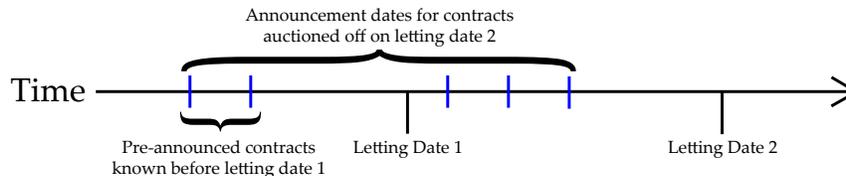
Figure 1: This figure shows an example of how information about future period auctions are known in the current period. There are five contracts being auctioned off (i.e. let) on letting date 2 and their announcement dates are represented by the blue vertical lines. Two of these contracts were known to bidders prior to letting date 1 since they were announced early (i.e. pre-announced). Three of these contracts were announced after letting date 1 and are not known to bidders before letting date 1.

the MDOT auction market. Most firms bidding for highway contracts in Michigan are single-plant firms and I treat the multi-plant firms as a collection of single plant firms. Thus, a bidder in my model is a plant, not a firm, and distance and capacity are measured at the plant level, not the firm level. Capacity is measured by the backlog of contracts that a plant won in previous auctions that have not yet been completed. The plants typically bid in at most one auction per letting. Therefore, at the plant level, the game is essentially a sequential auction game in which each plant decides whether to participate and bid in one of the available auctions or wait until the next letting. I run regressions that show that distance of the plant to the contract and backlog are major determinants of a plant's bidding decision: they are less likely to participate when they have high backlogs or when the auctions are further away, and they submit higher bids in those auctions if they do participate.

When a bidder chooses to participate in an auction, it draws a construction cost from a distribution that depends upon contract characteristics and backlog. A bidder's costs are stochastically increasing in its backlog due to capacity constraints. This is the source of the dynamics in the model. If a bidder wins a contract today, then it is more likely to draw higher costs in future auctions, and therefore less likely to win them. The bidder's continuation value captures this opportunity cost of winning. It causes a bidder to be less likely to participate in a letting, and to bid less aggressively if it does participate, than it would be in absence of any capacity constraints. Pre-announcements impact the bidder's participation and bidding decisions because they affect the bidder's continuation values.

Somewhat surprisingly, the participation decision in my model is static, and not a source of dynamics. The reason is that the bidder accounts for the opportunity cost of winning an auction when it chooses its optimal bid and, as a result, the continuation value of winning gets differenced out in calculating the expected payoff from bidding in an auction. Since the continuation value

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of losing is the same as the continuation value of not participating, this means that the bidder participates in an auction whenever the expected flow payoff from winning that auction exceeds the participation cost from doing so. The pre-announcements impact the participation decision, but they do so indirectly through the bids and the expected payoff from winning. This feature of the model greatly simplifies the estimation.

Using data on the participation, bids and bidder identities, backlogs and pre-announcements, I estimate the primitives of the model: the participation cost and the distribution of construction costs. My estimation strategy extends the approach developed by Jofre-Bonet & Pesendorfer (2003). The estimator leverages the fact that the expected discounted sum of future payoffs depends only on the distribution of bids, which is observable, and the participation cost, which is not. However, the latter can be estimated from the expected payoff from winning, which depends only the observed bid distributions, and participation decisions. To estimate the distribution of construction costs that rationalizes the observed distribution of bids, I follow Jofre-Bonet & Pesendorfer (2003) and use the bidder's first order condition to back out an estimate of its unobserved construction cost as a function of its bid, the distribution of the minimum rival bid, and the expected discounted sum of payoffs.

As is common with dynamic models, estimation requires approximations to reduce the dimensionality of the state space. In my application, there are hundreds of bidders competing on the dozens of auctions at each letting. This means that bidders need to track the backlogs of many rivals, the characteristics of contracts in the current letting, and the characteristics of pre-announced contracts. In my application, this curse of dimensionality is alleviated to some extent by the spatial aspect of competition: bidders primarily compete on contracts for nearby projects. Therefore, as a first approximation, they need to track only the backlogs of nearby rivals and the characteristics of nearby contracts (or moments of these states). The problem with this approach, however, is that a bidder needs to consider the states of bidders who are further away and not direct competitors because their states can influence the bidding decisions of nearby rivals. To account for this, I build a one-dimensional index that summarizes the level of competition that a bidder faces as a function of the states of all rivals.[1] The novelty of my index is that it is constructed using a random forest, which is flexible enough to weight certain rivals more heavily than others and to allow for complex interactions among the rivals' states that affect competition. It captures much the richness in strategic interactions that would be present when tracking the full state space.

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[1] This index is in the spirit of Ifrach & Weintraub (2017) in which players track moments of their rivals' states.

Given the estimates of the model primitives, I answer the positive question by quantifying the impact of pre-announcements on the participation and bidding decisions. Depending upon its backlog, a bidder who observes a pre-announcement of a nearby contract reduces the likelihood by 5% to 15% and increases its dynamic markup by 1% to 5%.

To answer the normative question, I run a counterfactual simulation in which the auctioneer does not issue pre-announcements. I find that eliminating information disclosure decreases the auctioneer's total expenditures by $15 million (0.6%) and increases the bidders' total costs by $8 million (0.4%). The change in the bidders' costs is decomposed as a $42 million (5.8%) increase in participation costs and a $34 million (2.1%) decrease in the construction costs. These effects are driven by the 5.7% increase in the number of bidders in the auctions. More participants leads to additional participation costs being incurred and more cost draws means it is more likely the winning bidder has a low construction cost. In terms of efficiency, I find that the fraction of auctions in which the lowest cost bidder did not win (i.e. "mis-allocated") increased from 6.4% to 7.4%. The additional construction cost due to mis-allocations increased by $3 million (27.3%) compared to the baseline. The inefficiency cost of no disclosure is less than the reduction in the government's procurement costs. Regardless of whether the goal is to minimize government expenditures or to maximize welfare by minimizing the sum of bidder costs and government expenditures, the results strongly suggest that the auctioneer should not pre-announce contracts in future lettings.[2]

The insights from my research on Michigan apply to other states and settings. Many states, such as California and New York, use similar highway procurement and information disclosure mechanisms. Considering that U.S. state and local governments spent $291 billion on transportation projects and maintenance in fiscal year 2017, the modest effects on efficiency and government expenditures I found in Michigan are likely to be large in aggregate. Milk delivery contracts for schools in a district is another setting in which governments hold procurement auctions in sequence and where bidders have information about contracts in future auctions. My dynamic model can also be modified to study the role of information disclosure in environments where there is learning-by-doing or where players are sequentially competing on objects that are complements.

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 provides evidence that bidder are forward looking. Section 4 develops the dynamic model and Section 5 outlines the estimation

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[2] These empirical results are consistent with Bulow & Klemperer (1996)'s theoretical result that an auctioneer gains more by adding a bidder than by optimizing the reserve price.

strategy. Sections 6 and 7 discuss the structural estimates and presents the policy counterfactuals. Section 8 concludes.

2   Literature Review

This 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, it differs in four ways. First, I model players as having information about contracts being offered in future auctions; JP assumes this is not the case even though the future auctions are pre-announced during the current auction cycle in California. Second, I account for the different market structure in Michigan. Michigan auctions off multiple contracts simultaneously on a single date each month and there are scores of competing bidders; in JP's market, contracts are auctioned in sequence every day and there are ten main bidders. Third, I model auction participation as endogenous and costly; in JP there is no participation cost so firms always bid. Fourth, firms are modeled as a collection of independent plants (i.e. establishments); in JP bidders are modeled at the firm level. Modeling firms at the plant level is a fundamentally different way of thinking about these bidders because it recognizes that when plants that have considerable distance between them are (effectively) independent from one another. Moreover, this allows the model to capture how a firm can have excess capacity but does not compete in an auction because the plant best suited to complete the contract does not have the capacity to handle it. Other papers that have built on JP are Groeger (2014), which endogenized participation to investigate synergies that result from participation in similar types of auctions, and Balat (2017), which endogenized the number of bidders in an auction and incorporated observed and unobserved heterogeneity to measure the impact of accelerated procurement processes on auctioneer expenditures. My paper differs from these by modeling the information disclosure via pre-announcements and endogenizing the choice of which, if any, of the multiple auctions in a period bidders decide to participate in.

Other related works in the theoretical 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. 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. In a theoretical model, Kawai et al. (2020) find that in competitive dynamic auctions, participation is as-if static; my paper is the first empirical application of this idea. There is a growing literature that empirically studies dynamic auctions using sequential Ebay auctions. Papers in this literature include Backus & Lewis (2016), Coey et al. (2020), Bodoh-Creed et al. (2020), and Hendricks et al. (2020). My research differs from these papers with its focus on the policy of information disclosure via pre-announcements. Moreover, compared to the empirical papers that study Ebay auctions, my setting has fewer bidders (several hundred vs thousands) and spatial competition which results in different modeling assumptions.

This paper also contributes to the literature that tests whether agents are foward looking such as Einav et al. (2015) and Dalton et al. (2020). Most closely related is Zeithammer (2006), which 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. This paper also tests if bidders are forward looking but additionally tests whether this behavior holds true for participation. The results should be very convincing in the MDOT auction environment because there are clearly defined auction cycles, information disclosure is exogenous, and the pre-announcements are centrally located, easy to find, and not too numerous. These features of my empirical environment mean that, in contract to Ebay auctions, I do not have to worry about auctions that close in the future overlapping with current period auctions and that any search costs of obtaining information about the future is minimal. I view my finding that bidders are forward looking as complementing the results in Zeithammer (2006).

My estimation approach uses methods from the dynamic optimization and games literature. In the seminal work, Rust (1987) demonstrated how to solve a dynamic 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), Aguirregabiria & Mira (2002), and Arcidiacono & Miller (2011). 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.

This paper contributes to a relatively new literature on the role of information disclosure in

dynamic settings by studying the effects in a repeated auction environment. Theoretical papers that study contests where participants can make multiple submissions over time include Aoyagi (2010), Ederer (2010), Rieck (2010), Goltsman & Mukherjee (2011), and Klein & Schmutzler (2017). These papers show that the effects of information disclosure policies (e.g. a public leaderboard) have theoretically ambiguous effects on player behavior. Lemus & Marshall (2020) empirically study the effect of real-time public leaderboards in prediction contests.

Finally, this paper is related to the literature analyzing of highway procurement auctions. In addition to papers discussed above, these include Porter & Zona (1993) and Bajari & Ye (2003), which investigate bidder collusion. Krasnokutskaya & Seim (2011), Lewis & Bajari (2011), and Bajari et al. (2014) study how bidder preference programs, time incentives, and contract structures affect bids and auction outcomes. Einav & Esponda (2008) and Li & Zheng (2009) study the effects of endogenous participation. Krasnokutskaya (2011) and Somaini (2018) demonstrate how to identify and estimate costs with unobserved auction heterogeneity and with interdependent cost signals, respectively. This paper is the first, to my knowledge, to carefully study the role of information disclosure via pre-announcements in this setting.

3 The Empirical Environment, Data, and Evidence of Dynamics

3.1 The Empirical Environment

The Michigan Department of Transportation (MDOT) uses first-price sealed-bid auctions to award 50–80 highway construction and maintenance contracts once per month. For 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. These requirements result in firms having capacity constraints.

Contracts are announced on MDOT's website up to six weeks prior to the letting date. These announcement notices, which are called advertisements, 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 announcements 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 contractors as simply deciding on the total bid.[3]

In order to submit a bid, a firm must submit a form to become eligible to bid and be placed on the plan holder list. In this form, which can be submitted as late as 5:00 PM the day prior to the letting, a firm lists all the auctions in which it is interested in bidding. The plan holder list contains a set of potential bidders for each auction because firms are not required to participate in auctions that they have expressed interest. It is often the case that these potential bidders do not submit a bid and become actual bidders. This means that a firm bidding in an auction is not certain about the identities of their rivals who actually submit bids. 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 for 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 between $100,000 and $3,000,000. These contracts account for a large subset of the MDOT auctions with a typical letting date having 25–45 HMA projects being offered. These HMA auctions

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[3] 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).

attract bids from 52–85 firms on a typical letting date. The reason for focusing on HMA projects is that they involve similar types of work that contractors should view as substitutable conditional on observable characteristics. One such relevant characteristic is distance because temperature is a key factor in the quality of HMA, which needs to be heated and mixed at a plant, and the mix cools during transport. The problems due to the cooling of HMA can be alleviated by incurring additional equipment and labor costs; for example, a material transfer vehicle can be used to remix onsite. This suggests a contractor's distance to a project is a cost shifter and an important determinant into whether it bids on a project.

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

3.2   Data

I will be using data from all MDOT HMA auctions from 2002–2010 that includes in 3,746 auctions and 19,463 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). Using the bid data, I construct a list of potential bidders. I deem any contractor that bid on a HMA auction in a given year to be a potential bidder.

I also collected data on the announcement dates for each auction. This data states the earliest date that contractors are made aware of the contracts being put up for auction. I classify a letting date $t + 1$ auction as pre-announced if it was announced at least two days prior to letting date t. The motivation for this definition is that following period auctions announced very close to the current letting date may not be seen/accounted for by contractors participating in the current period auctions.

I complement the MDOT contract and bid data with the locations of the firms' plants and of the projects at the street-address level. A firm's plant is the location where the contractor is located and where materials/equipment are stored. A plant can have the ability to produce HMA onsite (i.e. it has an HMA production facility) but this is not the case for all plants. The plant 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). I combine the data from these sources to get a list of firms' plants. I use the MDOT data on HMA production facilities to classify

plants into two types: vertically integrated (VI) if they can produce HMA onsite and non-vertically integrated (non-VI) otherwise. The project location data was provided by Somaini (2018); for the few contracts I did not have street-level location data for, I used the project's county centroid as the location. I construct a plant distance variable by computing the haversine distance between the plant and project location.

I will be treating firms as a collection of independent plants because I assume a firm's payoff is additive across its plants. This means I think of each plant as being a separate and independent bidder. I further assume that if a multi-plant firm wins a contract at auction, the closest plant completes the projects. This assumption is motivated by the fact that HMA cools during transport so it should be cost effective for the closest plant to do the work.

In contrast to the literature, which imputed the project progress based on the scheduled start and end dates, I collected data on actual project progress and backlog (remaining work) in dollar amounts. This is important because project progress is lumpy: there are weeks when a lot of construction work is done and weeks when little work is completed. In addition, I observe if a project gets completed past its scheduled end date. This data means I avoid any measurement error that arises from assuming that an equal fraction of a project's work is completed between the scheduled start and end dates. I use this data to construct a backlog variable for each plant. This variable captures the amount of remaining work, in dollar amounts, the plant still has to do for the contracts it has previously won in auctions. The assumption that a firm's closest plant is allocated the project is how I can compute a plant's backlog in a multi-plant firm. Following JP and Balat (2017), I construct a plant specific normalized backlog by taking the backlog in dollars less the plant's mean backlog divided by the standard deviation of the plant's backlog. The interpretation of the normalized backlog of a plant is how many standard deviations away from the mean is the current backlog and that higher values correspond to more constrained plants.

3.2.1   Descriptive Statistics

Table 1 provides summary statistics of the data. The average project has a engineer's estimate of $821K and there is quite a bit of variation in the project sizes. A typical auction attracts 5.2 bidders and it is quite rare to only have a single bidder auction. The winners leave quite a bit of money on the table: the runner up bid is typically 6.7% larger than the lowest bid. The engineer's estimate typically overstates the actual procurement price with average the winning bid being 7.0% below the estimate. The winning bidder is about 12km (7.5mi) closer to the project and has a lower

Table 1: Auction Summary Statistics

Variable	N	Mean	SD	Pctl25	Pctl50	Pctl75
Eng Est ($000)	3,746	821.456	653.367	329.917	599.401	1,129.313
Lowest Bid ($000)	3,746	762.167	621.072	297.638	545.059	1,039.825
(Runner Up Bid/Lowest Bid−1)×100	3,684	6.742	7.479	2.037	4.636	8.955
(Lowest Bid/Eng Est−1)×100	3,746	−6.960	12.341	−14.714	−7.485	−0.111
Number of Bidders	3,746	5.196	3.594	3	4	7
$\hookrightarrow$ VI Plants	3,746	1.350	1.083	0	1	2
$\hookrightarrow$ Non-VI Plants	3,746	3.662	3.910	1	2	6
Distance of Bidders (km)	19,463	52.662	48.658	19.274	40.806	70.248
$\hookrightarrow$ Winners	3,746	42.950	49.764	11.876	29.849	53.589
$\hookrightarrow$ Losers	15,717	54.976	48.103	21.781	43.688	72.916
Normalized Backlog of Bidders	19,463	−0.036	0.843	−0.682	0	0.578
$\hookrightarrow$ Winners	3,746	−0.265	0.926	−0.929	−0.402	0.416
$\hookrightarrow$ Losers	15,717	0.018	0.813	−0.607	0	0.611

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. VI (non-VI) plants are those with (without) a HMA plant onsite. Winners are plants that bid in auctions and submitted the lowest bid. Losers are plants that bid in auctions and did not submit the lowest bid.

normalized backlog (i.e. is less constrained) than a losing bidder. This suggests that distance and capacity constraints are important determinants of costs because the contracts are only awarded on the basis of being the low bidder.

Table 2 shows the distribution of the number period $t+1$ auctions conditioning on whether MDOT issued any pre-announcements or not. The distribution is quite similar across the conditioning events which suggests that the government is not being strategic with regard to whether it issues pre-announcements. I further check if MDOT is being strategic with regard to the number pre-announced of period $t+1$ auctions. That is to say, I test whether if the number of pre-announced period $t+1$ auctions (conditional on at least one) is informative about the number of period $t+1$ auctions that were not announced as of letting date t ("unannounced auctions"). The correlation between the two variables is -0.068. A Fischer test of the null hypothesis of zero correlation against the two sided alternative cannot reject the null with a P-value of 0.525.[4] Taken together, these results suggest that MDOT is not being strategic with regard to issuing pre-announcements.

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[4] A Fischer test when I do not condition on at least one pre-announced auction, rejects the null hypothesis with a correlation of -0.380 and a P-value of 2.5×10^{-5}. 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). See Figure 5 for a scatterplot of the number of pre-announced period $t+1$ auctions and the number of unannounced period $t+1$ auctions.

Table 2: Number of Period $t + 1$ HMA Auctions Given Period t Pre-announcement State

Variable	N	Mean	Pctl25	Pctl50	Pctl75
No pre-annnouncements issued	11	33	25	34	40
Pre-annnouncements issued	105	37	24	31	48

Compares the number of period $t + 1$ HMA auctions given the pre-announcement state in period t. No pre-announcements means that the government did not pre-announce any period $t+1$ projects (this includes non-HMA projects) more than one day prior to the period t letting date.

Table 3: Number of Plants by Type

Variable	N	Mean	SD	Pctl25	Pctl50	Pctl75
Firms with HMA Plants: VI Plants	17	4.765	4.969	2	3	6
Firms with HMA Plants: Non-VI Plants	17	1.471	1.908	0	1	3
Firms without HMA Plants: Non-VI Plants	188	1.452	0.606	1	1	2

• The statistics summarized the number of plants by type depending on whether the firm has HMA plants or not. N refers to the number of firms.
• Excludes firms that submitted fewer than 10 bids.

3.2.2 Plant Types

As mentioned above, I classify plants as VI and non-VI types. This distinction is important because a VI plant should have lower participation and construction costs. The reasons for this are that a VI plant does not need to get price quotes for the HMA before bidding on a project and that it does not have to pay a markup on the HMA. I assume that VI and non-VI plants are part of firms that submitted at least ten bids in the sample. Plants part of firms that submitted fewer than ten bids are treated as fringe bidders and excluded for the remainder of the analysis.

Table 3 shows that the 17 firms with VI plants are typically multi-plant firms. These firms own a total of 81 VI plants and 25 non-VI plants and a typical firm has 4.8 VI plants and 1.5 non-VI plants. In contrast, the 188 firms without VI plants are typically single-plant firms and account for 273 non-VI plants.

Both types of plants are important players in this market. A typical auction has 1.4 VI plant bidders and 3.7 non-VI plant bidders. The data strongly suggests that the hypothesis that VI plants are likely to have lower costs than non-VI plants is true. Table 4 shows that VI plants win over 40% of the auctions and are twice as likely to win an auction conditional on bidding compared to a non-VI plant. These patterns hold true across project sizes.

The set of auctions available to bid on a letting date plays an important role in a plant's decision to bid. Table 5, shows the plants' auction choice (which includes not bidding) by distance after conditioning on whether there is an auction within 25km of the plant or between 25km and

Table 4: Number of Bids and Wins by Plant Type

	VI Plants			Non-VI Plants		
Variable	No. Bids	No. Wins	Win Rate	No. Bids	No. Wins	Win Rate
All Projects	5,058	1,585	31%	13,718	2,060	15%
Projects < $750K	2,983	926	31%	7,886	1,208	15%
Projects ≥ $750K	2,075	659	32%	5,832	852	15%

Table 5: Auction Choice by Distance

	$\mathbf{1}$(Auction Within ...			% Choosing			
Plant Type	$[0, 25]$km)	$(25, 50]$km)	N	Not Bidding	$[0, 25]$km	$(25, 50]$km	$(50, \infty)$km
Non-VI	0	0	9,211	87%	-	-	13%
	0	1	7,262	67%	-	19%	14%
	1	0	3,763	59%	31%	-	10%
	1	1	6,312	54%	20%	15%	12%
VI	0	0	1,818	77%	-	-	23%
	0	1	1,567	44%	-	47%	9%
	1	0	2,018	33%	62%	-	5%
	1	1	956	34%	34%	26%	5%

This table shows the choice of auction a plant made on a letting date conditional on whether there is an auction within 25km of the plant and whether there is an auction within 25km to 50km of the plant. There is always an auction at least 50km away from the plant. N refers to the number of plant-letting date observations given the plant type and auction availability within 50km. The last four columns show the percentage of plant-letting date observations that made a given choice: either not bidding or bidding on an auction within one of the three distance categories. A "-" indicates to a choice that is not available so the percentage of plants making that choice is zero by construction. For example, a plant cannot bid on an auction within 25km if there are not any such auctions on the letting date.

50km of the plant on letting date t.[5] The table shows that plants often choose not to bid on any auctions in a letting date. The probability of not bidding sharply decreases when a plant has the choice to participate in close by auctions (those within 50km). This suggests that distance is an important driver of the participation decision and is likely a cost shifter. While plants prefer bidding in auctions that are nearby, note that plants still bid on projects that are far away even if a closer one is available. This means that though very important, distance does not fully explain the participation decisions. The table also shows that VI plants are more likely to bid than non-VI plants conditional on the set of available auctions on letting date t, which suggests they have lower participation costs as hypothesized above.

Finally, Table 6 shows that conditional on submitting at least one bid on a letting date, over 60% of the VI and non-VI plants submit only one bid; approximately 85% submit up to two bids. Considering that plants often choose not to bid, the data suggests that it is reasonable to think about plants as choosing whether or not to bid on a letting date and only bidding in one auction

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[5] The table looks similar and shows the same patterns when I use different distance bins.

Table 6: Number of bids submitted by a plant conditional on having submitted at least one bid on the letting date.

	VI Plant		Non-VI Plants	
Bids Submitted	N	Percent	N	Percent
1	2,159	66	4,909	61
2	715	22	1,825	23
3	238	7	719	9
4+	157	5	598	7

Each observation corresponds to a plant-letting date.

should they choose to bid.

3.3 Evidence of Forward Looking Behavior

The pre-announcements, which are issued exogenously and only include information about the future, provide a novel way of testing the null hypothesis that all bidders are myopic using regressions. The null hypothesis implies that the pre-announcements should have statistically insignificant effects on participation decisions and bid levels. The intuition of the test is that if all bidders are myopic, then pre-announcements will be ignored as they have no relevance to the current period payoffs. The alternative hypothesis is that at least some of the bidders are forward looking. It is possible for myopic bidders to respond to pre-announcements if the information indirectly affects their current period payoffs through their forward looking rivals' actions.

The regressions use the notation that i refers to a plant and the tuple (j,t) refers to auction j held on letting date t. The logit specification to measure the effects of pre-announcements on participation is as follows:[6]

$$
\begin{aligned}
\mathbf{1}(i \text{ bid in } (j,t)) = {}& \gamma_0 + \boldsymbol{\gamma}_1 \text{Dist}_{i,j,t} + \gamma_2 \text{NormBacklog}_{i,t} + \boldsymbol{\gamma}_3 \boldsymbol{w}_{j,t} + \varepsilon_{i,j,t} \\
& + \gamma_4 \mathbf{1}\big(\geq 1 \text{ pre-announced auction, Dist} \in [0, 25]\text{km, EngEst} \leq 750\text{K}\big)_{i,t} \\
& + \gamma_5 \mathbf{1}\big(\geq 1 \text{ pre-announced auction, Dist} \in [0, 25]\text{km, EngEst} > 750\text{K}\big)_{i,t} \quad (3.1) \\
& + \gamma_6 \mathbf{1}\big(\geq 1 \text{ pre-announced auction, Dist} \in (25, 50]\text{km, EngEst} \leq 750\text{K}\big)_{i,t} \\
& + \gamma_7 \mathbf{1}\big(\geq 1 \text{ pre-announced auction, Dist} \in (25, 50]\text{km, EngEst} > 750\text{K}\big)_{i,t},
\end{aligned}
$$

with year and month fixed effects.[7] $\text{Dist}_{i,j,t}$ is the distance in kilometers between plant i and auction

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[6] This specification produces similar results as a logit that predicts the outcome that a plant bids in at least one letting date t auction.

[7] In relatively small samples where the probability of a success is low, using too many fixed effects will bias the coefficient estimates because they absorb much of the variation. Since there are many auctions on a letting date and

(j, t) and is binned in estimation. The distance bins are within 25km, between 25km and 50km, and more than 50km. The auction-level covariates, denoted $\boldsymbol{w}_{j,t}$, include the number of line items in the contract, the percentage of the contract that must be subcontracted to a disadvantaged business, and the natural logarithm of the engineer's estimate. I differentiate the pre-announcements based on distance since bidders likely to be more responsive to information about close by auctions in the future. I further differentiate based on the size of the auction, measured by the engineer's estimate, because capacity constrained bidders are likely to be sensitive to how much work gets added to their backlog. For example, if a bidder observes a pre-announcement of a period $t + 1$ with a large engineer's estimate that it wants to participate in, it may less inclined to bid in a current period auction so it has available capacity to take on the period $t + 1$ project if it wins the auction. These regressions are run separately for VI and non-VI plants because they descriptive statistics suggest they have very different participation patterns.

The estimates for non-VI and VI plants are reported in Table 7 columns (1) and (2). These estimates show that distance matters: bidders are far less likely to participate in auctions that are further away. As expected, the higher a plant's normalized backlog (i.e. more constrained) the less likely the bidder is to participate. The effect of backlog is larger for non-VI plants than VI plants. The importance of backlog contrasts with Groeger (2014) and Somaini (2018), who find that backlog does not have a significant impact on participation/bids in MDOT auctions. One reason for this difference is that my backlog variable is based on observable data and is not imputed like in the literature. Another reason is that I am studying bidders at the plant level, which can produce different results. For example, while a bidder might appear to be constrained at the firm level, it can bid in an auction if it has available capacity at one of its plants. The auction specific covariates in $\boldsymbol{w}_{j,t}$ all have statistically significant effects on the participation decision and the direction of the effect depends on the type of plant. The coefficients for pre-announcements of auctions within 50km of the plant are typically negative and significant at conventional levels. This is consistent with the idea that participation should fall when the option value of not participating is higher. There is one case for which the estimate is not the expected sign for VI plants but the coefficient is not significant.

The OLS specification to see how bids are affected by pre-announcements is similar to the logit specification in (3.1) with three differences. One, the dependent variable is $\frac{\text{Bid}_{i,j,t}}{\text{EngEst}_{j,t}/100}$, which

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a bidder typically only bids in one auction if they choose to participate, this is a concern in this context. For this reason, I use simple time fixed effects and exclude firm and/or plant fixed effects.

Table 7: Participation and Bid Regressions

	Dependent variable:			
	$\mathbf{1}(i$ bid in $(j,t))$		Bid / EngEst $\times$ 100	
	Logit		OLS	
	Non-VI	VI	Non-VI	VI
	(1)	(2)	(3)	(4)
Dist $\in (25, 50]$km	−0.640***	−0.730***	2.678***	−0.267
	(0.026)	(0.048)	(0.337)	(0.491)
Dist $\in (50, \infty)$km	−3.051***	−4.005***	4.254***	5.541***
	(0.023)	(0.048)	(0.305)	(0.575)
Norm Backlog	−0.120***	−0.070***	0.970***	0.933***
	(0.013)	(0.025)	(0.157)	(0.261)
ln(EngEst)	−0.305***	0.356***		
	(0.015)	(0.029)		
Line Items	0.010***	−0.019***	0.039***	0.074***
	(0.0003)	(0.001)	(0.004)	(0.007)
% Subcont. to Disadvantaged Business	0.008***	−0.050***	−0.367***	−0.341***
	(0.003)	(0.006)	(0.037)	(0.067)
$\mathbf{1}(\geq 1$ Pre-announced $n\jmath$ Period t+1 Auction)	−0.133***	0.034	0.792**	0.156
	(0.024)	(0.049)	(0.344)	(0.578)
$\mathbf{1}(\geq 1$ Pre-announced $n\ell$ Period t+1 Auction)	−0.072***	−0.051	2.044***	2.609***
	(0.025)	(0.052)	(0.357)	(0.642)
$\mathbf{1}(\geq 1$ Pre-announced $m\jmath$ Period t+1 Auction)	−0.022	−0.219***	0.327	0.206
	(0.021)	(0.045)	(0.319)	(0.549)
$\mathbf{1}(\geq 1$ Pre-announced $m\ell$ Period t+1 Auction)	−0.067***	−0.321***	1.723***	0.512
	(0.022)	(0.048)	(0.319)	(0.566)
Observations	513,834	47,726	13,670	5,048
Log Likelihood	-52,288.370	-10,479.260		
R^2			0.147	0.195
Adjusted R^2			0.139	0.175

*p<0.1; **p<0.05; ***p<0.01. Asymptotic standard errors are reported for the logit estimates. White standard errors are reported for the OLS estimates.

• Columns (1) and (2) report the logit regression estimates specified in (3.1). This regression includes year and month fixed effects (not reported).

• Columns (3) and (4) report the OLS regression of normalized bids that is specified similarly to (3.1). The regression includes year, month, and number of bidders fixed effects (not reported).

• An $t + 1$ auction is deemed to be pre-announced if it was announced at least two days prior to letting date t.

• A $n\jmath$ ($n\ell$) auction is between 0km and 25km from the bidder and has an engineer's estimate below (above) \$750K. A $m\jmath$ ($m\ell$) auction is between 25km and 50km from the bidder and has an engineer's estimate below (above) \$750K.

represents the bid as a percentage of the engineer's estimate. Defining the dependent variable in this way means that the coefficients have a natural interpretation as the marginal effect of the covariate on the bid as a percentage of the engineer's estimate. Two, the natural logarithm of the engineer's estimate is excluded from $\boldsymbol{w}_{j,t}$ because the engineer's estimate is used to scale the bids. Three, I additionally include the number of bidders in the auction as a fixed effect.

The bid regression results are reported in Table 7 columns (3) and (4). The bids are increasing in distance. For VI plants, however, the bids on auctions between 25km and 50km of the plant are slightly lower than for those within 25km of the plant. While unexpected, the estimated coefficient is not significant and the negative sign is not robust (see Heckit regressions below). Bids are

also increasing in normalized backlog and the effect is somewhat larger for non-VI plants than VI plants as in the participation regressions. The two auction-level covariates are significant even after scaling the bid to account for the engineer's estimate which hints that contracts differ by characteristics other than location and size. The effect of pre-announcements of close period $t + 1$ auctions is expected to be positive because they increase the option value of losing since bidders' prefer contracts in their vicinity. These coefficients have the expected sign and many are significant at conventional levels. The estimates say that non-VI plants respond to the pre-announcements and that the effect is particularly sharp for pre-announcements of auctions for contracts that have an engineer's estimate greater than \$750K. VI plants respond similarly though the effect is only significant for pre-announcements of auctions within 25km that have a size that is at least \$750K. The relative strength of the effect of pre-announcements of large period $t + 1$ auctions suggests that winning an auction in the current period makes it more costly to win a large project in the following period (winning large projects uses capacity and takes longer to work off).

Both the logit and OLS estimates show that pre-announcements have a significant impact on both participation and bidding. These results provide strong evidence against the null hypothesis that all bidders are myopic. I interpret these estimates to mean that bidders are forward looking. This interpretation is bolstered by the estimates that participation (bids) is decreasing (increasing) in backlog, which suggests bidders are capacity constrained. If bidders' costs are intertemporally linked over time through backlog, they have reason to be forward looking: winning a project this period makes them weaker in the next period because they are more constrained.

I also run a Heckit regression to see if there is selection based on unobservables. The selection and outcome equations use the participation and bidding specifications described above; the selection equation is assumed to have normally distributed errors. There are no exclusion restrictions so identification of the coefficients comes off the function form restrictions of the Heckit model. The coefficient estimates are in line with the results discussed in the previous paragraphs (estimates are reported in Table 15 in the appendix). The estimates of the correlation parameter, ρ, is -0.011 for non-VI plants and -0.043 for VI plants; the standard errors are 0.104 and 0.091, respectively. The estimates are not significantly different from zero. I interpret this result as suggesting that bidders do not know their cost of completing the project before deciding to bid. If costs were known prior to bidding then the correlation parameter would be negative and significant. This is because bidders would choose to participate in the auctions for which they have low costs and submit relatively low bids.

There are four takeaways from these regression estimates. First, distance appears to be important to participation and bidding, which I interpret to mean that costs are increasing in distance. Second, backlog has a significant impact on strategies which suggests that bidders are capacity constrained. Third, pre-announcements affect both participation probabilities and bid levels which I interpret as evidence that bidders are forward looking. Fourth, the auction participation decision does not appear to be selective. I now proceed to use these four patterns to build a dynamic model of participation and bidding.

4   The Model of Participation and Bidding

This section details the model of participation and bidding. I begin by describing the environment and timing of the stage game. Next, I delineate the transition laws, bidder strategies, and the equilibrium concept. I conclude the section by showing the payoffs of participation and bidding and explain how they are affected by pre-announcements. The notation will follow the convention that random variables are capital letters and their realizations are lowercase letters.

In the model, time is discrete with an infinite horizon and is indexed by $t = 1, 2, \ldots$. Lettings are held every period and at each letting, the buyer (auctioneer) offers J contracts to complete projects in separate low-bid first price sealed bid auctions with no reserve price. The contracts (which I will also call projects) are indexed by j. Let $z_{j,t} = (l_{j,t}, \zeta_{j,t})$ denote the characteristics of contract j in period t where $l_{j,t}$ is the project's location and $\zeta_{j,t}$ is the project's size as measured by an engineer's estimate.[8] Define $\boldsymbol{z}_t = (z_{1,t}, \ldots, z_{J,t})$. Each contract's characteristics are an independent draw from the exogenous distribution $F_Z(\cdot)$.

Bidders are risk-neutral single plant firms and are indexed by $i = 1, \ldots, I$. The number of plants is fixed and does not vary across periods. The characteristics of a plant are its location, backlog, mean backlog, standard deviation of backlog, and type. A plant's location, l_i, is where the contractor is located and where materials are stored; this location is fixed over time. Let $\boldsymbol{l}_{-i}$ denote the vector locations of bidder i's rivals. A bidder's backlog varies over time depending on which contracts it has won in previous lettings and the work done on those contracts. Let $s_{i,t} \in \mathcal{S}_i$ denote bidder i's backlog at the beginning of period t and define $\boldsymbol{s}_{-i,t}$ to be the backlogs of i's rivals. The vector $\boldsymbol{s}_t = (s_{i,t}, \boldsymbol{s}_{-i,t}) \in \mathcal{S} = \times_{i=1}^{I} \mathcal{S}_i$ represents the backlog of all plants that is observable to all bidders and the econometrician. Each plant has a mean and standard deviation of backlog, denoted

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[8] The model can be extended to allow for other observable contract characteristics.

$\bar{s}_i$ and $sd(s)_i$, that are fixed over time and capture observable differences in bidders' capacities. A bidder's type is represented by τ_i captures if it is VI or non-VI.[9] Define $z_{0,i} = (l_i, \bar{s}_i, sd(s)_i, \tau_i)$ to be bidder i's characteristics that are fixed over time and $\boldsymbol{z}_0 = (z_{0,1}, \ldots, z_{0,I})$. All bidders share a common discount factor $\delta \in (0,1)$.

Bidder i's construction cost of completing contract j, denoted $c_{i,j,t}$, is privately known and independently distributed conditional on contract characteristics and its backlog. A bidder's costs are (stochastically) increasing in project size but the contract location also matters because it determines the distance that the contractor and materials have to travel to work on the contract. Let $F(\cdot|s_{i,t}, z_{0,i}, z_{j,t})$ denote this conditional construction cost distribution and assume it has support on $[\underline{c}, \bar{c}]$. This specification captures three of the patterns documented in the reduced form work. First, it allows capacity constraints to affect costs through backlog. Second, it includes distance because the bidder's location (l_i) and the project location ($l_{j,t}$) enter the conditioning variables. Third, the plant's type can affect the cost distribution.

For the remainder of the section assume, for simplicity of exposition, that all plants are of the same type and have identical mean and standard deviations of backlog (i.e. for all plants i and i': $\tau_i = \tau_{i'}$, $\bar{s}_i = \bar{s}_{i'}$, $sd(s)_i = sd(s)_{i'}$). This means I only have to discuss how location affects strategies. When this assumption is relaxed, these characteristics enter the model in a similar fashion as location.

4.1   The Stage Game

The sequence of events in period t is as follows.

1. The buyer reveals $\boldsymbol{z}_t$, the characteristics of the contracts being procured in the period.

2. The buyer pre-announces a (possibly empty) subset of elements in $\boldsymbol{z}_{t+1}$; call this set $\boldsymbol{z}_{t+1}^A$.

3. Each bidder chooses to participate in at most one auction. The participation decisions of the rival bidders are not observed.

4. If bidder i decides to not participate, it earns a payoff that is normalized to zero. If it chooses to participate and bid in auction j, it incurs a cost κ and draws a cost estimate c for completing the contract from $F(\cdot|s_{i,t}, z_{0,i}, z_{j,t})$.

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[9] The model can have more than two bidder types.

5. Each bidder who participates submits a bid $b \in \mathcal{B}$, which is the price at which it is willing to provide the contracted work.

6. The buyer awards the contracts to the bidders who submit the lowest bids and makes public the bids and identities of the bidders for each contract.

The first (last) three steps constitute the participation (bid) stage.

The buyer announces period $t + 1$ auctions in the participation stage $(\boldsymbol{z}_{t+1}^A)$; these are the pre-announcements that disclose information about the future. Let $\boldsymbol{z}_{t+1}^U$ denote the period $t + 1$ contracts that were unannounced in t. By construction, $(\boldsymbol{z}_{t+1}^A, \boldsymbol{z}_{t+1}^U) = \boldsymbol{z}_{t+1}$. Note that by the independence assumption, the elements of $\boldsymbol{z}_{t+1}^A$ and $\boldsymbol{z}_{t+1}^U$ are independent of each other.

The cost incurred if the bidder participates, κ, includes the bid preparation cost and the flow payoff of not participating. The latter cost is included in κ because not participating has its flow payoff normalized to zero. The flow payoff from not participating is derived from the income the bidder can make by working on projects other than those that the auctioneer is procuring; this payoff is assumed to be constant over time.[10]

Notice that the bidder's participation decision is taken before it observes its cost draw and it always bids if it participates. This implies that there is no selection problem (participation is based on observables) and that every cost draw has an associated, observable bid. Moreover, the bidders do not observe their rivals' participation decisions, which means that this is a simultaneous move game in participation and bidding.

4.2   The Transition Laws

The transition law of the backlogs maps the bidders' backlogs at the beginning of period t, the period t contract characteristics, and the identities of the low bidder in each of the J period t auctions to the bidders' backlog in period $t + 1$. The transition has two parts: how existing backlog is worked off and how the auction outcomes affect the backlog.

The evolution of bidder i's backlog at the beginning of period t, $s_{i,t}$, excluding contracts won is stochastic. I assume that working off of existing backlog is random because the work is affected by external factors such as weather and how the buyer dictates the work schedule; this process

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[10] In the application, this will involve doing either private work or non-HMA MDOT auctions. For example, suppose that lettings are held on the first of each month. Then each period goes from the second of the month to the first of the following month (e.g. April 2 - May 1). So if a bidder decided to participate in the letting on May 1, the model assumes that it forewent private work it could have obtained from April 2 - May 1 (the length of a period).

is independent of auction outcomes.[11] Since the bidder is working off its backlog, $s_{i,t}$ can either stay the same or fall. So bidder i's transition law for its backlog if it did not participate in period t follows the probability distribution $\Pr(S_{i,t+1}|s_{i,t}, i \text{ doesn't bid})$, which has support for $S_{i,t+1} \in [0, s_{i,t}]$. This specification of the transition law precludes information about the contracts that constitute $s_{i,t}$ from affecting the transition probability. Only the total backlog at the beginning of period t is informative about how much of the backlog is worked off.[12] I can model the working off of existing backlog as stochastic because in the application, I observe this process in the data.

The auction outcomes affect the backlog in a deterministic fashion. If bidder i wins auction j in period t, then that contract's size $\zeta_{j,t}$ gets added to the remaining backlog at the beginning of period $t + 1$. To be clear, the remaining backlog excludes work completed in period t as described in the previous paragraph. Winning an auction means that the transition law, $\Pr(S_{i,t+1}|s_{i,t}, i \text{ won contract } j)$, has support on $S_{i,t+1} \in [\zeta_{j,t}, s_{i,t} + \zeta_{j,t}]$. Note that this assumes the non-HMA work that a bidder undertakes if it decides to not participate does not add to its backlog (i.e. all non-HMA work gets completed in a period).

To make the backlog transition law concrete, consider the following example. Suppose bidder i has backlog of \$1 million at the beginning of period t. If i did not participate (or lost) in a period t auction, the probability its backlog falls to \$0.75 million is p and the probability its backlog stays at \$1.0 million is $1 - p$. If i won a contract with size \$0.5 million, the probability its backlog equals \$1.25 million (0.75 + 0.5) is p and the probability its backlog equals \$1.5 million (1.0 + 0.5) is $1 - p$. Notice that i's backlog when it does not participate is weakly decreasing and that winning an auction affects the transition law in a deterministic way.

The other state variables, the contract characteristics and pre-announcements, are independent draws from an exogenous distributions.

4.3   Strategies

Bidders are restricted to Markovian strategies. These strategies only depend on the period t state variables; they do not depend on time or the history of states and actions. I focus on symmetric Markov perfect equilibria. A strategy profile σ consists of a participation function $\rho(\cdot)$ and a bid function $\beta(\cdot)$.

A participation strategy for bidder i is $\rho_i(s_t, z_t, z_{t+1}^A, z_0)$ that maps the backlogs, offered con-

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[11] The stochastic evolution of existing backlog includes a deterministic transition as a special case.
[12] This assumption could be relaxed but would involve having to track the information about the contracts that comprise $s_{i,t}$ in the state space.

tracts, pre-announced contracts, and bidder characteristics into a choice $j \in \{0, 1, \ldots, J\}$, where $j = 0$ corresponds to the outside option of not participating. A bidding strategy for i in auction j is a function $\beta_{i,j}(c, \boldsymbol{s}_t, \boldsymbol{z}_t, \boldsymbol{z}_{t+1}^A, \boldsymbol{z}_0)$ that maps the bidder's cost, backlog, offered contracts, pre-announced contracts, and bidder characteristics into a bid; define $\beta_i(\cdot) := \big(\beta_{i,1}(\cdot), \ldots, \beta_{i,j}(\cdot), \ldots, \beta_{i,J}(\cdot)\big)$. These strategies are symmetric in the sense that all bidders use the same functions and if the backlog and location of two bidders were switched, their strategies would be switched as well. The participation strategy, for example, can be written as

$$\rho(s_{i,t}, \boldsymbol{s}_{-i,t}, \boldsymbol{z}_t, \boldsymbol{z}_{t+1}^A, z_{0,i}, \boldsymbol{z}_{0,-i}) = \rho_i(\boldsymbol{s}_t, \boldsymbol{z}_t, \boldsymbol{z}_{t+1}^A, \boldsymbol{z}_0) \quad \text{for all } i,$$

for some function $\rho(\cdot)$. For notational convenience, however, I will frequently use the i subscripts on strategies even the underlying strategy functions are the same for all bidders. I will also suppress the strategies dependence on fixed bidder characteristics, $\boldsymbol{z}_0$, to keep the notation compact.

4.4 Payoffs

The stage game states that the way a bidder obtains payoffs in the model is by participating in and winning auctions. I will first describe bidder i's expected payoff in the bid stage when its rivals are using the strategy profile $\sigma = (\rho, \beta)$. Then I will use the bid stage payoff to describe the expected payoff in the participation stage, which involves choosing the auction with the highest expected payoff.

Before detailing the payoffs, I introduce some notation. Let $V_{i,j}^B(c, \boldsymbol{s}_t, \boldsymbol{z}_t, \boldsymbol{z}_{t+1}^A, \boldsymbol{z}_0; \sigma)$ be the value function that represents i's expected discounted sum of future payoffs if it bids in auction j and has cost draw c. Let $V_i^P(\boldsymbol{s}_t, \boldsymbol{z}_t, \boldsymbol{z}_{t+1}^A, \boldsymbol{z}_0; \sigma)$ be the value function that represents i's expected discounted sum of future payoffs in the participation stage. As with the strategies, I use the i subscripts to keep notation compact; there exist value functions $V_j^B(\cdot)$ and $V^P(\cdot)$ that are common to all bidders. I will also suppress the value functions' dependence on σ and $\boldsymbol{z}_0$ for compactness.

4.4.1 The Bidding Stage

Let $G_{j,M_i}(\cdot | \boldsymbol{s}_t, \boldsymbol{z}_t, \boldsymbol{z}_{t+1}^A, \boldsymbol{z}_0; \sigma)$ denote the distribution of i's minimum rival bid, M_i, in auction j given the state variables when the rivals are playing strategy profile σ. Define $\widetilde{G}_{j,M_i}(\cdot | \cdot) := 1 - G_{j,M_i}(\cdot | \cdot)$. As with the value functions, I will supress the dependence on σ and $\boldsymbol{z}_0$. Bidder i's bid stage value

function when it participates in auction j and has cost draw c is

$$
\begin{aligned}
V_{i,j}^B(c, \boldsymbol{s}_t, \boldsymbol{z}_t, \boldsymbol{z}_{t+1}^A) = \max_b \bigg\{ & (b-c)\widetilde{G}_{j,M_i}(b|\boldsymbol{s}_t, \boldsymbol{z}_t, \boldsymbol{z}_{t+1}^A) \\
& + \delta\mathbb{E}\bigg[V_i^P(\boldsymbol{S}_{t+1}, \boldsymbol{Z}_{t+1}, \boldsymbol{Z}_{t+2}^A)\bigg|\boldsymbol{s}_t, \boldsymbol{z}_t, \boldsymbol{z}_{t+1}^A, i \text{ wins } j\bigg]\widetilde{G}_{j,M_i}(b|\boldsymbol{s}_t, \boldsymbol{z}_t, \boldsymbol{z}_{t+1}^A) \\
& + \delta\mathbb{E}\bigg[V_i^P(\boldsymbol{S}_{t+1}, \boldsymbol{Z}_{t+1}, \boldsymbol{Z}_{t+2}^A)\bigg|\boldsymbol{s}_t, \boldsymbol{z}_t, \boldsymbol{z}_{t+1}^A, i \text{ loses } j\bigg]G_{j,M_i}(b|\boldsymbol{s}_t, \boldsymbol{z}_t, \boldsymbol{z}_{t+1}^A) \bigg\},
\end{aligned}
\tag{4.1}
$$

where the expectation operator $\mathbb{E}$ is taken over $\boldsymbol{S}_{t+1}$, $\boldsymbol{Z}_{t+1}$, and $\boldsymbol{Z}_{t+2}^A$ and $\widetilde{G}_{j,M_i}(b|\cdot)$ $\left(G_{j,M_i}(b|\cdot)\right)$ is the probability of winning (losing) the auction when bidding b. The first term inside the braces is the expected flow revenue from bidding in auction auction j: it is the bid less the cost times the probability of winning. The functional form of the revenue function comes from the assumption that bidders are risk-neutral. The second and third terms inside the braces are the continuation values of winning and losing auction j, respectively, multiplied by the probability of each outcome. The expectation of $\boldsymbol{S}_{t+1}$ also accounts for potential outcomes of all the J auctions held in the period. The key thing to notice is that if bidder i wins auction j, its backlog will be higher than if it lost as described by the transition law. When the bidder is capacity constrained, the higher backlog results the continuation value of winning being smaller than the continuation value of losing, all else equal.

The first order condition of (4.1) with respect to the bid is:

$$
\begin{aligned}
c = b - \frac{\widetilde{G}_{j,M_i}(b|\boldsymbol{s}_t, \boldsymbol{z}_t, \boldsymbol{z}_{t+1}^A)}{g_{j,M_i}(b|\boldsymbol{s}_t, \boldsymbol{z}_t, \boldsymbol{z}_{t+1}^A)} - \delta\bigg(& \mathbb{E}\bigg[V_i^P(\boldsymbol{S}_{t+1}, \boldsymbol{Z}_{t+1}, \boldsymbol{Z}_{t+2}^A)\bigg|\boldsymbol{s}_t, \boldsymbol{z}_t, \boldsymbol{z}_{t+1}^A, i \text{ loses } j\bigg] \\
& - \mathbb{E}\bigg[V_i^P(\boldsymbol{S}_{t+1}, \boldsymbol{Z}_{t+1}, \boldsymbol{Z}_{t+2}^A)\bigg|\boldsymbol{s}_t, \boldsymbol{z}_t, \boldsymbol{z}_{t+1}^A, i \text{ wins } j\bigg]\bigg),
\end{aligned}
\tag{4.2}
$$

where $g_{j,M_i}(\cdot)$ is the density function associated with $G_{j,M_i}(\cdot)$. 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 bidder i faces in period t; call this the "static markup". The second markup term accounts for the opportunity cost of winning on future profits since costs are increasing in backlog; call this the "dynamic markup". Bidder i can account for the opportunity cost of winning in its bid because the bid level affects the expected flow revenue and the *probability* that it gets a one of the continuation values in (4.1).

The pre-announcements, $\boldsymbol{z}_{t+1}^A$, affect the bid through both markup terms. If the auctioneer has

pre-announced contracts in period $t+1$ that are (ex-ante) low cost for i, then winning in period t is "bad news" because it will be more constrained in $t+1$ and will be less likely to take advantage of those contracts. This impacts the dynamic markup because the pre-announcement changes the continuation values of winning and losing. Since all bidders adjust their dynamic markup in response to pre-announcements, it follows that the information disclosure affects the minimum rival bid distribution as well and thus, the static markup. This first order condition makes it clear that if all bidders were myopic ($\delta = 0$) then pre-announcements would have no impact on the bid levels.

Taking the first order condition and the bidding strategy $\beta(\cdot)$ and plugging them into (4.1) yields the expected bid stage payoff under optimal bidding:

$$
\begin{aligned}
V_{i,j}^B(c, \boldsymbol{s}_t, \boldsymbol{z}_t, \boldsymbol{z}_{t+1}^A) = {} & \frac{\widetilde{G}_{j,M_i}\left(\beta_{i,j,t}(c)\big|\boldsymbol{s}_t, \boldsymbol{z}_t, \boldsymbol{z}_{t+1}^A\right)^2}{g_{j,M_i}\left(\beta_{i,j,t}(c)\big|\boldsymbol{s}_t, \boldsymbol{z}_t, \boldsymbol{z}_{t+1}^A\right)} \\
& + \delta \mathbb{E}\left[V_i^P(\boldsymbol{S}_{t+1}, \boldsymbol{Z}_{t+1}, \boldsymbol{Z}_{t+2}^A)\big|\boldsymbol{s}_t, \boldsymbol{z}_t, \boldsymbol{z}_{t+1}^A, i \text{ loses } j\right],
\end{aligned}
\tag{4.3}
$$

where $\beta_{i,j,t}(c) := \beta_{i,j}(c, \boldsymbol{s}_t, \boldsymbol{z}_t, \boldsymbol{z}_{t+1}^A)$. Notice that the continuation value of winning has dropped out because bidder i accounts for the opportunity cost of winning in its bid. So when i wins the auction, its flow payoff has increased (compared to the static model) to compensate it for getting the lower continuation value. Through algebraic manipulation, I take a portion of this increased flow payoff and add it to the continuation value to produce expression (4.3). The manipulation means that the first term in the expression is *not* the expected flow payoff of the auction; the expected flow payoff is higher. Similarly, the second term is larger than the actual expected continuation value. However, for simplicity of exposition, I will interpret the first term as the "flow payoff" and the second term as the "continuation value" of bidding.

The continuation value of losing is the same regardless of which (if any) auction bidder i chose to participate and bid in. This follows from the assumption that the period stage game is simultaneous move in participation and bidding. This means the rivals who win the J auctions when bidder i participates in auction j and loses is the same as the case in which i did not participate because all the rivals participation decisions and bid levels are the same between the two scenarios. This implies that the transition law of the state variables is the same regardless of the conditioning event.

4.4.2   The Participation Stage

The stage game implies that the participation value function is

$$V_i^P(\boldsymbol{s}_t, \boldsymbol{z}_t, \boldsymbol{z}_{t+1}^A) = \max_{j \in \{0,1,\dots,J\}} \left\{ \mathbb{E}_C \Big[V_{i,j}^B(C, \boldsymbol{s}_t, \boldsymbol{z}_t, \boldsymbol{z}_{t+1}^A) \Big| \boldsymbol{s}_t, \boldsymbol{z}_t, \boldsymbol{z}_{t+1}^A \Big] - \kappa \times \mathbf{1}(j \neq 0) \right\}. \qquad (4.4)$$

This states that bidder i will participate in the auction (if any) that will maximize the expected discounted sum of future payoffs. The bid stage value function under optimal bidding allows us to re-write this as

$$V_i^P(\boldsymbol{s}_t, \boldsymbol{z}_t, \boldsymbol{z}_{t+1}^A) = \max_{j \in \{0,1,\dots,J\}} \left\{ \pi_{i,j}\left(\boldsymbol{s}_t, \boldsymbol{z}_t, \boldsymbol{z}_{t+1}^A\right) + \delta \mathbb{E}\Big[V_i^P(\boldsymbol{S}_{t+1}, \boldsymbol{Z}_{t+1}, \boldsymbol{Z}_{t+2}^A) \Big| \boldsymbol{s}_t, \boldsymbol{z}_t, \boldsymbol{z}_{t+1}^A, i \text{ doesn't bid} \Big] \right\}$$
$$(4.5)$$

where

$$\pi_{i,j}\left(\boldsymbol{s}_t, \boldsymbol{z}_t, \boldsymbol{z}_{t+1}^A\right) = \begin{cases} \displaystyle\int_{\underline{b}}^{\infty} \frac{\widetilde{G}_{j,M_i}\left(b\big|\boldsymbol{s}_t, \boldsymbol{z}_t, \boldsymbol{z}_{t+1}^A\right)^2}{g_{j,M_i}\left(b\big|\boldsymbol{s}_t, \boldsymbol{z}_t, \boldsymbol{z}_{t+1}^A\right)} g_{j,B_i}(b|\boldsymbol{s}_t, \boldsymbol{z}_t, \boldsymbol{z}_{t+1}^A)db - \kappa & \text{if } j \neq 0; \\[2em] 0 & \text{if } j = 0; \end{cases}$$

$g_{j,B_i}(b|\boldsymbol{s}_t, \boldsymbol{z}_t, \boldsymbol{z}_{t+1}^A)$ is bidder i's bid distribution for auction j, and $\underline{b}$ is the lower bound of the support of the bids. Note that I integrated out the costs by changing the variable of integration from costs to bids (see Appendix A for details).

Notice that the participation decision is effectively static because the participation choice does not impact the continuation value. This occurs because the bidder anticipates that its bid will account for the opportunity cost of winning as discussed earlier. While the participation decision is static, pre-announcements still affect the choice. This is because the pre-announcements impact the bids, which affects the expected flow payoff of participating in each auction. Bidder i's participation decision involves choosing the j that has the highest expected flow payoff $\pi_{i,j}\left(\boldsymbol{s}_t, \boldsymbol{z}_t, \boldsymbol{z}_{t+1}^A\right)$.

Equilibrium existence: The discussion of the existence of an equilibrium in JP applies to the present model.

5   The Estimation Method

The model of participation and bidding described in Section 4 is computationally intractable because of the extremely large state space. In the application, I treat the entire state of Michigan

as a single market so a bidder has to track dozens of available auctions and pre-announcements as well as the backlogs of hundreds of rivals. I begin the section by discussing a set of assumptions made to reduce the state space dimensionality so I can estimate the model. Then I describe the value functions under the tractable state space. The section concludes by detailing the estimation procedure and the parametric specifications.

5.1   The Estimation State Space

The state space dimension reduction is motivated by the empirical pattern that competition is local: bidders mainly participate in auctions for nearby contracts. This suggests that bidders' strategies are primarily driven by the characteristics of nearby contracts and are competing with rivals in their vicinity. For this reason, bidder behavior can be well approximated if they are modeled as only tracking auctions and rivals that are close by.

5.1.1   The Auction Bins Assumption

I begin by discretizing the auction characteristics. Define three distance bins, denoted d, to capture how bidders approximate the locations of each project up for auction: near ($d = n$, 0-25km), medium ($d = m$, 25-50km), and far ($d = f$, >50km). Project sizes, denoted ζ, are also discretized into bins: small ($\zeta = \jmath$) and large ($\zeta = \ell$). Small (large) projects are those with an engineer's estimate below (above) \$0.75MM and are set to be \$0.5MM (\$1.0MM) in estimation. The cartesian product of distance bins and size bins produces six bins of projects: near small ($d\zeta = n\jmath$), near large ($d\zeta = n\ell$), medium small ($d\zeta = m\jmath$), medium large ($d\zeta = m\ell$), far small ($d\zeta = f\jmath$), and far large ($d\zeta = f\ell$). Going forward, when I refer to an auction of a given "bin", I am referring to the six $d\zeta$ bins just defined.

Assume that the bidders cost distribution for each contract in a given bin are identical. Further assume that bidders think that the level of competition for auctions in the same bin is identical. The implication of these two assumptions is that bidder i views contracts in the same bin as identical *before costs are drawn*. To account for differences between auctions in the same bin that exist in the theoretical model, I give each auction an independent ε shock in the participation stage. When a bidder decides to participate in an auction in a bin, it chooses the one with the highest ε shock. This means the choice of auction conditional on a bin is random. It follows that the bidder's participation decision space can be modeled as choosing whether to bid on one of these auction

bins or declining to bid.[13]

Since a bidder's participation decision is which, if any, of the auction bins to participate in, it follows that it only needs to track if there is at least one auction in a each bin available to bid on in period t. This informs the bidder of its participation choice space: it cannot participate is an auction bin if one is not available in period t. Let $y_{i,t,d\zeta}$ be an indicator variable that is one if there is a bin $d\zeta$ contract up for auction in period t. Then the bidder has to track $\boldsymbol{y}_{i,t} := (y_{i,t,n\jmath}, y_{i,t,n\ell}, y_{i,t,m\jmath}, y_{i,t,m\ell})$. Following a pattern in the data, I assume that each bidder always has far small and far large auctions available to bid on (i.e. $y_{i,t,f\jmath} = y_{i,t,f\ell} = 1$ for all i and t) so it has no reason to track these bins in the state space. Then bidder i's action space in the participation stage is either not bidding or bidding in one of the available auction bins (bin $d\zeta$ is in the action space if $y_{i,t,d\zeta} = 1$).[14]

It also follows that bidder i only needs to track if there is at least one auction of each bin (excluding the far distance bin) pre-announced in period t. This is informative about the auction bins the bidder can participate in during period $t+1$. Let $\boldsymbol{x}_{i,t} := (x_{i,t,n\jmath}, x_{i,t,n\ell}, x_{i,t,m\jmath}, x_{i,t,m\ell})$ track the pre-announcements of period $t+1$ auctions in period t. The state is $x_{i,t,d\zeta} = 1$ if a $d\zeta$ period $t+1$ auction is pre-announced in the period t participation stage. If a $d\zeta$ auction is not pre-announced, the state distinguishes between whether the auctioneer (i) pre-announced any auctions (i.e. $\boldsymbol{z}_{t+1}^{A} \neq \emptyset$) or (ii) did not issue pre-announcements (i.e. $\boldsymbol{z}_{t+1}^{A} = \emptyset$). In the former case $x_{i,t,d\zeta} = 0$ and in the latter case $x_{i,t,d\zeta} = -1$.[15] The distinction between the pre-announcement state being 0 or -1 is because even though no auctions in bin $d\zeta$ are announced, the amount of information they provide is different. Specifically, if the auctioneer has announced some period $t+1$ auctions and there were none of bin $d\zeta$, that yields a different probability that there is a $d\zeta$ period $t+1$ auction than the case when no period $t+1$ auctions were pre-announced. For example, suppose there are $J = 10$ auctions held every period. If the auctioneer pre-announces 9 auctions and there are none of bin $d\zeta$, then the probability of a $d\zeta$ auction being available in period $t+1$ is lower than if there were no pre-announced auctions for some exogenous reason. This specification captures the idea that pre-announcements, or the absence thereof, conveys information to the bidders.

The auction bins assumption means that bidder i can track $\boldsymbol{y}_{i,t}$, and $\boldsymbol{x}_{i,t}$ to determine what its participation choice sets are in period t and period $t+1$ in lieu of $\boldsymbol{z}_t$ and $\boldsymbol{z}_{t+1}^{A}$.

---

[13] In the application, modeling the decision as which bin to participate in mainly has bite for the $f\jmath$ and $f\ell$ auctions as there are typically multiple auctions in those bins. For the $n\jmath$, $n\ell$, $m\jmath$, and $m\ell$ bins, conditional on there being at least one auction in a bin, there is usually only one auction in that bin.

[14] See (B.2) in the appendix for an expression that defines the action space.

[15] By construction, $x_{i,t,d\zeta} = -1$ implies that $x_{i,t,d'\zeta'} = -1$ for any auction bin $d'\zeta'$.

5.1.2   The Index Assumption

While the auction bin assumption discretizes the contract characteristics, the bidders still need to track the full state space because it affects the strategic interactions. To obviate the need to track the full state space, I assume that the bidder strategies are restricted to be a function of own backlog, available auction bin, pre-announced auction bin, and a one dimensional index. The index is a function of the full state space (i.e. before the discretization) and fixed bidder characteristics that yields a real number that summarizes the strategic interactions. The index can capture the spatial aspect of competition by putting more weight on rivals/auctions that are in its vicinity and less weight on those further away. For example, bidder i is primarily bidding against its close by rivals so it will weight their backlogs higher than its further away rivals. The further away rivals indirectly affect bidder i through their competition with the rivals near bidder i.

Further assume that the index function is invariant to bidder i's own backlog $s_{i,t}$ and available auctions and pre-announcements in the near and medium distance bins. I make this additional assumption to simplify estimation because it ensures that the transition law of the index is independent to the transition laws of the other discretized states. This assumption can be relaxed if there is sufficient data to compute the transition laws while allowing for correlations among states.

Taken together, these two assumptions imply that bidder i can measure the level of competition by tracking

$$\lambda_{i,t} := \lambda\left(\boldsymbol{s}_{-i,t}, \boldsymbol{z}_{i,t}, \boldsymbol{z}_{i,t+1}^{A}; z_{0,i}, \boldsymbol{z}_{0,-i}\right),$$

where $\lambda(\cdot)$ is the index function, and $\boldsymbol{z}_{i,t}$ $\left(\boldsymbol{z}_{i,t+1}^{A}\right)$ are the available auctions (pre-announcements) in the far distance bin.

The index and auction bins assumptions mean that bidder i's strategies are restricted to depend on $s_{i,t}$, $\boldsymbol{y}_{i,t}$, $\boldsymbol{x}_{i,t}$, and $\lambda_{i,t}$. So it only has to track those variables in the state space. It follows that it views the distribution of the minimum rival bid in auction j as satisfying

$$G_{j,M_i}\left(M|\boldsymbol{s}_t, \boldsymbol{z}_t, \boldsymbol{z}_{t+1}^{A}\right) = G_{j,M_i}\left(M|s_{i,t}, \boldsymbol{y}_{i,t}, \boldsymbol{x}_{i,t}, \lambda_{i,t}\right).$$

Intuitively, this expression captures that the idea of the index. If the distribution of the minimum rival bid (i.e. the level of competition) is affected by $\boldsymbol{s}_t$, $\boldsymbol{z}_t$, and $\boldsymbol{z}_{t+1}^{A}$ through several moments of the full state space, then the bidder should be indifferent between knowing those moments (own backlog, the index value, etc.) and the underlying covariates.

Under the restriction on strategies that bidders are tracking the simplified state space, I assume that bidders are playing a Markov perfect equilibrium.[16] These restrictions, however, are not selecting an equilibrium that bidders are playing if they were tracking the full state space. This is because it is unlikely that the equilibrium where bidders strategies that use the index could be sustained in an environment in which players can track the full state space. That is to say if bidder i's rivals were playing strategies that were based on the index, then i's best reply when it can use the full state is probably different from the best reply when it is restricted to use the index. If the state space reduction is viewed as an *approximation* of the Markov perfect equilibrium that bidders are playing, then these restrictions can be thought of as selecting equilibria for which this approximation is valid.

While the index assumption restricts the strategies bidders can play, it allows for rich competitive effects as long as the index function is sufficiently flexible. The reasons for this is that the index could have a lot of variation and that the support of the index values can vary across bidders. The support of the index values can vary across bidders because of their different locations, which are incorporated into $\lambda()$. Intuitively, the index should incorporate how a bidder with many nearby rivals faces stiffer competition than one who has fewer rivals in its vicinity. I will discuss the importance of using a flexible functional form for the index when describing how it is constructed below.

5.2   The Value Functions for Estimation

Under this compact state space, the bid stage value function and the bid first order condition are similar to those derived in (4.2) and (4.3).[17] The key difference is that the state variables in those equations are replaced with $s_{i,t}$, $\boldsymbol{y}_{i,t}$, $\boldsymbol{x}_{i,t}$, and $\lambda_{i,t}$. The participation stage value function is similar to (4.5) and uses the compact state variables. This tractable participation stage value function, however, has two key differences compared to that in the theoretical model. One, the participation decision is over which auction bin to participate in. Two, there is an epsilon shock associated with each participation decision (including not participating). For tractability, I assume that the maximum epsilon shock associated with each auction bin follows a Gumbel distribution

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[16] This implicitly assumes that $\lambda_{i,t}$ follows a Markov process; $s_{i,t}$, $\boldsymbol{y}_{i,t}$, and $\boldsymbol{x}_{i,t}$ are all Markov by construction. If the index does not follow a Markov process, I assume that the bidders *perceive* the transition probabilities to be Markovian and that these perceptions are consistent with the outcomes observed in equilibrium play. This perception will mean that bidders are playing a moment-based Markov equilibrium (MME) as described in Ifrach & Weintraub (2017). This MME can be thought of as an approximation of a Markov perfect equilibrium.

[17] The equations are written out in Appendix B.1.

with location parameter 0 and scale parameter $1/\omega$. The scale parameter of the shock is estimated so that the estimates of the primitives do not depend on the units of the payoff function (i.e. it will not matter whether the flow profit is computed in dollars or in millions of dollars).

In summary, the tractability assumptions result in a model that captures the key features of the full theoretical model and that has the same estimation strategy.

5.3   The Estimation Approach

The model primitives to recover are the cost distribution, $F(\cdot)$, and the participation cost, κ, given data on participation, bids, and bidder state variables. Equations (4.3) and (4.5) suggest a multi-step estimator to recover the cost primitives. The participation decision involves choosing the action that has the highest flow profit, which is a function of the bid distributions and κ. The bid distributions can be estimated directly off the data so I can estimate κ by finding the parameter that rationalizes the observed participation data. Once κ is estimated, I can recover the participation value functions because the present discounted sum of future payoffs is a function of the bid distributions and the participation cost. Then with estimates of the bid distributions and value functions, I can find the cost distribution that rationalizes the bid data using the first order condition. This estimation strategy means that I have to complete the following steps:

1. Construct the index function $\lambda(\cdot)$.

2. Estimate $G_{j,B_i}(\cdot)$ and $G_{j,M_i}(\cdot)$ from the bid data.

3. Estimate the auction choice probabilities given the state (i.e. conditional choice probabilities, which I abbreviate as CCP's) and transition laws off the data. Call these "offline CCP's".

4. Recover κ by matching the estimated offline CCP's with model predicted CCP's.

5. Use $\hat{G}_{j,B_i}(\cdot|\cdot)$, $\hat{G}_{j,M_i}(\cdot|\cdot)$, and $\hat{V}_i^P(\cdot)$ with the bid first order condition to recover the cost distribution, $\hat{F}(\cdot)$.

This procedure can be used to estimate the cost primitives separately for each plant but this requires a large amount of data. To reduce the data burden I pool data across bidders to estimate the primitives.

When pooling data across bidders, I need to control for the observable differences between them. Recall that in the model, bidders differ by location (l_i), type (τ_i), mean backlog $(\bar{s}_i)$, and

standard deviation of backlog $(sd(s)_i)$ in addition to the time varying state variables. The first order condition makes it clear that bidders with the same state variables will have different bid functions due to their observable differences. One reason for this is the different bidder locations which means that bidders will have different probabilities of having auctions in their vicinity. For example, one bidder may be more likely to have a near large auction available in each period than another bidder. This would mean that the former bidder is less likely to respond as strongly to pre-announcements of a near large auction because the announcement doesn't convey much additional information. Another reason for this is that type and mean and standard deviation of backlog affect the cost distribution so the intertemporal links in costs are different across bidders. These differences in the bid functions imply that the value functions and participation decisions differ across bidders as well. Since these bidder characteristics are observable, I will control for this in estimation.

I assume that the cost primitives are the same for all bidders of type τ; this means I will pool data by bidder type. To account for the observable capacity differences between bidders of a given type, I assume the construction cost distribution is of the form $F_\tau(\cdot|\tilde{s}_{i,t}, d\zeta)$, where $\tilde{s} = \frac{s_{i,t} - \bar{s}_i}{sd(s)_i}$ is the normalized backlog. Note that the auction bins assumption means that the cost distribution depends on $d\zeta$ (i.e. the distance and size affect the costs in a discrete manner). To simplify the estimation of the cost distribution, I assume that the cost draw is proportional to the engineer's estimate (i.e. the cost is of the form $c_{i,j,t} = h_{i,j,t}\zeta_{j,t}$ where $h_{i,j,t}$ is a draw from a distribution). This implies that the bids are also proportional to the engineer's estimate, which simplifies the estimation of the bid distributions.

For the remainder of the section, I will provide a high-level overview of the estimation steps. The details can be found in Appendix B.

5.3.1   Constructing the Index Function

I build the index function by predicting the minimum rival bid as a fraction of the engineer's estimate that a bidder faces for auctions within 50km of its location (this encompasses the near and medium distance bins) using the random forest estimator described in Aradillas-Lopez et al. (2020). This variant of the standard random forest has the feature that it is less likely to overfit when the forest is trained on the same sample for which it will be used for prediction. The minimum rival bid is scaled by the engineer's estimate of the project since the size is a common component of the cost for all bidders in the auction under the specification of the cost distribution. The reason I

focus on the near and medium distance bins is that this is where the bidder primarily participates, which is where I want to get a good approximation of the level of competition that the bidder is likely to face. In the full state space, competition between bidders is driven by weighting certain rivals more heavily and through complex interactions between the state variables. The random forest can capture these effects because it is a very flexible estimator that can incorporate complex interactions between covariates. This means that the one dimensional index should be able to capture much of the richness in strategic interactions that would be present when tracking the full state space.

While I could include all the auction characteristics, pre-announcements, and rival states as separate covariates in the random forest, in practice this is computationally burdensome. To lessen the computational burden but still capture the richness of the state space, I insert moments of the states based on their distance from the bidder. For example, I include the number of rivals by type within 0-25km of the bidder, the average normalized backlog of rivals by type within 50-75km of the bidder, and the number of large pre-announced auctions within 75-100km of the bidder. I will present the full set of moments I use when reporting the estimates.

A drawback of using the random forest estimator is that it is unclear how this affects the standard errors of the estimates of the cost primitives. I plan to compute standard errors by bootstrapping the estimation procedure but it is still an open question as to whether this approach is valid when a random forest is involved.

5.3.2 Estimating the Bid Distributions

The bid distribution is specified to follow a three parameter Weibull distribution as utilized by JP and Athey et al. (2011). Since the bidders' costs have the engineer's estimate as a common, multiplicative component, I work with normalized bids, $\tilde{b}_{i,j,t} := \frac{b_{i,j,t}}{\zeta_{j,t}}$. The Weibull distribution has the parameters ξ, k_τ, and $\psi_\tau(\cdot)$, which represent the support, shape, and scale parameters, respectively. The support parameter is common for all bidders and the shape parameter is type specific. The scale is parameterized as $\ln \psi_\tau(W) = W\gamma$ where W represents the state variables and γ is how the states affect the parameter. While the dynamic model assumes that time doesn't matter after conditioning on the state, time fixed effects are included in W as well to get precise estimates; the time fixed effects are zeroed out when incorporating the bid distribution into the dynamic model.

The distribution of the minimum rival bid is specified similarly. The key difference is that the

shape parameter is restricted to be at least 1 to ensure that bids are increasing in costs.

Both the bid and minimum rival bid distributions are estimated via a two step estimator as in JP. In the first step, I estimate the support parameter by taking the minimum bid as a fraction of the engineer's estimate. In the second step, I use maximum likelihood to estimate the shape and scale parameters.

5.3.3 Estimating Transition Probabilities and CCP's

The transition probabilities that need to be estimated are $\Pr(S_{i,t+1}|s_{i,t}, i \text{ doesn't bid})$, $\Pr(Y_{i,t+1,d\zeta}|x_{i,t,d\zeta})$, $\Pr(\lambda_{i,t+1}|\lambda_{i,t}, i \text{ doesn't bid})$, and $\Pr(\lambda_{i,t+1}|\lambda_{i,t}, i \text{ won auction bin } d\zeta)$.

To estimate the backlog transition, $\Pr(S_{i,t+1}|s_{i,t}, i \text{ doesn't bid})$, I assume that backlog $s_{i,t}$ either stays the same or 1 discrete amount gets worked off. Since I observe the backlog independent of whether a plant won a project or not, I can estimate the probability that the backlog falls by one notch. This estimate also gives the the transition law of backlog when i wins an auction because that has a deterministic effect on backlog.

The transition probabilities $\Pr(Y_{i,t+1,d\zeta}|x_{i,t,d\zeta})$ are estimated separately for each bidder using a frequency estimator. The assumption that all auction characteristics are independent draws from $F_Z(\cdot)$ implies that I can estimate the probabilities separately for each auction bin.

To estimate the index transition laws, I discretize the index into two values: high and low. The high and low index value are allowed to differ across bidders. Then I assume that the transition law between the high and low index values is the same across all bidders of a type and estimate the transition probabilities using a logit regression. I rely on this structure for the transition law because I do not have sufficient data to compute this separately for each bidder. Specifically, many bidders have only won a $d\zeta$ auction a handful of times so a per bidder frequency estimate of the conditional probability will be noisy.

The participation CCP's are estimated using a multinomial/conditional logit model. I use a parametric model because given the richness of the state space, the data requirement for a nonparametric estimator is impractical. The specification includes year and month fixed effects; these are zeroed out when I incorporate these offline CCP's into the model.

5.3.4 Estimating the Participation Cost

To recover the participation cost, κ, I use the least squares estimator of Pesendorfer & Schmidt-Dengler (2008), which utilizes the insight that in equilibrium, the CCP's 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. Since the flow revenue of an action is known through the offline estimates of the bid distribution and minimum rival bid distribution, I only need to search over κ.

Let $\Pi_i(a, s_{i,t}, \boldsymbol{y}_{i,t}, \boldsymbol{x}_{i,t}, \lambda_{i,t}; \kappa)$ be the flow profit of bidder i who takes action a given their state variables when the participation cost is κ. The i subscript encapsulates how the flow revenue depends on bidder i's fixed characteristics. Since the participation decision is static, the Gumbel distributional assumption implies the model states that the probability i takes action a in a given state is

$$p_i(a, s_{i,t}, \boldsymbol{y}_{i,t}, \boldsymbol{x}_{i,t}, \lambda_{i,t}; \kappa) = \frac{\exp\left[\omega\Pi_i(a, s_{i,t}, \boldsymbol{y}_{i,t}, \boldsymbol{x}_{i,t}, \lambda_{i,t}; \kappa)\right]}{\displaystyle\sum_{a' \in \mathcal{A}(\boldsymbol{y}_{i,t})} \exp\left[\omega\Pi_i(a', s_{i,t}, \boldsymbol{y}_{i,t}, \boldsymbol{x}_{i,t}, \lambda_{i,t}; \kappa)\right]}. \tag{5.1}$$

Let $\hat{\boldsymbol{q}}_i(a')$ be the stacked $N \times 1$ vector of the offline estimated probability of action a' (computed earlier) for all N states and $\boldsymbol{p}_i(a'; \kappa)$ be the associated model predicted probability given κ. Then estimating κ is a matter of minimizing the objective function:

$$\hat{\kappa} = \arg\min_\kappa \sum_{a' \neq 0} [\boldsymbol{p}_i(a'; \kappa) - \hat{\boldsymbol{q}}_i(a')]' \boldsymbol{W}_{a'} [\boldsymbol{p}_i(a'; \kappa) - \hat{\boldsymbol{q}}_i(a')], \tag{5.2}$$

where $\boldsymbol{W}_{a'}$ is a positive definite weight matrix.[18] 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. In estimation I use a diagonal weight matrix where all states have equal weight; each action in a state is weighted according to the number of auction choice bins available.

Static participation means that estimating κ is very fast compared to typical dynamic models because computing $\boldsymbol{p}_i(a'; \kappa)$ is simple. Moreover, once I have $\hat{\kappa}$, the participation value function can be computed in one step (see appendix).

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

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[18] I search over ω, the inverse of the Gumbel distribution scale parameter, alongside κ. I excluded ω from the notation to keep the expressions compact.

participation cost).[19]

5.3.5 Estimating the Cost Distribution

To infer the distribution of construction costs, I leverage the monotonicity of bids in costs. This implies that the probability the bid is less than b is equal to the probability the construction cost is less than $\beta_{i,j,t}^{-1}(b)$, the cost associated with the bid. This means I can recover the cost distribution that rationalizes the observed bid distribution and the bid first order condition. The first order condition can be used to map the bids to a cost because it depends on the minimum rival bid distribution and participation value functions that were estimated in previous steps.

6 Structural Estimates

This section discusses the estimates of the dynamic auction model for the non-VI and VI plants. The estimates assume that the monthly discount rate for all bidders is $\delta = 0.99$, which corresponds to an annual discount rate of approximately 0.9. I begin by reporting the offline estimates of the index function, the bid distributions, and the CCP's. Next I present the participation costs and the value functions. Then I discuss the estimates of the construction cost distribution. I finish the section by reporting comparative statics that demonstrate the effect of pre-announcements on participation and bidding.

6.1 The Offline Estimates

The index function is constructed with a random forest that consists of 2,400 trees and the covariates include the normalized backlog of rivals, the number of rivals, the number of available auctions, and the number of pre-announcements. The predicted index values for the plants typically fall between 0.91 and 0.97 which is consistent with the minimum rival bids as a fraction of the engineer's estimate observed in the data. The interpretation of the index is that higher values correspond to more constrained rivals (i.e. weaker competition). When building the index, I assume that the level of competition a plant faces is not affected by rivals/auctions that are more than 100km away (i.e. the indirect effects of distant rivals/actions have tapered off to zero). This means that the random

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[19] I could also estimate the bid distribution and minimum rival bid distribution parameters from the participation data using the least squares estimator and appeal to the proposition for identification. This approach, however, is slower because the expected auction revenue would have computed for each guess of the parameters and integration is computationally expensive.

Variable Importance Plot of λ(.)
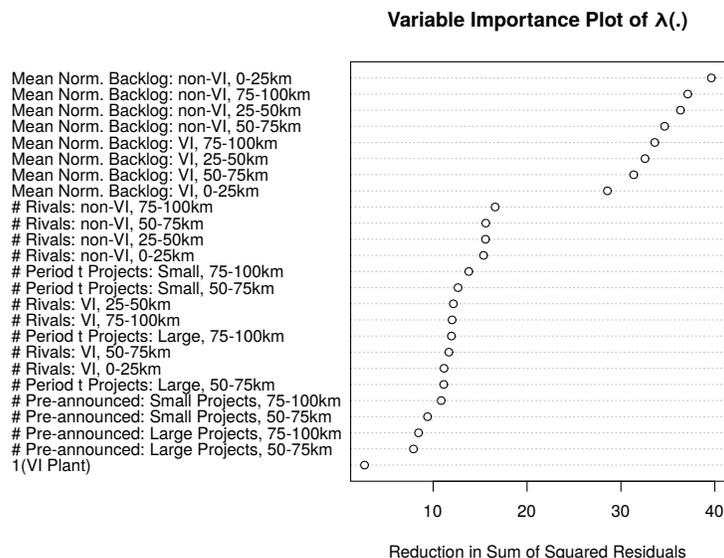
Figure 2: This plot shows the variable importance plot of the index function. Importance is measured as the total decrease in node impurities as measured by the residual sum of squares from splitting on the variable. Values further to the right correspond to variables that are more important in the sense they helped the random forest fit the data better.

forest covariates do not include any information about the state space that refer to rivals/auctions that are located more than 100km away from the plant.

The full set of covariates included in the random forest is reported in the variable importance plot shown in Figure 2. Variable importance is measured by computing the total reduction in the sum of squared residuals that is due to splitting on that variable. This importance measure does not correspond to marginal effects; it is a measurement how useful a variable is in improving predictive power. The plot shows that the normalized backlog of rivals by type are by far the strongest predictors of the level of competition. Non-VI plants appear to affect the level of competition by more than VI plants; this is likely driven by the fact that most bidders in an auction are non-VI plants. Pre-announcements have a relatively modest impact on the index and is similar in magnitude to the number of available actions and number of rivals. A bidder's own plant type has the lowest importance. This is driven by the fact that while a bidder's rivals take into account the type of plant they are facing, there are many players competing so a single bidder type will have a small effect on the overall level of competition. The importance plot also shows that distance matters when evaluating the level of competition.

The estimates of the parameters of the bid distribution $G_{\tau,\tilde{B}}(\cdot)$ are reported in Table 8. The distributions were estimated separately for non-VI and VI plants and are assumed to have the

Table 8: $G_{\tau,\tilde{B}}$ Estimates

	Non-VI	VI
Shape: $\ln(k)$	0.892*** (0.006)	0.837*** (0.010)
Constant	-1.619*** (0.143)	-2.395*** (0.360)
$\tilde{s}_{i,t}$ [norm. backlog]	0.027*** (0.005)	0.034*** (0.008)
$sd(s)_i$ [backlog std. dev.]	-0.041*** (0.005)	-0.035*** (0.007)
$\mathbf{1}(a = n\jmath)$ [bid on a near small auction]	-2.079*** (0.199)	-1.457*** (0.406)
$\mathbf{1}(a = n\ell)$ [bid on a near large auction]	-2.106*** (0.228)	-0.967** (0.426)
$\mathbf{1}(a = m\jmath)$ [bid on a medium small auction]	-2.060*** (0.199)	-1.673*** (0.427)
$\mathbf{1}(a = m\ell)$ [bid on a medium large auction]	-2.046*** (0.243)	-1.139** (0.476)
$\mathbf{1}(a = f\jmath)$ [bid on a far small auction]	-0.047 (0.187)	1.094*** (0.423)
$y_{i,t,n\jmath}$ [near small auction available in period t]	0.004 (0.009)	-0.010 (0.016)
$y_{i,t,n\ell}$ [near large auction available in period t]	-0.004 (0.009)	0.047*** (0.017)
$y_{i,t,m\jmath}$ [medium small auction available in period t]	-0.004 (0.009)	0.066*** (0.015)
$y_{i,t,m\ell}$ [medium large auction available in period t]	0.0002 (0.008)	0.011 (0.015)
$\mathbf{1}(\boldsymbol{x}_{i,t} \neq -1)$ [one if any pre-announcements (aka pre-a.)]	-0.002 (0.012)	0.021 (0.020)
$\Pr(Y_{i,t+1,n\jmath} = 1|x_{i,t,n\jmath}) + \delta\Pr(X_{i,t+1,n\jmath} = 1)$ [near small pre-a.]	0.026** (0.011)	0.019 (0.019)
$\Pr(Y_{i,t+1,n\ell} = 1|x_{i,t,n\ell}) + \delta\Pr(X_{i,t+1,n\ell} = 1)$ [near large pre-a.]	0.029*** (0.011)	0.079*** (0.020)
$\Pr(Y_{i,t+1,m\jmath} = 1|x_{i,t,m\jmath}) + \delta\Pr(X_{i,t+1,m\jmath} = 1)$ [medium small pre-a.]	0.028*** (0.011)	0.016 (0.020)
$\Pr(Y_{i,t+1,m\ell} = 1|x_{i,t,m\ell}) + \delta\Pr(X_{i,t+1,m\ell} = 1)$ [medium large pre-a.]	0.028*** (0.011)	0.010 (0.020)
$\lambda_{i,t}$ [index value]	0.685*** (0.151)	1.272*** (0.370)
$\mathbf{1}(a = n\jmath) \times \lambda_{i,t}$	2.135*** (0.212)	1.425*** (0.420)
$\mathbf{1}(a = n\ell) \times \lambda_{i,t}$	2.090*** (0.244)	0.770* (0.441)
$\mathbf{1}(a = m\jmath) \times \lambda_{i,t}$	2.207*** (0.212)	1.638*** (0.444)
$\mathbf{1}(a = m\ell) \times \lambda_{i,t}$	2.099*** (0.261)	1.045** (0.494)
$\mathbf{1}(a = f\jmath) \times \lambda_{i,t}$	0.146 (0.200)	-0.951** (0.436)
Log Likelihood	7,702.183	2,851.793
Observations	13,219	4,920

*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). The support parameter was estimated to be 0.7001. The shape and scale parameters were estimated via maximum likelihood. The estimates in the table refer to the scale parameter estimates unless otherwise stated. Descriptions of the covariates are in brackets.

• The scale parameter is parameterized as $\ln(\psi) = W\gamma$. Includes year and month fixed effects (not reported). The table reports $\hat{\gamma}$.

• A near (n) auction is defined to be one that is within 25km of the plant. A medium (m) distance auction is defined to be one that is between 25km and 50km from the plant. A far (f) auction is defined to be one that more than 50km away from the plant. A small ($\jmath$) auction is one with an engineer's estimate below \$750K otherwise it is a large (ℓ) auction.

same support parameter. When estimating the bid distributions, I exclude auctions where there were bids were more than 30% below the engineer's estimate; this occurred in approximately 2% of the auctions. I believe that these auctions represent contracts for which MDOT made errors when computing the engineer's estimate, which is why multiple bidders submitted relatively low bids. Since I am using the engineer's estimate as a normalization factor that allows me to pool auctions with different sizes, I do not want to use bids from auctions where the scaling factor is likely to be incorrect. The support parameter of the normalized bid distribution is estimated to be 0.7001, which is the minimum bid as a fraction of the engineer's estimate after excluding the outlier auctions.[20] The scale parameter depends on bidder characteristics, contract characteristics, pre-announcements, and the competition index. The estimates of the scale parameter covariates

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[20] Including the outliers increases the expected auction revenue each period. This will result in larger estimates of κ as the model will rationalize relatively low participation rates with a higher participation cost.

are similar to what was observed in the reduced-form estimates. I find that the mean of the bid distribution is increasing in distance and in normalized backlog (as a reminder, the mean of a Weibull distribution is increasing in the scale parameter). The covariates also include the standard deviation of the plant's backlog. This sign is negative as expected because conditional on normalized backlog, a plant with a larger standard deviation of backlog is stronger (bids more aggressively) because it will be less constrained by winning a project than one with a smaller standard deviation. The pre-announcements result in higher bids which is consistent with the reduced form regression results. The non-VI plants respond to both near and medium distance bin auctions being pre-announced; VI plants have a particularly responsive to the pre-announcement of a near large auction. The competition index has the expected sign as well and shows that if rivals are constrained, plants will bid less aggressively. When accounting for the interactions with auction bins, notice that the effect of the index is larger for auctions in the near and medium distance bins; this is because the index is built to capture the level of competition in these bins.

The minimum rival bid distribution estimates are reported in Table 9. The minimum rival bid is observed for all bidders regardless of whether they participated in an auction or not, so the distribution is estimated on more observations than $G_{\tau,\tilde{B}}()$. The estimated support parameter is the same as that of the bid distribution. The restriction that the shape parameter be at least one, so the equilibrium bid function is monotonic, was not binding. The scale parameter estimates suggest that the level of competition does vary across auction bins. Since the index was constructed by fitting the minimum rival bid for the near and medium distance bins, it is no surprise that it has good predictive power for the auctions in those distance bins. The index is also informative about $\tilde{M}$ in the far bin, though its effect is smaller. The index appears to capture most of the strategic effects because the bidder's own backlog has a minor effect. Pre-announcements (excluding those included in the index) have a small, but heterogeneous effect on the distribution. This suggests that while pre-announcements can have a significant impact on individual bidders, the aggregate effect is small. This is also driven by the fact that the pre-announcements included in the scale parameter are from bidder i's perspective and the other bidders will respond differently to these because of their different locations.

The multinomial/conditional logit estimates of the participation conditional choice probabilities are reported in Table 10. These results are quite similar to the reduced form patterns: bidders prefer to participate in auctions for closer projects and are less likely to participate when constrained. The pre-announcements of near and medium distance bin auctions of both sizes reduces the probability

Table 9: $G_{\tau,\tilde{M}}$ Estimates

	Non-VI	VI
Shape: ln(k - 1)	0.211*** (0.001)	0.197*** (0.001)
Constant	−1.667*** (0.013)	−1.610*** (0.025)
$\tilde{s}_{i,t}$ [norm. backlog]	−0.0002 (0.001)	−0.003** (0.001)
$\mathbf{1}(d\zeta = n\jmath)$ [auction is near small]	−3.477*** (0.061)	−3.682*** (0.124)
$\mathbf{1}(d\zeta = n\ell)$ [auction is near large]	−3.331*** (0.074)	−2.830*** (0.134)
$\mathbf{1}(d\zeta = m\jmath)$ [auction is medium small]	−3.396*** (0.046)	−3.386*** (0.097)
$\mathbf{1}(d\zeta = m\ell)$ [auction is medium large]	−3.064*** (0.054)	−2.814*** (0.103)
$\mathbf{1}(d\zeta = f\jmath)$ [auction is far small]	0.028* (0.016)	0.010 (0.031)
$y_{i,t,n\jmath}$ [near small auction available in period t]	−0.006*** (0.001)	−0.006*** (0.002)
$y_{i,t,n\ell}$ [near large auction available in period t]	−0.003*** (0.001)	−0.007*** (0.002)
$y_{i,t,m\jmath}$ [medium small auction available in period t]	0.002* (0.001)	0.002 (0.002)
$y_{i,t,m\ell}$ [medium large auction available in period t]	−0.0003 (0.001)	−0.011*** (0.002)
$\mathbf{1}(\boldsymbol{x}_{i,t} \neq -1)$ [one if any pre-announcements]	−0.002 (0.001)	0.004 (0.003)
$\mathbf{1}(x_{i,t,n\jmath} = 1)$ [near small pre-announcement]	−0.008*** (0.001)	−0.006** (0.002)
$\mathbf{1}(x_{i,t,n\ell} = 1)$ [near large pre-announcement]	0.005*** (0.001)	0.005** (0.002)
$\mathbf{1}(x_{i,t,m\jmath} = 1)$ [medium small pre-announcement]	−0.005*** (0.001)	−0.005** (0.002)
$\mathbf{1}(x_{i,t,m\ell} = 1)$ [medium large pre-announcement]	0.006*** (0.001)	0.003 (0.002)
$\lambda_{i,t}$ [index value]	0.224*** (0.013)	0.167*** (0.026)
$\mathbf{1}(d\zeta = n\jmath) \times \lambda_{i,t}$	3.719*** (0.065)	3.947*** (0.130)
$\mathbf{1}(d\zeta = n\ell) \times \lambda_{i,t}$	3.517*** (0.079)	2.990*** (0.140)
$\mathbf{1}(d\zeta = m\jmath) \times \lambda_{i,t}$	3.631*** (0.049)	3.623*** (0.101)
$\mathbf{1}(d\zeta = m\ell) \times \lambda_{i,t}$	3.230*** (0.058)	2.992*** (0.107)
$\mathbf{1}(d\zeta = f\jmath) \times \lambda_{i,t}$	0.031* (0.017)	0.055* (0.032)
$\tilde{s}_{i,t} \times \mathbf{1}(d = n)$	−0.006 (0.005)	0.005 (0.007)
$\tilde{s}_{i,t} \times \mathbf{1}(d = m)$	0.004 (0.003)	0.007 (0.005)
Log Likelihood	846,999.7	219,068.5
Observations	1,044,167	276,062

*p<0.1; **p<0.05; ***p<0.01.
- Reports the three parameter Weibull distribution estimates of the normalized min rival bid distribution (i.e. $\frac{M}{\zeta}$ where ζ is the engineer's estimate). The support parameter was estimated to be 0.7001. The shape and scale parameters were estimated via maximum likelihood. The estimates in the table refer to the scale parameter estimates unless otherwise stated. Descriptions of the covariates are in brackets.
- The scale parameter is parameterized as $\ln(\psi) = W\gamma$. Includes year and month fixed effects (not reported). The table reports $\hat{\gamma}$.
- A near (n) auction is defined to be one that is within 25km of the plant. A medium (m) distance auction is defined to be one that is between 25km and 50km from the plant. A far (f) auction is defined to be one that more than 50km away from the plant. A small ($\jmath$) auction is one with an engineer's estimate below \$750K otherwise it is a large (ℓ) auction.
- Pooled all observations of the min rival bids given plant type regardless of whether the plant submitted a bid.

of participating. For non-VI plants, the effect of pre-announcements is similar across auction bins. For VI plants, pre-announcements of medium large ($m\ell$) projects has the sharpest impact on participation. While the competition index has the expected sign for VI plants, it does not for the non-VI plants. That non-VI plants are less likely to participate when their rivals are constrained suggests that there are factors that impact this decision that are not being modeled. A possible explanation for this is that when the non-VI plant's rivals are constrained, there are shortages of workers or paving equipment which means the plant does not participate because it cannot complete the job; this is less likely to be an issue for VI plants who are larger.

There are two differences in the multinomial/conditional logit estimates relative to the $G_{\tau,\tilde{B}}(\cdot)$ estimates that merit discussion. First, for VI plants, participation is strongly impacted by pre-

Table 10: Multinomial/Conditional Logit Estimates for Conditional Choice Probabilities

	Non-VI	VI
$\mathbf{1}(a = n\jmath)$ [Bid in a near small auction]	-0.372 (0.479)	-2.812^{***} (0.786)
$\mathbf{1}(a = n\jmath) \times \lambda_{i,t}$ [Bid in a near small auction $\times$ the index]	-1.240^{**} (0.502)	3.329^{***} (0.814)
$\mathbf{1}(a = n\ell)$ [Bid in a near large auction]	0.317 (0.583)	-4.530^{***} (0.871)
$\mathbf{1}(a = n\ell) \times \lambda_{i,t}$	-2.055^{***} (0.621)	5.123^{***} (0.903)
$\mathbf{1}(a = m\jmath)$ [Bid in a medium small auction]	-0.484 (0.489)	-1.681^{**} (0.852)
$\mathbf{1}(a = m\jmath) \times \lambda_{i,t}$	-1.645^{***} (0.516)	1.213 (0.889)
$\mathbf{1}(a = m\ell)$ [Bid in a medium large auction]	0.476 (0.638)	-4.172^{***} (1.050)
$\mathbf{1}(a = m\ell) \times \lambda_{i,t}$	-2.963^{***} (0.681)	3.480^{***} (1.092)
$\mathbf{1}(a = f\jmath)$ [Bid in a far small auction]	-0.082 (0.476)	-4.436^{***} (0.994)
$\mathbf{1}(a = f\jmath) \times \lambda_{i,t}$	-2.653^{***} (0.500)	2.534^{**} (1.034)
$\mathbf{1}(a = f\ell)$ [Bid in a far large auction]	-0.830 (0.522)	-6.597^{***} (1.209)
$\mathbf{1}(a = f\ell) \times \lambda_{i,t}$	-2.109^{***} (0.549)	4.258^{***} (1.253)
$\tilde{s}_{i,t}$ [norm. backlog]	-0.170^{***} (0.022)	-0.096^{***} (0.037)
$sd(s)_i$ [backlog std. dev.]	1.330^{***} (0.037)	1.025^{***} (0.051)
$y_{i,t,n\jmath}$ [near small auction available in period t]	0.052 (0.035)	-0.144^{**} (0.071)
$y_{i,t,n\ell}$ [near large auction available in period t]	-0.054 (0.038)	-0.222^{***} (0.076)
$y_{i,t,m\jmath}$ [medium small auction available in period t]	0.037 (0.035)	-0.050 (0.068)
$y_{i,t,m\ell}$ [medium large auction available in period t]	0.011 (0.034)	-0.011 (0.069)
$\Pr(Y_{i,t+1,n\jmath} = 1 \mid x_{i,t,n\jmath}) + \delta\Pr(X_{i,t+1,n\jmath} = 1)$ [near small pre-a.]	-0.102^{**} (0.046)	0.044 (0.089)
$\Pr(Y_{i,t+1,n\ell} = 1 \mid x_{i,t,n\ell}) + \delta\Pr(X_{i,t+1,n\ell} = 1)$ [near large pre-a.]	-0.174^{***} (0.046)	-0.174^{*} (0.090)
$\Pr(Y_{i,t+1,m\jmath} = 1 \mid x_{i,t,m\jmath}) + \delta\Pr(X_{i,t+1,m\jmath} = 1)$ [medium small pre-a.]	-0.173^{***} (0.045)	-0.250^{***} (0.088)
$\Pr(Y_{i,t+1,m\ell} = 1 \mid x_{i,t,m\ell}) + \delta\Pr(X_{i,t+1,m\ell} = 1)$ [medium large pre-a.]	-0.166^{***} (0.044)	-0.587^{***} (0.087)
Log Likelihood	-22,657.455	-6,428.014
Observations	23,620	6,011

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

• Reports multinomial/conditional logit estimates probability of bidding in an auction. The outside option of not participating is normalized to have 0 utility. Includes year and month fixed effects (not reported).

• A near (n) auction is defined to be one that is within 25km of the plant. A medium (m) distance auction is defined to be one that is between 25km and 50km from the plant. A far (f) auction is defined to be one that more than 50km away from the plant. A small ($\jmath$) auction is one with an engineer's estimate below \$750K otherwise it is a large (ℓ) auction.

announcements of medium large auctions but bids are most responsive to pre-announcements of near large auctions. Second, for non-VI plants, the participation probability is decreasing in the index but their bids are increasing in the index. These differences will primarily affect the estimates of κ, which is estimated by matching offline CCP's with model predicted CCP's (the latter of which depend on $\hat{G}_{\tau,\tilde{B}}(\cdot)$, $\hat{G}_{\tau,\tilde{M}}(\cdot)$, and a guess of κ). The effect on the estimated cost distribution $\hat{F}(\cdot)$ will be minor as this is primarily identified using $\hat{G}_{\tau,\tilde{B}}(\cdot)$ and $\hat{G}_{\tau,\tilde{M}}(\cdot)$; κ will affect this cost distribution through its impact on the value function that enters the bid first order condition used to trace out the cost distribution.

6.2   The Estimates of κ and the Value Functions

I estimate a separate participation cost κ for small projects and large projects. The costs are recovered by minimizing the distance between model predicted CCP's and offline estimated CCP's on the discretized state space. The state variables are: own backlog ($s_{i,t}$), available auction bins

Table 11: κ Estimates

Variable	Non-VI	VI
Small Project κ (Fraction of EngEst)	0.110	0.120
Large Project κ (Fraction of EngEst)	0.080	0.110
Epsilon Scale Parameter	0.016	0.023
Least Squares Estimator Objective	24.025	100.692

 Reports the estimates of the participation costs κ. Parameters are using a dynamic least squares estimator that minimizes the difference between the model predicted CCP's and the offline estimates of CCP's. Matched the CCP's for the participation decisions in 11,424 states across the non-VI and VI plants.
• A small (large) project has an engineer's estimate of \$0.5MM (\$1.0MM).
• "Epsilon Scale Parameter" is the scale parameter of the Gumbel distribution with location parameter 0.
• The reported least squares estimator objective is averaged across the bidders used to estimate κ.

$(\boldsymbol{y}_{i,t})$, pre-announced auction bins $(\boldsymbol{x}_{i,t})$, and the competition index $(\lambda_{i,t})$. The available auctions and pre-announcements are already discrete variables so it remains to discretize own backlog and the index. The backlog goes from zero to \$5 million in increments of \$250 thousand and the competition index is discretized into two levels, high (constrained rivals) and low (unconstrained rivals). Note that the index values that correspond to high and low index levels vary across bidders. This results in 11,424 different states.[21]

I report the participation cost estimates in Table 11. The objective function for the estimates of κ are reported and show that comparatively, the model was not as successful as fitting the participation decision for the VI plants relative to the non-VI plants; this is due to differences in the offline CCP estimates relative to the offline $\hat{G}_{\tau,\tilde{B}}$ estimates. These estimates of the participation costs are relatively high: 11-12% (8-11%) of the engineer's estimate for small (large) projects. This corresponds to participation costs on the order of \$55-60K (\$80-110K) for small (large) projects. In discussions with civil engineers, I was told that the bid preparation costs for HMA projects are on the order of five to ten thousands dollars with the exact amount depending on the complexity of the project. One reason my estimates are orders of magnitude larger is that κ includes the expected flow payoff of not participating, which inflates the estimates. While these estimates are high, they are similar to the participation costs estimated in the literature.[22] I also estimated the scale parameter of the epsilon shock that bidders receive for each available choice given the state. The scale parameter estimates are relatively small and correspond to a mean shock of \$10-15K; this suggests the model is not relying too heavily on the epsilons to rationalize the participation

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[21] The number of each state variable is as follows: There are 21 backlog states; $2^4 = 16$ available auction states; $2^4 + 1 = 17$ pre-announcement states (the additional state is when no pre-announcements occurred so $\boldsymbol{x}_{i,t} = -1$); 2 index states.

[22] Examples from the literature on the analysis of highway procurement auctions include Li & Zheng (2009), which estimated entry costs to be 8% of the winning bid, and Groeger (2014), which estimated entry costs to be 7-15% of the engineer's estimate.
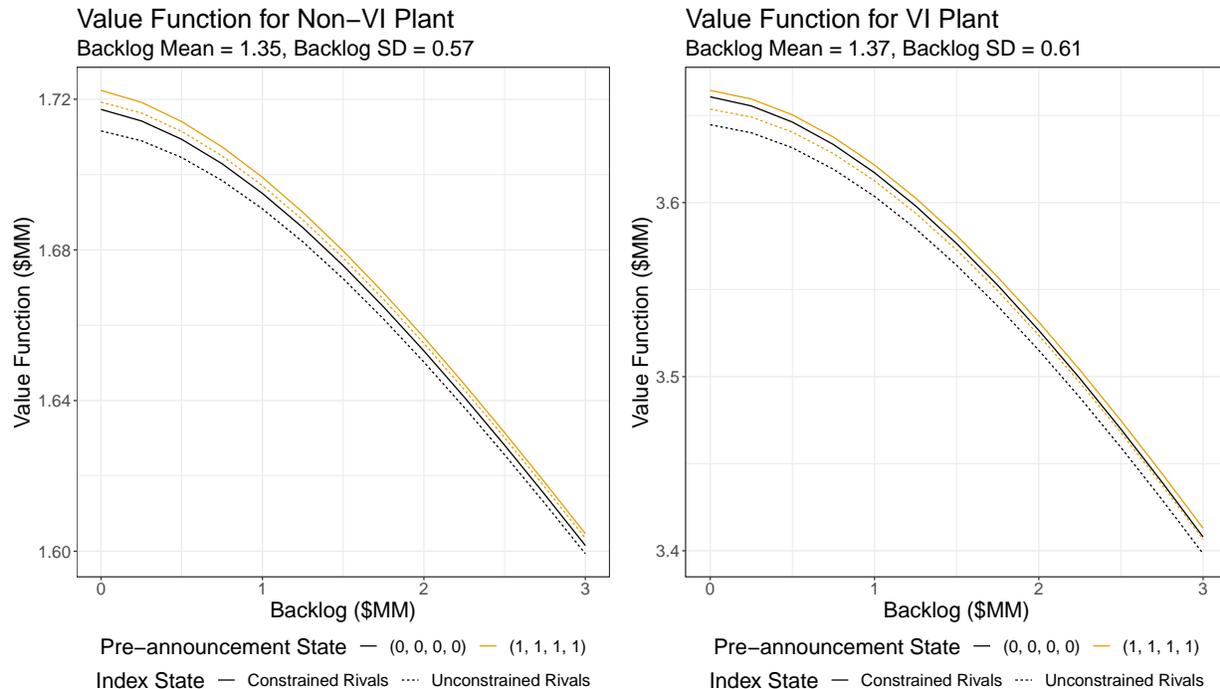
Figure 3: These figures show the value functions when near small, near large, medium small, and medium large auctions are available to bid on in period t (i.e. $\boldsymbol{y}_{i,t} = 1$). A pre-announcement state refers to $\boldsymbol{x}_{i,t}$ as defined in the text. $\boldsymbol{x}_{i,t} = 1$ ($\boldsymbol{x}_{i,t} = 0$) means the government issued pre-announcements which (did not) included auctions in the near small, near large, medium small, and medium large bins.

decisions.

With the estimates of the participation costs in hand, I can recover the participation value functions. The value functions are different for each plant because of their differences in type, location, mean backlog, and standard deviation of backlog. I present the value function estimates for one non-VI plant and one VI plant; the two plants have similar means and standard deviations of backlog that are approximately \$1.36MM and \$0.59MM, respectively. Figure 3 depicts the value functions when the bidder has near and medium distance auctions of both sizes available to bid on in period t. The VI plant has a larger participation value function which is consistent with them being stronger bidders. The value functions are decreasing in backlog as expected. Going from a backlog of 0 (norm backlog ≈ -2) to \$2.5MM (norm backlog ≈ 2) reduces the value function by \$91K for the non-VI plant and by \$189K for the VI plant. The level of competition, as captured by the index, affects the value function as well. When the bidder's rivals are constrained (high index value), its participation value functions are higher because the expected profit from participating in an auction is higher; the effect is on the order of \$1K to \$16K. Pre-announcements have a modest impact on the value function. The plots show two cases: when pre-announcements occur

but there are none in the near and medium distance bins ($\boldsymbol{x}_{i,t} = 0$), and when near and medium distance bin auctions of both sizes are pre-announced ($\boldsymbol{x}_{i,t} = 1$). When a full pre-announcement state occurs ($\boldsymbol{x}_{i,t} = 1$), the value function increases because it is good news about near and medium distance auction availability in the following period. In the plots shown, the increase in the value function varies from \$2K to \$9K. Though not shown in the plots, the value function is higher when the government did not issue pre-announcements ($\boldsymbol{x}_{i,t} = -1$) than when they did issue pre-announcements but there are none in bidder i's vicinity ($\boldsymbol{x}_{i,t} = 0$). This is because observing pre-announcements and learning that none of them were for close by auctions is relatively bad news about their appearance in period $t + 1$ compared to the case where there was no information disclosure for an exogenous reason.

It should be noted that the impact of the index and pre-announcements depends on the available auction state. The index has a smaller impact when the there are no available auctions in the near and medium distance bins ($\boldsymbol{y}_{i,t} = 0$): the gain from having constrained rivals is smaller when there are no preferred auctions in which to bid. In contrast, the pre-announcements have a larger effect when $\boldsymbol{y}_{i,t} = 0$: it is beneficial to learn that the following period will have auctions in the near and medium distance bins when the current period does not have close by auctions available to bid on.

6.3   The Estimates of Construction Costs

The cost distributions for non-VI and VI plants for large projects are depicted in Figure 4. When estimating the cost distribution, there were instances where the cost associated with a bid were negative; this typically occurred for bids at the lower end of their support. Since negative costs are implausible, I set the cost to zero whenever the inferred cost would be negative. The plots illustrate that the VI plants' cost distribution stochastically dominates in the first order sense that of the non-VI plants. For example, a VI plant's median cost for a near large project (\$634K) when its normalized backlog is zero is approximately 22% lower than a non-VI plant's median cost (\$817K) for the same project bin. The figures show that costs are increasing in distance (panel (a)) and backlog (panel (b)). The shift in cost for when going from near to far is sharper for VI plants than non-VI plants. This is likely due to the increased transportation costs of moving the HMA for VI plants since non-VI plants will likely purchase the HMA from a supplier that is closer to the project. While the VI plant's cost are increasing in backlog, the effects are relatively small in comparison to non-VI plants. A possible explanation for this is that VI plants have existing relationships with other contractors that arise from HMA sales that makes it easier to hire additional workers and

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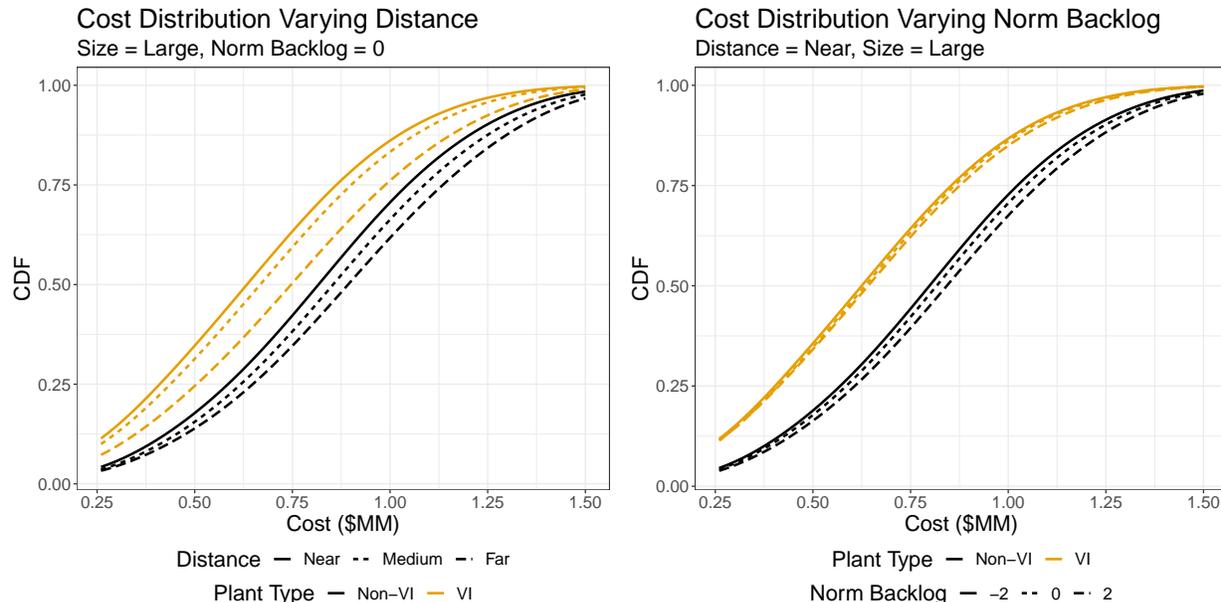
Figure 4: These figures show the estimated distribution of the cost of completing a large ($1.0MM) contract. Panel (a) shows how the cost varies with distance when the bidder's normalized backlog is 0. Panel (b) shows how the cost varies with normalized backlog when looking at a near ($\leq$ 25km) auction.

equipment they need when they are constrained.[23] Finally, the figures show that there is still considerable variation in the distributions even after controlling for distance and backlog.

6.4   The Effect of Pre-announcements on Strategies

To measure the effects of pre-announcements on participation and bidding, I compare how the plants' strategies change when adjusting how the pre-announcement states, $x_{i,t}$, holding all other states fixed.[24] I compare the effect of the government pre-announcing near and medium distance bin auctions of both sizes ($x_{i,t} = 1$) to the case where there were no pre-announcements issued ($x_{i,t} = -1$). I do a similar exercise to see the effect of the government issuing pre-announcements but there are none in the near and medium distance bins ($x_{i,t} = 0$). I then present the distribution of the effects after aggregating the measurements across plants and states.

The effects of pre-announcements on participation strategies is presented in Table 12. Pre-announcing all the near and medium distance auctions of both sizes has a large impact on the

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[23] Another explanation is that VI plants are part of multi-plant firms so there may be some reallocation of equipment and workers between plants. This explanation is possible even though the model assumes that plants are independent as long as the closest plant is working on the project and the re-allocation does not affect a plant's capacity (i.e. wouldn't change the mean or standard deviation of backlog in the model). The idea is that re-allocation within the same firm is costly, but cheaper than renting/hiring equipment/workers on the open market.

[24] The index, which is held fixed, depends on the pre-announcements of auctions in the far distance bin. Since the index is discretized into two levels and pre-announcements have a relatively minor impact on the index (see Figure 2), pre-announcements are unlikely to lead to a change in the index level.

Table 12: The Effect of Pre-announcements on Non-Participation Probabilities

Variable	Plant Type	Norm. Backlog	Mean	Pctl25	Pctl75
$\Pr(a = 0\|\boldsymbol{x}_{i,t} = 1) - \Pr(a = 0\|\boldsymbol{x}_{i,t} = -1)$	Non-VI	-2	7.787	6.034	8.264
		0	6.014	4.570	6.998
		2	5.009	3.703	5.773
	VI	-2	15.060	12.277	17.457
		0	13.934	10.533	16.255
		2	12.572	9.486	14.717
$\Pr(a = 0\|\boldsymbol{x}_{i,t} = 0) - \Pr(a = 0\|\boldsymbol{x}_{i,t} = -1)$	Non-VI	-2	-1.592	-1.998	-1.311
		0	-1.363	-1.673	-1.087
		2	-0.989	-1.311	-0.702
	VI	-2	-0.058	-0.853	0.653
		0	-0.319	-1.165	0.624
		2	-0.110	-0.834	0.680

Shows how the probability of not participating in an auction ($a = 0$) changes when the pre-announcement state goes from the case where the government did not pre-announce any auctions ($\boldsymbol{x}_{i,t} = -1$) to the case where the government pre-announced auctions in the near and medium distance bins of both sizes ($\boldsymbol{x}_{i,t} = 1$). A similar exercise is done to document the change when the government pre-announces auctions but there are none in the near and medium distance bins ($\boldsymbol{x}_{i,t} = 0$).
• Difference in probabilities is reported in percentage points.
• The distribution comes from computing this probability across plants and current auction availability states ($\boldsymbol{y}_t$) when rivals are unconstrained.

non-participation probability: non-VI (VI) plants are 5.0-7.8% (12.5-15.1%) more likely to not participate relative to the no pre-announcements issued state. The particularly large impact for VI plants is mainly driven by presence of pre-announcements of near large projects which are low cost projects with expected auction revenues. Pre-announcements can also increase the participation probability. This occurs when the government pre-announces auctions but none of these auctions is close by (i.e. $\boldsymbol{x}_{i,t} = 0$). Bidders are more likely to participate in this case because if the government issued pre-announcements and there are none of those auctions are in their vicinity, it is likely that there won't be any near or medium auctions of any size available to bid on in the following period. Since the following period is unlikely to have low cost auctions available, the bidder is more inclined to participate in a current period auction.

Table 13 shows how the pre-announcements affect the dynamic bid markups for a near large auction. I focus on dynamic bid markups because these are the objects primarily impacted by the pre-announcements. Moreover, they do not depend on the cost draw which simplifies the comparative statics. The non-VI (VI) plant dynamic markups for near large auctions increase by 1.0-4.5% (2.2-5.4%) when $\boldsymbol{x}_{i,t} = 1$. The occurs because informing bidders that the following period has low cost auctions available increases the option value of losing. As with the participation decision, pre-announcements can also have the opposite effect. When $\boldsymbol{x}_{i,t} = 0$, it is relatively bad news about the auction availability in the following period, which decreases the dynamic markup

Table 13: The Effect of Pre-announcements on the Dynamic Bid Markup

Variable	Plant Type	Norm. Backlog	Mean	Pctl25	Pctl75
% Increase in dynamic bid markup going from $\boldsymbol{x}_{i,t} = -1$ to $\boldsymbol{x}_{i,t} = 1$	Non-VI	-2	4.527	1.860	5.279
		0	2.004	0.684	2.384
		2	0.972	0.492	1.775
	VI	-2	5.352	2.189	7.553
		0	2.205	0.939	2.485
		2	2.963	0.931	2.698
% Increase in dynamic bid markup going from $\boldsymbol{x}_{i,t} = -1$ to $\boldsymbol{x}_{i,t} = 0$	Non-VI	-2	-1.123	-1.568	-0.731
		0	-0.530	-0.756	-0.207
		2	-0.121	-0.398	-0.186
	VI	-2	-1.542	-1.786	-0.845
		0	-0.814	-1.085	-0.576
		2	-0.885	-0.783	-0.396

Shows how the dyanamic bid markup (i.e. the opportunity cost of winning) for a near large auction changes when the pre-announcement state goes from the case where the government did not pre-announce any auctions ($\boldsymbol{x}_{i,t} = -1$) to the case where the government pre-announced auctions in the near and medium distance bins of both sizes ($\boldsymbol{x}_{i,t} = 1$). A similar exercise is done to document the change when the government pre-announces auctions but there are none in the near and medium distance bins ($\boldsymbol{x}_{i,t} = 0$).
• The distribution comes from computing this probability across plants and current auction availability states ($\boldsymbol{y}_t$) when rivals are unconstrained.

by 0.2-1.5%. While the pre-announcements have a significant impact on the dynamic markups, their effect in dollar amounts is relatively modest and on the order of $500-3,100. The results are qualitatively similar for the other auction bins.

These measurement exercises show that pre-announcements have a significant impact on the participation strategies and a modest impact on the bids.

7   Counterfactual Analysis

The measurement exercises in the previous section demonstrate how information disclosure via pre-announcements can affect efficiency and prices. When pre-announcements of low expected cost (i.e. close by) auctions are issued, bidders are less likely to participate in current period auctions because the following period auctions are a better match. Higher quality matching reduces the expected cost of completing the contract, which increases efficiency, and can lower the prices the auctioneer pays because lower cost bidder can submit lower bids; this is the matching effect. However, this superior matching can reduce the number of participants in the auctions, reducing competition and increasing prices; this is the participation effect. The effect that information disclosure has on the total price the auctioneer pays is ambiguous because the two effects go in opposite directions. In addition, the matching and participation effects results in an efficiency-price trade-off, which means the overall impact of information disclosure on total welfare, which is optimized by minimizing the

sum of auctioneer expenditures and bidder costs, is ambiguous. To answer the research question of whether the government should pre-announce future period auctions during the current auction cycle, I run counterfactual simulations. I answer the question in two ways depending on whether the goal is to one, minimize government expenditures, or two, maximize welfare.

I simulate the auctions from 2002-2010 under two policy regimes (i) the current, baseline policy under which pre-announcements occur and (ii) the counterfactual policy in which the government ceases issuing pre-announcements. In these simulations, I hold the schedule of auctions fixed to what was observed in the data. For the baseline policy, the timing of the pre-announcements is also set to match what was observed in the data. In the counterfactual policy, I assume all pre-announcements of period $t+1$ auctions are delayed until after letting date t's auctions are held.

Simulating the counterfactual policy is possible because the data contains periods in which the government did not issue pre-announcements. This means the participation and bidding strategies, which are endogenous objects, can be estimated directly off the data. When bidder i knows its cost primitives, there are two equilibrium objects that it needs to know in order to compute its strategies: (i) the minimum rival bid distribution $G_{\tau,M}(\cdot)$ and (ii) the transition law of the competition index $\lambda_{i,t}$. Computing these endogenous, equilibrium objects from the model primitives is computationally intractable because there are many players and the state space is large (even after the dimension reduction). Even if $G_{\tau,M}(\cdot)$ and the index transition are known, it is still computationally intensive to compute the participation and bid strategies. This is because the two decisions have to be solved for simultaneously. To see this, recall that the optimal bid depends on knowing the participation value function, which depends on both the bidding and participation strategies. Fortunately, I can estimate both the counterfactual equilibrium objects and strategies off of the data so I sidestep the computational concerns.

To compute the counterfactual index transition law, I compute $\lambda_{i,t}$ when there are no pre-announcements for all bidders in each period. Then, I compute how $\lambda_{i,t}$ transitions between the high and low states using the logit specification described in (B.5); the logit is re-estimated using the index values assuming there are no pre-announcements. Similarly, I can compute the counterfactual $G_{\tau,M}(\cdot)$ and $G_{\tau,B}(\cdot)$ distributions by including a covariate that controls for whether the policy was active in estimation. This control variable ($\mathbf{1}(\boldsymbol{x}_{i,t} = -1)$) can be seen in the estimates of the bid distributions reported in the previous section. The estimates of the bid distributions allow me to compute the participation strategies for all the states. I then compute the participation value function, which allows me to compute the bidding strategies in conjunction with the estimates of

Table 14: Comparing Policy Outcomes

Variable	Baseline	No Pre-announcements	Change	
			Absolute	Percentage
Government Expenditures ($MM)	2,432.930	2,418.232	−14.699	−0.600
Bidders' Costs of Projects and Participation Costs ($MM)	2,280.658	2,288.769	8.111	0.400
Bidders' Costs of Projects Excluding Participation Costs ($MM)	1,563.117	1,529.590	−33.526	−2.100
Number of Bidders	2.648	2.799	0.151	5.700
↪ VI Plants	0.582	0.621	0.039	6.800
↪ Non-VI Plants	2.066	2.178	0.112	5.400
Fraction of Auctions where Lowest Cost Bidder Won	0.936	0.926	−0.009	−1.000
↪ Additional cost due to mis-allocation ($MM)	11.806	15.031	3.225	27.300
↪ Average mis-allocation cost |mis-allocation (fraction of eng. est.)	0.077	0.083	0.006	8.500

Reports the mean outcomes of the HMA auctions from 2002-2010 over 200 simulations. The baseline policy is the case where MDOT discloses information about future period auctions. The no pre-announcements policy is the case where MDOT ceases information disclosure.

$G_{\tau,M}(\cdot)$. Additional details regarding this approach are delineated in Appendix C.

This strategy for recovering the equilibrium objects rests on the assumption that the absence of pre-announcements do not signal to the bidders that the following period is different in some significant way (e.g. has fewer auctions). In the descriptive section, I provided evidence that MDOT does not appear to be strategic with regard to the number of pre-announcements issued in period t. So the data suggests that this assumption is reasonable.

Each policy is simulated 200 times and the results are reported in Table 14. The counterfactual simulations suggest that if a planner were trying to minimize government expenditures, the cost of completing the projects, and bidder participation costs, it would select the policy where the auctioneer does not issue pre-announcements. The same policy would be appropriate if the goal is to minimize government expenditures. Compared to the baseline policy, no pre-announcements reduces government expenditures by $14.7 million while the bidders' costs go up by $8.1 million. The increase in bidders' costs can be decomposed as coming from a $41.6 million increase in participation costs and a $33.5 decrease in construction costs. This shows that increase in bidders' cost is primarily driven by increased participation: excluding the participation cost κ, the counterfactual policy has a lower cost of completing the projects. The reason increased participation lowers the cost of completing the projects is because of the independent private cost assumption and that there is considerable variation in the cost distribution outside of backlog, size, and distance. This means it is more likely to get a lower cost draw when an additional bidder participates, even if it is has a slightly higher expected cost draw due to its state.

The simulation results show that the lack of pre-announcements reduces the quality of matching of bidders to projects. Under the counterfactual policy, the lowest cost bidder did not get allocated the project in 7.4% of the auctions which is higher than the 6.4% of the time in the baseline policy.

The additional cost of completing the contracts due to mis-allocations increased from $11.8 million in the baseline to $15.0 million in the counterfactual policy. When this mis-allocation occurs, the bidder who gets allocated the project typically has a higher cost that by approximately 8.3% of the engineer's estimate for both small and large projects; in the baseline, this additional cost is on the order of 7.7% of the project size.

The baseline simulation shows that a typical auction gets about 2.6 bidders, which is below the 5.2 bidders seen in the data. One reason for the under-prediction is that plants can only participate in at most one auction per period. While this is a good approximation of bidder behavior, precluding plants from bidding in multiple auctions in a period will lower the number of predicted bidders. A second reason for this is that firms that bid nine times or fewer are excluded from the set of potential bidders because they are fringe bidders. Though the simulation is under-shooting the number of bidders, I find that eliminating pre-announcements increases the number of bidders by 5.7%. This is of particular interest to auctioneers in procurement environments where getting multiple bids is an important check on the prices paid.

8   Conclusion

This research highlights the importance of timing in information disclosure in dynamic settings, which has received limited attention in the literature. When agents' behavior have dynamic considerations, which is common in many economic environments, when they receive information about the future plays an important role in their decisions. This paper studies the effects of an information disclosure policy in the MDOT auction market. In this repeated auction environment, I demonstrate that bidders' current period decisions are responsive to pre-announcements about future period auctions. This result provides strong evidence that bidders are forward looking, which supports a commonly untested assumption in the dynamic auctions literature. I construct a dynamic model of participation and bidding that incorporates capacity constraints, spatial competition, and information disclosure via pre-announcements. The model captures how pre-announcements can improve efficiency by enabling bidders to intertemporally match with expected low cost auctions and how better matching can reduce participation, and thus weaken competition.

The model estimates demonstrate the importance of information disclosure with pre-announcements of nearby, low expected cost contracts reducing the probability participation probabilities by 5.0-15.1% and increasing the dynamic bid markups by 2.2-5.4%. Moreover, the estimates showed that

information disclosure can have heterogeneous effects on behavior: notifying bidders that the following period is unlikely to have low expected cost contracts increases participation probabilities and lowers bids in the current period.

The aggregate impact of pre-announcements on efficiency and auctioneer expenditures is theoretically ambiguous so I use the model estimates to evaluate the effects via simulation. The results show that ceasing the information disclosure policy reduces government expenditures by \$14.7 million and increases bidders' costs by \$8.1 million compared to the policy observed in the data. This outcome is driven by the weakening of bidders' ability to intertemporally match with auctions which increases participation by 5.7%. This finding hearkens back to Bulow & Klemperer (1996)'s result that adding a bidder reduces auctioneer expenditures by more than changes to auction design. Regardless of whether the goal is to minimize government expenditures or to maximize welfare, the simulations suggest that MDOT should not pre-announce future period auctions during the current auction cycle.

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A   Deriving the Participation Value Function

In this section, I detail the derivation of the participation stage value function in (4.5). To begin, I take the bid stage value function under optimal bidding in equation (4.3) and substitute it into

the participation value function in (4.4):

$$V_i^P(\boldsymbol{s}_t, \boldsymbol{z}_t, \boldsymbol{z}_{t+1}^A) = \max_{j \in \{0,1,\ldots,J\}} \left\{ \left(\mathbb{E}_C\left[\frac{\widetilde{G}_{j,M_i}(\beta_{i,j,t}(C)|\boldsymbol{s}_t, \boldsymbol{z}_t, \boldsymbol{z}_{t+1}^A)^2}{g_{j,M_i}(\beta_{i,j,t}(C)|\boldsymbol{s}_t, \boldsymbol{z}_t, \boldsymbol{z}_{t+1}^A)} \middle| \boldsymbol{s}_t, \boldsymbol{z}_t, \boldsymbol{z}_{t+1}^A \right] - \kappa \right) \times \mathbf{1}(j \neq 0) \right.$$
$$\left. + \delta \mathbb{E}[V_i^P(\boldsymbol{S}_{t+1}, \boldsymbol{Z}_{t+1}, \boldsymbol{Z}_{t+2}^A)|\boldsymbol{s}_t, \boldsymbol{z}_t, \boldsymbol{z}_{t+1}^A, i \text{ loses } j] \right\}$$

$$\text{(A.1)}$$

The value function incorporates the normalization that not participating ($j = 0$) has zero payoff. I remains to integrate out the costs.

$$\mathbb{E}_C\left[\frac{\widetilde{G}_{j,M_i}(\beta_{i,j,t}(C)|\boldsymbol{s}_t, \boldsymbol{z}_t, \boldsymbol{z}_{t+1}^A)^2}{g_{j,M_i}(\beta_{i,j,t}(C)|\boldsymbol{s}_t, \boldsymbol{z}_t, \boldsymbol{z}_{t+1}^A)} \middle| \boldsymbol{s}_t, \boldsymbol{z}_t, \boldsymbol{z}_{t+1}^A \right] = \int_{\underline{c}}^{\infty} \frac{\widetilde{G}_{j,M_i}(\beta_{i,j,t}(c)|\boldsymbol{s}_t, \boldsymbol{z}_t, \boldsymbol{z}_{t+1}^A)^2}{g_{j,M_i}(\beta_{i,j,t}(c)|\boldsymbol{s}_t, \boldsymbol{z}_t, \boldsymbol{z}_{t+1}^A)} f_{i,j}(c|\boldsymbol{s}_t, \boldsymbol{z}_t, \boldsymbol{z}_t^A) dc$$
$$= \int_{\underline{b}}^{\infty} \frac{\widetilde{G}_{j,M_i}(b|\boldsymbol{s}_t, \boldsymbol{z}_t, \boldsymbol{z}_{t+1}^A)^2}{g_{j,M_i}(b|\boldsymbol{s}_t, \boldsymbol{z}_t, \boldsymbol{z}_{t+1}^A)} g_{j,B_i}(b|\boldsymbol{s}_t, \boldsymbol{z}_t, \boldsymbol{z}_t^A) db,$$

$$\text{(A.2)}$$

where $g_{j,B_i}(\cdot)$ is the density function of bidder i's bid in auction j. The second line comes from changing the variable of integration from costs to bids. The change of variables comes from the equilibrium bidding assumption which states that $F_{i,j}(c|\boldsymbol{s}_t, \boldsymbol{z}_t, \boldsymbol{z}_t^A) = G_{j,B_i}(\beta_{i,j,t}(c)|\boldsymbol{s}_t, \boldsymbol{z}_t, \boldsymbol{z}_t^A)$. Note that $F_{i,j}(\cdot)$ is the cost distribution of bidder i in auction j given the state. While the cost distribution only depends on the bidder's characteristics $z_{0,i}$ (which is encapsulated by the i subscripts), backlog, and the auction characteristics, I can express the distribution as conditioning on the other state variables; these other state variables have no effect on the cost distribution. The equality of the two distributions implies that $f_{i,j}(c|\boldsymbol{s}_t, \boldsymbol{z}_t, \boldsymbol{z}_t^A) = g_{j,B_i}(\beta_{i,j,t}(c)|\boldsymbol{s}_t, \boldsymbol{z}_t, \boldsymbol{z}_t^A) \frac{d\beta_{i,j,t}(c)}{dc}$, which is the expression need to change the variable of integration. Plugging (A.2) into (A.1) yields the participation value function (4.5).

B   Estimation Details

B.1   Estimating Equations Details

The estimating equations are the participation stage value function and the bid first order condition. Below, I present these estimating equations under the compact state space; these are similar to those derived in Section 4 under the full state space.

The participation stage value function can be written as:

$$
V_i^P(s_{i,t}, \boldsymbol{y}_{i,t}, \boldsymbol{x}_{i,t}, \lambda_{i,t}) = \mathbb{E}_{\boldsymbol{\varepsilon}}\left[\max_{a \in \mathcal{A}(\boldsymbol{y}_{i,t})} \left\{ \pi_i(d\zeta = a, s_{i,t}, \boldsymbol{y}_{i,t}, \boldsymbol{x}_{i,t}, \lambda_{i,t}) + \varepsilon(a) \right.\right.
$$
$$
\left.\left. + \delta\mathbb{E}[V_i^P(S_{i,t+1}, \boldsymbol{Y}_{i,t+1}, \boldsymbol{X}_{i,t+1}, \Lambda_{i,t+1})|s_{i,t}, \boldsymbol{y}_{i,t}, \boldsymbol{x}_{i,t}, \lambda_{i,t}, i \text{ doesn't bid}] \right\}\right],
$$

(B.1)

where

$$
\mathcal{A}(\boldsymbol{y}_{i,t}) = \{0, f\jmath, f\ell\}
$$
$$
\cup \{n\jmath\} \qquad \text{if } y_{i,t,n\jmath} = 1
$$
$$
\cup \{n\ell\} \qquad \text{if } y_{i,t,n\ell} = 1 \qquad\qquad \text{(B.2)}
$$
$$
\cup \{m\jmath\} \qquad \text{if } y_{i,t,m\jmath} = 1
$$
$$
\cup \{m\ell\} \qquad \text{if } y_{i,t,m\ell} = 1
$$

and

$$
\pi_i(d\zeta, s_{i,t}, \boldsymbol{y}_{i,t}, \boldsymbol{x}_{i,t}, \lambda_{i,t}) = \begin{cases} 0 & \text{if } d\zeta = 0; \\ \displaystyle\int_{\underline{b}}^{\infty} \frac{\widetilde{G}_{d\zeta, M_i}(b|s_{i,t}, \boldsymbol{y}_{i,t}, \boldsymbol{x}_{i,t}, \lambda_{i,t})^2}{g_{d\zeta, M_i}(b|s_{i,t}, \boldsymbol{y}_{i,t}, \boldsymbol{x}_{i,t}, \lambda_{i,t})} g_{d\zeta, B_i}(b|s_{i,t}, \boldsymbol{y}_{i,t}, \boldsymbol{x}_{i,t}, \lambda_{i,t})db - \kappa & \text{otherwise;} \end{cases}
$$

and not participating is denoted with $d\zeta = 0$. The expectation operator without the ε subscript is taken over $S_{i,t+1}$, $\boldsymbol{Y}_{i,t+1}$, $\boldsymbol{X}_{i,t+1}$, and $\Lambda_{i,t+1}$. Note that the epsilon shock is the maximum shock over all the auctions within an available auction bin.

The first order condition of the bid stage value function when bidder i participates in a $d\zeta$ auction bin with cost draw c under this dimension reduction is:

$$
c = b - \frac{\widetilde{G}_{d\zeta, M_i}(b|s_{i,t}, \boldsymbol{y}_{i,t}, \boldsymbol{x}_{i,t}, \lambda_{i,t})}{g_{d\zeta, M_i}(b|s_{i,t}, \boldsymbol{y}_{i,t}, \boldsymbol{x}_{i,t}, \lambda_{i,t})}
$$
$$
- \delta\bigg(\mathbb{E}[V_i^P(S_{i,t+1}, \boldsymbol{Y}_{i,t+1}, \boldsymbol{X}_{i,t+1}, \Lambda_{i,t+1})|s_{i,t}, \boldsymbol{y}_{i,t}, \boldsymbol{x}_{i,t}, \lambda_{i,t}, i \text{ doesn't bid}] \qquad \text{(B.3)}
$$
$$
- \mathbb{E}[V_i^P(S_{i,t+1}, \boldsymbol{Y}_{i,t+1}, \boldsymbol{X}_{i,t+1}, \Lambda_{i,t+1})|s_{i,t}, \boldsymbol{y}_{i,t}, \boldsymbol{x}_{i,t}, \lambda_{i,t}, i \text{ wins } d\zeta]\bigg),
$$

where the expectation is taken over $S_{i,t+1}$, $\boldsymbol{Y}_{i,t+1}$, $\boldsymbol{X}_{i,t+1}$, and $\Lambda_{i,t+1}$.

B.2   Index Estimation Details

In this subsection I describe the procedure used to construct the index function, which is reproduced from Aradillas-Lopez et al. (2020) with permission. The notation in this subsection is entirely self-contained and not consistent with the notation in the body of the paper.

The random forest algorithm is as follows:

1. Given training data $\boldsymbol{d} = (\boldsymbol{X}, \boldsymbol{y})$, where $\boldsymbol{X}$ is a $n \times p$ matrix and $\boldsymbol{y}$ is a $n \times 1$ vector, fix $m \leq p$ and the number of trees Q.

2. For $q = 1, \ldots, Q$ do the following:

   (a) Create a bootstrap version of the training data $\boldsymbol{d}_q^*$. The sample can be represented by the bootstrap frequency vector $\boldsymbol{w}_b^*$.

   (b) Grow a maximal-depth tree $\hat{r}_q(x)$ using $\boldsymbol{d}_q^*$, sampling m of the p features at random prior to making each split. For classification, use $m = \lfloor\sqrt{p}\rfloor$; for regression, use $m = \lfloor p/3 \rfloor$. Growing a tree involves recursively splitting variables at a certain point to maximize the reduction in either the mean squared error (if it is a regression problem) or node impurity (if it is a classification problem). The algorithm is "greedy" and splits the variable which will improve the fit the best. The stopping rules either (i) if splitting a node results in one of the two resulting nodes having too few data points (1 for classification and 5 for regression) and (ii) a branch from the tree stump has hit a predefined number of levels (32).

   (c) Save the tree, as well as the bootstrap sampling frequencies $\boldsymbol{w}_b^*$ for each of the training observations.

3. The random forest prediction at any point x_0 is the average

$$\hat{r}_{rf}(x_0) = \frac{1}{Q} \sum_{q=1}^{Q} \hat{r}_q(x_0).$$

The index estimation procedure is as follows:

1. For $l = 1, \ldots, L$

   (a) Randomly split the sample into K equal sized folds.

(b) Estimate K random forests which have Q trees each. Each random forest is estimated on $K-1$ folds (i.e. leave one fold out), so each fold is excluded from the estimation of exactly 1 random forest.

(c) Combine the trees from the K random forests from (b) into one random forest. This random forest has $Q \times K$ trees. Call this random forest RF_l.

2. Combine the L random forests $\{RF_1, \ldots, RF_L\}$ into a random forest denoted λ. This is the function used as an index.

When estimating the $\lambda(\cdot)$ index, I use $L = 24$, $K = 2$, and $Q = 50$.

This predictor has the feature that it will not overfit compared to the standard implementation of the random forest when training and predicting on the same data. When fitting a random forest, each data point in the training sample will be included in approximately $\frac{2}{3}$ of the trees due to the bootstrapping. This means that when obtaining the predicted value of a given x_0, two thirds of the trees in the forest will be using its associated y_0 to generate a prediction. The index algorithm reduces the number of times a data point is used to train a tree. Under the parameters selected, each data point is used to train approximately $\frac{1}{3}$ of the trees.

B.3   Bid Distribution Estimation Details

When estimating the bid distributions, I pool auctions across different bins. This means that the bin $d\zeta$ will be a conditioning variable.

The bid distribution for bidders of type τ is

$$G_{\tau,\tilde{B}}(\tilde{b}_{i,t}|s_{i,t}, \bar{s}_i, sd(s)_i, \boldsymbol{y}_{i,t}, \boldsymbol{x}_{i,t}, \lambda_{i,t}, d\zeta) = 1 - \exp\left(-\left(\frac{\tilde{b}-\xi}{\psi_\tau(s_{i,t}, \bar{s}_i, sd(s)_i, \boldsymbol{y}_{i,t}, \boldsymbol{x}_{i,t}, \lambda_{i,t}, d\zeta)}\right)^{k_\tau}\right),$$

where ξ, k_τ, and $\psi_\tau(\cdot)$ are the support, shape, and scale parameters, respectively. The scale is parameterized according to

$$\ln \psi_\tau(s_{i,t}, \bar{s}_i, sd(s)_i, \boldsymbol{y}_{i,t}, \boldsymbol{x}_{i,t}, \lambda_{i,t}, d\zeta) = \gamma_{d\zeta} + \gamma_{\tilde{s}}\tilde{s}_{i,t} + \gamma_{sd(s)}sd(s)_i + \gamma_{d\zeta,\lambda}\lambda_{i,t}$$

$$+ \sum_{d'\zeta' \in \{n\eth, n\ell, m\eth, m\ell\}} \gamma_{d'\zeta',y} y_{i,t,d'\zeta'}$$

$$+ \sum_{d'\zeta' \in \{n\eth, n\ell, m\eth, m\ell\}} \gamma_{d'\zeta',x} \left(\Pr(Y_{i,t+1,d'\zeta'} = 1|x_{d'\zeta'}) + \delta \Pr(X_{i,t+1,d'\zeta'} = 1)\right).$$

The parameterization says that the scale parameter depends on the auction bin, backlog, available auctions, index value, and pre-announcements. The backlog enters through the normalized backlog and the standard deviation of backlog. Since the cost distribution is shifted by normalized backlog, it follows that the bid distribution will depend on that variable as well. The standard deviation of backlog captures how a plant with a larger standard deviation is not as constrained by winning a project as one with a smaller standard deviation of backlog. The pre-announcements enter through the terms with coefficients $\gamma_{d'\zeta',x}$. Notice that if $x_{i,t,d'\zeta'} = 1$ then $\Pr(Y_{i,t+1,d'\zeta'} = 1|x_{d'\zeta'}) = 1$. This specification captures how different plants can have different probabilities of an auction bin being available in the following period *even if their pre-announcement states are identical* because of their different locations. The probability of pre-announcements in period $t+1$ of a $d\zeta$ auction also differs based on location. Since a period $t + 1$ pre-announcement is informative about the availability of a $d\zeta$ auction in period $t + 2$, I enforce that the effect on bids is the same (up to the discount rate) as a period t pre-announcement that is informative about a period $t + 1$ auction.

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

$$\int_{\underline{b}}^{\infty} \frac{\widetilde{G}_{d\zeta,M_i}(b|s_{i,t}, \boldsymbol{y}_i, \boldsymbol{x}_{i,t}, \lambda_{i,t})^2}{g_{d\zeta,M_i}(b|s_{i,t}, \boldsymbol{y}_i, \boldsymbol{x}_{i,t}, \lambda_{i,t})} g_{d\zeta,B_i}(b|s_{i,t}, \boldsymbol{y}_i, \boldsymbol{x}_{i,t}, \lambda_{i,t})db$$
$$= \zeta \int_{\underline{b}/\zeta}^{\infty} \frac{\widetilde{G}_{\tau,\tilde{M}}(\tilde{b}|s_{i,t}, \bar{s}_i, sd(s)_i, \boldsymbol{y}_i, \boldsymbol{x}_{i,t}, \lambda_{i,t}, d\zeta)^2}{g_{\tau,\tilde{M}}(\tilde{b}|s_{i,t}, \bar{s}_i, sd(s)_i, \boldsymbol{y}_i, \boldsymbol{x}_{i,t}, \lambda_{i,t}, d\zeta)} g_{\tau,\tilde{B}}(\tilde{b}|s_{i,t}, \bar{s}_i, sd(s)_i, \boldsymbol{y}_i, \boldsymbol{x}_{i,t}, \lambda_{i,t}, d\zeta)d\tilde{b}, \tag{B.4}$$

where i is of type τ. Note that the first line implicitly includes the mean and standard deviation of backlog of bidder i through the i subscripts on B and M.

B.4 Estimating Transition Probabilities and CCP's Details

To estimate $\Pr(\lambda_{i,t+1}|\lambda_{i,t}, i$ doesn't bid$)$ and $\Pr(\lambda_{i,t+1}|\lambda_{i,t}, i$ won auction bin $d\zeta)$ between the high and low levels, I use the following logit regression for bidders of type τ (excluding the shock):

$$\mathbf{1}(\lambda_{i,t+1} = \text{High}) = \gamma_0 + \gamma_1 \mathbf{1}(\lambda_{i,t} = \text{High}) + \gamma_{2,x}\mathbf{1}(\boldsymbol{x}_{i,t} = -1)$$
$$+ \sum_{d'\zeta' \in \{n\jmath,n\ell,m\jmath,m\ell,f\jmath,f\ell\}} \mathbf{1}(i \text{ won } d'\zeta')\Big(\gamma_{3,d'\zeta'}\mathbf{1}(\lambda_{i,t} = \text{High}) + \gamma_{4,d'\zeta'}\mathbf{1}(\lambda_{i,t} = \text{Low})\Big). \tag{B.5}$$

To estimate the participation conditional choice probabilities, I use multinomial/conditional logit. The linear payoff, excluding the shock, of i of choosing action a in $\mathcal{A}(\boldsymbol{y}_{i,t}) - \{0\}$ is specified

to be:

$$u(a = d\zeta) = \gamma_{d\zeta} + \gamma_{\tilde{s}}\tilde{s}_{i,t} + \gamma_{sd(s)}sd(s)_i + \gamma_{d\zeta,\lambda}\lambda_{i,t} + \sum_{d'\zeta' \in \{n\jmath, n\ell, m\jmath, m\ell\}} \alpha_{d'\zeta',y}y_{i,t,d'\zeta'}$$
$$+ \sum_{d'\zeta' \in \{n\jmath, n\ell, m\jmath, m\ell\}} \alpha_{d'\zeta',x}\Big(\Pr(Y_{i,t+1,d'\zeta'} = 1|x_{d'\zeta'}) + \delta\Pr(X_{i,t+1,d'\zeta'} = 1) \Big). \tag{B.6}$$

with year and month fixed effects and $u(0)$ is normalized to equal 0. This specification is similar to that of the scale parameter of $G_{\tau,\tilde{B}}(\cdot)$ because the participation decision depends on the bid distribution as shown in the model. As such, the interpretation of the forces captured by the covariates have similar interpretations. As with the estimates of the bid distributions, the time fixed effects are zeroed out when I incorporate these offline estimates into the model.

B.5 Estimating the Participation Cost Details

This subsection details how to estimate the participation cost in order to highlight how static participation simplifies computation. In addition, I detail how to recover the participation value function in one step.

Let $\mathbf{\Pi}_i(\kappa)$ be a vector with the flow profit of bidder i for all N states when the participation cost is κ. Then the pseudo-value function in the participation stage is

$$\underbrace{V_i^P}_{N\times 1} = \sum_a \Big[\underbrace{\boldsymbol{q}_i(a)}_{N\times 1} * \underbrace{\mathbf{\Pi}_i(\kappa)}_{N\times 1} \Big] + \underbrace{\boldsymbol{D}_i}_{N\times 1} + \delta\Big[\sum_a \boldsymbol{q}_i(a) * \underbrace{\boldsymbol{T}_i(a)}_{N\times N} \Big]V_i^P$$
$$= \Big[\boldsymbol{I}_N - \delta\sum_a \boldsymbol{q}_i(a) * \boldsymbol{T}_i(a) \Big]^{-1}\Big[\sum_a \big[\boldsymbol{q}_i(a) * \mathbf{\Pi}_i(\kappa) \big] + \boldsymbol{D}_i \Big], \tag{B.7}$$

where $*$ is the Hadamard (element-by-element) product[25], $\boldsymbol{q}_i(a)$ is the stacked CCP of choice a for all states, $\boldsymbol{T}_i(a)$ is the transition matrix given action a, $\boldsymbol{I}_N$ is the identity matrix, and $\boldsymbol{D}_i$ is the expected value of the epsilon shock. Note that when action a is not available in a given state $q_i(a; s_{i,t}, \boldsymbol{y}_{i,t}, \boldsymbol{x}_{i,t}, \lambda_{i,t}) = 0$ and that $D_i(s_{i,t}, \boldsymbol{y}_{i,t}, \boldsymbol{x}_{i,t}, \lambda_{i,t}) = \sum_{a' \in \mathcal{A}(\boldsymbol{y}_{i,t})} \mathbb{E}\big[\varepsilon(a)|a = a', s_{i,t}, \boldsymbol{y}_{i,t}, \boldsymbol{x}_{i,t}, \lambda_{i,t}\big]q_i(a'; s_{i,t}, \boldsymbol{y}_{i,t}, \boldsymbol{x}_{i,t}, \lambda_{i,t})$.[26] Similar to the flow profit, the conditional transition matrices are bidder specific due to their different locations. Equation (B.7) can be evaluated over any flow profit given parameters, $\mathbf{\Pi}_i(\kappa)$, and CCP's, $\boldsymbol{q}_i(\cdot)$. When the true flow profit and the true

---

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

[26] Under the assumption that the epsilons are i.i.d. Gumbel with location parameter 0 and scale parameter $1/\omega$, $\mathbb{E}\big[\varepsilon(a)|a, s_{i,t}, \boldsymbol{y}_{i,t}, \boldsymbol{x}_{i,t}, \lambda_{i,t}\big] = \frac{1}{\omega}\Big(\gamma - \ln\big(\Pr(a|s_{i,t}, \boldsymbol{y}_{i,t}, \boldsymbol{x}_{i,t}, \lambda_{i,t})\big)\Big)$, where γ is the Euler–Mascheroni constant.

CCP's are plugged into (B.7), the pseudo-value function equals the value function (assuming that the transition laws and discount factor are known).

Under the Gumbel distribution assumption, the probability of action a in state $(s_{i,t}, \boldsymbol{y}_{i,t}, \boldsymbol{x}_{i,t}, \lambda_{i,t})$ with participation cost κ is

$$p_i(a, s_{i,t}, \boldsymbol{y}_{i,t}, \boldsymbol{x}_{i,t}, \lambda_{i,t}; \kappa) = \frac{\exp\left[\omega\Pi_i(a, s_{i,t}, \boldsymbol{y}_{i,t}, \boldsymbol{x}_{i,t}, \lambda_{i,t}; \kappa) + \omega\delta\boldsymbol{T}_i(a; s_{i,t}, \boldsymbol{y}_{i,t}, \boldsymbol{x}_{i,t}, \lambda_{i,t})V_i^P(\kappa, \hat{\boldsymbol{q}}_i)\right]}{\displaystyle\sum_{a' \in \mathcal{A}(\boldsymbol{y}_{i,t})} \exp\left[\omega\Pi_i(a', s_{i,t}, \boldsymbol{y}_{i,t}, \boldsymbol{x}_{i,t}, \lambda_{i,t}; \kappa) + \omega\delta\boldsymbol{T}_i(a'; s_{i,t}, \boldsymbol{y}_{i,t}, \boldsymbol{x}_{i,t}, \lambda_{i,t}; \kappa)V_i^P(\kappa, \hat{\boldsymbol{q}}_i)\right]},$$
$$(B.8)$$

where $\Pi(a, s_{i,t}, \boldsymbol{y}_{i,t}, \boldsymbol{x}_{i,t}, \lambda_{i,t}; \kappa)$ is the flow profit of action a given the state and participation cost parameter, $\boldsymbol{T}_i(a; s_{i,t}, \boldsymbol{y}_{i,t}, \boldsymbol{x}_{i,t}, \lambda_{i,t})$ is the row of the conditional transition matrix that corresponds to the state, and $V_i^P(\kappa, \hat{\boldsymbol{q}}_i)$ is the pseudo-value function given κ and the offline CCP estimate $\hat{\boldsymbol{q}}_i$ evaluated using (B.7). Computing $p_i(\cdot)$ is typically computationally expensive because it involves computing the pseudo-value function, which requires a matrix inversion.[27] However, since participation in this model is as-if static (i.e. $\boldsymbol{T}_i(0) = \boldsymbol{T}_i(a')$ for all a'), the pseudo-value function drops out of (B.8) and yields (5.1) in the main text.

Static participation means that I can compute the value function in one step. This is because once κ is estimated, the CCP's implied by the model parameters, $\boldsymbol{p}(a; \hat{\kappa})$, can be computed using (5.1). If participation were not static, value function iteration would be required to compute the CCP's. Then, I can compute V_i^P using (B.7) where $\boldsymbol{q}_i(a)$ is replaced with $\boldsymbol{p}(a; \hat{\kappa})$ and the flow profit is replaced with $\boldsymbol{\Pi}_i(\hat{\kappa})$.

B.6   Estimating the Cost Distribution Details

Under the compact state space, notice that:

$$F_i(c|d\zeta, s_{i,t}, \boldsymbol{y}_{i,t}, \boldsymbol{x}_{i,t}, \lambda_{i,t}) = G_{B_i}(\beta_{i,d\zeta}(c|s_{i,t}, \boldsymbol{y}_{i,t}, \boldsymbol{x}_{i,t}, \lambda_{i,t})|d\zeta, s_{i,t}, \boldsymbol{y}_{i,t}, \boldsymbol{x}_{i,t}, \lambda_{i,t})$$
$$\Leftrightarrow F_i(\beta_{i,d\zeta}^{-1}(b|s_{i,t}, \boldsymbol{y}_{i,t}, \boldsymbol{x}_{i,t}, \lambda_{i,t})|d\zeta, s_{i,t}, \boldsymbol{y}_{i,t}, \boldsymbol{x}_{i,t}, \lambda_{i,t}) = G_{B_i}(b|d\zeta, s_{i,t}, \boldsymbol{y}_{i,t}, \boldsymbol{x}_{i,t}, \lambda_{i,t}),$$

where $\beta_{i,d\zeta}^{-1}(\cdot)$ is the inverse bid function and the i subscripts capture how bidders have different observable characteristics. The inverse bid function was derived in (B.3). The inverse bid function requires estimates of the participation value function, which is a byproduct of estimating κ, and the minimum rival bid distribution, which is estimated off the data. Using the above equation allows me

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[27] The inverse of the matrix in (B.7) could be saved to avoid repeated calculations. However, if the state space is large and/or there are many bidders, RAM limitations become an issue.

to recover the cost distribution given bin, backlog, the available auction state, pre-announcement state, and index value. The latter three state variables do not impact the cost distribution in the model. In order to recover the cost distribution over auction bin and backlog only, I average the estimates across the current auction, pre-announcement, and index states.

C   Counterfactual Simulation Details

In this section, I detail the simulation algorithm used to compute the outcomes of the baseline and counterfactual policies. I begin by describing how I compute the the bidders' participation probabilities and the bid functions given the states which are required to run the simulation.

As was discussed in the main text, the estimates of $G_{\tau,\tilde{M}}(\cdot)$ and $G_{\tau,\tilde{B}}(\cdot)$ include controls for whether the baseline or counterfactual policy was active. With these distributions and estimates of the participation costs, I can compute the expected profit from participating in each available auction bin $d\zeta$ for all states using the formulas in equations (B.1) and (B.4). With the flow profits for all states in hand, I can compute the equilibrium participation probabilities using (5.1). Then I can estimate the participation value function using (B.7). Note that calculating the value function is where the transition law of the index discussed in the main text is needed.

The bid function can be traced out using the first order condition in (B.3) as long as the minimum rival bid distribution and participation value function are known. I use the estimates from the previous paragraph to compute the costs associated with bids, represented as a fraction of the engineer's estimate that go from 0.7001 to 2.5. The grid of bids is quite fine and includes the bids 0.7001, the sequence from 0.71 to 1.31 in increments of 0.02, and the sequence from 1.34 to 2.50 in increments of 0.04. I do this for every state for each bidder, which gives the bid function $\beta_i(c; s_{i,t}, \boldsymbol{y}_{i,t}, \boldsymbol{x}_{i,t}, \lambda_{i,t})$. I use linear interpolation to evaluate the bid function for costs that are not exactly on the grid of costs and bids.

I simulate the auctions from 2002 to 2010 in the order I observe them being let in the data. I initialize each bidder's backlog to be what I observed in the data at the start of 2002. The simulation procedure is as follows:

1. In period t, compute the index for all bidders and classify the index value as high or low.

2. Each bidder draws an epsilon shock associated with each participation action available and chooses the action that has the highest expected flow payoff. If the bidder decided to participate in a $d\zeta$ bin auction, then it participates in one of the auctions that satisfies the criteria.

     If multiple auctions satisfy the criteria, it picks one at random.

3. If a bidder decides to participate, draw a cost from the distribution $F_\tau(\cdot|\tilde{s}_{i,t}, d\zeta)$. Since the cost distribution was computed on a grid of normalized backlogs from -4 to 4 in increments of 0.2, a bidder's normalized backlog is set to be the closest point on the grid. Note that this does not change the bidder's backlog $s_{i,t}$, which is in millions of dollars.

4. Given a cost draw, each bidder submits a bid in accordance to the bid function.

5. The backlog at the beginning of period t, $s_{i,t}$, either stays the same or falls by \$250K with some probability. Then the low bidders in each auction get allocated the project and its magnitude ζ is added to its backlog.

6. Return to step 1 unless it is the last month in the period from 2002-2010.

Following this procedure produces the outcomes from one simulation of a policy.

D   Additional Tables and Figures
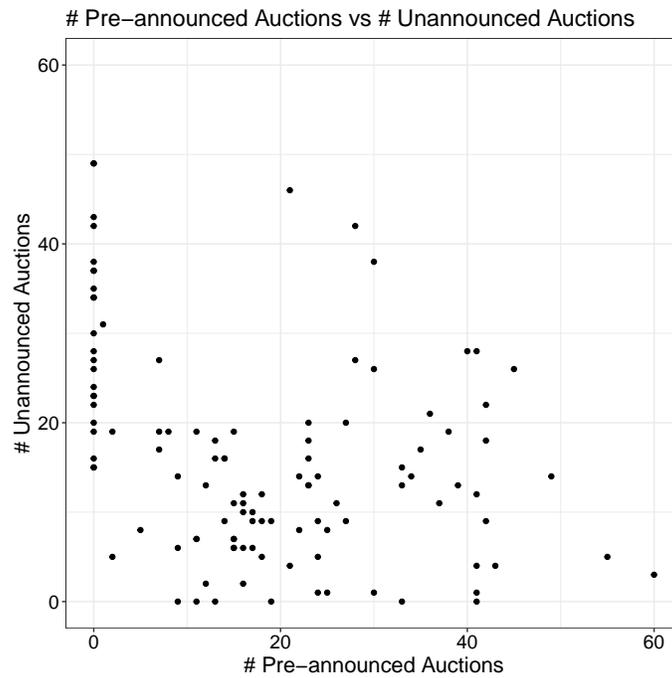
Figure 5: Each point represents the number of pre-announced and unannounced period $t+1$ HMA auctions on letting date t. A period $t+1$ auction is deemed to be pre-announced if was advertised at least two days prior to letting date t otherwise it is deemed to be unannounced.

Table 15: Heckit Regressions

	Non-VI		VI	
	Selection $\mathbf{1}(i \text{ bid in } (j,t))$	Outcome $\frac{\text{Bid}_{i,j,t}}{\text{EngEst}_{j,t}/100}$	Selection $\mathbf{1}(i \text{ bid in } (j,t))$	Outcome $\frac{\text{Bid}_{i,j,t}}{\text{EngEst}_{j,t}/100}$
	(1)	(2)	(3)	(4)
Dist $\in (25,50]$km	-0.356^{***}	2.586^{***}	-0.425^{***}	0.220
	(0.015)	(0.562)	(0.029)	(0.647)
Dist $\in (50,\infty)$km	-1.459^{***}	4.252^{**}	-2.150^{***}	6.685^{***}
	(0.012)	(1.945)	(0.025)	(2.337)
Line Items	0.004^{***}	0.034^{***}	-0.008^{***}	0.084^{***}
	(0.0001)	(0.006)	(0.0003)	(0.011)
% Subcont. to Disadvantaged Business	-0.006^{***}	-0.391^{***}	-0.015^{***}	-0.311^{***}
	(0.001)	(0.037)	(0.003)	(0.066)
Norm Backlog	-0.048^{***}	0.927^{***}	-0.039^{***}	0.888^{***}
	(0.006)	(0.176)	(0.013)	(0.270)
$\mathbf{1}(\geq 1 \text{ Pre-announced } ns \text{ Period t+1 Auction})$	-0.063^{***}	0.245	0.026	-0.400
	(0.011)	(0.355)	(0.026)	(0.584)
$\mathbf{1}(\geq 1 \text{ Pre-announced } n\ell \text{ Period t+1 Auction})$	-0.034^{***}	1.488^{***}	-0.039	2.780^{***}
	(0.012)	(0.364)	(0.028)	(0.627)
$\mathbf{1}(\geq 1 \text{ Pre-announced } ms \text{ Period t+1 Auction})$	-0.004	-0.471	-0.129^{***}	-0.244
	(0.010)	(0.303)	(0.024)	(0.563)
$\mathbf{1}(\geq 1 \text{ Pre-announced } m\ell \text{ Period t+1 Auction})$	-0.024^{**}	0.760^{**}	-0.177^{***}	0.349
	(0.010)	(0.315)	(0.026)	(0.606)
Constant	-0.916^{***}	98.928^{***}	0.864^{***}	91.299^{***}
	(0.025)	(2.429)	(0.057)	(1.298)
σ	15.071^{***} (0.092)		15.425^{***} (0.159)	
ρ	-0.011 (0.104)		-0.043 (0.091)	
Log Likelihood	$-108{,}743.011$		$-31{,}535.983$	
Observations	$512{,}249$		$47{,}573$	

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

• Reports the estimates of the heckit regression where the selection equation predicts whether a bidder participated in auction (j,t) and the outcome equation predicts the bid level as a percentage of the engineer's estimate. The regression includes year and month fixed effects (not reported). Estimation was via maximum likelihood.

• An $t+1$ auction is deemed to be pre-announced if it was announced at least two days prior to letting date t.

• A ns ($n\ell$) auction is within 25km of the bidder and has an eng. est. below (above) \$750K. A ms ($m\ell$) auction is between 25km and 50km of the bidder and has an eng. est. below (above) \$750K.