Resident Bid Preference, Affiliation, and Procurement Competition: Evidence from New Mexico

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Abstract

In public procurement auctions, governments occasionally offer preferences to qualified firms in the form of bid discounts. Previous studies on bid discounts do not account for affiliation – a particular form of cost dependence that is likely to occur in a public procurement setting. Utilizing data from the New Mexico Department of Transportation's Resident Preference Program, this paper addresses that issue via an empirical model of firm bidding and entry behavior that allows for affiliation and bid discounting. I find evidence that firms have affiliated project-completion costs and show how this type of affiliation changes preference auction outcomes.

1 Introduction

Procurement auctions are widely used by governments as a means of securing goods and services for the lowest possible price. Internationally, government procurement accounts for anywhere from 10 to 25 percent of GDP, and in the Unites States alone, government spending on goods and services accounted for 15.2 percent of GDP in 2013, totaling $2.55 trillion.[1] In these procurement auctions, governments occasionally offer preferential treatment to a certain subset of bidders. This treatment often takes the form of bid discounting – a policy where the government will lower the bids of preferred bidders for comparison purposes and pay the full asking price conditional on winning. These preferential policies can affect auction outcomes and have been studied extensively in the literature.[2]

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[1] These numbers are taken from the World Bank national accounts data and OECD National Accounts data files.

[2] See Krasnokutskaya and Seim (2011), Marion (2007), and Hubbard and Paarsch (2009) for papers discussing bid discounting.

The purpose of offering many of these preference programs is to encourage the participation of a particular type of bidder. For example, California offers a bid discount to small businesses to encourage these business to bid on larger projects, and the Inter-American Development Bank offers a bid discount to domestic firms to encourage domestic development. The total effect of these programs, however, has been shown to be ambiguous. Although offering bid discounts can encourage preferred bidders to bid less aggressively, bid discounts also encourage non-preferred bidders to bid more aggressively and can increase competition and discourage preferred participation. This type of trade-off is highlighted in McAfee and McMillan (1989) where the authors show that the government can minimize procurement costs by choosing an optimal discount level when participation is fixed and in Corns and Schotter (1999) where the authors use experiments to show that preferences can lead to increases in both cost effectiveness and the representation of preferred bidders.[3] Krasnokutskaya and Seim (2011) show that these effects are altered when participation is endogenous.

Another potential issue in evaluating these programs is the possibility of dependence between the project-completion costs of bidders. These costs are private information and are typically taken to be independent, implying that a firm that learns her own cost has no additional information on the costs of other bidders. There are a number of reasons why this independence assumption may not hold. For instance, firms may use the same subcontractors when submitting a bid, so firms sharing subcontractors should have some form of dependence in their private information. Firms may also buy raw materials from the same suppliers which again implies some dependence in project-completion costs, especially if firms are located near each other. In fact, 30 percent of items[4] on construction projects qualifying for bid preferences had at least two firms bid the same amount in the data. This statistic is indicative of cost symmetries across firms and can be problematic if costs are taken to be independent.[5]

This paper contributes to the bid preference literature by allowing firms to have affiliated private project-completion costs in procurement auctions with bid discounting and endogenous entry.[6] Affiliation is a stronger notion of positive correlation, and it captures the idea that firm project-completion costs may be related to each other. Using copula methods developed by Hubbard, Li, and Paarsch (2012) and extended by Li and

[3]Additional studies that show the theoretical implications of granting preference to certain groups of bidders include Vagstad (1995) who extends the analysis of McAfee and McMillan (1989) to incentive contracts and Naegelen and Mougeot (1998) who extend the analysis of McAfee and McMillan (1989) to include objectives concerning the distribution of contracts over preferred and non-preferred bidders.

[4]Items are portions of a construction project. The final bid is calculated as the sum of the bids on each item.

[5]Correlations across bids can also be generated by unobserved project heterogeneity (project characteristics that are unobserved to the econometrician yet observed by all bidders). Section 6.2 presents evidence that supports the notion that affiliation outweighs unobserved project heterogeneity in this empirical setting. In other environments where unobserved auction heterogeneity dominates affiliation, econometric methods developed in Krasnokutskaya (2011) and empirical methods found in Hong and Shum (2002) and Haile et al. (2006) would be more suitable. Balat (2016) discusses identification in environments with both affiliation and unobserved project heterogeneity.

[6]This paper also complements the existing literature on auctions with endogenous entry. These papers include Athey et al. (2011),Li (2005) and Bajari and Hortacsu (2003)

Zhang (2013), this paper shows how affiliation and bid preference can *jointly* affect procurement auctions, and to my knowledge, this is the first paper to empirically do so.

In order to evaluate the impact of affiliation and bid preferences on procurement auctions, this paper uses data from New Mexico Department of Transportation (NMDOT) highway construction contracts. New Mexico is one of the few states that offers qualified resident firms a 5 percent bid discount on state-funded projects. Affiliation is plausible in this setting; firms located closely to each other are more likely to buy from the same suppliers and use similar subcontractors, potentially generating dependence in project-completion costs.

To then determine the extent to which affiliation is present in NMDOT highway construction contracts, compare outcomes under affiliation and independence, and investigate alternative discount levels, an empirical model of bidding and endogenous entry is estimated using the data. The estimates confirm that firms do have affiliated project-completion costs and that removing this affiliation causes firms to behave differently. In particular, affiliation lowers firm incentives to participate, resulting in higher overall procurement costs. Counterfactual auctions using alternative discount levels show that New Mexico's current program accounts for a 1.8 percent increase in procurement costs, while an increase in procurement costs of 6 percent is generated by affiliation. The results highlight the influence of affiliation in public procurement auctions.

The remainder of the paper proceeds as follows. Section 2 gives the details of the New Mexico procurement process and describes the data. Section 3 provides a definition of affiliation, and section 4 presents the theoretical framework by which the effect of affiliation on bidding and entry behavior is analyzed. Section 5 shows how the theoretical model is estimated. Section 6 presents the empirical findings, while section 7 contains the counterfactual policy analysis. Section 8 concludes.

2 New Mexico's Highway Procurement Market and Data

This section describes the process by which the NMDOT awards their highway construction contracts and the data collected for the empirical portion of this paper. The sample contains 376 highway construction contracts awarded by the NMDOT between 2010 and 2014 for the maintenance and construction of transportation systems. Preferences are applied to resident firms on state-funded projects. Over the sample period, there are a total 23 of these state-funded contracts while the remaining 353 projects are federally assisted projects. An immediate limitation of the New Mexico data is that there are a relatively small number of preference projects. In response to this limitation, much of the analysis relies on the empirical model of entry and bidding outlined in section 5. The empirical model allows for information in both the preference and non-preference auctions to be used in identifying the model primitives while accounting for strategic behavior attributed to bid discounting.

2.1 Letting

Four weeks prior to the date of bid opening, the NMDOT advertises construction projects estimated to cost more than $60,000. The Contracts Unit is responsible for gathering the necessary contract documents used during this advertisement phase. Each document is unique to the work required on each project and contains details such as the location of the project, the nature of the work, the number of working days to complete the project, and the length of the project. These details are summarized in an "Invitation for Bids" document and are included in the set of project-specific covariates.

Another feature of advertising is providing a rough approximation of firms who could potentially bid for a contract. To advertise potential competitors, the NMDOT publishes a list of "planholders" ten days prior to bid opening. Status as a planholder requires that the firms provide some documented evidence that they have the contract documents either directly through the NMDOT or through written communication.[7] Moreover, failure to seek planholder status results in the bid becoming unresponsive and subsequently rejected. Given that the list of planholders is known prior to bidding and planholder status is required to submit a valid bid, the firms who are registered as planholders are used as a measure of the set of potential bidders.[8]

In awarding these construction projects, the NMDOT uses a competitive first-price sealed-bid procurement auction format. Potential firms who decide to bid on a project submit bids in a sealed envelope or secure online submission website to the NMDOT. The firm with the lowest bid (usually) wins the contract, and the state pays the winner their bid. The submitted bids as well as an engineer's estimate are tabulated and published by the NMDOT in an Apparent Low Bids document directly after bid opening. The bids and estimates in these documents are used as the bids and estimates received by the NMDOT for each project.

2.2 Resident Preference Program

New Mexico offers bid preference to qualified resident firms on construction projects using state funds. The preference is implemented through a 5 percent discount on bids, which lowers resident bids by 5 percent

[7]For more information the planholder requirement, see the NMDOT website.

[8]This measure is not perfect. Some firms seek planholder status after the list is published, resulting in a larger set of potential bidders than what is represented on the planholder document. To account for this difference, any actual bidders that do not appear in the planholder document are included in the set of potential entrants. Moreover, the set of planholders may contain firms that do not have the means to bid as a main contractor. In order to get a more accurate representation of the set of firms who could potentially bid, firms who are unsuccessful in submitting a valid bid during the sample period are not included as planholders.

in evaluation and pays the full asking price conditional on winning. To illustrate, suppose two bidders are bidding for a contract and the resident contractor bids $\$1,000,000$ and the out-of-state contractor bids $\$975,000$. After applying the five percent discount to the resident contractor, her bid is lowered to $\$950,000$, she wins the contract, and the state pays her $\$1,000,000$.

To qualify for resident preference, firms must meet a certain list of conditions. In particular, firms must have paid property taxes on real property owned in the state of New Mexico for at least five years prior to approval and employ at least 80 percent of its workforce from the state of New Mexico. There are also a number of penalties in place to prevent firms from exploiting residency status. Providing false information to the state of New Mexico in order to qualify as a resident results in automatic removal of any preferences, ineligibility to apply for any more preference for at least five years, and administrative fines of up to $\$50,000$ for each violation. A list of qualified resident firms is obtained through the New Mexico Inspection of Public Records Act, which allows anyone to view public documents. Out of the 110 different firms observed in the data, 66 firms are residents while the remaining 44 firms are non-residents. Resident firms account for 80 percent of planholders and 72 percent of submitted bids.

3 Affiliation

The possibility of cost dependence across firms is modeled through affiliation. First introduced into auctions by Milgrom and Weber (1982), affiliation is a concept and can arise as a result of shared subcontractors and suppliers. Theoretically, affiliation describes the relationship between two or more random variables; if two or more random variables are affiliated, then they exhibit some form of positive dependence. de Castro (2010) shows that affiliation is a sufficient condition for positive correlation, so affiliation can roughly be interpreted as a stronger form of positive correlation.[9] Formally, affiliation is defined as follows:

Definition. The density function $f : [\underline{c}, \overline{c}]^n \rightarrow \mathbb{R}_+$ is affiliated if $f(c) f(c') \leq f(c \wedge c') f(c \vee c')$, where $c \wedge c' = (\min\{c_1, c'_1\}, ..., \min\{c_n, c'_n\})$ and $c \vee c' = (\max\{c_1, c'_1\}, ..., \max\{c_n, c'_n\})$.

In a procurement setting, affiliation in project-completion costs means that when a firm draws a high project-completion cost, it is more likely that competing firms also have drawn high project-completion costs.

[9] See de Castro (2010) for a detailed discussion on the relationship between affiliation and other notions of positive dependence.

4 Theoretical Model

This section provides the theoretical foundation by which the market for NMDOT construction contracts is analyzed. In order to preserve the main institutional features, New Mexico's market for highway construction contracts is modeled as a first-price sealed-bid procurement auction with asymmetric bidders, affiliated private values, and endogenous entry. The model proceeds in two stages as in Levin and Smith (1994), Krasnokutskaya and Seim (2011), and Li and Zhang (2013). In the first stage, potential resident and non-resident bidders decide whether to pay the entry cost and participate in the auction. Bidders will enter if their expected profits from participation exceed their cost of preparing a bid. The entry stage captures the effort required to gather information about the project and the opportunity cost of time which, in the New Mexico setting, is analogous to reading the invitation for bids and requesting project information. In the second stage, bidders are informed of the identity and number of actual competitors, draw their project-completion costs from an affiliated distribution, and submit a bid for the project. Note that affiliation in project-completion cost gives bidders extra information on the opponent's project-completion costs, which is plausible if bidders are located close to each other and share similar subcontractors.

4.1 Environment

Formally, N_R potential resident bidders and N_{NR} potential non-resident bidders compete in a first-price sealed-bid procurement auction for the completion of one indivisible construction project. Resident and non-resident bidders are risk neutral and draw bid-preparation costs, k_i, independently from the distribution $G_k^m(\cdot)$ where $m \in \{R, NR\}$ denotes firm i's group affiliation. Project-completion costs, c_i, are drawn from the joint distribution $F_{\boldsymbol{c}}(\cdot, \ldots, \cdot)$ with support $[\underline{c}, \overline{c}]^n$ where n is the total number of actual bidders. Project-completion cost distributions can be affiliated, but project-completion costs are assumed to be independent of bid-preparation costs.[10] These distributions are common knowledge to every potential bidder.

Additionally, resident firms in auctions that use state funds receive a discount of δ on their submitted bid. In terms of the model, the auctioneer will lower every resident bid by a factor of $(1-\delta)$ when comparing it against a non-resident bid in a preference auction, so a resident will win if her bid is less than the lowest competing resident bid and the lowest competing non-resident bid scaled by a factor of $\frac{1}{1-\delta}$. The value of the discount is 5 percent for New Mexico residents.

[10]This assumption implies that bidders do not base entry decisions on their realized project-completion costs. Samuleson (1985) discusses the opposite case where bidders are completely informed of their project-completion costs prior to entry, and Roberts and Sweeting (2010) discuss the intermediate case where bidders are partially informed. Within the independent private values paradigm, Li and Zheng (2009) provide evidence that supports a model in which bidders are initially uniformed prior to entry in a procurement setting.

4.2 Bidding

After bidders learn of their project-completion costs and the number of actual entrants, bidders submit their bids to complete the construction contract. Heterogeneity in residency status along with bid discounting leads to group-symmetric equilibria as in Krasnokutskaya and Seim (2011) where bidders of each group m follow potentially different monotone and differentiable bid functions $\beta_m(\cdot) : [\underline{c}, \overline{c}] \to \mathbb{R}_+$. In particular, a bidder of group m solves the following optimization problem to determine the equilibrium bids:

$$\pi(c_i; n_{NR}, n_R) = \max_{b_i} (b_i - c_i) \Pr\left((1-\delta)^{D_R} b_i < B_j \,\forall j \in NR, (1-\delta)^{-D_{NR}} b_i < B_l \,\forall l \in R \mid c_i\right)$$

where $\pi(c_i; n_{NR}, n_R)$ is the value function, b_i is the bid choice of bidder i, B_j and B_l are the competing bids, D_m is an indicator variable that takes on a value of one if firm i is associated with group m and zero otherwise, and $\delta = 0$ if the auction is not a preference auction. The objective function illustrates how firms view preference when submitting a bid. For positive δ, preference increases the probability of a resident beating a non-resident bidder without requiring the resident bidder to submit a lower bid. Residents therefore have a higher probability of winning a preference auction with the same choice of b_i when compared to a non-preference auction yet face the same payment if they win.[11]

Let n_m denote the actual number of bidders in group m. Furthermore, let $\bar{F}_{\boldsymbol{c}_{-i}}(c_1, \ldots, c_{i-1}, c_{i+1}, \ldots, c_n \mid c_i) = \Pr(C_1 > c_1, \ldots, C_{i-1} > c_{i-1}, C_{i+1} > c_{i+1}, \ldots, C_n > c_n \mid c_i)$ be the joint survival function of project-completion cost signals without bidder i conditional on bidder i's signal,[12] and define $\boldsymbol{\beta}_{NR}^{-1}\left((1-\delta)^{D_R} b_i\right) = \left(\beta_{NR}^{-1}\left((1-\delta)^{D_R} b_i\right), \ldots, \beta_{NR}^{-1}\left((1-\delta)^{D_R} b_i\right)\right) \in \mathbb{R}^{n_{NR}-D_{NR}}$ as a vector that collects the inverse bid functions of non-residents and $\boldsymbol{\beta}_{R}^{-1}\left((1-\delta)^{-D_{NR}} b_i\right) = \left(\beta_{R}^{-1}\left((1-\delta)^{-D_{NR}} b_i\right), \ldots, \beta_{R}^{-1}\left((1-\delta)^{-D_{NR}} b_i\right)\right) \in \mathbb{R}^{n_R-D_R}$ as a vector that collect the inverse bid function of residents. The first order condition that charac-

[11] This intuition assumes that all else (opposing bids, object being auctioned, etc.) is equal.

[12] See section 5.1 for a detailed description on how to write the conditional survival function in terms of the cumulative density function

terizes the optimal bid is then given by

$$\begin{aligned}
0 &= (b_i - c_i) \\
&\times \left[\sum_{j=1}^{n_{NR}-D_{NR}} \bar{F}_{\boldsymbol{c}_{-i},j} \left(\boldsymbol{\beta}_{NR}^{-1} \left((1-\delta)^{D_R} b_i \right), \boldsymbol{\beta}_R^{-1} \left((1-\delta)^{-D_{NR}} b_i \right) \mid c_i \right) \right. \\
&\times \beta_{NR,1}^{-1} \left((1-\delta)^{D_R} b_i \right) (1-\delta)^{D_R} \\
&+ \sum_{j=n_{NR}-D_{NR}+1}^{n-1} \bar{F}_{\boldsymbol{c}_{-i},j} \left(\boldsymbol{\beta}_{NR}^{-1} \left((1-\delta)^{D_R} b_i \right), \boldsymbol{\beta}_R^{-1} \left((1-\delta)^{-D_{NR}} b_i \right) \mid c_i \right) \\
&\times \left. \beta_{R,1}^{-1} \left((1-\delta)^{-D_{NR}} b_i \right) (1-\delta)^{-D_{NR}} \right] \\
&+ \bar{F}_{\boldsymbol{c}_{-i}} \left(\boldsymbol{\beta}_{NR}^{-1} \left((1-\delta)^{D_R} b_i \right), \boldsymbol{\beta}_R^{-1} \left((1-\delta)^{-D_{NR}} b_i \right) \mid c_i \right)
\end{aligned}$$

where $\bar{F}_{\boldsymbol{c}_{-i},j} (\cdot, \ldots, \cdot \mid c_i)$ is the partial derivative of the conditional survival function with respect to the j'th coordinate, $\beta_{NR,1}^{-1} (\cdot)$ is the partial derivative of a non-resident's inverse bid function with respect to its first coordinate, and $\beta_{R,1}^{-1} (\cdot)$ is the partial derivative of a resident's inverse bid function with respect to its first coordinate. These first order conditions form a system of differential equations that characterize the equilibrium bids.

Affiliation and bid preferences both have implications for equilibrium bidding in the second stage. Affiliation affects how aggressively bidders bid given their cost realization. Indeed, a bidder who draws a low (high) cost when costs are affiliated would be less (more) willing to bid higher than if costs were independent since affiliation makes it more likely that competing bidders have also drawn low (high) costs. Bid preferences drives a wedge between resident and non-resident bidders in the sense that residents will bid less aggressively than non-residents to account for the fact that residents have their bids discounted, and this wedge is amplified when costs are affiliated.[13] The interaction of these two forces determine the outcome of a preference auction.

A complete characterization of the bidding equilibrium requires a specification of boundary conditions. Following Hubbard and Paarsch (2009) and Krasnokutskaya and Seim (2011), four group specific boundary conditions are imposed.

[13]These effects hold under intermediate levels of affiliation relevant to this empirical setting. Numerical simulations reveal that bidders behave differently under more extreme forms of affiliation. In particular, bidders will know that their competitors have costs very similar to their own and will bid close to their cost for any cost draw.

4.2.1 Left Boundary Condition

The left boundary condition requires that bidders who draw the lowest project-completion cost submit the same bid when bid preferences are taken into account. Therefore, the left boundary condition for resident bidders is as follows:

$$\beta_R^{-1}\left(\frac{\underline{b}}{(1-\delta)}\right) = \underline{c}.$$

Likewise, the left boundary condition for non-resident bidders is

$$\beta_{NR}^{-1}\left(\underline{b}\right) = \underline{c}$$

where $\underline{b}$ is the common low bid.

4.2.2 Right Boundary Condition

The right boundary condition restricts bidding behavior at the highest possible project-completion cost draw. This condition can loosely be interpreted as bidders who draw the highest project-completion cost bid their project-completion costs while making any necessary adjustments for the group affiliation of the competing bidders. The right boundary condition for resident bidders is formally

$$\beta_R^{-1}\left(\overline{b}\right) = \overline{c}$$

where $\overline{b} = \overline{c}$ if $n_R > 1$ and $\overline{b} = \arg\max_b \left[(b - \overline{c}) \Pr\left((1-\delta)\, b < b_j \,\forall j \in NR \mid \overline{c}\right)\right]$ if $n_R = 1$. That is to say, if there is only one resident bidder on a project, she will choose a bid that maximizes her expected profits since the discount may lower her bid enough to be competitive with the non-resident bidders. The right boundary condition for non-resident bidders is

$$\beta_{NR}^{-1}\left(\overline{c}\right) = \overline{c}.$$

Observe that bid preference introduces another equilibrium feature mentioned by Hubbard and Paarsch (2009) and Krasnokutskaya and Seim (2011). In particular, if a non-resident draws a project-completion cost $c \in \left[(1-\delta)\,\overline{b}, \overline{c}\right]$, then she also bids her project-completion cost. Note that a project-completion cost draw in this region for a non resident will never win the auction, yielding a payoff of zero as long as the non-resident bidder does not bid below her cost. Since bidders are indifferent between not winning an auction and winning an auction with a bid equal to their cost, this assumption can be made without changing the equilibrium payoffs.

Existence and uniqueness of a bidding equilibrium is key in empirically implementing these types of auctions. Existence establishes that there is, in fact, a solution to the auction, while uniqueness establishes that the bidders are playing one equilibrium as opposed to potentially multiple different equilibria. Reny and Zamir (2004) show that a monotone pure strategy equilibrium exists in a more general setting than this type of auction. Uniqueness follows from Theorem 1 in Lebrun (2006) once addition structure is imposed on the conditional survival function.[14]

4.3 Entry

In the entry stage, firms make participation decisions based on their knowledge of the number of potential entrants of each group, their knowledge of their own entry cost k_i and their knowledge of the distributions of project-completion costs and bid-preparation costs. Ex ante expected profits are calculated as

$$\Pi_m\left(N_m, N_{-m}\right) = \sum_{n_m-1\subseteq N_m, n_{-m}\subseteq N_{-m}} \int_{\underline{c}}^{\overline{c}} \pi\left(c_i; n_m, n_{-m}\right) dF_c^m\left(c_i\right) \Pr\left(n_m-1, n_{-m} \mid N_m, N_{-m}\right)$$

where the $-m$ subscript indicates the bidders not affiliated with the group of bidder i and $F_c^m(\cdot)$ is the marginal project-completion cost distribution of group m.[15] These profits are only a function of the observed number of potential bidders since the number of potential bidders and the bid-preparation cost are the only payoff relevant information available before entry. Also note that the subscript is group specific since members of the same group face the same ex-ante expected profits. The group specific equilibrium entry probabilities p_m are determined by the known entry cost distribution. That is

$$p_m = \Pr\left(k_i < \Pi_m\right) = G_k^m\left(\Pi_m\right)$$

where $G_k^m(\cdot)$ is the marginal distribution of bid-preparation costs for a bidder in group m, and the above equality is formed using the equilibrium assumption of belief consistency. Existence of threshold probabilities p_m that satisfy the above equation are guaranteed through an application of Brouwer's fixed point theorem.[16]

[14] In particular, the conditional survival function must be log concave. This structure is assumed in section 5.1

[15] When computing these profits, there is a case where no competing bidders enter the auction. This case is problematic since the NMDOT does not explicitly post a reserve price. The NMDOT does, however, reserve the right to reject all bids if the lowest price is excessively high. To capture this power to reject bids, this paper follow Krasnokutskaya and Seim (2011) in assuming that firms compete against the government (represented by a resident bidder) when faced with no other competition.

[16] Uniqueness, however, is not guaranteed and must be verified through simulation.

5 Empirical Model and Estimation

While the theoretical model provides a foundation for understanding the market for NMDOT procurement contracts, it does not lend itself to estimation without further distributional assumptions. This section outlines those distributional assumptions needed to produce an empirical model that can be estimated from the data. First, methods in modeling affiliation using copulas are discussed. Next, the remaining distributional assumptions and estimation routine are specified. A discussion of how affiliation is parametrically identified through the estimation procedure is included at the end of this section.

5.1 Copula Representation

One difficulty in implementing empirical auction models with affiliation is dealing with the joint cost distribution. To overcome this difficulty, the empirical model relies on copula methods as developed by Hubbard, Li, and Paarsch (2012). Copulas are an expression of the joint distribution of random variables as a function of the marginals. Formally, if $c_1, c_2, \ldots, c_n$ are n possibly correlated random variables with marginal distributions $F_c^1(c_1), F_c^2(c_2), \ldots, F_c^n(c_n)$ respectively, then the joint distribution can be written as a function of the marginal distributions as

$$F_{\boldsymbol{c}}\left(c_1, c_2, \ldots, c_n\right) = \boldsymbol{C}\left[F_c^1\left(c_1\right), F_c^2\left(c_2\right), \ldots, F_c^n\left(c_n\right)\right]$$

where $C\left[\cdot, \ldots, \cdot\right]$ is the copula function.

The particular type of copula used to represent the joint cost distribution of resident and non-resident bidders is a Clayton copula. This type of copula has the following closed-form representation:

$$\boldsymbol{C}\left[F_c^1\left(c_1\right), F_c^2\left(c_2\right), \ldots, F_c^n\left(c_n\right)\right] = \left(\sum_{i=1}^{n} F_c^i\left(c_i\right)^{-\theta} - n + 1\right)^{-\frac{1}{\theta}}$$

where $\theta \in [-1, \infty) \setminus \{0\}$ is the dependence parameter. Besides having a tractable representation, Clayton copulas are useful in the sense that affiliation only requires θ to be greater than zero.[17] Moreover, θ has the nice interpretation that a higher value of θ implies a higher degree of affiliation between the random variables, so θ contains all of the relevant information on cost dependence.

Since this paper focuses on procurement auctions, the conditional survival function is the distribution of interest. Two results from Hubbard, Li, and Paarsch (2012) are used to construct an expression for the

[17] For a formal proof of this statement, see Muller and Scarsini (2005)

conditional survival function using copulas:

Result 1:

The survival function, $\bar{F}_{\boldsymbol{c}}(c_1, c_2, \ldots, c_n)$, can be written as

$$\begin{aligned}
\bar{F}_{\boldsymbol{c}}(c_1, c_2, \ldots, c_n) &= \Pr(C_1 > c_1, C_2 > c_2 \ldots, C_n > c_n) \\
&= 1 - \sum_{i=1}^{n} \Pr(C_i < c_i) + \sum_{1 \le i < j \le n} \Pr(C_i < c_i, C_j < c_j) \\
&- \cdots + (-1)^n \Pr(C_1 < c_1, C_2 < c_2 \ldots, C_n < c_n).
\end{aligned}$$

This result provides an expression of the survival function in terms of the cumulative density function (CDF) which has a copula representation. Let $\boldsymbol{S}\left[1 - F_c^1(c_1), 1 - F_c^2(c_2), \ldots, 1 - F_c^n(c_n)\right]$ denote the survival copula evaluated at the survival marginals. The first result shows that the survival copula can be expressed as follows:

$$\begin{aligned}
\boldsymbol{S}\left[1 - F_c^1(c_1), 1 - F_c^2(c_2), \ldots, 1 - F_c^n(c_n)\right] &= 1 - \sum_{i=1}^{n} \boldsymbol{C}\left[F_c^i(c_i)\right] + \sum_{1 \le i < j \le n} \boldsymbol{C}\left[F_c^i(c_i), F_c^j(c_j)\right] \\
&- \cdots + (-1)^n \boldsymbol{C}\left[F_c^1(c_1), \ldots, F_c^n(c_n)\right].
\end{aligned}$$

Result 2:

$\Pr(C_2 > c_2 \ldots, C_n > c_n \mid c_1) = \boldsymbol{S}_1\left[1 - F_c^1(c_1), 1 - F_c^2(c_2), \ldots, 1 - F_c^n(c_n)\right]$ where $\boldsymbol{S}_1[\cdot, \ldots, \cdot]$ is the partial derivative of the survival copula with respect to the first coordinate.

Result 2 shows that the conditional survival copula is equivalent to the partial derivative of the full survival copula with respect to the conditioning argument.

Given these two results, the second stage profits of bidder 1 can be rewritten using copulas as

$$\begin{aligned}
\pi(c_1; n_{NR}, n_R) &= \max_{b_1}(b_1 - c_1) \\
&\times \boldsymbol{S}_1\left[1 - F_c^{m_1}(c_1), 1 - F_c^{NR}\left(\beta_{NR}^{-1}\right), \ldots, 1 - F_c^{NR}\left(\beta_{NR}^{-1}\right), 1 - F_c^{R}\left(\beta_R^{-1}\right), \ldots, 1 - F_c^{R}\left(\beta_R^{-1}\right)\right]
\end{aligned}$$

where m_1 is the group affiliation of bidder 1, $\beta_{NR}^{-1} = \beta_{NR}^{-1}\left((1-\delta)^{D_R} b_1\right)$, and $\beta_R^{-1} = \beta_R^{-1}\left((1-\delta)^{-D_{NR}} b_1\right)$.

The first order conditions are now given by

$$
\begin{aligned}
& \boldsymbol{S}_1\left[1-F_c^{m_1}\left(c_1\right), 1-F_c^{NR}\left(\beta_{NR}^{-1}\right), \ldots, 1-F_c^{NR}\left(\beta_{NR}^{-1}\right), 1-F_c^{R}\left(\beta_{R}^{-1}\right), \ldots, 1-F_c^{R}\left(\beta_{R}^{-1}\right)\right] \\
= & \left(b_1-c_1\right)\Bigg[\left(n_{NR}-D_{NR}\right)\beta_{NR,1}^{-1}\left(1-\delta\right)^{D_R} f_c^{NR}\left(\beta_{NR}^{-1}\right) \\
& \times\boldsymbol{S}_{12}\left[1-F_c^{m_1}\left(c_1\right), 1-F_c^{NR}\left(\beta_{NR}^{-1}\right), \ldots, 1-F_c^{NR}\left(\beta_{NR}^{-1}\right), 1-F_c^{R}\left(\beta_{R}^{-1}\right), \ldots, 1-F_c^{R}\left(\beta_{R}^{-1}\right)\right] \\
& +\left(n_R-D_R\right)\beta_{R,1}^{-1}\left(1-\delta\right)^{-D_{NR}} f_c^{R}\left(\beta_{R}^{-1}\right) \\
& \times\boldsymbol{S}_{1n}\left[1-F_c^{m_1}\left(c_1\right), 1-F_c^{NR}\left(\beta_{NR}^{-1}\right), \ldots, 1-F_c^{NR}\left(\beta_{NR}^{-1}\right), 1-F_c^{R}\left(\beta_{R}^{-1}\right), \ldots, 1-F_c^{R}\left(\beta_{R}^{-1}\right)\right]\Bigg]
\end{aligned} \tag{1}
$$

where $f_c^m(\cdot)$ is the marginal probability density function (PDF) associated with the marginal CDF $F_c^m(\cdot)$.

5.2 Parametric Specifications

The size of the data requires that a parametric approach be taken in estimating the theoretical model. For this purpose, an auction, indexed by w, is taken to be characterized by the vector of observables $(\boldsymbol{x}_w, \boldsymbol{z}_w, n_{Rw}, n_{NRw}, N_{Rw}, N_{NRw})$ where $\boldsymbol{x}_w$ is a vector of auction-level observables that affect project-completion costs, $\boldsymbol{z}_w$ is a vector of auction-level observables that affect bid-preparation costs, n_{Rw} and n_{NRw} are the observed number of resident and non-resident entrants respectively and N_{Rw} and N_{NRw} are the advertised number of potential resident entrants and non-resident entrants respectively. The group-specific marginal distributions of project-completion costs conditional on $\boldsymbol{x}_w$ are given by $F_c^m(\cdot \mid \boldsymbol{x}_w)$, and the group-specific marginal distribution of bid-preparation costs conditional on $\boldsymbol{z}_w$ are given by $G_k^m(\cdot \mid \boldsymbol{z}_w)$.

Parametric assumptions on the probability firms assign to the entry of competing firms are required to address entry. To this end, entry probabilities $p_{mw}(\boldsymbol{x}_w, \boldsymbol{z}_w, N_{Rw}, N_{NRw})$ are taken to be characterized by a binomial distribution:

$$
\Pr\left(n_{Rw}, n_{NRw} \mid \boldsymbol{x}_w, \boldsymbol{z}_w, N_{Rw}, N_{NRw}\right) = \Pr\left(n_{Rw} \mid \boldsymbol{x}_w, \boldsymbol{z}_w, N_{Rw}, N_{NRw}\right) \times \Pr\left(n_{NRw} \mid \boldsymbol{x}_w, \boldsymbol{z}_w, N_{Rw}, N_{NRw}\right)
$$

where

$$
\Pr\left(n_{mw} \mid \boldsymbol{x}_w, \boldsymbol{z}_w, N_{mw}, N_{-mw}\right) = \begin{pmatrix} N_{mw} \\ n_{mw} \end{pmatrix} \left(p_{mw}\right)^{n_{mw}} \left(1-p_{mw}\right)^{N_{mw}-n_{mw}}
$$

and

$$p_{mw} = G_k^m \left(\Pi_{mw} \left(\boldsymbol{x}_w, N_{mw}, N_{-mw}\right) \mid \boldsymbol{z}_w\right). \tag{2}$$

This assumption on entry probabilities means that each firm calculates the probability that firms in their group and firms in their competing group enter the auction given their knowledge of the project-completion and entry cost distributions. Observe that equation 2 comes from the equilibrium condition that beliefs are consistent.

A complication that arises in empirically implementing the theoretical model is the presence of the inverse bid function in the first order conditions of the second-stage bidding problem. This complication requires that the inverse bid function be approximated for every set of second-stage parameter guesses. To address that issue, this paper relies on approximations based on indirect methods introduced by (Guerre, Perrigne, and Vuong, 2000, henceforth abbreviated GPV) further extended by Krasnokutskaya (2011) for the case of unobserved auction heterogeneity and Hubbard, Li, and Paarsch (2012) for the case of affiliation using copulas. In particular, a firm's cost can be inferred from the observed bid distribution by noting that $F_b^m(b) = F_c^m\left(\beta_m^{-1}(b)\right)$ and $f_b^m(b) = f_c^m\left(\beta_m^{-1}(b)\right)\beta_{m,1}^{-1}(b)$.[18] Making these substitutions in the first order conditions of the second stage bidding problem obviates the need for estimating the inverse bid function when determining project-completion costs. As a result, the empirical model will now focus on the marginal distribution of bids, $F_b^m(\cdot \mid \boldsymbol{x}_w)$, instead of the marginal distribution of project-completion costs, $F_c^m(\cdot \mid \boldsymbol{x}_w)$.

The final set of distributional assumptions are placed on the distribution of bids and bid-preparation costs. In order to have positive bids and allow for affiliation, the log of the submitted bids is modeled as follows:

$$\log\left(b_{iw}\right) = \boldsymbol{x}_{iw}'\beta + \epsilon_{iw}^{m_i}$$

where

$$\epsilon_{iw}^{m_i} \mid \boldsymbol{x}_{iw} \sim \mathcal{N}\left(0, \exp\left(\boldsymbol{x}_{iw}'\sigma\right)^2\right)$$

$$\left(\epsilon_{1w}^{NR}, \ldots, \epsilon_{n_{NR}w}^{NR}, \epsilon_{n_{NR+1}w}^{R}, \ldots, \epsilon_{n_{NR}+n_Rw}^{R} \mid \boldsymbol{x}_{iw}\right) \equiv \boldsymbol{\epsilon}_w \sim F_{\boldsymbol{\epsilon}_w}$$

$$F_{\boldsymbol{\epsilon}_w} = \boldsymbol{C}\left[F_{\epsilon_{1w}^{NR}}, \ldots, F_{\epsilon_{n_{NR}w}^{NR}}, F_{\epsilon_{n_{NR+1}}^{R}}, \ldots, F_{\epsilon_{n_{NR}+n_R}^{R}}\right].$$

Likewise, the bid-preparation costs are assumed to take the following form:

[18] For a complete description on how to approximate the inverse bid functions using GPV (2000) in this setting, see the appendix.

$$\log(k_{iw}) = \boldsymbol{z}'_{iw}\gamma + u^{m_i}_{iw}$$

where

$$u^{m}_{iw} \mid \boldsymbol{z}_{iw} \sim \mathcal{N}\left(0, \exp(\boldsymbol{z}'_{iw}\alpha)^2\right).$$

5.3 Estimation

The parameters of the empirical model are estimated using a generalized method of moments (GMM) approach. The theoretical predictions of the empirical model are essentially matched to the data by selecting the parameter values that minimize the weighted distance between model moments and data moments. This subsection gives a general overview of how the moment conditions are constructed and used in estimation. For a more detailed explanation on how the moments are derived from the empirical model, see the appendix.

The first set of moment conditions are used to identify the parameters of the bid distribution. These moment conditions are

$$E\left[\boldsymbol{x}_{iw}\left(\log(b_{iw}) - \boldsymbol{x}'_{iw}\beta\right)\right] = 0 \tag{3}$$

and

$$E\left[\boldsymbol{x}_{iw}\left(\log(b_{iw}) - \boldsymbol{x}'_{iw}\beta\right)\left(\log(b_{iw}) - \boldsymbol{x}'_{iw}\beta\right)\right] = E\left[\boldsymbol{x}_{iw}\exp(\boldsymbol{x}'_{iw}\sigma)^2\right]. \tag{4}$$

Observe that equation 4 yields the standard deviation parameter, σ, and equations 3 and 4 yield the mean parameter, β.

In addition to identifying the parameters of the marginal distributions, the affiliation parameter, θ, must also be identified through the moment conditions of the model. This parameter is estimated by relying on methods developed by Oh and Patton (2013) to estimate copulas using method of moments. In particular, the degree of dependence between two random variables can be summarized by a statistic called Kendall's tau. This statistic's equation for Clayton copulas together with its closed form solution motivate the following moment condition:

$$\frac{\theta}{\theta+2} = 4E\left[\boldsymbol{C}\left[\Phi\left(\frac{\log(b_{iw}) - \boldsymbol{x}'_{iw}\beta}{\exp(\boldsymbol{x}'_{iw}\sigma)}\right), \Phi\left(\frac{\log(b_{jw}) - \boldsymbol{x}'_{jw}\beta}{\exp\left(\boldsymbol{x}'_{jw}\sigma\right)}\right)\right]\right] - 1 \quad i \neq j \tag{5}$$

where $\Phi(\cdot)$ is the standard normal CDF.

The last set of moment conditions are used to identify the parameters of the unobserved bid-preparation cost distribution. These moment conditions are

$$E\left[n_{mw}\right]=\int N_{mw}p_{mw}dF\left(\boldsymbol{x}_w,\boldsymbol{z}_w,N_{mw},N_{-mw}\right), \tag{6}$$

$$E\left[n_{mw}^2\right] = \int N_{mw}p_{mw}\left(1-p_{mw}\right)+N_{mw}^2p_{mw}^2dF\left(\boldsymbol{x}_w,\boldsymbol{z}_w,N_{mw},N_{-mw}\right), \tag{7}$$

$$\begin{aligned} E\left[n_{mw}^3\right] &= \int N_{mw}p_{mw}\Big(1-3p_{mw}+3N_{mw}p_{mw}+2p_{mw}^2-3N_{mw}p_{mw}^2 \\ &+ N_{mw}^2p_{mw}^2\Big)dF\left(\boldsymbol{x}_w,\boldsymbol{z}_w,N_{mw},N_{-mw}\right), \end{aligned} \tag{8}$$

and

$$\begin{aligned} E\left[n_{mw}^4\right] &= \int N_{mw}p_{mw}\Big(1-7p_{mw}+7N_{mw}p_{mw}+12p_{mw}^2-18N_{nw}p_{mw}^2+6N_{mw}^2p_{mw}^2 \\ &- 6p_{mw}^3+11N_{mw}p_{mw}^3-6N_{mw}^2p_{mw}^3+N_{mw}^3p_{mw}^3\Big)dF\left(\boldsymbol{x}_w,\boldsymbol{z}_w,N_{mw},N_{-mw}\right) \end{aligned} \tag{9}$$

where

$$p_{mw}=G_k^m\left(\Pi\left(\boldsymbol{x}_w,N_{mw},N_{-mw}\right)\mid \boldsymbol{z}_w\right)$$

is the group-specific entry probability. These moment conditions are derived from the assumption that entry is dictated by a joint binomial distribution where the probabilities bidders assign to entry is consistent with the actual entry probabilities.

5.4 Parametric Identification

Given that part of the estimation strategy aims to measure affiliation, it is suitable to briefly discuss how the affiliation parameter is identified from the data. In that light, there are two pathways through which the affiliation parameter is identified in estimation. The first pathway is through the dependence of bids as measured by Kendall's tau; if the observed bids tend to be positively dependent conditional on the observables, then the model will attribute that dependence to the affiliation parameter. The second pathway is through the entry probabilities of firms, specifically through the computation of the ex-ante profits in the entry probabilities. These profits represent the expected benefit from entering the auction and are subject to change depending on the degree of affiliation between project-completion costs. Changing the ex-ante profits will therefore change the entry probability of firms, aiding in the identification of the affiliation parameter.

6 Empirical Results

This section presents the empirical findings from the NMDOT highway procurement data. Descriptive summary statistics and reduced-form regressions are first shown to highlight some of the main patterns in the data relevant to residency status and firm bidding and entry behavior. Next, the structural parameter estimates from the empirical model are displayed and interpreted. These estimates suggest affiliation among bidder project-completion costs and higher entry costs for resident firms relative to non-resident firms.

6.1 Summary Statistics

Table 1: Summary Statistics for New Mexico Highway Construction Projects

	Federal-Aid Projects	State Projects	All Projects
Number of Contracts	353.00	23.00	376.00
Average Bid (in 1000s)	4068.05	5469.58	4156.93
Average Engineer's Estimate (in 1000s)	3679.79	4628.75	3737.84
Average Resident Planholders	9.50	9.91	9.52
Average Resident Bidders	2.97	3.39	3.00
Average Non-Resident Planholders	2.34	2.22	2.33
Average Non-Resident Bidders	1.17	0.91	1.15
Fraction of Projects by Type of Road:			
Federal Highway	0.59	0.52	0.59
Other Road	0.41	0.48	0.41
Fraction of Projects by Type of Work:			
Road Work	0.61	0.52	0.60
Bridge Work	0.20	0.09	0.19
Other Work	0.20	0.39	0.21

Table 1 contains the summary statistics for all highway procurement contracts in the sample tabulated by the source of funding. For each auction, the following project characteristics are observed: an engineer's estimated cost, the number of projected working days, the nature and location of the work, the number of licenses required, the length in miles, and the number of bidders and planholders. Additionally, the number of subprojects[19] are observed as well as any Disadvantaged Business Enterprise (DBE) subcontracting requirements. Residency status and entry decisions are observed at the firm level.

The top panel of table 1 summarizes the average estimated cost, bid, number of potential entrants, and number of actual entrants. Relative to federal-aid projects, state-funded projects are slightly larger and more expensive on average. The average estimated cost across state-funded projects exceeds that of federal-aid projects by about $\$949,000$, while the bids received on state-funded projects are about $\$1,401,000$ higher than the bids received on federal-aid projects. Across the potential and actual entrant dimensions, federal-aid and state-funded projects are similar, attracting around the same average number of resident and non-resident planholders and bidders.

The remaining portion of table 1 separates state and federal aid projects by the type of road and the nature of the work requested. The nature of work is separated into three mutually exclusive categories: road work, bridge work, and other work. State and federal-aid projects are similar in terms of their location; roughly $50-60$ percent of work is conducted on federal highways. State and federal-aid projects differ, however, in the nature of the work requested. Relative to federal-aid projects, state-funded projects require less road and bridge work while work falling into neither of these categories is relatively higher.

6.2 Descriptive Regressions

In order to understand the different bidding patterns in the data, a descriptive difference-in-differences regression analysis is performed on the log bids of all entering firms. This regression takes the form

$$\log(b_{iw}) = \beta_1 NM_w + \beta_2 RESIDENT_i + \beta_3 NM_w \times RESIDENT_i + \psi' \mathbf{X}_w + \epsilon_{iw}$$

where b_{iw} is the submitted bid for firm i in auction w, NM_w is an indicator variable that takes on a value of one if the project is state-funded, $RESIDENT_i$ is an indicator variable that takes on a value of one if the bidder qualifies for resident preferences, and $\mathbf{X}_w$ is a vector of project characteristics.[20] The error terms, ϵ_{iw}, account for clustering at the project level in order to allow for auction level correlations across bids. Here the main object of interest in this specification is the sum of the β_2 and β_3 parameters; this sum captures the difference in how resident and non-resident firms bid in a preference auction holding all other observables constant.

[19] A subproject is a smaller portion of the main project. For example, if a roadway rehabilitation project requires the installation of a fence, the fence installation would be a subproject of the main roadway rehabilitation project.

[20] Consistent with the theoretical assumptions, this regression does not address selection. To see why, note the model takes entry costs and project-completion costs as draws from independent distributions. Since ex-ante profits and entry costs do not depend on the realized project-completion cost, the bidding decision is independent of the entry decision.

The bid regression is further separated into three distinctive specifications – each allowing for a different number of fixed effects. The first regression specification has no fixed effects, while the second specification allows for month, year, and district fixed effects. These fixed effects account for monthly and yearly trends in the data as well as differences across administrative districts. The final specification includes contract fixed effects as a means of controlling for unobserved project heterogeneity.

Table 2: OLS Regression on Bids

	Dependent variable:		
	log(Bid)		
	(1)	(2)	(3)
Resident	-0.019^{**}	-0.019^{**}	-0.021^{**}
	(0.009)	(0.009)	(0.010)
New Mexico Project	-0.151^{**}	-0.158^{**}	
	(0.068)	(0.068)	
log(Engineer's Estimate)	0.933^{***}	0.930^{***}	
	(0.019)	(0.018)	
log(Working Days)	0.054^{**}	0.042^{*}	
	(0.021)	(0.023)	
Urban	-0.068^{***}	-0.052^{**}	
	(0.017)	(0.023)	
Number of Licenses Required	0.022	0.028^{*}	
	(0.017)	(0.017)	
log(Length+1) (in miles)	0.021	0.024	
	(0.015)	(0.015)	
DBE Goal (%)	−0.006	−0.003	
	(0.004)	(0.004)	
log(Subprojects)	0.038^{*}	0.040^{*}	
	(0.023)	(0.024)	
Federal Highway	−0.013	−0.028	
	(0.018)	(0.017)	
Resident × NM Project	0.116^{*}	0.115^{*}	0.112^{**}
	(0.065)	(0.064)	(0.050)
District/Month/Year FEs		X	
Project FEs			X
Observations	1,561	1,561	1,561
Adjusted R^2	0.974	0.976	0.986

Note: *p<0.1; **p<0.05; ***p<0.01
Descriptive OLS regressions of the submitted bids. Each regression specification has controls for the type of work requested, the number of resident and non-resident bidders, and the number of resident and non-resident planholders. Errors are clustered at the project level.

The results from each regression specification are reported in table 2. The first column indicates that residents bid 9.7 percent higher than non-residents on state-funded projects conditional on the observables. As additional fixed effects are added in columns 2 and 3, this effect diminishes slightly but remains more or less the same, decreasing to 9.6 percent with the addition of month, year, and district fixed effects and 9.1 percent with the addition of contract fixed effects. A caveat to this finding, though, is that some of these reduced-form differences in bidding patterns could also be attributed to differences in how residents and non-residents bid on state-funded projects independent of how bids are discounted. Without additional variation in the preference level, it is difficult to evaluate these other sources of variation without relying on the theoretical implications of the empirical model.

In order to analyze potential differences in entry behavior, a probit regression is estimated as a model of a firm's entry decision. The dependent variable is the decision of a firm to enter an auction, and project characteristics as well as the number of resident and non-resident planholders are included as covariates. As with the bid regression, the entry regression is separated into three specifications. Relative to the first specification, the second specification includes additional controls for the location of the project as well as controls for the month and year the project was awarded. These additional controls account for changes in entry due to a project's location and award date. The third specification consists of project-level dummies to the address project-specific entry differences. In all three specifications, the errors account for clustering at the project level.

Table 3: Entry Regression

	Dependent variable:		
	Entry		
	(1)	(2)	(3)
Resident	−0.202***	−0.204***	−0.211***
	(0.020)	(0.020)	(0.020)
New Mexico Project	−0.056	−0.072	
	(0.065)	(0.065)	
Resident × NM Project	0.092	0.113	0.102
	(0.080)	(0.081)	(0.087)
District/Month/Year Effects		X	
Project Effects			X
Observations	4,456	4,456	4,456

Note: *p<0.1; **p<0.05; ***p<0.01
The table reports the marginal effects from a probit model of bidder entry decisions. All regression specifications have controls for the project characteristics, resident and non-resident planholders, and the type of work requested. Errors are clustered at the project level.

The marginal effects of the probit regression are reported in table 3. The marginal effects suggest that, across all three specifications, residents have a lower propensity to enter auctions relative to non-residents conditional on attaining planholder status. Residents have an increased propensity to enter when the auction is a preference auction relative to a non-preference auction, though. The theoretical model provides two explanations for these lower resident entry rates: either residents have lower expected profits for participating in a project, or residents have higher bid-preparation costs. Given that ex-ante profits and entry costs are not observed in the data, it is tough to judge the relative influence of these separate explanations.

6.3 Structural Estimates

The estimated empirical model is used to disentangle strategic participation and bidding decisions. Both preference and non-preference auctions are used in estimation, but projects with 20 or more planholders are dropped for computational reasons – amounting to 1 state-funded project and 10 federally-funded projects. In order to mitigate the effect of unobserved project heterogeneity on submitted bids, the number of potential entrants in each group are used in the set of control variables. The idea behind these controls is that unobservable project characteristics may attract more potential entrants, which is reflected in the number of planholders for each project. A rich set of project controls are also used so that the correlation in submitted bids is primarily generated through affiliation in costs as opposed to unobserved project characteristics that are common knowledge to the bidders.

Table 4 contains the parameter estimates for the bid distribution. The difference in the log bids of residents and non residents is found to be small and statistically insignificant; residents only bid 1 percent less than non-residents across procurement projects. Conversely, the affiliation parameter estimate is positive and statistically significant, which indicates the presence of affiliation in firm project-completion costs.

In order to evaluate differences in the marginal resident and non-resident project-completion costs, methods of bid inversion developed by GPV (2000) are used on the estimated bid distributions. These methods use the equilibrium bid distributions in conjunction with the first-order conditions on optimal bidding to back out the cost associated with an observed bid. Heterogeneity in project characteristics will result in different marginal cost distributions for each separate project in the data. To keep the analysis concise, resident and non-resident marginal cost distributions are calculated for two types of projects: one project with the average characteristics of a preference project and one project with the average characteristics of a non-preference project. For each of these projects, bids are simulated from the estimated marginal bid distributions and inverted to obtain costs using the average number of resident and non-resident bidders as the number of participants and taking into account the estimated affiliation parameter. The marginal cost distribution is

Table 4: Estimated Parameters for the Log-Bid Distribution

	Coefficient	Standard Error
Constant	0.849	0.175
Resident	-0.011	0.011
New Mexico project	-0.034	0.069
log(Engineer's Estimate)	0.913	0.020
log(Length+1) (in miles)	0.038	0.015
log(Working Days)	0.070	0.023
Resident Planholders	0.001	0.004
Non-Resident Planholders	-0.005	0.007
Bridge Work	-0.021	0.033
Road Work	-0.0001	0.034
Number of Licenses Required	0.013	0.019
Federal Highway	-0.004	0.021
Urban	-0.044	0.018
DBE Goal(%)	-0.008	0.004
log(Subprojects)	0.077	0.025
Standard Deviation Parameters		
Constant	0.697	0.325
Resident	0.263	0.707
log(Engineer's Estimate)	-0.180	0.030
Affiliation Parameter		
Theta	0.831	0.189

Note : Standard deviation of the bid distribution is estimated as $\sigma = \exp(b_0 + b_1 resident + b_2 engineer)$ where *resident* is an indicator for being a resident bidder and *engineer* is the log of the enginner's estimate.

estimated non-parametrically with a kernel density estimator, yielding a marginal cost CDF for both types of bidders.

Figure 1 displays the different marginal project-completion cost CDFs for the average preference and non-preference project. As evidenced by the shape of the CDFs and consistent with the observed marginal bid distributions, residents have a more disperse cost distribution than non-residents across projects. Also, no one cost distribution first order stochastically dominates the other in any of the average projects, which can lead to ambiguity in the ranking of resident and non-resident firms in terms of cost efficiency.

Turning to firm entry costs, table 5 presents the estimated parameters for the log-normal entry cost distribution. The entry parameters have the expected signs and magnitudes although some of the parameters are statistically insignificant due to high standard errors relative to the bid distribution parameters. The entry parameters suggest noticeable differences among resident and non-resident costs of entry. Residents have higher average entry costs compared to non-residents and more variation in these entry costs.[21] A

[21] Recall that these parameter estimates are the mean and variance of the natural logarithm of bids. The mean of the actual

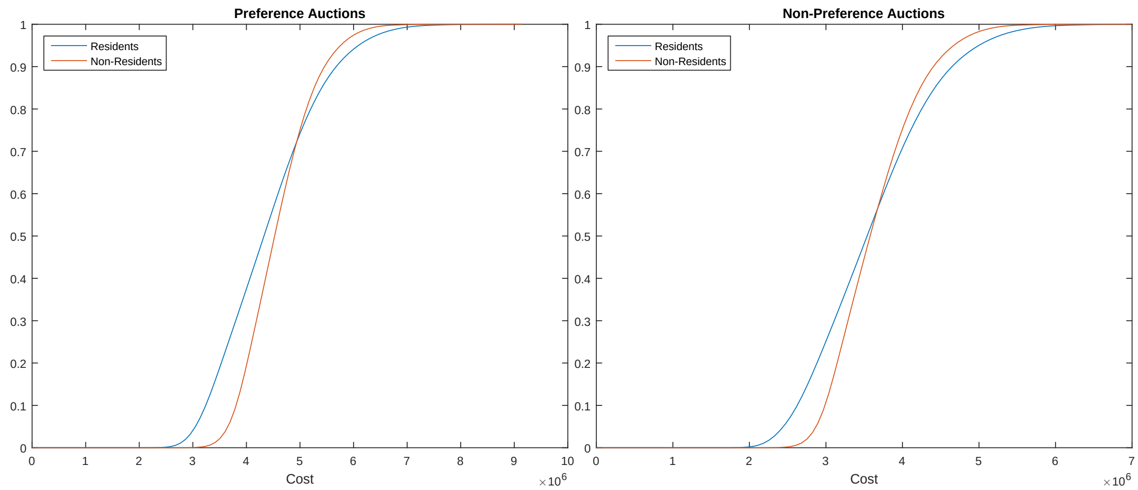

Figure 1: Kernel Density Estimates of the Marginal Cost CDFs for the Average Preference and Non-Preference Auctions

Table 5: Estimated Parameters for the Log-Entry Cost Distribution

	Coefficient	Standard Error
Constant	-0.121	0.800
log(Engineer's Estimate)	0.565	0.757
Resident	2.256	0.410
Resident Planholders	0.228	0.994
Non-Resident Planholders	0.109	0.244
Standard Deviation Parameters		
Constant	-0.589	0.190
Resident	1.854	0.301

Note : Standard deviation of the entry distribution is estimated as $\alpha = \exp(b_0 + b_1 resident)$ where *resident* is an indicator for being a resident bidder.

plausible explanation for these differences is that there may be a separate entry process into planholder status that selects non-resident firms who have innately lower bid-preparation costs, which is outside the scope of the data and model. The parameter estimates are nonetheless consistent with the lower conversion rate of potential resident bidders into actual bidders observed in the data.

distribution of bids is calculated as $\exp\left(\mu + \frac{\sigma^2}{2}\right)$ while the variance is $\left(\exp\left(\sigma^2\right) - 1\right)\exp\left(2\mu + \sigma^2\right)$ where μ is the mean of the natural logarithm of the bids and σ is the standard deviation of the natural logarithm of the bids.

7 Counterfactual Analysis

This section contains counterfactual policy experiments using the structural parameter estimates from section 6.3. Given the computational burden associated with calculating equilibrium bid functions, the counterfactual section focuses on a representative construction project qualifying for preference in the data.[22] This section first explores how affiliation and bid preferences affect bidding under fixed participation; then, bidder responses to different discount levels are compared under the estimated level of affiliation and independence, allowing for endogenous entry decisions.

A number of steps are taken to simulate counterfactual bidding and entry behavior. First, the underlying marginal project-completion cost distributions, F_c^R and F_c^{NR}, are estimated nonparametrically by inverting a large number of bids drawn from the bid distribution implied by the empirical model using GPV (2000).[23] These group-specific cost distributions are primitives of the model and are fixed across all counterfactual policies and affiliation levels. Next, the equilibrium inverse bid functions are estimated and inverted using a modified version of the third algorithm found in Bajari (2001), which essentially approximates inverse bid functions using polynomials.[24] The estimated bid functions and project-completion cost distributions together with the entry cost distributions determine ex-ante profits, and, when entry is endogenous, the entry decisions are simulated given the entry cost draws and the group-specific ex-ante profits. For entrants, project-completion costs are drawn from an affiliated distribution using methods described in Marshall and Olkin (1988), and the bid functions are applied to the costs to determine the counterfactual bids. For the auction simulations across discount levels, the number of potential entrants is set to the average preference auction level of 10 resident and 2 non-resident bidders, but the simulated number of entrants can vary given draws of the entry costs. A total of $1,000$ auctions are simulated for each grid point in a grid of preferences to generate the outcomes across discount levels.

7.1 Affiliation, Bid Preferences, and Optimal Bidding

As a first step in understanding how affiliation interacts with bid preferences, the numerical methods are used to approximate bid functions under fixed participation and varying degrees of preference and cost

[22] To construct this project, the average of all numerical observables on projects qualifying for preference are taken as the representative project characteristics. For categorical variables, the most common category is used as the representative category.

[23] Note that the marginal project-completion cost distribution will depend on the number of bidders and must be truncated to be consistent with the theory. Following Athey et al. (2013), a common configuration of three resident entrants and one non-resident entrant is used to determine the marginal project-completion cost distribution. To deal with truncation, the support of the nonparametric project-completion cost distribution is truncated to an interval large enough to contain $10,000$ randomly generated project-completion costs, corresponding to an interval with lower bound $\$1,851,500$ and upper bound $\$9,257,500$ for the representative construction project.

[24] See the appendix for a detailed explanation of how the bid functions are estimated

dependence. The bid functions use the cost distributions and average number of participants associated with the representative preference contract, comparing bids under the estimated affiliation parameter with counterfactual bids under independence. To investigate the impact of bid preferences, bid functions are further compared across auctions with the 5 percent preference policy and auctions without any preference.

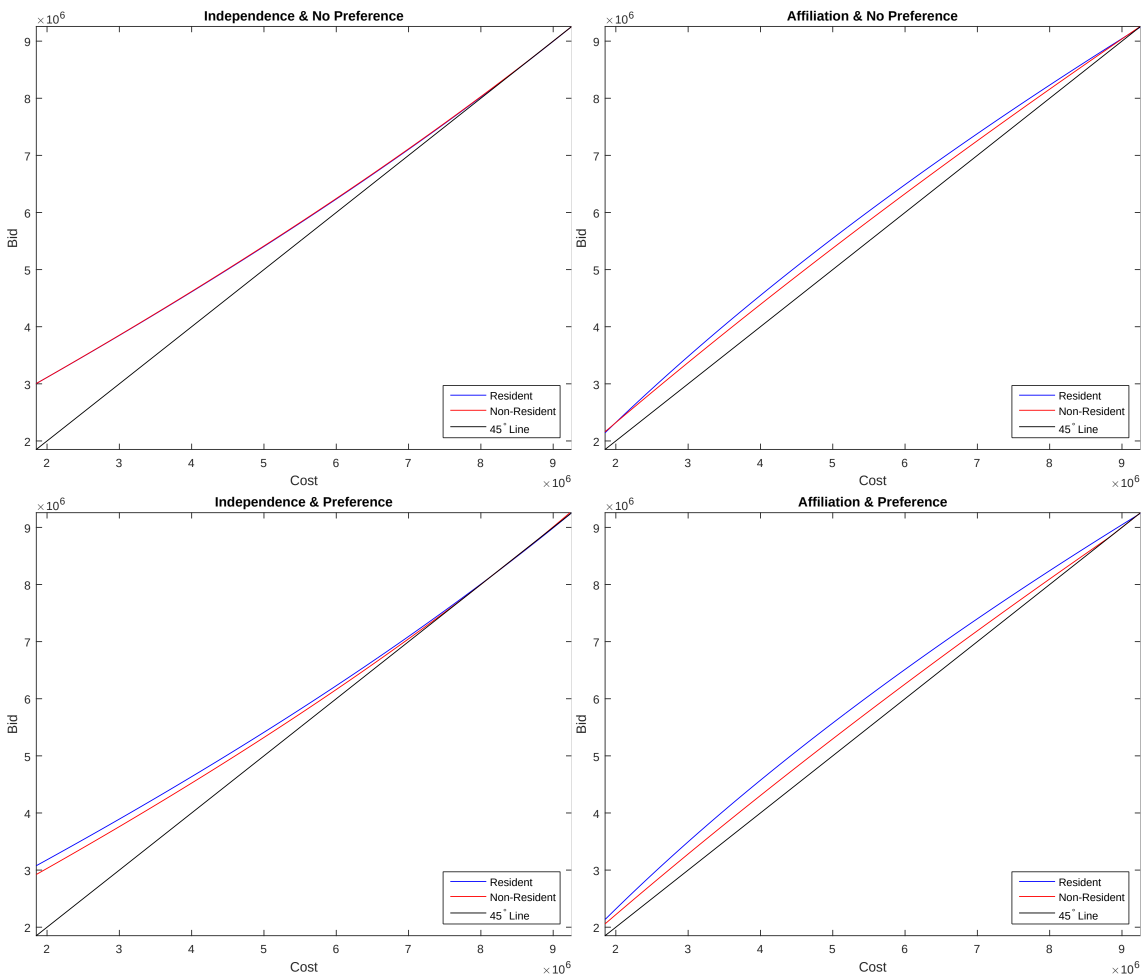

Figure 2: Bid Functions under Fixed Participation ($n_R = 3$, $n_{NR} = 1$)

Figure 2 presents the equilibrium bid functions. There are a couple of changes affiliation in project-completion costs introduces into procurement auctions with bid preferences relative to independent project-completion costs. One change is that affiliation causes bidders to bid more aggressively for low project-completion cost draws and less aggressively for high project-completion cost draws independent of the level of preference. The intuition here is that when a bidder draws a low project-completion cost in an auction with affiliation, other bidders are more likely to draw low project-completion costs, implying that bidding should be more aggressive. The same logic can be applied to a high project-completion cost draw in that bidding should be less aggressive in an auction with affiliation since other bidders are more likely to have drawn high project-completion costs. Affiliation also changes the difference between how preferred and non-preferred bidders submit bids in preference auctions. Bid preferences drive a wedge between preferred and non-preferred bidders, meaning that preferred bidders bid more with the same project-completion cost than a non-preferred bidder with the same cost. Affiliation accentuates this difference for most project-completion cost draws since these costs are more likely to be similar.

7.2 Alternative Discount Rates

Although New Mexico offers a 5 percent discount for its resident bidders, the discount level for preferred bidders can vary across states and the type of good being procured. Different discount levels will have different implications for the participation and bidding behavior of firms, and these changes in behavior are investigated for the representative construction project using the structural parameter estimates in conjunction with the project-completion cost distribution estimates.

Figure 3 shows the how the procurement cost, the fraction of preferred winners, and the expected participation changes across affiliation and preference levels. Increasing the discount level increases the average procurement cost in these preference auctions. Specifically, an increase in the discount rate from 0 percent to its current level of 5 percent increases the average procurement cost of the representative construction project by 1.8 percent under affiliation. This increase is less than the 6 percent increase in procurement costs that comes from affiliation at the current discount level relative to independence. Also, affiliation leads to a lower expected participation rate of both groups of bidders, which can explain the higher average procurement costs. Despite the lower overall participation, though, affiliation results in a higher proportion of resident winners across all counterfactual discount levels relative to independence. A higher proportion of resident winners is also a result of increasing the discount level under the estimated level of affiliation.

Taken together, these simulations suggest that the discount rate can be used as a mechanism to increase the proportion of contracts won by resident bidders at the expense of higher procurement costs. Relative to the independence case, affiliation leads to higher expected procurement costs, a higher proportion of resident winners, and lower expected participation. These differences illustrate the significance of affiliation in public procurement.

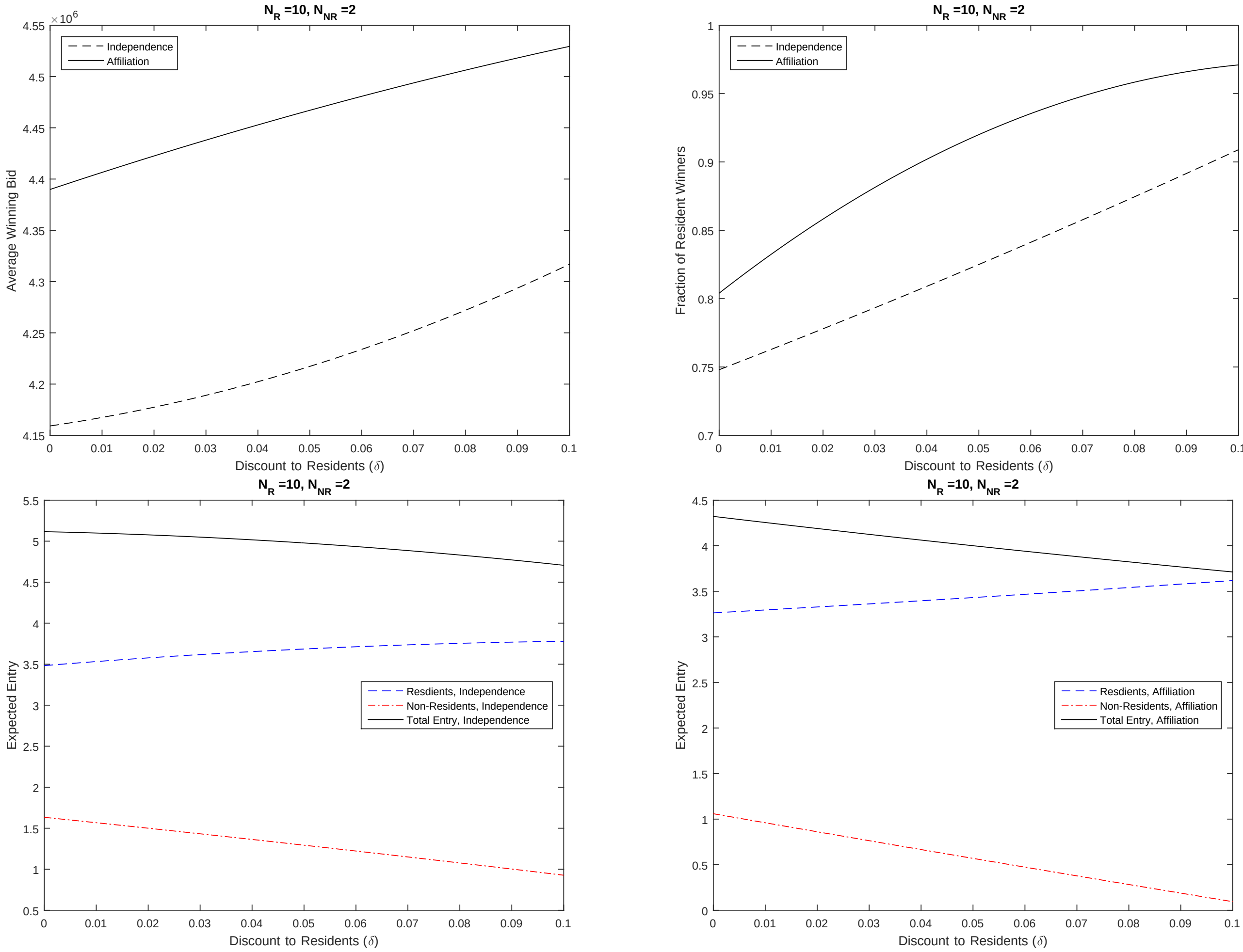

Figure 3: Average Winning Bid, Fraction of Resident Winners, and Entry under Alternative Discount Rates

8 Conclusion

This paper empirically examines the presence of affiliation and its effect on procurement auctions in an environment where bid discounts are offered to preferred bidders. The focus of the analysis is on NMDOT construction contracts – a unique environment where resident bidders receive a 5 percent discount over non-resident bidders in construction contracts that use state funds. For the purpose of measuring affiliation and its effect on procurement, a two-stage theoretical model is developed where firms with potentially affiliated private project-completion costs first decide entry and then decide how much to bid. The theoretical model is empirically implemented through the use of copulas, capturing affiliation through a tractable parametric assumption on the project-completion cost distribution. A descriptive reduced-form analysis on bids and entry decisions is then used to investigate any possible differences in bidding and entry behavior between resident and non-resident bidders, and the model is estimated via GMM to disentangle these two separate decisions.

The structural analysis establishes the presence of affiliation and demonstrates the importance of affiliation in these procurement auctions. The parameter that measures affiliation is found to be positive and significant, indicating that firms have affiliated project-completion costs. Counterfactual policy simulations reveal that affiliation lowers the participation rate of preferred and non-preferred bidders in preference auctions and results in a 6 percent increase in procurement costs. In contrast, New Mexico's current policy is only responsible for a 1.8 percent increase in procurement cost.

In line with how the NMDOT awards preferences on its procurement auctions, this paper focuses on the interaction of affiliation and a particular type of preference policy where bid discounts are offered to preferred bidders. An interesting research direction for the future would be to explore how affiliation acts in settings where other types of preference policies are used such as group-specific entry fees and reserve prices. The investigation of these other settings is left to future research.

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A Applying GPV to Auctions with Bid Preferences and Affiliation

The first order conditions in equation 1 can be rewritten as follows:

$$c_1 = b_1 - \frac{\boldsymbol{S}_1\left[1 - F_c^{m_1}(c_1), 1 - F_c^{NR}\left(\beta_{NR}^{-1}\right), \ldots, 1 - F_c^{NR}\left(\beta_{NR}^{-1}\right), 1 - F_c^{R}\left(\beta_{R}^{-1}\right), \ldots, 1 - F_c^{R}\left(\beta_{R}^{-1}\right)\right]}{\frac{\partial \boldsymbol{S}_1\left[1 - F_c^{m_1}(c_1), 1 - F_c^{NR}\left(\beta_{NR}^{-1}\right), \ldots, 1 - F_c^{NR}\left(\beta_{NR}^{-1}\right), 1 - F_c^{R}\left(\beta_{R}^{-1}\right), \ldots, 1 - F_c^{R}\left(\beta_{R}^{-1}\right)\right]}{\partial b_1}} \tag{10}$$

where

$$\begin{aligned} & \frac{\partial \boldsymbol{S}_1\left[1 - F_c^{m_1}(c_1), 1 - F_c^{NR}\left(\beta_{NR}^{-1}\right), \ldots, 1 - F_c^{NR}\left(\beta_{NR}^{-1}\right), 1 - F_c^{R}\left(\beta_{R}^{-1}\right), \ldots, 1 - F_c^{R}\left(\beta_{R}^{-1}\right)\right]}{\partial b_1} \\ = & \left(n_{NR} - D_{NR}\right)\beta_{NR,1}^{-1}\left(1 - \delta\right)^{D_R} f_c^{NR}\left(\beta_{NR}^{-1}\right) \\ & \times \boldsymbol{S}_{12}\left[1 - F_c^{m_1}(c_1), 1 - F_c^{NR}\left(\beta_{NR}^{-1}\right), \ldots, 1 - F_c^{NR}\left(\beta_{NR}^{-1}\right), 1 - F_c^{R}\left(\beta_{R}^{-1}\right), \ldots, 1 - F_c^{R}\left(\beta_{R}^{-1}\right)\right] \\ & + \left(n_R - D_R\right)\beta_{R,1}^{-1}\left(1 - \delta\right)^{-D_{NR}} f_c^{R}\left(\beta_{R}^{-1}\right) \\ & \times \boldsymbol{S}_{1n}\left[1 - F_c^{m_1}(c_1), 1 - F_c^{NR}\left(\beta_{NR}^{-1}\right), \ldots, 1 - F_c^{NR}\left(\beta_{NR}^{-1}\right), 1 - F_c^{R}\left(\beta_{R}^{-1}\right), \ldots, 1 - F_c^{R}\left(\beta_{R}^{-1}\right)\right]. \end{aligned}$$

Define $\tilde{b} = (1-\delta)^{D_R} b$ as the adjusted resident bid and $\hat{b} = (1-\delta)^{-D_{NR}} b$ as the adjusted non-resident bid. These adjusted bids are the bids from the competing group that the bidder calculating the optimal bid faces. Following the methodology outlined in GPV (2000), the marginal CDF and PDF of costs can be expressed solely as functions of the bids by noting that

$$\begin{aligned} F_b^{NR}\left(\tilde{b}\right) &= F_c^{NR}\left(\beta_{NR}^{-1}\left(\tilde{b}\right)\right) \\ F_b^{R}\left(\hat{b}\right) &= F_c^{R}\left(\beta_{R}^{-1}\left(\hat{b}\right)\right) \end{aligned}$$

and

$$\begin{aligned} f_b^{NR}\left(\tilde{b}\right) &= f_c^{NR}\left(\beta_{NR}^{-1}\left(\tilde{b}\right)\right)\beta_{NR,1}^{-1}\left(\tilde{b}\right) \\ f_b^{R}\left(\hat{b}\right) &= f_c^{NR}\left(\beta_{R}^{-1}\left(\hat{b}\right)\right)\beta_{R,1}^{-1}\left(\hat{b}\right). \end{aligned}$$

Equation 10 can now be written as

$$c_1 = b_1 - \frac{\boldsymbol{S}_1\left[1 - F_b^{m_1}(b_1), 1 - F_b^{NR}\left(\tilde{b}_1\right), \ldots, 1 - F_b^{NR}\left(\tilde{b}_1\right), 1 - F_b^{R}\left(\hat{b}_1\right), \ldots, 1 - F_b^{R}\left(\hat{b}_1\right)\right]}{\frac{\partial \boldsymbol{S}_1\left[1 - F_b^{m_1}(b_1), 1 - F_b^{NR}\left(\tilde{b}_1\right), \ldots, 1 - F_b^{NR}\left(\tilde{b}_1\right), 1 - F_b^{R}\left(\hat{b}_1\right), \ldots, 1 - F_b^{R}\left(\hat{b}_1\right)\right]}{\partial b_1}}$$

which expresses costs as the sum of the bid and a strategic markdown.

B Solving for the Inverse Bid Functions

In order to solve for the inverse bid functions, a modified version of the third algorithm found in Bajari (2001) is implemented. In particular, suppose that the equilibrium inverse bid functions for bidders in group $m \in \{R, NR\}$ can be approximated by the following flexible functional form:

$$\hat{\beta}_m^{-1}(b) = \underline{b} + \sum_{k=0}^{K} \alpha_{m,k} (b - \underline{b})^k$$

where $\underline{b}$ is the unknown common low bid and $\{\alpha_{m,k}\}$, $k = 0, \ldots, K$ are polynomial coefficients for bidders in group m. The first order conditions can now be expressed in terms of the polynomial approximations. Let $\boldsymbol{\alpha}$ be a vector that collects the polynomial coefficients of all groups of bidders, $\hat{\beta}_{NR}^{-1} = \hat{\beta}_{NR}^{-1}\left((1-\delta)^{D_R} b\right)$, $\hat{\beta}_R^{-1} = \hat{\beta}_R^{-1}\left((1-\delta)^{-D_{NR}} b\right)$, and define $G_m(b; \underline{b}, \boldsymbol{\alpha})$ as the first order conditions with the approximated inverse bid functions set equal to 0 at b:

$$\begin{aligned}
G_m(b;\underline{b},\boldsymbol{\alpha}) = \\
& \boldsymbol{S}_1\left[1-F_c^m\left(\hat{\beta}_m^{-1}\right), 1-F_c^{NR}\left(\hat{\beta}_{NR}^{-1}\right), \ldots, 1-F_c^{NR}\left(\hat{\beta}_{NR}^{-1}\right), 1-F_c^{R}\left(\hat{\beta}_{R}^{-1}\right), \ldots, 1-F_c^{R}\left(\hat{\beta}_{R}^{-1}\right)\right] \\
- & \left(b-\hat{\beta}_m^{-1}\right)\Bigg[(n_{NR}-D_{NR})\,\hat{\beta}_{NR,1}^{-1}(1-\delta)^{D_R} f_c^{NR}\left(\hat{\beta}_{NR}^{-1}\right) \\
\times & \boldsymbol{S}_{12}\left[1-F_c^m\left(\hat{\beta}_m^{-1}\right), 1-F_c^{NR}\left(\hat{\beta}_{NR}^{-1}\right), \ldots, 1-F_c^{NR}\left(\hat{\beta}_{NR}^{-1}\right), 1-F_c^{R}\left(\hat{\beta}_{R}^{-1}\right), \ldots, 1-F_c^{R}\left(\hat{\beta}_{R}^{-1}\right)\right] \\
& + (n_R-D_R)\,\hat{\beta}_{R,1}^{-1}(1-\delta)^{-D_{NR}} f_c^{R}\left(\hat{\beta}_{R}^{-1}\right) \\
\times & \boldsymbol{S}_{1n}\left[1-F_c^m\left(\hat{\beta}_m^{-1}\right), 1-F_c^{NR}\left(\hat{\beta}_{NR}^{-1}\right), \ldots, 1-F_c^{NR}\left(\hat{\beta}_{NR}^{-1}\right), 1-F_c^{R}\left(\hat{\beta}_{R}^{-1}\right), \ldots, 1-F_c^{R}\left(\hat{\beta}_{R}^{-1}\right)\right]\Bigg].
\end{aligned}$$

These first order conditions are evaluated at T evenly-spaced grid points within the intervals $b \in \left[\frac{\underline{b}}{(1-\delta)}, \overline{b}\right]$ for residents and $b \in \left[\underline{b}, (1-\delta)\,\overline{b}\right]$ for non-residents. Here, $\overline{b}$ is determined by the number of resident bidders: $\overline{b} = \overline{c}$ if $n_R > 1$ and $\overline{b} = \arg\max_b \left[(b-\overline{c}) \Pr\left((1-\delta)\, b < b_j \; \forall j \in NR \mid \overline{c}\right)\right]$ if $n_R = 1$. In order to capture the flat spot in the inverse bid functions, non-residents who have costs $c \in \left[(1-\delta)\,\overline{b}, \overline{c}\right]$ are assumed to bid their cost. Taken together, the modified boundary conditions are

$$\begin{aligned}
0 &= \hat{\beta}_R^{-1}\left(\frac{\underline{b}}{(1-\delta)}\right) - \underline{c} \\
0 &= \hat{\beta}_{NR}^{-1}(\underline{b}) - \underline{c} \\
0 &= \hat{\beta}_R^{-1}(\overline{b}) - \overline{c} \\
0 &= \hat{\beta}_{NR}^{-1}\left((1-\delta)\,\overline{b}\right) - (1-\delta)\,\overline{c}
\end{aligned}$$

Define $H(\underline{b};\boldsymbol{\alpha})$ as

$$\begin{aligned} H(\underline{b};\boldsymbol{\alpha}) &= \sum_m \sum_{t=1}^{T} G_m(b_t;\underline{b},\boldsymbol{\alpha}) + T\left(\hat{\beta}_R^{-1}\left(\frac{\underline{b}}{(1-\delta)}\right) - \underline{c}\right) + T\left(\hat{\beta}_{NR}^{-1}(\underline{b}) - \underline{c}\right) \\ &+ T\left(\hat{\beta}_R^{-1}(\overline{b}) - \overline{c}\right) + T\left(\hat{\beta}_{NR}^{-1}((1-\delta)\overline{b}) - (1-\delta)\overline{c}\right) \end{aligned}$$

Approximating the inverse bid functions is equivalent to finding a vector of polynomial coefficients $\hat{\boldsymbol{\alpha}}$ to minimize $H(\underline{b};\boldsymbol{\alpha})$. Note that T is used as a weight so that the minimization routine gives equal consideration to boundary conditions and the first-order conditions.

C Estimation Method

The parameters of the model are estimated via GMM which essentially matches the predictions of the empirical model to the moments of the data. This matching process requires assumptions on the bid distribution and bid-preparation cost distribution which were outlined in section 5.2. For completeness, these assumptions are given below:

$$\log(b_{iw}) = \boldsymbol{x}_{iw}'\beta + \epsilon_{iw}^{m_i}$$

$$\epsilon_{iw}^{m_i} \mid \boldsymbol{x}_{iw} \sim \mathcal{N}\left(0, \exp(\boldsymbol{x}_{iw}'\sigma)^2\right)$$

$$\left(\epsilon_{1w}^{NR},\ldots,\epsilon_{n_{NR}w}^{NR},\epsilon_{n_{NR+1}w}^{R},\ldots,\epsilon_{n_{NR}+n_R w}^{R} \mid \boldsymbol{x}_{iw}\right) \equiv \boldsymbol{\epsilon}_w \sim F_{\boldsymbol{\epsilon}_w}$$

$$F_{\boldsymbol{\epsilon}_w} = \boldsymbol{C}\left[F_{\epsilon_{1w}^{NR}},\ldots,F_{\epsilon_{n_{NR}w}^{NR}},F_{\epsilon_{n_{NR+1}}^{R}},\ldots,F_{\epsilon_{n_{NR+n_R}}^{R}}\right]$$

$$\log(k_{iw}) = \boldsymbol{z}_{iw}'\gamma + u_{iw}^{m_i}$$

$$u_{iw}^{m} \mid \boldsymbol{z}_{iw} \sim \mathcal{N}\left(0, \exp(\boldsymbol{z}_{iw}'\alpha)^2\right).$$

The first and second moment conditions are derived from the first and second moments of the bidding distribution:

$$E\left[\boldsymbol{x}_{iw}\left(\log(b_{iw}) - \boldsymbol{x}_{iw}'\beta\right)\right] = E\left[E\left[\boldsymbol{x}_{iw}\left(\log(b_{iw}) - \boldsymbol{x}_{iw}'\beta\right) \mid \boldsymbol{x}_{iw}\right]\right]$$

$$= E\left[\boldsymbol{x}_{iw} E\left[\left(\log\left(b_{iw}\right) - \boldsymbol{x}_{iw}'\beta\right) \mid \boldsymbol{x}_{iw}\right]\right] = E\left[\boldsymbol{x}_{iw} E\left[\epsilon_{iw} \mid \boldsymbol{x}_{iw}\right]\right] = 0$$

and

$$E\left[\boldsymbol{x}_{iw}\left(\log\left(b_{iw}\right) - \boldsymbol{x}_{iw}'\beta\right)\left(\log\left(b_{iw}\right) - \boldsymbol{x}_{iw}'\beta\right)\right] =$$

$$E\left[\boldsymbol{x}_{iw} E\left[\left(\log\left(b_{iw}\right) - \boldsymbol{x}_{iw}'\beta\right)\left(\log\left(b_{iw}\right) - \boldsymbol{x}_{iw}'\beta\right) \mid \boldsymbol{x}_{iw}\right]\right] =$$

$$E\left[\boldsymbol{x}_{iw} E\left[\epsilon_{iw}^2 \mid \boldsymbol{x}_{iw}\right]\right] = E\left[\boldsymbol{x}_{iw} \exp\left(\boldsymbol{x}_{iw}'\sigma\right)^2\right].$$

The corresponding empirical moments are

$$\frac{1}{W}\sum_{w=1}^{W}\frac{1}{n_{Rw}+n_{NRw}}\sum_{i=1}^{n_{Rw}+n_{NRw}}\left[\boldsymbol{x}_{iw}\left(\log\left(b_{iw}\right) - \boldsymbol{x}_{iw}'\beta\right)\right]$$

for the first moment and

$$\frac{1}{W}\sum_{w=1}^{W}\frac{1}{n_{Rw}+n_{NRw}}\sum_{i=1}^{n_{Rw}+n_{NRw}}\left[\boldsymbol{x}_{iw}\left(\log\left(b_{iw}\right)^2 - \left(\boldsymbol{x}_{iw}'\beta\right)^2 - \exp\left(\boldsymbol{x}_{iw}'\sigma\right)^2\right)\right]$$

for the second moment.

The next moment condition is derived from the equation for Kendall's tau for Clayton copulas. In particular, when the dependence between random variables can be modeled as a copula, Kendall's tau takes the following form:

$$\tau_{ij} = 4E\left[\boldsymbol{C}\left[F_u^i\left(u_i\right), F_u^j\left(u_j\right)\right]\right] - 1 \tag{11}$$

where τ_{ij} is Kendall's tau, and u_i and u_j are random variables that are related through the copula $\boldsymbol{C}[\cdot,\cdot]$ with marginal distributions F_u^i and F_u^j respectively. Given the assumption that the copula is a Clayton copula, the equation for Kendall's tau has a closed-form solution:

$$\tau_{ij} = \frac{\theta}{\theta+2}. \tag{12}$$

Combining equations 11 and 12 gives the next moment condition which can be expressed as

$$\frac{\theta}{\theta+2} = 4E\left[\boldsymbol{C}\left[\Phi\left(\frac{\log\left(b_{iw}\right) - \boldsymbol{x}_{iw}'\beta}{\exp\left(\boldsymbol{x}_{iw}'\sigma\right)}\right), \Phi\left(\frac{\log\left(b_{jw}\right) - \boldsymbol{x}_{jw}'\beta}{\exp\left(\boldsymbol{x}_{jw}'\sigma\right)}\right)\right]\right] - 1 \quad i \neq j,$$

and the empirical counterpart for the above moment condition is

$$\frac{4}{W}\sum_{w=1}^{W}\frac{1}{\begin{pmatrix} n_{Rw}+n_{NRw} \\ 2 \end{pmatrix}}\sum_{1\leq i<j\leq n_{Rw}+n_{NRw}}\boldsymbol{C}\left[\Phi\left(\frac{\log\left(b_{iw}\right)-\boldsymbol{x}_{iw}'\beta}{\exp\left(\boldsymbol{x}_{iw}'\sigma\right)}\right),\Phi\left(\frac{\log\left(b_{jw}\right)-\boldsymbol{x}_{jw}'\beta}{\exp\left(\boldsymbol{x}_{jw}'\sigma\right)}\right)\right]$$

$$-1-\frac{\theta}{\theta+2}.$$

There is one subtlety in the above equation. The equation for τ_{ij} (equation 11) is given for copulas with two random variables, yet many auctions require that bids be drawn from copulas with three or more random variables. In response to this requirement, the above equation first takes averages over all combinations of pairs of bids in an auction then averages over all auctions in order to use all of the information in the sample. In other words, for each auction the average Kendall's tau is taken for each possible pair of bids and use that average when computing the empirical moment condition.

The final set of moment conditions are derived from the moments of the entry distribution. Given that entry is assumed to follow a binomial distribution, the first, second, third and fourth moments of the entry distribution given the number of potential entrants and project characteristics are

$$E\left[n_{mw}\mid\boldsymbol{x}_w,\boldsymbol{z}_w,N_{mw},N_{-mw}\right]=N_{mw}p_{mw},$$

$$E\left[n_{mw}^2\mid\boldsymbol{x}_w,\boldsymbol{z}_w,N_{mw},N_{-mw}\right] = N_{mw}p_{mw}\left(1-p_{mw}\right)+N_{mw}^2p_{mw}^2,$$

$$E\left[n_{mw}^3\mid\boldsymbol{x}_w,\boldsymbol{z}_w,N_{mw},N_{-mw}\right]=N_{mw}p_{mw}\Big(1-3p_{mw}+3N_{mw}p_{mw}+2p_{mw}^2-3N_{mw}p_{mw}^2+N_{mw}^2p_{mw}^2\Big),$$

and

$$E\left[n_{mw}^4 \mid \boldsymbol{x}_w, \boldsymbol{z}_w, N_{mw}, N_{-mw}\right] = N_{mw}p_{mw}\Big(1 - 7p_{mw} + 7N_{mw}p_{mw} + 12p_{mw}^2 - 18N_{nw}p_{mw}^2 + 6N_{mw}^2p_{mw}^2 - 6p_{mw}^3 + 11N_{mw}p_{mw}^3 - 6N_{mw}^2p_{mw}^3 + N_{mw}^3p_{mw}^3\Big)$$

respectively. Taking unconditional expectations over the number of potential entrants and the project characteristics yields the moment conditions described in section 5.3. These moment conditions are

$$E\left[n_{mw}\right] = \int N_{mw}p\left(\boldsymbol{x}_w, \boldsymbol{z}_w, N_{mw}, N_{-mw}\right) dF\left(\boldsymbol{x}_w, \boldsymbol{z}_w, N_{mw}, N_{-mw}\right),$$

$$E\left[n_{mw}^2\right] = \int N_{mw}p\left(\boldsymbol{x}_w, \boldsymbol{z}_w, N_{mw}, N_{-mw}\right)\left(1 - p\left(\boldsymbol{x}_w, \boldsymbol{z}_w, N_{mw}, N_{-mw}\right)\right) + N_{mw}^2 p\left(\boldsymbol{x}_w, \boldsymbol{z}_w, N_{mw}, N_{-mw}\right)^2 dF\left(\boldsymbol{x}_w, \boldsymbol{z}_w, N_{mw}, N_{-mw}\right),$$

$$E\left[n_{mw}^3\right] = \int N_{mw}p_{mw}\Big(1 - 3p_{mw} + 3N_{mw}p_{mw} + 2p_{mw}^2 - 3N_{mw}p_{mw}^2 + N_{mw}^2p_{mw}^2\Big) dF\left(\boldsymbol{x}_w, \boldsymbol{z}_w, N_{mw}, N_{-mw}\right),$$

and

$$E\left[n_{mw}^4\right] = \int N_{mw}p_{mw}\Big(1 - 7p_{mw} + 7N_{mw}p_{mw} + 12p_{mw}^2 - 18N_{nw}p_{mw}^2 + 6N_{mw}^2p_{mw}^2 - 6p_{mw}^3 + 11N_{mw}p_{mw}^3 - 6N_{mw}^2p_{mw}^3 + N_{mw}^3p_{mw}^3\Big) dF\left(\boldsymbol{x}_w, \boldsymbol{z}_w, N_{mw}, N_{-mw}\right)$$

The corresponding empirical moments are then given by

$$\frac{1}{W}\sum_{w=1}^{W}\left[n_{mw} - N_{mw}p_{mw}\right],$$

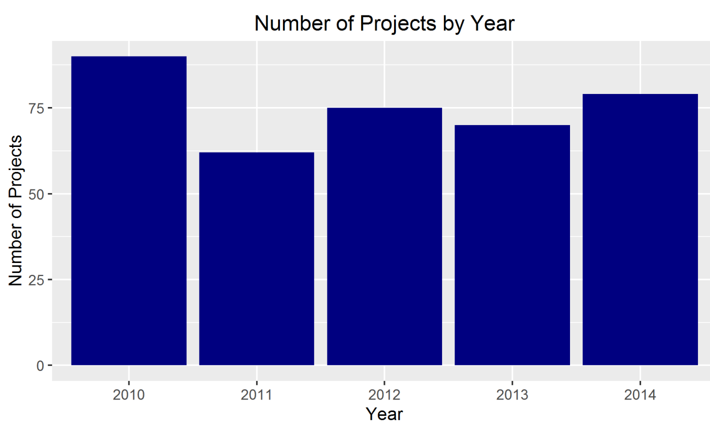
$$\frac{1}{W}\sum_{w=1}^{W}\left[n_{mw}^2 - N_{mw}p_{mw}\left(1 - p_{mw}\right) - N_{mw}^2p_{mw}^2\right],$$

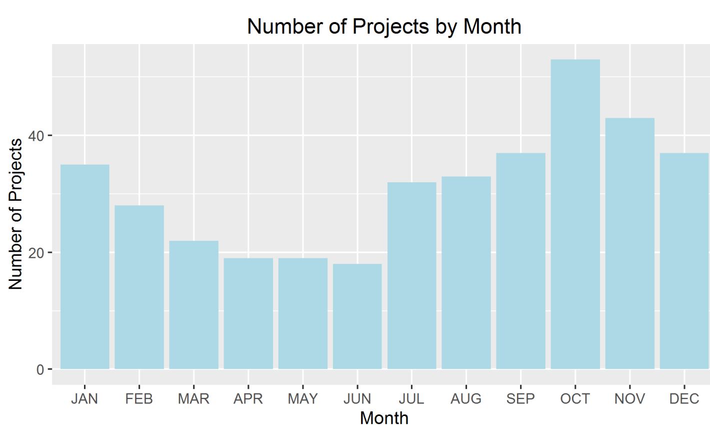
$$\frac{1}{W}\sum_{w=1}^{W}\Big[n_{mw}^3 - N_{mw}p_{mw}\Big(1 - 3p_{mw} + 3N_{mw}p_{mw} + 2p_{mw}^2 - 3N_{mw}p_{mw}^2 + N_{mw}^2p_{mw}^2\Big)\Big],$$

and

$$\begin{aligned}\frac{1}{W}\sum_{w=1}^{W}\Big[n_{mw}^4 \quad & - \quad N_{mw}p_{mw}\Big(1 - 7p_{mw} + 7N_{mw}p_{mw} + 12p_{mw}^2 - 18N_{nw}p_{mw}^2 + 6N_{mw}^2p_{mw}^2 \\ & - \quad 6p_{mw}^3 + 11N_{mw}p_{mw}^3 - 6N_{mw}^2p_{mw}^3 + N_{mw}^3p_{mw}^3\Big)\Big]\end{aligned}$$

D Additional Figures





Projects by County