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

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RESIDENT BID PREFERENCE, AFFILIATION, AND PROCUREMENT COMPETITION: EVIDENCE FROM NEW MEXICO*

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Abstract

In public procurement auctions, governments routinely offer preferences to qualified firms in the form of bid discounts. Previous studies on bid discounting do not account for affiliation – a form of cost dependence between bidders that is likely to occur in a public procurement environment. Utilizing data from the New Mexico Department of Transportation's Resident Preference Program, I develop and estimate an empirical model of firm bidding and entry that allows for affiliation in firms' project costs. I find evidence of affiliation and show how it changes preference auction outcomes.

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I. 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 United 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 routinely offer preferential treatment to a certain group 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 to the winner. These preferential policies can affect auction outcomes and have been studied extensively in the literature.[2]

In many cases, the purpose of offering 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, which means they bid further from their costs, bid discounts also encourage non-preferred bidders to bid more aggressively, or closer to their costs, and can increase competition and discourage non-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 the magnitudes of these effects are altered when participation is endogenous.

Another potential factor in evaluating these programs is the possibility of affiliation, or dependence, between a firm's cost of completing a project, which I will now call its project cost, and the project costs of its competitors. These costs are private information, and the literature has typically taken them to be independent, which implies that a firm that learns its own project cost has no additional information on the project 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

[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.

[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.

should have some form of dependence in their project costs. Firms may also buy raw materials from the same suppliers, which again can generate dependence in project costs.

The existence of affiliation can potentially change a number of preference auction outcomes. For a given number of participants, affiliation makes firms more 'similar' in the sense that they are more likely to have similar project costs relative to independence. Firms will therefore adjust how they bid, which can change both procurement costs and firm profits conditional on entry. If a firm's incentive to participate is influenced by the expected profitability of a project, then affiliation can also affect the number of favored entrants and auction efficiency. Consequently, the total effectiveness of these preference programs can hinge on the presence of affiliation.

This paper contributes to the bid preference literature by allowing firms to have affiliated private project costs in procurement auctions with bid discounting and endogenous entry.[4] Affiliation is a stronger notion of positive correlation, and it captures the idea that firm project costs may be related to each other. Using copula methods developed by Hubbard, Li, and Paarsch [2012] and extended by Li and Zhang [2015], I evaluate a bid preference program favoring resident bidders in New Mexico and show the bias that can arise from assuming independence.

I collect the data from New Mexico Department of Transportation (NMDOT) highway construction contracts. New Mexico is one of a few states that offer qualified resident firms a 5 percent bid discount on state-funded projects. Affiliation is plausible in this setting; firms located close to each other are more likely to buy from the same suppliers and use similar subcontractors, potentially generating dependence in project costs. In fact, 30 percent of items[5] on construction projects qualifying for bid preferences had at least two firms bid the same amount in the data. This statistic suggests that firms may have similar costs of completing some portions of a project.

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, I develop and estimate an empirical model of bidding with endogenous entry, where I allow for affiliation in firm project costs. I obtain a positive and statistically significant estimate on the parameter that measures affiliation, which indicates that firms have affiliated project costs. Counterfactual auctions with alternative discount levels reveal that New Mexico's preference program actually led to a slight *decrease* in procurement costs of 0.4 percent. By comparing counterfactual outcomes under affiliation and independence, I find that

[4]This paper also complements the existing literature on auctions with endogenous entry. These papers include Athey et al. [2011], Li [2005], Sweeting and Bhattacharya [2015] and Bajari and Hortacsu [2003].

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

affiliation makes procurement more expensive (by about 3.3 percent under the current program), but gives discounting more leverage in affecting the proportion of preferred winners. Finally, I find that affiliation can lead to substantial differences in efficiency, highlighting the relevance of affiliation in the evaluation of public procurement auctions with bid discounting.

The remainder of the paper proceeds as follows. Section II. outlines New Mexico's procurement process and describes the data. Section III. presents the theoretical framework by which I analyze the effect of affiliation on bidding and entry behavior, and section IV. shows how I represent affiliated distributions using copulas. Section V. shows the different ways in which affiliation can affect bidding, and section VI. shows how I estimate the theoretical model. Section VII. presents the empirical findings, while section VIII. contains the counterfactual policy analysis. Section IX. concludes.

II. NEW MEXICO'S HIGHWAY PROCUREMENT MARKET AND DATA

This section describes the process by which the NMDOT awards their highway construction contracts and summarizes the data collected for the empirical portion of this paper. The sample contains 376 highway construction contracts awarded by the NMDOT through sealed bidding between 2010 and 2014 for the maintenance and construction of roads, bridges, ramps, and other types of transportation systems.[6] New Mexico applies preferences to resident firms on state-funded construction projects. Over the sample period, there are a total 23 of these state-funded contracts, while the remaining 353 projects are federally assisted projects.

The New Mexico data has a couple of advantages and disadvantages. A benefit of the New Mexico data is that it is unusually detailed in its project advertisements, which allows me to construct an extensive set of observable project characteristics. This feature is particularly important because any unobserved project heterogeneity, or project characteristics observed by the bidders but unobserved by the researcher, will bias my estimates. An immediate limitation of the New Mexico data is that there are a small number of preference projects relative to the number of non-preference projects.[7] In response to this limitation, much of my analysis relies on the empirical model of entry and bidding. Although the small number of preference

[6] For a detailed description of the type of work required on these projects, see Appendix E.

[7] Based on my conversations with NMDOT employees, one reason why there are so few state-funded projects is that a project must be entirely funded by state funds in order to be listed as a state project. Some projects use a mix of state and federal funds, but if any part of the project uses federal funds, then that project is listed as a federally assisted project. Every once in a while, the state will receive 'capital outlay' funds for NMDOT projects or use state maintenance funds or state severance tax funds to fund entire projects, but these sources of funding are not prevalent in financing these types of auctions.

auctions might limit how well the empirical model can predict preference outcomes, the model allows me to use both preference and non-preference auction data to identify the model primitives while accounting for changes due to bid discounting.

II.(i). *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. Every 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. The NMDOT summarizes these details in an 'Invitation for Bids' document, and I use this document to form the set of observable project characteristics.

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. Firms attain planholder status by providing some documented evidence that they have the contract documents, either directly through the NMDOT or through written communication. Moreover, failure to seek planholder status results in the bid becoming unresponsive and subsequently rejected.[8] Given that the list of planholders is known prior to bidding and that planholder status is required to submit a valid bid, I use the firms who are registered as planholders as a measure of the set of potential bidders.[9]

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 through a 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 NMDOT tabulates and publishes submitted bids as well as an engineer's estimate for the cost of the project in an Apparent Low Bids document directly after bid opening. I use the bids and estimates in these documents as the bids and estimates received by the NMDOT for each project. Projects can be renegotiated after letting for a number of different reasons; in order to keep my analysis tractable, I abstract away from the renegotiation process.

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

[9] 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 listed in the planholder document. To account for this difference, I include any actual bidders that do not appear in the planholder document in the set of potential entrants. Moreover, the set of planholders may contain firms that do not have the means to bid as a prime contractor. In order to get a more accurate representation of the set of firms who could potentially bid, I do not include firms who are unsuccessful in submitting a valid bid during the sample period in the set of planholders.

II.(ii). *Resident Preference Program*

Similar to other states such as Alaska, Nevada, Ohio, and Wyoming, New Mexico offers bid preferences to qualified resident firms on construction projects funded exclusively by the state. Like these other states, New Mexico implements its preference through a 5 percent discount on bids, which lowers resident bids by 5 percent for evaluation purposes and pays the full asking price conditional on winning. For example, suppose that a resident firm and a non-resident firm are the only two firms bidding for a contract. Furthermore, suppose that the resident firm bids $1,000,000 and the non-resident firm bids $975,000. After applying the five percent discount to the resident firm, its bid is lowered to $950,000, it wins the contract, and the state pays it $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 their 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. I obtain a list of qualified resident firms through the New Mexico Inspection of Public Records Act, which allows anyone to view public documents.

In general, non-resident firms tend to be local despite their status, and resident firms tend to be more prevalent in the data. Most non-resident firms have main offices within the state (60 percent of bidders and 64 percent of planholders), while only a small number of non-resident firms have main offices outside of states bordering New Mexico (15 percent of bidders and 12 percent of planholders). Out of the 110 different firms observed in the data, 66 firms are residents and 44 firms are non-residents.

II.(iii). *Descriptive Statistics*

[Place Table I approximately here]

Table I summarizes the project and firm characteristics. For each contract, I observe the following project characteristics: the 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, I observe the number of subprojects[10] as well as any Disadvantaged Business Enterprise (DBE) participation goals. I observe residency status, bids, and entry decisions at the firm level.

The top panel of Table I summarizes the estimated costs, bids, winning bids, number of potential entrants, number of actual entrants, and percent of resident winners. Relative to federally funded (or 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. The winning bidder bids an average of $698,000 more on state-funded projects relative to 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.

These set of descriptive statistics also indicate substantial differences in how both groups of bidders enter and bid in auctions. Residents tend to bid less than non-residents and have less variance in their bids. Residents are also less likely to enter auctions; on average, only about 3 of the possible 10 resident planholders become actual bidders, while about 1 out of every 2 non-resident planholders becomes an actual bidder. Despite the lower entry rates, residents win the majority of state and federal contracts.

The next two panels of Table I separate state and federal-aid projects by the type of road and the nature of the work requested. I separate the nature of work 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 to 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.

The bottom panel of Table I lists the summary statistics on the remaining project-level observables. State and federally funded contracts are, on average, similar across these observable dimensions with the exception being the level of the DBE participation goal. New Mexico does not specify DBE participation goals on its state-funded projects, which explains the lack of DBE participation goals observed on state projects in the data.

[10] 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. For an example of project and subproject descriptions in the data, see the appendix.

III. THEORETICAL MODEL

This section provides the theoretical foundation by which I analyze the market for NMDOT construction contracts. In order to preserve the main institutional features, I model New Mexico's market for highway construction contracts 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 [2015]. 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 costs of entry. In the New Mexico setting, the entry cost represents the effort required to gather information about the project and the opportunity cost of time, which is analogous to reading the invitation for bids and requesting project information. In the second stage, bidders learn the identity and number of actual competitors, draw their project costs from a potentially affiliated distribution, and submit a bid for the project.

III.(i). *Affiliation*

I model the possibility of project cost dependence across firms through affiliation. First introduced into auctions by Milgrom and Weber [1982], affiliation 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.[11] 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 costs means that when a firm draws a high project cost, it is more likely that competing firms also have drawn high project costs. Note that affiliation essentially gives bidders extra information on the opponent's project costs, which is plausible if bidders are located close to each other and share similar subcontractors.

Affiliation is also the key modeling assumption that explains the correlations across bids observed in the data. Other studies such as Krasnokutskaya and Seim [2011], Athey et al. [2011], and Athey et al. [2013] explain these correlations under the independent private value paradigm with unobserved auction

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

heterogeneity. While similar in explaining the observed bidding patterns, these two approaches have distinct implications on how firms bid and therefore on how bid preferences affect auctions; a firm's own cost realization impacts their belief about other firms' costs under affiliation but not under independence. In the data, each project has an engineer's estimate, which contains a detailed break down of each project's tasks. Since the engineer's estimate together with the other observed project characteristics explain a large part of the variation in observed bids, I treat affiliation as the prime explanation for correlations across bids.[12]

III.(ii). *Environment*

Turning to the bidding environment, 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 entry costs, k_i, independently from the distribution $G_k^m(\cdot)$, where $m \in \{R, NR\}$ denotes whether firm i is a resident (R) or a non-resident (NR). Firms draw their project costs, c_i, 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. The marginal distribution for a bidder of group m is $F_c^m(\cdot)$, which allows for heterogeneity in the group-specific marginal distributions. Joint project cost distributions can be affiliated, but I assume that project costs are independent of entry costs.[13] These distributions are common knowledge to every potential bidder.

Additionally, resident firms in auctions funded exclusively by the state of New Mexico 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 firm will win if its 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 in preference auctions.

III.(iii). *Bidding*

After bidders learn their project 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

[12] In other environments where unobserved auction heterogeneity may dominate 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.

[13] This assumption implies that bidders do not base entry decisions on their realized project costs. Samuleson [1985] discusses the opposite case where bidders are completely informed of their project costs prior to entry, and Roberts and Sweeting [2010] discuss the intermediate case where bidders are partially informed. Sweeting and Bhattacharya [2015] study various auction designs when entry is endogenous and selective in the sense that bidders with higher valuations are more likely to enter. Within a procurement setting, Li and Zheng [2009] provide evidence that supports a model in which bidders are initially uninformed prior to entry.

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 relative to a non-preference auction yet face the same payment if they win.[14]

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 cost signals $(C_1, \ldots, C_{i-1}, C_{i+1}, \ldots, C_n)$ without bidder i conditional on her signal, 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 conditions that characterizes the optimal bid are then given by

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

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

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

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.

A complete characterization of the bidding equilibrium requires one to specify boundary conditions. Following Hubbard and Paarsch [2009] and Krasnokutskaya and Seim [2011], I set four group-specific boundary conditions.

The left boundary condition requires that bidders who draw the lowest project cost submit the same bid while accounting for the level of the bid discount. Let $\underline{b}$ be the common low bid. The left boundary conditions for both groups of bidders is as follows:

1. *Resident left boundary:*

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

2. *Non-resident left boundary:*

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

The right boundary condition restricts bidding behavior at the highest possible project cost draw. This condition can loosely be interpreted as bidders who draw the highest project cost bid their project costs while making any necessary adjustments for possible discounts received by competing bidders. The right boundary condition for both groups of bidders is as follows:

3. *Resident right boundary:*

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

   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 firm bidding on a project, it will choose a bid that maximizes its expected profits since the discount may lower its bid enough to be competitive with the non-resident firms.

4. *Non-resident right boundary:*

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

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 firm draws a project cost $c \in \left[(1-\delta)\,\overline{b}, \overline{c}\right]$, then it also bids its project cost. Note that, as long as there is at least one competing resident bidder, a project 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 firm does not bid below its 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 are 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 Li and Zhang [2015] for the class of joint project cost distributions that I use in this paper.

III.(iv). *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, and their knowledge of the distributions of project costs and entry costs. Firms calculate ex-ante expected profits as

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

where the $-m$ subscript indicates the bidders not affiliated with the group of bidder i and $F_c^m(\cdot)$ is the marginal project cost distribution of group m.[15] These profits are only a function of the observed number of potential bidders since the only payoff-relevant information available to a given firm before entry is the number of potential bidders and its entry cost. Also note that the subscript is group specific since members of the same group face the same ex-ante expected profits. The entry cost distribution determines the group-specific

[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, I follow Krasnokutskaya and Seim [2011] in assuming that firms compete against the government (which is modeled as a resident bidder) when faced with no other competition.

equilibrium entry probabilities, which I denote as p_m. 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 entry costs for a bidder in group m. The above equality follows from the fact that a firm's beliefs about its competitors' entry probabilities must be consistent with their actual entry probabilities in equilibrium. An application of Brouwer's fixed point theorem demonstrates the existence of the threshold probabilities p_m.[16] Note here that the existence and uniqueness results from the bidding equilibrium still hold after entry since bidders behave as if entry was exogenous upon entering.

IV. THE COPULA REPRESENTATION

One difficulty in implementing auction models with affiliation is dealing with the joint cost distribution. To overcome this difficulty, I rely on copula methods 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 $C[\cdot, \ldots, \cdot]$ is the copula function.

The particular type of copula I use to model 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 random variables, so θ contains all of the relevant information on cost dependence.[18]

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

[17] For a formal proof of this statement, see Müller and Scarsini [2005].

[18] A limitation of the Clayton copula, however, is that there is only one parameter governing the affiliation between both groups of bidders. If residents and non-residents have different degrees of affiliation between them, then this setup may not

Since I study procurement auctions in this paper, I must model the conditional survival function. For this reason, I use two results from Hubbard, Li, and Paarsch [2012] to construct an expression for the 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

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

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

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

capture those differences. To assess whether this is the case for resident and non-resident bidders in New Mexico, I calculate and compare the intraclass correlations between bids for residents and non-residents, where the classes are the separate auctions. I find that the correlations across bids for the two groups of bidders do not differ substantially from each other or the entire sample, suggesting that a single parameter governing all affiliation is reasonable.

where m_1 is bidder 1's group, F_c^m is the marginal distribution of a bidder in group m, $\beta_{NR}^{-1} = \beta_{NR}^{-1}\left((1-\delta)^{D_R} b_1\right)$, and $\beta_R^{-1} = \beta_R^{-1}\left((1-\delta)^{-D_{NR}} b_1\right)$. The first-order conditions are now given by

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

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

V. A SIMULATION STUDY

Before moving into the estimation methodology and to illustrate the possible effects affiliation can have on bid preference auctions at the bidding stage, I conduct simulations over a range of different affiliated distributions with a fixed number of entrants. This section presents the results from those simulation studies. Here, I parameterize the group-specific marginal project cost distributions as beta distributions in order to remain flexible with their shape; I set the copula joining these marginal distributions to a Clayton copula. Figure 1 shows the full set of marginal project cost distribution CDFs used in this analysis.

[Place Figure 1 approximately here]

I calculate bid functions in a variety of different environments. Except in a few special cases, the solution to the system of equations in (1) together with the boundary conditions does not have a closed-form solution. As a result, I approximate and invert each group's inverse bid functions with a modified version of the third algorithm found in Bajari [2001], which essentially approximates inverse bid functions using polynomials.[19]

I set the remaining simulation parameters to mirror a common New Mexico preference auction. I set the number of actual bidders to a commonly observed configuration of one non-resident bidder and three resident bidders, and I set the discount to New Mexico's current five percent level. For each marginal project cost distribution, I approximate bid functions under independence and affiliation, where affiliation is calculated

[19]See the appendix for a detailed explanation of how I numerically approximate the bid functions.

by setting the affiliation parameter to 1. This parameter choice means that project costs are 33.3 percent more likely to be concordant than discordant.[20] I denote independence by an affiliation parameter of 0.

V.(i). *Equal Strength Bidders*

As a start, I study a case where both groups of bidders are of equal strength. Let α_R and β_R be the parameters characterizing the resident beta distribution, and let α_{NR} and β_{NR} be the parameters characterizing the non-resident beta distribution. I construct the equal strength case by setting each group's beta distribution parameters to $\alpha_R, \alpha_{NR} = 1$ and $\beta_R, \beta_{NR} = 1$ so that project costs are symmetric. This parameterization is equivalent to a uniform cost distribution. Observe that in this case, the preference is the sole driver of any asymmetry between bidders. Figure 2 displays the equilibrium bid functions corresponding to these marginal project cost distributions.

[Place Figure 2 approximately here]

Several patterns emerge from these simulations:

1. With affiliation, a bidder with a low project cost bids more aggressively relative to independence. Intuitively, competing bidders are more likely to have similar project costs when the joint distribution is affiliated. A bidder with a low project cost draw is then more likely to face competitors with low project costs and will, therefore, bid more aggressively relative to independence.

2. For higher project cost draws, bidders tend to bid less aggressively relative to independence. Note that a bidder who draws a high project cost will believe that other bidders also have high project costs when these costs are affiliated, but her beliefs will not change when these costs are independent. This difference in beliefs will affect equilibrium bids because a bidder bids less aggressively when she believes her competition has higher project costs.

3. Affiliation can affect the separation in resident and non-resident bid functions caused by bid preferences. Indeed, the simulations show that the common low bid for both groups of bidders decreases when project costs become affiliated. The left boundary condition then implies that the common low bids are closer together. For higher project cost draws, there is more separation under affiliation. This separation

[20] Concordance is similar to affiliation in that more concordant random variables exhibit a higher degree of positive dependence. Formally, if $(x_1, y_1) \ldots (x_n, y_n)$ are n observations from random variables X and Y such that all values of x_i and y_i, $i = 1 \ldots n$, are unique, then a pair of observations (x_i, y_i) and (x_j, y_j), $i \neq j$, are concordant if $x_i > x_j$ and $y_i > y_j$.

comes from both groups of bidders bidding less aggressively and resident bidders receiving a preference (which makes them bid even less aggressively).

V.(ii). *A Weak Group and a Strong Group of Bidders*

Next, I turn to a case where both groups of bidders differ in strength. For this case, the 'weak' bidders are the resident bidders, and I set their beta distribution parameters to the previous configuration of $\alpha_R = 1$ and $\beta_R = 1$. The 'strong' bidders here are the non-resident bidders, and I set their beta distribution parameters to $\alpha_{NR} = 1$ and $\beta_{NR} = 1.1$. Note that this arrangement of distribution parameters generates a situation where the resident project cost distribution first-order stochastically dominates the non-resident project cost distribution, which means that residents are more likely to draw higher project costs. Figure 3 shows the results from this case.

[Place Figure 3 approximately here]

Many of the same patterns observed in the equal strength bidder case appear in this case as well. Bidders still bid more aggressively for low cost realizations and less aggressively for high cost realizations when their joint project cost distribution is affiliated. The main difference here, especially when there is affiliation, is the amount of separation due to bid preferences, and that difference is generated by the asymmetry in resident and non-resident project costs. The idea here is that the resident marginal project cost distribution now first-order stochastically dominates the non-resident marginal project cost distribution. Whether costs are independent or affiliated, this asymmetry causes non-residents to bid less aggressively relative to the equal strength case since non-residents are more likely to have lower project costs compared to residents. Affiliation intensifies this effect in that affiliation causes residents and non-residents to draw from similar *quantiles* on their respective distributions, so a low cost draw for a resident is likely to be even lower for a non-resident relative to independence.[21] As a result, non-residents bid closer to residents under affiliation.

[21]To illustrate this point with an example, suppose that a resident bidder draws a cost in the 10^{th} percentile of her marginal project cost distribution. Under affiliation, this draw means that competing bidders are more likely to draw their project costs from the 10^{th} percentile of their marginal distributions. Since the resident marginal distribution first-order stochastically dominates the non-resident marginal distribution, the project cost corresponding to the 10^{th} percentile of the resident marginal distribution is higher than the project cost corresponding to the 10^{th} percentile of the non-resident marginal distribution, so that resident bidder would believe competing non-resident bidders have even lower project costs relative to the equal strength case.

V.(iii). *A High Variance Group and a Low Variance Group of Bidders*

The final case I consider in this section is a case where each group of bidders has different levels of dispersion in their project cost distributions. This case is motivated by the observation that non-resident bidders have more variable bids in the data, which might be a result of more disperse costs. In constructing this case, I set the resident beta distribution parameters to $\alpha_R = 1.5$ and $\beta_R = 1.5$ while fixing the non-resident beta distribution parameters at $\alpha_{NR} = 1$ and $\beta_{NR} = 1$. Observe that this composition of distribution parameters implies that residents and non-residents have the same mean project cost, but non-residents have more variance in their project costs relative to residents. Figure 4 presents the bid functions corresponding to these distributions.

[Place Figure 4 approximately here]

There are a few differences between this asymmetry's effect on equilibrium bidding relative to the previous cases. Perhaps the most visible difference is that resident bidders bid much more aggressively for low project cost draws and slightly less aggressively for high project cost draws with affiliation. Intuitively, residents and non-residents become more likely to draw from the same quantiles with affiliation. When residents have less variable project costs than non-residents, this property of affiliation means that high draws for residents likely lead to even higher draws for non-residents, while low draws for residents likely lead to even lower draws for non-residents. As a result, residents bid less aggressively for high project cost draws and more aggressively for low project cost draws.

These results, although conditional on a fixed number of entrants, have implications for entry decisions. Bidders who face more (less) aggressive bidding conditional on entry due to affiliation are less (more) likely to enter because their expected profits are lower (higher). Affiliation can, therefore, alter entry decisions within and across groups of bidders, which can change the procurement costs and the composition of actual bidders.

VI. 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 the distributional assumptions needed to produce an empirical model that can be estimated from the data. First, I discuss the distributional assumptions; then, I lay out the estimation routine. I end this section with a discussion of how the parameters are parametrically identified through the estimation procedure.

VI.(i). *Parametric Specifications*

The size of the data requires that I take a parametric approach in estimating the theoretical model. For this purpose, I assume that an auction, indexed by w, is 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 costs, $\boldsymbol{z}_w$ is a vector of auction-level observables that affect entry 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 costs conditional on $\boldsymbol{x}_w$ are given by $F_c^m (\cdot \mid \boldsymbol{x}_w)$, and the group-specific marginal distribution of entry costs conditional on $\boldsymbol{z}_w$ are given by $G_k^m (\cdot \mid \boldsymbol{z}_w)$.

To address entry, I require parametric assumptions on the probability firms assign to the entry of competing firms. To this end, I model entry probabilities, $p_{mw} (\boldsymbol{x}_w, \boldsymbol{z}_w, N_{Rw}, N_{NRw})$, as a binomial distributions:

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

where

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

and

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

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 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 would require that the inverse bid functions be approximated for every set of second-stage parameter guesses. Instead, 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, I infer a firm's cost from the observed bid distribution by noting that $F_b^m(b) = F_c^m\left(\beta_m^{-1}(b)\right)$ and $f_b^m(b) = f_c^m\left(\beta_m^{-1}(b)\right)\beta_{m,1}^{-1}(b)$.[22] 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 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 costs, $F_c^m(\cdot \mid \boldsymbol{x}_w)$.

I place the final set of distributional assumptions on the distribution of bids and entry costs. In order to have positive bids, allow for affiliation, and allow for heterogeneity across resident and non-resident bidders, I model the log of the submitted bids as follows:

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

where

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

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

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

$\boldsymbol{x}_{iw}$ is the set of auction-level observables with a residency status indicator variable for bidder i, and $\boldsymbol{y}_{iw}$ is a subset of the $\boldsymbol{x}_{iw}$ covariates also containing the resident indicator. Likewise, I assume that the entry costs take the following form:

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

where

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

$\boldsymbol{z}_{iw}$ is the set of auction-level observables with an indicator for residency status, and $\boldsymbol{v}_{iw}$ is a subset of

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

the $\boldsymbol{z}_{iw}$ covariates that also includes the resident indicator.

VI.(ii). *Estimation*

I estimate the parameters of the empirical model using generalized method of moments (GMM). In using GMM, I match the theoretical predictions of the empirical model 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 I construct and use the moment conditions in estimation. For a more detailed explanation on how to derive the moments from the empirical model, see the appendix.

I use the first set of moment conditions to identify the parameters of the bid distribution. These moment conditions are

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

and

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

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

In addition to estimating the parameters of the marginal distributions, the affiliation parameter, θ, must also be estimated through the moment conditions of the model. I estimate this parameter by relying on methods developed by Oh and Patton [2013] to estimate copulas using method of moments. In particular, one can summarize the degree of dependence between two random variables 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:

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

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

I use the last set of moment conditions to identify the parameters of the unobserved entry 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

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

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. I derive these moment conditions 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.

VI.(iii). *Parametric Identification*

Given the intricacy of the model, I conclude this section with a brief discussion of the data features that identify the model's parameters. The parameters of the model are the mean and standard deviation parameters of the bid distribution, β and σ, the mean and standard deviation of the entry cost distribution, γ and α, and the affiliation parameter, θ.

The data contains a number of different contracts, each with multiple bids. In the model, those bids correspond to equilibrium bidding under a first-price, sealed-bid procurement auction format, so I use the first and second moments of those observed bids to identify the mean and standard deviation parameters of the equilibrium bid distribution. Within contracts, bids can potentially be positively dependent conditional on contract-level observables. I use this dependence to identify the affiliation parameter, which is measured by Kendall's tau in equation (5).[23] Finally, I observe resident and non-resident bidders entering auctions at different rates. In the model, firms enter if their cost of entry is smaller than their ex-ante expected profit. Different entry rates, therefore, map to different distributions of entry costs, so I use the observed entry rates to pin down the entry parameters.

VII. EMPIRICAL RESULTS

This section presents the empirical findings from the NMDOT highway procurement data. I first display and interpret the structural parameter estimates from the empirical model and the corresponding cost distributions. These estimates suggest affiliation among bidder project costs and higher entry costs for resident firms relative to non-resident firms. I then assess the model's fit to the data.

VII.(i). *Structural Estimates*

I use the estimated empirical model to disentangle strategic participation and bidding decisions. I use both preference and non-preference auctions in estimation, but I drop projects with 20 or more planholders for computational reasons – amounting to 1 state-funded project and 10 federally funded projects. I include the number of planholders and the number of actual bidders as control variables in my bid distribution estimates because those observables can potentially change the distribution of equilibrium bids. Additionally, I use a rich set of project controls so that the correlation in submitted bids is primarily generated through affiliation in costs as opposed to unobserved project heterogeneity. I include a group-specific indicator for residency status in the set of control variables to allow for heterogeneity between resident and non-resident bidders.

[Place Table II approximately here]

Table II contains the parameter estimates for the bid distribution. The coefficients indicate that the submitted bids vary according to a project's size and observable characteristics. The coefficients also show

[23] Note here that a limitation of using bid dependence to identify affiliation is that any unobserved heterogeneity would also be attributed to the affiliation parameter. As a result, the estimates from this paper should be viewed as an upper bound on the affiliation parameter.

statistically insignificant differences in how the two groups of bidders bid that varies depending on whether the project is state or federally funded. Specifically, residents bid about 1.5 percent less than non-residents on federal-aid projects and 5 percent more than non-residents on state projects.

The affiliation parameter estimate is positive and statistically significant, which indicates the presence of affiliation in firm project costs. This estimate can be interpreted using Kendall's tau as a measure of concordance. In particular, the value of Kendall's tau for the Clayton copula is $\tau = \frac{\theta}{\theta+2}$. Applying that formula to the estimated affiliation parameter of $\theta = 0.893$ results in a Kendall's tau of 0.309, which means that a given pair of project cost draws is 30.9 percent more likely to be concordant than discordant.

This tau estimate can be compared to others found in studies using a similar affiliated private value framework. On one hand, the Kendall's tau of 0.309 estimated here is higher than the tau of 0.06 estimated by Li and Zhang [2015] for the case of timber sales auctions in Oregon, implying that the costs for firms competing for NMDOT construction contracts are more concordant than the values of firms competing for Oregon timer sales auctions. On the other hand, Hubbard, Li, and Paarsch [2012] estimate a tau of 0.655 using Michigan Department of Transportation data under the assumption that costs are drawn from a Clayton copula. The difference between the Michigan and New Mexico tau estimates suggests that affiliation can vary in prevalence across states for similar types of auctions.

In order to evaluate differences in the marginal resident and non-resident project costs, I use methods of bid inversion developed by GPV [2000] 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, I calculate resident and non-resident marginal cost distributions 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, I simulate and invert bids from the estimated marginal bid distributions 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. I estimate the marginal project cost distribution using a kernel density estimator with a normal kernel and optimal bandwidth, yielding a marginal cost CDF for both types of bidders.

[Place Figure 5 approximately here]

Figure 5 displays the different marginal project 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, non-residents have a more disperse project cost distribution than residents across projects. Also, no one project 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.

[Place Table III approximately here]

Turning to firm entry costs, Table III presents the estimated parameters for the log-normal entry cost distribution. The entry parameters have the expected signs and magnitudes and suggest that there are differences among resident and non-resident costs of entry. In particular, residents have higher average entry costs compared to non-residents and more variance in these entry costs.[24] In the data, a higher average entry cost means that residents typically enter auctions less frequently than non-residents, and a higher variance for residents means that the random part of the entry cost explains more of the resident entry patterns relative to non-residents. A 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 and less variable entry costs, which is outside the scope of the data and model. The parameter estimates are nonetheless consistent with the entry rates observed in the data.

VII.(ii). *Model Fit*

With the entry cost and equilibrium bid distributions estimated, I can now assess how well the model can predict data outcomes. This exercise is crucial in understanding whether my parametric assumptions on equilibrium bidding are appropriate for New Mexico's highway procurement data.

I investigate model fit by simulating outcomes under fixed and endogenous entry. For simulations where entry is fixed, I use the bid distribution estimates to draw bids according to the observed number of resident and non-resident participants. When entry is endogenous, I use the entry cost estimates to simulate entry and bidding in two steps. I first draw each group of bidders' entry costs and compare them to their expected profits from entry; firms with entry costs lower than their expected profits enter. Then, I draw bids from each group's equilibrium bid distribution given the number of entrants. My simulations are based on the data

[24]Recall that these parameter estimates are the mean and variance of the natural logarithm of the entry costs. Let μ be the mean of the natural logarithm of the entry costs, and let σ be the standard deviation of the natural logarithm of the entry costs. The mean of the actual distribution of entry costs is then calculated as $\exp\left(\mu + \frac{\sigma^2}{2}\right)$, while the variance is calculated as $\left(\exp\left(\sigma^2\right) - 1\right)\exp\left(2\mu + \sigma^2\right)$.

used in estimation, which does not have auctions with 20 or more planholders. As a result, the outcomes from the actual data will be slightly different than the statistics reported in Table I.

Table IV reports the average data outcomes and the average model outcomes under fixed and endogenous entry. I obtain standard errors with a bootstrapping procedure, where I re-simulate the average auction outcomes using the estimated bid and entry cost distributions and calculate standard errors from the bootstrap repetitions.

[Place Table IV approximately here]

In general, I find that the model does well in predicting the bidding and entry patterns observed in state-funded and federally funded projects. Note here that not all outcomes were targeted in estimation; the average winning bid and the percent of resident winners are moments of the data that were not used in estimation. The fit of the model to these moments demonstrates the model's flexibility in accounting for these data patterns. I do find that the predicted percentage of resident bidders is about 10 percentage points lower than the actual percentage on state projects with endogenous entry, though. That pattern arises because the model underpredicts the number of resident entrants on state projects.

VIII. COUNTERFACTUAL ANALYSIS

I now use the structural parameter estimates to run counterfactual policy experiments. Given the computational burden associated with calculating equilibrium bid functions, I focus on a representative construction project qualifying for preference in the data.[25] I first describe how I simulate the counterfactuals and then explore how affiliation and bid preferences affect bidding under fixed participation. As a final point, I compare bidder responses to different discount levels under the estimated level of affiliation and independence, allowing for endogenous entry decisions.

VIII.(i). *Simulation Method*

I simulate counterfactual bidding and entry in a number of different steps. First, I obtain a kernel density estimate of the underlying marginal project cost distributions, F_c^R and F_c^{NR}, by inverting a large number of

[25]To construct this project, I take the average of all numerical observables on projects qualifying for preference as the representative project characteristics. For categorical variables, I use the most common category as the representative category.

bids drawn from the estimated bid distributions by using GPV [2000].[26] These group-specific cost distributions are primitives of the model and are fixed across all counterfactual policies and affiliation levels. Next, I approximate and invert the group-specific inverse bid functions using the modified third algorithm of Bajari [2001]. Different discount levels will result in different equilibrium bid functions, so I recalculate the bid functions every time the discount changes. I use the estimated bid functions and project cost distributions to simulate group-specific ex-ante profits, and, when entry is endogenous, I simulate entry decisions by comparing draws from the estimated entry cost distribution and the simulated ex-ante profits. For entrants, I draw project costs from an affiliated cost distribution using methods described in Marshall and Olkin [1988], and I apply the bid functions to the costs to determine the counterfactual bids.

The average number of resident and non-resident planholders are similar for preference auctions and non-preference auctions in the data, suggesting that the number of potential entrants may not be sensitive to the discount. For this reason, I set the number of potential entrants to the average preference auction level of 10 resident and 2 non-resident bidders for the auction simulations across discount levels in section VIII.(iii)., but the simulated number of entrants can vary given draws of the entry costs. I simulate a total of 10,000 auctions for each grid point in a grid of discount levels to generate the auction outcomes.

VIII.(ii). *Affiliation, Bid Preferences, and Optimal Bidding*

As a first step in understanding the interplay between affiliation and bid preferences in New Mexico's auctions, I use the numerical methods to approximate bid functions under fixed participation and varying degrees of preference and cost dependence. The bid functions use the cost distributions and the average number of participants associated with the representative preference project, comparing bids under the estimated affiliation parameter with counterfactual bids under independence. To investigate the impact of bid preferences, I compare bid functions across auctions with the 5 percent preference policy and auctions without any preference. Figure 6 presents the equilibrium bid functions.[27]

[Place Figure 6 approximately here]

[26]Note that the marginal project cost distribution will depend on the number of bidders and must be truncated to be consistent with the theory. Following Athey et al. [2013], I use a common configuration of three resident entrants and one non-resident entrant to determine the marginal project cost distribution. To deal with truncation, I truncate the support of the nonparametric project cost distribution to an interval of 0.5 to 1.6 times the engineer's estimate, corresponding to an interval with a lower bound of $2,314,400 and an upper bound of $7,406,000. This particular interval is tight enough to avoid extended regions of the project cost distribution with no density, which adversely affects bid function estimation, yet large enough to contain the vast majority (about 98%) of inverted project cost draws.

[27]For an analysis of the error associated with these simulated bid functions, see the appendix.

In general, the bid functions from New Mexico resemble the bid functions simulated with a high and low variance group of bidders, so many of the observations from those simulations apply to firms bidding on NMDOT construction contracts. In particular, affiliation, which can be seen by comparing the left two panels and the right two panels of Figure 6, causes firms to bid more aggressively for lower project costs and less aggressively for higher project costs independent of the level of preference since competing firms are more likely to have similar project costs. Another feature of affiliation is that it changes the relative aggression of resident and non-resident bidders. Comparing the top-left and top-right panels of Figure 6, residents and non-residents behave almost as if the auction is symmetric when project costs are independent, but when project costs become affiliated, bid functions become more distinct, with residents bidding more aggressively than non-residents for lower project costs and non-residents bidding more aggressively than residents for higher project costs. This change comes from the lower variance in the resident bid distribution; since affiliation makes it more likely for groups of firms to draw project costs from the same quantiles of their marginal distributions, low draws for a resident are likely to be even lower for a non-resident, while high draws for a resident are likely to be even higher for a non-resident. Residents will, therefore, bid more aggressively relative to non-residents for lower project costs and less aggressively for higher project costs.

Moving on to preference auctions, affiliation also affects how residents and non-residents adjust their bids when there is bid discounting. Bid preferences drive a wedge between preferred and non-preferred bidders, meaning that non-preferred bidders lower their bids and preferred bidders increase their bids relative to the no preference case to account for discounting. The size of this wedge, which can be seen by comparing the top two panels with the bottom two panels of Figure 6, depends on how aggressively firms bid and is therefore tied to affiliation. Observe that when there are preferences in the independence case, the wedge between resident and non-resident bidders is large for lower project costs and decreases for higher project costs. When there is affiliation, the wedge is slightly smaller than independence for lower project costs (since firms are bidding closer to their project costs) but becomes visibly larger for higher project cost draws. These differences suggest that affiliation can affect how firms adjust bids with discounting.

VIII.(iii). *Alternative Discount Rates, Efficiency, and the Role of Affiliation*

Although New Mexico offers a five percent discount for its resident bidders, the discount level for preferred bidders can vary across states and the type of good being procured. Here, I investigate how different discount levels would affect New Mexico's representative construction project. In order to assess the role of affiliation in these auctions, I contrast firm bidding and participation under the estimated affiliation level against auctions where costs are assumed independent.

Figure 7 plots the how the procurement cost, the proportion of preferred winners, and the expected participation changes across affiliation and discount levels. Procurement costs decrease initially and then increase with increasing discount levels. This pattern comes from the composition of winning bidders: non-residents tend to bid more aggressively than residents with more discounting but become a smaller proportion of the winning bidders at higher discount levels. Relative to independence, affiliation leads to higher procurement costs for all counterfactual discount levels because there is a wider range of project cost values where firms bid further from their costs under affiliation as evidenced by Figure 6.

[Place Figure 7 approximately here]

The expected participation rate under affiliation is similar to the expected participation rate under independence, but the drop-off in non-resident bidders and increase in resident bidders is more pronounced under affiliation as the discount rises. I also find that the proportion of resident winners increases more dramatically with affiliation. The intuition behind these results is that firm project costs become more similar with affiliation, so higher discount levels are more likely to deter non-resident entry and encourage resident entry. The increased number of resident entrants will then lead to a rise in the proportion of resident winners.

In addition to changing bidding and participation, changes in the discount can also alter economic efficiency. In the auction literature, an efficient auction is one that allocates an object to the firm with the lowest cost. Although auctions with symmetric bidders will always be efficient, auctions with asymmetric bidders, such as the ones considered in this paper, may not allocate objects efficiently. To gauge how efficiency changes over discount levels, I calculate the average efficiency loss, which is the average simulated difference in cost between the lowest cost bidder and the winning bidder, and the percent of inefficient auctions for all potential and actual bidders at different discount levels. In order to measure affiliation's effect on efficiency, I calculate the efficiency statistics for auctions with the estimated level of affiliation and for auctions that assume independence.

[Place Table V approximately here]

Table V breaks down the average procurement cost and efficiency loss over the counterfactual affiliation and discount levels. New Mexico's current policy is actually responsible for a small decrease in procurement costs: increasing the discount rate from 0 percent to its current level of 5 percent under affiliation decreases the average procurement cost of the representative construction project by $17,330, which is a 0.4 percent cost decrease. This decrease is relatively smaller than the bias associated with the independence assumption. At the established 5 percent discount level, procurement costs are 3.3 percent higher than they would be if costs were assumed independent.

Table V also illustrates the role of affiliation in the evaluation of economic efficiency. Starting with the actual bidders, both the efficiency loss and the percent of inefficient auctions first increases and then decreases under affiliation. In other words, the NMDOT can increase economic efficiency by increasing the discount rate beyond 7.5 percent, which is counterintuitive given the wedge caused by bid preferences. A key driver of this outcome is that higher discount levels tend to attract few non-resident bidders, so New Mexico can essentially achieve higher efficiency by discouraging non-resident entrants, making auctions more symmetric in the process. This observation becomes more apparent when comparing the affiliation outcomes with the independence outcomes, which trend upward because there is less of an effect on non-resident entry.

Given that efficiency obtained through discouraging entry may not be desirable, I recalculate the efficiency loss and the percent of inefficient auctions for all potential bidders. This measure of efficiency is less sensitive to the composition of entrants. My efficiency results for all potential bidders suggest that there are small differences in the percent of inefficient auctions under affiliation versus independence, but the difference in efficiency loss is more striking. In particular, the efficiency loss for all potential bidders at New Mexico's five percent level is $288,240 (or 52.1 percent) lower with affiliation and remains more or less constant across different discount levels. This result emerges from the increased similarity in project costs due to affiliation.

Taken together, these simulations suggest that New Mexico can use the discount rate as a mechanism to increase the proportion of contracts won by resident bidders and alter the proportion of inefficient auctions and procurement costs. Relative to the independence case, affiliation makes procurement more expensive but gives discounting more leverage in increasing the proportion of preferred winners. For actual bidders, affiliation tends to lead to a higher efficiency loss, while the efficiency loss for potential bidders is considerably smaller with affiliation. These results illustrate the significance of accounting for affiliation in public procurement with bid preferences.

IX. CONCLUSION

In this paper, I examine how affiliation affects procurement auctions in an environment where preferred bidders have their bids discounted. My analysis is based on NMDOT construction contracts – a unique environment where resident bidders receive a 5 percent discount over non-resident bidders in construction contracts using state funds. For the purpose of measuring affiliation and its effect on procurement, I develop a two-stage theoretical model, where firms with potentially affiliated private project costs first decide entry and then decide how much to bid. I implement the theoretical model through the use of copulas, capturing affiliation through a tractable parametric assumption on the project cost distribution. I then estimate the model via GMM by using moments from firm bidding and entry decisions.

My structural analysis establishes the presence of affiliation and demonstrates the importance of affiliation in assessing procurement auctions with bid discounting. I find that the parameter measuring affiliation is positive and significant, indicating that firms have affiliated project costs. My counterfactual policy simulations reveal that affiliation can lead to differences in the proportion of preferred winners, the proportion of inefficient auctions, and the efficiency losses generated from auctions with asymmetric bidders, and these differences are contingent on the discount level. In fact, although New Mexico's current policy is responsible for a 0.4 percent decrease in procurement costs, I find that affiliation results in a 3.3 percent increase in procurement costs relative to independence under New Mexico's policy.

There are a couple of areas open to future research. In line with how the NMDOT awards preferences in its procurement auctions, I focus on how affiliation can affect a particular type of preference policy where preferred bidders have their bids discounted. An interesting research direction for the future would be to explore how affiliation acts in settings where governments use other types of preference policies, such as group-specific entry subsidies and reserve prices. Also, I have one parameter governing the affiliation between all bidders. In other settings where the two groups of bidders are more distinct, a richer copula structure may be a promising modeling possibility.

Appendix A. Applying GPV to Auctions with Bid Preferences and Affiliation

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

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

where

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

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 come from the opposing group of bidders calculating their optimal bid. 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

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

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

Appendix B. Solving for the Inverse Bid Functions

In order to solve for the inverse bid functions, I implement a modified version of the third algorithm found in Bajari [2001]. In particular, I assume that the equilibrium inverse bid functions for bidders in group $m \in \{R, NR\}$ take on the following flexible functional form:

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

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:

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

I evaluate these first-order conditions 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. I determine $\overline{b}$ 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, I assume non-residents who have costs $c \in \left[(1-\delta)\overline{b}, \overline{c}\right]$ bid their cost. Taken together, the modified boundary conditions are

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

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

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

where I use the $w(T)$ terms as positive weights to get the boundary conditions to hold. Approximating the inverse bid functions is equivalent to finding a vector of polynomial coefficients $\hat{\boldsymbol{\alpha}}$ to minimize $H(\underline{b};\boldsymbol{\alpha})$.

In practice, I set the simulation parameters as follows. I use a cubic polynomial to approximate each group's inverse bid function ($K = 3$), and I set the number of grid points to 50 ($T = 50$). After performing an extensive set of simulation studies, I find that this particular arrangement of grid points and polynomials produces the most numerically stable results for the range of actual entrants possible during the counterfactual simulations. I set the weighting function for the left boundary conditions to $w(T) = 48T$ under affiliation and $w(T) = 26T$ when project costs are independent, and I use weighting functions of $w(T) = 17T$ under affiliation and $w(T) = 500T$ under independence for the right boundary conditions. I determine these weights by simulating the bid functions and choosing the lowest coefficient on T sufficient for the boundary conditions to hold during the simulations.

Appendix C. Inverse Bid Function Accuracy

In order to evaluate the accuracy of the approximated inverse bid functions, I assess the first-order conditions of the resident and non-resident bidding problem (or $G_m(b;\underline{b},\boldsymbol{\alpha})$) on a grid of 100 bid points for the bid functions displayed in Figure 6. In the model, equilibrium bidding requires that the first order conditions are zero, so my approximations are more accurate if, when inserted into $G_m(b;\underline{b},\boldsymbol{\alpha})$, they yield values that are near zero. Figure 8 shows the results; the vertical axis corresponds to the value of $G_m(b;\underline{b},\boldsymbol{\alpha})$, and the horizontal axis corresponds to the bid. To my knowledge, the literature has not yet established a benchmark accuracy for the approximation of inverse bid functions with asymmetric bidders, but the results from this paper's approximations appear to be reasonable.

[Place Figure 8 approximately here]

Appendix D. Estimation Method

I estimate the parameters of the model with 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 entry cost distribution, which were outlined in section VI.(i).. For completeness, I list these assumptions below:

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

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

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

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

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

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

I derive the first and second moment conditions from the first and second moments of the bidding distribution:

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

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

and

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

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

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

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

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

for the second moment.

I derive the next moment condition from the equation for Kendall's tau for Clayton copulas. In particular, when the dependence between random variables is 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 takes the following form:

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

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

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

The empirical counterpart for the above moment condition is

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

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

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 I draw bids from copulas with three or more random variables. In response to this requirement, I first take averages over all combinations of pairs of bids in an auction and then average over all auctions in order to use all of the information in the sample. In other words, I find the average Kendall's tau for each possible pair of bids in each auction and I use that average when computing the empirical moment condition.

I derive the final set of moment conditions from the moments of the entry distribution. Given that I assume entry follows 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

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

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

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

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

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

and

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

The corresponding empirical moments are then given by

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

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

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

and

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

Appendix E. Project and Subproject Examples

[Place Table VI approximately here]

[Place Figure 9 approximately here]

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Table I: Summary Statistics for New Mexico Highway Construction Projects

	Federal-Aid Projects	State Projects	All Projects
Number of Contracts	353.00	23.00	376.00
Number of Bidders	1469.00	92.00	1561.00
Number of Planholders	4195.00	261.00	4456.00
Average Bid (in 1000s)	4068.05	5469.58	4156.93
Average Winning Bid (in 1000s)	3522.36	4220.64	3565.07
Average Engineer's Estimate (in 1000s)	3679.79	4628.75	3737.84
Average Resident Bid (in 1000s)	3735.20	4261.57	3771.63
Std. of Resident Bids (in 1000s)	5328.22	7652.71	5517.79
Average Non-Resident Bid (in 1000s)	4913.45	9956.50	5157.47
Std. of Non-Resident Bids (in 1000s)	6875.47	11542.64	7232.36
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
Percent of Resident Winners	76.20	78.26	76.33
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
Average Contract Observables:			
Length (in miles)	5.02	3.79	4.94
Working Days	123.76	121.87	123.65
Number of Licenses Required	1.50	1.48	1.50
DBE Goal (%)	2.06	0.00	1.93
Number of Subprojects	8.14	7.65	8.11

Table II: Estimated Parameters for the Log-Bid Distribution

	Coefficient	Standard Error
Constant	0.814	0.115
Resident	-0.015	0.011
New Mexico Project	-0.140	0.066
Resident x NM Project	0.065	0.072
log(Engineer's Estimate)	0.921	0.014
log(Length+1) (in miles)	0.035	0.013
log(Working Days)	0.045	0.021
Resident Planholders	0.009	0.005
Non-Resident Planholders	0.002	0.007
Bridge Work	-0.003	0.038
Road Work	-0.004	0.037
Number of Licenses Required	0.021	0.017
Federal Highway	-0.001	0.018
Urban	-0.042	0.017
DBE Goal(%)	-0.010	0.004
log(Subprojects)	0.069	0.022
Resident Bidders	-0.010	0.007
Non-Resident Bidders	-0.014	0.011
Standard Deviation Parameters		
Constant	0.849	0.066
Resident	-0.222	0.146
log(Engineer's Estimate)	-0.166	0.021
Affiliation Parameter		
Theta	0.893	0.047

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.

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

	Coefficient	Standard Error
Constant	0.188	0.096
log(Engineer's Estimate)	0.746	0.103
Resident	0.289	0.079
Standard Deviation Parameters		
Constant	-0.365	0.177
Resident	0.173	0.272

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.

Table IV: Model Fit

		Bidding Only		Bidding and Entry	
	Actual	Predicted	Std. Error	Predicted	Std.Error
Federal-Aid Projects (n = 343)					
Avg. Bid (1000s)	3836.02	3792.13	(2.28)	3913.93	(7.95)
Avg. Res. Bid (1000s)	3532.29	3496.36	(1.98)	3742.31	(8.93)
Avg. Non-Res. Bid (1000s)	4614.37	4550.08	(4.22)	4381.68	(15.02)
Avg. Winning Bid (1000s)	3366.02	3312.47	(1.94)	3304.12	(2.22)
Perc. Res. Win	76.38	71.27	(0.13)	70.91	(0.15)
Avg. Res. Entrants	2.92			3.04	(0.00)
Avg. Non-Res. Entrants	1.14			1.11	(0.00)
State Projects (n = 22)					
Avg. Bid (1000s)	5467.59	5233.78	(13.28)	5511.42	(42.96)
Avg. Res. Bid (1000s)	4201.37	4127.60	(9.8)	4066.95	(49.02)
Avg. Non-Res. Bid (1000s)	10215.90	9381.93	(33.67)	9500.33	(96.23)
Avg. Winning Bid (1000s)	4195.74	4083.62	(10.94)	4091.45	(15.54)
Perc. Res. Win	81.82	78.24	(0.46)	71.14	(0.54)
Avg. Res. Entrants	3.41			2.95	(0.02)
Avg. Non-Res. Entrants	0.91			1.06	(0.01)

Note: This table compares the actual outcomes from New Mexico's state and federal auctions used in estimation to the outcomes predicted by the model. Standard errors calculated from 250 bootstrap samples are reported in parentheses.

Table V: Counterfactual Preference Simulations

	Discount (%)				
	0.0	2.5	5.0	7.5	10.0
Winning Bid ($1000s)					
Affiliation	4190.42	4158.29	4173.09	4217.40	4276.32
Independence	4075.97	4030.02	4039.39	4045.17	4075.60
Difference (%)	2.81	3.18	3.31	4.26	4.92
Efficiency Loss (Actual, $1000)					
Affiliation	8.57	13.55	16.67	17.73	12.09
Independence	0.07	0.75	3.48	7.01	10.61
Difference	8.50	12.80	13.19	10.72	1.48
% Inefficient (Actual)					
Affiliation	7.89	9.81	11.11	9.88	5.20
Independence	0.50	2.10	4.60	5.99	6.94
Difference	7.39	7.71	6.51	3.89	-1.75
Efficiency Loss (Potential, $1000)					
Affiliation	566.15	561.61	552.91	487.91	405.96
Independence	847.93	853.93	841.15	778.09	742.88
Difference	-281.78	-292.33	-288.24	-290.18	-336.91
% Inefficient (Potential)					
Affiliation	74.81	78.58	79.45	80.54	80.40
Independence	78.59	79.76	79.72	78.94	79.08
Difference	-3.78	-1.18	-0.27	1.60	1.32

Note: Average auction outcomes under affiliation and independence for 10,000 simulated preference auctions. Efficiency is calculated for the actual number of bidders and all potential entrants.

Table VI: New Mexico Highway Construction Project Types

Project Type	Federal Projects	State Projects	All Projects
Bridge Rehabilitation	43	2	45
Bridge Replacement	26	0	26
Drainage Improvements	4	0	4
Erosion Control Measures	2	0	2
Fencing	0	2	2
Intelligent Transportation System	1	0	1
Landscaping	1	0	1
Lighting	5	0	5
Miscellaneous	4	2	6
Parking Lot	0	1	1
Pedestrian Trail Rehabilitation	1	0	1
Permanent Signing	3	0	3
Ramp Reconstruction	2	0	2
Ramp Rehabilitation	1	0	1
Rest Area	0	1	1
Roadway New Construction	13	2	15
Roadway Reconstruction	64	3	67
Roadway Rehabilitation	138	6	144
Safety	27	3	30
Signalization	9	0	9
Stockpiling	6	1	7
Structures	2	0	2
Wetland Mitigation	1	0	1

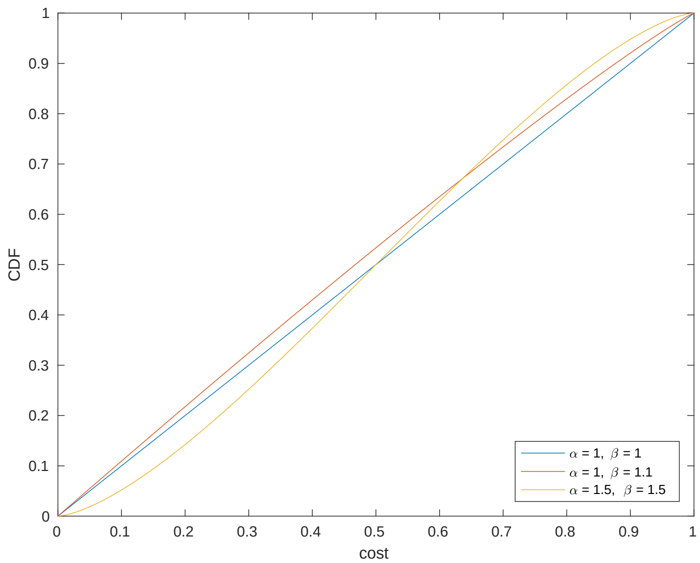

Figure 1: Beta (Marginal Cost) Distribution CDFs

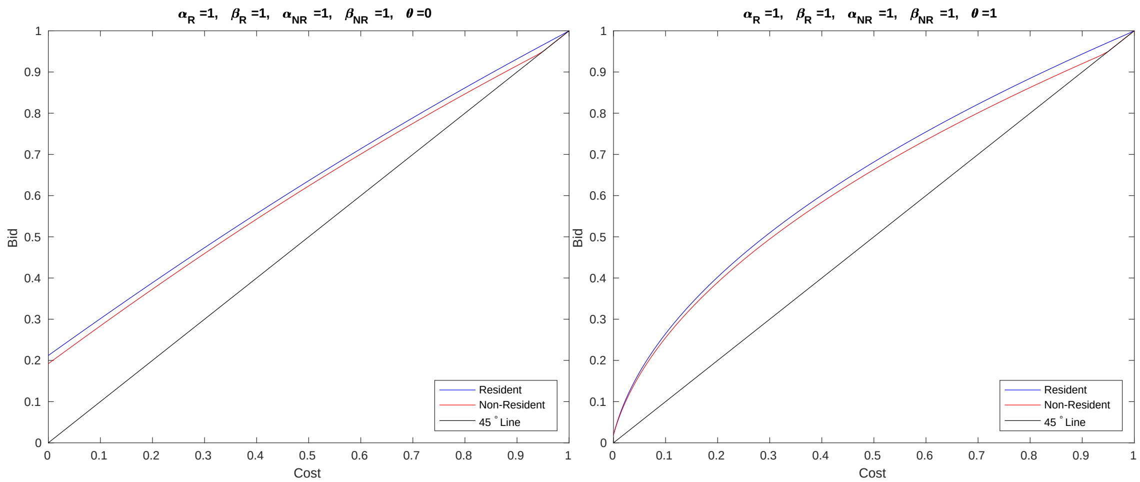

Figure 2: Bid Functions with Equal Strength Bidders ($n_R = 3$, $n_{NR} = 1$)

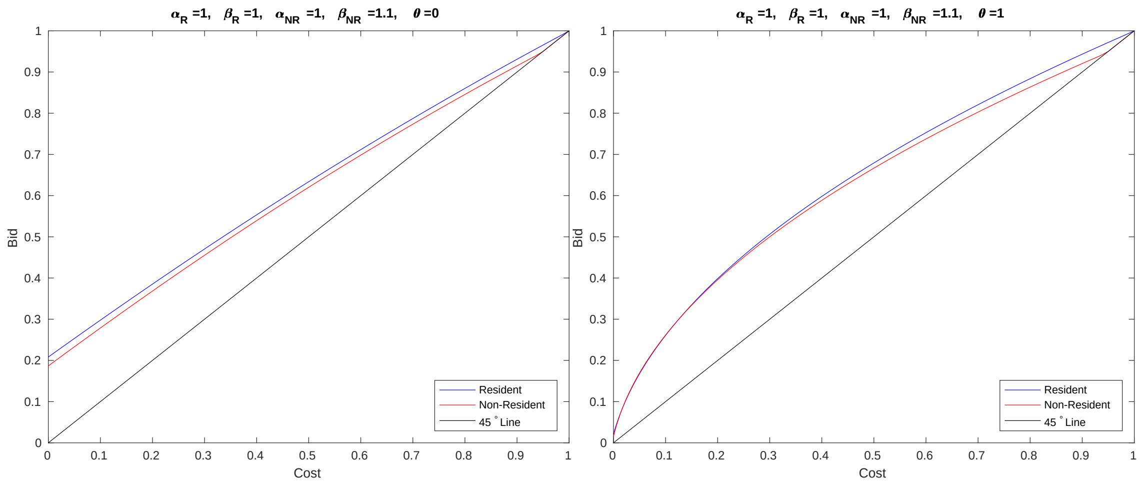

Figure 3: Bid Functions with a Weak and Strong Group of Bidders ($n_R = 3$, $n_{NR} = 1$)

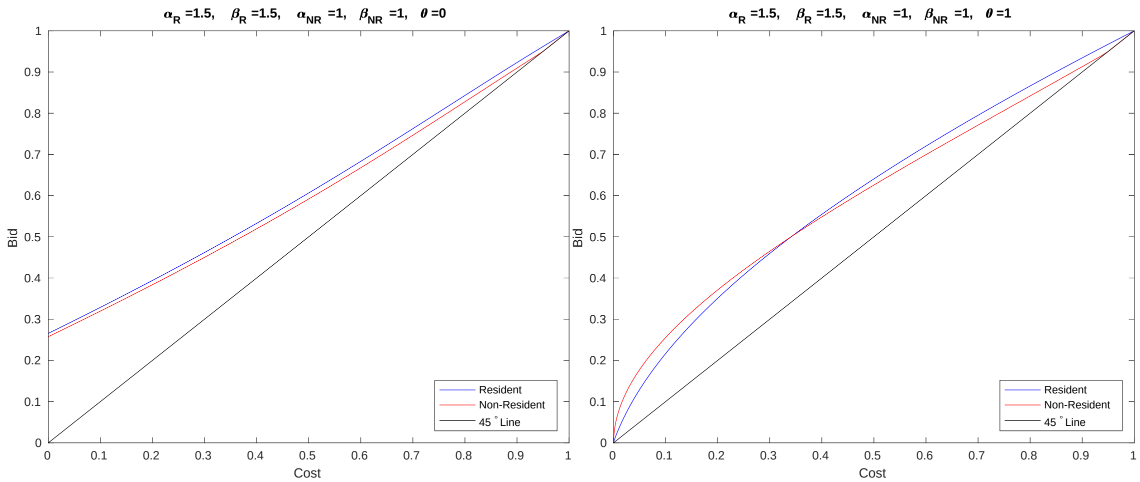

Figure 4: Bid Functions with a High and Low Variance Group of Bidders ($n_R = 3$, $n_{NR} = 1$)

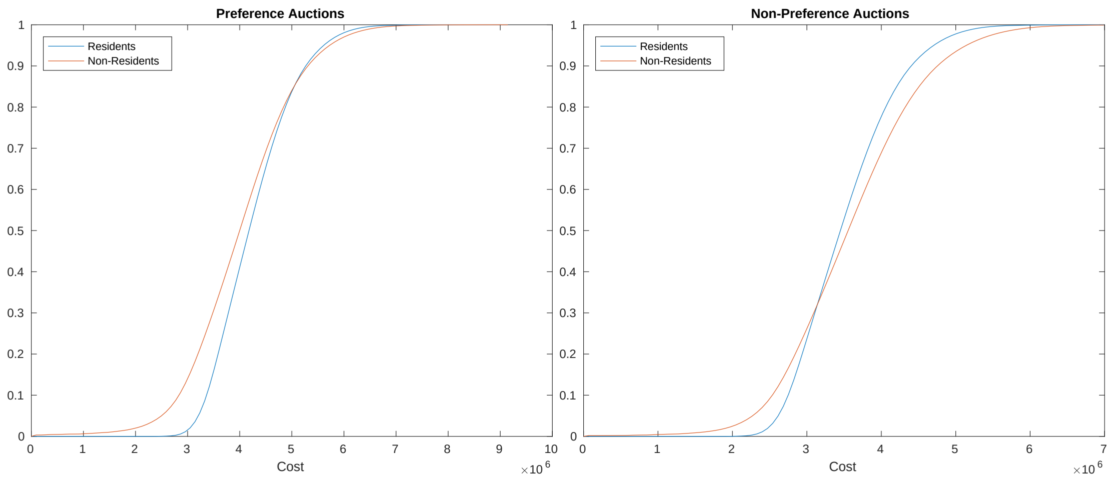

Figure 5: Kernel Density Estimates of the Marginal Cost CDFs for the Average Preference and Non-Preference Auctions

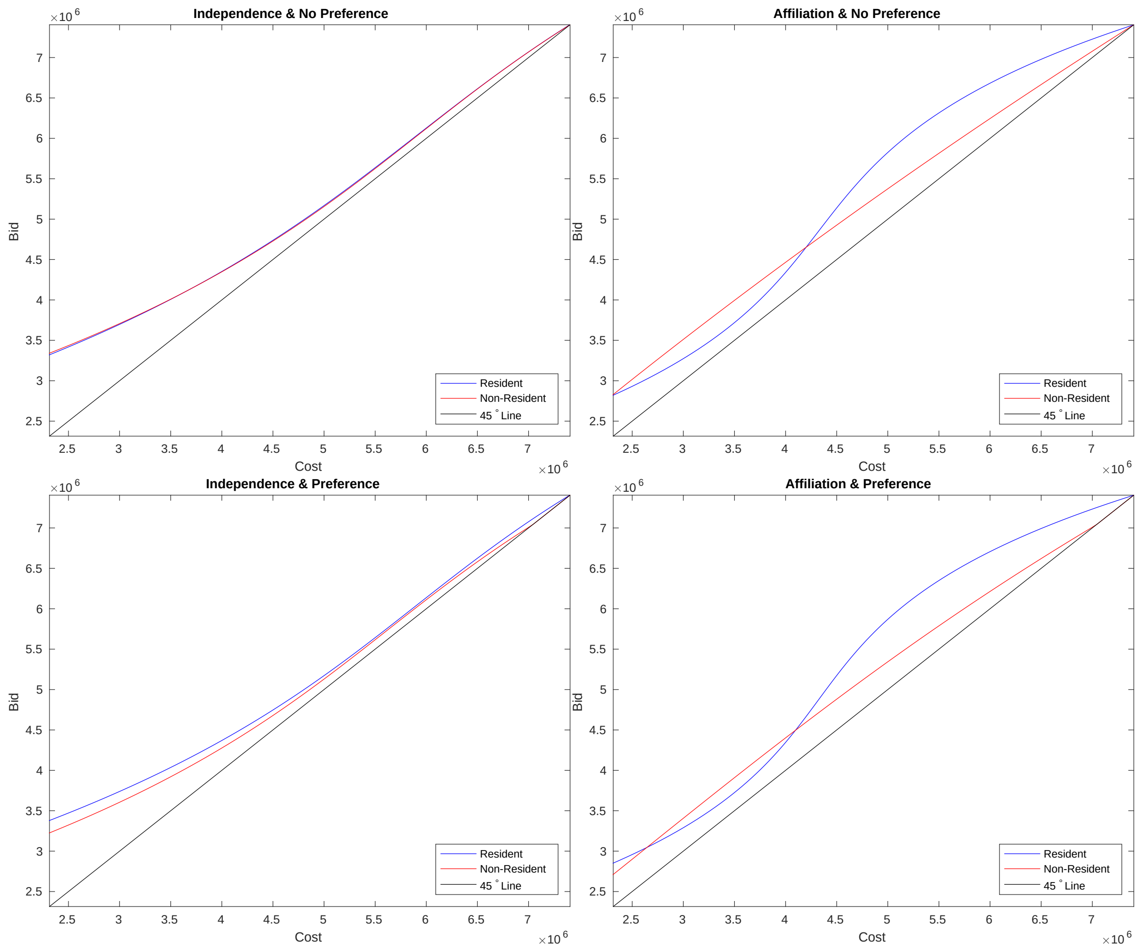

Figure 6: Bid Functions under Fixed Participation ($n_R = 3$, $n_{NR} = 1$)

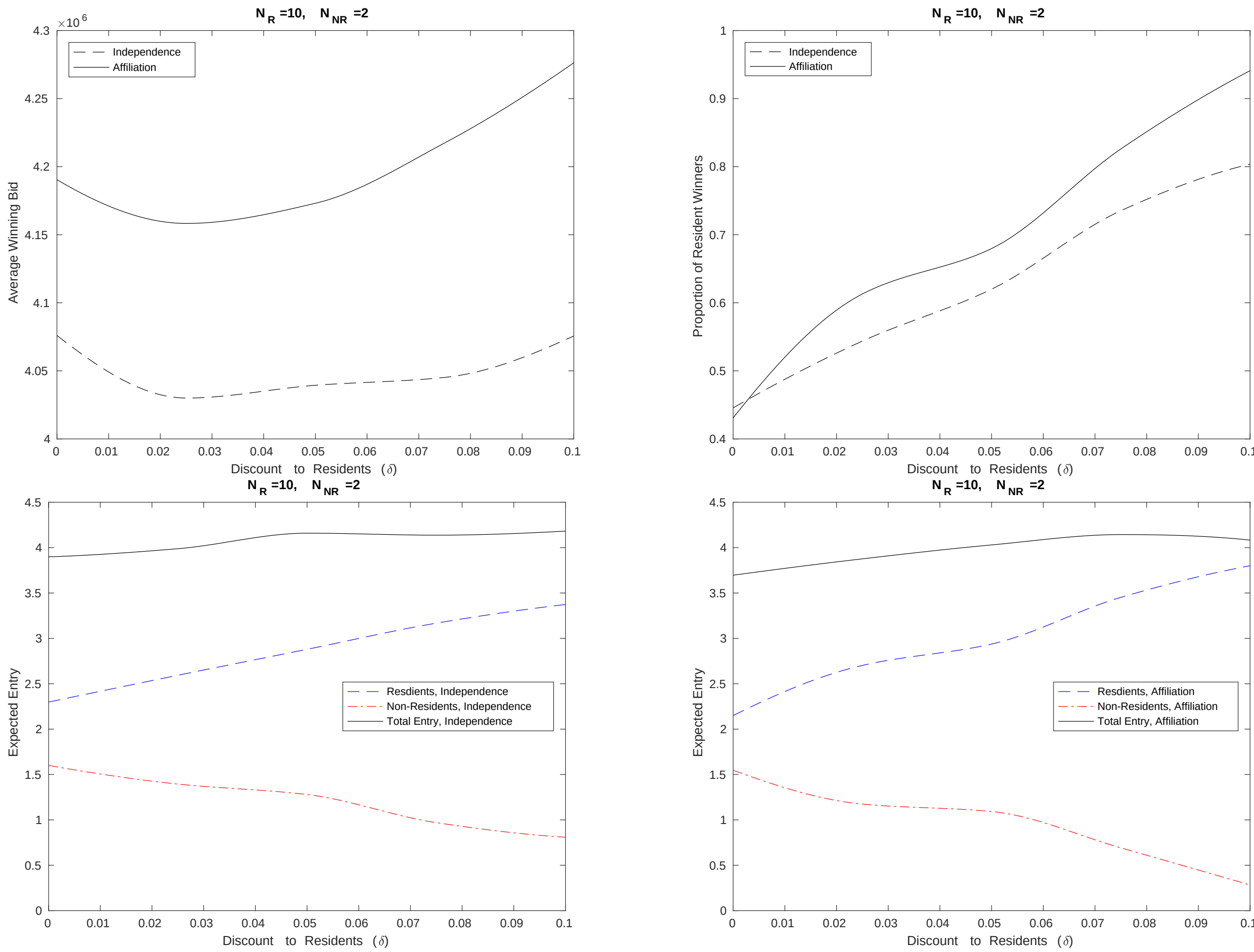

Figure 7: Average Winning Bid, Proportion of Resident Winners, and Entry under Alternative Discount Rates

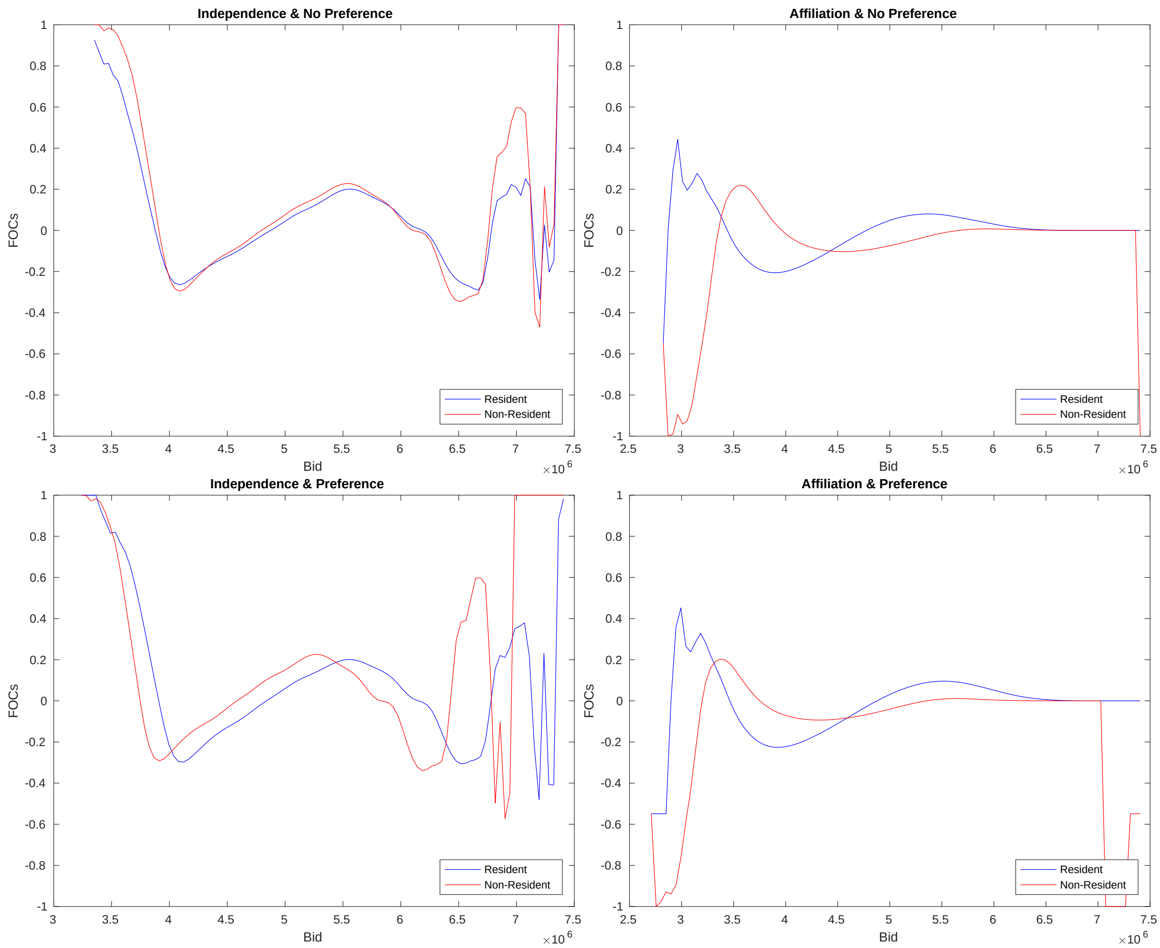

Figure 8: Errors for Approximated Bid Functions

Note: This figure plots the first-order conditions associated with the bid functions approximated in Figure 6. I evaluate the first-order conditions on a grid of potential bids, with accuracy determined by how close the first-order conditions are to zero.

(1)
NEW MEXICO PROJECT
A300013
CN A300013

NM 45, MP 11.600 to MP 12.700 located in Bernalillo County. The approximate length is 0.963 miles.

Construction Consists Of:
ROADWAY REHABILITATION, Cold Milling w/Inlay (Flexible), In-Place Recycling and Stabilization (Flexible), Curb & Gutter w/Sidewalk, Traffic Control (Phasing), Permanent Signing and Miscellaneous Construction.

This contract has a Physical Completion date of May 21, 2014.

(4)
FEDERAL AID PROJECT
1100510
CN 1100510

NM 549, MP 23.400 to MP 24.400 located in Luna County. The approximate length is 1.000 miles.

Construction Consists Of:
BRIDGE REPLACEMENT (Replace Existing Bridge w/ 3 Span Prestressed Concrete Girders, Cast-in-Place Concrete Deck , Approach Slabs, Metal Railing), Roadway Reconstruction, Pavement Sections (Flexible), Earthwork (Borrow, Subexcavation), Metal Barrier Installation, Structures (Culverts, Drop Inlet), MSE Walls, Erosion Control Measures, Traffic Control (Phasing), Permanent Signing and Miscellaneous Construction.

This contract must be completed in 250 working days.

Figure 9: Examples of Projects and Subprojects

Note: This figure has two example project descriptions in the data. The project descriptions include one state project (left) and one federal-aid project (right). The main project is written in capital letters under the 'Construction Consists Of:' line, and the subprojects are listed afterward.