Essays On Preference Programs In Government Procurement

Benjamin Rosa

University of Pennsylvania, brosa@sas.upenn.edu

Follow this and additional works at: https://repository.upenn.edu/edissertations

Part of the Economics Commons

Recommended Citation

This paper is posted at ScholarlyCommons. https://repository.upenn.edu/edissertations/2832
For more information, please contact repository@pobox.upenn.edu.
Abstract
In public-sector procurement, governments frequently offer programs that give preferential treatment to certain groups of firms. My dissertation examines how these programs affect procurement outcomes. I study two types of preference programs: subcontracting requirements, where the government requires that a particular percentage share of a contract be completed by preferred subcontractors, and bid discounts, where the government lowers the bids of preferred firms for comparison purposes and pays the full price to the firm with the lowest bid. My dissertation has two chapters.

My first chapter addresses subcontracting requirements applied under New Mexico's Disadvantaged Business Enterprise Program. This program uses subcontracting requirements to support firms considered disadvantaged in federal procurement, which are small firms owned and controlled by minorities or women. Theoretically, I find that subcontracting requirements need not substantially increase the final cost of procurement, even when preferred firms are relatively more costly. The intuition behind this result is that, by restricting the pool of subcontractors, firms know more about their competitors' costs, which causes firms to reduce their markups. Using an empirical version of the theoretical model estimated on New Mexico's federal procurement data, I find that subcontracting requirements only increased procurement costs by 0.3 percent yet led to a 12.7 percent increase in the amount of money awarded to preferred subcontractors.

My second chapter investigates bid discounts awarded to resident firms under New Mexico's Resident Preference Program. Unlike other papers in the bid discounting literature, my methodology accounts for potentially affiliated project costs -- which is likely to arise in these procurement settings since firms typically share subcontractors and suppliers. Using an empirical auction model estimated on data from New Mexico's Resident Preference Program, I find that offering preference to resident bidders led to a 1.2 percent increase in procurement costs; however, procurement costs are 2.9 percent higher than would be predicted if the model did not account for project-cost affiliation. This chapter highlights the importance of accounting for affiliation in the evaluation of bid preference programs.

Degree Type
Dissertation

Degree Name
Doctor of Philosophy (PhD)

Graduate Group
Economics

First Advisor
Hanming Fang

Keywords
Preferences, Procurement

This dissertation is available at ScholarlyCommons: https://repository.upenn.edu/edissertations/2832
Subject Categories
Economics

This dissertation is available at ScholarlyCommons: https://repository.upenn.edu/edissertations/2832
ESSAYS ON PREFERENCE PROGRAMS IN GOVERNMENT PROCUREMENT

Benjamin V. Rosa

A DISSERTATION

in

Economics

Presented to the Faculties of the University of Pennsylvania

in

Partial Fulfillment of the Requirements for the

Degree of Doctor of Philosophy

2018

Supervisor of Dissertation

Hanming Fang, Class of 1965 Term Professor of Economics

Graduate Group Chairperson

Jesus Fernandez-Villaverde, Professor of Economics

Dissertation Committee

Katja Seim, Associate Professor of Business Economics and Public Policy

Jose Miguel Abito, Assistant Professor of Business Economics and Public Policy
ESSAYS ON PREFERENCE PROGRAMS IN GOVERNMENT PROCUREMENT

© COPYRIGHT

2018

Benjamin Victor Rosa II

This work is licensed under the Creative Commons Attribution NonCommercial-ShareAlike 3.0 License

To view a copy of this license, visit

http://creativecommons.org/licenses/by-nc-sa/3.0/
Dedicated to my supportive family.
ACKNOWLEDGEMENT

First and foremost, I would like to thank my dissertation committee – Hanming Fang, Katja Seim, and Mike Abito – for their guidance and support. I would also like to thank other colleagues who have had a substantial impact on my work. In particular, I would like to thank Andrew Sweeting, Aviv Nevo, Jorge Balat, Holger Seig, and Petra Todd as well as participants in the Wharton IO seminar, the AEA Summer Mentoring Pipeline Conference, the International Industrial Organization Conference, and the Penn Empirical Micro and Theory Lunches for their comments and suggestions. My dissertation would not be possible without data from New Mexico; thus, I gratefully acknowledge David Coriz and Patricia Silva of the New Mexico Department of Transportation for providing parts of the data.
ABSTRACT

ESSAYS ON PREFERENCE PROGRAMS IN GOVERNMENT PROCUREMENT

Benjamin V. Rosa
Hanming Fang

In public-sector procurement, governments frequently offer programs that give preferential treatment to certain groups of firms. My dissertation examines how these programs affect procurement outcomes. I study two types of preference programs: subcontracting requirements, where the government requires that a particular percentage share of a contract be completed by preferred subcontractors, and bid discounts, where the government lowers the bids of preferred firms for comparison purposes and pays the full price to the firm with the lowest bid. My dissertation has two chapters.

My first chapter addresses subcontracting requirements applied under New Mexico’s Disadvantaged Business Enterprise Program. This program uses subcontracting requirements to support firms considered disadvantaged in federal procurement, which are small firms owned and controlled by minorities or women. Theoretically, I find that subcontracting requirements need not substantially increase the final cost of procurement, even when preferred firms are relatively more costly. The intuition behind this result is that, by restricting the pool of subcontractors, firms know more about their competitors’ costs, which causes firms to reduce their markups. Using an empirical version of the theoretical model estimated on New Mexico’s federal procurement data, I find that subcontracting requirements only increased procurement costs by 0.3 percent yet led to a 12.7 percent increase in the amount of money awarded to preferred subcontractors.

My second chapter investigates bid discounts awarded to resident firms under New Mexico’s Resident Preference Program. Unlike other papers in the bid discounting literature, my methodology accounts for potentially affiliated project costs – which is likely to arise in
these procurement settings since firms typically share subcontractors and suppliers. Using an empirical auction model estimated on data from New Mexico’s Resident Preference Program, I find that offering preference to resident bidders led to a 1.2 percent increase in procurement costs; however, procurement costs are 2.9 percent higher than would be predicted if the model did not account for project-cost affiliation. This chapter highlights the importance of accounting for affiliation in the evaluation of bid preference programs.
<table>
<thead>
<tr>
<th>Section</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.6 A Simulation Study</td>
<td>57</td>
</tr>
<tr>
<td>2.7 Empirical Model and Estimation</td>
<td>62</td>
</tr>
<tr>
<td>2.8 Empirical Results</td>
<td>68</td>
</tr>
<tr>
<td>2.9 Counterfactual Analysis</td>
<td>74</td>
</tr>
<tr>
<td>2.10 Conclusion</td>
<td>81</td>
</tr>
<tr>
<td>APPENDIX</td>
<td>83</td>
</tr>
<tr>
<td>BIBLIOGRAPHY</td>
<td>113</td>
</tr>
</tbody>
</table>
List of Tables

TABLE 1 : Summary Statistics ................................................. 27
TABLE 2 : OLS Regression of the Winning Bids .............................. 28
TABLE 3 : OLS Regressions of the DBE Shares .............................. 29
TABLE 4 : OLS Regressions of the Share-Bidder Interaction ............ 30
TABLE 5 : Parameter Estimates for the Log-Normal Cost Distribution .... 32
TABLE 6 : Parameter Estimates for the DBE Pricing and Fine Functions .... 33
TABLE 7 : Model Fit ............................................................ 35
TABLE 8 : Counterfactual Goal Levels ...................................... 36
TABLE 9 : Counterfactual Quota Levels ..................................... 37
TABLE 10 : Counterfactual Subsidy Levels .................................. 38
TABLE 11 : Policy Comparisons .............................................. 40
TABLE 12 : Summary Statistics for New Mexico Highway Construction Projects 68
TABLE 13 : Estimated Parameters for the Log-Bid Distribution .......... 71
TABLE 14 : Estimated Parameters for the Log-Entry Cost Distribution .... 73
TABLE 15 : Counterfactual Preference Simulations ......................... 79
TABLE 16 : Capacity Regressions ............................................ 99
TABLE 17 : Entry Regressions ............................................... 100
TABLE 18 : New Mexico Highway Construction Project Types ........... 112
List of Figures

FIGURE 1: DBE Pricing and Fine Functions ............................. 17
FIGURE 2: DBE Share Function ........................................... 18
FIGURE 3: Bid Function .................................................. 19
FIGURE 4: DBE Share and Winning Bid Outcome Fit ................. 34
FIGURE 5: Beta (Marginal Cost) Distribution CDFs ................. 58
FIGURE 6: Bid Functions with Equal Strength Bidders \((n_R = 3, n_{NR} = 1)\) .................................................. 59
FIGURE 7: Bid Functions with a Weak and Strong Group of Bidders \((n_R = 3, n_{NR} = 1)\) .................................................. 60
FIGURE 8: Bid Functions with a High and Low Variance Group of Bidders \((n_R = 3, n_{NR} = 1)\) .................................................. 62
FIGURE 9: Kernel Density Estimates of the Marginal Cost CDFs for the Average Preference and Non-Preference Auctions .................... 72
FIGURE 10: Bid Functions under Fixed Participation \((n_R = 3, n_{NR} = 1)\) .................................................. 76
FIGURE 11: Average Winning Bid, Proportion of Resident Winners, and Entry under Alternative Discount Rates .................... 78
FIGURE 12: The DBE Pricing Function as a Fraction of the Engineer’s Estimate 91
FIGURE 13: Fine Function as a Fraction of the Engineer’s Estimate ..... 92
FIGURE 14: DBE Cost Ratios .............................................. 93
FIGURE 15: DBE Share Functions with Quotas and Subsidies .......... 94
FIGURE 16: Bid Functions with Quotas and Subsidies .................. 95
FIGURE 17: Procurement Cost with Subsidies ........................... 96
FIGURE 18: IFB Example .................................................. 97
FIGURE 19: Errors for Approximated Bid Functions .................... 105
1.1. Abstract

Government procurement contracts are frequently subject to policies that specify, as a percentage of the total project, a subcontracting requirement for the utilization of historically disadvantaged firms. I study how such subcontracting policies affect procurement auction outcomes using administrative data from New Mexico’s Disadvantaged Business Enterprise (DBE) Program. My analysis is based on a procurement auction model with endogenous subcontracting. Theoretically, I show that subcontracting requirements need not translate into substantially higher procurement costs – even when disadvantaged firms are relatively more costly. The intuition behind this result is that subcontracting programs require that prime contractors select their subcontractors from a common pool of disadvantaged firms, which reduces the private information prime contractors have on their own project-completion costs. As a result of losing private information, prime contractors strategically reduce their markups in their bids, and the reduction in markups can be sufficiently high to mitigate the cost increases from using more costly subcontractors. I estimate an empirical version of the model and find that New Mexico’s past subcontracting requirements led to only small increases in procurement costs.

1.2. Introduction

Public procurement is a sizable part of US government spending. In 2013, public procurement amounted to 26.1 percent of US government spending and just over 10 percent of US GDP. The government awards a portion of that spending to firms that, because of either size or past practices of discrimination, it considers to be disadvantaged. In 2013, the US federal government awarded 23.4 percent of its procurement spending to small businesses and 8.61 percent of its procurement spending to small businesses owned and controlled by disadvantaged

---

1See the OECD’s Government at a Glance 2015 report for more information on other countries.
To obtain these levels of participation, the US regularly establishes subcontracting requirements on its federal procurement projects, which specify a percentage of the total award amount that should be given to preferred firms. For example, if a contract valued at $100,000 has a 5 percent subcontracting requirement, then $5,000 of that award must go to preferred firms. In this paper, I study how these subcontracting policies affect procurement outcomes.

A key feature of subcontracting requirements is that they require prime contractors to complete more of their projects with subcontractors from a common set of disadvantaged firms. I use a procurement auction model with endogenous subcontracting to show that this feature can mitigate cost increases associated with using more costly subcontractors. In the model, prime contractors can complete projects by using a mix of private resources and subcontractors from a shared pool of disadvantaged firms. I derive a prime contractor’s bid in this environment as a strategic markup over its project costs, where the markup increases as prime contractors use more of their own private resources. With subcontracting requirements, prime contractors use less of their private resources and more disadvantaged subcontractors, which lowers the amount of private information prime contractors have on their own project costs. Prime contractors, therefore, reduce their markups in their bids. The main finding in my paper is that the reduction in markups can be sufficiently high to leave the cost of procurement virtually unchanged, even if the additional subcontracting increases project costs.

I estimate an empirical version of the model with administrative highway procurement auction data from the New Mexico Department of Transportation (NMDOT) in order to evaluate their Disadvantaged Business Enterprise (DBE) Program. This program relies on subcontracting requirements to increase the representation of small businesses owned and controlled by socially and economically disadvantaged individuals – who are primarily

---

ethnic minorities and women – on federal procurement projects. I find that New Mexico’s past subcontracting requirements are responsible for a 12.7 percent increase in the amount of money awarded to DBE subcontractors yet only increased procurement costs by 0.3 percent. These results suggest that New Mexico’s subcontracting requirements were not responsible for large increases in procurement costs.

I then use the model to compare subcontracting requirements with two alternative policies geared towards increasing DBE participation: a quota and a subsidy. I implement the quota by removing prime contractors’ rights to subcontract below the DBE subcontracting requirement, which is currently possible under New Mexico’s program; I design the subsidy as a payment from the NMDOT to prime contractors proportional to their DBE utilization. My analysis of these two policies reveals that New Mexico can achieve the same level of DBE participation at even lower costs of procurement with subsidies relative to subcontracting requirements and quotas. This outcome is a consequence of subsidies distorting the subcontracting decisions of low project cost prime contractors less than the other policies. At the level of DBE participation achieved under New Mexico’s current subcontracting requirements, quotas result in larger amounts of money awarded to DBE subcontractors relative to the other policies. These results imply that quotas are best for governments seeking to increase DBE awards, while subsidies are best for governments aiming to reduce procurement costs.

My paper fits into the literature on subcontracting and how it affects firms and auction outcomes. Jeziorski and Krasnokutskaya (2016) study subcontracting in a dynamic procurement auction, and their model is closely related to the model in my paper. The main difference between their model and mine is that I study how different subcontracting policies affect bidding and DBE subcontracting in a static setting. These policies are frequently used in government procurement and can lead to a variety of different procurement outcomes. Additionally, their empirical application relies on calibrated parameters, whereas my empirical model allows me to identify and estimate all of its primitives. Other studies of
subcontracting include Marion (2015) who looks at the effect of horizontal subcontracting on firm bidding strategies, Miller (2014) who explores the effect of incomplete contracts on subcontracting in public procurement, Nakabayashi and Watanabe (2010) who use laboratory experiments to investigate subcontract auctions, Branzoli and Decarolis (2015) who study how different auction formats affect entry and subcontracting choices, Moretti and Valbonesi (2012) who use Italian data to determine the effects of subcontracting by choice as opposed to subcontracting by law, and De Silva et al. (2016) who study how subcontracting affects the survival of firms competing for road construction projects.

There are additional papers within the subcontracting literature that focus on the relationship between prime contractors and their subcontractors and suppliers. In construction, Gil and Marion (2013) study how the relationships between prime contractors and their subcontractors shape firm entry and pricing decisions. Papers in other industries include Kellogg (2011), Masten (1984), and Joskow (1987). My paper abstracts away from many of these more dynamic relationship issues and focuses on a firm’s static incentive to subcontract with disadvantaged firms.

My paper’s empirical application to DBE subcontracting requirements complements the literature on subcontracting-based affirmative action policies in government procurement. De Silva et al. (2012) also study DBE subcontracting requirements and find that DBE subcontracting requirements have negligible effects on a firm’s cost of completing asphalt projects in Texas. I extend their work by considering how prime contractors allocate shares of a project to DBE subcontractors and how subcontracting requirements alter those decisions. Marion (2009, 2017) uses changes in DBE procurement policies to identify the effects of DBE programs on outcomes such as procurement costs and DBE utilization. My approach differs in that I use a model to back out a firm’s cost components. The estimated cost components allow me to compare outcomes across a broad range of counterfactual subcontracting policies. Additional studies on the effects of these affirmative action policies include De Silva et al. (2015) who find that affirmative action programs can generate sub-
stantial savings for the government and Marion (2011) who studies the effects of affirmative action programs on DBE utilization in California.

There are a variety of recent studies on similar preference programs in government procurement. Athey et al. (2013) study set-asides and subsidies for small businesses in US Forest Service timber auctions. They find that set-asides reduce efficiency and that a subsidy to small businesses is a more effective way to achieve distributional objectives. My results on quotas and subsidies for disadvantaged subcontractors are similar in that I find that subsidies are generally less costly for the government relative to quotas. Nakabayashi (2013) investigates set-asides for small and medium enterprises in Japanese public construction projects and finds that enough of these smaller enterprises would exit the procurement market in the absence of set-asides to increase the overall cost of procurement. Empirical papers on bid discounting, which is yet another type of preference program, include Krasnokutskaya and Seim (2011) and Marion (2007) who study a bid discount program for small businesses in California and Rosa (2016) who investigates bid discounts for residents in New Mexico. Hubbard and Paarsch (2009) use numerical simulations to explore how discounts affect equilibrium bidding.

The remainder of the paper proceeds as follows. Section 1.3 describes the NMDOT’s procurement process and DBE Program. Section 2.4 shows how I model bidding and DBE subcontracting, and section 1.5 contains a numerical example from my model. Section 1.6 shows how I estimate an empirical version of the model, while section 1.7 contains my descriptive analysis and estimation results. Section 2.9 presents my counterfactual simulations; section 2.10 concludes.

1.3. New Mexico Highway Procurement

This section describes how the NMDOT awards its construction projects, how the NMDOT’s current DBE Program operates, and how prime contractors solicit goods and services from DBE subcontractors. The contents of this section provide the institutional details that
guide my modeling choices in later sections.

1.3.1. Letting

The NMDOT advertises new construction projects four weeks prior to the date of bid opening. As part of the advertising process, the NMDOT summarizes each project’s main requirements in an Invitation for Bids (IFB) document. This document contains information on each project’s type of work, location, completion deadline, DBE subcontracting requirements (if applicable), and licensing requirements. I use the information in the IFB documents to construct my set of project-level observables.

Interested firms then request the full set of contract documents from the NMDOT and write a proposal for the completion of each project. In the contract documents, the NMDOT provides firms with an engineer-estimated cost of the project, which I refer to as the project’s engineer’s estimate. I include the engineer’s estimates as an additional variable in my set of project-level observables. The contract proposals contain a plan for completing the required work, which includes a list of all firms used as subcontractors and a price for completing each required task. I use data compiled by the NMDOT from the contract documents on the winning firm’s DBE subcontractors to calculate the share of work allocated to DBE firms.

Firms submit their proposals to the NMDOT through a secure website prior to the date of bid opening. On the date of bid opening, the NMDOT evaluates all proposals and selects the firm that offers the lowest total price on all tasks as the winner. The NMDOT can reject the lowest bid if the lowest bidding firm fails to meet DBE subcontracting requirements or quality standards. For a more detailed description of the circumstances where the NMDOT will reject a low bid, see the NMDOT’s Consultant Services Procedures Manual available at http://dot.state.nm.us/en/Program_Management.html.

3 I model this process as a first-price sealed-bid procurement auction.
1.3.2. DBE Certification and Subcontracting Requirements

To qualify as a DBE, a firm must show the NMDOT that it is a small business owned and controlled by socially and economically disadvantaged individuals, who are primarily ethnic minorities and women. Ownership requires that at least 51 percent of the firm be owned by these disadvantaged individuals, while control generally requires that disadvantaged individuals have the power to influence the firm’s choices. The Small Business Administration, which is the federal agency that supports and manages small business programs, determines whether a firm qualifies as a small business in a particular industry by considering economic characteristics such as the size of the firm relative to the industry’s average firm size. As part of the certification process, the NMDOT visits the offices and job sites of DBE applicants to verify their information. The NMDOT will also routinely check certified DBEs to ensure that they meet the eligibility requirements. Firms that attempt to participate in the DBE Program based on false information can be subject to administrative fines and suspension from federal contracting. There are a total of 235 qualified DBE firms as of April 2016.\(^4\)

As a recipient of federal funds, the NMDOT is also required to set an overall state goal for the utilization of qualified DBE firms on federally assisted construction contracts. The state expresses its DBE utilization goal as a percentage of total federal funds it awards to DBE firms and has historically been between 7 and 9 percent. If the NMDOT suspects that DBE utilization will fall short of the overall state goal due to either unanticipated levels of contracts, unforeseen types of contracts, or corrigible deficiencies in the utilization of DBE firms, the NMDOT can set subcontracting requirements on individual projects, which, similar to the state goal, requires that prime contractors allocate a pre-specified percentage of the total award amount to DBE subcontractors.

In setting these requirements on individual contracts, the NMDOT takes a number of factors

\(^4\)For additional information on the NMDOT’s DBE Program, see the DBE Program Manual available at http://dot.state.nm.us/en/OEOP.html#c.
into consideration. In particular, the NMDOT bases their DBE subcontracting requirements on the type of work involved on a project, the project’s location, and the availability of DBE subcontractors to perform the type of work requested on a project. Additionally, the NMDOT will only consider projects with both subcontracting opportunities and estimated costs of more than $300,000 eligible for DBE subcontracting requirements. Since those projects are the only ones eligible for subcontracting requirements, much of my empirical and counterfactual analysis focuses on those larger projects.

Once established, the NMDOT gives prime contractors a number of incentives to meet a project’s subcontracting requirement. Although the requirement is not a binding quota, contractors who fall short of the requirement incur additional costs in the form of showing satisfactory effort to use DBE subcontractors to the NMDOT. Moreover, a prime contractor that fails to meet a project’s requirement can be fined according to the difference between the established goal and the achieved level of DBE participation. I model these costs as fines paid by prime contractors who miss the subcontracting requirement.

1.3.3. Subcontracting with DBE Firms

New Mexico maintains an online DBE system that is accessible to all governments and contractors. Through this system, prime contractors can find potential DBE subcontractors and request competitive quotes for each part of a project that requires subcontracting. DBE firms selected as subcontractors have the value of their services count towards the subcontracting requirement provided that they are performing a commercially useful function. Given that the DBE system is accessible to all governments and contractors, it is likely that there are similarities in the cost of using DBE subcontractors across firms.

In the model, I represent the cost of using DBE subcontractors with an upward-sloping pricing function common to all prime contractors. Unfortunately, the New Mexico data does not keep track of the subcontractors used by bidders who do not win, so I cannot directly test whether DBE subcontractor utilization is common with the data. In other
states that have similar DBE systems and that keep public records of DBE commitments on projects with subcontracting requirements, bidders rarely use different firms in satisfying the DBE subcontracting requirement. In a sample of lettings from Iowa, for example, 82.4 percent of lettings with subcontracting requirements and more than one bid had overlap in DBE subcontractors. The advantage of using New Mexico over these states is that I also have data on DBE commitments without subcontracting requirements. This data variation allows me to separately identify all of my model’s primitives.

In the data, the use of DBE firms as subcontractors is prevalent – even when a project does not have a DBE subcontracting requirement. In particular, 78 percent of all contracts use at least one DBE subcontractor and 62 percent of contracts without a DBE subcontracting requirement use at least one DBE subcontractor. DBE subcontractors account for a total of 7.1 percent of all contract dollars awarded by the NMDOT.

1.4. Theoretical Model

In this section, I develop a theoretical model that formalizes the different channels through which DBE subcontracting requirements affect a prime contractor’s bidding and DBE subcontracting decisions. My model is closely related to the subcontracting model proposed by Jeziorski and Krasnokutskaya (2016) but adds a policy that encourages the use of DBE subcontractors.

For each project, prime contractors decide how much work to give DBE subcontractors and how much to bid. Prime contractors base their decisions on their non-DBE costs of completing the entire project, which includes work completed in-house and by non-DBE subcontracting requirements on both the set of planholders, which is typically used as a measure of the potential number of bidders, and the fraction of planholders that eventually become bidders. Moreover, different measures of capacity have little influence on both bidding and DBE subcontractor shares. As a result, the analysis targets bidding and subcontracting strategies rather than entry and capacity constraints.

---

5This statistic comes from the Iowa Department of Transportation’s January 2011 letting, which is available at https://www.bidx.com/ia/letting?lettingid=11%2F01%2F19. Other lettings from Iowa have a similar pattern.

6Jeziorski and Krasnokutskaya (2016) also include capacity dynamics and entry in their model. In the data, there is no effect of DBE subcontracting requirements on both the set of planholders, which is typically used as a measure of the potential number of bidders, and the fraction of planholders that eventually become bidders. Moreover, different measures of capacity have little influence on both bidding and DBE subcontractor shares. As a result, the analysis targets bidding and subcontracting strategies rather than entry and capacity constraints.
subcontractors. My model also incorporates subcontracting requirements when set by the NMDOT.

1.4.1. Environment and Objective Function

Formally, $N$ risk-neutral bidders compete against each other for the rights to complete a single, indivisible highway construction project. Bidders are ex-ante symmetric in that each bidder draws their cost of completing the entire project without DBE subcontractors, $c_i$, independently from the same distribution, $F$, with support on the interval $[c, \bar{c}]$. This cost, which I refer to as a bidder’s non-DBE cost, includes work done by the prime contractor and non-DBE subcontractors. Bidders know the realization of their own non-DBE cost and the distribution of non-DBE costs prior to submitting bids.

In addition to the standard setup of a first-price sealed-bid procurement auction, all bidders can choose to subcontract out portions of their projects to DBE firms. That is to say, bidders choose a share of the project, $s_i \in [0, 1]$, to subcontract to DBE firms, which reduces their portion of the cost of completing the project from $c_i$ to $c_i (1 - s_i)$. I model a bidder’s cost of using DBE subcontractors as an increasing, convex, and twice continuously differentiable pricing function $P : [0, 1] \rightarrow \mathbb{R}_+$, which is known to all bidders and maps the share of the project using DBE subcontractors into a price of using DBE subcontractors.\footnote{This pricing function represents the prices received by prime contractors from DBE subcontractors through the quote solicitation process. Ideally, I would model the DBE subcontracting market separately, and the price would be an endogenous outcome of that market. However, since the data only contains information on the prices listed by DBE subcontractors, I can only use prices to infer the cost of using DBE subcontractors. For a discussion of the microfoundations of $P$, see Appendix A.1.2.} The cost of using a DBE subcontracting share of $s_i$ is then $P(s_i)$, and I will now refer to this cost as a bidder’s DBE cost. A limitation of placing this type of structure on the DBE subcontracting market is that it assumes away any type of private information that a bidder may have on using DBE subcontractors. For example, this assumption precludes the possibility that contractors may form relationships with certain DBE subcontracting firms to get discounts on prospective construction projects relative to other contractors. Instead, each bidder has access to the same DBE subcontracting technology.
Some of the NMDOT’s highway construction projects are subject to DBE subcontracting requirements. Namely, for every prospective highway construction project, the NMDOT specifies a total share of the project, \( \pi \in [0, 1] \), that is to be completed by DBE subcontractors, and this DBE subcontracting requirement is known to all bidders prior to any bidding or DBE subcontracting decisions. A choice of \( \pi = 0 \) in this environment is analogous to not having a subcontracting requirement.

I assume that the NMDOT enforces their subcontracting requirements through fines. These fines represent any additional costs to bidders who miss the subcontracting requirement, including any actual fines, the increased probability of bid rejection, and any additional effort required to show the NMDOT satisfactory effort to use DBE subcontractors. Formally, subcontracting requirements alters a bidder’s optimal choice of DBE subcontracting and bidding through a fine function \( \varphi : [0, 1] \rightarrow \mathbb{R}_+ \), which is common knowledge and maps a bidder’s choice of DBE subcontracting given the DBE subcontracting requirement into a non-negative value. For technical reasons, I assume that \( \varphi \) is non-increasing, convex, and continuously differentiable in all of its arguments.

In sum, a bidder’s optimization problem is

\[
\max_{\{b_i, s_i\}} (b_i - c_i (1 - s_i) - P (s_i) - \varphi (s_i; \pi)) \times \Pr (b_i < b_j \forall j \in N \setminus \{i\}).
\]

A strategy in this environment is a 2-tuple that consists of a bid function \( b_i : [c, \bar{c}] \rightarrow \mathbb{R}_+ \) and a DBE subcontracting share function \( s_i : [c, \bar{c}] \rightarrow [0, 1] \), which, for all levels of \( \pi \), maps non-DBE costs into bidding and DBE subcontracting choices. In order to reduce the problem’s complexity, I focus on symmetric Nash equilibria in bidding and DBE subcontracting; therefore, I drop the \( i \) subscript from the bidding and DBE subcontracting strategies without loss of generality.

The DBE subcontracting market introduces a couple of interesting changes into the competitive bidding environment. Perhaps the most salient of these changes is that the DBE
subcontracting market allows all bidders to substitute between completing projects with non-DBE resources and with DBE subcontractors. This substitution benefits the bidders in that increasing the DBE subcontracting share reduces their non-DBE portion of the cost of completing the contract; however, this substitution is costly in that it requires bidders to give up a portion of their profits to their DBE subcontractors. Another notable change is that DBE subcontracting creates a shared component in bidders’ costs of completing the entire project, since all bidders have equal access to DBE subcontracting.

1.4.2. DBE Subcontracting Strategies

I begin my analysis of bidding and DBE subcontracting behavior by solving for the optimal DBE subcontracting share given a non-DBE cost realization and a DBE subcontracting requirement. I use the first-order conditions to characterize an optimal DBE subcontracting share \( s(c_i; \bar{s}) \). My analysis of the second-order conditions is contained in the appendix; see Appendix A.1.1. For an interior choice of \( s(c_i; \bar{s}) \), the first-order conditions require that

\[
c_i = P'(s_i) + \varphi'(s_i; \bar{s}) .
\]  

(1.2)

For bidders whose optimal choice is to use no DBE subcontractors, the following condition must hold:

\[
c_i < P'(0) + \varphi'(0; \bar{s}) .
\]  

(1.3)

Likewise, bidders whose optimal choice is to subcontract the entire project to DBE firms must have the following condition hold:

\[
c_i > P'(1) + \varphi'(1; \bar{s}) .
\]  

(1.4)

There are a couple of key properties of optimal DBE subcontracting. Similar to Jeziorski and Krasnokutskaya (2016), the optimal DBE subcontracting decision does not depend on
the probability of winning the auction. Intuitively, subcontracting only affects a bidder’s objective function through the payoff conditional on winning and does not directly affect the probability of winning. Bidders, therefore, do not take the probability of winning into account when deciding how to use DBE subcontractors. Another characteristic of optimal DBE subcontracting is that the optimal share does not depend on the bid. In this sense, one can reinterpret the optimal decisions of a bidder as follows: upon the realization of \( c_i \), bidders first determine how much of the project to subcontract out to DBE firms; then, bidders determine how much to bid given their optimal choice of \( s_i \).

Before moving into the bidding strategies, note the effect of DBE subcontracting requirements on DBE subcontracting decisions. With an interior choice of \( s(c_i; \tilde{s}) \), assigning a positive DBE subcontracting requirement on a project only affects the DBE subcontractor choice through the marginal fine rather than the fine’s value. From a policy perspective, bidders are more likely to change their subcontracting behavior if \( \varphi \) changes rapidly in \( s_i \), implying that policies that impose larger marginal fines for missing the DBE subcontracting requirement are more effective in changing equilibrium DBE subcontracting shares.

1.4.3. Bidding Strategies

In addition to selecting a DBE subcontracting share, bidders must also decide on how to bid. To characterize that decision, I first separate a bidder’s non-DBE cost of completing the project from its total cost of completing the project, which I will now refer to as its project cost. A bidder’s project cost consists of its non-DBE cost, its DBE costs, and any fines.\(^8\) Formally, I define a bidder’s project cost as

\[
\phi(c_i; \tilde{s}) = c_i \left(1 - s(c_i; \tilde{s})\right) + P(s(c_i; \tilde{s})) + \varphi(s(c_i; \tilde{s}); \tilde{s}).
\]

\(^8\)Recall that one can calculate optimal subcontracting independently of the bid. Therefore, the project cost can be found prior to bidding and can be substituted in the objective function, obviating the need to optimize over \( s_i \).
Substituting $\phi$ into equation (1.1) and removing the optimization over $s_i$ reduces the problem to a first-price sealed-bid procurement auction, where bidders draw a project cost rather than a non-DBE cost. This transformed optimization problem together with boundary condition $b \left( \bar{\phi} \right) = \bar{\phi}$ has a unique solution that is increasing in $\phi$, given arguments from Reny and Zamir (2004), Athey (2001) and Lebrun (2006).\(^9\) As a result, I focus on symmetric bidding strategies that are increasing in $\phi$.

There is a tight relationship between a bidder’s project cost and a bidder’s non-DBE cost. In particular, observe that

$$\phi' (c_i; \bar{s}) = (1 - s (c_i; \bar{s})) \geq 0, \quad (1.5)$$

where the above inequality uses the first-order conditions on DBE subcontracting to eliminate the extra terms in the derivative. Equation (1.5) demonstrates that the project cost is increasing in $c_i$ whenever $s (c_i; \bar{s}) \in [0, 1)$ and flat whenever $s (c_i; \bar{s}) = 1$. Intuitively, bidders with lower non-DBE costs should also have lower project costs unless their non-DBE costs are high enough that it is optimal to subcontract the entire project to DBE firms. Furthermore, this relationship implies that the bid function is increasing in $c_i$, except when $s (c_i; \bar{s}) = 1$.

Using an envelope theorem argument based on Milgrom and Segal (2002) and equation (1.5), I derive an expression for the optimal bid function in terms of non-DBE costs. Proposition 1 presents the bid function expression, with the details of its derivation contained in Appendix A.1.1.\(^10\)

**Proposition 1.** The optimal bid function is

---

\(^9\)Observe that $\bar{\phi} = P (1) + \varphi (1; \bar{s})$ is the project cost of a bidder that subcontracts the entire project to DBE firms. I derive this expression from the previous result that the optimal DBE subcontracting share is increasing in $c_i$.

\(^10\)The NMDOT does not use reservation prices in its procurement auctions, so my model does not include a reservation price. The absence of reservation prices can potentially be problematic, though: when there is only one bidder in an auction, the lack of competition could give rise to unusually high equilibrium bids. To address this problem, I follow Li and Zheng (2009) in assuming that auctions with one bidder face additional competition from the NMDOT in the form of an additional bidder during the structural estimation and counterfactual policy simulations. This assumption approximates the right of the NMDOT to reject high winning bids. In the data, only 4.6 percent of all auctions have one bidder.
There are a couple of key features of the bid function. In particular, one can interpret the optimal bid function as a strategic markup\textsuperscript{11} over project costs. An increase in DBE subcontracting necessarily reduces a bidder’s markup and total non-DBE costs. Moreover, the fine function appears as an additive term in the bid function, meaning that bidders pass fines through to their bids.

\textit{1.4.4. The Role of DBE Subcontracting Requirements}

Subcontracting requirements can introduce several interesting changes in equilibrium bidding and DBE subcontracting, which come from the features of the equilibrium bid and DBE subcontracting functions. I summarize those changes in the next proposition and corollaries and provide the proofs of each statement in Appendix A.1.1.

\textbf{Proposition 2.} For a given non-DBE cost draw \( c_i \), if \( s(c_i; 0) \neq s(c_i; \bar{s}) \), then \( s(c_i; 0) < s(c_i; \bar{s}) \).

Proposition 2 says that when the policy can affect a bidder’s DBE subcontracting, subcontracting requirements will increase the share of work given to DBE subcontractors. The idea behind the proof is that prime contractors want to increase the share of work given to DBE subcontractors to avoid incurring any fines. Therefore, prime contractors will increase the share of work given to DBE subcontractors when DBE subcontractors are sufficiently low priced. The next corollary addresses how subcontracting requirements affect project costs.

\textsuperscript{11}Technically, the markup term contains the bidder’s markup and the markups of all non-DBE subcontractors. I will continue to refer to this term as the markup where this distinction does not cause confusion.
Corollary 1. *DBE subcontracting requirements weakly raise project costs.*

The intuition behind corollary 1 is that, in the absence of DBE subcontracting requirements, bidders will choose their share of DBE subcontractors to extract the highest possible profits, which in this case is analogous to minimizing their project costs. As shown in proposition 2, subcontracting requirements can change DBE subcontracting decisions, and that change leads to higher project costs. The next corollary ties DBE subcontracting requirements to a bidder’s markup.

**Corollary 2.** *DBE subcontracting requirements weakly lower markups.*

The proof of corollary 2 relies on propositions 1 and 2. In particular, the expression for the optimal bid function in proposition 1 implies that an increase in DBE subcontracting reduces the bidder’s markup, while proposition 2 shows that DBE subcontracting requirements (weakly) increase total DBE subcontracting. From those two propositions, it immediately follows that DBE subcontracting requirements weakly lower markups. Intuitively, subcontracting requirements distort a bidder’s DBE subcontracting decisions towards completing a project with more DBE subcontractors and less non-DBE resources. Since bidders can only markup components of their costs that are private and the cost of DBE subcontractors is common, that distortion leads to a reduction in markups.

1.5. Numerical Example

In this section, I turn to a numerical example to illustrate the main points of the theory. For this example, I assume that two prime contractors (\(N = 2\)) are competing for a single construction project. I assume that the prime contractors’ non-DBE costs are distributed uniformly on the interval \([0, 1]\). For simplicity, I assume that the pricing functions and the fine function are quadratic and that prime contractors are only fined if their total share of
work going to DBE subcontractors is below the subcontracting requirement:

\[ P(s_i) = \frac{\xi s_i^2}{2} \]

\[ \varphi(s_i; \bar{s}) = \begin{cases} \frac{\lambda(s_i - \bar{s})^2}{2} & \text{if } s_i < \bar{s} \\ 0 & \text{if } s_i \geq \bar{s} \end{cases} \]

where \( \xi \) and \( \lambda \) are coefficients that control the steepness of the pricing and fine functions respectively. To keep this example simple, I set \( \xi = 2 \); I set the fine coefficient, \( \lambda \), to 3 so that the fine is sufficiently steep to visibly change subcontracting behavior. I use a subcontracting requirement of 30 percent (\( \bar{s} = 0.3 \)) when it applies. Figure 1 contains plots of the pricing function and the fine function.

![DBE Pricing and Fine Functions](image)

Figure 1: DBE Pricing and Fine Functions

I begin my analysis by first solving for the optimal DBE subcontracting share as a function of non-DBE costs. To highlight the effects of subcontracting requirements, I perform this calculation twice: once when there is a requirement and once where there is no requirement. Figure 2 contains plots of these functions.

Subcontracting requirements lead to a couple of interesting changes to DBE subcontracting behavior. In particular, subcontracting requirements increase the share of work allocated
to DBE subcontractors for prime contractors with lower non-DBE cost draws and leaves shares unchanged for prime contractors with higher non-DBE cost draws, which is consistent with proposition 2. Intuitively, prime contractors with lower non-DBE cost draws find it more profitable to use non-DBE resources instead of the relatively more expensive DBE subcontractors. The fine gives these contractors an extra incentive to increase their DBE shares, which is why DBE subcontracting is higher for them when there is a requirement. Prime contractors with higher non-DBE costs are more inclined to use DBE subcontractors to lower their project costs and may even subcontract above and beyond the requirement. When prime contractors do subcontract above the requirement, the fine is no longer effective, so there is no change in DBE subcontracting behavior.

Given the solutions for optimal DBE subcontracting, I next analyze equilibrium bidding with and without the subcontracting requirement. Specifically, I use equation (1.6) to obtain a solution for the equilibrium bids given the uniform assumption on non-DBE costs and the functional forms for the DBE pricing function and the fine function. I plot these functions in figure 3. A striking feature of the bid functions is that bids are virtually unchanged with subcontracting requirements relative to without subcontracting require-
ments, even when prime contractors draw low non-DBE costs. For this range of non-DBE cost draws, the reduction in markups is sufficiently high to mitigate the cost of using more DBE subcontractors. Also note that firms that would subcontract beyond the requirement do not change their bidding behavior, which is why the bid functions overlap.

Taken together, the simulations demonstrate that subcontracting requirements can increase the share of work allocated to DBE subcontractors without substantially changing final cost of procurement. The requirement mainly affects prime contractors with low non-DBE costs, causing them to increase their usage of DBE subcontractors. With sufficiently high markups, increased DBE subcontracting only slightly changes optimal bidding, implying small changes in procurement costs.

1.6. Empirical Model and Estimation

Although the theoretical model can account for a number of different ways in which subcontracting requirements can affect bidding and DBE subcontracting, it cannot be applied to the New Mexico data without additional assumptions on the model’s primitives. In this section, I outline those assumptions and provide a description of the estimation procedure. I
end this section by discussing the sources of variation in the data that identify the empirical model’s parameters.

1.6.1. Parametric Assumptions

To account for a rich set of observed project characteristics while avoiding the curse of dimensionality, I estimate a parametric version of the simplified model. I assume that a project, indexed by \( w \), is uniquely determined by the vector \((x_w, z_w, \bar{s}_w, u_w, N_w)\), where \( \bar{s}_w \) is the DBE subcontracting requirement, \( x_w \) and \( z_w \) are potentially overlapping vectors of the remaining project-level observables that affect non-DBE costs and DBE pricing respectively, \( u_w \) is a project characteristic unobservable by the econometrician but observable to the bidders that affects DBE pricing, and \( N_w \) is the number of bidders on a project.

I use the project characteristic \( u_w \) to represent unobserved conditions in the DBE subcontracting market, such as the availability of DBE firms to act as subcontractors and the concentration of DBE subcontractors in a particular area. Given that the NMDOT may have extra information on these unobservable characteristics when establishing a DBE subcontracting requirement, I allow \( u_w \) to depend on \( \bar{s}_w \). Specifically, I assume the distribution of \( u_w \) follows a gamma distribution with a shape parameter of 1 and a scale parameter of \( \sigma_u = \exp(\sigma_{u0} + \sigma_{u1} DBE \text{ req}) \), where \( DBE \text{ req} = \bar{s}_w \times 100 \).

I also parameterize the non-DBE cost distribution so that it is consistent with the theory. In particular, I assume that non-DBE costs follow a truncated log-normal distribution:

\[
c_i \sim T\mathcal{LN}(\psi'x_w, \sigma_c^2, \bar{c}_w | x_w),
\]

where \( \psi \) is a vector of structural parameters that shift the non-DBE cost distribution and \( \bar{c}_w \) is the project-specific upper bound on the non-DBE cost distribution. Given that \( c_i \) is log normal, its support is bounded below by 0. I use the variable \( \bar{c}_w \) to get the upper limit of integration when solving for the equilibrium bids in equation (1.6), and I construct \( \bar{c}_w \).
by using the highest bid normalized by the engineer’s estimate in the sample. Specifically, let \( \hat{x}_w \in x_w \) be a project’s engineer’s estimate, and suppose \( k \) is the maximum of the ratio of bids relative to the engineer’s estimate \( k = \max \left\{ \frac{b_{iw}}{\hat{x}_w} \right\} \). Then \( \tau_w = k \hat{x}_w \).

I use parametric functional forms for the pricing and fine functions similar to the ones used by Jeziorski and Krasnokutskaya (2016). In particular, I assume that the DBE pricing function and fine function take the following functional forms:

\[
P(s_i) = \left( \alpha_0 + \alpha_1 s_i + \alpha_2 \frac{s_i}{1 - s_i} + \alpha_3' z_w + u_w \right) s_i \hat{x}_w \quad (1.7)
\]

\[
\varphi(s_i; \bar{s}_w) = \begin{cases} 
\gamma (s_i - \bar{s})^2 \hat{x} & \text{if } s_i < \bar{s} \\
0, & \text{if } s_i \geq \bar{s}
\end{cases} \quad (1.8)
\]

The hyperbolic term in equation (1.7) prevents firms from subcontracting entire projects to DBE subcontractors. In the data, no firms select a DBE share of 100%, so I use this functional form to mirror that empirical fact. The scaling by \( \hat{x} \) in \( P \) and \( \varphi \) ensures that the problem scales properly, since projects vary in size; the scaling by \( s_i \) in \( P \) ensures that a prime contractor that allocates none of the project to DBE subcontractors does not have a DBE cost. I use a piecewise functional form in equation (1.8) so that only prime contractors who fail to meet the DBE subcontracting requirement will ever be fined. It is important to note, however, that the parameter values must be constrained for the problem to have desirable properties, such as an interior maximum, an increasing price function, and a non-increasing fine function for different parameter guesses. I present these constraints in appendix A.1.3.

\footnote{Observe that this upper limit is only valid if the observation in which this ratio is maximized has no share of the project allocated to DBE subcontractors, since the boundary condition on bids is in terms of project costs rather than non-DBE costs. While I do not observe the share of the project allocated to DBE subcontractors for losing bidders, the winning bidder in the auction I use to set \( k \) has a DBE share of 0, which makes this approximation plausible.}
1.6.2. Estimation

Given a set of structural parameters, my empirical model generates unique solutions for DBE subcontracting shares and equilibrium bids. The final set of structural parameters are the ones whose predictions are closest to the outcomes observed in the data. I obtain these parameters with an indirect inference estimator, which matches the parameters from an auxiliary model estimated with the true data and simulated data.\footnote{Indirect inference was first used by Smith (1993) in a time-series setting and extended by Gourieroux et al. (1993) to a more general form. I use methods from this extended version in estimating the empirical model.}

I simulate the data in several steps. Given a guess for the structural parameters $\theta = (\psi, \sigma_c, \sigma_u, \alpha_0, \alpha_1, \alpha_2, \alpha_3, \gamma)$, I first simulate $N_w$ non-DBE costs for each auction. Since bids are increasing in non-DBE costs, I take the lowest of the $N_w$ non-DBE costs as the non-DBE cost of the winning bidder. Let $W$ denote the total number of auctions observed in the data and $H$ the total number of simulations. In total, I select $WH$ non-DBE costs from the $\sum_w N_w H$ simulated non-DBE costs. Next, I calculate the equilibrium DBE subcontracting shares using the first-order conditions on DBE subcontracting in equation (1.2). To account for the corner solutions, I take the maximum of 0 and the DBE shares obtained from solving the first-order conditions for $s_i$; the other corner solution is ruled out by the functional form of $P(s_i)$. With the shares calculated, I solve for the equilibrium winning bids using equation (1.6). This step requires an approximation of the optimal DBE share function, so I use polynomial approximations obtained by fitting a polynomial on a grid of optimal DBE shares for each auction.

To then implement the indirect inference estimator, I need to select an auxiliary model. In general, the auxiliary model should be straightforward to estimate and account for the endogenous outcomes. The two endogenous outcomes are the equilibrium bids and DBE subcontracting shares, so I use a linear ordinary least squares (OLS) regression of the log-winning bid and a linear OLS regression of the winning bidder’s DBE subcontracting share as the two components of my auxiliary model. Specifically, if $s_w$ is the share of the project...
the winning bidder allocates to DBE subcontractors in auction \( w \) and \( b_w \) is the winning bidder’s bid in auction \( w \), then my auxiliary model for the DBE share and winning bid is

\[
s_w = \begin{bmatrix} x_w \\ s_w \end{bmatrix}' \beta_s + \epsilon_{sw} \]

\[
\log(b_w) = \begin{bmatrix} x_w \\ s_w \end{bmatrix}' \beta_b + \epsilon_{bw},
\]

where \( \beta_s \) are the parameters of the DBE share regression, \( \beta_b \) are the parameters of the winning bid regression, \( \epsilon_{sw} \) is the error term on the DBE share regression, and \( \epsilon_{bw} \) is the error term on the winning bid regression.

I use a Wald criterion function to match the true data to the simulated data. The indirect inference structural parameter estimates, \( \hat{\theta} \), are then the solution the following optimization problem:

\[
\min_{\theta \in \Theta} \left[ \hat{\beta}_W - \tilde{\beta}_{HW} (\theta) \right]' \hat{\Omega}_W \left[ \hat{\beta}_W - \tilde{\beta}_{HW} (\theta) \right],
\]

where \( \hat{\beta}_W \) are the auxiliary model parameters estimated from the data, \( \tilde{\beta}_{HW} (\theta) \) are the auxiliary model parameters estimated from the structural parameters, and \( \hat{\Omega}_W \) is some positive definite weighting matrix. In practice, I use the indirect inference estimator’s optimal weight matrix as the weighting matrix, and I use the estimator’s asymptotic distribution to calculate standard errors. For a detailed explanation of the optimal weight matrix and standard errors, see Appendix A.1.3.

1.6.3. Parametric Identification

I conclude this section by discussing the variation in the data that identifies the model’s structural parameters. These parameters are the mean and standard deviation of the non-DBE cost distribution (\( \psi \) and \( \sigma_c \)), the parameters of the observed components of the DBE pricing function (\( \alpha_0, \alpha_1, \alpha_2 \) and \( \alpha_3 \)), the parameters of the unobserved component of the
DBE pricing function ($\sigma_{u0}$ and $\sigma_{u1}$), and the fine function parameter ($\gamma$).

In the data, I observe projects without subcontracting requirements where prime contractors use no DBE subcontractors. The bids on these projects allow me to identify the non-DBE cost distribution parameters, since the bid function does not depend on the DBE pricing or fine functions when there are no DBE subcontractors and no subcontracting requirements.

From there, I can identify the parameters of the observed and unobserved parts of the DBE pricing function from two types of projects: projects with no subcontracting requirements and projects with subcontracting requirements where prime contractors exceed the subcontracting requirement. Given the non-DBE cost distribution parameters, the variation in bids and DBE shares on these projects correspond to changes in the DBE pricing function. I observe additional variation in bidding and DBE subcontracting between these two types of projects, and this variation allows me to identify the $\sigma_{u1}$ parameter – which accounts for the possibility that the NMDOT assigns subcontracting requirements when it is less costly. Put differently, if firms tend to use more DBE subcontractors when there is no requirement, then the model would suggest that the NMDOT uses subcontracting requirements when DBE subcontractors are more costly.

The last parameter that needs to be identified is the fine parameter, $\gamma$. Given the non-DBE cost distribution parameters and DBE pricing function parameters, I identify $\gamma$ from the bids and DBE shares of prime contractors who miss the DBE subcontracting requirement. The idea here is that fines only affect bids and subcontracting when a prime contractor fails to reach a given requirement, so the model attributes differences in bidding and subcontracting between prime contractors who meet and do not meet the requirement to $\gamma$.

1.7. Empirical Analysis

In this section, I perform the empirical analysis on the procurement data from New Mexico. My analysis begins with a description of the data and variables. I then present summary statistics and descriptive regressions to highlight the bidding and DBE subcontracting pat-
terns present in the data. Finally, I provide the structural parameter estimates and a discussion of the model’s fit.

1.7.1. Data Description and Variables

The data contains federally funded highway construction contracts issued by the NMDOT from 2008 until 2014 for the maintenance and construction of transportation systems. In order to be consistent with the model, I do not include contracts won by DBE prime contractors.\textsuperscript{14} I construct the subcontracting portion of the data from administrative records from New Mexico’s SHARE system. The SHARE data is part of New Mexico’s state-wide accounting system and tracks all of the transactions between the NMDOT and the contractors who are ultimately awarded projects using federal aid. This data contains information on the subcontractors used in each construction project, including each subcontractor’s DBE status and individual award amount.

I augment the SHARE data with data on contract characteristics. In particular, I include the competition each winning contractor faces in terms of the actual number of bidders and the number of bidders who request information about each project, the advertised DBE subcontracting requirement, the type of work necessary to complete each project, an engineer’s estimated cost of completing each project, and the expected number of days needed to complete each project in the set of observable project characteristics. I gather this data from publicly available NMDOT bidding records, which includes the IFB documents the NMDOT uses to advertise their projects and spreadsheets containing each project’s received bids and eligible bidders.

I define the complete set of variables observed in the full data set as follows. \textit{DBE share} is the percentage share of the total project awarded to DBE subcontractors. \textit{Engineer’s estimate} an engineer’s estimated cost of a project, which is provided by engineers from the NMDOT. \textit{Winning bid} is the bid that ultimately wins the procurement auction. \textit{Subprojects}

\textsuperscript{14}My model assumes that the prime contractor is not a DBE firm, which is the case for the majority of contracts awarded by the NMDOT. Moreover, prime DBE contractors are not affected by DBE subcontracting requirements, since the prime contractor must perform most of the work.
are smaller portions of a larger project, which are specified in the IFB documents and are used as a measure of how easily a contract can use subcontractors. Working days are the number of days a given project is expected to take to complete, and licenses refers to the number of separate license classifications required to complete the project. Length indicates the length of the construction project, and DBE req is the level of the DBE subcontracting requirement. Planholders refers to the number of firms requesting the documents necessary to submit a bid, and federal highway and urban are indicator variables that take on a value of one if a project is located on a federal highway or an urban county respectively.

I use additional observables to distinguish a project’s location and the type of work requested for each project. District is a variable that indicates a project’s administrative district. In New Mexico, there are a total of six mutually exclusive districts – each serving a different region of the state. I separate the type of work requested for each project into six different categories: road work, bridge work, lighting, safety work, stockpiling, and other. I use the other category as the reference class.

1.7.2. Summary Statistics

Table 12 presents the summary statistics from the entire sample of NMDOT highway construction contracts. I divide projects into four categories: projects with subcontracting requirements, projects without subcontracting requirements, projects eligible for subcontracting requirements yet do not have any, and the entire sample of projects. Recall that New Mexico considers all projects estimated to cost more than $300,000 eligible for subcontracting requirements.

Table 12 indicates a couple of differences across projects with and without subcontracting requirements. Projects with subcontracting requirements have, on average, 2.4 more subprojects and are estimated to cost $1.4 million more than eligible projects without subcontracting requirements. Also, projects with subcontracting requirements allocate 4.9 percentage points more to DBE subcontractors relative to eligible projects without subcontracting requirements.

---

15See Appendix A.1.7 for an example of subprojects.
tracting requirements. Despite these differences, projects with subcontracting requirements tend to attract a similar number of bidders as eligible projects without subcontracting requirements, and on projects with requirements, many of the prime contractors comply with the requirement – allocating an average of 5.0 percentage points more than the required amount to DBE subcontractors.

1.7.3. Descriptive Regressions

In order to explore bidding patterns in the data, I run OLS regressions of the log-winning bids on the covariates collected from the NMDOT bidding data. Table 2 reports regression coefficients. The main parameter of interest is the coefficient on the DBE requirement variable, since it shows the correlation between the winning bids and the DBE subcontracting requirement. Column (1) only controls for the variable of interest and the engineer’s estimate. Column (2) includes additional controls for complexity (length, subprojects, working days and licensing requirements) and the type of work requested. I capture the competitive bidding environment in the second column by the number of planholders and the number of bidders, while I include other control variables such as administrative district (not displayed in the regression tables), whether a project is in an urban or rural county, and whether the project takes place on a federal highway to account for a project’s proposed location. Column (3) adds month and year fixed effects as a control for seasonality. I repeat these regression specifications in columns (4) - (6) for a sample limited to projects eligible for DBE subcontracting requirements.

The regressions indicate that the winning bids are uncorrelated with DBE subcontracting
Table 2: Descriptive OLS regressions of the winning bid on project-level observables.

<table>
<thead>
<tr>
<th>Dependent variable: log(Winning Bid)</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>log(Engineer’s Estimate)</td>
<td>0.982***</td>
<td>0.938***</td>
<td>0.938***</td>
<td>0.971***</td>
<td>0.926***</td>
<td>0.927***</td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
<td>(0.020)</td>
<td>(0.020)</td>
<td>(0.009)</td>
<td>(0.021)</td>
<td>(0.021)</td>
</tr>
<tr>
<td>DBE Req (%)</td>
<td>−0.002</td>
<td>0.002</td>
<td>0.002</td>
<td>−0.002</td>
<td>0.001</td>
<td>0.001</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.004)</td>
<td>(0.004)</td>
<td>(0.003)</td>
<td>(0.004)</td>
<td>(0.003)</td>
</tr>
<tr>
<td>log(Length + 1)</td>
<td>0.021</td>
<td>0.026*</td>
<td>0.019</td>
<td>0.023*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.014)</td>
<td>(0.014)</td>
<td>(0.014)</td>
<td>(0.013)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>log(Planholders)</td>
<td>−0.050</td>
<td>0.014</td>
<td>−0.064</td>
<td>−0.031</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.044)</td>
<td>(0.054)</td>
<td>(0.043)</td>
<td>(0.047)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>log(Subprojects)</td>
<td>0.079***</td>
<td>0.068**</td>
<td>0.083***</td>
<td>0.082***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.026)</td>
<td>(0.027)</td>
<td>(0.025)</td>
<td>(0.024)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Licenses Required (#)</td>
<td>0.038**</td>
<td>0.032*</td>
<td>0.043**</td>
<td>0.039**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.018)</td>
<td>(0.018)</td>
<td>(0.018)</td>
<td>(0.018)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>log(Working Days)</td>
<td>0.018</td>
<td>0.012</td>
<td>0.017</td>
<td>0.009</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.025)</td>
<td>(0.024)</td>
<td>(0.026)</td>
<td>(0.025)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Bidders</td>
<td>−0.024***</td>
<td>−0.017***</td>
<td>−0.024***</td>
<td>−0.017***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td>(0.005)</td>
<td>(0.005)</td>
<td>(0.005)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Federal Highway</td>
<td>0.006</td>
<td>0.001</td>
<td>0.008</td>
<td>0.004</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.021)</td>
<td>(0.021)</td>
<td>(0.020)</td>
<td>(0.021)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Urban</td>
<td>−0.054*</td>
<td>−0.056*</td>
<td>−0.052*</td>
<td>−0.048</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.030)</td>
<td>(0.029)</td>
<td>(0.030)</td>
<td>(0.029)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

| Work/District Controls               | X   | X   | X   | X   |
| Month/Year FEs                       | X   | X   |
| Observations                         | 389 | 389 | 389 | 373 |
| Adjusted R²                          | 0.976 | 0.980 | 0.982 | 0.973 |

Note: *p<0.1; **p<0.05; ***p<0.01

Requirements: across all specifications, the coefficient on the DBE requirement variable is small and statistically insignificant. These results suggest that DBE subcontracting requirements are not associated with the ultimate cost of procurement and are comparable to De Silva et al. (2012) who find a lack of an effect of DBE subcontracting requirements on asphalt procurement auctions in Texas.

Given that winning bids and DBE subcontracting requirements are uncorrelated, it is reasonable to question whether DBE subcontracting requirements have any impact on DBE subcontracting. To address this question, I conduct a regression analysis of the percentage

---

16Observe that these coefficients will be biased if there are unobservable factors that affect both bidding (later, DBE subcontracting decisions) and the decision of whether to include DBE subcontracting requirements on a particular project. While the control variables account for many of the factors used in setting DBE subcontracting requirements, the possibility of biased regression estimates still remains. My empirical model explicitly accounts for this type of bias because it allows the subcontracting requirements to affect the price of using DBE subcontractors through unobservable factors.
of projects allocated to DBE subcontractors by winning contractors by using the same six regression specifications as the winning bid regressions. I report the results in table 3.

Table 3: OLS Regressions of the DBE Shares

<table>
<thead>
<tr>
<th></th>
<th>Dependent variable:</th>
<th>DBE Share (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1) (2) (3) (4) (5) (6)</td>
<td></td>
</tr>
<tr>
<td>log(Engineer’s Estimate)</td>
<td>0.240 −0.304 −0.353 0.308 −0.204 −0.139</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.351) (0.581) (0.622) (0.306) (0.559) (0.530)</td>
<td></td>
</tr>
<tr>
<td>DBE Req (%)</td>
<td>1.108*** 0.984*** 1.016*** 1.101*** 0.971*** 0.922***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.142) (0.152) (0.183) (0.142) (0.156) (0.182)</td>
<td></td>
</tr>
<tr>
<td>log(Length + 1)</td>
<td>−0.116 0.017 −0.298 −0.205</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.506) (0.511) (0.460) (0.459)</td>
<td></td>
</tr>
<tr>
<td>log(Planholders)</td>
<td>−0.567 1.650 −1.190 1.540</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.795) (1.940) (1.626) (1.952)</td>
<td></td>
</tr>
<tr>
<td>log(Subprojects)</td>
<td>1.946** 1.412 2.209** 1.847**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.840) (0.870) (0.865) (0.869)</td>
<td></td>
</tr>
<tr>
<td>Licenses Required (#)</td>
<td>1.509* 1.758* 1.060 1.052</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.905) (0.929) (0.826) (0.785)</td>
<td></td>
</tr>
<tr>
<td>log(Working Days)</td>
<td>−0.407 −0.606 −0.280 −0.533</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.608) (0.603) (0.610) (0.608)</td>
<td></td>
</tr>
<tr>
<td>Bidders</td>
<td>−0.076 −0.060 0.003 −0.011</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.213) (0.215) (0.197) (0.215)</td>
<td></td>
</tr>
<tr>
<td>Federal Highway</td>
<td>−0.133 −0.237 0.638 0.009</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.701) (0.686) (0.698) (0.688)</td>
<td></td>
</tr>
<tr>
<td>Urban</td>
<td>2.055** 1.903** 1.847** 1.549*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.934) (0.970) (0.841) (0.871)</td>
<td></td>
</tr>
<tr>
<td>Work/District Controls</td>
<td>X X X X X</td>
<td></td>
</tr>
<tr>
<td>Month/Year FEs</td>
<td>X X</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>389 389 389 373 373 373</td>
<td></td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.152 0.216 0.229 0.162 0.217 0.235</td>
<td></td>
</tr>
</tbody>
</table>

Note: *p<0.1; **p<0.05; ***p<0.01

Descriptive OLS regressions of the DBE subcontractor share on project-level observables. Columns (1)-(3) use all projects, while columns (4)-(6) only use projects eligible for subcontracting requirements. Standard errors are robust.

Unlike the winning bid regressions, DBE subcontracting requirements have a positive and significant correlation with DBE participation. Increasing the DBE subcontracting requirement by one percent increases the share of DBE firms used as subcontractors by about one percent over the different regression specifications. These results suggest that the DBE subcontracting requirements, although uncorrelated with the winning bids, are associated with their goal of increasing the utilization of DBE firms.17

17A property of DBE subcontracting from the model, which is shown in Appendix A.1.1, is that the total share of work given to DBE subcontractors is non-decreasing in $c_i$. This property can potentially be rejected by the data if bidders who submit higher bids choose lower DBE subcontracting shares, since bids are also increasing in $c_i$ for $s(c_i; \bar{s}) \in [0, 1)$. Although the data cannot directly address this issue, I can test this property by using bids as a proxy for non-DBE costs in DBE subcontracting regressions. When included in a DBE subcontracting regression, the coefficient on the submitted bids is positive, suggesting that DBE subcontracting shares are associated with higher non-DBE costs.
Evidence that Higher DBE Shares Reduce Markups

My final piece of descriptive evidence addresses how the share of work allocated to DBE subcontractors relates to firm markups. In the model, increasing the number of competing bidders affects bids by reducing markups. The share of work given to DBE subcontractors also reduces markups, so the reduction in bids due to an increase in the number of competing bidders should be attenuated by the amount of work assigned to DBE subcontractors. In the reduced form, this attenuation effect will appear in the coefficient of an interaction term between the number of bidders and the share of work allocated to DBE subcontractors; a positive coefficient indicates that the share of work given to DBE subcontractors reduces the loss in markups due to an increased number of competitors.

Table 4: OLS Regressions of the Share-Bidder Interaction

<table>
<thead>
<tr>
<th></th>
<th>Dependent variable: log(Winning Bid)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
</tr>
<tr>
<td>log(Engineer’s Estimate)</td>
<td>0.986***</td>
</tr>
<tr>
<td></td>
<td>(0.008)</td>
</tr>
<tr>
<td>DBE Share (%)</td>
<td>−0.002</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
</tr>
<tr>
<td>Bidders</td>
<td>−0.038***</td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
</tr>
<tr>
<td>DBE Share × Bidders</td>
<td>0.001**</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
</tr>
<tr>
<td>Proj./Work/Dist. Controls</td>
<td>X</td>
</tr>
<tr>
<td>Month/Year FEs</td>
<td>X</td>
</tr>
<tr>
<td>Observations</td>
<td>389</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.979</td>
</tr>
</tbody>
</table>

Note: *p<0.1; **p<0.05; ***p<0.01

Descriptive OLS regressions of the winning bid on project-level observables with bidder-share interaction terms. Columns (1)-(3) use all projects, while columns (4)-(6) only use projects eligible for subcontracting requirements. Standard errors are robust.

To investigate whether there is evidence of this attenuation effect in the data, I perform regressions of the log-winning bid on the project-level covariates, with an additional control for the DBE share and an interaction term between the DBE share and the number of bidders. The regression specifications follow the same format as the winning bid regressions, and the coefficient of interest here is the coefficient on the interaction term.
I present the results for the entire sample of winning bids and the winning bids on projects eligible for DBE subcontracting requirements in table 4. Consistent with the model, there is a positive and statistically significant coefficient on the interaction term across all regression specifications. Taken together with the negative and statistically significant coefficient on the number of bidders, these regressions suggest that DBE utilization may work to reduce markups.

To summarize the main results, the descriptive regressions provide evidence for how DBE subcontracting requirements affect bidding, how DBE subcontracting requirements affect the amount of work subcontracted to DBE firms, and how the share of work given to DBE subcontractors affects firm markups. I find that winning bids are uncorrelated with DBE subcontracting requirements and that DBE subcontracting requirements are associated with higher DBE shares. These two results appear to be contradictory given the expected increase in procurement costs associated with using disadvantaged subcontractors, motivating the need to investigate the channels proposed in the theoretical model. Finally, I find evidence that the share of work given to DBE subcontractors reduces firm markups, which is consistent with the implications of the model.

1.7.4. Structural Parameter Estimates

Next, I turn to the parameter estimates from the empirical model. I assume that the distribution of log-non-DBE costs is linear in a project’s engineer’s estimate, complexity, location, and type of work required with a constant variance. The parameters of the DBE pricing function follow the functional form outlined in equation (1.7), with the distribution of the unobserved price shock allowed to depend on the DBE subcontracting requirement and a control for the number of subprojects. The parameters of the fine function follow equation (1.8). Since the subcontracting requirement can affect the realization of the unobserved pricing component, I only use projects eligible for DBE subcontracting requirements in the data.
I present the results for the non-DBE cost distribution parameter estimates in table 5. A firm’s non-DBE cost is affected by a number of observable factors. In particular, I find that non-DBE costs are heavily influenced by the engineer’s estimate; a one percent increase in the engineer’s estimate corresponds to a 0.92 percent non-DBE cost increase, and this coefficient is statistically significant. Although much of a firm’s non-DBE cost is driven by the engineer’s estimate, other observable project characteristics can influence the mean of the log-non-DBE cost distribution. For example, a project’s district ranges from decreasing non-DBE costs by 6.9 percent to 0.2 percent relative to a project that is located in district 1. The effect of the type of work requested on non-DBE costs ranges from decreasing non-DBE costs by 6.5 percent to increasing non-DBE costs by 19.6 percent relative to projects classified as other.

The second set of parameter estimates include the parameters of the DBE pricing function.
Table 6: Parameter Estimates for the DBE Pricing and Fine Functions

<table>
<thead>
<tr>
<th></th>
<th>Coefficient</th>
<th>Standard Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\sigma_u$</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>0.333</td>
<td>0.331</td>
</tr>
<tr>
<td>DBE Req (%)</td>
<td>-0.186</td>
<td>0.059</td>
</tr>
<tr>
<td>Pricing Constant ($\alpha_0$)</td>
<td>0.171</td>
<td>0.120</td>
</tr>
<tr>
<td>$s_i$ ($\alpha_1$)</td>
<td>0.518</td>
<td>0.316</td>
</tr>
<tr>
<td>$\frac{s_i}{1-s_i}$ ($\alpha_2$)</td>
<td>0.637</td>
<td>0.300</td>
</tr>
<tr>
<td>1/Subprojects ($\alpha_3$)</td>
<td>0.122</td>
<td>0.044</td>
</tr>
<tr>
<td>Fine Parameter ($\gamma$)</td>
<td>7.371</td>
<td>30.477</td>
</tr>
</tbody>
</table>

*Note:* Parameter estimates for the DBE pricing and fine functions. The standard deviation of DBE pricing shocks is modeled as $\sigma_u = \exp(\sigma_{u0} + \sigma_{u1}DBE\,req)$, where $DBE\,req$ is the level of the DBE subcontracting requirement.

and the fine function. I summarize these estimates in Table 6. Higher DBE subcontracting requirements are associated with lower DBE pricing shocks, implying that the NMDOT sets these requirements when DBEs are more readily available. The DBE pricing function parameters imply that – when the level of $u_w$, the number of subprojects, and the level of the DBE subcontracting requirement are all fixed at their respective means on DBE-eligible projects – choosing a DBE subcontracting share of 1 percent requires a payment of 1.15 percent of the project’s engineer’s estimate to DBE subcontractors. The parameter of the fine function, although noisy due to the small number of firms who do not comply with DBE requirements, implies that the fine associated with missing the DBE subcontracting requirement by five percent is about 1.8 percent of the project’s engineer’s estimate. For the average engineer’s estimate on projects with DBE subcontracting requirements, this fine amounts to about $101,900.

1.7.5. Model Fit

I evaluate the model’s fit by comparing the predicted DBE shares and winning bids to the DBE shares and winning bids observed in the data on projects eligible for DBE subcontracting requirements. Figure 4 contains histograms comparing these two outcomes. In
these histograms, the red lines represent the density of the simulated DBE shares, the blue lines represent the density of the simulated winning bids, and the black lines represent the density of the actual DBE shares and bids. I report winning bids in logs for visual clarity.

![DBE Share Fit](image1)

![Winning Bid Fit](image2)

**Figure 4: DBE Share and Winning Bid Outcome Fit**

*Note:* Histograms of the actual and predicted DBE shares and Winning bids. The black lines correspond to the densities observed in the data, the red lines correspond to the predicted DBE share densities, and the blue lines correspond to the predicted winning bid densities.

The model fits the winning bids fairly well but has difficulty replicating some of the distribution of DBE shares. The model overpredicts DBE shares of zero and underpredicts DBE shares between 0.05 and 0.10. Given that this region of the DBE share distribution corresponds to the actual DBE subcontracting requirements, the model appears to have difficulty fitting the behavior of prime contractors who set their DBE shares as to just meet the subcontracting requirement.

To then compare how the model fit differs with DBE subcontracting requirements, I calculate the simulated and actual average DBE shares and winning bids for projects with and without DBE subcontracting requirements. I present the results in table 7. The model moments match these data moments reasonably well. The model’s average DBE subcontractor shares are within 0.12 percentage points of the true average DBE subcontractor shares, and the model’s average winning bids are within $140,000 of the average winning bids in the
data.

<table>
<thead>
<tr>
<th></th>
<th>With Req.</th>
<th></th>
<th>W/o Req.</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Actual</td>
<td>Predicted</td>
<td>Actual</td>
<td>Predicted</td>
</tr>
<tr>
<td>DBE Share (%)</td>
<td>9.15</td>
<td>9.05</td>
<td>4.30</td>
<td>4.18</td>
</tr>
<tr>
<td>Winning Bid (in Millions)</td>
<td>5.26</td>
<td>5.12</td>
<td>3.71</td>
<td>3.76</td>
</tr>
</tbody>
</table>

*Note:* The predicted and actual average winning bid and average DBE shares.

1.8. Counterfactual Analysis

I use the model’s parameter estimates to predict counterfactual bidding and DBE subcontracting decisions under a variety of different policy alternatives. I first investigate changes in New Mexico’s past subcontracting requirements; this exercise allows me to evaluate how subcontracting requirements affected past procurement outcomes. I then explore other policies aimed at encouraging the use of DBE subcontractors. In particular, I consider various quota and subsidy policies and compare their outcomes with the outcomes obtained with subcontracting requirements. In order to be consistent with the projects that New Mexico sees fit for government intervention, I only use projects with positive DBE subcontracting requirements in my analysis.

1.8.1. Counterfactual Subcontracting Requirements

The level of the DBE subcontracting requirements can vary from state to state and will impact how prime contractors use DBE subcontractors. To investigate how different levels of DBE subcontracting requirements would have affected New Mexico’s procurement auctions, I simulate a range of different auction outcomes under a variety of different subcontracting requirements, including an elimination of all subcontracting requirements. My analysis in this section focuses on percent changes to the existing DBE subcontracting requirements. This type of policy adjustment is akin to a uniform change in all DBE subcontracting requirements, with more change given to projects with higher past subcontracting require-
ments. The reported policy experiments include outcomes from the model simulated under a 50 percent increase in the DBE subcontracting requirement, no change in the DBE subcontracting requirement, a 50 percent decrease in the DBE subcontracting requirement, and an elimination of all subcontracting requirements.

I report the averages of six auction outcomes for each policy experiment. DBE Share is the simulated share of work going to DBE subcontractors, while Winning Bid refers to the simulated winning bid. Project Cost corresponds to the simulated project costs, and Markup Reduction is the dollar value of the reduction in markups associated with using DBE subcontractors. Theoretically, the markup reduction outcome coincides with the expression

$$\int_{c_i s} c_i (1 - F(\tilde{c}))^N - 1 d\tilde{c}.$$  

DBE Cost is the portion of the winning bid that is paid to DBE subcontractors, and Non-DBE Profits is the markup term, which contains the prime contractor’s and non-DBE subcontractor’s profits.

<table>
<thead>
<tr>
<th>Table 8: Counterfactual Goal Levels</th>
</tr>
</thead>
<tbody>
<tr>
<td>Increase (50%)</td>
</tr>
<tr>
<td>----------------</td>
</tr>
<tr>
<td>DBE share (%)</td>
</tr>
<tr>
<td>Winning Bid (in 1000s)</td>
</tr>
<tr>
<td>Project Cost (in 1000s)</td>
</tr>
<tr>
<td>Markup Reduction (in 1000s)</td>
</tr>
<tr>
<td>DBE Cost (in 1000s)</td>
</tr>
<tr>
<td>Non-DBE Profits (in 1000s)</td>
</tr>
</tbody>
</table>

Note: Average auction outcomes for different requirement levels on auctions with DBE subcontracting requirements. Effective costs are the costs to complete the entire project, which accounts for DBE subcontracting. Markup reduction is the dollar value of markups non-DBE firms lose as a result of DBE subcontracting. DBE cost is the average simulated DBE cost, and non-DBE profits are the profits of the winning prime contractor and its non-DBE subcontractors.

I display the results of the policy experiments in table 8. As a general trend, increasing the subcontracting requirements decreases non-DBE profits, while the remaining outcomes increase. To provide some intuition, the increase in the requirements gives prime contractors an incentive to use more DBE subcontractors, and more DBE subcontractors result in higher payments to DBE firms. The increased payments lead to higher project costs, lower non-DBE profits, and higher winning bids. These effects are modest, though, since the fine function only affects the decisions of prime contractors that would otherwise subcontract.
below the DBE subcontracting requirement. Conversely, DBE subcontracting has a more pronounced effect on non-DBE profits. At New Mexico’s past requirement levels, DBE subcontracting reduced average markups by $103,390 or 11.3 percent.

To evaluate New Mexico’s subcontracting requirement policy, I compare the baseline model’s predictions to the predictions of the model when there are no DBE subcontracting requirements. These simulations predict that New Mexico’s past requirements resulted in a 0.6 percentage point (or 7.5 percent) increase in the average share of work allocated to DBE subcontractors and a $35,390 (or 12.7 percent) increase in the average money awarded to DBE subcontractors. These increases correspond to a $13,220 (or 0.3 percent) increase in the average procurement cost and a $6,570 (or 0.8 percent) decrease in average non-DBE firm profits.

### 1.8.2. Counterfactual Quotas

So far, my analysis shows that using fines to enforce DBE subcontracting requirements can lead to higher DBE subcontracting shares. The fine, however, does not guarantee that prime contractors fulfill the subcontracting requirements, since prime contractors can miss the requirement and pay the corresponding fee. In contrast, quotas ensure that prime contractors meet the requirement and can, therefore, lead to different auction outcomes relative to fines. To explore how outcomes would change under a quota, I re-simulate the auctions with the additional constraint that prime contractors must meet the quota, and for simplicity, I fix the quota level across all simulated auctions.

<table>
<thead>
<tr>
<th>Table 9: Counterfactual Quota Levels</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
</tr>
<tr>
<td>DBE share (%)</td>
</tr>
<tr>
<td>Winning Bid (in 1000s)</td>
</tr>
<tr>
<td>Project Cost (in 1000s)</td>
</tr>
<tr>
<td>Markup Reduction (in 1000s)</td>
</tr>
<tr>
<td>DBE Cost (in 1000s)</td>
</tr>
<tr>
<td>Non-DBE Profits (in 1000s)</td>
</tr>
</tbody>
</table>

*Note: Average auction outcomes for different quota levels on auctions with DBE subcontracting requirements.*
Table 9 summarizes the outcomes for different quota levels. As expected, quotas lead to higher average shares of work completed by DBE subcontractors and become more binding at higher levels, since the average share is closer to the quota level. Similar to subcontracting requirements enforced by fines, higher quota levels lead to higher winning bids, higher project costs, and lower non-DBE profits. Quotas appear to be more effective than fines in increasing DBE participation, though. In fact, a uniform 5 percent quota leads to higher DBE subcontracting shares than a 50 percent increase in all DBE subcontracting requirements (which corresponds to an average subcontracting requirement of 6.3 percent).

### 1.8.3. Counterfactual Subsidies

As an alternative to enforcing subcontracting requirements, the NMDOT can increase DBE subcontracting shares by subsidizing DBE utilization. To investigate how subsidies would affect NMDOT procurement auctions, I simulate the auction outcomes under the assumption that the government subsidizes a share of the DBE costs. That is to say, rather than facing a DBE pricing function of $P(s_i)$, prime contractors now face a subsidized pricing function of $(1 - \text{sub})P(s_i)$, where $\text{sub} \in [0, 1]$ is the fraction of the total DBE cost paid by the government. To track the subsidy’s cost, I include *Subsidy Cost* and *Procurement Cost* as additional outcome variables, where *Subsidy Cost* is the average cost of the subsidy and *Procurement Cost* is the average cost of the subsidy added to the average winning bid.

<table>
<thead>
<tr>
<th></th>
<th>0% Subsidy</th>
<th>5% Subsidy</th>
<th>10% Subsidy</th>
<th>15% Subsidy</th>
<th>20% Subsidy</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>DBE share (%)</strong></td>
<td>8.42</td>
<td>9.30</td>
<td>10.30</td>
<td>11.42</td>
<td>12.69</td>
</tr>
<tr>
<td><strong>Winning Bid (in 1000s)</strong></td>
<td>5103.56</td>
<td>5079.47</td>
<td>5051.96</td>
<td>5020.46</td>
<td>4984.26</td>
</tr>
<tr>
<td><strong>Project Cost (in 1000s)</strong></td>
<td>4287.33</td>
<td>4272.35</td>
<td>4255.05</td>
<td>4235.01</td>
<td>4211.69</td>
</tr>
<tr>
<td><strong>Markup Reduction (in 1000s)</strong></td>
<td>96.82</td>
<td>105.94</td>
<td>116.15</td>
<td>127.61</td>
<td>140.49</td>
</tr>
<tr>
<td><strong>DBE Cost (in 1000s)</strong></td>
<td>278.71</td>
<td>321.52</td>
<td>371.88</td>
<td>431.18</td>
<td>504.16</td>
</tr>
<tr>
<td><strong>Non-DBE Profits (in 1000s)</strong></td>
<td>816.23</td>
<td>807.11</td>
<td>796.91</td>
<td>785.44</td>
<td>772.56</td>
</tr>
<tr>
<td><strong>Subsidy Cost (in 1000s)</strong></td>
<td>0</td>
<td>16.08</td>
<td>37.19</td>
<td>64.68</td>
<td>100.83</td>
</tr>
<tr>
<td><strong>Procurement Cost (in 1000s)</strong></td>
<td>5103.56</td>
<td>5095.54</td>
<td>5089.15</td>
<td>5085.14</td>
<td>5085.09</td>
</tr>
</tbody>
</table>

*Note: Average auction outcomes for different subsidy levels on auctions with DBE subcontracting requirements.*

Table 10 contains the results from the subsidy simulations. As is evident from the table, subsidies increase the average share of projects awarded to DBE subcontractors but are
associated with lower winning bids. Intuitively, the subsidy makes DBE subcontractors cheaper, which encourages prime contractors to use them to obtain lower project costs. Increased DBE subcontractor utilization also leads to lower markups, and the combination of lower markups and lower project costs results in lower average equilibrium bids. Subsidies also lead to lower non-DBE profits, which comes from prime contractors using more DBE subcontractors instead of either their own resources or non-DBE subcontractors.

A more counterintuitive result with subsidies is that they produce lower average procurement costs. This outcome is possible because subsidies are less likely to affect the most efficient\textsuperscript{18} prime contractor’s DBE subcontracting decisions yet make every competing firm more competitive. To illustrate this point with an example, consider a firm that is so efficient that it would never use DBE subcontractors – even with the subsidy. If that firm wins, there would be no subsidy cost, but the firm would have to lower its markup to compete with the other firms that can now obtain lower project costs with the subsidy.\textsuperscript{19}

1.8.4. Comparing Quotas and Subsidies

With the set of outcomes established for different quota and subsidy levels, I now shift my analysis towards comparing these policies. In particular, I compare outcomes under a subsidy and a quota constrained to match the average DBE share obtained by the past subcontracting requirements. I calculate these subsidy and quota levels by using cubic splines to interpolate the non-simulated outcomes.

Table 11 contains the policy comparisons. In general, many of the outcomes under subsidies and quotas are similar to the outcomes with subcontracting requirements. Subsidies result in lower winning bids, higher non-DBE profits, and lower procurement costs relative to subcontracting requirements, but subsidies also result in lower payments to DBE subcontractors. These results are intuitive, since subsidies distort more efficient prime contractors’ DBE subcontracting decisions less than subcontracting requirements do, and more

\textsuperscript{18}Efficiency refers to a prime contractor’s non-DBE cost. A more efficient prime contractor has a lower non-DBE cost.

\textsuperscript{19}I explore this result using simulations in the appendix; see appendix A.1.6.
Table 11: Policy Comparisons

<table>
<thead>
<tr>
<th></th>
<th>Quota</th>
<th>Subsidy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Δ Winning Bid (%)</td>
<td>0.156</td>
<td>-0.595</td>
</tr>
<tr>
<td>Δ DBE Cost (%)</td>
<td>5.187</td>
<td>-1.585</td>
</tr>
<tr>
<td>Δ Non-DBE Profits (%)</td>
<td>0.178</td>
<td>0.005</td>
</tr>
<tr>
<td>Δ Procurement Cost (%)</td>
<td>0.156</td>
<td>-0.375</td>
</tr>
</tbody>
</table>

*Note:* Percent change in the average auction outcomes for policies that achieve the baseline average DBE subcontracting share.

efficient prime contractors are more likely to win. Relative to subcontracting requirements and subsidies, quotas lead to higher payments to DBE subcontractors because prime contractors must use the specified share of DBEs instead of paying the fine or not using the subsidy, even if DBEs are unusually more costly. Taken together, these results suggest that quotas are appropriate for governments aiming to increase the amount of money given to DBE subcontractors, while subsidies are best for governments pursuing policies with lower procurement costs.

1.9. Conclusion

This paper theoretically and empirically examines how subcontracting requirements affect government procurement auctions. The subcontracting policy requires that prime contractors select subcontractors from a common pool of preferred firms, leading to a shared component in their project costs. Theoretically, this shared cost component reduces markups, and the reduction in markups can be sufficiently high to mitigate cost increases from using more costly subcontractors.

The policy experiments illustrate the impact of subcontracting requirements on procurement in New Mexico. I estimate that New Mexico’s past subcontracting requirements increased the money given to DBE subcontractors by 12.7 percent, increased procurement costs by only 0.3 percent, and decreased non-DBE profits by only 0.8 percent. These results suggest that New Mexico’s subcontracting requirements, although effective in increasing DBE subcontractor utilization, was not responsible for large increases in procurement costs.
2.1. Abstract

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

2.2. 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 subset of bidders. This treatment often takes the form of bid discounting – a policy where the government will lower the bids of preferred bidders for comparison purposes and pay the full asking price upon winning. 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

\(^1\)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.
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 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 that they are

3Additional 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.
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. 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 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

---

4This 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).

5Items are portions of a construction project. The final bid is calculated as the sum of the bids on each item.
entry, where I allow for affiliation in firm project costs. The parameter that captures the
degree of affiliation is positive and statistically significant, which indicates that firms do
have affiliated project costs. Counterfactual auctions using alternative discount levels show
that New Mexico’s preference program accounts for a 1.2 percent increase in procurement
costs. At New Mexico’s current discount level, procurement costs are 2.9 percent higher
than would be predicted if project costs were distributed independently. Furthermore, I
find that the proportion of preferred winners is more responsive to the discount level with
affiliation and that affiliation can lead to substantial differences in efficiency at particular
discount levels relative to independence. These results highlight the relevance of affiliation
in the evaluation of public procurement auctions with bid discounting.

The remainder of the paper proceeds as follows. Section 2.3 gives the details of the New
Mexico procurement process and describes the data. Section 2.4 presents the theoretical
framework by which I analyze the effect of affiliation on bidding and entry behavior, and
section 2.5 shows how I represent affiliated distributions using copulas. Section 2.6 shows the
different ways in which affiliation can affect bidding, and section 2.7 shows how I estimate
the theoretical model. Section 2.8 presents the empirical findings, while section 2.9 contains
the counterfactual policy analysis. Section 2.10 concludes.

2.3. New Mexico’s Highway Procurement Market and Data

This section describes the process by which the NMDOT awards their highway construction
contracts and the data collected for the empirical portion of this paper. The sample con-
tains 376 highway construction contracts awarded by the NMDOT through sealed bidding
between 2010 and 2014 for the maintenance and construction of transportation systems. For
a detailed description of the type of work required on these projects, see appendix A.2.5.
New Mexico applies preferences to resident firms on state-funded projects. Over the sample
period, there are a total 23 of these state-funded contracts while the remaining 353 projects
are federally-assisted projects. An immediate limitation of the New Mexico data is that
there are a small number of preference projects relative to the number of non-preference
In response to this limitation, much of the analysis relies on the empirical model of entry and bidding. The empirical model allows me to use information in both the preference and non-preference auctions in identifying the model primitives while accounting for strategic behavior due to bid discounting.

2.3.1. Letting

Four weeks prior to the date of bid opening, the NMDOT advertises construction projects estimated to cost more than $60,000. The Contracts Unit is responsible for gathering the necessary contract documents used during this advertisement phase. Each document is unique to the work required on each project and contains details such as the location of the project, the nature of the work, the number of working days to complete the project, and the length of the project. 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. Given that the list of planholders is known prior to bidding and 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.

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.

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

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 awarding these construction projects, the NMDOT uses a competitive first-price sealed-bid procurement auction format. Potential firms who decide to bid on a project submit bids in a sealed envelope or secure online submission website to the NMDOT. The firm with the lowest bid (usually) wins the contract, and the state pays the winner their bid. The 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.

2.3.2. Resident Preference Program

New Mexico offers bid preferences to qualified resident firms on construction projects funded exclusively by the state. 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 offices within the state (60 percent of bidders and 64 percent of planholders), while only a small number of non-resident firms have 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 while the remaining 44 firms are non-residents. Resident firms account for 80 percent of planholders and 72 percent of submitted bids, and resident firms win 76 percent of federally-assisted projects and 78 percent of state-funded projects.

2.4. 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.

2.4.1. 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.9 Formally, affiliation is defined as follows:

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

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 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 breakdown of each project’s tasks. Since the engineer’s estimate explains a large part of the variation in observed bids, I treat affiliation as the prime explanation for correlations across bids.10

---

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

10In 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.
2.4.2. 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 $G^m_k(\cdot)$, 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 $F_c(\cdot, \ldots, \cdot)$ 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 $F^m_c(\cdot)$, 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.\footnote{This assumption implies that bidders do not base entry decisions on their realized project costs. Samuelson (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.} 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 $\delta$ 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.

2.4.3. 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 potentially different monotone and differentiable bid functions $\beta_m(\cdot) : [\underline{c}, \overline{c}] \rightarrow \mathbb{R}_+$. In particular, a bidder of group $m$ solves the
following optimization problem to determine the equilibrium bids:

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

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 \( \delta \), 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.\(^{12}\)

Let \( n_m \) denote the actual number of bidders in group \( m \). Furthermore, let

\[
\bar{F}_{c_i} (c_1, \ldots, c_{i-1}, c_{i+1}, \ldots, c_n | c_i) = \Pr (C_1 > c_1, \ldots, C_{i-1} > c_{i-1}, C_{i+1} > c_{i+1}, \ldots, C_n > c_n | c_i)
\]

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 bidder \( i \)'s signal, and define

\[
\beta_{NR}^{-1} \left( (1 - \delta)^{D_R} b_i \right) = \left( \beta_{NR}^{-1} \left( (1 - \delta)^{D_R} b_1 \right), \ldots, \beta_{NR}^{-1} \left( (1 - \delta)^{D_R} b_i \right) \right) \in \mathbb{R}^{n_{NR} - D_R}
\]

as a vector that collects the inverse bid functions of non-residents and

\[
\beta_{R}^{-1} \left( (1 - \delta)^{-D_R} b_i \right) = \left( \beta_{R}^{-1} \left( (1 - \delta)^{-D_R} b_1 \right), \ldots, \beta_{R}^{-1} \left( (1 - \delta)^{-D_R} b_i \right) \right) \in \mathbb{R}^{n_R - D_R}
\]

as a vector that collect the inverse bid function of residents. The first-order conditions that

\(^{12}\)This intuition assumes that all else (opposing bids, object being auctioned, etc.) is equal.
characterizes the optimal bid is then given by

\[ 0 = (b_i - c_i) \times \left[ \sum_{j=1}^{n_{NR}-D_{NR}} \bar{F}_{c_{i,j}}(\beta_{NR}^{-1}((1-\delta)^{D_{R}}b_i), \beta_R^{-1}((1-\delta)^{-D_{NR}}b_i) | c_i) \right. \]

\[ \times \beta_{NR,1}^{-1}((1-\delta)^{D_{R}}b_i)(1-\delta)^{D_{R}} + \sum_{j=n_{NR}-D_{NR}+1}^{n-1} \bar{F}_{c_{i,j}}(\beta_{NR}^{-1}((1-\delta)^{D_{R}}b_i), \beta_R^{-1}((1-\delta)^{-D_{NR}}b_i) | c_i) \]

\[ \left. \times \beta_R^{-1}((1-\delta)^{-D_{NR}}b_i)(1-\delta)^{-D_{NR}} \right] \]

\[ + \bar{F}_{c_{i}}(\beta_{NR}^{-1}((1-\delta)^{D_{R}}b_i), \beta_R^{-1}((1-\delta)^{-D_{NR}}b_i) | c_i) \], \]

where \( \bar{F}_{c_{i,j}}(\cdot, \ldots, \cdot | c_i) \) is the partial derivative of the conditional survival function with respect to the \( j \)th coordinate, \( \beta_{NR,1}^{-1}(\cdot) \) is the partial derivative of a non-resident’s inverse bid function with respect to its first coordinate, and \( \beta_R^{-1}(\cdot) \) 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 \( b \) be the common low bid. The left boundary conditions for both groups of bidders is as follows:

1. Resident left boundary:

\[ \beta_R^{-1}\left(\frac{b}{(1-\delta)} \right) = \xi \]
2. Non-resident left boundary:

\[ \beta_{NR}^{-1}(b) = c. \]

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:

\[ \beta_{R}^{-1}(b) = \bar{c}, \]

where \( \bar{b} = \bar{c} \) if \( n_R > 1 \) and \( \bar{b} = \arg \max_b [(b - \bar{c}) \Pr ((1 - \delta) b < b_j \forall j \in NR | \bar{c})] \) 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:

\[ \beta_{NR}^{-1}(\bar{c}) = \bar{c}. \]

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 \( c \in [(1 - \delta) \bar{b}, \bar{c}] \), 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 is key in empirically implementing these types of auctions. Existence establishes that there is, in fact, a solution to the auction, while uniqueness establishes that the bidders are playing one equilibrium as opposed to potentially multiple different equilibria. Reny and Zamir (2004) show that a monotone pure strategy equilibrium exists in a more general setting than this type of auction. Uniqueness follows from Li and Zhang (2015) for the class of joint project cost distributions that I use in this paper.

2.4.4. 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

\[
\Pi_m (N_m, N_{-m}) = \sum_{n_m - 1 \leq n_m, n_{-m} \leq N_{-m}} \int_{c} \pi (c; n_m, n_{-m}) dF_c^m (c) \Pr (n_m - 1, n_{-m} \mid N_m, N_{-m}),
\]

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 \(m\). 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

\(^{13}\)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,

$$p_m = \Pr (k_i < \Pi_m) = G^m_k (\Pi_m),$$

where $G^m_k (\cdot)$ 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 $p_m$.\textsuperscript{14} 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.

2.5. 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 $F_1^c (c_1), F_2^c (c_2), \ldots, F_n^c (c_n)$ respectively, then the joint distribution can be written as a function of the marginal distributions as

$$F_c (c_1, c_2, \ldots, c_n) = C \left[ F_1^c (c_1), F_2^c (c_2), \ldots, F_n^c (c_n) \right],$$

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

\textsuperscript{14}Uniqueness, however, is not guaranteed and must be verified through simulation.
representation:

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

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 \( \theta \) to be greater than zero.\(^{15}\) Moreover, \( \theta \) has the nice interpretation that a higher value of \( \theta \) implies a higher degree of affiliation between random variables, so \( \theta \) contains all of the relevant information on cost dependence.\(^{16}\)

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, \( \bar{F}_c(c_1, c_2, \ldots, c_n) \), can be written as

\[
\bar{F}_c(c_1, c_2, \ldots, c_n) = \Pr(C_1 > c_1, C_2 > c_2, \ldots, C_n > c_n)
= 1 - \sum_{i=1}^{n} \Pr(C_i < c_i) + \sum_{1 \leq i < j \leq n} \Pr(C_i < c_i, C_j < c_j)
= \cdots + (-1)^n \Pr(C_1 < c_1, C_2 < c_2, \ldots, C_n < c_n).
\]

This result provides an expression of the survival function in terms of the cumulative density

\(^{15}\)For a formal proof of this statement, see Müller and Scarsini (2005).

\(^{16}\)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 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 does not differ substantially from each other or the entire sample, suggesting that a single parameter governing all affiliation is reasonable.
function (CDF), which has a copula representation. Let \( S \left[ 1 - F^1_c (c_1), 1 - F^2_c (c_2), \ldots, 1 - F^n_c (c_n) \right] \) denote the survival copula evaluated at the survival marginals. The first result shows that the survival copula can be expressed as

\[
S \left[ 1 - F^1_c (c_1), 1 - F^2_c (c_2), \ldots, 1 - F^n_c (c_n) \right] = 1 - \sum_{i=1}^{n} C \left[ F^i_c (c_i) \right] + \sum_{1 \leq i < j \leq n} C \left[ F^i_c (c_i), F^j_c (c_j) \right] - \cdots + (-1)^n C \left[ F^1_c (c_1), \ldots, F^n_c (c_n) \right].
\]

**Result 2:**

\[
\Pr(C_2 > c_2, \ldots, C_n > c_n \mid c_1) = S_1 \left[ 1 - F^1_c (c_1), 1 - F^2_c (c_2), \ldots, 1 - F^n_c (c_n) \right],
\]

where \( S_1 \left[ \cdot, \ldots, \cdot \right] \) 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

\[
\pi(c_1; n_{NR}, n_R) = \max_{b_1} (b_1 - c_1) \times S_1 \left[ 1 - F^{m_1} (c_1), 1 - F^{NR}_{m_1} \left( \beta^{-1}_{NR} \right), \ldots, 1 - F^{NR}_{m_1} \left( \beta^{-1}_{NR} \right), 1 - F^R \left( \beta^{-1}_R \right), \ldots, 1 - F^R \left( \beta^{-1}_R \right) \right],
\]

where \( m_1 \) is bidder 1’s group, \( F^{m_1}_c \) is the marginal distribution of a bidder in group \( m \), \( \beta^{-1}_{NR} = \beta^{-1}_{NR} \left( (1 - \delta)D_R b_1 \right) \), and \( \beta^{-1}_R = \beta^{-1}_R \left( (1 - \delta)^{-D_{NR}} b_1 \right) \). The first-order conditions...
are now given by

\[ S_1 \left[ 1 - F_{e_{m1}}(c_1), 1 - F_{e_{NR}}^R(\beta_{NR}^{-1}), \ldots, 1 - F_{e_{NR}}^R(\beta_{NR}^{-1}), 1 - F_{e_{R}}^R(\beta_{R}^{-1}), \ldots, 1 - F_{e_{R}}^R(\beta_{R}^{-1}) \right] \]

\[ = (b_1 - c_1) \left[ (n_{NR} - D_{NR}) \beta_{NR1}^{-1} (1 - \delta)^{D_{NR}} f_{e_{c}}^N(\beta_{NR}^{-1}) \right] \]

\[ \times S_{12} \left[ 1 - F_{e_{m1}}(c_1), 1 - F_{e_{NR}}^R(\beta_{NR}^{-1}), \ldots, 1 - F_{e_{NR}}^R(\beta_{NR}^{-1}), 1 - F_{e_{R}}^R(\beta_{R}^{-1}), \ldots, 1 - F_{e_{R}}^R(\beta_{R}^{-1}) \right] \]

\[ \times S_{1n} \left[ 1 - F_{e_{m1}}(c_1), 1 - F_{e_{NR}}^R(\beta_{NR}^{-1}), \ldots, 1 - F_{e_{NR}}^R(\beta_{NR}^{-1}), 1 - F_{e_{R}}^R(\beta_{R}^{-1}), \ldots, 1 - F_{e_{R}}^R(\beta_{R}^{-1}) \right], \]

where \( f_{e_{c}}^m(\cdot) \) is the marginal probability density function (PDF) associated with the marginal CDF \( F_{e_{c}}^m(\cdot) \).

### 2.6. 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 5 shows the full set of marginal project cost distribution CDFs used in this analysis.

I calculate bid functions in a variety of different environments. Except in a few special cases, the solution to the system of equations in (2.1) 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.\(^{17}\)

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 1 non-resident bidder and 3 resident bidders, and I set the preference level to New Mexico’s

---

\(^{17}\)See the appendix for a detailed explanation of how I numerically approximate the bid functions.
current discount of 5 percent. For each marginal project cost distribution, I approximate bid functions under independence and affiliation, where affiliation is calculated by setting the affiliation parameter to 1. I denote independence by an affiliation parameter of 0.

2.6.1. Equal Strength Bidders

As a start, I study a case where both groups of bidders are of equal strength. Let $\alpha_R$ and $\beta_R$ be the parameters characterizing the resident beta distribution, and let $\alpha_{NR}$ and $\beta_{NR}$ 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 6 displays the equilibrium bid functions corresponding to these marginal project cost distributions.

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 comes from both groups of bidders bidding less aggressively and resident bidders receiving a preference (which makes them bid even less aggressively).
2.6.2. 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 7 shows the results from this case.

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 aggres-
sively 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.¹⁸ As a result, non-residents bid closer to residents under affiliation.

2.6.3. 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. I construct this case by holding the resident beta distribution parameters at their previous levels of \( \alpha_R = 1 \) and \( \beta_R = 1 \) while setting the non-resident beta distribution parameters to \( \alpha_{NR} = 2 \) and \( \beta_{NR} = 2 \). Observe that this composition of distribution parameters implies that residents and non-residents have the same mean project cost, but residents have more variance in their project costs relative to non-residents. Figure 8 presents the bid functions corresponding to these distributions.

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 non-resident bidders bid less aggressively for high project cost draws and more aggressively for low project cost draws with affiliation. Intuitively, residents and non-residents become more likely to draw from the same quantiles with affiliation. When residents have more variable project costs than non-residents, this property of affiliation means that high draws for non-residents likely lead to even higher draws for residents, while low draws for non-residents likely lead to even lower draws for residents. As a result, non-residents bid less aggressively for high project cost draws and more aggressively for low project cost draws.

¹⁸To illustrate this point with an example, suppose that a resident bidder draws a cost in the 10th 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 10th 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 10th percentile of the resident marginal distribution is higher than the project cost corresponding to the 10th 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.
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.

2.7. Empirical Model and Estimation

While the theoretical model provides a foundation for understanding the market for NM-DOT 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.

2.7.1. 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 \(( x_w, z_w, n_{Rw}, n_{NRw}, N_{Rw}, N_{NRw})\), where \( x_w \) is a vector of auction-
level observables that affect project costs, \( z_w \) 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 \( x_w \) are given by \( F^m_c (\cdot | x_w) \), and the group-specific marginal distribution of entry costs conditional on \( z_w \) are given by \( G^m_k (\cdot | z_w) \).

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, \( p_{mw} (x_w, z_w, N_{Rw}, N_{NRw}) \), as a binomial distributions:

\[
\Pr(n_{Rw}, n_{NRw} | x_w, z_w, N_{Rw}, N_{NRw}) = \Pr(n_{Rw} | x_w, z_w, N_{Rw}, N_{NRw}) \times \Pr(n_{NRw} | x_w, z_w, N_{Rw}, N_{NRw}),
\]

where

\[
\Pr(n_{mw} | x_w, z_w, N_{mw}, N_{-mw}) = \binom{N_{mw}}{n_{mw}} (p_{mw})^{n_{mw}} (1 - p_{mw})^{N_{mw} - n_{mw}},
\]

and

\[
p_{mw} = G^m_k (\Pi_{mw} (x_w, N_{mw}, N_{-mw}) | z_w).
\]

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 (2.2) 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 prob-
lem. 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 $F_m^b(b) = F_c^m(\beta^{-1}_m(b))$ and $f_m^b(b) = f_c^m(\beta^{-1}_m(b)) \beta^{-1}_{m_1}(b).^{19}$ 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, $F_m^b(\cdot | x_w)$, instead of the marginal distribution of project costs, $F_c^m(\cdot | x_w)$.

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:

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

where

$$\epsilon_{iw}^{m_i} | x_{iw} \sim \mathcal{N}\left(0, \exp(y_{iw}'\sigma)^2\right),$$

$$\left(\epsilon_{1w}^{NR}, \ldots, \epsilon_{nNRw}^{NR}, \epsilon_{1w}^{R}, \ldots, \epsilon_{nNR+nRw}^{R} | x_{iw}\right) \equiv \epsilon_w \sim \mathcal{F}_{\epsilon_w},$$

$$F_{\epsilon_w} = C\left[F_{\epsilon_{1w}^{NR}}, \ldots, F_{\epsilon_{nNRw}^{NR}}, F_{\epsilon_{1w}^{R}}, \ldots, F_{\epsilon_{nNR+nRw}^{R}}\right],$$

$x_{iw}$ is the set of auction-level observables with an indicator variable for bidder $i$’s residency status, and $y_{iw}$ is a subset of the $x_{iw}$ covariates also containing the resident indicator. Likewise, I assume that the entry costs take the following form:

---

19 For a complete description on how to approximate the inverse bid functions using GPV (2000) in this setting, see the appendix.
\[
\log (k_{iw}) = z^{' iw} \gamma + u^m_{iw},
\]

where

\[
u^m_{iw} \mid z_{iw} \sim N \left(0, \exp \left(v^{' iw} \alpha \right)^2 \right),
\]

\(z_{iw}\) is the set of auction-level observables with an indicator for residency status, and \(v_{iw}\) is a subset of the \(z_{iw}\) covariates that also includes the resident indicator.

### 2.7.2. 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

\[
E \left[ x_{iw} \left( \log (b_{iw}) - x^{' iw} \beta \right) \right] = 0 \quad (2.3)
\]

and

\[
E \left[ y_{iw} \left( \log (b_{iw}) - x^{' iw} \beta \right) \left( \log (b_{iw}) - x^{' iw} \beta \right) \right] = E \left[ y_{iw} \exp (y^{' iw} \sigma)^2 \right]. \quad (2.4)
\]

Observe that equation (2.4) yields the standard deviation parameter, \(\sigma\), and equations (2.3) and (2.4) yield the mean parameter, \(\beta\).

In addition to estimating the parameters of the marginal distributions, the affiliation pa-
rameter, $\theta$, 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:

$$\frac{\theta}{\theta + 2} = 4E \left[ C \left( \Phi \left( \frac{\log (b_{iw}) - x'_{iw} \beta}{\exp (y'_{iw} \sigma)} \right), \Phi \left( \frac{\log (b_{jw}) - x'_{jw} \beta}{\exp (y'_{jw} \sigma)} \right) \right) \right] - 1 \quad i \neq j, \quad (2.5)$$

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

$$E [n_{mw}] = \int N_{mw} p_{mw} dF (x_w, z_w, N_{mw}, N_{-mw}), \quad (2.6)$$

$$E [n_{mw}^2] = \int N_{mw} p_{mw} (1 - p_{mw}) + N_{mw}^2 p_{mw}^2 dF (x_w, z_w, N_{mw}, N_{-mw}), \quad (2.7)$$

$$E [n_{mw}^3] = \int N_{mw} p_{mw} \left( 1 - 3p_{mw} + 3N_{mw}p_{mw} + 2p_{mw}^2 - 3N_{mw}p_{mw}^2 \right) dF (x_w, z_w, N_{mw}, N_{-mw}), \quad (2.8)$$

and
\[ E [n_{mw}^4] = \int N_{mw}p_{mw} \left( 1 - 7p_{mw} + 7N_{mw}p_{mw} + 12p_{mw}^2 - 18N_{mw}p_{mw}^2 + 6N_{mw}^2p_{mw}^2 ight. \\
\left. - 6p_{mw}^3 + 11N_{mw}p_{mw}^3 - 6N_{mw}^2p_{mw}^3 + N_{mw}^3p_{mw}^3 \right) dF (x_w, z_w, N_{mw}, N_{-mw}), \quad (2.9) \]

where

\[ p_{mw} = G_k^m (\Pi (x_w, N_{mw}, N_{-mw}) | \ z_w) \]

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.

### 2.7.3. Parametric Identification

This section concludes with a brief discussion on what features of the data I use to identify the model’s parameters. The parameters of the model are the mean and standard deviation parameters of the bid distribution, \( \beta \) and \( \sigma \), the mean and standard deviation of the entry cost distribution, \( \gamma \) and \( \alpha \), and the affiliation parameter, \( \theta \).

To identify the model’s parameters, observe that the data contains a number of different contracts, each with multiple bids. I use the first and second moments of those observed bid distributions to identify the mean and standard deviation of the bid distribution parameters. 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 (2.5).\(^{20}\) Finally, I observe resident and non-resident bidders entering auctions at different rates. In the model, the entry rates correspond to a firm’s cost of entering relative to its expected profit, and the expected profit can be calculated from

\(^{20}\)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.
the observed bid distributions and affiliation parameter. I therefore use the entry rates to pin down the entry cost parameters.

2.8. Empirical Results

This section presents the empirical findings from the NMDOT highway procurement data. I first show descriptive summary statistics to illustrate some of the main components of the data relevant to residency status and firm bidding and entry behavior. Next, I 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.

2.8.1. Descriptive Statistics

<table>
<thead>
<tr>
<th>Table 12: Summary Statistics for New Mexico Highway Construction Projects</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Federal-Aid Projects</strong></td>
</tr>
<tr>
<td>Number of Contracts</td>
</tr>
<tr>
<td>Number of Bidders</td>
</tr>
<tr>
<td>Number of Planholders</td>
</tr>
<tr>
<td>Average Bid (in 1000s)</td>
</tr>
<tr>
<td>Average Winning Bid (in 1000s)</td>
</tr>
<tr>
<td>Average Engineer’s Estimate (in 1000s)</td>
</tr>
<tr>
<td>Average Resident Planholders</td>
</tr>
<tr>
<td>Average Resident Bidders</td>
</tr>
<tr>
<td>Average Non-Resident Planholders</td>
</tr>
<tr>
<td>Average Non-Resident Bidders</td>
</tr>
<tr>
<td>Fraction of Projects by Type of Road:</td>
</tr>
<tr>
<td>Federal Highway</td>
</tr>
<tr>
<td>Other Road</td>
</tr>
<tr>
<td>Fraction of Projects by Type of Work:</td>
</tr>
<tr>
<td>Road Work</td>
</tr>
<tr>
<td>Bridge Work</td>
</tr>
<tr>
<td>Other Work</td>
</tr>
<tr>
<td>Average Contract Observables:</td>
</tr>
<tr>
<td>Length (in miles)</td>
</tr>
<tr>
<td>Working Days</td>
</tr>
<tr>
<td>Number of Licenses Required</td>
</tr>
<tr>
<td>DBE Goal (%)</td>
</tr>
<tr>
<td>Number of Subprojects</td>
</tr>
</tbody>
</table>

Table 12 contains the summary statistics for all highway procurement contracts in the
sample tabulated by the source of funding. For each auction, I observe the following project characteristics: an engineer’s estimated cost, the number of projected working days, the nature and location of the work, the number of licenses required, the length in miles, and the number of bidders and planholders. Additionally, I observe the number of subprojects as well as any Disadvantaged Business Enterprise (DBE) participation goals. I observe residency status and entry decisions at the firm level.

The top panel of table 12 summarizes the average estimated cost, bid, winning bid, number of potential entrants, and number of actual entrants. Relative to federal-aid projects, state-funded projects are slightly larger and more expensive on average. The average estimated cost across state-funded projects exceeds that of federal-aid projects by about $949,000, while the bids received on state-funded projects are about $1,401,000 higher than the bids received on federal-aid projects. 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 bidders of both groups 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.

The next two panels of table 12 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.

---

21 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.
The bottom panel of table 12 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.

2.8.2. 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. In order to mitigate the effect of unobserved project heterogeneity on submitted bids, I include the number of potential entrants in each group in the set of control variables. The idea behind these controls is that unobservable project characteristics may attract more potential entrants in the form of planholders, since the NMDOT advertises projects before they publish the list of planholders. 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 characteristics that are common knowledge to the bidders. 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.

Table 13 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 small and statistically insignificant differences in how the two groups of bidders bid. Residents bid only 1 percent less than non-residents across procurement projects, which need not be attributed to similarities in resident and non-resident costs.

Conversely, the affiliation parameter estimate is positive and statistically significant, which indicates the presence of affiliation in firm project costs. This estimate can be interpreted
Table 13: Estimated Parameters for the Log-Bid Distribution

<table>
<thead>
<tr>
<th></th>
<th>Coefficient</th>
<th>Standard Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>0.849</td>
<td>0.175</td>
</tr>
<tr>
<td>Resident</td>
<td>-0.011</td>
<td>0.011</td>
</tr>
<tr>
<td>New Mexico project</td>
<td>-0.034</td>
<td>0.069</td>
</tr>
<tr>
<td>log(Engineer’s Estimate)</td>
<td>0.913</td>
<td>0.020</td>
</tr>
<tr>
<td>log(Length+1) (in miles)</td>
<td>0.038</td>
<td>0.015</td>
</tr>
<tr>
<td>log(Working Days)</td>
<td>0.070</td>
<td>0.023</td>
</tr>
<tr>
<td>Resident Planholders</td>
<td>0.001</td>
<td>0.004</td>
</tr>
<tr>
<td>Non-Resident Planholders</td>
<td>-0.005</td>
<td>0.007</td>
</tr>
<tr>
<td>Bridge Work</td>
<td>-0.021</td>
<td>0.033</td>
</tr>
<tr>
<td>Road Work</td>
<td>-0.0001</td>
<td>0.034</td>
</tr>
<tr>
<td>Number of Licenses Required</td>
<td>0.013</td>
<td>0.019</td>
</tr>
<tr>
<td>Federal Highway</td>
<td>-0.004</td>
<td>0.021</td>
</tr>
<tr>
<td>Urban</td>
<td>-0.044</td>
<td>0.018</td>
</tr>
<tr>
<td>DBE Goal(%)</td>
<td>-0.008</td>
<td>0.004</td>
</tr>
<tr>
<td>log(Subprojects)</td>
<td>0.077</td>
<td>0.025</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Standard Deviation Parameters</th>
<th>Coefficient</th>
<th>Standard Error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>0.697</td>
<td>0.325</td>
</tr>
<tr>
<td>Resident</td>
<td>0.263</td>
<td>0.707</td>
</tr>
<tr>
<td>log(Engineer’s Estimate)</td>
<td>-0.180</td>
<td>0.030</td>
</tr>
<tr>
<td>Affiliation Parameter</td>
<td>0.831</td>
<td>0.189</td>
</tr>
</tbody>
</table>

Note: Standard deviation of the bid distribution is estimated as $\sigma = \exp(b_0 + b_{\text{resident}} + b_{\text{engineer}})$, where resident is an indicator for being a resident bidder and engineer is the log of the engineer’s estimate.

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 $\theta = 0.831$ results in a Kendall’s tau of 0.294, which means that a given pair of cost draws are 29.4 percent more likely to be concordant than discordant.

This tau estimate can be compared to other studies using a similar affiliated private value framework. On one hand, the Kendall’s tau of 0.294 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 timber sales auctions. On the other hand, Hubbard, Li, and Paarsch (2012) estimate a tau of 0.655 using Michigan Department

\[22\] 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 $y_i > y_j$. 

71
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.

Figure 9: Kernel Density Estimates of the Marginal Cost CDFs for the Average Preference and Non-Preference Auctions

72
Figure 9 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, residents have a more disperse cost distribution than non-residents across projects. Also, no one cost distribution first-order stochastically dominates the other in any of the average projects, which can lead to ambiguity in the ranking of resident and non-resident firms in terms of cost efficiency.

<table>
<thead>
<tr>
<th>Table 14: Estimated Parameters for the Log-Entry Cost Distribution</th>
</tr>
</thead>
<tbody>
<tr>
<td>Parameter</td>
</tr>
<tr>
<td>Constant</td>
</tr>
<tr>
<td>log(Engineer’s Estimate)</td>
</tr>
<tr>
<td>Resident</td>
</tr>
<tr>
<td>Resident Planholders</td>
</tr>
<tr>
<td>Non-Resident Planholders</td>
</tr>
<tr>
<td>Standard Deviation Parameters</td>
</tr>
<tr>
<td>Constant</td>
</tr>
<tr>
<td>Resident</td>
</tr>
</tbody>
</table>

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

Turning to firm entry costs, table 14 presents the estimated parameters for the log-normal entry cost distribution. The entry parameters have the expected signs and magnitudes, although some of the parameters are statistically insignificant due to high standard errors relative to the bid distribution parameters. The entry parameters suggest noticeable differences among resident and non-resident costs of entry. Residents have higher average entry costs compared to non-residents and more variation in these entry costs.\(^{23}\) 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 entry costs, which is outside the scope of the data and model. The parameter estimates are nonetheless consistent with the lower conversion rate of potential resident bidders into actual bidders observed in the data.

\(^{23}\)Recall that these parameter estimates are the mean and variance of the natural logarithm of the entry costs. Let \( \mu \) be the mean of the natural logarithm of the entry costs, and let \( \sigma \) 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 \( \left( \exp (\sigma^2) - 1 \right) \exp (2\mu + \sigma^2) \).
2.9. Counterfactual Analysis

This section contains counterfactual policy experiments using the structural parameter estimates from section 2.8.2. Given the computational burden associated with calculating equilibrium bid functions, I focus on a representative construction project qualifying for preference in the data.\footnote{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.} 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.

2.9.1. Simulation Method

I take a number of steps to simulate counterfactual bidding and entry behavior. First, I obtain a kernel density estimate of the underlying marginal project cost distributions, $F^R_c$ and $F^{NR}_c$, by inverting a large number of bids drawn from the bid distributions implied by the empirical model using GPV (2000).\footnote{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 99.9%) of inverted project cost draws.} 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 preference level 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 preference level. 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 2.9.3, 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.

2.9.2. 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 10 presents the equilibrium bid functions. 

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 10, 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 10, residents and non-residents behave almost as if the auction is symmetric when project

\(^{26}\)For an analysis of the error associated with these simulated bid functions, see the appendix.
costs are independent, but when project costs become affiliated, bid functions become more distinct, with residents bidding less aggressively than non-residents for lower project costs and non-residents bidding less aggressively than residents for higher project costs. This change comes from the higher 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 non-resident are likely to be even lower for a resident, while high draws for a non-resident are likely to be even higher for a resident. Residents will, therefore, bid less aggressively relative to non-residents for lower project costs and more 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 10, depends on how aggressively firms bid and is therefore tied to affiliation. Observe that when preferences are offered 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 smaller than independence for lower project costs (since firms are bidding closer to their project costs) but becomes large enough to decrease the separation in the two bid functions for higher project cost draws. These differences suggest that the degree of affiliation can lead to substantial changes in how firms adjust bids with discounting.

2.9.3. Alternative Discount Rates, Efficiency, and the Role of Affiliation

Although New Mexico offers a 5 percent discount for its resident bidders, the discount level for preferred bidders can vary across states and the type of good being procured. Different discount levels will have different implications for the participation and bidding behavior of firms, and I investigate these changes in behavior for the representative construction project using the structural parameter estimates in conjunction with the project cost and entry cost distribution estimates. In order to assess the role of affiliation in these auctions, I contrast bidding and participation behavior under the estimated affiliation level against auctions where costs are assumed independent.

Figure 11 plots the how the procurement cost, the proportion of preferred winners, and the expected participation changes across affiliation and preference levels. Increasing the discount level increases the average procurement cost in these preference auctions, since there is less overall participation when the discount level increases. Relative to independence, affiliation leads to higher average procurement costs for all counterfactual discount levels because there is a wider range of project cost values where firms bid further from their
Figure 11: Average Winning Bid, Proportion of Resident Winners, and Entry under Alternative Discount Rates

costs under affiliation as evidenced by figure 10. The expected participation rate under affiliation is similar to the expected participation rate under independence, but the drop-off in non-resident bidders is more pronounced under affiliation. Despite the similarities in expected participation, affiliation tends to result in a lower proportion of resident winners relative to independence, and that difference decreases with higher discount levels. This behavior comes from how aggressively non-residents bid for lower project costs to account for affiliation, and that difference becomes smaller with higher discount levels because there are less non-resident participants.

In addition to changing bidding and participation, changes in the preference level 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 preference levels, I calculate the average efficiency loss, which is the average difference in cost between the lowest cost bidder and the winning bidder over auction simulations, and the proportion of inefficient auctions for a number of counterfactual preference levels. Project cost dependence may affect economic efficiency, so I calculate efficiency for auctions with the estimated level of affiliation and for auctions that assume independence.

Table 15: Counterfactual Preference Simulations

<table>
<thead>
<tr>
<th>Discount (%)</th>
<th>Winning Bid ($1000s)</th>
<th>Efficiency Loss ($)</th>
<th>Prop. Inefficient</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.0</td>
<td>4384.73</td>
<td>4257.80</td>
<td>2.98</td>
</tr>
<tr>
<td>2.5</td>
<td>4411.00</td>
<td>4286.74</td>
<td>2.90</td>
</tr>
<tr>
<td>5.0</td>
<td>4439.36</td>
<td>4313.84</td>
<td>2.91</td>
</tr>
<tr>
<td>7.5</td>
<td>4454.92</td>
<td>4337.30</td>
<td>2.71</td>
</tr>
<tr>
<td>10.0</td>
<td>4460.31</td>
<td>4343.78</td>
<td>2.68</td>
</tr>
</tbody>
</table>

This table shows the average winning bid, the average efficiency loss, and the proportion of inefficient auctions under independent and affiliated project-completion costs for 10,000 simulated preference auctions. Each potential entrant is given a draw from their group’s respective entry cost distribution, and the number of entrants is determined endogenously by comparing their entry cost to their expected profit. Upon entry, each participating firm draws their project cost from their group’s marginal project cost distribution to determine bids. Under affiliation, there will be dependence in the project cost draws.

Table 15 breaks down the average procurement cost and efficiency loss over the counterfactual affiliation and preference levels. New Mexico’s current policy is responsible for a small change in procurement costs. An increase in the discount rate from 0 percent to its current level of 5 percent under affiliation increases the average procurement cost of the representative construction project by $54,631, which is a 1.2 percent cost increase. This increase is relatively smaller than the bias associated with the independence assumption.

At the established 5 percent discount level, procurement costs are 2.9 percent higher than they would be if costs were assumed independent.

Table 15 also illustrates the role of affiliation in the evaluation of economic efficiency. At the 5 percent discount level, the average efficiency loss under affiliated project costs is $1,106.25 (0.025 percent of the average winning bid) and generally decreases with the dis-
count level; the average efficiency loss under independence is $1,299.34 (0.030 percent of the average winning bid) and generally increases with the discount level. These patterns reverse themselves at the 10 percent discount level. The proportion of inefficient auctions under affiliation decreases with the discount level, but the proportion of inefficient auctions under independence first increases and then decreases with the discount level.

These patterns are generated by differences in bidding under affiliation and independence. Intuitively, efficiency is driven by the separation in the bid functions, which depends on both the level of affiliation and the composition of bidders. As bid functions become more distinct, the likelihood of an inefficient auction increases, and more separation is likely to increase the average efficiency loss.

With that in mind, the proportion of inefficient auctions first increases under independence because firms are virtually symmetric when there is no discount, which can be seen in figure 10. As the discount level increases, the separation in the bid functions also increases, leading to more inefficient auctions. The decrease in the proportion of inefficient auctions comes from the change in the composition of bidders. A higher discount level deters non-residents from entering, so auctions are more likely to be efficient since they only have resident bidders. The efficiency loss follows a similar pattern.

With affiliation, there is generally more separation in the bid functions with no preference, which explains why the proportion of inefficient auctions and the efficiency loss is higher than independence. Although increasing the preference leads to more separation in the bid functions for lower project cost draws, the bid functions are generally closer together with higher project cost draws under affiliation. That and the lower participation of non-resident bidders leads to a decrease in the proportion of inefficient auctions with higher discount levels. The general decrease in the efficiency loss under affiliation comes from the proportion of inefficient auctions together with the discount change. As the discount level increases, both the number of inefficient auctions and the average number of non-resident entrants decreases. The combination of these two forces leads to a general decrease in the
efficiency loss. At the 10 percent discount level, the increased separation in the bid function is sufficiently large to increase the average efficiency loss despite the decreased proportion of inefficient auctions from the 7.5 percent discount level.

Taken together, these simulations suggest that the discount rate can be used as a mechanism to increase the proportion of contracts won by resident bidders and alter the proportion of inefficient auctions at the expense of higher procurement costs. Relative to the independence case, affiliation leads to a higher expected procurement cost, a lower proportion of resident winners, and a lower average efficiency loss under New Mexico’s current policy. These results depend on the discount level, which illustrates the significance of accounting for affiliation in public procurement with bid preferences.

2.10. Conclusion

In this paper, I empirically examine the presence of affiliation and its effect on 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 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 loss generated from auctions with asymmetric bidders, and these differences are contingent on the discount level. In fact, I find that although New Mexico’s current policy is responsible for a 1.2 percent increase in procurement costs, affiliation results in a 2.9 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.1. Appendix for Subcontracting Requirements and the Cost of Government Procurement

A.1.1. Proofs

Properties of the Optimal DBE Subcontracting Decision: Second-Order Conditions

The sufficient condition on optimal DBE subcontracting is given by the following expression:

\[-P''(s_i) - \varphi''(s_i; \bar{s}) < 0.\]

Observe that this condition is satisfied by the convexity assumption on \( \varphi \) and \( P \).

Properties of the Optimal DBE Subcontracting Decision: Comparative Statics

The concern here is in understanding how the optimal DBE subcontracting share changes with \( c_i \). Differentiating equation (1.2) while taking into account the optimal DBE subcontracting strategy yields

\[1 = P''(s(c_i; \bar{s})) s'(c_i; \bar{s}) + \varphi''(s(c_i; \bar{s}); \bar{s}) s'(c_i; \bar{s}).\]

After some algebraic manipulation, the above equation reduces to

\[s'(c_i; \bar{s}, \tau_i) = \frac{1}{P''(s(c_i; \bar{s})) + \varphi''(s(c_i; \bar{s}); \bar{s})},\]

which is increasing given the second-order conditions.
Derivation of the Bid Function (Proposition 1)

I derive the bid function from an envelope theorem argument. In particular, the profit a bidder gains from a non-DBE cost realization \( c_i \) is

\[
\Pi (c_i; \bar{s}) = (b(c_i; \bar{s}) - c_i (1 - s(c_i; \bar{s})) - P(s(c_i; \bar{s})) - \varphi(s(c_i; \bar{s}); \bar{s})) \\
\times (1 - F(c_i))^{N-1}.
\]

Alternatively, if bidder \( i \) is playing a best response, it must be the case that

\[
\Pi (c_i; \bar{s}) = \max_{\{b_i, s_i\}} (b_i - c_i (1 - s_i) - P(s_i) - \varphi(s_i; \bar{s})) (1 - F(b^{-1}(b_i)))^{N-1}.
\]

Apply the envelope theorem to get\(^1\)

\[
\frac{d}{dc} \Pi (c; \bar{s}) \bigg|_{c=c_i} = (s(c_i; \bar{s}) - 1) (1 - F(c_i))^{N-1}.
\]

Integrate the above expression to get another expression for \( \Pi (c_i; \bar{s}) \):

\[
\Pi (c_i; \bar{s}) = \Pi (\bar{c}; \bar{s}) + \int_{c_i}^{\bar{c}} (1 - s_t(\hat{c}; \bar{s})) (1 - F(\hat{c}))^{N-1} d\hat{c}.
\]

Given that I assume bids are increasing in project costs, it must be the case that any bidder who draws a non-DBE cost of \( \bar{c} \) cannot win with positive probability in equilibrium.

---

\(^1\)To invert the bid function in this step, I implicitly assume that bids are increasing in \( c_i \) rather than project costs. Indeed, bids will be increasing in \( c_i \) so long as \( s(c_i; \bar{s}) < 1 \) using the results from equation (1.5), but this assumption could be problematic if \( s(c_i; \bar{s}) = 1 \), since project costs are flat in \( c_i \). As a result, the following analysis only holds for \( s(c_i; \bar{s}) \in [0, 1) \), but the derived expression for the bid function in terms of \( c_i \) will also hold when \( s(c_i; \bar{s}) = 1 \).
Therefore, I set \( \Pi(c; \bar{s}) = 0 \) and equate the right hand side of equations (A.1) and (A.2) to get the optimal bid function in equation (1.6).

It is important to understand the shape of the bid function, since there is a region where two different draws of \( c_i \) could potentially lead to the same bid. Specifically, the optimal bid function will be flat in \( c_i \) whenever \( s(c_i; \bar{s}) = 1 \) and increasing in \( c_i \) whenever \( s(c_i; \bar{s}) \in [0, 1) \). This result is intuitive, since prime contractors who subcontract the entire project to DBE firms will have the same project cost independent of their non-DBE cost. In the data, no prime contractors subcontract the entire project to DBE firms, so the empirical application avoids this potential theoretical problem.

**Proof of Increasing DBE Subcontractor Shares (Proposition 2)**

**Proposition.** For a given non-DBE cost draw \( c_i \), if \( s(c_i; 0) \neq s(c_i; \bar{s}) \), then \( s(c_i; 0) < s(c_i; \bar{s}) \).

**Proof.** By the first-order conditions on optimal DBE subcontracting,

\[
c_i = P'(s_i) + \varphi'(s_i ; \bar{s}).
\]

Given the assumption \( s(c_i; 0) \neq s(c_i; \bar{s}) \), it must be the case that \( \varphi'(s_i ; \bar{s}) < 0 \). When that inequality holds, prime contractors find it optimal to increase their DBE shares \( s_i \) when there is a DBE subcontracting requirement. There are now three possible cases for \( s(c_i; 0) \) and \( s(c_i; \bar{s}) \): both solutions are interior solutions, one of the two solutions is an interior solution while the other is a corner solution, or both solutions occur at different corners. In either of these three cases \( s(c_i; 0) < s(c_i; \bar{s}) \).

\footnote{Since prime contractors find it optimal to increase the share when there is a requirement, any case where \( s(c_i; 0) > s(c_i; \bar{s}) \) is not possible. The assumption that \( s(c_i; 0) \neq s(c_i; \bar{s}) \) rules out the cases where both solutions occur at the same corner.}
Proof of Weakly Higher Project Costs (Corollary 1)

**Corollary.** DBE subcontracting requirements weakly raise project costs.

**Proof.** Suppose bidder $i$ wins an auction with a bid of $b$. Without subcontracting requirements, he would choose shares, $s(c_i;0)$, such that

$$s(c_i;0) \in \arg \max_{s_i} \left\{ b - c_i (1 - s_i) - P(s_i) \right\},$$

or analogously,

$$s(c_i;0) \in \arg \min_{s_i} \left\{ c_i (1 - s_i) + P(s_i) \right\}.$$

Define $C(s_i;0) = c_i (1 - s_i) + P(s_i)$ as the project cost of bidder $i$ when there are no DBE subcontracting requirements, and consider the optimal share with subcontracting requirements, $s(c_i;\bar{s})$. Since $s(c_i;0)$ is the minimizer of $C(\cdot;0)$, $C(s(c_i;0);0) \leq C(s(c_i;\bar{s});0)$. Since fines are non-negative, $C(s(c_i;\bar{s});0) \leq C(s(c_i;\bar{s});0) + \phi(s(c_i;\bar{s});\bar{s}) = \phi(c_i;\bar{s})$. \qed

Proof of Weakly Lower Markups (Corollary 2)

**Corollary.** DBE subcontracting requirements weakly lower markups.

**Proof.** Proposition 2 implies that $s(c_i;0) \leq s(c_i;\bar{s})$ for all non-DBE costs, $c_i$. Therefore, markups are weakly lower with DBE subcontracting requirements, since

$$\int_{c_i}^{\bar{c}} (1 - s(\tilde{c};\bar{s})) (1 - F(\tilde{c}))^{N-1} d\tilde{c} \leq \int_{c_i}^{\bar{c}} (1 - s(\tilde{c};0)) (1 - F(\tilde{c}))^{N-1} d\tilde{c}.$$

\qed
A.1.2. Microfoundations for the DBE Pricing Function

My theoretical model takes the DBE pricing function as given in its formulation of the optimal bidding and DBE subcontracting strategies. Theoretically, the DBE pricing function can arise from a variety of different market structures, each unique to the required work. This section explores two different types of market structures and derives their respective DBE pricing functions. Throughout this section, DBE subcontractors will have a thrice continuously differentiable cost function $C : [0, 1] \rightarrow \mathbb{R}$, which maps the requested share of work into a cost for the subcontractors. I will refer to that cost function as the DBE cost function. Furthermore, I assume that $C', C'', C''' > 0$ so that the DBE cost function will result in an increasing and convex DBE pricing function consistent with the pricing function presented in the paper.

**Perfect Competition**

Some projects may have DBE subcontractors that behave competitively as price takers. For these projects, DBE subcontractors solve the following profit maximization problem:

$$\max_{s \geq 0} Ps - C(s).$$

The first-order conditions generate the following relationship between prices and costs:

$$P(s) = C'(s).$$

In other words, the DBE pricing function reflects the marginal cost of the DBE subcontractors.
Monopoly

In contrast to the competitive case, there may be some projects where there is only one DBE subcontractor in the market. This DBE firm will then behave as a monopolist, solving the following profit maximization problem:

$$\max_{s \geq 0} P(s) s - C(s).$$

The monopolist’s pricing decision that arises from its first-order conditions can be written as

$$P(s) = \frac{1}{1 + \frac{1}{\epsilon}} C'(s),$$

where $\epsilon = \frac{ds/s}{dp/p}$ is the price elasticity of demand in the market for that DBE’s services. In words, the DBE pricing function represents the monopolist’s markup over its marginal cost.\(^3\) Note here that not all market demand functions will result in a one-to-one relationship between prices and DBE shares; a sufficient condition for this relationship to be a function is that the market demand’s elasticity is constant.

\(A.1.3.\ Estimation \ Appendix\)

In order to maintain desirable properties of the model across different parameter guesses, I must restrict the model’s set of possible parameter values. I include these restrictions along with details on the optimal weighting matrix and asymptotic standard errors in this appendix.

\(^3\)Observe that I implicitly assume that the monopolist firm does not strategically take the fine function into consideration when determining its prices.
Parametric Restrictions

I restrict the parameters so that the pricing function is convex and increasing in the DBE share and the fine function is convex and non-increasing in the share. To illustrate these restrictions, consider the first and second-order conditions of the DBE pricing function and the fine function for any given auction:

\[
P'(s_i) = \left( \alpha_0 + \alpha_1 s_i + \alpha_2 \frac{s_i}{1-s_i} + \alpha_3 z_w + u_w \right) \hat{x}_w + \left( \alpha_1 + \frac{\alpha_2}{(1-s_i)^2} \right) s_i \hat{x}_w
\]

\[
\varphi'(s_i; \bar{s}) = \begin{cases} 
2\gamma (s_i - \bar{s}) \hat{x} & \text{if } s_i < \bar{s} \\
0 & \text{if } s_i \geq \bar{s}
\end{cases}
\]

\[
P''(s_i) = 2 \left( \alpha_1 + \frac{\alpha_2}{(1-s_i)^2} \right) \hat{x}_w + \left( \frac{2\alpha_2}{(1-s_i)^3} \right) s_i \hat{x}_w
\]

\[
\varphi''(s_i; \bar{s}) = \begin{cases} 
2\gamma \hat{x} & \text{if } s_i < \bar{s} \\
0 & \text{if } s_i \geq \bar{s}
\end{cases}
\]

Observe that restricting \(\alpha_0 > 0, \alpha_1 > 0, \alpha_2 > 0\) and \(\alpha_3 > 0\) will generate a DBE pricing function that is convex and increasing in the DBE share for \(s_i \in [0,1)\). Similarly, restricting \(\gamma > 0\) will produce a fine function that is convex and non-increasing for \(s_i \in [0,1]\). In estimation, I restrict the structural parameter values to the aforementioned range of possible values to maintain those properties across parameter guesses.

Standard Errors and Optimal Weighting Matrix

Following Gourieroux et al. (1993), the asymptotic distribution of the indirect inference estimator takes the following form:
\[
\sqrt{W} (\hat{\theta}_{HW} - \theta_0) \xrightarrow{d} N(0, V_0)
\]

with
\[
V_0 = \left(1 + \frac{1}{H}\right) \left(D'\Omega D\right)^{-1} D'\Omega \hat{\beta}_0 \Omega D \left(D'\Omega D\right)^{-1},
\]
\[
D = \frac{\partial \beta_0}{\partial \theta_0'}
\]

and
\[
\sqrt{W} (\hat{\beta}_{HW} - \beta_0) \xrightarrow{d} N(0, V_{\beta_0}).
\]

Notation wise, \(\hat{\theta}_{HW}\) are the structural parameters estimated from the data, \(\theta_0\) are the true structural parameters, \(\Omega\) is a positive definite weighting matrix, \(\beta_0\) are the auxiliary parameters evaluated using the true structural parameters, and \(\xrightarrow{d}\) denotes convergence in distribution. The optimal weight matrix in this setting is \(\Omega^* = (V_{\beta_0})^{-1}\), yielding an asymptotic variance of \(V_\theta = \left(1 + \frac{1}{H}\right) \left(D'\Omega^* D\right)^{-1}\).

In practice, I replace the objects of the asymptotic distribution by consistent estimators. Specifically, I use the following consistent estimators in place of their asymptotic counterparts:
\[
\hat{D} = \frac{\partial \beta_{HW}}{\partial \hat{\theta}_{HW}}
\]
and
\[
\hat{\Omega}^* = \left(\hat{V}_{\beta_{HW}}(\hat{\theta}_{HW})\right)^{-1}.
\]

In constructing \(\hat{V}_{\beta_{HW}}(\hat{\theta}_{HW})\), the estimator for \(V_{\beta_0}\), I use a parametric bootstrap procedure.
A.1.4. Estimated Pricing and Fine Functions

![Graph showing DBE Subcontractor Share vs. Price (Fraction of the Engineer’s Estimate)](image)

Figure 12: The DBE Pricing Function as a Fraction of the Engineer’s Estimate

Note: This figure shows a plot of the price of using DBE subcontractors as a fraction of the engineer’s estimate, which corresponds to the expression $\frac{P(s)}{\hat{x}}$. Here, the pricing function is evaluated using the mean level of subprojects in the DBE-eligible data and the mean level of the unobservable pricing shock term ($\sigma_u$) when there is an established DBE subcontracting requirement of 7.5 percent.

A.1.5. Relative Cost of DBE Subcontractors

A common criticism of requiring the use of DBE subcontractors is that they are more costly. To assess whether this criticism is supported by the data, I generate a measure of the cost of using DBE subcontractors relative to non-DBE costs for the two most common types of projects with subcontracting requirements: road projects and bridge projects. Given that these two projects can vary along other dimensions, I use the modal project characteristics for each type of project in the DBE-eligible data to calculate these measures.

I construct the relative cost measure as the ratio of a prime contractor’s DBE cost of subcontracting $s_i$ percent of a project ($P(s_i)$) to that contractor’s non-DBE cost of completing $s_i$ percent of a project ($c_i s_i$). I will now refer to this measure as the DBE cost ratio. When the DBE cost ratio is one, it is just as costly for a prime contractor to use DBE subcontractors as their own resources, and when the DBE cost ratio is greater than one, DBE
subcontractors are relatively more expensive. Given that the price of DBE subcontractors also depends on the realization of the DBE pricing shock, I plot this ratio for the 25th, 50th, and 75th percentiles of the shock’s distribution.

Figure 14 illustrates how the DBE cost ratio changes across different projects and price shock realizations. For both types of projects, DBE subcontractors are likely to be relatively more costly since the DBE cost ratio is greater than one for most draws of the pricing shock. There are regions of the pricing shock’s distribution where DBE subcontractors are less costly, which suggests that DBE utilization is sensitive to the realization of the shock.

A.1.6. Subsidy and Quota Simulations

In this section, I repeat the numerical simulations with quotas and subsidies. I maintain the environment and functional form assumptions from section 1.5; for completeness, I list those assumptions below:

- $N = 2$
Figure 14: DBE Cost Ratios

Note: DBE cost ratios for the modal bridge and road construction projects. The vertical axis has the DBE cost ratio, and the horizontal axis has the DBE share. The different lines correspond to different levels of the unobserved shock on the DBE pricing function, where “low” corresponds to the 25th percentile, “medium” corresponds to the 50th percentile, and high corresponds to the 75th percentile of the shock’s distribution.

- \( c_i \sim U[0, 1] \), where \( U[\cdot, \cdot] \) denotes the uniform distribution.
- \( P(s_i) = \frac{\xi s_i^2}{2} \)
- \( \varphi(s_i; \bar{s}) = \begin{cases} \frac{\lambda(s_i - \bar{s})^2}{2} & \text{if } s_i < \bar{s} \\ 0, & \text{if } s_i \geq \bar{s} \end{cases} \)
- \( \xi = 2, \lambda = 3 \)

I set the quota and subsidy to 30% to match the simulations with subcontracting requirements.

Figure 15 shows the DBE subcontracting functions when there is a quota (the left panel) and subsidy (the right panel) and compares them to the subcontracting functions when there is no policy. For quotas, the DBE subcontracting functions are flat at the quota share if prime contractors would have subcontracted below the quota and match the non-quota DBE subcontracting functions otherwise. This shape comes from the constraint that prime contractors must meet the quota. For subsides, the DBE subcontracting function is
a rotation of the unsubsidized DBE subcontracting function. This shape is intuitive: prime contractors with lower non-DBE costs are less likely to use DBE subcontractors when they are subsidized. An important difference between subsidies and subcontracting requirements is that subsidies distort the more efficient contractors’ subcontracting decisions less, while subcontracting requirements distort the less efficient contractors’ subcontracting decisions more.

Next, I simulate the bid functions, which are displayed in figure 16. The bid function under the quota is similar to the bid function under subcontracting requirements, but the bids are relatively higher for prime contractors with lower non-DBE costs. This property comes from prime contractors losing the option to pay a fine instead of using DBE subcontractors, which leads to higher project costs.

The bid function under the subsidy is visibly lower than the bid function under subcontracting requirements. This effect is intensified for prime contractors with high non-DBE costs. Intuitively, DBE subcontractors are cheaper with the subsidy, which leads to lower project costs. Since prime contractors use more DBE subcontractors with a subsidy, their markups are also lower, leading to lower equilibrium bids.

![Figure 15: DBE Share Functions with Quotas and Subsidies](image)

My last simulation shows how procurement costs change with the subsidy; this simulation is contained in figure 17. Interestingly, procurement costs for prime contractors with low
non-DBE costs are lower with the subsidy, and the reverse is true for prime contractors with high non-DBE costs. The idea behind this result is that prime contractors with low non-DBE costs are less likely to use the subsidy but still bid lower than the unsubsidized case, leading to lower procurement costs.

A.1.7. Invitation for Bids

I gather the majority of the observable variables from the invitation for bids document that the NMDOT publishes to advertise its available construction projects. Figure 18 contains an excerpt from the NMDOT’s January 22nd, 2010 advertisement. The first paragraph specifies the county, which is later aggregated up to administrative district, and length. The second paragraph lists the project’s components. In my empirical analysis, I take the component in uppercase letters (in this case, roadway rehabilitation) as the main project, and I take the following components as the subprojects. The third paragraph gives the working days, and the fourth paragraph states whether there is a DBE subcontracting requirement (or goal). The last paragraph gives the licensing requirements.

A.1.8. Additional Regressions and Graphs

Tables 16 and 17 motivate the main modeling assumptions of the paper. Table 16 contains a regression specification very similar to the first three columns of tables 2 and 3, but I
include a control for firm capacity (as measured by the project backlog of a firm divided by the maximum backlog of the firm during the sample period) as an additional observable. This regression motivates the absence of capacity constraints in my paper’s main analysis; the statistically insignificant coefficient on the capacity measure shows that there is insufficient descriptive evidence in favor of including firm capacity in firm bidding and DBE subcontracting decisions. Similarly, table 17 is a regression that explores firm entry decisions as measured by the number of planholders and the fraction of bidders over the number of planholders. Although entry is typically modeled as an endogenous decision in these types of procurement models, the lack of an economically and statistically significant coefficient on the DBE requirement variable suggests that entry is not a first-order concern in evaluating these DBE participation policies.
Figure 18: IFB Example

Note: This figure shows the distribution of non-zero DBE subcontracting requirements.
Note: This figure shows the percentage difference between the share of DBE subcontractors actually used on a given project and the DBE subcontracting requirement conditional on the project having a subcontracting requirement. Although there is some bunching at 0 percent, there is a non-trivial mass of projects where contractors exceed the subcontracting requirement by more than 1 percent. Consequently, a continuous function is used to approximate the change in incentives induced by having a DBE subcontracting requirement rather than a discrete function. This figure is truncated at 15 percent for visual clarity.
Table 16: Capacity Regressions

<table>
<thead>
<tr>
<th></th>
<th>log(Winning Bid)</th>
<th>DBE Share (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>log(Engineer’s Estimate)</td>
<td>0.927***</td>
<td>−0.352</td>
</tr>
<tr>
<td></td>
<td>(0.017)</td>
<td>(0.624)</td>
</tr>
<tr>
<td>DBE Req (%)</td>
<td>0.002</td>
<td>1.014***</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.184)</td>
</tr>
<tr>
<td>log(Length + 1)</td>
<td>0.043***</td>
<td>0.016</td>
</tr>
<tr>
<td></td>
<td>(0.014)</td>
<td>(0.511)</td>
</tr>
<tr>
<td>Capacity</td>
<td>−0.019</td>
<td>−0.355</td>
</tr>
<tr>
<td></td>
<td>(0.040)</td>
<td>(1.161)</td>
</tr>
<tr>
<td>log(Planholders)</td>
<td>0.007</td>
<td>1.610</td>
</tr>
<tr>
<td></td>
<td>(0.056)</td>
<td>(1.940)</td>
</tr>
<tr>
<td>log(Subprojects)</td>
<td>0.049*</td>
<td>1.432</td>
</tr>
<tr>
<td></td>
<td>(0.028)</td>
<td>(0.880)</td>
</tr>
<tr>
<td>Number of Licenses Required</td>
<td>0.044**</td>
<td>1.773*</td>
</tr>
<tr>
<td></td>
<td>(0.020)</td>
<td>(0.924)</td>
</tr>
<tr>
<td>log(Working Days)</td>
<td>0.038*</td>
<td>−0.613</td>
</tr>
<tr>
<td></td>
<td>(0.020)</td>
<td>(0.605)</td>
</tr>
<tr>
<td>Bidders</td>
<td>−0.018***</td>
<td>−0.058</td>
</tr>
<tr>
<td></td>
<td>(0.005)</td>
<td>(0.215)</td>
</tr>
<tr>
<td>Federal Highway</td>
<td>−0.034</td>
<td>−0.240</td>
</tr>
<tr>
<td></td>
<td>(0.022)</td>
<td>(0.690)</td>
</tr>
<tr>
<td>Urban</td>
<td>−0.018</td>
<td>1.899*</td>
</tr>
<tr>
<td></td>
<td>(0.034)</td>
<td>(0.970)</td>
</tr>
<tr>
<td>Observations</td>
<td>389</td>
<td>389</td>
</tr>
<tr>
<td>Adjusted R^2</td>
<td>0.985</td>
<td>0.227</td>
</tr>
</tbody>
</table>

Note: *p<0.1; **p<0.05; ***p<0.01

Regression includes controls for district and type of work as well as month and year fixed effects. Standard errors are robust.
Table 17: Entry Regressions

<table>
<thead>
<tr>
<th></th>
<th>Bidders/Planholders</th>
<th>Planholders</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>log(Engineer’s Estimate)</td>
<td>0.008</td>
<td>1.392***</td>
</tr>
<tr>
<td></td>
<td>(0.008)</td>
<td>(0.353)</td>
</tr>
<tr>
<td>DBE Req (%)</td>
<td>0.0005</td>
<td>0.105</td>
</tr>
<tr>
<td></td>
<td>(0.002)</td>
<td>(0.087)</td>
</tr>
<tr>
<td>log(Length + 1)</td>
<td>0.010</td>
<td>−1.239***</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.314)</td>
</tr>
<tr>
<td>log(Subprojects)</td>
<td>−0.001</td>
<td>3.417***</td>
</tr>
<tr>
<td></td>
<td>(0.016)</td>
<td>(0.589)</td>
</tr>
<tr>
<td>Number of Licenses Required</td>
<td>−0.022**</td>
<td>1.194***</td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
<td>(0.457)</td>
</tr>
<tr>
<td>log(Working Days)</td>
<td>−0.018*</td>
<td>1.554***</td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td>(0.408)</td>
</tr>
<tr>
<td>Federal Highway</td>
<td>0.001</td>
<td>−0.543</td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td>(0.429)</td>
</tr>
<tr>
<td>Urban</td>
<td>0.002</td>
<td>1.522**</td>
</tr>
<tr>
<td></td>
<td>(0.016)</td>
<td>(0.619)</td>
</tr>
<tr>
<td>Observations</td>
<td>389</td>
<td>389</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.115</td>
<td>0.708</td>
</tr>
</tbody>
</table>

*Note:*

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

Regression includes controls for district and type of work as well as month and year fixed effects. Standard errors are robust.
A.2. Appendix for Resident Bid Preference, Affiliation, and Procurement Competition: Evidence from New Mexico

A.2.1. Applying GPV to Auctions with Bid Preferences and Affiliation

The first-order conditions in equation 2.1 can be rewritten as follows:

\[
c_1 = b_1 - \frac{S_1 \left[ 1 - F_{c}^{m_1} (c_1), 1 - F_{c}^{NR} \left( \beta_{NR}^{-1} \right), \ldots, 1 - F_{c}^{NR} \left( \beta_{NR}^{-1} \right), 1 - F_{c}^{R} \left( \beta_{R}^{-1} \right), \ldots, 1 - F_{c}^{R} \left( \beta_{R}^{-1} \right) \right]}{\partial S_1 \left[ 1 - F_{c}^{m_1} (c_1), 1 - F_{c}^{NR} \left( \beta_{NR}^{-1} \right), \ldots, 1 - F_{c}^{NR} \left( \beta_{NR}^{-1} \right), 1 - F_{c}^{R} \left( \beta_{R}^{-1} \right), \ldots, 1 - F_{c}^{R} \left( \beta_{R}^{-1} \right) \right]} \left(\frac{\partial S_1}{\partial b_1}\right),
\]

where

\[
\frac{\partial S_1 \left[ 1 - F_{c}^{m_1} (c_1), 1 - F_{c}^{NR} \left( \beta_{NR}^{-1} \right), \ldots, 1 - F_{c}^{NR} \left( \beta_{NR}^{-1} \right), 1 - F_{c}^{R} \left( \beta_{R}^{-1} \right), \ldots, 1 - F_{c}^{R} \left( \beta_{R}^{-1} \right) \right]}{\partial b_1} = (n_{NR} - D_{NR}) \beta_{NR}^{-1} f_c^{NR} \left( \beta_{NR}^{-1} \right) \left(1 - \delta\right)^D\left(1 - \delta\right)^{D_{NR}} f_c^{NR} \left( \beta_{NR}^{-1} \right) + (n_{R} - D_{R}) \beta_{R}^{-1} f_c^{R} \left( \beta_{R}^{-1} \right) \left(1 - \delta\right)^{D_{NR}} f_c^{R} \left( \beta_{R}^{-1} \right) \left(1 - \delta\right)^D.
\]

Define \( \tilde{b} = (1 - \delta)^D b \) 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

\[
F_{b}^{NR} \left( \tilde{b} \right) = F_{c}^{NR} \left( \beta_{NR}^{-1} \left( \tilde{b} \right) \right) \quad \text{and} \quad F_{b}^{R} \left( \hat{b} \right) = F_{c}^{R} \left( \beta_{R}^{-1} \left( \hat{b} \right) \right)
\]

and

101
\[ f_{b}^{NR} (\hat{b}) = f_{c}^{NR} (\tilde{b})^\beta_{NR} (b) \beta_{NR,1}^{-1} (\hat{b}) \]
\[ f_{b}^{R} (\hat{b}) = f_{c}^{NR} (\tilde{b})^\beta_{R} (b) \beta_{R,1}^{-1} (\hat{b}). \]

Equation A.3 can now be written as
\[
c_{1} = b_{1} - \left[ 1 - F_{b}^{m_{1}} (b_{1}), 1 - F_{b}^{NR} (\hat{b}_{1}), \ldots, 1 - F_{b}^{NR} (\hat{b}_{1}) \right]
\frac{\partial S_{1}}{\partial b_{1}} \left[ 1 - F_{b}^{m_{1}} (b_{1}), 1 - F_{b}^{NR} (\hat{b}_{1}), \ldots, 1 - F_{b}^{NR} (\hat{b}_{1}) \right],
\]
which expresses costs as the sum of the bid and a strategic markdown.

**A.2.2. 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:
\[
\hat{\beta}_{m}^{-1} (b) = b + \sum_{k=0}^{K} \alpha_{m,k} (b - \tilde{b})^{k},
\]
where \( \tilde{b} \) 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 \( \alpha \) be a vector that collects the polynomial coefficients of all groups of bidders, \( \hat{\beta}_{NR}^{-1} = (1 - \delta)^{DR} b, \hat{\beta}_{R}^{-1} = (1 - \delta)^{-DNR} b \), and define \( G_{m} (b; \tilde{b}, \alpha) \) as the first-order conditions with the approximated inverse bid functions set
equal to 0 at $b$:

$$G_m (b; \mathbf{b}, \mathbf{c}) =
\begin{align*}
&\mathbf{s}_1 \left[ 1 - F_c^m \left( \hat{\beta}_{m}^{-1} \right), 1 - F_{c}^{NR} \left( \hat{\beta}_{NR}^{-1} \right), \ldots, 1 - F_{c}^{NR} \left( \hat{\beta}_{NR}^{-1} \right), 1 - F_{c}^{R} \left( \hat{\beta}_{R}^{-1} \right), \ldots, 1 - F_{c}^{R} \left( \hat{\beta}_{R}^{-1} \right) \right] \\
&- (b - \hat{\beta}_{m}^{-1}) \left( n_{NR} - D_{NR} \right) \hat{\beta}_{NR,1}^{-1} (1 - \delta)^{D_{NR}} f_{c}^{NR} \left( \hat{\beta}_{NR}^{-1} \right) \\
&\times \mathbf{s}_{12} \left[ 1 - F_c^m \left( \hat{\beta}_{m}^{-1} \right), 1 - F_{c}^{NR} \left( \hat{\beta}_{NR}^{-1} \right), \ldots, 1 - F_{c}^{NR} \left( \hat{\beta}_{NR}^{-1} \right), 1 - F_{c}^{R} \left( \hat{\beta}_{R}^{-1} \right), \ldots, 1 - F_{c}^{R} \left( \hat{\beta}_{R}^{-1} \right) \right] \\
&\times \mathbf{s}_{1n} \left[ 1 - F_c^m \left( \hat{\beta}_{m}^{-1} \right), 1 - F_{c}^{NR} \left( \hat{\beta}_{NR}^{-1} \right), \ldots, 1 - F_{c}^{NR} \left( \hat{\beta}_{NR}^{-1} \right), 1 - F_{c}^{R} \left( \hat{\beta}_{R}^{-1} \right), \ldots, 1 - F_{c}^{R} \left( \hat{\beta}_{R}^{-1} \right) \right].
\end{align*}$$

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

\begin{align*}
0 &= \hat{\beta}_{R}^{-1} \left( \frac{b}{(1 - \delta)} \right) - \xi \\
0 &= \hat{\beta}_{NR}^{-1} (b) - \xi \\
0 &= \hat{\beta}_{R}^{-1} (\bar{b}) - \bar{c} \\
0 &= \hat{\beta}_{NR}^{-1} ((1 - \delta) \bar{b}) - (1 - \delta) \bar{c}
\end{align*}

Define $H (b; \mathbf{c})$ as

$$H (b; \mathbf{c}) = \sum_{m} \sum_{t=1}^{T} G_m (b; b, \mathbf{c}) + w (T) \left( \hat{\beta}_{R}^{-1} \left( \frac{b}{(1 - \delta)} \right) - \xi \right) + w (T) \left( \hat{\beta}_{NR}^{-1} (b) - \xi \right) + w (T) \left( \hat{\beta}_{R}^{-1} (\bar{b}) - \bar{c} \right) + w (T) \left( \hat{\beta}_{NR}^{-1} ((1 - \delta) \bar{b}) - (1 - \delta) \bar{c} \right),$$

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 $\hat{\alpha}$ to minimize $H(b; \alpha)$.

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 boundary conditions to $w(T) = 4T$ under affiliation and $w(T) = 15T$ when project costs are independent, and 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.

A.2.3. 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 on a grid of 100 bid points for the bid functions displayed in figure 10. Here, accuracy is determined by how close the first-order conditions are to reaching zero. Figure 19 shows the results. 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.

A.2.4. 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 2.7.1. For completeness, I list these assumptions below:

$$\log(b_{iw}) = \mathbf{x}_{iw}' \beta + \epsilon_{iw}^{m_i}$$
Figure 19: Errors for Approximated Bid Functions

This figure plots the first-order conditions associated with the bid functions approximated in figure 10. 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.

\[
\epsilon_{iw}^{m_i} \mid x_{iw} \sim \mathcal{N} \left( 0, \exp \left( y'_{iw} \sigma \right)^2 \right)
\]

\[
\left( \epsilon_{1w}^{NR}, \ldots, \epsilon_{n_N R+1w}^{NR}, \ldots, \epsilon_{n_N R+n_Rw}^{R} \mid x_{iw} \right) \equiv \epsilon_w \sim F_{\epsilon_w}
\]

\[
F_{\epsilon_w} = C \left[ F_{\epsilon_{1w}^{NR}}, \ldots, F_{\epsilon_{n_N R+1w}^{NR}}, F_{\epsilon_{n_N R+n_Rw}^{R}}, \ldots, F_{\epsilon_{n_N R+n_Rw}^{R}} \right]
\]

\[
\log \left( k_{iw} \right) = z'_{iw} \gamma + u_{iw}^{m_i}
\]

105
\[ u_{iw}^m \mid z_{iw} \sim \mathcal{N} \left( 0, \exp (v_{iw} \alpha)^2 \right). \]

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

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

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

and

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

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

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

The corresponding empirical moments are

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

for the first moment and

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

for the second moment.

I derive the next moment condition from the equation for Kendall’s tau for Clayton copulas.

106
In particular, when the dependence between random variables is modeled as a copula, Kendall’s tau takes the following form:

$$\tau_{ij} = 4E \left[ C \left[ F_u(u_i), F_u(u_j) \right] \right] - 1,$$  \hspace{1cm} (A.4)

where $\tau_{ij}$ is Kendall’s tau, and $u_i$ and $u_j$ are random variables that are related through the copula $C[\cdot, \cdot]$ 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:

$$\tau_{ij} = \frac{\theta}{\theta + 2}. \hspace{1cm} (A.5)$$

Combining equations A.4 and A.5 gives the next moment condition, which can be expressed as

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

The empirical counterpart for the above moment condition is

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

There is one subtlety in the above equation. The equation for $\tau_{ij}$ (equation A.4) 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

\[
E \left[ n_{mw} \mid x_w, z_w, N_{mw}, N_{-mw} \right] = N_{mw} p_{mw},
\]

\[
E \left[ n_{mw}^2 \mid x_w, z_w, N_{mw}, N_{-mw} \right] = N_{mw} p_{mw} (1 - p_{mw}) + N_{mw}^2 p_{mw}^2,
\]

\[
E \left[ n_{mw}^3 \mid x_w, z_w, N_{mw}, N_{-mw} \right] = N_{mw} p_{mw} \left( 1 - 3p_{mw} + 3N_{mw} p_{mw} + 2p_{mw}^2 - 3N_{mw} p_{mw}^2 + N_{mw}^2 p_{mw}^2 \right),
\]

and

\[
E \left[ n_{mw}^4 \mid x_w, z_w, N_{mw}, N_{-mw} \right] = N_{mw} p_{mw} \left( 1 - 7p_{mw} + 7N_{mw} p_{mw} + 12p_{mw}^2 - 18N_{mw} p_{mw}^2 + 6N_{mw}^2 p_{mw}^2 - 6p_{mw}^3 + 11N_{mw} p_{mw}^3 - 6N_{mw}^2 p_{mw}^3 + N_{mw}^3 p_{mw}^3 \right)
\]

respectively. Taking unconditional expectations over the number of potential entrants and
the project characteristics yields the moment conditions described in section 2.7.2. These
moment conditions are
\[ E[n_{mw}] = \int N_{mw} p(x_w, z_w, N_{mw}, N_{-mw}) dF(x_w, z_w, N_{mw}, N_{-mw}), \]

\[ E[n_{mw}^2] = \int N_{mw} p(x_w, z_w, N_{mw}, N_{-mw}) \left( 1 - p(x_w, z_w, N_{mw}, N_{-mw}) \right) + \int N_{mw}^2 p(x_w, z_w, N_{mw}, N_{-mw})^2 dF(x_w, z_w, N_{mw}, N_{-mw}), \]

\[ E[n_{mw}^3] = \int N_{mw} p_{mw} \left( 1 - 3p_{mw} + 3N_{mw} p_{mw} + 2p_{mw} - 3N_{mw} p_{mw}^2 \right) + \int N_{mw}^2 p_{mw}^2 dF(x_w, z_w, N_{mw}, N_{-mw}), \]

and

\[ E[n_{mw}^4] = \int N_{mw} p_{mw} \left( 1 - 7p_{mw} + 7N_{mw} p_{mw} + 12p_{mw}^2 - 18N_{mw} p_{mw}^2 + 6N_{mw}^2 p_{mw}^2 \right) - 6p_{mw}^3 + 11N_{mw} p_{mw}^3 - 6N_{mw}^2 p_{mw}^3 + N_{mw}^3 p_{mw}^3 dF(x_w, z_w, N_{mw}, N_{-mw}) \]

The corresponding empirical moments are then given by

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

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

and

\[
\frac{1}{W} \sum_{w=1}^{W} \left[ n_{mw}^4 - N_{mw} p_{mw} \left( 1 - 7p_{mw} + 7N_{mw} p_{mw} + 12p_{mw}^2 - 18N_{mw} p_{mw}^2 + 6N_{mw}^2 p_{mw}^2 \right.ight.
\]

\[
\left. - 6p_{mw}^3 + 11N_{mw} p_{mw}^3 - 6N_{mw}^2 p_{mw}^3 + N_{mw}^3 p_{mw}^3 \right) \right]
\]

A.2.5. Project and Subproject Examples

This section contains two example project descriptions in the data: 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 afterwards.
NEW MEXICO PROJECT
A300013
CN A300013

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.

FEDERAL AID PROJECT
3100340
CN 3100340

Construction Consists Of:
BRIDGE REPLACEMENT (Replace Existing Bridge w/3-Span Prestressed Girders, Approach Slabs, Concrete Barrier Railing), Roadway Reconstruction, Pavement Sections (Flexible), Earthwork (Borrow, Subexcavation), Curb & Gutter w/Sidewalk, Concrete Wall Barrier, Structures (Culverts, Drop Inlets), Erosion Control Measures, Traffic Control (Phasing), Permanent Signing, Lighting and Miscellaneous Construction.
### A.2.6. Construction Project Types

**Table 18: New Mexico Highway Construction Project Types**

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


R. Gil and J. Marion. Self-enforcing agreements and relational contracting: Evidence from


T. Li and B. Zhang. Affiliation and entry in first-price auctions with heterogeneous bidders:


