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HIGHWAY PROCUREMENT DURING THE GREAT RECESSION AND STIMULUS

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ABSTRACT

We study highway procurement in Texas during the Great Recession and stimulus period, finding increased competition with more bidders and lower bids. We argue that the recession reduced opportunity costs, in part due to a slump in private-sector construction. We evaluate costs and efficiency by developing methods to estimate an empirical auction model tailored for public bidding and demonstrate that contracts became more efficient and less costly. A counterfactual analysis confirms that infrastructure procurement during recessions not only stimulates the economy but also enables the government to complete necessary projects at lower costs.

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1 Introduction

Sharp reductions in private-sector activity often mark recessionary periods—with the commercial and residential construction industry facing significant declines during the 2007-2009 Great Recession. In response, the U.S. government enacted the American Recovery and Reinvestment Act of 2009 (ARRA), a substantial $789 billion stimulus package geared toward revitalizing economic activity. Congress allocated a significant portion of this spending towards boosting government purchases through public procurement. In highway procurement, this funding was a boon to contractors who typically balance private and public sector work (Kroft et al., 2023) and saw their options in the private sector dwindle.

By viewing public contracting expenses as economic costs—which include direct costs, such as buying and pouring concrete for highway overpasses, and opportunity costs, which are dictated by foregone alternatives like laying foundation for residential or commercial buildings—we posit that the Great Recession effectively reduced economic costs by limiting contractors' outside alternatives. This reduction in economic costs influences two key decisions contractors make: whether to "enter" by submitting a bid on a contract and the bid's amount. If economic costs decline for both project completion and bid submission, contractors generally respond by bidding lower amounts on a broader array of projects. Intuitively, contractors weigh their economic entry costs against expected profit when deciding whether to bid, entering when profit potential justifies the cost. With reduced economic costs, contractors had greater incentive to participate and could afford to bid lower, as reduced project costs enabled them to maintain profitability with more competitive bids.

Data from highway contracting at the time seem puzzling at face value but are consistent with this reasoning. A national review conducted by the U.S. Department of Transportation (USDOT) on ARRA-funded projects found that bids from state transportation departments routinely came in 10 to 30 percent *below* engineering estimates (FHWA, 2015). In Texas, and reflective of the national trends, bids averaged 10 percent under state estimates, yet contracts attracted an average of nearly two additional bidders. Was this rise in competition influenced by lower economic costs? Can the decrease in bid amounts be credited to reduced markups from heightened competition, or were bids dropping because of declining economic costs? What are the implications for government procurement during booms and busts? We address these questions using the unique market conditions created by the Great Recession and ARRA, focusing specifically on highway construction contracts in Texas.

In our analysis, we develop and estimate an empirical auction model that aligns with the award process for public highway contracts, allowing us to obtain economic costs that would otherwise be unobservable. The model contributes to the extant literature by simultaneously incorporating two features prevalent in many public sealed bidding environments: positive dependence in project costs—or affiliation—and a particular form of endogenous entry where bidders observe potential but not actual competition. Affiliation often occurs when contractors share subcontractors or suppliers, a practice common on complex construction projects. Our entry model is consistent with many state and federal bidding practices, which typically inform contractors about eligible bidders but not the actual number of bids received. Through a re-weighting of the standard bid-inversion conditions, our approach allows us to recover unobserved project and entry costs.

We find significant cost reductions in conjunction with diminished private-sector construction activity during the recession and stimulus, even when controlling for the highly predictive measures of direct costs available in the data. On projects with comparable work requirements, we estimate a decrease in economic entry costs by about 2.5 percent of total project engineer-estimated cost, while the economic cost of project completion declined by 7.9 to 10.6 percent of the engineer's estimate, varying with project size. Although profit margins also decreased, they did not diminish by enough to account for the total reduction in bid amounts. These results suggest that the dearth of private construction projects likely reduced contractor opportunity costs, which then contributed to the budget-efficient nature of projects procured during this period.

We then utilize our cost estimates to evaluate contract efficiency. Our efficiency measure considers the total cost of bidding on and completing a contract for all contractors, including the entry costs for those deciding to bid and the winner's cost of completing the required work. We document an efficiency gain for projects procured under recessionary market conditions relative to similar projects procured before the Great Recession, driven primarily by lower overall economic costs. These results have broader implications for understanding government interventions during recessionary periods, suggesting that governments can satisfy two objectives at once: stimulating the economy during an economic downturn and procuring necessary projects more efficiently and at a lower cost.

Our empirical model relates to and expands on other papers in the auction literature. Many studies estimate an endogenous entry model based on either Levin and Smith (1994), where bidders observe the number of entrants before bidding and learn their private costs after incurring an entry fee, or Samuelson (1985), where bidders learn their private cost before paying an entry fee to enter. For example, research by Li and Zhang (2015) and Athey et al. (2011) study timber auctions, while studies by De Silva and Rosa (2024) and Krasnokutskaya and Seim (2011) consider highway procurement auctions. Further contributions by Gentry and Li (2014), Bhattacharya et al. (2014), Roberts and Sweeting (2013), and Sweeting and Bhattacharya (2015) allow for the possibility of selection in the entry process. Li and Zheng (2012), Li and Zheng (2009), and Carril et al. (2022) consider entry processes that most closely align with our entry model. We build on their analyses by allowing for an affiliation component, reflecting the interdependence often seen among contractors who share subcontractors or suppliers.

The related empirical literature on affiliation in auctions is relatively smaller. Li et al. (2002) show that the affiliated private value auction model is identified. Our study, like Li and Zheng (2012), Rosa (2019), and Li and Zhang (2015) employs copula methods to incorporate affiliation in private value auctions—which provide a tractable way of estimating joint distributions. Somaini (2020) and Compiani et al. (2020) use copulas to estimate the affiliation that arises in common value auctions, where bidders observe a signal of their value instead of their actual values. We adapt the existing copula methods to our entry environment, allowing us to capture many of the competitive forces at play in a typical highway contracting market.

Additionally, our topic connects to a broader literature on various aspects of the Great Recession and stimulus. Studies like Conley and Dupor (2013), which found that the ARRA spending expanded government employment but did not conclusively affect private-sector employment, provide a backdrop against which one can contextualize our findings. The market analysis for credit rating agencies leading up to the Great Recession by Chu and Rysman (2019), the investigation into the drivers of the housing bust by Garriga and Hedlund (2020), and the Allen et al. (2023) study of how insolvent banks were resolved complement our exploration of the economic landscape during this turbulent period. Moreover, the mortality implications of the Great Recession studied in Finkelstein et al. (2024) adds a dimension of human impact to the economic analyses, illustrating the broad scope of the recession's effects.

There is a more focused body of literature on the Great Recession and stimulus spending on highway procurement. For instance, Balat (2017) studies procurement in California. We build on that study by modeling the entry process explicitly, allowing for the affiliation likely to arise from common subcontracting, and accounting for the private-sector construction opportunities that shape underlying opportunity costs. Similarly, a study by Gugler et al. (2015) considers Austrian construction, finding that markups decreased by 1.5 percent during the recession. We expand their analysis by simultaneously accounting for endogenous entry and affiliation—which can substantially impact estimated costs and markups.

The remainder of the paper proceeds as follows. Section 2 describes the Texas Department of Transportation (TxDOT) procurement market and ARRA spending. Section 3 presents a descriptive analysis of the data. Section 4 contains a theoretical bidding model with endogenous entry, and Section 5 shows how we bring the model to the data. Section 6 presents the empirical results from the model, while 7 explores various counterfactual scenarios. Section 8 concludes.

2 Institutional Details

This section describes the TxDOT procurement process and how it was affected by the Great Recession and ARRA. Our data contain information on highway structures projects[1] offered one year before the recession (December 2006) until the end of the stimulus funds (October 2010). In our sample period, TxDOT procured 868 structures projects: 242 projects before the recession and 626 projects during the recession and ARRA.

2.1 TxDOT Procurement

TxDOT procures construction projects monthly. At the start of the fiscal year, TxDOT sets monthly project award days and releases plans for each project to be procured at least 28 days ahead of each scheduled award day. These plans include the type and grade of required materials, estimated days to complete the project, and the project's location. TxDOT also includes a state engineer-estimated cost, which TxDOT updates monthly for input price changes and contains an estimate for each part of the work to be completed. Together, these controls have high explanatory power, explaining up to 98 percent of the variation in observed prices.

When the plans are available, prequalified[2] firms can "purchase" them for a nominal printing fee or download them for free. Because this process is virtually costless and does not obligate contractors to submit bids, we assume that every prequalified contractor desiring plans will acquire them. After purchasing a plan, firms become "plan holders," and TxDOT makes the identities of plan holders available to all plan-holding firms before the award date. Because plan holder status is required to submit a responsive bid and observed by all participants, we treat the number of plan holders as the set of potential bidders.

Plan holders decide whether to submit a bid on a project without knowing how many other bids TxDOT has received. On the award date, TxDOT opens all bids and takes the lowest one as the winner. As such, we model the award process as a low-price sealed-bid auction with endogenous entry, where the number of bidders is unobserved. Using other firms as subcontractors to complete parts of the larger project is common in contracting, especially in construction.[3] We model the potential correlation in costs shared subcontractors and suppliers can create by allowing for affiliation between contractor costs of project completion—which we refer to as their project cost.

[1]Structures projects are contracts where TxDOT lists most of the work items as "structures" work. Typically, these projects are for bridges and overpasses.

[2]To prequalify, firms must submit their total assets and liabilities, certified by an independent third-party accountant.

[3]See Branzoli and Decarolis (2015), Rosa (2024), and Marion (2015), for example. In our data, firms subcontract 27.8 percent of work.

2.2 The Great Recession and the American Recovery and Reinvestment Act of 2009

During the Great Recession, many firms increased their bidding frequency on public contracts, primarily due to the lack of opportunities in the private sector. For example, in conversations with Minnix Construction—a TxDOT contractor and commercial and residential building construction firm in Lubbock, Texas—Minnix expressed facing a tighter housing market during the Great Recession. Thus, they increased their bidding frequency on TxDOT projects to compensate. More generally, firms submitted 2.3 bids per month during the Great Recession, up from 1.8 bids per month before the downturn. As a result, more firms entered TxDOT auctions, which heightened competition and potentially drove down prices.[4]

The Great Recession prompted the US government to enact the ARRA in 2009. The Act's funds translated to a 72% supplement to the US Department of Transportation's budget, with $27.5 billion allocated to highway construction projects (Mallett, 2020). The US government aimed to expedite the implementation of projects planned and approved by the states but scheduled beyond the fiscal year 2009 calendar—thereby stimulating construction activities across the US. The Act mandated that states identify and schedule all ARRA projects for bid letting by March 1, 2010, with a substantial portion of contracts awarded by the summer of 2009. The ARRA funding window for structure projects in Texas spans April 2009 to October 2010.

3 Descriptive Analysis

Having outlined TxDOT's main institutional features and consequences of the Great Recession and ARRA, we now conduct a descriptive analysis of our data. We first consider overall estimated spending. We display our results graphically in Figure 1 by plotting the total value of the engineers' estimates for structure projects from 2006 to 2010. With the ARRA funding, TxDOT managed to keep spending in 2009 and 2010 somewhat similar to the levels from 2006 through 2008.[5] In 2009 and 2010, ARRA funding accounted for 37.8 and 27.3 percent of the contract value awarded, respectively. Without ARRA funding, TxDOT's budget for structure projects would have seen an average reduction of $250 million for 2009 and 2010, highlighting how TxDOT used ARRA funding to maintain project continuity and spending levels during the Great Recession.

Table 1 outlines the structures projects awarded before (2006:12 – 2007:11) and during the

[4]We do not find evidence of new firms joining the TxDOT market. The increase in bidding was mainly among firms that had previously been contractors.

[5]We do not use data before December 2006 in our main analysis, as oil prices increased from 2004 through early to mid-2006. Consequently, contractors would routinely bid above the engineer's estimate because Texas would not adjust contracts for oil prices.

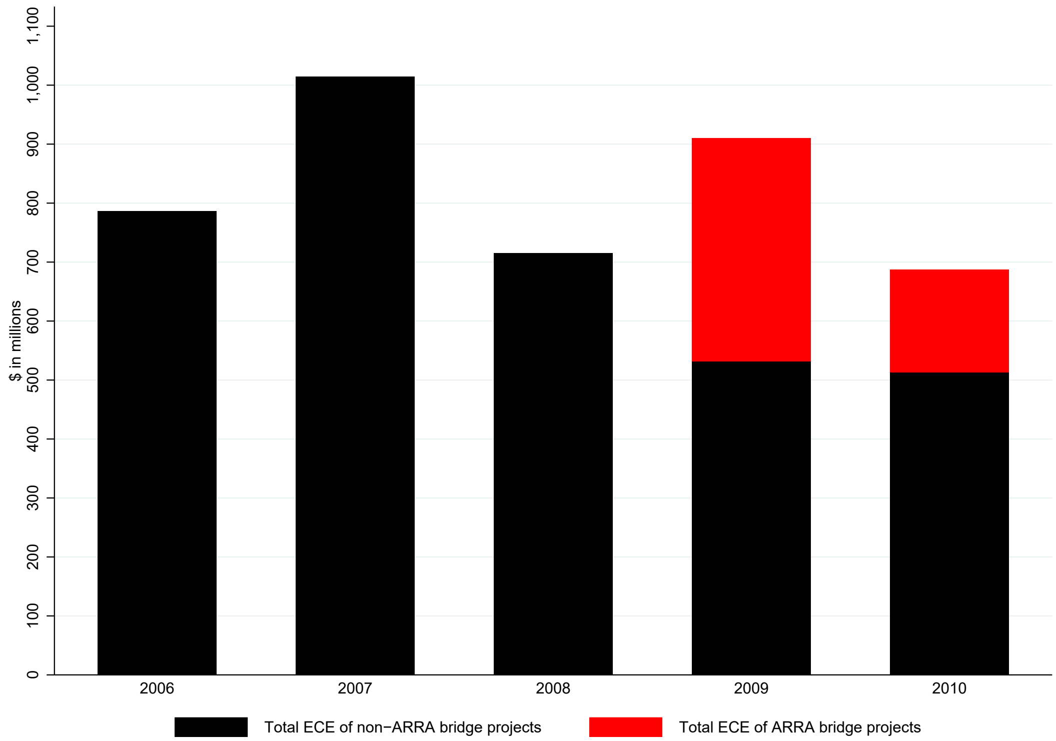


Figure 1: Size of Structure Projects in Texas

Great Recession and ARRA (2007:12 – 2010:10). Important auction-level variables include the average bid, the average Engineer's Cost Estimate (ECE), the average number of plan holders, and the average number of bidders. To account for inflation, we deflate all monetary values to 2000 dollars.

The average bid value was about 4.26 million dollars before the Great Recession, falling to 3.44 million dollars during the GR-ARRA months. On average, the ECE was about 4.06 million dollars before the GR-ARRA months and 3.71 million dollars during the GR-ARRA months. To better compare bids across periods, we normalize them by dividing them by the ECE. We refer to these normalized bids as *relative bids*, as they are relative to the ECE. Relative bids were about 0.93 during the GR-ARRA period, while before the recession, they were about 1.05. In percentage terms, these numbers translate into bids being 105 percent of the ECE before the recession and falling to 93 percent afterward.

Figure 2 plots a time series of monthly average relative bids and winning bids. In this figure, and in the subsequent time-series plots, we denote the start and end of the Great Recession by solid vertical lines, and we use dashed lines to mark the beginning and end of ARRA-funded projects. We find that bids were substantially below estimated costs during the GR-ARRA months, indicating a more competitive bidding environment and significant cost savings for TxDOT.

Table 1: Summary statistics

Variable	All projects	Non GR and non ARRA months	GR and ARRA months
	(1)	(2)	(3)
Number of projects	868	242	626
Average bid (in millions)	3.616	4.264	3.444
	(9.898)	(12.727)	(8.990)
Average ECE (in millions)	3.810	4.056	3.714
	(10.861)	(11.911)	(10.440)
Average number of plan holders in an auction	10.969	8.504	11.922
	(4.673)	(2.861)	(4.887)
Average number of bidders in an auction	6.565	4.950	7.118
	(3.041)	(1.893)	(3.170)
Three month moving average total value of	1,030.959	1,501.808	869.525
building permits for TX (in $ millions)	(333.884)	(93.263)	(207.21)
Three month moving average of the total	16.644	18.731	15.915
ECE in the zone (in $ millions)	(16.785)	(18.373)	(16.199)
Auctions in metro district	0.457	0.450	0.460
	(0.498)	(0.499)	(0.499)

ECE and the total value of building permits are in year 2000 dollar values. Standard deviations are in parentheses.

In line with this more competitive bidding environment, the data also reveal a sharp increase in plan holders and bidders. Average plan holding was approximately 40.2 percent higher higher—and bids received 43.8 percent higher—during the GR-ARRA months compared to before the recession. Figure 3 plots a time series of the monthly averages, showing an increase in competition during the GR-ARRA time frame.

Other variables include proxies for a contractor's outside opportunities in the public and private sectors. In Texas, contractors must obtain a building permit before beginning work on a private construction project. The cost of a permit depends on the size of the project, with larger projects requiring a more expensive permit. As such, we use the three-month moving average of the total value of building permits per month in Texas as a proxy for outside private-sector opportunities. The summary statistics in Table 1 indicate that during the GR-ARRA months, the total value of building permits was about 632 million dollars less than the preceding 12 months, a drop of about 42.1 percent. Figure 4 presents a time series of the monthly total value of building permits (in logs) in Texas, depicting a sharp decline in our proxy for a contractor's private sector opportunities.

Additionally, we report the three-month moving average of the total ECE by geographical zone[6] as a proxy for public-sector options. During the GR-ARRA period, the moving average of the total ECE was almost three million dollars lower than the pre-GR-ARRA period, a drop

[6]TxDOT divides its market into five zones, each varying by topography and climate. For instance, the Houston area has a subtropical climate, while an arid climate characterizes West Texas.

Figure 2: Time Series of Relative Bids (Bid/ECE)

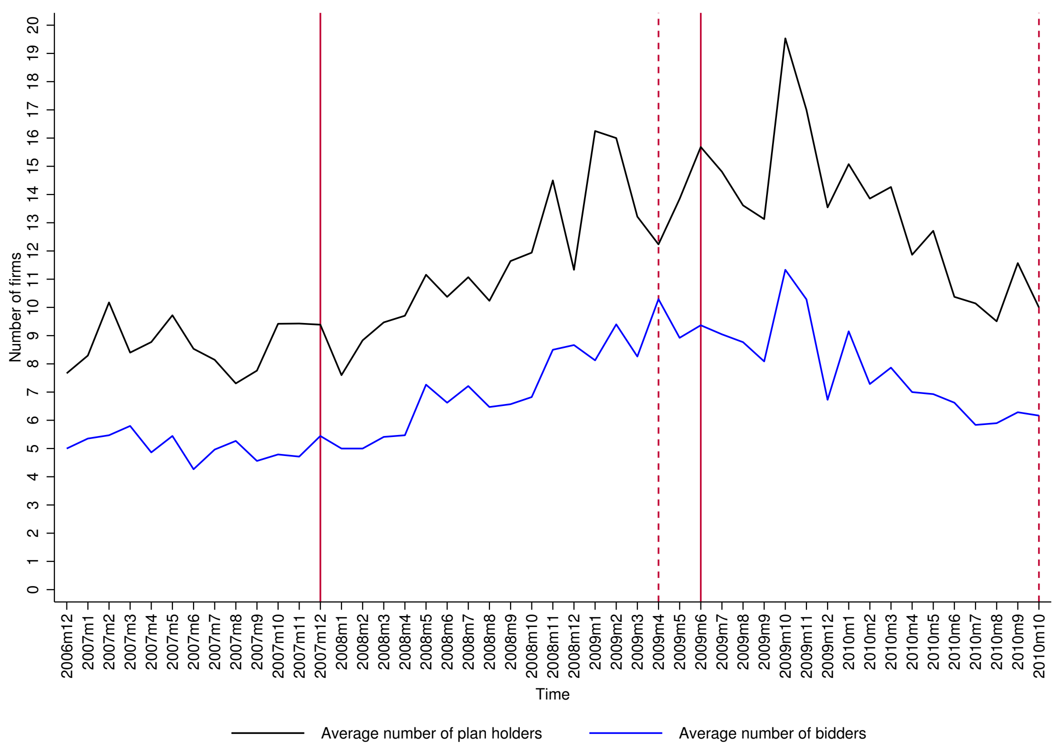


Figure 3: Time Series of the Average Number of Bidders and Plan Holders

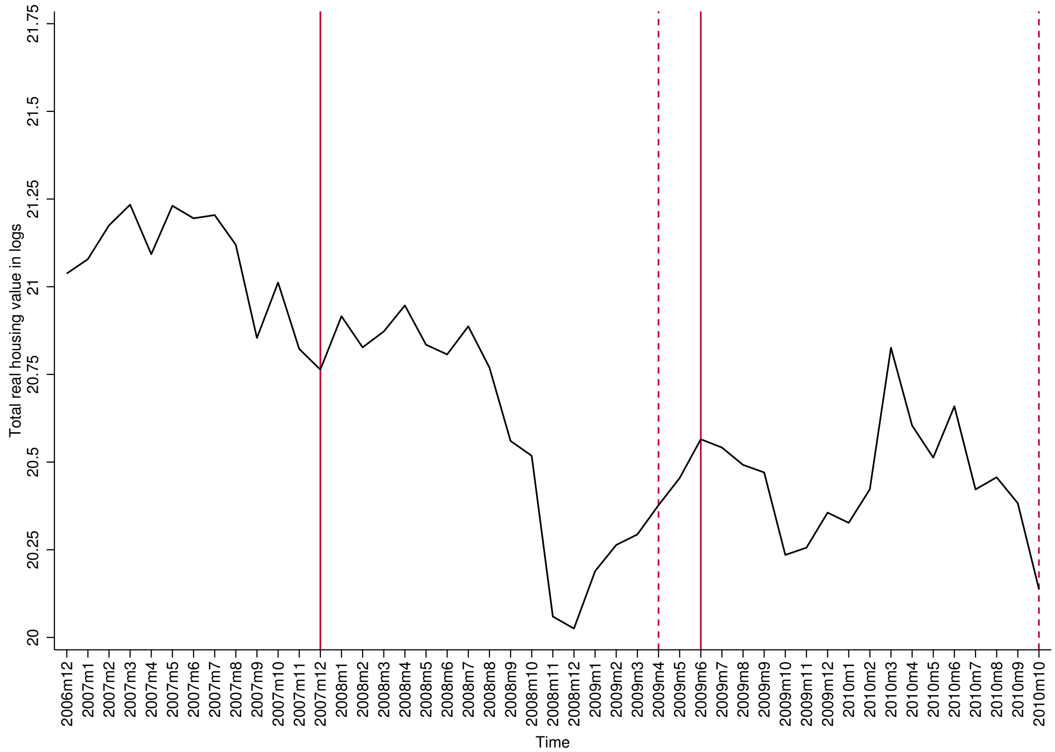


Figure 4: Time Series of Total Building Permit Values in Texas (in Logs)

of about 15.0 percent. As start dates for private or public construction projects vary by a few months from their award dates, we take the three-month moving average to capture general economic activity in the market.[7]

The final summary statistic in Table 1 concerns metro districts, which will be important for our structural analysis. TxDOT has 25 highway districts, with an average of five or six districts per zone. We follow TxDOT's district classification methodology in defining a metro district as one with a population of over 1 million people. These districts tend to contain major cities, such as Dallas, Houston, and Austin. About 46 percent of contracts are in a metro highway district in our sample.

To further explore how bidding and bids were affected by the recession and stimulus, we conduct a regression analysis for a contractor's decision on whether and how much to bid. Table 2 reports our findings. The first two columns of Table 2 report regression results for the number of bidders in an auction, a measure of competition. We estimate these count models via a Poisson Pseudo Maximum Likelihood method, which adjusts for over- and under-dispersion. In Column 1, we present the empirical specification without including proxies for public- and private-sector opportunities; we add these proxies in Column 2. We also include an indicator

[7]De Silva et al. (2008) take a similar approach in their analysis of Oklahoma and Texas highway procurement.

Table 2: Regression results for number of bidders and bids

Variables	Number of biders		Log of bids	
	(1)	(2)	(3)	(4)
GR and TX ARRA auction months	0.132*	0.034	-0.065*	0.035
	(0.029)	(0.042)	(0.018)	(0.024)
2006:12 – 2007:05	0.062	0.070	-0.007	-0.012
	(0.042)	(0.042)	(0.024)	(0.024)
Log of ECE	-0.030*	-0.036*	0.911*	0.917*
	(0.015)	(0.015)	(0.009)	(0.009)
Log of real three month average value of total building permits for TX		-0.195*		0.192*
		(0.060)		(0.032)
Log three month moving average of the total ECE in the zone		0.002		0.009
		(0.012)		(0.006)
Log number of plan holders	Yes	Yes	Yes	Yes
Metro districts	Yes	Yes	Yes	Yes
Other auction level controls	Yes	Yes	Yes	Yes
Observations	868	868	5,698	5,698
R-squared	0.619	0.625	0.983	0.983

Robust standard errors are in parentheses. * $p<0.05$

variable for the GR-ARRA period—our main variable of interest—and controls for location, plan holders, contract characteristics, and seasonality.

Results in Column 1 show that, after converting the Poisson coefficients to a percent change,[8] the expected number of bidders was 14.1 percent higher during the GR-ARRA period relative to six months before the recession (June 2007 to November 2007), our reference group. On a project with the approximate sample average of 11 plan holders, this result translates into adding roughly 1.6 bidders. However, the relationship attenuates and becomes statistically insignificant when we include our proxies. This result suggests that net of our controls for public and private opportunities, the association between number of bids and the GR-ARRA months is statistically indistinguishable from zero, and the increase in bidders correlates with the drop in private-sector construction work.

We present the results for bidding in Columns 3 and 4. The coefficients indicate that bids were approximately 6.5 percent lower during the GR-ARRA period compared to six months prior. As with the number-of-bidders analysis, this relationship diminishes and becomes statistically insignificant when we include proxies for opportunity costs. In sum, the regression results corroborate the overall increase in competitiveness observed in our graphical analysis and reinforce our cautious confidence that our proxies effectively control for private and public options.

[8]For a Poisson regression, the percent increase on a binary variable with coefficient β is $[\exp(\beta) - 1] \times 100$.

4 A Model of Contractor Bidding and Entry

This section presents the theoretical model underlying our empirical analysis. Throughout, we stress that all costs are *economic costs*, containing direct costs and opportunity costs. For now, we hold direct costs fixed and use m to denote opportunity costs. Thus, the model's primitives will change with m.

4.1 Model Overview

In line with the TxDOT procurement process, we model contractor bidding as a two-stage game. In the first stage, plan-holding contractors observe the total number of plan holders, N; draw an entry cost, k, from the distribution $H(\cdot \mid m)$; and decide whether to incur that cost to learn their project cost, c. Because contractors must incur k to learn c and submit a bid, one can interpret k as an information acquisition and bid preparation cost, similar to the interpretation in Li and Zheng (2012). A contractor paying k then becomes one of n bidders, but n is unobserved by those deciding to bid. In the second stage, contractors that paid the entry cost submit a bid. Figure 5 outlines the sequence of events. We aim to characterize the Bayesian Nash equilibrium of this game.

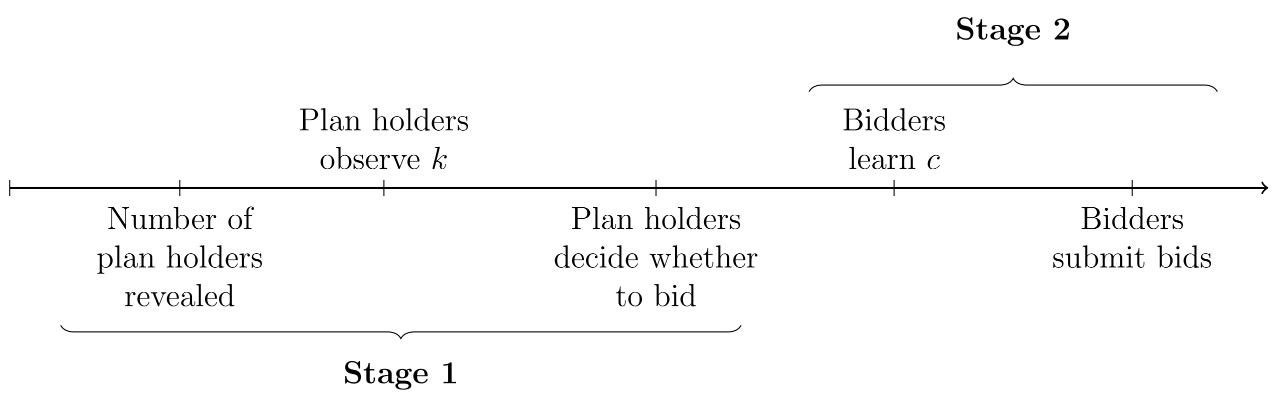


Figure 5: Sequence of Events

4.2 Stage 2: Equilibrium Bidding

We work through the model backwards by starting at the bidding stage and then moving to the entry stage. We assume bidders are symmetric and discuss the empirical plausibility of this assumption later in Section 6.3. A bidding contractor faces n actual bidders. Because n is unknown when bidding, contractors form beliefs, $q \in [0, 1]$, where q corresponds to the probability that a competing plan holder bids. In equilibrium, these beliefs will be consistent with auction entry probabilities, and we will derive these equilibrium beliefs later when we characterize auction entry decisions. We denote equilibrium beliefs by $q_N^*(m)$; for now, we take them as given.

With beliefs $q_N^*(m)$, the probability of facing n total actual bidders conditional on entry—or equivalently, the probability that $n-1$ of a contractor's $N-1$ rivals enter—follows a binomial distribution. This probability can be written as

$$\Pr(n \mid N, q_N^*(m)) = \binom{N-1}{n-1} q_N^*(m)^{n-1}(1-q_N^*(m))^{N-n}.$$

Having paid their auction entry cost, bidding contractor i would have also observed c_i, their project cost. As is the case in many highway procurement settings, contractors may share subcontractors and suppliers,[9] leading to a positive dependence in project costs. We account for this feature by assuming the n contractors who become actual bidders have affiliated project costs, $c_1, c_2, \ldots, c_n$, drawn from a joint distribution, $\mathcal{F}_n(c_1, c_2, \ldots, c_n \mid m)$. As outlined by Milgrom and Weber (1982), affiliation is a stronger version of positive correlation, roughly capturing the idea that project costs are related.[10]

Observe that there is no reservation price in our setup, which is consistent with how TxDOT runs its highway procurement auctions. Consequently, a contractor facing no competitors would want to raise their bid indefinitely. In practice, TxDOT can reject unreasonably high bids at their discretion. Following Li and Zheng (2009), we emulate this bid-rejection power by assuming TxDOT always enters as a competing bidder.

Let $G_n(\cdot \mid c_i, m)$ denote the distribution function of the lowest competing project cost for contractor i given n total competitors. If all other competitors $j \neq i$ follow a strictly increasing bid strategy $b_j = b_N(c_j; m)$, contractor i wins if $b_i < b_N(c_j; m)$ (or, equivalently, $b_N^{-1}(b_i; m) < c_j$) for all $j \neq i$. Thus, contractor i chooses their bid to solve

$$\max_{b_i} \quad (b_i - c_i) \sum_{n=1}^{N} \Pr(n \mid N, q_N^*(m))(1 - G_n(b_N^{-1}(b_i; m) \mid c_i, m)), \tag{1}$$

which is the payoff from bidding b_i times the probability of winning with bid b_i.

The first-order condition characterizing optimal bidding is

$$c_i = b_N(c_i; m) - \frac{\sum_{n=1}^{N} \Pr(n \mid N, q_N^*(m))(1 - G_n(c_i \mid c_i, m))}{\sum_{n=1}^{N} \Pr(n \mid N, q_N^*(m)) g_n(c_i \mid c_i, m) \frac{1}{b_N'(c_i; m)}}, \tag{2}$$

with $g_n(\cdot \mid c_i, m)$ being the derivative of $G_n(\cdot \mid c_i, m)$. The optimal bid function that solves (2)

[9] See Rosa (2019) for an example in New Mexico and Hubbard et al. (2012) for an application in Michigan.

[10] For a more formal definition, let $\mathbf{c} = (c_1, c_2, \ldots, c_n)$ and $\mathbf{c}' = (c_1', c_2', \ldots, c_n')$ be points in $\mathbb{R}^n$. A density function $f : [\underline{c}, \overline{c}]^n \to \mathbb{R}_+$ is affiliated if $f(\mathbf{c})f(\mathbf{c}') \leq f(\mathbf{c} \wedge \mathbf{c}')f(\mathbf{c} \vee \mathbf{c}')$, where $\mathbf{c} \wedge \mathbf{c}' = (\min\{c_1, c_1'\}, \ldots, \min\{c_n, c_n'\})$ and $\mathbf{c} \vee \mathbf{c}' = (\max\{c_1, c_1'\}, \ldots, \max\{c_n, c_n'\})$.

subject to the constraint $b_N(\overline{c}; m) = \overline{c}$ is

$$b_N(c_i; m) = c_i + \frac{\sum_{n=1}^{N} \Pr(n \mid N, q_N^*(m)) \int_{c_i}^{\overline{c}} (1 - G_n(\tilde{c} \mid \tilde{c}, m)) d\tilde{c}}{\sum_{n=1}^{N} \Pr(n \mid N, q_N^*(m)) \, (1 - G_n(c_i \mid c_i, m))}, \tag{3}$$

depicting a strategic markup over a project's cost. We derive this result in Appendix A using an envelope theorem argument based on Milgrom and Segal (2002).

4.3 Stage 1: Equilibrium Auction Entry

Contractors decide whether to enter the auction and bid by comparing their cost of bidding to their expected profits. Expected profits depend on beliefs, which correspond to actual entry probabilities in equilibrium.

In deriving equilibrium beliefs, we note that a contractor's expected profits from submitting a bid with project cost c_i is

$$\begin{aligned} \pi_N(c_i; m) &= (b_N(c_i; m) - c_i) \sum_{n=1}^{N} \Pr(n \mid N, q_N^*(m)) \, (1 - G_n(c_i \mid c_i, m)) \\ &= \sum_{n=1}^{N} \Pr(n \mid N, q_N^*(m)) \int_{c_i}^{\overline{c}} (1 - G_n(\tilde{c} \mid \tilde{c}, m)) d\tilde{c}, \end{aligned}$$

where the second line inserts the equation for $b_N(c_i; m)$.

Let $F_c(\cdot \mid m)$ denote the marginal distribution function for c, with density $f_c(\cdot \mid m)$. Ex-ante profits (before knowing c_i) are then

$$\Pi_N(m) = \int_{\underline{c}}^{\overline{c}} \pi_N(\check{c}; m) f_c(\check{c} \mid m) d\check{c}.$$

Contractors submit a bid whenever $\Pi_N(m) \geq k_i$. Let $k_N^*(m)$ be the auction entry cost that makes contractors indifferent. Then,

$$\Pi_N(m) = k_N^*(m) = \int_{\underline{c}}^{\overline{c}} \left[\sum_{n=1}^{N} \Pr(n \mid N, q_N^*(m)) \int_{\check{c}}^{\overline{c}} (1 - G_n(\tilde{c} \mid \tilde{c}, m)) d\tilde{c} \right] f_c(\check{c} \mid m) d\check{c}. \tag{4}$$

Belief consistency requires that

$$q_N^*(m) = H(k_N^*(m) \mid m). \tag{5}$$

Applying Brouwer's Fixed Point Theorem to equation (5) suggests an entry equilibrium exists. With affiliation, the entry equilibrium may not be unique because it gives rise to an affiliation effect—which can increase bids as the number of competitors increases (Pinkse and

Tan, 2005). We verify uniqueness numerically for our estimates.[11]

Notice that equilibrium bidding and entry depend on opportunity costs. Intuitively, if the opportunity cost of time decreases during the recession, contractors would have lower economic costs on average, even if direct costs do not change. When this decrease is large enough,[12] contractors would be willing to bid less and enter more on projects procured during the recession.

5 The Empirical Model and Estimation

Having established the theory behind TxDOT contracting, we now describe the empirical model taken to the data. We first outline our estimation approach. We then describe our empirical specification and how we use it to obtain estimates of the model's primitives. We end with an identification discussion.

5.1 Estimation Approach

In estimating the model, we rely on bid-inversion methods similar to those developed by Guerre et al. (2000). With this approach, we aim to express the first-order conditions of a contractor's bidding problem in terms of functions of observed variables. We can then back out the unobserved project cost distribution and use it to estimate unobserved entry costs.

In the model, equation (2) depicts a contractor's first-order bidding conditions. Let $\breve{G}_n(\cdot \mid b_i, m)$ denote the distribution function for a contractor's lowest competing equilibrium bid, and let $\breve{g}_n(\cdot \mid b_i, m)$ be its density. Because bids are monotone in project costs,

$$\breve{G}_n(b_N(c_i; m) \mid b_N(c_i; m), m) = G_n(c_i \mid c_i, m).$$

The corresponding density function is then

$$\breve{g}_n(b_N(c_i; m) \mid b_N(c_i; m), m) b'_N(c_i; m) = g_n(c_i \mid c_i, m).$$

Therefore, one can rewrite equation (2) as

$$c_i = b_i - \frac{\sum_{n=1}^{N} \Pr(n \mid N, q^*_N(m))(1 - \breve{G}_n(b_i \mid b_i, m))}{\sum_{n=1}^{N} \Pr(n \mid N, q^*_N(m)) \breve{g}_n(b_i \mid b_i, m)}. \tag{6}$$

[11] Specifically, we verify that $1 - G_n(c_i \mid c_i, m)$ is nonincreasing in n. When this condition holds, ex-ante profits are nonincreasing in $q^*_N(m)$ and are thus nonincreasing in $k^*_N(m)$ from equation (5), as shown by Li and Zheng (2009). Because $k^*_N(m)$ is increasing in $k^*_N(m)$, the entry cost cutoff is unique from the requirement in equation (4).

[12] By "enough" here, we mean enough to outweigh any potential markup changes, as opportunity costs may affect markups too.

This result is similar to the bid-inversion condition for an affiliated private value auction, except the entry beliefs appear here as weights on the bid distribution and density functions. Notice, though, that the consistency requirement between beliefs and entry probabilities means that we can estimate $q_N^*(m)$ from observed entry probabilities. Thus, we can construct the right-hand side of equation (6) from observables.

For our empirical model, this approach requires estimating joint bid distributions *and* entry probabilities. From there, we can back out expected profits and use them to estimate entry costs.

5.2 The Empirical Specification

We estimate the model parametrically to account for a rich set of contract-level controls that would be infeasible to incorporate otherwise. On each contract, l, we observe the number of plan holders, N_l, the number of bidders, n_l, and various contract characteristics. We split our contract-level controls into two groups. The first group of controls is $\mathbf{x}_l$, which includes variables affecting a contractor's direct cost of project completion and proxies for the opportunity cost. By changing project costs, these controls—together with the number of plan holders—will affect equilibrium bids and entry probabilities. The other group of controls is $\mathbf{z}_l$, which affect entry costs. These controls will also impact equilibrium bidding and entry probabilities because they affect contractor entry incentives. In our analysis, $\mathbf{z}_l$ will be a subset of $\mathbf{x}_l$, so we simplify notation by excluding $\mathbf{z}_l$ when controlling for $\mathbf{x}_l$.

We note that bids have a multiplicative separability property common in most auction models, allowing us to normalize bids and primitives by the engineer's cost estimate without losing generality.[13] For example, if a bid on a contract is b_{il}, we use the relative bid, $b_{il}^0 = b_{il}/ECE_l$. Throughout, we denote relative bids, relative project costs, and relative entry costs as b_{il}^0, c_{il}^0, and k_{il}^0, respectively. Thus, many of our results will be relative to the engineer's estimate.

5.2.1 The Bid Distribution

Because project costs are affiliated, we assume participating contractors draw their relative project costs from the joint distribution $\mathcal{F}_n(c_1^0, c_2^0, \ldots, c_n^0 \mid \mathbf{x}_l)$, with marginal distribution $F_{c^0}(\cdot \mid \mathbf{x}_l)$. We model the joint distribution with copulas, using methods developed by Hubbard et al.

[13] In Appendix A, we show this result formally. Namely, we show that if $z > 0$ is some constant, multiplying project and entry costs by z produces equilibrium bids that are z times as high. Auction entry and plan holding probabilities do not change. Bajari et al. (2010) take a similar approach in their application to California highway procurement auctions.

(2012). The copula representation of the joint distribution is

$$\mathcal{F}_n(c_1^0, c_2^0, \ldots, c_n^0 \mid \mathbf{x}_l) = \mathcal{C}_n[F_{c^0}(c_1^0 \mid \mathbf{x}_l), F_{c^0}(c_2^0 \mid \mathbf{x}_l), \ldots, F_{c^0}(c_n^0 \mid \mathbf{x}_l)],$$

where $\mathcal{C}_n[\cdot]$ is the copula function. Copulas are well-suited for our model because they allow us to separate dependence in variables from their marginal distributions in a computationally undemanding way.

We assume a Clayton copula function, meaning that

$$\mathcal{C}_n[F_{c^0}(c_1^0 \mid \mathbf{x}_l), F_{c^0}(c_2^0 \mid \mathbf{x}_l), \ldots, F_{c^0}(c_n^0 \mid \mathbf{x}_l)] = \left(\sum_{i=1}^{n} F_{c^0}(c_i^0 \mid \mathbf{x}_l)^{-\theta} - n + 1\right)^{-\frac{1}{\theta}}, \ \theta \in [-1, \infty)\backslash\{0\}.$$

One can interpret the Clayton copula as follows. The parameter θ is a dependence parameter. A higher θ implies that relative project costs are more positively dependent. Affiliation requires that $\theta > 0$, and the copula tends to independence as θ approaches 0.

Another appealing feature of copula functions is that they are invariant to increasing transformations of the random variables (Nelsen, 2006). Because bids increase in project costs, we can model the joint equilibrium bid distribution with the same copula function by replacing the marginal relative project cost distribution with the marginal relative bid distribution. That is to say, if the marginal relative bid distribution is $F_{b^0}(\cdot \mid \mathbf{x}_l, N_l)$, then the joint distribution is

$$\mathcal{C}_n[F_{b^0}(b_1^0 \mid \mathbf{x}_l, N_l), F_{b^0}(b_2^0 \mid \mathbf{x}_l, N_l), \ldots, F_{b^0}(b_n^0 \mid \mathbf{x}_l, N_l)].$$

We ensure relative bids are positive by assuming their marginal distribution is log-normal. Letting $\mathbf{y}_l$ be some of the characteristics in $\mathbf{x}_l$, we model the log mean of relative bids as $\mu_b(\mathbf{x}_l, N_l) = [\mathbf{x}_l', N_l]\beta$ and the log standard deviation as $\sigma_b(\mathbf{y}_l) = \exp(\mathbf{y}_l'\psi)$. The exponential transformation keeps the standard deviation parameter positive. The marginal density function is then

$$F_{b^0}(b^0 \mid \mathbf{x}_l, N_l) = \Phi\left(\frac{\log(b^0) - \mu_b(\mathbf{x}_l, N_l)}{\sigma_b(\mathbf{y}_l)}\right),$$

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

Although our specification models the joint distribution, we note that deriving project costs from bids requires the conditional distribution and density of the lowest competing bid, which we have not expressed here. These objects have copula representations, and we derive them in Appendix B.

5.2.2 Entry Costs and Entry Probabilities

We assume relative entry costs follow an exponential distribution,[14] ensuring that they remain positive in the structural analysis. We model the mean of the distribution as $\mu_k(\mathbf{z}_l) = \exp(\mathbf{z}_l'\gamma)$. The distribution function is then

$$F_{k^0}(k^0 \mid \mathbf{z}_l) = 1 - \exp\left(-\frac{k^0}{\mu_k(\mathbf{z}_l)}\right).$$

Our final specification concerns a parameterization for the equilibrium entry probabilities. We assume that these objects follow a logistic distribution. Thus,

$$q^*(\mathbf{x}_l, N_l) = \frac{1}{1 + \exp(-([\mathbf{x}_l', N_l]\lambda))}.$$

This specification allows us to estimate entry probabilities using a logistic regression.

5.3 Estimation

We estimate the model in two steps. First, we estimate the equilibrium entry probabilities and equilibrium relative bid distribution. Then, we use the bid-inversion equation to back out relative project costs, construct ex-ante profits, and estimate relative entry costs.

5.3.1 Equilibrium Joint Bid Distribution and Entry Probabilities

We estimate the entry probability parameters through a logistic regression. In estimating the joint relative bid distributions, we use generalized method of moments (GMM), which chooses the parameters minimizing a set of sample moments. We select these moments to capture various features of the relative bid data.

Our first set of moments aim to match the marginal relative bid distributions. To this end, we use the first, second, third, and fourth moments of the log-normal distribution in estimation.

[14] One may be concerned that the exponential assumption is limiting, but we find that it fits the data well, which we will show later when discussing model fit.

Our first set of moments are then

$$0 = E\left[\begin{bmatrix}\mathbf{x}_l \\ N_l\end{bmatrix}\left(\log(b_{il}^0) - \mu_b(\mathbf{x}_l, N_l)\right)\right]$$

$$0 = E\left[\mathbf{y}_l\left\{\left(\log(b_{il}^0) - \mu_b(\mathbf{x}_l, N_l)\right)^2 - \sigma_b(\mathbf{y}_l)^2\right\}\right]$$

$$0 = E\left[\begin{bmatrix}\mathbf{x}_l \\ N_l\end{bmatrix}\left(\log(b_{il}^0) - \mu_b(\mathbf{x}_l, N_l)\right)^3\right]$$

$$0 = E\left[\mathbf{y}_l\left\{\left(\log(b_{il}^0) - \mu_b(\mathbf{x}_l, N_l)\right)^4 - 3\sigma_b(\mathbf{y}_l)^4\right\}\right].$$

Next, we need a moment condition to estimate the Clayton copula's dependence parameter, θ. For this part, we follow Oh and Patton (2013), who suggest using "pure" dependence measures—that is, measures unaffected by the marginal distribution. One such measure is Kendall's tau, which can be expressed as a function of the Clayton copula. Namely, by letting τ^{ij} denote the Kendall's tau measure for a pair of observations i and j, $i \neq j$, we have that

$$\tau^{ij} = 4E\left[\mathcal{C}_2\left[F_{b^0}(b_i^0 \mid \mathbf{x}_l, N_l), F_{b^0}(b_j^0 \mid \mathbf{x}_l, N_l)\right]\right] - 1.$$

Furthermore, Genest and Mackay (1986) derive an expression for τ^{ij} in terms of the dependence parameter for a Clayton copula, finding that $\tau^{ij} = \theta/(\theta + 2)$. These results motivate our final bid-distribution moment:

$$0 = 4E\left[\mathcal{C}_2\left[\Phi\left(\frac{\log(b_i^0) - \mu_b(\mathbf{x}_l, N_l)}{\sigma_b(\mathbf{y}_l)}\right), \Phi\left(\frac{\log(b_j^0) - \mu_b(\mathbf{x}_l, N_l)}{\sigma_b(\mathbf{y}_l)}\right)\right]\right] - 1 - \frac{\theta}{\theta + 2}, \quad i \neq j.$$

In practice, we calculate this expression for every pairing of bidder i with competitor j in an auction and average it to obtain the moment for bidder i.

5.3.2 The Entry Cost Distribution

With the entry probabilities and bid distributions in hand, we use GMM to estimate the remaining entry cost parameters. For this part, we invert bids to get relative project costs and markups. Then, we use Monte Carlo integration to obtain expected profits and the relative entry cost that makes contractors indifferent.

Let $k^*(\mathbf{x}_l, N_l)$ be the indifference entry cost. Then, the probability that a contractor enters an auction is $p(\mathbf{x}_l, N_l)$, where $p(\mathbf{x}_l, N_l) = F_{k^0}(k^*(\mathbf{x}_l, N_l) \mid \mathbf{z}_l)$. Because the probability of facing n bidders follows a binomial distribution, our moment condition is

$$0 = E\left[\begin{bmatrix}\mathbf{x}_l \\ N_l\end{bmatrix}\left(n_l - p(\mathbf{x}_l, N_l)N_l\right)\right].$$

To minimize the noise in our estimates, we use the optimal weight matrix in every GMM implementation. We also find meaningful differences in within-auction bid correlations and entry patterns across projects of different sizes. As such, we estimate the model once for large projects and once for small projects, where "large" projects have an ECE above one million.

5.4 Identification

Although the empirical model is parametric, it can be estimated semiparametrically, as we show formally in Appendix C. Here, we outline the intuition and discuss how the moment conditions identify the parametric portions of the model.

Identification of the project cost distribution follows immediately from equation (6), as it expresses project costs as a function of observed bid distributions and entry probabilities. With the project cost distribution identified, we can construct ex-ante profits and use the belief consistency condition in equation (5) to estimate the entry cost distribution. Namely, the entry cost distribution is the one that equates the left- and right-hand sides of equation (5).

The moment conditions identify the model's parametric features. The marginal relative bid distribution parameters are the ones that best match the moments of the marginal relative bid distributions observed in the data. We identify the affiliation parameter through the Kendall's tau moment, matching the dependence in relative bid residuals within auction to an analytic function of the Clayton copula's dependence parameter. Finally, we identify the exponential relative entry cost parameters by calculating ex-ante expected profits and choosing the parameters that best replicate average entry in the data.

6 Empirical Results

In this section, we report parameter values estimated from the empirical model, assess the model's fit, and discuss various modeling choices.

6.1 Parameter Estimates

The first set of parameters are the logit estimates of a contractor's equilibrium entry probability. Table 3 presents our findings separated by large projects (ECE $>$ \$1M) and small projects

Table 3: Entry Logit Parameters

	Large Projects		Small Projects	
	Coeff.	S.E.	Coeff.	S.E.
Constant	9.6234	2.6907	11.2387	2.3852
Metro	0.2505	0.0726	0.0864	0.0622
Log items	-0.0575	0.0542	0.0731	0.0592
Log days	0.0970	0.0715	0.0433	0.0586
Log permit value	-0.4894	0.1246	-0.5100	0.1095
Log zone ECE	0.0376	0.0382	-0.0206	0.0333
Number of plan holders	-0.0340	0.0071	-0.0496	0.0074
Observations	4231		5291	

Note: Parameter estimates for the logit entry probabilities. Specification includes zone and quarter effects.

(ECE $\leq \$1M$). Although not shown in the table, our specification also includes quarter effects to account for seasonality in entry patterns and zone effects to capture zone-level differences in entry.

Our estimates indicate that contractors have a higher propensity to enter projects in metropolitan highway districts, but mainly when the project is large. For every project size, contractors are less likely to enter when there are more plan holders, suggesting that ex-ante expected profits decrease in the number of plan holders.

The coefficients on the opportunity cost proxies (i.e., permit values and zone ECE) suggest that contractors are less likely to enter when private construction opportunities increase, consistent with the descriptive analysis. The zone ECE coefficient for public opportunities is relatively much smaller and statistically insignificant, so public contracting opportunities outside of a given project do not appear to statistically influence entry.

Table 4 reports our estimates for the equilibrium relative bid distribution. The mean and standard deviation parameters characterize the log-normal marginal bid distribution—where, like the entry logit estimates, the mean specification controls for quarter and zone effects.[15] The marginal relative bid distribution is statistically unaffected by many of our direct cost measures (i.e., items, days, and metro), suggesting that the engineer's estimate accounts for much of the change in equilibrium relative bids.

In contrast, we observe significant changes to the relative bid distribution in response to our opportunity cost proxies. Similar to our earlier descriptive analysis, we find that the mean and variance of equilibrium relative bids increase with outside opportunities in public and private contracting. This result suggests that bids decrease during the recession and stimulus.

[15] Note that the log-normal distribution has a mean of $\exp(\mu_b(\mathbf{x}_l, N_l) + \sigma_b(\mathbf{y}_l)^2/2)$ and variance $[\exp(\sigma_b(\mathbf{y}_l)^2) - 1]\exp(2\mu_b(\mathbf{x}_l, N_l) + \sigma_b(\mathbf{y}_l)^2)$.

Table 4: Relative Bid Distribution Parameters

	Large Projects		Small Projects	
	Coeff.	S.E.	Coeff.	S.E.
Mean parameters				
Constant	-3.5739	0.3011	-3.3246	0.3878
Metro	0.0114	0.0080	0.0038	0.0099
Log items	0.0034	0.0069	0.0513	0.0066
Log days	0.0014	0.0080	-0.0293	0.0150
Log permit value	0.1612	0.0140	0.1547	0.0174
Log zone ECE	0.0170	0.0043	0.0070	0.0052
Number of plan holders	-0.0031	0.0008	-0.0007	0.0010
Std. parameters				
Constant	-1.7897	0.0240	-1.6646	0.0372
Metro	-0.0468	0.0300	-0.0162	0.0437
Affilation parameter				
Constant	1.0052	0.1820	0.6849	0.1123
Observations	2428		3269	

Note: Parameter estimates for the log-normal bid distribution. The standard deviation estimates are the psi coefficients of the expression $\sigma = \exp(\psi_0 + \psi_1 \times \text{Metro})$. Mean specification includes zone and quarter effects.

Perhaps surprisingly, we estimate an insignificant effect of plan holders on relative bids for small projects. However, this estimate is consistent with the theoretical results in Li and Zheng (2009), who find that bids need not be monotone decreasing in the number of plan holders. Intuitively, when the number of plan holders increases, contractors become less likely to enter, which then increases bids as a result. Li and Zheng (2009) refer to this phenomenon as the "entry effect" and estimate an insignificant effect of plan holding on bidding for mowing contracts in Texas.

The affiliation parameter estimates imply some degree of correlation between bids within an auction. One can interpret these coefficients through the Kendall's tau measure, which is $\tau^{ij} = \theta/(\theta + 2) = 0.335$ for large projects and 0.255 for small projects. The large project Kendall's tau implies that relative bids on large projects are 33.5 percent more likely to be concordant than discordant—roughly meaning that if a contractor has a "high" relative bid, their competitor is 33.5 percent more likely to submit a "high" relative bid than a "low" relative bid.[16] For small projects, relative bids are 25.5 percent more likely to be concordant than discordant. These Kendall's tau estimates are within range of other estimates in the literature, including the Hubbard et al. (2012) estimate of 0.655 for Michigan construction contracts and

[16]For a more formal definition of concordance, let $(x_1, y_1) \ldots (x_n, y_n)$ be n observations of random variables X and Y so that every x_i and y_i are unique. A pair of observations (x_i, y_i) and (x_j, y_j), $i < j$, are concordant if either $x_i > x_j$ and $y_i > y_j$ or $x_i < x_j$ and $y_i < y_j$. The observations are discordant otherwise.

the Rosa (2019) estimate of 0.309 for construction contracts in New Mexico.

Table 5: Relative Project Costs and Margins

	Relative Project Cost			Profit Margins (%)		
	Median	Mean	S.D.	Median	Mean	S.D.
Large projects	0.9428	0.9733	0.1942	4.5309	4.5924	1.7621
Small projects	1.0147	1.0495	0.2477	5.4481	5.8484	3.2868
Metro projects	0.9837	1.0156	0.2195	4.6449	4.9227	2.1861

Note: Relative project costs and margins implied by the estimated parameters. Margins are calculated as $100 \times (b - c)/b$.

With estimates of the relative bid distribution parameters, we can calculate relative project costs and profit margins via bid inversion. We do so for the bids observed in the data and report our findings in Table 5. Relative project costs tend to be around one, meaning that project costs are close to the engineer's estimate. Profit margins are the profit a contractor would receive as a percent of their bid, or $100 \times (b_i - c_i)/b_i$. We estimate profit margins of around 5 percent, towards the upper range of publicly traded construction firms reported in Bajari et al. (2010).

Table 6: Relative Entry Cost Parameters

	Large Projects		Small Projects	
	Coeff.	S.E.	Coeff.	S.E.
Constant	-18.8433	1.8527	-16.1576	1.6310
Metro	-0.2766	0.0559	-0.0379	0.0493
Log permit value	0.7842	0.0885	0.6128	0.0772
Log zone ECE	-0.0112	0.0289	0.0411	0.0243

Note: Parameter estimates for the exponential entry cost distribution. The estimates are the gamma coefficients of the expression $\mu = \exp(\mathbf{z}'\gamma)$ for an exponential distribution with mean μ.

Next, we report the parameters of the exponential relative entry cost distribution. Table 6 contains the coefficients. Our results are largely consistent with the equilibrium entry probabilities. Contractors on large projects have lower economic costs for entry in metro highway districts and higher entry costs on both types of projects when private-sector construction opportunities are more abundant.

To further interpret these parameter values, we simulate $1,000$ relative entry costs (without conditioning on entry) for each project in the data and report the mean and median in Table 7.[17] Large projects have a slightly lower mean and median relative entry cost than small projects. The

[17]Note that the exponential distribution will have a standard deviation equal to its mean.

Table 7: Relative Entry Costs

	Median	Mean
Large projects	0.034	0.053
Small projects	0.041	0.060
Metro projects	0.035	0.053

Note: Relative entry costs implied by the estimated parameters.

average entry cost for large projects is 5.3 percent of the engineer's estimate and 6.0 percent of the engineer's estimate for small projects. The median entry costs for large and small projects—which are less sensitive to outliers in the right tail of the exponential distribution—are 3.4 percent and 4.1 percent of the engineer's estimate, respectively. These estimates are slightly higher than the mean entry cost of 1.5 percent of the ECE estimated by Bhattacharya et al. (2014) in Oklahoma, but are close to Bajari et al. (2010), who find entry cost 4.5 are about percent of the ECE, and De Silva and Rosa (2024), who estimate that entry costs are 5.1 percent of the ECE.

6.2 Model Fit

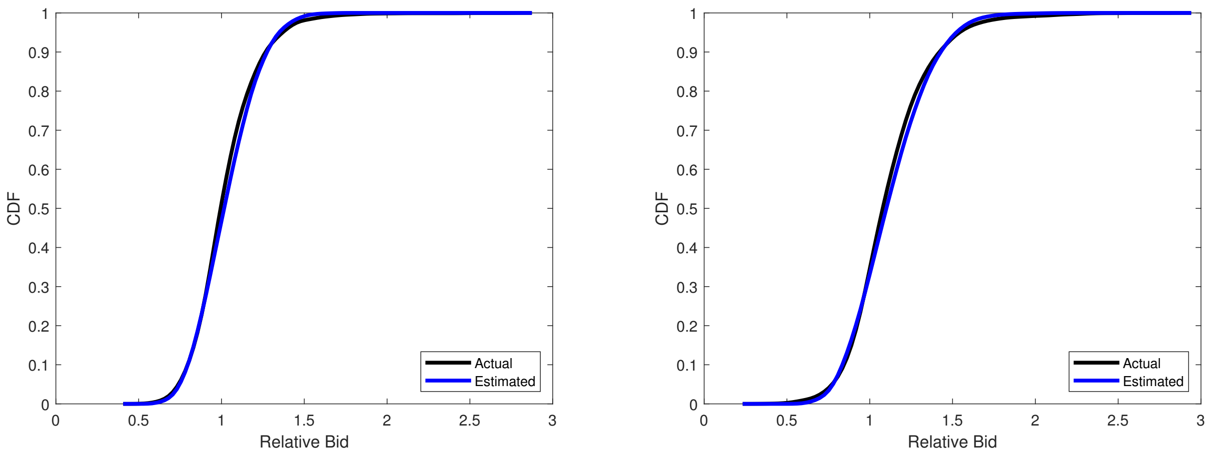
Our empirical model relies on parametric assumptions for the relative bid and entry cost distributions. These assumptions might not mesh well with observed bid and entry behavior, resulting in a lack of model fit. As such, we use the estimated parameters to explore how well the model matches the data.

We first explore the marginal relative bid distribution. For this part, we simulate $1,000$ bids from each project's equilibrium bid distribution and compare them to the relative bids observed in the data. Figure 6 contains our results for the actual and predicted marginal relative bid distribution function for large projects (left panel) and small projects (right panel). Visually, the estimated distributions appear to fit the actual ones well.

We then consider how well the parametric relative entry cost assumption generates entry patterns observed in the data. We consider average entry in two scenarios: once for the entire sample and again for projects procured during the Great Recession and stimulus (GR-ARRA). In all cases, the model appears to match entry well, even for those recession outcomes that are not targeted in estimation.

6.3 Discussion

Before moving into our counterfactual analysis, we pause to discuss several modeling choices.



(a) Large projects (b) Small projects

Figure 6: Actual vs. Estimated Relative Bid Distributions

Table 8: Model Fit to Observed Entry

	Actual	Predicted
Moments used in estimation		
Large projects	6.544	6.524
Small projects	6.577	6.608
Metro projects	6.912	6.885
Moments not used in estimation		
Large projects (GR-ARRA)	7.254	7.192
Small projects (GR-ARRA)	7.134	7.174
Metro projects (GR-ARRA)	7.567	7.500

Note: Actual versus predicted entrants. The GR-ARRA notation refers to projects procured durring the Great Recession and ARRA spending periods.

Backlog and Other Asymmetries

Our main analysis is based on a symmetric model, where bidders draw their project costs from the same underlying distribution. However, one could argue that asymmetries caused by bidder heterogeneity may affect our results. In auction literature, factors such as firm-level backlog or capacity utilization and distance between a firm and the project location are often sources of bidder asymmetries.

To investigate the prevalence of asymmetries in our data, we conducted a robustness exercise by including backlog (or capacity utilization) and a firm's distance to the project location relative to the minimum distance of rivals in our bid regressions. We find no evidence that either measure affects bidding in our model, suggesting that these asymmetries may not have a first-order effect on our results.[18]

Wages and Input Prices

During the Great Recession and stimulus, it is possible that the direct cost of completing a contract was affected in ways our controls cannot capture. For example, input prices and wages may have changed, which could generate the dip in relative bids we observe in the data.

The institutional setting makes this possibility unlikely. TxDOT routinely adjusts their engineer's estimates for changes in input prices, so the estimate would capture any price changes in materials. Indeed, the engineer's estimate explains much of the data variation, with an R^2 of 0.98 in our sample across years. As for wages and compensation, TxDOT requires all firms to adhere to US federal labor laws on its contracts, including the Davis-Bacon Act—requiring contractors to pay workers the prevailing wage in a market—and the Copeland "Anti-Kickback" Act—preventing employees from giving up any part of their compensation. These protections make it difficult for contractors to cut wages to lower bids on TxDOT contracts.

Unobserved Heterogeneity

In some environments, contractors observe project characteristics that researchers cannot observe, leading to unobserved auction heterogeneity. Empirically, unobserved heterogeneity tends to bias markup estimation, as researchers would attribute their uncertainty in unobserved features to contractor uncertainty in private information.

Our estimates and observables suggest that unobserved heterogeneity is unlikely to be a first-order concern in our setting. As mentioned earlier, the observables have a high explanatory power, largely from our observation of the engineer's estimate. Moreover, our empirical estimates produce reasonable markups. We estimate profit margins between 5 and 6 percent, and markups are similar.[19] Gugler et al. (2015) estimates a comparable markup when accounting for unobserved heterogeneity, and our average profit margin estimates are similar to other studies incorporating unobserved heterogeneity, such as Bajari et al. (2010).

7 Counterfactual Analysis

We now use our empirical estimates of equilibrium relative bids, entry costs, and entry probabilities to assess how market conditions during the Great Recession and stimulus affected highway procurement in Texas. To keep projects comparable across periods, we focus our analysis on two representative projects: one large project and one small project. We take the median contract

[18] See Table 11 in Appendix D.
[19] Markups in percentage terms are $100 \times (b_i - c_i)/c_i$.

characteristics in the data to represent each project type. For categorical variables, we use the mode. Thus, the representative large project reflects the tendency of larger projects to be more complex, longer, and more likely to be located in a metro highway district compared to the smaller projects in the data.

To explore how the market conditions before the Great Recession (Pre-GR) and during the Great Recession and ARRA (GR-ARRA) affected procurement, we consider each period separately. In the Pre-GR period, we use the median number of plan holders, permit values, and sum totals of zone-level engineer's estimates for each project type before the recession—holding the other contract characteristics fixed. The GR-ARRA period uses the median plan holder and opportunity cost values afterward. Thus, a representative project procured during the GR-ARRA period has more potential competition and different market conditions than projects procured before the Great Recession.

On each representative project, we simulate entry by taking draws from the standard (support $[0, 1]$) uniform distribution for each plan holder. Plan holders with draws below the empirically predicted entry probability enter, and we use the entry cost distribution function's inverse to find entry costs.[20] For entering bidders, we draw equilibrium relative bids from the affiliated bid distribution using methods proposed by Marshall and Olkin (1988). We then invert those bids to obtain relative project costs.[21] We simulate each representative project in each period $1,000$ times.

7.1 An Analysis of Costs and Margins

Our first counterfactual analyzes costs and margins across periods. Table 9 reports simulated averages of these outcomes for the representative project types.

We find that entry costs would have decreased by about 2.5 percent of the engineer's estimate, explaining part of the rise in entry observed during the GR-ARRA period. We also find a decrease in project costs despite fixing the contract characteristics. Project costs decrease by about 10.6 and 7.9 percent of the engineer's estimate on the representative large and small projects, respectively. These declines in costs on otherwise similar contracts suggest market conditions changing a contractor's opportunity cost of time—in this case, lowering it. We also find that margins decreased by approximately 1.5–1.6 percentage points, but this change does not entirely explain the decrease in bids.

[20]For example, a contractor with a draw of 0.5 when the equilibrium entry probability is $q_N^* = 0.6$ would enter and have an entry cost of $\widehat{H}^{-1}(0.5)$, where $\widehat{H}(\cdot)$ is the estimated entry cost distribution function.

[21]Observe that our counterfactuals do not require us to solve the model directly. Instead, we use the parameter estimates to predict equilibrium behavior under counterfactual market conditions and invert bids to obtain relative project costs.

Table 9: Counterfactual Analysis of Costs and Margins

	Representative Project Type	
	Large project	Small project
Relative entry cost		
Pre-GR	0.0655	0.0820
GR-ARRA	0.0404	0.0575
Δ	-0.0251	-0.0245
$\%\Delta$	-38.3496	-29.8837
Relative project cost		
Pre-GR	1.0575	1.1059
GR-ARRA	0.9515	1.0267
Δ	-0.1060	-0.0792
$\%\Delta$	-10.0259	-7.1605
Profit margin (%)		
Pre-GR	5.7476	7.5829
GR-ARRA	4.2665	5.9378
Δ	-1.4811	-1.6451
$\%\Delta$	-25.7687	-21.6954

Note: Average outcomes for the representative projects. GR-ARRA denotes the recession and stimulus months, while Pre-GR is pre-recession. The Δ denotes a difference and $\%\Delta$ a percent change.

7.2 An Analysis of Efficiency

We now turn to an analysis of efficiency. Following Bhattacharya et al. (2014), we measure efficiency through a project's *social cost*, where social cost is the sum of entering contractors' entry costs plus the winning contractor's project cost. A contract with a lower social cost is more efficient than a contract with a higher one. Because project and entry costs are relative to the engineer's estimate in our analysis, we normalize social costs too and report relative social costs.

Table 10 breaks down relative social costs for each representative project by period. Contrasting the GR-ARRA period against the Pre-GR one, we find two competing effects. On the one hand, the higher entry in the GR-ARRA period raised the sum of entrant entry costs—increasing social costs. On the other hand, the lower project costs in the GR-ARRA period reduced the winning contractor's project cost—thus decreasing social costs. We find that the second effect dominates, meaning that social costs were lower and efficiency was higher in the GR-ARRA period on each representative project. Consequently, comparable projects were less expensive for TxDOT during the Great Recession and ARRA, and TxDOT procured them more efficiently due to the changing market conditions.

Table 10: Counterfactual Analysis of Efficiency

	Representative Project Type	
	Large project	Small project
Sum of relative entry costs of entrants		
Pre-GR	0.1073	0.1331
GR-ARRA	0.1148	0.1493
Δ	0.0075	0.0162
$\%\Delta$	6.9444	12.1681
Low relative project cost		
Pre-GR	0.9358	0.9311
GR-ARRA	0.8253	0.8400
Δ	-0.1104	-0.0911
$\%\Delta$	-11.8018	-9.7865
Relative social cost		
Pre-GR	1.0431	1.0643
GR-ARRA	0.9401	0.9893
Δ	-0.1030	-0.0749
$\%\Delta$	-9.8729	-7.0402

Note: Average outcomes for the representative projects. GR-ARRA denotes the recession and stimulus months, while Pre-GR is pre-recession. Social cost is the sum of entry costs for all entrants plus the winner's project cost.

8 Concluding Remarks

In the wake of the 2007-2009 Great Recession, the US government enacted the ARRA, an economic stimulus package allocating \$27.5 billion to highway construction projects. Our study explores how the market conditions during the Great Recession and ARRA—characterized by limited private-sector construction prospects—affected highway procurement, focusing on projects procured in Texas. We find that procurement became *more* competitive in that period, attracting around two additional bidders despite bids being 10 to 30 percent below engineering estimates. We argue that the recessionary market conditions in the private sector lowered economic costs by lowering contractor opportunity costs. Thus, contractors would be more willing to bid and bid lower amounts on projects than they would have been before the Great Recession.

We explore this cost channel by developing and providing methods to estimate an auction model that aligns with standard public procurement procedures, accounting for the affiliated costs shared among contractors and the strategic entry decisions based on perceived competition. We find that the economic costs associated with entry and project completion decrease substantially with private-sector construction despite controlling for the highly predictive direct-cost measures available in the data. These results are in accordance with our opportunity cost explanation and underscore how the recession's constraint on the private sector generated a budget-efficient procurement environment during the Great Recession and stimulus. A further counterfactual analysis comparing projects with similar work requirements reveals that procurement was generally more efficient in addition to being less costly for the government.

Our results have broader implications for understanding the dual role of governmental intervention in times of economic distress: supporting the economy through direct spending while achieving procurement efficiencies by capitalizing on the lower economic costs faced by contractors. This phenomenon suggests that well-timed public investment can deliver twofold benefits: it boosts economic activity and allows governments to obtain services or complete projects at lower costs than in non-recessionary times. The study also enhances auction literature by integrating aspects of contractor affiliation and competitive entry, which are vital considerations for cost estimation in public procurement.

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A Theoretical Appendix

This appendix contains various theoretical results relevant to our empirical analysis. We first derive the equilibrium bid function. Then, we show how assuming multiplicative separability in costs affects equilibrium outcomes, finding that bids become multiplicatively separable while entry probabilities are unaffected. We use this result as a basis for working with relative bids and relative entry costs.

A.1 Bid Function Derivation

Proposition 1. *Let $G_n(c_i \mid c_i, m)$ be the distribution function for the lowest project cost given c_i, $q_N^*(m) \in [0,1]$ be a contractor's belief that a plan holder will enter, and $\Pr(n \mid N, q_N^*(m))$ be the probability of facing n total competitors. Then, the equilibrium bid function is*

$$b_N(c_i; m) = c_i + \frac{\sum_{n=1}^{N} \Pr(n \mid N, q_N^*(m)) \int_{c_i}^{\overline{c}} (1 - G_n(\tilde{c} \mid \tilde{c}, m)) d\tilde{c}}{\sum_{n=1}^{N} \Pr(n \mid N, q_N^*(m)) \left(1 - G_n(c_i \mid c_i, m)\right)}.$$

Proof. We use an envelope theorem approach in deriving the bid function. The expected profit contractor i obtains in equilibrium is

$$\pi_N(c_i; m) = (b_N(c_i; m) - c_i) \sum_{n=1}^{N} \Pr(n \mid N, q_N^*(m)) \left(1 - G_n(c_i \mid c_i, m)\right). \tag{7}$$

Similarly, a contractor's expected profits are the maximum of their objective:

$$\pi_N(c_i; m) = \max_{b_i} (b_i - c_i) \sum_{n=1}^{N} \Pr(n \mid N, q_N^*(m))(1 - G_n(b_N^{-1}(b_i; m) \mid c_i, m)).$$

Applying the envelope theorem yields

$$\begin{aligned} \frac{d}{dc}\pi_N(c; m)\Big|_{c=c_i} &= -\sum_{n=1}^{N} \Pr(n \mid N, q_N^*(m)) \left(1 - G_n(b_N^{-1}(b_N(c_i; m); m) \mid c_i, m)\right) \\ &= -\sum_{n=1}^{N} \Pr(n \mid N, q_N^*(m)) \left(1 - G_n(c_i \mid c_i, m)\right). \end{aligned}$$

Integrating the above expression from c_i to $\overline{c}$ yields

$$\pi_N(\overline{c}; m) - \pi_N(c_i; m) = -\sum_{n=1}^{N} \Pr(n \mid N, q_N^*(m)) \int_{c_i}^{\overline{c}} \left(1 - G_n(\tilde{c} \mid \tilde{c}, m)\right) d\tilde{c}.$$

Because bids increase in c, a bidder with the highest project cost draw cannot make positive profits in equilibrium, meaning $\pi_N(\bar{c}; m) = 0$. Thus,

$$\pi_N(c_i; m) = \sum_{n=1}^{N} \Pr(n \mid N, q_N^*(m)) \int_{c_i}^{\bar{c}} (1 - G_n(\tilde{c} \mid \tilde{c}, m))\, d\tilde{c}. \tag{8}$$

Setting the right-hand sides of equations (7) and (8) equal to each other and solving for $b_N(c_i; m)$ yields the result. □

A.2 Multiplicative Separability and Equilibrium Outcomes

Proposition 2. *Suppose that $z > 0$. If $b_N(c; m)$ and $q_N^*(m)$ are the equilibrium bids and entry probabilities with costs c and k, then $zb_N(c; m)$ and $q_N^*(m)$ are the equilibrium bids and entry probabilities with costs zc and zk.*

Proof. Suppose contractor i with cost zc_i is contemplating a bid $z\check{b}_i$. If all competing contractors $j \neq i$ with costs zc_j use the increasing bid strategy $zb_N(c_j; m)$ we show that contractor i will use the same strategy.

Contractor i wins if $z\check{b}_i < zb_N(c_j; m)$ for all $j \neq i$, which can be rewritten as $b_N^{-1}(\check{b}_i; m) < c_j$. Thus, contractor i chooses their bid to solve

$$\max_{\check{b}_i} \quad (z\check{b}_i - zc_i) \sum_{n=1}^{N} \Pr(n \mid N, \check{q}_N^*(m))(1 - G_n(b_N^{-1}(\check{b}_i; m) \mid c_i, m)),$$

or

$$\max_{\check{b}_i} \quad z(\check{b}_i - c_i) \sum_{n=1}^{N} \Pr(n \mid N, \check{q}_N^*(m))(1 - G_n(b_N^{-1}(\check{b}_i; m) \mid c_i, m)), \tag{9}$$

where $\check{q}_N^*(m)$ is the equilibrium entry probability when costs are zc.

Because z is a positive scalar, the objective in equation (9) has the same maximizer as the original objective in equation (1), provided that equilibrium entry probabilities are the same. In that case, $\check{b}_N(c_i; m) = b_N(c_i; m)$ and the contractor bids $zb_N(c_i; m)$.

We now show that entry probabilities are, indeed, the same in equilibrium. The expected profit from submitting bid $zb_N(c_i; m)$ is then

$$z\check{\pi}_N(c_i; m) = z \sum_{n=1}^{N} \Pr(n \mid N, \check{q}_N^*(m)) \int_{c_i}^{\bar{c}} (1 - G_n(\tilde{c} \mid \tilde{c}, m)) d\tilde{c}.$$

Ex-ante profits are

$$z\check{\Pi}_N(m) = z \int_{\underline{c}}^{\bar{c}} \check{\pi}_N(\check{c}; m) f_c(\check{c} \mid m) d\check{c}.$$

Contractors with entry costs zk enter whenever $z\check{\Pi}_N(m) \geq zk$, which can be rewritten as

$\check{\Pi}_N(m) \geq k$. If $\check{k}^*_N(m)$ is the entry cost making contractors indifferent, then $\check{k}^*_N(m) = \check{\Pi}_N(m)$. Belief consistency requires that

$$\check{q}^*_N(m) = H(\check{k}^*_N(m) \mid m), \tag{10}$$

which is the same as equation (5). Thus, $\check{q}^*_N(m) = q^*_N(m)$. □

Remark 1. If z is the engineer's cost estimate, then $b_N(c_i; m)$, c_i, and k_i are the relative bid, relative project cost, and relative entry cost—respectively.

B Estimation Appendix

This appendix expands on the steps needed to estimate the model given its parameterization.

B.1 Expressing the Bid Inversion Equation with Copulas

For notational convenience, we consider a single project with characteristics fixed, allowing us to drop l subscripts and dependence on $\mathbf{x}_l$. To write the bid inversion condition (equation (6)) in terms of copulas, we need the probability contractor i draws a relative project cost, c^0_i, below the lowest competing relative project cost: $1 - G_n(c^0_i \mid c^0_i)$. Recall that when the joint distribution of relative project costs follows a Clayton copula,

$$\mathcal{F}_n(c^0_1, c^0_2, \ldots, c^0_n) = \mathcal{C}_n[F_{c^0}(c^0_1), F_{c^0}(c^0_2), \ldots, F_{c^0}(c^0_n)] = \left(\sum_{i=1}^{n} F_{c^0}(c^0_i)^{-\theta} - n + 1 \right)^{-\frac{1}{\theta}}.$$

To attain our distribution of interest, we use several results from Hubbard et al. (2012). The first result concerns the joint survival function, $\overline{\mathcal{F}}_n(c^0_1, c^0_2, \ldots, c^0_n)$ which is the probability that random variables $C^0_1, C^0_2, \ldots, C^0_n$ are *above* $c^0_1, c^0_2, \ldots, c^0_n$, respectively.

Result 1:

$$\begin{aligned} \overline{\mathcal{F}}_n(c^0_1, c^0_2, \ldots, c^0_n) \;\; &= \;\; 1 - \sum_{i=1}^{n} \Pr(C^0_i < c^0_i) + \sum_{i \leq j \leq n} \Pr(C^0_i < c^0_i, C^0_j < c^0_j) - \ldots \\ &\quad + (-1)^n \Pr(C^0_1 < c^0_1, C^0_2 < c^0_2, \ldots, C^0_n < c^0_n). \end{aligned}$$

The next result shows that the survival function has a copula representation, which we denote as $\mathcal{S}_n[1 - F_{c^0}(c^0_1), 1 - F_{c^0}(c^0_2), \ldots, 1 - F_{c^0}(c^0_n)]$.

Result 2:

$$\mathcal{S}_n[1-F_{c^0}(c_1^0),1-F_{c^0}(c_2^0),\ldots,1-F_{c^0}(c_n^0)] = 1-\sum_{i=1}^{n}\mathcal{C}_1[F_{c^0}(c_i^0)]+\sum_{i\leq j\leq n}\mathcal{C}_2[F_{c^0}(c_i^0),F_{c^0}(c_j^0)]-\ldots$$
$$+(-1)^n\mathcal{C}_n[F_{c^0}(c_1^0),F_{c^0}(c_2^0),\ldots,F_{c^0}(c_n^0)].$$

The final result concerns the conditional survival function: $\overline{\mathcal{F}}_n(c_2^0,\ldots,c_n^0 \mid c_1^0)$.

Result 3:

$$\overline{\mathcal{F}}_n(c_2^0,\ldots,c_n^0 \mid c_1^0)=\mathcal{S}_{1,n}[1-F_{c^0}(c_1^0),1-F_{c^0}(c_2^0),\ldots,1-F_{c^0}(c_n^0)],$$

where $\mathcal{S}_{1,n}$ denotes the partial derivative of $\mathcal{S}_n$ with respect to its first argument. By observing that the government acts as an additional competitor, we have that $1-G_n(c_1^0 \mid c_1^0)=\mathcal{S}_{1,n+1}[1-F_{c^0}(c_1^0),1-F_{c^0}(c_1^0),\ldots,1-F_{c^0}(c_1^0)]$.

Focusing on bidder 1, without loss of generality, one can write the objective function in (1) as

$$\max_{b_1^0}\quad (b_1^0-c_1^0)\sum_{n=1}^{N}\Pr(n \mid N,q_N^*)\mathcal{S}_{1,n+1}[1-F_{c^0}(c_1^0),1-F_{c^0}(b_N^{-1}(b_1^0)),\ldots,1-F_{c^0}(b_N^{-1}(b_1^0))].$$

Let $\mathcal{S}_{1j,n}$ denote the cross partial derivative of $\mathcal{S}_n$ with respect to its first and jth argument. Taking first-order conditions yields

$$\begin{aligned}&(b_1^0-c_1^0)\Bigg\{\sum_{n=1}^{N}\Pr(n \mid N,q_N^*)\sum_{j=2}^{n+1}f_{c^0}(b_N^{-1}(b_1^0))\tfrac{db_N^{-1}(b_1^0)}{db_1^0}\times\\&\mathcal{S}_{1j,n+1}[1-F_{c^0}(c_1^0),1-F_{c^0}(b_N^{-1}(b_1^0)),\ldots,1-F_{c^0}(b_N^{-1}(b_1^0))]\Bigg\}=\\&\sum_{n=1}^{N}\Pr(n \mid N,q_N^*)\mathcal{S}_{1,n+1}[1-F_{c^0}(c_1^0),1-F_{c^0}(b_N^{-1}(b_1^0)),\ldots,1-F_{c^0}(b_N^{-1}(b_1^0))],\end{aligned}$$

which we can rewrite as

$$c_1^0=b_1^0-\frac{\sum_{n=1}^{N}\Pr(n \mid N,q_N^*)\mathcal{S}_{1,n+1}[1-F_{c^0}(c_1^0),1-F_{c^0}(b_N^{-1}(b_1^0)),\ldots,1-F_{c^0}(b_N^{-1}(b_1^0))]}{\sum_{n=1}^{N}\Pr(n \mid N,q_N^*)\mathcal{S}_{12,n+1}[1-F_{c^0}(c_1^0),1-F_{c^0}(b_N^{-1}(b_1^0)),\ldots,1-F_{c^0}(b_N^{-1}(b_1^0))]\frac{f_{c^0}(b_N^{-1}(b_1^0))}{b_N'(b_N^{-1}(b_1^0))}n}. \tag{11}$$

Let $F_{b^0}(\cdot)$ be the marginal equilibrium relative bid distribution, and let $f_{b^0}(\cdot)$ be the corresponding density. Observing that

$$F_{b^0}(b_N(c_1^0))=F_{c^0}(c_1^0)$$

and

$$f_{b^0}(b_N(c_1^0))b_N'(c_1^0)=f_{c^0}(c_1^0),$$

we can write equation (11) in terms of observables:

$$c_1^0 = b_1^0 - \frac{\sum_{n=1}^{N} \Pr(n \mid N, q_N^*) \mathcal{S}_{1,n+1}[1 - F_{b^0}(b_1^0), 1 - F_{b^0}(b_1^0), \ldots, 1 - F_{b^0}(b_1^0)]}{\sum_{n=1}^{N} \Pr(n \mid N, q_N^*) \mathcal{S}_{12,n+1}[1 - F_{b^0}(b_1^0), 1 - F_{b^0}(b_1^0), \ldots, 1 - F_{b^0}(b_1^0)] f_{b^0}(b_1^0) n}. \tag{12}$$

Remark 2. This expression also holds for raw project costs and bids by replacing the relative project cost (c_1^0) with the actual project cost (c_1) while swapping the relative bid (b_1^0) and relative bid distributions (F_{b^0} and f_{b^0}) with bids (b_1) and bid distributions (F_b and f_b).

C Identification Appendix

This appendix discusses the model's identification formally. A challenge absent from most standard auction models is that we need to account for the government acting as an additional bidder, requiring us to extend the affiliated project cost distribution beyond N to $N + 1$. For this reason, we restrict the joint distribution so that it belongs to a class of copula functions characterized by a parametric generator function. Because the marginal distributions are flexible, identification in the model is semiparametric.

To be flexible with the copula function, we consider copulas in the Archimedean family. A d-dimensional copula $\mathcal{C}_d : [0,1]^d \to [0,1]$ is Archimedean if

$$\mathcal{C}_d[u_1, u_2, \ldots, u_d] = \zeta\left(\sum_{i=1}^{d} \zeta^{-1}(u_i)\right).$$

Here, $\zeta : [0, \infty) \to [0,1]$ is a convex, continuous, and decreasing generator function such that $\zeta(0) = 1$ and $\lim_{x\to\infty} \zeta(x) = 0$. Furthermore, we will assume that the generator function has a single parameter, θ. These assumptions allow for the Clayton copula, which has a generator function $\zeta(x;\theta) = \frac{1}{\theta}(x^{-\theta} - 1)$, and other commonly used copulas highlighted in Hubbard et al. (2012), like the Frank and Gumbel copulas.

An appealing property of Archimedean copulas is that the generator function generates a copula in *any* dimension—allowing us to extend the joint distribution to $N + 1$. The single-parameter assumption means that θ characterizes the dependence structure and distinguishes different copula functions. Thus, an Archimedean copula generated by $\zeta(\cdot;\theta)$ is the same as an Archimedean copula generated by $\zeta(\cdot;\tilde{\theta})$ if and only if $\theta = \tilde{\theta}$.

C.1 Technical Assumptions

We make the following assumptions in our identification argument.

Assumption 1. *The distribution $\mathcal{F}_{N+1}(c_1, \ldots, c_{N+1})$ is symmetric and affiliated with support $[\underline{c}, \overline{c}]^{N+1}$ and copula $\mathcal{C}_{N+1}[F_c(c_1), \ldots, F_c(c_{N+1})]$.*

Assumption 2. *The marginal distribution $F_c(\cdot)$ is absolutely continuous with density $f_c(\cdot)$.*

Assumption 3. *The copula $\mathcal{C}_{N+1}[F_c(c_1), \ldots, F_c(c_{N+1})]$ is Archimedean, with a single-parameter generator function $\zeta(\cdot; \theta)$ known up to θ.*

Assumption 4. *The equilibrium entry probability q_N^* satisfies $0 < q_N^* \leq 1$, and all contractors play the same equilibrium in every auction.*

Assumption 5. *The entry cost distribution $H(\cdot)$ is continuous, and entry costs are independent of project costs.*

C.2 Propositions and Proofs

Proposition 3. *Under assumptions 1 to 5, the equilibrium inverse bid function is identified.*

Proof. The marginal bid distribution $F_b(\cdot)$ and density $f_b(\cdot)$ are observed from the data directly. So too is the copula function $\mathcal{C}_2[F_b(b_1), F_b(b_2)] = \Pr(B_1 \leq b_1, B_2 \leq b_2)$. Therefore, θ is identified. With θ known, one can construct the copula $\mathcal{C}_d[F_b(b_1), \ldots, F_b(b_d)] = \zeta(\sum_{i=1}^{d} \zeta^{-1}(F_b(b_i); \theta); \theta)$ for $d = 1, \ldots, N+1$. Because the survival copula is a function of the copula functions, the inverse bid function on the right-hand side of equation (12) is a function of observed distributions. Thus, the inverse bid function is identified. $\square$

Proposition 3 immediately implies the following corollary.

Corollary 1. *The distribution $\mathcal{F}_{N+1}(c_1, \ldots, c_{N+1}) = \mathcal{C}_{N+1}[F_c(c_1), \ldots, F_c(c_{N+1})]$ is identified.*

We now consider the entry cost distribution.

Proposition 4. *Let $\Upsilon_N = \int_{\underline{c}}^{\overline{c}} \left[\sum_{n=1}^{N} \Pr(n \mid N, q_N^*) \int_{\check{c}}^{\overline{c}} \mathcal{S}_{1,n+1}[1 - F_c(\tilde{c}), \ldots, 1 - F_c(\tilde{c})] d\tilde{c}\right] f_c(\check{c}) d\check{c}$ be the equilibrium entry cost cutoff expressed in terms of copulas. Then, under assumptions 1 to 5, $H(\cdot)$ is identified at Υ_N.*

Proof. From Corollary 1, the joint and marginal distributions of project costs are known. Therefore, Υ_N is known. Belief consistency (i.e., equation 5) requires that $q_N^* = H(\Upsilon_N)$. $\square$

Remark 3. Without variation in N, knowing $H(\cdot)$ at one point is sufficient to identify some parametric distributions, like the exponential distribution in our empirical model. To see why, we consider two exponential distributions $H(\cdot)$ and $\tilde{H}(\cdot)$ with mean parameters μ and $\tilde{\mu}$, respectively. If $\Upsilon_N > 0$ and $H(\Upsilon_N) = \tilde{H}(\Upsilon_N)$,

$$\begin{aligned} 1 - \exp(-\tfrac{\Upsilon_N}{\mu}) &= 1 - \exp(-\tfrac{\Upsilon_N}{\tilde{\mu}}) \\ -\tfrac{\Upsilon_N}{\mu} &= -\tfrac{\Upsilon_N}{\tilde{\mu}} \\ \mu &= \tilde{\mu}. \end{aligned}$$

With variation in N, one can identify $H(\cdot)$ at multiple points because Υ_N and q_N^* depend on N and $H(\cdot)$ does not.

Remark 4. Identifying $H(\cdot)$ almost everywhere, requires a continuous exclusion restriction. That is, a continuous variable affecting project costs (and thus Υ_N and q_N^*) that does not affect entry costs. Let $w \in [\underline{w}, \overline{w}]$ be such a variable, and let $\Upsilon_N(w)$ and $q_N^*(w)$ be the corresponding equilibrium entry cost cutoff and entry probability, respectively. Then, $q_N^*(w) = H(\Upsilon_N(w))$ for every $w \in [\underline{w}, \overline{w}]$. If the range of $q_N^*(w)$ is $(0, 1]$, $H(\cdot)$ is identified almost everywhere.

D Variables and Robustness

In this appendix, we explore whether common sources of bidder asymmetries affect contractor bidding on TxDOT projects. Before discussing these results, we plot the average monthly backlog for bidders during our sample period in Texas; see Figure 7. As expected, with increased competition, lower winning bids, and a generally constant number of available projects, the average backlog per firm declined during the GR-ARRA period compared to the pre-GR-ARRA period.

The rationale for using a firm's distance to the project location relative to the rivals' minimum distance is as follows: construction firms are typically clustered due to zoning laws or proximity to quarries. While direct distance matters for moving equipment or materials, we argue that normalizing a firm's distance by the minimum distance of its rivals better captures bidder asymmetry within an auction, especially when firms are located in different geographic clusters.

Table 11 presents our robustness results. We find that the inclusion of backlog (or capacity utilization) or relative distance does not affect our main findings. Importantly, backlog (or capacity utilization) and relative distance do not statistically influence bids, and the magnitude of the coefficients is negligible. Based on these results, we are cautiously confident that bidder asymmetries are insignificant. Thus, we do not model asymmetries in our structural analysis.

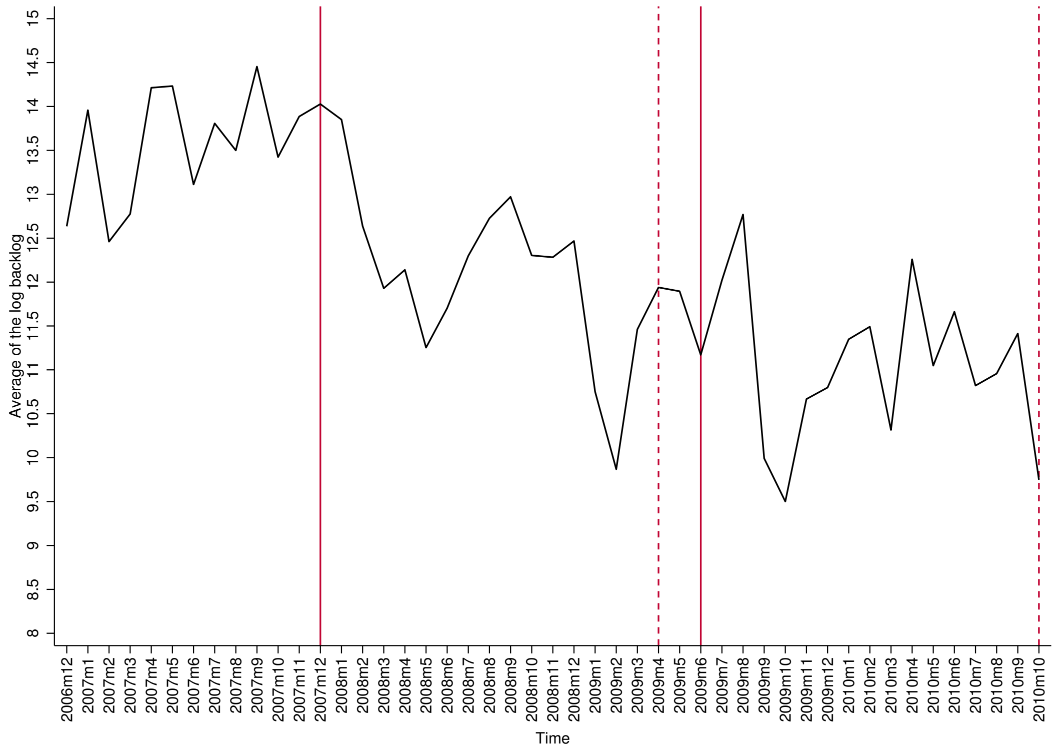


Figure 7: Time Series of Backlogs (in Logs)

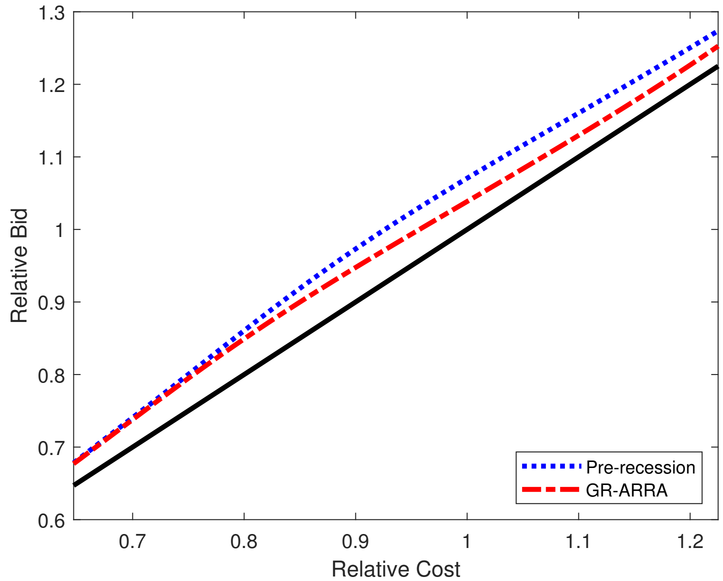
Table 11: Regression results for bids with alternate specifications

Variables	Log of bids	
	(1)	(2)
GR and TX ARRA auction months	0.034	0.034
	(0.024)	(0.024)
2006:12 – 2007:05	-0.012	-0.012
	(0.024)	(0.024)
Log of ECE	0.917*	0.917*
	(0.009)	(0.009)
Log of real three month average value of total building permits for TX	0.193*	0.193*
	(0.032)	(0.032)
Log three month moving average of the total ECE in the zone	0.009	0.009
	(0.006)	(0.006)
Log of backlog	-0.000	
	(0.001)	
Capacity utilization		-0.007
		(0.012)
Relative distance to project location	0.000	0.000
	(0.000)	(0.000)
Log number of plan holders	Yes	Yes
Metro districts	Yes	Yes
Other auction level controls	Yes	Yes
Observations	5,698	5,698
R-squared	0.983	0.983

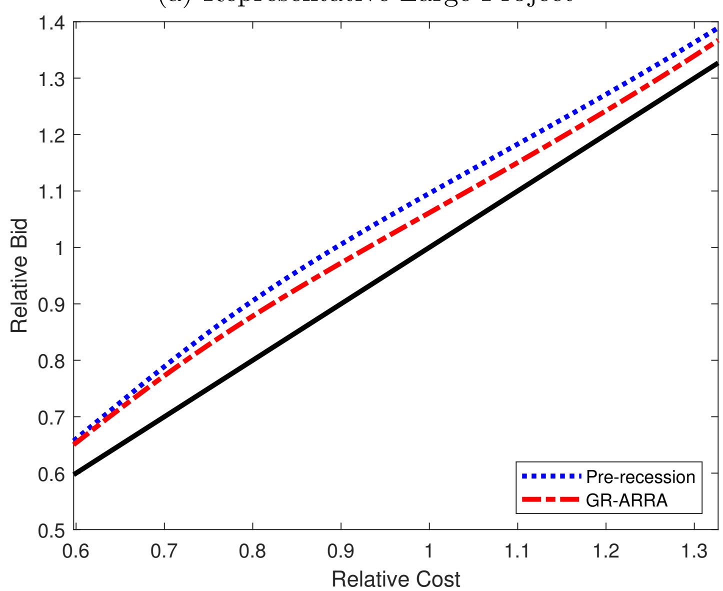
Robust standard errors are in parentheses. * $p<0.05$

E Relative Bid Functions

This section contains plots of the implied relative bid functions for the representative small and large projects. See Figure 8.



(a) Representative Large Project



(b) Representative Small Project

Figure 8: Relative Bid Functions