University of Toronto
Department of Economics

Working Paper 732

Bidding for Contracts under Uncertain Demand: Skewed Bidding and Risk Sharing

By Yao Luo and Hidenori Takahashi

September 01, 2022

Bidding for Contracts under Uncertain Demand: Skewed Bidding and Risk Sharing

Yao Luo* Hidenori Takahashi†

September 1, 2022

Abstract

Procurement projects often involve substantial uncertainty in inputs at the time of contracting. Whether the procurer or contractor assumes such risk depends on the specific contractual agreement. We develop a model of auction contracts where bidders have multidimensional private information. Bidders balance skewed bidding and risk exposure; both efficient and inefficient bidders submit a low bid via skewed bidding. We document evidence of i) risk-balancing behavior through bid portfolio formation and ii) opportunistic behavior via skewed bidding using auction data. Counterfactual experiments suggest the onus of bearing project risk should fall on the procurer (contractor) when project risk is large (small).

Keywords: Contract, Unit-Price, Fixed-Price, Portfolio, Cost Overrun, Procurement, Scoring Auction

*University of Toronto; yao.luo@utoronto.ca.

†Kyoto Institute of Economic Research, Kyoto University; takahashi.hidenori@kier.kyoto-u.ac.jp. We would like to thank Victor Aguirregabiria, Andre Boik, Robert Clark, Francesco Decarolis, Isis Durrmeyer, Philip Haile, Takakazu Honryo, Ali Hortaçsu, Hiroyuki Kasahara, Ismael Mourifié, Salvador Navarro, Kathleen Nosal, Isabelle Perrigne, Andrea Pozzi, Junichi Suzuki, Yoichi Sugita, Yuya Takahashi, Quang Vuong, Naoki Wakamori, and seminar participants at Hitotsubashi, Western, Queen's, Indiana, Rice, Yale, Oklahoma, EARIE (2017), Banff Empirical Micro Conference (2019), and SEA (2019) for useful comments. We would also like to thank the editor and three anonymous referees for their comments. Yingcheng Luo and Jiaqi Zou provided excellent research assistance. We are also grateful for FDOT's provision of procurement data and Grant-in-aid for Young Scientists provided by Graduate School of Economics, Hitotsubashi University. Luo acknowledge the Social Sciences and Humanities Research Council of Canada for research support. All errors are our own.

1 Introduction

An infrastructure project is a collection of work items – the quantities of which may not be accurately predicted at the time of contracting. Which contracting party should assume such risk is a topic of heated debate. On the one hand, the experimental and empirical literature suggests that risk aversion plays a significant role in bidder behavior in auctions.[1] A contractor who undertakes the entirety of the project risk may demand a sizable risk premium, and thus sharing the project risk may reduce procurement costs. On the other hand, a procurer who undertakes a substantial portion of the project risk may suffer from excessive cost overruns triggered by opportunistic contractors. Despite the empirical relevance of risk allocation in contracts with uncertain demand, the empirical literature on this issue has been scarce.[2]

We compare fixed-price (FP) contracts with unit-price (UP) contracts, collected by the Florida Department of Transportation (FDOT), to investigate the role of risk allocation via contractual arrangements on firm behavior and contracting outcomes.[3] First, FDOT engineers estimate the quantity of each item required to complete the project. Second, prospective contractors bid using total price for FP contracts or using a list of itemized unit prices for UP contracts, where the lowest total price wins the contract. Third, upon completing the project, the winner receives the original total price in an FP contract and quantity-adjusted total price based on itemized unit prices for a UP contract.[4]

We provide a novel empirical framework that nests the two contract types and allows for a variety of counterfactual experiments. To the best of our knowledge, our article is among the first to identify and estimate a structural model of UP contracts in the presence of

[1] See, e.g., Cox, Smith, and Walker (1988), Athey and Levin (2001), Goeree, Holt, and Palfrey (2002), and Bajari and Hortacsu (2005).

[2] We use "project risk" and "uncertain demand" interchangeably in this article.

[3] FP contracts are widely used in public procurements, including procurement of public transport, operation of water facilities, and electricity. UP contracts are more prevalent for construction procurements, including highway contracting, pipeline construction, defense procurement, and procurement projects supported by the World Bank. UP contracts are also used in timber auctions.

[4] FDOT procures small infrastructure projects through either UP or FP contracts. Large projects are procured via so-called Design-Build (DB) auctions.

bid-skewing incentives. Our model incorporates multidimensional bidder heterogeneity, risk aversion, and endogenous entry. From an empirical standpoint, multidimensional bidder heterogeneity helps to rationalize the observed distribution of multidimensional itemized bids.[5] Risk aversion explains the empirical fact that bidders do not completely skew their bids and rationalizes FDOT's beliefs.[6] Endogenizing the entry decision of bidders is important, as altering contractual arrangements affects not only bidding behavior but also entry behavior. We solve this model explicitly by casting the bidder's itemized bidding problem as a portfolio choice problem. This enables a tractable equilibrium characterization, clear identification, and a simple multi-step estimation procedure.

Guided by our model, we document evidence of opportunistic behavior in contractors through skewed bidding. Skewed bidding is a strategy in which a bidder places a large (small) unit-price bid on the item he expects to overrun (underrun) in order to exploit cost overruns while remaining competitive in terms of winning a contract. This incentive to bid high on underestimated items and bid low on overestimated items leads to competitive bidding and lucrative ex-post payment. Because bidders differ from each other in terms of their input estimates, they also differ in their incentives to skew the bid and to win the contract. In the unique setting of UP contracts, bidders behave strategically at the time of bidding rather than *ex post*, during which the econometrician cannot observe how non-winning bidders would have behaved. This allows us to directly control for unobserved project heterogeneity in showing evidence of skewed bidding. We find that bidders who skew their unit-price bids are much more likely to win the contract than those who do not, even after controlling for unobserved auction and bidder heterogeneity.

We further document evidence of risk-balancing bidder behavior. Conversations with industry experts suggest that a project manager is more likely to employ UP contracts for

[5]The literature on multidimensional auctions is abundant. See, e.g., Che (1993), Asker and Cantillon (2008), and Lewis and Bajari (2014).

[6]On theoretical grounds, bidder risk aversion is explained by imperfect capital markets so that procurement-specific risks matter to bidders (Samuelson, 1987).

riskier projects.[7] Project risk, which likely increases contractor costs, may not be fully captured by the observables in the data. Endogenous contract choice may obscure the differences between UP and FP contracts; i.e., simple OLS may not indicate significant differences. Therefore, we estimate the Heckman (1976) selection model using FDOT district office caseload as an instrument. Our results suggest that although the adoption of FP contracts is negatively correlated with total price bids, i.e., bidder scores, the adoption of UP contracts is not. This finding is consistent with the hypothesis that, although unobserved contractor costs increase with project risk under FP contracts, these costs do not increase with project risk under UP contracts.

We show that the model for the subsample of UP contracts is semiparametrically identified from UP contracts, accounting for unobserved heterogeneity in project risk. The estimated model is consistent with empirical findings in that i) UP contracts reduce bidders' cost of project risk , ii) bidder scores are much more dispersed with FP versus UP contracts, iii) the composition of unit-price bids exhibits a substantial amount of within-auction heterogeneity, iv) bidders who skew their bids are more likely to win the contract. We find that the cost of project risk is more than three percent of the average construction cost, and structural estimates show a large amount of unobserved heterogeneity in project risk.

Based on the estimated model, we demonstrate numerically that FP (UP) contracts perform well for projects with low (high) project risk and show that our model is consistent with empirical findings i)-iv) listed above. Counterfactual experiments suggest that UP contracts perform well, at least for those projects in the data that were procured through UP contracts. Switching from UP to FP contracting would increase procurement costs by 1.39 (resp. 2.48) percent when project risk is small (resp. large). A simple adjustment to UP contracts placing a cap on non-lumpsum bids prevents inefficient bidders from skewing bids while still allowing efficient bidders to do so, and thus is expected to improve contract outcomes. However, this adjustment to UP contracts is shown to have a negligible impact

[7]The FDOT project guidelines lists tasks suited for FP and UP contracts. See Online Appendix Figure A.1.

on procurement costs.

Our framework serves several purposes. First, it makes explicit the tradeoff between the two contract formats and offers an economic interpretation of our reduced-form comparison. On the one hand, UP contracts allow bidders to hedge against uncertain demand by forming a portfolio of unit-price bids whereas FP contracts do not. On the other hand, UP contracts induce skewed bidding which may result in higher procurement costs through the selection of inefficient contractors. Second, it makes explicit the data and assumptions needed to recover the parameters governing bidder behavior. In particular, we show semiparametric identification relying solely on UP contracts data when we have information on both ex-ante and ex-post auction outcomes. Lastly, nesting both auction formats, the model allows for counterfactuals to explore how contract format affects bidder behavior and government expenditure.

Bolotnyy and Vasserman (2021) studies unit-price contracts of the Massachusetts DOT. Like us, they adopt CARA utility, normally distributed shocks, and a two-step equilibrium bidding characterization: an inner loop with a portfolio problem and an outer loop with a score bidding problem. Our frameworks differ, however, in several important ways. First, whereas Bolotnyy and Vasserman (2021) focuses on non-lumpsum items, we incorporate both lumpsum and non-lumpsum items. The lumpsum items account for 20 percent of the engineer estimate in our data. Second, our model allows multidimensional bidder heterogeneity, whereas Bolotnyy and Vasserman (2021) assumes scalar bidder heterogeneity and explains the remaining variation in itemized bids with i.i.d. measurement errors. Lastly, we take different approaches for identification and estimation. Bolotnyy and Vasserman (2021) projects bidder types onto bidder fixed effects and bidder-auction characteristics and conducts GMM estimation with instruments using itemized bids from the same bidder from multiple auctions. In contrast, we provide a constructive identification argument that adapts the standard FOC inversion of Guerre, Perrigne, and Vuong (2000) to our setting with two loops.[8]

The remainder of the article is organized as follows. Section 2 presents the related literature. Section 3 describes the data and the procurement procedures under both FP and UP contracts. Section 4 presents the model of contract bidding. Section 5 provides evidence that the procurer's choice of contract depends on unobserved project risk, together with evidence of skewed bidding. Section 6 shows semiparametric identification of the model. Section 7 provides estimation steps together with the results. Section 8 provides counterfactual experiments. Section 9 concludes.

2 Related Literature

We employ an equilibrium model of auction contracts with bid-skewing incentives in a private value framework, as in Ewerhart and Fieseler (2003). Athey and Levin (2001), on the other hand, considers a common value framework for timber auctions. When bidders are uncertain about the true value in procurement auctions, more optimistic bidders bid more aggressively, leading to the winner's curse (Somaini, 2020). Although we abstract away from common value for tractability, we allow for correlated or even identical ex-post adjustments that constitute the "common" part in actual quantities. [9]

On the empirical side, Bajari, Houghton, and Tadelis (2014) estimates a structural model in an incomplete contract setting using a sample of UP contracts from the California DOT, because the majority of ex-post adjustments originate from uncontracted items in their environment. In contrast, we consider a complete contract setting, given that the majority of ex-post adjustments in Florida originate from adjustments on contracted items. The contracting price can be renegotiated in Florida if quantity adjustments exceed 125% of original quantity estimates, whereas renegotiation in California only requires quantity adjustments

[8] We could use Vuong (1989)'s test to distinguish the two non-nested models. However, we are unaware of an existing method for comparing models estimated via their GMM estimator and our GPV estimator. Footnote 27 further explains how richer data would allow estimating a general model that nests both models.

[9] The number of bidders is strongly negatively correlated with bids, which also supports the idea that bidders compete in a private value paradigm rather than a common value paradigm.

in excess of 25%. This disparity accounts for the fact that Bajari et al. (2014) does not find evidence of skewed bidding. Bolotnyy and Vasserman (2021), studying UP contracts in Massachusetts, adopts a framework similar to Bajari, Houghton, and Tadelis (2014): bidders observe a common signal about (*ex-ante* unknown) actual item quantities and scalar private information on costs. In contrast, bidders in our model have multidimensional private information on actual item quantities, which accounts for differences in the extent of bid skewness among bidders in any given auction.

Uncertainty in auctions has received considerable attention in recent years. A few articles consider uncertainty in how bids are evaluated in multidimensional scoring auctions. In Takahashi (2018), bidders compete on price and quality in the face of uncertainty in reviewer quality evaluations. Some articles consider uncertainty in the scoring rule (see, e.g., Krasnokutskaya et al. (2018), Allen et al. (2019), and Kong et al. (2019)). The most closely related article to our study is Luo et al. (2018), which develops a structural model with risk-averse bidders in procurement auctions with ex-post uncertainty in inputs, and derives the model restrictions for identification. We contribute to this literature by providing a unified empirical framework for studying both UP and FP contracts under uncertainty.

Our article is more broadly related to the literature on contracting via auctions. The seminal article in the literature on procurement contracts through auction is McAfee and McMillan (1986), which compares the performance of fixed-price contracts and cost-plus contracts in an incomplete contract setting. Decarolis (2014) finds a perverse effect of first-price auctions on infrastructure procurement projects in Italy. Lewis and Bajari (2014) looks empirically at the tradeoff between effort and risk in the procurement setting. An and Tang (2017) considers the incomplete contracting setting, in which buyers endogenously specify the initial contract.

Our article is also related to the vast literature on the identification and estimation of auction models. Guerre et al. (2009) shows that risk-averse bidder utility functions and private value distributions can be nonparametrically identified via an exclusion restriction and observed bids from first-price auctions. Campo et al. (2011) shows that risk-averse bidder utility functions and private value distributions are semiparametrically identified under a conditional quantile restriction on the distribution of private bidder valuation and a parametrization of the bidder utility function. Li and Zheng (2009) estimates three competing endogenous entry models in procurement auctions and finds that the model that best fits the data is one with a common entry cost, where bidders draw their private costs upon entry. Marmer, Shneyerov, and Xu (2013) proposes a general entry model and a flexible nonparametric framework for testing different entry models.

3 Institutional Details

This section describes the procurement procedure, overviews the FDOT project guidelines, and provides descriptive statistics of the data. The description of the auction procedure specifies who makes what decisions at what point in time. The FDOT project guidelines shed light on why we should be concerned about the endogeneity of contract type. Lastly, we provide an OLS comparison of bidding behavior and project outcomes across the two types of contractual arrangements.

Procurement Procedure

FDOT has seven districts that procure infrastructure projects independently. Each district office announces a list of projects every month. The set of procured projects in any month is determined by FDOT's project managers and various department personnel. The procurement procedure can be decomposed into the design stage, followed by the auction stage, and finally, the construction stage. Online Appendix Figure A.2 shows the timeline.

In the design stage, FDOT's in-house engineers specify the plan of a project – namely, estimates of the quantity needed for each construction item and project cost. The project manager then decides whether to procure the project by FP or UP contract. The FDOT project guidelines explicitly state that FP contracts should be employed for "projects with low risk of unforeseen conditions."[10] Online Appendix Figure A.1, extracted from the guideline, lists the project types for which FP contracts are and are not suitable. Essentially, the guideline states that FP contracts should be used for simple projects, and UP contracts, otherwise. One to two months prior to project letting, FDOT posts an advertisement online, which lists information about project location, description of work, expected contract duration, and an engineer estimate of the project cost.

Next, the project enters the auction stage. If a project is procured through UP contract, every prospective contractor submits a list of unit prices on their bid form for each item given the quantity estimates from the FDOT project plan. For example, if the FDOT project plan indicates that 10 units of electronic message signs need to be implemented, each bidder must submit a dollar value for how much the contracting firm intends to charge for each unit of 10 message signs. FDOT then determines a score for each bidder by multiplying its planned quantities with the bidder's unit prices and summing across all construction items. Participating bidders are then ranked by their score, and the bidder with the lowest score wins the UP contract. The contracting firm is then obligated to provide the contracted items at the unit prices stated in their bid form. Alternatively, if the project were to be procured through FP contract, prospective contractors would instead submit a single-price bid, which is also their bidder score in this case, and the bidder with the lowest bid price would win the contract. The contracting firm would be obligated to implement the project at its bid price amount, unless significant changes are made to the contract during the construction stage.[11]

The auction stage is followed by the construction stage. Project implementation is closely monitored by an FDOT construction engineering inspector. If no changes are made to the construction plan, the contracting firm receives its own bid price upon delivery of the project under both UP and FP contracts. If the FDOT project manager finds a need to adjust the construction plan under a UP contract, contractor payment is adjusted based on FDOT

[10]Details can be found at Lumpsum Project Guideline.
[11]FDOT quantity estimates are also provided for FP contracts.

quantity adjustment(s) and the contractor bid form list of unit-prices. For example, if FDOT requires any additional days of construction work, and labour is contracted based on the number of workdays, then FDOT compensates the contractor by the number of additional days multiplied by the contractor's daily labour rate. Under an FP contract, no adjustments in payment would be made for changes to contracted items. FDOT, rather than the contractors, initiates more than 95% of these adjustments.

The share of contracted item adjustments out of all ex-post adjustments has a mean of 80 percent and a median of 100 percent. Occasionally, adjustments to uncontracted items may also occur. For example, storms during construction may damage construction machinery, and repairs may be needed. In contrast to the California DOT, where most ex-post adjustments originate from uncontracted items (Bajari, Houghton, and Tadelis, 2014), the majority of ex-post adjustments in our FDOT data originate from contracted items. In this case, the FDOT project manager files a claim, describing the extra work needed, the reason for the change, the associated cost, and the time extension required to implement the change. These additional uncontracted tasks could involve negotiation, and the compensation for these uncontracted tasks is determined the same way for FP and UP contracts.

We also conduct a simple accounting exercise to demonstrate the significance of ex-post adjustments. In this exercise, we assume that (i) bidder behavior is fixed, i.e., unit-price bids are given by the data, (ii) the same ex-post quantity adjustments are imposed on the project, regardless of which bidder wins the contract, and (iii) the auctioneer selects the winner based on the final payment rather than bidder score – that is, the auctioneer is assumed to foresee the ultimate quantities required for project completion at the time of the auction. We find that 10.3% of UP contracts in the data would have had a different winner if the auctioneer had been able to select the winner based on the final payment to the contractor.[12] We relax assumptions (i)-(iii) later in the structural modeling section, but this simple exercise demonstrates the extent of ex-post adjustments to contracted items.

[12]By construction, the probability of switching winners under FP contracts is not affected by this experiment.

A typical concern raised in the analysis of cost overrun is the possibility of default. Contractor default is particularly relevant in this context, because FP contracts may involve more frequent default than UP contracts if contractors are unable to supply extra work or items required to complete the project. During our sample period spanning 2004-2014, 25 projects (1.3% of the sample size) that were procured through either FP or UP contracts were terminated prematurely due to default.[13] The majority of these defaults were not due to adjustments in the project plan but due to contractors failing to perform work in accordance with the terms of the contract. Another possibility for default is binding project budget constraints from the FDOT district office. If a district office is unable to make additional payments for extra work or items under UP contracts, then project managers may decide not to complete the project due to insufficient funds. It turns out that FDOT district offices pool their annual budget across projects to ensure that all procured projects are completed.[14]

Data and Descriptive Analyses

We investigate a sample of infrastructure projects procured by FDOT under FP or UP contracts over the period 2004-2014.[15] The data contain detailed information on projects, including all participating bidders' bid prices (every unit-price bid for UP contracts), FDOT engineers' cost estimates, quantity estimates for UP contracts, final payment to contractors, project location, description of work, and the identities of all participating and non-participating bidders. There is no difference in the way the estimates are determined between FP and UP contracts. The FDOT procurement office determines cost estimates based on historical unit-price bids.[16] We define participating bidders as plan holders that submitted

[13]Our sample contains 22 of the 25 defaulted projects, of which 13 projects (9 projects) were procured through UP (FP) contract.

[14]FDOT requires every bidder to submit a surety bond, specifying a firm that would take over an incomplete project in case of contractor default. FDOT project managers state that every project is completed without exception. We also control for annual district budget amounts in the following regression analyses.

[15]The sample consists of relatively small projects, as FDOT uses another mechanism, the so-called Design-Build auction, for large projects. The average contracting price for Design-Build auctions during the sample period is about $14 million.

[16]The engineer cost estimate and expected contract duration are explicitly stated in the FDOT project advertisement, and thus these project characteristics are known to bidders at the time of bidding.

a bid and potential bidders as those who withheld their bid.[17]

Table 1 contains summary statistics for key variables. It shows, on average, that fewer bidders participate in FP versus UP auctions. UP contracts are used for relatively larger projects than those using FP contracts. We also see that FP projects are less susceptible to cost overruns, and the average cost overrun of UP projects is 3.5 times greater than that of FP projects. There is a sizable difference in Money on the Table across the two contract formats: the lowest score is 10.2% (resp. 7.20%) lower than the second lowest score under FP (resp. UP) contracts on average. Note that cost overruns under FP contracts originate from adjustments on uncontracted items. The number of participating bidders is fairly similar across the two contract formats. Indeed, the set of participating bidders shows considerable overlap, with 75.9% of bidders participating in both FP and UP contracts.[18]

Table 2 presents an OLS comparison of auction formats. We consider four dependent variables: entry, log(score), winner's log(score), and log(final payment). A potential bidder is considered to enter an auction if a plan holder submits a bid. For FP contracts, bidder score is equivalent to bid price for FP contracts; conversely, for UP contracts, the score is determined by bidder unit prices multiplied by FDOT quantity estimates and summed across all items. We find that bidders score 2.9% lower under FP versus UP contracting, despite no statistically significant differences in entry, winning score, and final payment to contractors across the two contract types.

Consistent with the procurement auction literature, we find that the variation in bidder scores and final payments are largely explained by variation in FDOT engineer cost estimates. The entry of an additional participating rival bidder is associated with a 2.2% reduction in bidder score on average, suggesting that competition drives down price.[19]

[17] A firm needs to request a project plan to participate in any given auction. The set of plan holders turns out to include many firms that never bid over the sample period, and we thus exclude plan holders that never bid in a given year and district.

[18] We also split the sample of auctions into four quartile groups based on FDOT engineers' cost estimates. We find that 55.8% (resp. 55.0%) of bidders participate in both FP and UP auctions for very small (resp. small) projects. Similarly, 36.4% (resp. 51.6%) of bidders participate in both for very large (resp. large) projects.

[19] The strong negative correlation between the score and the number of participating bidders suggests

4 Structural Model

To guide our empirical analysis, we construct a model that nests both UP and FP contracts. Our model extends Ewerhart and Fieseler (2003) on various dimensions to capture empirically relevant features of the environment. First, we introduce multidimensional bidder heterogeneities to add flexibility to multidimensional bidding strategies, i.e., itemized bids. For example, some bidders may have more labor endowment, while others have more heavy construction equipment. Such heterogeneity leads to different comparative advantages depending on the contracting items involved in a given project. Second, we introduce risk aversion to account for the fact that complete skewing is not observed in the data. Lastly, we endogenize the entry decision of bidders, because changes in contract format affect bidders' incentive to participate in a given auction. In particular, we will see that UP contracts induce more competition than FP contracts because, all else equal, skewed bidding and risk hedging raise the expected return from entering an auction.

UP contracts differ from FP contracts in that contractors are compensated through cost overruns on contracted items, and bidders can hedge against project risk by forming a portfolio of unit-price bids. As bidders may also differ in their quantity estimates, the portfolio of unit-price bids also differs: bidders may submit high unit prices for underestimated items and low unit prices for overestimated items. The bidder with the largest estimate has the greatest incentive to win the contract and would therefore want to bid competitively to get compensated through cost overruns. This incentive to skew unit-price bids dissipates with increasing project risk, as skewed bidding comes with an increase in payoff uncertainty.[20]

Contract: A contract/project involves $J+1$ items: one lumpsum item and J non-lumpsum items. Let q_j be the FDOT quantity estimate for item $j \in \{0, 1, 2, ..., J\}$. Hereafter, we use subscript 0 to denote the lumpsum item and subscript 1 to denote the vector

that bidders are competing in a private value paradigm rather than in a common value paradigm.

[20]We abstract from the moral hazard problem as i) the construction process is closely monitored by FDOT employees, and ii) most ex-post adjustments in the construction plan are initiated by FDOT project managers rather than contractors.

of non-lumpsum items; when there is potential for confusion, we expand the whole vector. For the lumpsum item, the actual (ex-post) quantity equals the estimated quantity.[21] For a non-lumpsum item, the ex-post actual quantity is affected by bidder heterogeneity and ex-post uncertainty. In particular, the actual quantity of item j needed for bidder i to complete the project is

$$q_j \times (e_{j,i} + \epsilon_{j,i}), \tag{1}$$

where $e_{j,i}$ is the quantity estimate of bidder i on item j at the time of bidding, and $\epsilon_{j,i}$ represents the ex-post demand shock to item j during the construction stage. We normalize the quantity of the lumpsum item $q_0 = 1$ and let $\epsilon_{0,i} = 0$ as there is no uncertainty in the lumpsum item.

Information Structure: We consider the private value paradigm where bidder i's estimates are assumed to be private information $\boldsymbol{e_i} = [e_{0,i}, e_{1,i}, ..., e_{J,i}]$, and are drawn independently across bidders from a common joint distribution H. Distribution H has a smooth density over a finite positive support.[22] Assume that $\mathrm{E}[e_{j,i}] = 1$, and $e_{j,i}$ can be interpreted as the bidder's own estimate normalized against the FDOT quantity estimate.

Ex-post shock $\epsilon_{j,i}$ may vary across items and bidders. Although we later impose parametric assumptions, the distribution of the random matrix $[\epsilon_{j,i}]_{j=1,...,J}^{i=1,...,n}$ can be flexible. We allow for ex-post changes to be arbitrarily correlated among items, and for some items to be more susceptible to quantity changes than others. Further, we allow bidders' ex-post shocks to have negative, zero, or positive correlation. In the extreme case of perfect correlation, bidders receive the same ex-post shocks. The bidder value in the setting here therefore contains a private component $\boldsymbol{e_i}$ as well as a common component $\boldsymbol{\epsilon_i}$.

Timing: At the beginning of a given auction, each of N potential risk-averse bidders

[21] There is no payment adjustment for ex-post adjustments on lumpsum items. As a result, the bidder's problem regarding lumpsum items remains the same regardless of whether lumpsum items involve uncertainty.

[22] Our model differs from Bajari, Houghton, and Tadelis (2014) in that we allow for the expected quantity of work items to differ across bidders and for bidders to face uncertainty in actual item quantity. Relaxing these assumptions explains the considerable variation in composition of unit-price bids in any given auction and also explains why bidders do not completely skew their bids.

independently draw entry cost k_i from a common distribution $F_{ec}(.)$. Bidders are privately informed about their own entry cost and simultaneously make their entry decision. All participating bidders learn the number of actual bidders n upon entry. We assume that all the primitives that are common to all potential bidders are common knowledge at the time of entry.[23]

Upon entry, bidder i learns his own private information $\boldsymbol{e_i} \in R^{J+1}$, drawn independently across bidders from H. Given the quantity estimates and private information, all participating bidders simultaneously submit itemized bids $\boldsymbol{b_i} \in R^{J+1}$ under UP contracts. Let $\boldsymbol{\iota} := [1, 1, ..., 1]$ be a $1 \times J$ vector of ones. The bidder with the lowest score $s_i := b_{0,i} + \boldsymbol{b_{1,i}}\boldsymbol{\iota}^T$, where $\boldsymbol{b_{1,i}} := [b_{1,i}, b_{2,i}, ..., b_{J,i}]$, wins the contract. Under FP contracts, bidders each submit a score and the lowest score wins.

The FDOT project manager may make adjustments to non-lumpsum items $\boldsymbol{\epsilon}_i := [\epsilon_{0,i}, \epsilon_{1,i}, \epsilon_{2,i}, ..., \epsilon_{J,i}]$, drawn from a multivariate normal distribution (i.e., $\boldsymbol{\epsilon}_i \sim \boldsymbol{N(0, \Sigma)}$).[24] The demand shock affects the quantity of each non-lumpsum item required to complete the project.[25] The contractor receives payment based on the contract format.

Expected Payoff: Each bidder is characterized by constant absolute risk-aversion (CARA) utility $u(.)$, parametrized by $\alpha \geq 0$.[26] At the time of bidding, bidder i observes his/her private information $\boldsymbol{e_i}$. Under UP contracts, the bidder submits itemized bids and obtains the following expected payoff,

[23]We assume that any given auction always has more than one participating bidder, preventing the unintuitive bidding strategy in which a bidder submits an infinitely high score when the bidder is the sole participant. Our data contain only a few auctions with only one participating bidder. See also Li and Zheng (2009).

[24]It is possible to allow for correlation between bidders' private information $e_{2,i}$ and ex-post shock ϵ, but this makes the model significantly more notationally involved and turns out to be not empirically relevant. Therefore, we present the model where ex-post shock is independently distributed from private estimate $e_{2,i}$.

[25]Because the demand shock on lumpsum items does not affect the characterization of the equilibrium bidding strategy, and its dispersion is not identifiable, we set $\epsilon_0 = 0$. This abstraction is justified under the CARA assumption because bidders would adjust their bids by exactly the risk premium. See Eso and White (2004).

[26]The assumption of CARA may seem restrictive, as projects are heterogeneous in project size, and bidders may be more risk averse for larger projects. To allow for heterogeneity in the level of risk aversion, we allow risk aversion to depend on project size (and project characteristics in general) later in the identification section.

$$\mathrm{E}\left[u\left(\sum_{j=0}^{J}(\tilde{b}_{j,i}-\tilde{c}_j)\times q_j\times(e_{j,i}+\epsilon_{j,i})\right)\right]\times\Pr\left(i\text{ wins}|\sum_{j=0}^{J}\tilde{b}_{j,i}q_j\right),$$

where $u(\cdot)$ is the bidder's utility function, $\tilde{b}_{j,i}=\frac{b_{j,i}}{q_j}$ represents the per unit itemized bid, and $\tilde{c}_j$ represents the per unit cost of item j.[27] Under FP contracts, the bidder submits a score s_i and obtains the following expected payoff,

$$\mathrm{E}\left[u\left(s_i-\sum_{j=0}^{J}\tilde{c}_j\times q_j\times(e_{j,i}+\epsilon_{j,i})\right)\right]\times\Pr\left(i\text{ wins}|s_i\right).$$

These costs are common to all participating bidders. Let $\theta_j:=\tilde{c}_jq_j$ denote the FDOT engineer's cost estimate for item j at FDOT quantity estimates. The expectation is taken over the joint distribution of ex-post changes.

Unit Price Contracts

First, consider UP contracts. The final payment to the winning bidder, denoted by $p_{u,i}$, is given by:

$$p_{u,i} \;=\; b_{0,i}+\boldsymbol{b_{1,i}}(\boldsymbol{e_{1,i}}+\boldsymbol{\epsilon}_i)^{\boldsymbol{T}}, \tag{2}$$

where there is no uncertainty in payment for the lumpsum item.

Note that the final payment to a contractor could differ from its score s_i for two reasons. First, the final payment may differ from bidder score s_i due to $e_{1,i}$. To demonstrate this point, suppose for simplicity that there is only one non-lumpsum item involved in an auction, and the non-lumpsum item is contracted based on the number of workdays. That is, $\boldsymbol{b_{1,i}}$ specifies how much contracting firm i receives if it completes the project on the auctioneer's expected

[27]We could allow bidder-specific itemized costs. Then, with some functional form changes, such as additive separability in the actual quantity (1), we obtain a general model that nests our model and Bolotnyy and Vasserman (2021)'s. However, identifying this model requires richer data, such as cost variables in Kroft et al. (2022).

completion date. In practice, contractors differ in terms of speed in delivering the project. Some contractors are fast ($e_{1,i} < 1$) while others are slow ($e_{1,i} > 1$). Therefore, the payment scheme implies that, all else equal, fast contractors receive a smaller payment than slow contractors. Second, the final payment may differ from score s_i due to demand shock $\boldsymbol{\epsilon}$. Bidder estimates are also imperfect and affected by unexpected changes in the project plan. Demand shock $\boldsymbol{\epsilon}_i \sim \boldsymbol{N(0, \Sigma)}$ captures unexpected delays in project implementation, where $\boldsymbol{\Sigma}$ captures project risk.[28]

The total cost of project implementation, $tc_{u,i}$, is defined as:

$$tc_{u,i} \quad = \quad \theta_0 e_{0,i} + \boldsymbol{\theta_1 (e_{1,i} + \epsilon_i)^T}, \tag{3}$$

which also depends on bidder heterogeneity and demand shock. Using the final payment and the total cost, we can calculate the expected payoff at the time of bidding for a bidder who observes private information e_i and submits itemized bids b_i:

$$\mathrm{E}\left[u\left(p_{u,i} - tc_{u,i}\right)|\mathcal{I}_i, s_i < s_j\, \forall j \neq i\right] = u(b_{0,i} + \boldsymbol{b_{1,i} e_{1,i}^T} - (\theta_0 e_{0,i} + \boldsymbol{\theta_1 e_{1,i}^T}) - \underbrace{\frac{\alpha}{2}(\boldsymbol{b_{1,i}} - \boldsymbol{\theta_1})\boldsymbol{\Sigma}(\boldsymbol{b_{1,i}} - \boldsymbol{\theta_1})^{\boldsymbol{T}}}_{\text{risk premium}}),$$

where $\alpha \geq 0$ represents the CARA risk-aversion coefficient. We remark that the argument in the utility function on the right-hand side is known as the certainty equivalent under the normal distribution assumption on risk and CARA utility. The quadratic term represents the risk premium.

As noted in Asker and Cantillon (2008), it is convenient to solve this problem in two steps: In the inner loop, find the optimal itemized bid $\{b_{0,i}, \boldsymbol{b_{1,i}}\}$ given score $s_i = \sum_{j=0}^{J} b_{j,i}$; in the outer loop, find the optimal score s_i. Specifically, for any score s_i that the bidder considers, the optimal itemized bid is determined by an optimal portfolio choice problem with one risk-free asset, i.e., the lumpsum item, and multiple risky ones, i.e., non-lumpsum

[28] The model could also allow for possible correlation between $e_{1,i}$ and ϵ_i, but we abstract from this possibility for the sake of simplicity and exposition.

items. Specifically, the bidder solves a linearly constrained quadratic optimization problem:

$$\begin{aligned} \max_{b_i} \quad & u\left(b_{0,i} + \boldsymbol{b_{1,i}}\boldsymbol{e_{1,i}^T} - (\theta_0 e_{0,i} + \boldsymbol{\theta_1}\boldsymbol{e_{1,i}^T}) - \frac{\alpha}{2}(\boldsymbol{b_{1,i}} - \boldsymbol{\theta_1})\boldsymbol{\Sigma}(\boldsymbol{b_{1,i}} - \boldsymbol{\theta_1})^{\boldsymbol{T}}\right) \\ s.t. \quad & s_i = b_{0,i} + \boldsymbol{b_{1,i}}\boldsymbol{\iota^T},\ b_{0,i} \geq 0,\ b_{1,i} \geq 0. \end{aligned}$$

Solving this simple constrained optimization problem gives:

$$\boldsymbol{b_{1,i}^*} = \boldsymbol{\theta_1} + \frac{\boldsymbol{e_{1,i}} - \boldsymbol{\iota}}{\alpha}\boldsymbol{\Sigma^{-1}} \tag{4}$$

as the interior solution for all non-lumpsum bids. A corner solution arises when the non-negativity constraint on either lumpsum or non-lumpsum bids binds. Focusing on interior solutions has potential implications for model solving, identification, estimation, and counterfactuals. Allowing for corner solutions, we can still solve our model.[29] We abstract from them, because we do not observe any completely skewed bids in the data, and hence the best-fitting parameters exclude corner solutions. Moreover, the assumption of interior solutions renders the identification argument more transparent. Specifically, we lose the one-to-one mapping between the bidder type and itemized bids and hence the ability to invert the first-order condition at a corner solution. Nevertheless, the absence of corner solutions in the data does not imply their absence in counterfactuals.[30]

Condition (4) shows an interesting relationship between project risk Σ and bid skewness. Bidder i bids high on non-lumpsum items with a large estimate whereas placing a low bid on items with a small estimate. For example, a slow inefficient bidder with large $\boldsymbol{e_{1,i}}$ would bid high on those non-lumpsum items in expectation to get paid for delays in project delivery. The extent of the skewing, however, dissipates with the degree of project risk $\boldsymbol{\Sigma}$. Given $b_{1,i}^*$, we have $b_{0,i}^* = s_i - \left(\boldsymbol{\theta_1} + \frac{\boldsymbol{e_{1,i}} - \boldsymbol{\iota}}{\alpha}\boldsymbol{\Sigma}^{-1}\right)\boldsymbol{\iota^T}$.

Plugging the optimal itemized bid $(b_{0,i}^*, \boldsymbol{b_{1,i}^*})$ into the certainty equivalent payoff of bidder

[29]See Bolotnyy and Vasserman (2021) for a formal treatment of corner solutions.

[30]We find this abstraction rarely binding in our counterfactuals.

i gives:

$$\mathrm{E}\left[u\left(p_{u,i} - tc_{u,i}\right)|\mathcal{I}_i, s_i < s_j \,\forall j \neq i\right] \;=\; u\left(s_i - c_{u,i}\right),$$

where $c_{u,i}$ is the pseudo-cost of bidder i defined as:

$$c_{u,i} \;:=\; \theta_0 e_{0,i} + \boldsymbol{\theta_1 \iota^T} - \frac{1}{2\alpha}(\boldsymbol{e_{1,i}} - \boldsymbol{\iota})\boldsymbol{\Sigma^{-1}}(\boldsymbol{e_{1,i}} - \boldsymbol{\iota})^{\boldsymbol{T}}. \tag{5}$$

Therefore, bidder i's outer loop problem reduces to a one-dimensional choice problem, such that:

$$\pi_{u,i} \;=\; \max_{s_i} \int \mathbf{1}\{s_i < s_j\}\, u\left(s_i - c_{u,i}\right) \boldsymbol{dF_{u,-i}}, \tag{6}$$

and $\boldsymbol{dF_{u,-i}}$ is the distribution of rival bidders' pseudo-costs.

Note that $c_{u,i}$ is hump-shaped in $\boldsymbol{e_{1,i}}$ and centered at $\boldsymbol{e_{1,i}} = \boldsymbol{\iota}$, which implies that bidder score s_i is non-monotone in $\boldsymbol{e_{1,i}}$ in a monotone equilibrium where s_i is non-decreasing in $c_{u,i}$. This means that the bidders whose estimates on non-lumpsum items differ substantially from FDOT engineer estimates bid more competitively than the bidders whose estimates are closer to the FDOT's. Using workdays as an example, the model captures that both efficient and inefficient bidders bid more competitively than bidders who can deliver the project on time as expected by the FDOT district office. While it is standard for efficient bidders to submit lower bids in procurement auctions, UP contracts provide a unique incentive for inefficient bidders to do the same, as inefficient bidders know that they would receive more payment if they win the contract. Therefore, less efficient contractors lower their bidder score by skewing their bids towards non-lumpsum items to obtain compensation in expectation through ex-post adjustments on non-lumpsum items.

Because the remaining equilibrium characterization relates to the auction literature, we summarize it in the following proposition.[31]

Proposition 1. *The unique symmetric, monotone, and differentiable equilibrium bidding strategy is characterized by the following differential equation and the initial condition:*

$$\begin{aligned} \frac{\partial s(c_u;n)}{\partial c_u} &= 1 + \frac{(n-1)f_u(c_u)}{\alpha(1-F_u(c_u))}\left(\exp\left\{\alpha(s(c_u;n)-c_u)\right\}-1\right), \\ s(\bar{c}_u;n) &= \bar{c}_u, \end{aligned} \tag{7}$$

where F_u and f_u are, respectively, the CDF and PDF of c_u, which is continuous and bounded over $[\underline{c}_u, \bar{c}_u]$.

Given the bidding strategy above, a potential bidder enters an auction if the expected profit from entering outweighs the cost of entry. As shown in Krasnokutskaya and Seim (2011), the unique symmetric equilibrium entry strategy is given by the entry threshold utility $\bar{u}$, which is determined by:

$$\sum_{n}^{N}\binom{N-1}{n-1}\delta(\bar{u}(N))^{n-1}(1-\delta(\bar{u}(N)))^{N-n}\int u\left(s(c_u;n)-c_u\right)\,\boldsymbol{dF_{u,n}} = \bar{u}(N), \tag{8}$$

where the left-hand side of equation (8) is the equilibrium expected profit from entering an auction, and $\boldsymbol{F_{u,n}}$ is the joint distributions of c_u over all n entering bidders. The equilibrium entry probability is determined by $\delta(\bar{u}(N)) := \Pr(u(-k) < \bar{u}(N))$. That is, a bidder participates in an auction if his entry cost k is below some threshold level which corresponds to the level of utility $\bar{u}(N)$.

[31] We characterize the equilibrium of the game among bidders given the procurement mechanism. Under symmetric strategies and interior solutions to the portfolio problem, the pseudo-cost is a sufficient statistic for a unique equilibrium characterization. Characterizing the DOT's optimal procurement mechanism is beyond the scope of this article.

Fixed Price Contracts

Now, let us consider the case of FP contracts. FP payment $p_{f,i}$ is given by:

$$p_{f,i} = s_i, \tag{9}$$

where s_i is bidder i's score in an FP auction. That is, bidder i's FP payment is the same as his score, which is equal to his submitted bid. Therefore, the interim expected payoff of bidder i under FP with CARA utility is given by:

$$\pi_{f,i} := \max_{s_i} \int \mathbf{1}\{s_i < s_j\}\, u\left(s_i - c_{f,i}\right) \boldsymbol{dF_{f,-i}}, \tag{10}$$

where the pseudo-cost of bidder i, $c_{f,i} \in [\underline{c}_f, \bar{c}_f]$, is defined as:

$$c_{f,i} := \theta_0 e_{0,i} + \boldsymbol{\theta_1 e_{1,i}^T} + \frac{\alpha}{2}\boldsymbol{\theta_1 \Sigma \theta_1^T}. \tag{11}$$

The first two terms in this aggregation represent the bidder's ex-ante item-specific estimated costs, and the third term represents his risk premium due to cost uncertainty arising from uncertain quantities of non-lumpsum items. Naturally, the risk premium is increasing in both risk aversion and risk. Moreover, this term is common across bidders, leading to an unambiguous increase in bidder scores. This prediction is consistent with our reduced-form evidence that bidders are more competitive under more risky FP contracts. The distributions of rival bidder pseudo-costs is denoted by $\boldsymbol{F_{f,-i}}$. The remainder of the FP equilibrium characterization is similar to that of UP contracts.

Comparative Statics

Equation (5) shows that bidders' pseudo-costs in UP contracts are lowered and homogenized across bidders of different types as project risk becomes larger, whereas equation (11) shows that pseudo-costs in FP contracts are increasing in project risk. Further, equation

(5) together with (4) shows that a bidder with large estimates of non-lumpsum items in UP contracts submits a portfolio of unit-price bids skewed toward non-lumpsum items while submitting a competitive score. Equation (8) shows that, as project risk increases, the incentive to bid for a UP contract increases while that for an FP contract decreases. Therefore, the overall effects of project risk and contract format on the winning score and the final payment is not clear. We explain the channels and demonstrate the effects of contract format on equilibrium outcomes under varying project risks via a numerical exercise.

Figure 1 shows the distribution of simulated pseudo-costs under varying project risks and contract formats.[32] On average, pseudo-cost is high under UP rather than FP contracts when project risk is low while the relation is reversed when project risk is high. This relationship between pseudo-cost and project risk under UP contracts reflects a mean-variance tradeoff in the optimal portfolio formation of unit-price bids. In the absence of project risk, bidders would completely skew their unit-price bids and place the entire weight on the item that will get overrun, as bidders focus on extracting rent through cost overruns. Increasing project risk makes bidders more homogeneous in terms of their pseudo-cost. This is because bidders hedge against risk more competitively, and non-lumpsum bids approach the risk-free price regardless of heterogeneity in bidder quantity estimates.

To visualize the above effects of project risk, we simulate the optimal bids and the expected final payment by FDOT. Figure 2 plots expected final payment against project risk.[33] As discussed above, bidders facing FP contracts simply pass the additional risk premium onto their pseudo-costs, and thereby their optimal bids. Therefore, the expected payment is strictly increasing in project risk under FP contracts. On the other hand, an increase in project risk under UP contracts lowers bid-skewing incentives, pseudo-costs, and also cost overruns. Bidder attention shifts to hedging against project risk as project risk

[32] The simulation is conducted using the estimates obtained in Section 7. The degree of project risk, $\sigma := \mathrm{Var}(\epsilon)$, is varied for given estimates of the model primitives. Changing parameter values would not alter the pattern observed here. Ex-ante bidder types are assumed to be jointly normally distributed.

[33] The expected final payment is calculated based on the estimates obtained in Section 7. The number of potential bidders is 13, which is the median number of potential bidders in the sample.

increases. This in turn reduces bid-skewing incentives and resulting cost overruns from skewed bidding. Therefore, UP contracts generate a lower final payment when project risk is large while FP contracts perform better when project risk is small.

5 Testing for Selection on Unobservables and Skewed Bidding

The model predicts that i) UP contracts are robust to project risk, ii) bidder scores are much more dispersed in FP versus UP auctions, iii) bidders are substantially heterogeneous with regards to a portfolio of unit-price bids, and iv) bidders who skew their unit-price bids towards non-lumpsum items are much more likely to win a project. Motivated by these predictions, we conduct several empirical tests.

Selection on Unobservables

Institutional facts indicate that contract choice could confound the effects of contractual arrangements on project outcomes. That is, if FDOT project managers follow the project guidelines, then bids could be low in FP versus UP contracts, because simple projects are procured via FP contracting and more complex projects via UP contracting. In this subsection, we test whether the FDOT project manager's contract choice depends on unobserved project heterogeneity in a way that is consistent with FDOT's belief that UP contracts are well suited for projects involving considerable uncertainty.

Specifically, we conduct the test via the correlation between procurers' contract choices and bidding strategies. To this end, let X be a vector of project and bidder characteristics, and let $Z \supset X$ be a vector of exogenous observables relevant to the FDOT project manager's contract choice, denoted by V. Let $score_f$ and $score_u$ denote bidder score under FP and UP contracts, respectively. Then, we consider:

$$\begin{aligned} V &= Z\gamma + \varepsilon_p, \\ \ln(score_f) &= X\beta_f + \varepsilon_f, \\ \ln(score_u) &= X\beta_u + \varepsilon_u, \end{aligned}$$

and the FDOT project manager's choice between FP and UP is governed by:

$$FP = \begin{cases} 1 & \text{if} \quad V \geq 0 \\ 0 & \text{if} \quad V < 0 \end{cases},$$

where γ, β_f, and β_u are vectors of parameters. We assume ε_p, ε_f, and ε_u are randomly distributed trivariate normal unobservables with $\text{Var}(\varepsilon_f) := \sigma_f^2$, $\text{Var}(\varepsilon_u) := \sigma_u^2$, $\text{corr}(\varepsilon_p, \varepsilon_f) := \rho_f$, and $\text{corr}(\varepsilon_p, \varepsilon_u) := \rho_u$. We normalize $\text{Var}(\varepsilon_p)$ to 1. Unobservables are assumed to be independent of at least one element in Z.

The intuition behind the test is as follows. Project managers are less likely to employ FP contracts when project risk is high. Additionally, if project risk is not fully captured by the observables, then unobservable ε_p captures unobserved project risk. We also expect unobserved project risk to be captured by ε_f as bidders' unobserved costs are likely increasing in unobserved project risk. Therefore, adoption of FP contracts and bidding strategy on FP projects are negatively correlated via project risk (i.e., $\rho_f < 0$). Similarly, we would expect a weak correlation between the adoption of UP contracts and the bidding strategy on UP projects if UP contracts are robust to project risk: bidders' unobserved costs are weakly related to project risk. In short, we test $H_0 : \rho_j = 0$ against $H_A : \rho_j \neq 0$ for $j \in \{f, u\}$.

To identify ρ_j without purely relying on functional form assumptions, we now introduce excluded variables in Z that affect FP/UP contract choice but do not affect the bidding strategy, i.e., do not enter X. Our excluded variables capture the extent of backlog experienced by the relevant parties of the auction process. First, for each FDOT district office, backlog is measured by the total dollar value of unfinished projects that the district office has at the time of procurement. It turns out, based on private discussion with FDOT project managers, FDOT needs considerably more personnel to keep track of the number of units used for all materials during the construction stage of a UP project. This large administrative cost associated with UP contracts renders FDOT project managers more likely to employ FP contracts when the office is heavily backlogged. Second, because prospective contractors are also likely backlogged when district offices are backlogged, we construct bidder backlog in the same manner and control for it directly. That is, we argue that the level of backlog at an FDOT district office has nothing to do with prospective contractor bidding strategies (e.g., bidders' unobserved costs), conditional on bidders' backlogs.[34]

Table 3 indicates a strong negative correlation between ε_p and ε_f, consistent with anecdotal evidence.[35] When project risk is large, project managers are less likely to adopt the FP contract and prospective contractors' costs tend to be high, which is passed onto their scores, i.e., $\rho_f < 0$.[36] The weak insignificant correlation between ε_p and ε_u is also consistent with anecdotal evidence that FDOT believes UP contracts are good for projects with large project risk. If UP contracts are robust to project risk, then bidder costs ε_u would be uncorrelated with project risk, because project risk does not translate into bidder costs. Therefore, our estimation results are in line with FDOT's belief that UP contracts should be used for projects with greater project risk.[37]

One concern with the approach here is that the excluded variable may be correlated with unobserved project heterogeneity. That is, FDOT project managers may anticipate the complexity of projects well before project letting, and accordingly, try to coordinate and

[34] We cluster standard errors at the district-year level, taking into account that scores are likely correlated within an auction, and that the excluded variables are correlated across time.

[35] The relevance of the excluded variables is tested in Online Appendix Table A.1. We find that a one standard deviation increase in district office backlog increases the probability of using FP contacts by 8.2 percentage points.

[36] Our results are robust to excluding the period of the financial crisis and stimulus spending that may have drawn in some construction firms that typically do not participate in public procurement auctions. See Online Appendix Table A.2.

[37] The estimation results also suggest that $\sigma_f > \sigma_u$: scores are more dispersed under FP than UP contracts. Our model is also consistent with this observation.

decide when to procure which project based on project complexity. A statistically significant correlation between our excluded variables and ex-post auction outcomes would cast doubt on the validity of our excluded variables.

Ideally, we would like to check if cost overruns are correlated with our excluded variables. However, we do not observe the actual cost overrun under FP contracts, by construction. Therefore, we instead test if time overruns are correlated with our excluded variables.[38] Table A.3 shows that FDOT district office backlogs and time overruns are not strongly correlated, and thus, we conclude that there is no evidence that our excluded variables are correlated with project risk.

Skewed Bidding

UP contracts may induce bidders to behave opportunistically by altering the composition of unit-price bids. As UP contracts compensate for cost overruns, bidders are incentivized to skew the distribution of unit-price bids towards the items for which they expect cost overruns. This induces bidders that expect large cost overruns to bid aggressively to win a contract as predicted by the model. Here, we show that the unit-price composition is indeed strongly related to the bidder's likelihood of winning. That is, bidders who skew the distribution of unit-price bids are more likely to win a contract.[39]

Table 4 presents estimation results from a regression of bidder score and winning status on the non-lumpsum item bids as a share of bidder score. The estimation results indicate that bidders who place a large share of bids on non-lumpsum items bid much more competitively than those with a small non-lumpsum item bid share. Note here that we control for auction fixed effects in all specifications, and therefore the obtained results reflect the fact that there is large variation in the share of non-lumpsum bids within an auction. This fact is also

[38]Time overrun is defined as the log-difference between actual construction days and expected contract days.

[39]Contractual arrangements differ across items. Indeed, some items are procured in a lumpsum manner, while other items are not. The top 10 most frequently used items in UP contracts are presented in Online Appendix Table A.4. Moreover, Figure A.3 shows the variation in non-lumpsum item values.

demonstrated in Online Appendix Table A.5 through variance decomposition. We find that a bidder with a one standard deviation larger share of non-lumpsum bids attains a 3.4% lower bidder score, and is 7.3% more likely to win a UP project based on the specification with only auction fixed effects. The correlation is even stronger after controlling for bidder fixed effects. One may suspect that more risk-averse bidders would want to place a larger share of bids on non-lumpsum items and bid more competitively than less risk-averse bidders if bidders are characterized by decreasing absolute risk aversion. If this were the case, however, the inclusion of bidder fixed effects should remove some of the confounding effects, and yet it does not strengthen the result.

The empirical pattern found here is consistent with the model in that a bidder who anticipates a large cost overrun on a non-lumpsum item places a high unit-price bid on the non-lumpsum item to obtain compensation through cost overruns. Because the bidder with a large estimate for the non-lumpsum item still needs to compete against other bidders to win the contract, he/she places a low unit-price bid on lumpsum items, which will neither overrun nor underrun on cost. Therefore, those bidders that place more weight on non-lumpsum items than on lumpsum items bid more competitively to win a contract, as they expect to receive additional payment from cost overruns.[40]

6 Identification

This section specifies the information structure of bidders, the set of model primitives to be identified, and the set of observables used to identify the model primitives. We show that the model for the subsample of UP contracts is semiparametrically identified from a set of observables in UP contracts when the sample size is infinite. We first abstract from

[40]Online Appendix Figure A.4 further supports this hypothesis, showing a clearly positive relationship between cost overrun under UP contracts and winners' bids on non-lumpsum items in dollars. We find that cost overrun is increasing in bids on non-lumpsum items on average, suggesting that skewed bidding is associated with larger cost overruns.

unobserved heterogeneity and discuss how it can be accounted for at the end of this section.[41]

Observables, Primitives, and Information Structure

Let X denote a vector of exogenous project characteristics, and let $W \subset X$ denote exogenous variables that affect bidding strategy but not entry decision. The econometrician observes the number of potential bidders N, the number of actual participating bidders n, bids on lumpsum and non-lumpsum items for all participating bidders, $\{b_{0,i}, \boldsymbol{b_{1,i}}\}_{i=1}^{n}$, and cost overruns from J non-lumpsum items $\boldsymbol{\Delta} := [\Delta_1, \Delta_2, ..., \Delta_J]$ under UP contracts. Without loss of generality, we rank bidders based on their score $s_{u,i} = b_{0,i} + \boldsymbol{b_{1,i}\iota^T}$, and the winner of an auction is assigned $i = 1$.

The primitives to be identified are the joint distribution of bidder types H, common lumpsum cost component $\theta_0(X)$, common non-lumpsum components $\boldsymbol{\theta_1(X)}$, risk-aversion parameter $\alpha(X)$, project risk $\boldsymbol{\Sigma(X)}$, and distribution of entry cost F_{ec}. Let $\mathcal{I}_i$ denote bidder i's state at the time of bidding. Identifying Assumption 1 summarizes what bidders know at the time of bidding.

Identifying Assumption 1. *At the time of bidding, state $\mathcal{I}_i$ of bidder i consists of auction heterogeneities, bidder i's private information, the joint distribution of rival bidders' private information, the number of participating bidders, estimated costs, project risk, and the number of actual bidders:* $\mathcal{I}_i := \{\theta_0(X), \boldsymbol{\theta_1(X)}, \alpha(X), \boldsymbol{\Sigma(X)}, e_{0,i}, \boldsymbol{e_{1,i}}, H, n\}$.

Identifying Assumption 1 is standard in the empirical auction literature. The assumption that the number of actual bidders is common knowledge can be tested. We find that bidder scores, and thereby bidding strategy, are strongly negatively correlated with the number of actual bidders, suggesting that auction entrants know how many rivals they face at the time of bidding and bid more competitively as the number of participating bidders increases.

[41]The model is not identified from a set of observables under FP contracts, the reason here being that unit prices do not convey any information about the extent of project risk, even when the researcher observes them.

Identifying Assumption 2. *Bidders' private information is i.i.d. across bidders and also independently distributed from entry cost, conditional on project characteristics. That is, the bid preparation cost is orthogonal to its productivity, conditional on project characteristics.*

Identifying Assumption 2 is required for identifying the distribution of bidders' private types H. Intuitively, the econometrician has no way of detecting which of bidders' private information, $e_{0,i}$ or $\boldsymbol{e_{1,i}}$, is correlated with their entry cost from the data, precluding the possibility of allowing for selective entry.

Identifying Assumption 3. *Ex-post shocks on non-lumpsum items* $\boldsymbol{\epsilon}$ *are independently distributed from non-lumpsum bids.*

Identifying Assumption 3 abstracts from the possibility that FDOT project manager demand for ex-post adjustments is endogenous – i.e., FDOT project managers reduce (increase) demand for ex-post adjustments when the contractor's non-lumpsum bid is high (low).[42] We argue that ex-post adjustments are exogenous in this context based on two grounds. First, if FDOT does not commit, the point of using UP contracts is jeopardized and bidders would adjust their beliefs about the distribution of ex-post adjustments accordingly.[43] Second, construction items and tasks are typically non-storable, so FDOT has little incentive to purchase non-lumpsum items to store for later use, even if they are priced low.

Identifying Assumption 4. *There is at least one variable* $W \subset X$ *that affects entry decision without affecting project implementation cost.*

Identifying Assumption 4 is required for identifying the entry cost distribution. Without variable W, all we can identify is the probability of entry, and any distribution of entry cost can be rationalized by the data.[44] To this end, we assume that the number of potential

[42]Identifying Assumption 3 does not imply mechanical correlation between $\boldsymbol{\epsilon}$ and non-lumpsum bids because $\boldsymbol{\epsilon}$ is independent of the signal $\boldsymbol{e_{1,i}}$.

[43]Based on private conversations with FDOT project managers, we confirm that this is indeed a concern of FDOT.

[44]See the Online Appendix of Krasnokutskaya and Seim (2011) for details.

bidders is relevant for the entry decision but has nothing to do with bidding strategy once entered.

Semiparametric Identification

We show that the model primitives are identified from the data on UP contracts and do not rely on variation in the use of contract formats.[45]

Proposition 2. *Under Identifying Assumptions 1-4, all the model primitives are identified.*

First, average itemized bids on non-lumpsum items identify market prices. Consider the non-lumpsum bidding strategy given in (4). It is straightforward to see that $\theta_j(X)$ is directly identified from equation (4), such that:

$$\mathrm{E}\left[\boldsymbol{b}_{\mathbf{1},\boldsymbol{i}}|X\right] \;=\; \boldsymbol{\theta}_{\mathbf{1}}(\boldsymbol{X}), \tag{12}$$

given $\mathrm{E}[e_{j,i}] = 1$.

Second, ex-post actual quantities identify risk and risk aversion. Given knowledge about $\theta_j(X)$, we identify $\alpha(X)$ and $\boldsymbol{\Sigma}(\boldsymbol{X})$ from the mean and covariance matrix of cost overruns. Note here that cost overrun is defined as $\boldsymbol{\Delta} := [\Delta_1, \Delta_2, ..., \Delta_J]$ and $\Delta_j := b_{j,1}(e_{j,1} - 1_j + \epsilon_j)$, where $b_{j,1}$ and $e_{j,1}$ denote the winning bidder's non-lumpsum bid and estimate for item j, respectively. Substituting the non-lumpsum bidding strategy from (4) into cost overrun gives:

$$\Delta_j \;=\; b_{j,1}(e_{j,1} - 1 + \epsilon_{j,1}), \tag{13}$$

$$\boldsymbol{\Delta} \;=\; \boldsymbol{b}_{,\mathbf{1}}(\alpha(X)(\boldsymbol{b}_{,\mathbf{1}} - \boldsymbol{\theta}_{\mathbf{1}}(\boldsymbol{X}))\boldsymbol{\Sigma}(\boldsymbol{X}) + \boldsymbol{\epsilon}), \tag{14}$$

where the second equality follows from the inversion of the system of first-order conditions with respect to $\boldsymbol{b}_{,\mathbf{1}}$. As a result, the vector of cost overruns (normalized by $\boldsymbol{b}_{,\mathbf{1}}$) has a mul-

[45] Identification fails if one only has information about FP contracts, as there are no payment adjustments associated with changes in non-lumpsum items, which is key in identifying the extent of project risk.

tivariate normal distribution with mean $\alpha(X)(\boldsymbol{b_{,1}} - \boldsymbol{\theta_1(X)})\boldsymbol{\Sigma(X)}$ and variance-covariance $\boldsymbol{\Sigma(X)}$. Note that $b_{,1}$ is observed and $\theta_1(X)$ is identified from the first step. Therefore, the extent of bidder risk aversion $\alpha(X)$ and project risk $\boldsymbol{\Sigma(X)}$ are identified from the mean and variance of cost overruns, conditional on $\boldsymbol{b_{,1}}$ and X.

Third, the inner loop first-order condition, determining the optimal itemized bids, identifies the private information on non-lumpsum items. Given knowledge about $\alpha(X)$, $\boldsymbol{\Sigma(X)}$, and $\boldsymbol{\theta_1(X)}$, the distribution of $\boldsymbol{e_1}$ can now be nonparametrically identified from the solution to the bidders' inner problem,

$$\alpha(X)(\boldsymbol{b_1} - \boldsymbol{\theta_1(X)})\boldsymbol{\Sigma(X)} + \boldsymbol{\iota} \quad = \quad \boldsymbol{e_1}. \tag{15}$$

Fourth, the outer loop first-order condition, determining the optimal score, identifies the private information on the lumpsum item. Let $G_n(.|X)$ and $g_n(.|X)$ denote, respectively, the CDF and PDF of score distributions with n participating bidders conditional on observables X. Expressing the first-order optimality condition (7) in terms of bid distributions gives:

$$\mathrm{E}\left[s_{u,i} - \boldsymbol{\theta_1(X)\iota^T} - \frac{1}{\alpha(X)} ln\left(1 + \alpha(X)\frac{1 - G_n(s_{u,i}|X)}{(n-1)g_n(s_{u,i}|X)}\right) + \frac{\alpha(X)}{2}(\boldsymbol{b_1} - \boldsymbol{\theta_1(X)})\boldsymbol{\Sigma(X)}(\boldsymbol{b_1} - \boldsymbol{\theta_1(X)})^{\boldsymbol{T}}|\boldsymbol{b_1}, X\right] = \theta_0(X). \tag{16}$$

See Online Appendix C for the derivation. Therefore, we identify $\theta_0(X)$. Given $\theta_0(X)$, we can now identify the distribution of $e_{0,i}$ nonparametrically:

$$\left(s_{u,i} - \boldsymbol{\theta_1(X)\iota^T} - \frac{1}{\alpha(X)} ln\left(1 + \alpha(X)\frac{(1 - G_n(s_{u,i}|X))}{(n-1)g_n(s_{u,i}|X)}\right) + \frac{\alpha(X)}{2}(\boldsymbol{b_1} - \boldsymbol{\theta_1(X)})\boldsymbol{\Sigma(X)}(\boldsymbol{b_1} - \boldsymbol{\theta_1(X)})^{\boldsymbol{T}}\right)/\theta_0(X) = e_0, \tag{17}$$

which corresponds to the inversion of the system of first-order conditions of Guerre, Perrigne, and Vuong (2000). Equation (17), together with (15), identifies the joint distribution of bidder private information H.

Fifth, the entry cost k is identified from the equilibrium entry condition, given by equation (8). Knowing $\theta_0(X)$, $\boldsymbol{\theta_1(X)}$, and H gives us the pseudo-cost distribution F_u, as well as interim expected payoff $\int u\left(s_u - c_u\right) \boldsymbol{dF_{u,n}}$ for each number of participating bidders n. In order to identify the distribution of entry costs, we need an additional identifying assumption.

Specifically, we need a variable that affects bidders' expected payoff but not their entry cost.[46]

Lastly, our previous analysis suggests that projects procured via FP contract differ systematically from projects procured via UP contract in unobserved ways. To deal with unobserved heterogeneity, which is non-separable in a bidder's payoff function, we could first apply Hu, McAdams, and Shum (2013) to identify the fraction of auctions in the observed sample that occurred with a higher risk and the conditional distribution of bids for a given risk level. Next, we can also show that the first-order conditions identify the bidder type distribution conditional on observable auction-specific characteristics and unobserved risk level. The key idea is to view bids as measurements of the unobserved state. Given the observables, when unobserved heterogeneity is absent, bids across bidders are independent because bidder types are. In other words, within-auction correlation of bids indicates the presence of unobserved heterogeneity.

Although we can allow the unobserved heterogeneity to flexibly impact the bid distribution, we consider project risk as the main source in our empirical analysis. This is because our reduced-form evidence suggests that bid data contain substantial unobserved heterogeneity in project risk. In addition, the identification argument of Hu, McAdams, and Shum (2013) requires that the maximum of bidders' values is monotone in the state, and introducing multiple unobserved heterogeneities (e.g., unobserved heterogeneity in both mean cost and project risk) violates the condition.

7 Structural Estimation

Following the identification section, we estimate the model for the subsample of UP contracts. The econometrician needs to deal with some practical challenges in estimating the model. Nonparametric estimation of the model would overfit and induce large standard errors. As we do not observe all construction items repeatedly across projects, and often a large number

[46]Without this exclusion restriction, we can only identify entry probabilities. See the Online Appendix of Krasnokutskaya and Seim (2011) for details.

of items is involved in a construction project, estimation of project risk for each construction item is not feasible. We address this issue by aggregating non-lumpsum items and estimate a scalar project risk parameter, defined as σ (i.e., $\boldsymbol{\Sigma(X)} := \sigma(X)$). That is, we i) multiply FDOT's quantity estimates with unit-price bids and sum across all non-lumpsum items in a given contract to generate a single non-lumpsum bid (i.e., $\boldsymbol{b_{1,i}\iota^T} = b_{1,i}$), and ii) sum across all the adjustments on all the items in a given auction to construct a total adjustment. For clarity, we hereafter introduce auction index a.

Our dimension reduction is restrictive, but it is only required for estimation because our identification procedure assumes that the sample size is infinite. However, the two-dimensional problem still captures the mean-variance trade-off in choosing itemized bids. Moreover, it preserves the normal distribution of ex-post shock, as the sum of normally distributed shocks is also normally distributed. [47]

We incorporate observable covariates using a single-index structure. More specifically, we rescale all the model primitives by observables X_a for a given auction a. Define:

$$\begin{aligned} \theta_j(X_a) &= \theta_j \exp\{X_a\beta\} \quad \text{for } j \in \{0,1\}, \\ \sigma^t(X_a) &= \sigma^t, \\ \alpha(X_a) &= \alpha/\exp\{X_a\beta\}, \end{aligned} \tag{18}$$

where θ_0 and θ_1 are the mean lumpsum and mean non-lumpsum costs, respectively. The multiplicatively separable cost specification is commonly employed in the auction literature to account for project heterogeneity. See Haile, Hong, and Shum (2003). Rescaling wealth in CARA utility requires normalization of the CARA coefficient by observed project characteristics. See Theorem 1 in Raskin and Cochran (1986).

One implication of the above econometric specification on the equilibrium bidding strat-

[47] Still, it may suffer from misspecification biases unless all non-lumpsum items are subject to the same risk given auction-specific covariates. Therefore, we introduce unobserved heterogeneity to help alleviate this concern.

egy is that the scoring strategy, non-lumpsum bidding strategy, and cost overrun are all multiplicatively separable in observables. Let $b_{1,ia} := b_1\left(\theta_1(X_a), \sigma(X_a), \alpha(X_a), e_{1,ia}\right)$, $s_{u,ia} := s_u\left(\theta_0(X_a), \theta_1(X_a), \sigma(X_a), \alpha(X_a), e_{0,ia}, e_{1,ia}, n\right)$, and $\Delta_a := \Delta\left(\theta_1(X_a), \sigma(X_a), \alpha(X_a), e_{1,1a}, \epsilon_a\right)$.

Define $b^0_{1,ia} := b_1\left(\theta_1(0), \sigma(0), \alpha(0), e_{1,ia}\right)$, $s^0_{u,ia} := s_u\left(\theta_0(0), \theta_1(0), \sigma(0), \alpha(0), e_{0,ia}, e_{1,ia}, n\right)$, and $\Delta^0_a := \Delta\left(\theta_1(0), \sigma(0), \alpha(0), e_{1,1a}, \epsilon_a\right)$ as "normalized" non-lumpsum score, normalized score, and normalized cost overrun, respectively. This multiplicative separability of project characteristics allows for a bid homogenization approach in a setting with CARA bidders and reduces computational burden by reducing the number of auctions the econometrician has to solve. See Online Appendix D for details.

Another practical challenge here is that our reduced-form evidence suggests that the bid data contain a substantial degree of unobserved heterogeneity in project risk. Therefore, the econometrician needs to address the possibility that the extent of project risk may differ across projects in a way that is unobserved to the econometrician. Let t denote the unobserved state (unobserved to the econometrician), and let $\sigma^t(X)$ denote the level of project risk in state t. That is, the project risk is allowed to differ across projects in a way that is unobserved to the econometrician. However, the model is highly nonlinear due to the CARA assumption, which precludes the deconvolution approach in dealing with unobserved project heterogeneity.

Applied works in the procurement auction literature often assume *constant relative risk aversion* (CRRA), rather than CARA, due to its simplicity and goodness of fit. However, we assume CARA, because using CRRA would require the approximation of certainty equivalent payoffs via Taylor expansion, which is valid only for small ex-post adjustments. Because the data contain a large degree of ex-post uncertainty, we assume CARA together with normally distributed ex-post adjustments. This means that the common deconvolution approach to deal with unobserved project heterogeneity is not feasible here, as additive separability or multiplicative separability of project risk does not translate into additive separability or multiplicative separability of scoring strategy.

Specifically, we estimate a finite mixture model that allows for a finite number of discrete unobserved states in project risk $\sigma^t(X)$. A finite mixture model requires *a priori* knowledge about the number of unobserved states. To this end, we conduct an elbow test based on the variance of (normalized) non-lumpsum bids, $b^0_{1,ia}$, following Lin and Ng (2012), Landau et al. (2011), Syakur et al. (2018), and Tibshirani et al. (2001). More specifically, we apply k-means clustering on the variance of $b^0_{1,ia}$ for each number of potential clusters, and determine the number of clusters where the sum of squared errors stops dropping radically. The result of the elbow test is presented in Online Appendix Figure A.5. K-means clustering suggests two unobserved states in variance of $b^0_{1,ia}$. We interpret this as suggestive evidence that the data contain two unobserved states, high and low, in project risk σ^t where $t \in \{L, H\}$.[48]

Estimation Procedure

Our econometric specification suggests an easy-to-estimate multi-step estimation procedure, which allows for the estimation of model primitives, together with the distribution of unobserved project heterogeneity. We parameterize the distribution of bidder types by bivariate normal with standard deviations $\{\sigma_{e0}, \sigma_{e1}\}$ and correlation $\rho := \text{corr}(e_{0,i}, e_{1,i})$ to allow for within-bidder correlation in types, which captures correlation in a given bidder's productivity across items. The probability that the state is H is denoted by P and the state is L by $1 - P$.

Step 1: Estimate θ_1 and β by non-linear least squares using the aggregated non-lumpsum bid $b_{1,ia}$:

$$b_{1,ia} \;=\; b^0_{1,ia} \exp\{X_a\beta\} = \theta_1 \exp\{X_a\beta\} + \frac{e_{1,ia} - 1}{\alpha\sigma^t} \exp\{X_a\beta\}.$$

Step 2: Using the predicted classification of unobserved state $t \in \{L, H\}$ via K-means clustering, estimate CARA parameter α, the marginal distribution of $e_{1,ia}$, the unobserved

[48] We exclude unobserved heterogeneity in mean costs θ_0 and θ_1, because multi-dimensional unobserved heterogeneity violates the first-order stochastic dominance condition of Hu, McAdams, and Shum (2013).

project risk σ^t, and its probability distribution P using the cost overrun equation:

$$\frac{\Delta_a}{b_{1,1a}} = \alpha\sigma^t(\widehat{b}^0_{1,1a} - \widehat{\theta}_1) + \epsilon_a,$$

where $\widehat{b}^0_{1,1a} - \widehat{\theta}_1$ is the estimate of $b^0_{1,1a} - \theta_1$ obtained from Step 1.[49] Note here that $Var(\epsilon_a) = \sigma^t$ helps estimation of α and σ^t.

Step 3: Given the obtained estimates $\widehat{\theta}_1$,$\widehat{\alpha}$,$\widehat{\sigma}^t$, predicted type $\widehat{e}_{1,ia}$, and predicted unobserved state, we estimate θ_0, ρ, and σ_{e0} by inverting the first order condition for the scoring strategy:[50]

$$\theta_0 e_{0,i} = s^0_{u,ia} - \widehat{\theta}_1 - \frac{1}{\widehat{\alpha}} \ln\left(1 + \widehat{\alpha}\frac{(1 - G_n(s^0_{u,ia}))}{(n-1)g_n(s^0_{u,ia})}\right) + \frac{\widehat{\alpha}\widehat{\sigma}^t}{2}(\widehat{b}^0_{1,ia} - \widehat{\theta}_1)^2. \tag{19}$$

Step 4: Estimate reduced-form entry probability, denoted by $\widehat{\delta}(N_a)$, by probit of bidding status on the number of potential bidders N_a.

Step 5: Given the parameter estimates obtained from Steps 1-4, compute the expected payoff using $\widehat{\delta}(N_a)$. This pins down the threshold entry cost $\bar{k}_N$ for each N. Estimate the mean entry cost μ_{ec} and the standard deviation of entry cost σ_{ec} via non-linear least squares where $\Pr\left(k_{ia} < \bar{k}_N\right) := \Phi\left(\frac{\bar{k}_N - \mu_{ec}}{\sigma_{ec}}\right)$ and $\Phi\left(.\right)$ is a standard normal CDF.

Estimation Results

Table 5 shows the structural estimation results. There is a considerable amount of project risk even in the low state. The cost of project risk in the low state is 0.032, which is 3.24% of the mean cost.[51] Also, the standard deviation of pseudo-costs among bidders under UP

[49] The classification based on K-means clustering is, for example, adopted in Lin and Ng (2012), and Lu and Su (2017).

[50] An alternative way to estimate the model without taking the classification as given is to apply indirect inference by matching the moments of the bidder score distribution in the data with the moments of the scores generated via simulation. We obtain quantitatively similar estimation results either way,

[51] The cost of project risk is estimated as $\frac{1}{2}\widehat{\alpha}\left(\widehat{\sigma}^L\widehat{\theta}_1\right)^2 = 0.032$. The mean cost estimate is $\widehat{\theta}_0 + \widehat{\theta}_1 = 0.986$. Note that the cost of project risk is invariant with respect to project size or project characteristics in general given the econometric specification here.

contract is 38.9% of the mean total cost $\theta_0 + \theta_1$, indicating a significant amount of bidder heterogeneity within an auction. The estimated distribution of bidder types ($e_{0,i}$ and $e_{1,i}$) in Figure 3 shows that bidder types are fairly normally distributed. Moreover, Table 6 shows that the actual homogenized bids computed directly from the data closely resemble the distribution of simulated bids. For brevity, we tabulate by the number of bidders when it is odd; the patterns are similar for even numbers.

An important observation here is that bidder types are highly positively correlated (i.e., $\rho \approx 0.75$). Highly correlated types have an important implication for the effect of employing UP over FP contracts When bidder types are positively correlated, winning bidders tend to be bidders with low $e_{1,i}$, because efficient bidders (i.e., those with estimate $e_{1,i}$ lower than 1) also bid competitively.[52] Therefore, we expect an increase in ρ to be associated with an increase in allocative efficiency. That is, the adverse effect of skewed bidding for UP versus FP contracts diminishes as ρ increases, and therefore, the use of UP contracts can be justified, even when project risk is small.

8 Do UP contracts do well?

A natural question here is whether the UP contract is a mechanism that minimizes procurement costs. In this section, we consider two hypothetical scenarios: i) switching from UP to FP contract, and ii) imposing a cap on non-lumpsum bids. FP contracts are an obvious alternative to UP contracts, especially when project risk is relatively small.

We consider imposing a cap r on non-lumpsum bids (or, equivalently, reserve price) at the estimated mean cost of non-lumpsum item θ_1. We maintain the interior solution assumption for both lumpsum and non-lumpsum bids in the counterfactual equilibrium. This experiment allows us to see how the performance of UP contracts can be improved in a simple and costless manner.[53] The intuition is simple but differs from that of reserve price in a typical first-price

[52] An OLS regression of estimated types e_1 and e_0 on an auction winner indicator shows a strong negative association (see Online Appendix Table A.6.) This suggests that auction winners are efficient on average.

[53] Item-wise reserve price is a very common practice in timber auctions, which generally employs UP

auction. A cap on the non-lumpsum bid at θ_1 would preclude only inefficient types ($e_{1,i} \geq 1$) from skewing their bids and continue to allow efficient types ($e_{1,i} < 1$) to skew their bids. Given that cost overruns occur due to the skewing of inefficient bidders, setting a cap $r = \theta_1$ reduces the extent of cost overruns for inefficient types, which in turn limits their incentive to bid competitively, and results in efficient selection of contractors via UP contract. More specifically, a bidders' non-lumpsum bidding strategy under reserve price r is given by:

$$b_{1,i} = \begin{cases} \theta_1 + \frac{e_{1,i}-1}{\alpha\sigma} & \text{if } e_{1,i} < 1, \\ \theta_1 & \text{if } e_{1,i} \geq 1, \end{cases}$$

pseudo-cost of a bidder, c_r, is given by:

$$c_{r,i} = \begin{cases} \theta_0 e_{0,i} + \theta_1 - \frac{(e_{1,i}-1)^2}{2\alpha\sigma} & \text{if } e_{1,i} < 1, \\ \theta_0 e_{0,i} + \theta_1 & \text{if } e_{1,i} \geq 1, \end{cases}$$

and the scoring strategy is a function of $c_{r,i}$ where $c_{u,i}$ in equation (7) is replaced by c_r.[54]

Table 7 presents the percentage change in the expected final payment due to switching from the UP to FP contract format. We find that switching from a UP to FP contract would increase the expected procurement cost in all cases, rationalizing the use of UP contracts by FDOT. We also find that the cost savings effect of UP contracts is larger when project risk is large, and that the cost of project risk is large. The change in the expected final payment is calculated in two steps: one with fixed entry behavior and one with endogenously adjusted entry behavior. We find that the equilibrium entry effect moderates the effect of switching contract format.

Table 8 shows the effect of the non-lumpsum reserve price on the expected final payment.

contracts to select a contractor. See Athey and Levin (2001), for example.

[54]One thing to note here is that the non-lumpsum bidding strategy and the pseudo-cost under the cap on non-lumpsum bids is valid as long as the bidding strategy is given by the interior solution before imposing a cap. This is because the non-lumpsum bid is always equal to or smaller with a cap than the non-lumpsum bid without a cap.

We find that the effect of the reserve price is surprisingly small. There are two explanations for this phenomenon. First, because within-bidder types are highly positively correlated, winning contractors tend to be efficient (i.e., low $e_{0,i}$ and low $e_{1,i}$) and therefore, placing a cap on non-lumpsum bids does not do much in affecting the final payment. Second, the scope of skewing is limited by large project risk. Risky projects shift the attention of bidders from skewing to risk hedging, and therefore, leave little disparity between efficient and inefficient bidders in terms of non-lumpsum bids.

We compare equilibrium outcomes from the numerical comparative statics of changing type correlation ρ. Figure 4 shows the expected final payment, the coefficient of variation of pseudo-cost, the average cost overrun, and the average winner's non-lumpsum efficiency type e_1. The right subfigure shows that a higher type correlation determines a winner with higher efficiency in non-lumpsum items, leading to improved allocative efficiency and less cost overrun. Note that the pseudo-cost becomes more homogeneous when type correlation increases, leading to more competitive bidding, which in turn reduces the average final payment. In summary, the average final payment decreases with type correlation through two distinct channels: i) a more efficient allocation from selecting a winner with lower potential cost overrun, and ii) a more efficient winner through more competitive bidding.

9 Conclusion

We analyze the performance of unit-price (UP) contracts relative to fixed-price (FP) contracts and find that procurer choice of contract type depends on unobserved project heterogeneity, consistent with the Florida Department of Transportation (FDOT)'s belief that UP contracts should be used for projects with larger project risk. Skewed bidding for UP contracts is economically and statistically significant, suggesting that UP projects may select inefficient contractors that expect additional compensation through cost overruns. We build a simple estimable model of auction contracts, which is consistent with the empirical findings. Our empirical specification of the model allows for unobserved project heterogeneity in both expected cost and project risk. We find that UP (FP) contracts are ideal for projects with large (small) project risk, and the estimated model rationalizes FDOT's practice.

We abstract from the moral hazard problem in this article, as FDOT closely monitors the construction process and initiates most ex-post adjustments. Nevertheless, we can adapt the framework to study this problem in suitable settings, because it nests FP and UP contracts. FP contracts are free of moral hazard, as the final payment is independent of the actual quantities. All else equal, comparing outcomes under UP and FP allows for gauging the significance of moral hazard. Empirically, this requires a valid instrument that exogenously changes the auction format. For instance, if the DOT adopts FP when the project size is smaller than a cutoff and UP otherwise, a regression discontinuity design allows for identifying the effects of the auction format. Unfortunately, we have no such variation in the Florida data.

References

Allen, J., Clark, R., Hickman, B., and Richert. E.. "Resolving Failed Banks: Uncertainty, Multiple Bidding & Auction Design." Working Paper, Bank of Canada, 2019

An, Y., and Tang, X.. "Specification and negotiation in incomplete contracts." *RAND Journal of Economics*, Vol. 50 (2019), pp. 57-92.

Asker, J., and Cantillon, E.. "Properties of scoring auctions." *The RAND Journal of Economics*, Vol. 39 (2008), pp. 69-85.

Athey, S., and Levin, J.. "Information and Competition in U.S. Forest Service Timber Auctions." *Journal of Political Economy*, Vol. 109 (2001), pp. 375-417.

Bajari, P., and Hortacsu, A.. "Are Structural Estimates of Auction Models Reasonable? Evidence from Experimental Data." *Journal of Political Economy*, Vol. 113 (2005), pp. 703-741.

Bajari, P., Houghton, S., and Tadelis, S.. "Bidding for Incomplete Contracts: An Empirical Analysis of Adaptation Costs." *American Economic Review*, Vol. 104 (2014), pp. 1288-1319.

Bajari, P., and Lewis, G.. "Moral Hazard, Incentive Contracts, and Risk: Evidence from Procurement." *Review of Economic Studies,* Vol. 81 (2014), pp. 1201-1228.

Bolotnyy, V., and Vasserman, S.. "Scaling Auctions as Insurance: A Case Study in Infrastructure Procurement." Working Paper, 2021

Campo, S., Guerre. E., Perrigne, I., and Vuong, Q.. "Semiparametric Estimation of First-Price Auctions With Risk-Averse Bidders." *Review of Economic Studies*, Vol. 78 (2011), pp. 112-147.

Che, Y. K.. "Design competition through multidimensional auctions." *The RAND Journal of Economics*, Vol. 24 (1993), pp. 668-680.

Cox, J. C., Smith, V. L., and Walker, J. M.. "Theory and individual behavior of first-price auctions." *Journal of Risk and Uncertainty*, Vol. 1 (1988), pp. 61-99.

Decarolis, F.. "Awarding Price, Contract Performance and Bids Screening: Evidence from Procurement Auctions." *American Economic Journal: Applied Economics*, Vol. 6 (2014), pp. 108-132.

Eso, P., and White, L.. "Precautionary Bidding in Auctions." *Econometrica*, Vol. 72 (2004), pp. 77-92.

Ewerhart, C., and Fieseler, K.. "Procurement Auctions and Unit-Price Contracts." *RAND Journal of Economics*, Vol. 34 (2003), pp. 569-581.

Goeree, J., Holt, C., and Palfrey, T.. "Quantal response equilibrium and overbidding in private-value auctions." *Journal of Economic Theory*, Vol. 104 (2002), pp. 247-272.

Guerre, E., Perrigne, I., and Vuong, Q.. "Optimal Nonparametric Estimation of First-Price Auctions." *Econometrica*, Vol. 68 (2000), pp. 525-574.

Guerre, E., Perrigne, I., and Vuong, Q.. "Nonparametric Identification of Risk Aversion in First-Price Auctions Under Exclusion Restrictions." *Econometrica*, Vol. 77 (2009), pp. 1193-1227.

Haile, P., Hong, H., and Shum, M.. "Nonparametric tests for common values in first-price sealed-bid auctions." Cowles Foundation Discussion Paper 1444, 2003

Heckman, J.J.. "The Common Structure of Statistical Models of Truncation, Sample Selection, and Limited Dependent Variables and a Simple Estimator for Such Models." *Annals of Economic and Social Measurement*, Vol. 5 (1976), pp. 475-492.

Krasnokutskaya, E., and Seim, K.. "Bid Preference Programs and Participation in Highway Procurement." *American Economic Review*, Vol. 101 (2011), pp. 2653-2686.

Krasnokutskaya, E., Song, K., and Tang, X.. "Estimating Unobserved Individual Heterogeneity Using Pairwise Comparisons," *Journal of Econometrics*, Vol. 226 (2022), pp. 477-497.

Kong, Y., Vuong, Q., and Perrigne, I.. "Multidimensional auctions of contracts: An empirical analysis." *American Economic Review*, Vol. 112 (2022), pp. 1703-36.

Kroft, K., Luo, Y., Mogstad, M., and Setzler, B.. "Imperfect competition and rents in labor and product markets: The case of the construction industry." Working Paper, National Bureau of Economic Research, 2022.

Hu, Y., McAdams, D., & Shum, M.. "Identification of first-price auctions with non-separable unobserved heterogeneity." *Journal of Econometrics*, Vol. 174 (2013), pp. 186-193.

Landau, S., Leese, M., Stahl, D., and Everitt, B. S.. *Cluster analysis.* John Wiley & Sons, 2011

Li, T., and Zheng, X.. "Entry and Competition Effects in First-Price Auctions: Theory and Evidence from Procurement Auctions." *Review of Economic Studies*, Vol. 76 (2009), pp. 1397-1429.

Lin, C. C., and Ng, S.. "Estimation of panel data models with parameter heterogeneity when group membership is unknown." *Journal of Econometric Methods*, Vol. 1 (2012), pp. 42-55.

Lu, X., and Su, L.. "Determining the number of groups in latent panel structures with an application to income and democracy." *Quantitative Economics*, Vol. 8 (2017), pp. 729-760.

Luo, Y., Perrigne, I., and Vuong, Q.. "Auctions with *ex post* Uncertainty." *RAND Journal of Economics*, Vol. 49 (2018), pp. 574-593.

Marmer, V., Shneyerov, A., and Xu, P.. "What Model for Entry in First-Price Auctions? A Nonparametric Approach." *Journal of Econometrics*, Vol. 176 (2013), pp. 46-58.

McAfee, P., and McMillan, J.. "Bidding for Contracts: A Principal-Agent Analysis." *RAND Journal of Economics*, Vol. 17 (1986), pp. 326-338.

Raskin, R., and Cochran, M.J.. "Interpretations and transformations of scale for the Pratt-Arrow absolute risk aversion coefficient: implications for generalized stochastic dominance." *Western Journal of Agricultural Economics*, Vol. 11 (1986), pp. 204-210.

Samuelson, W.. "Auctions with contingent payments: Comment." *American Economic Review*, Vol. 77 (1987), pp. 740-745.

Somaini, P.. "Identification in Auction Models with Interdependent Costs." *Journal of Political Economy*, Vol. 128 (2020), pp. 3820-3871.

Syakur, M. A., Khotimah, B. K., Rochman, E. M. S., and Satoto, B. D.. "Integration k-means clustering method and elbow method for identification of the best customer profile cluster." *IOP conference series: materials science and engineering*, Vol. 336 (2018), p. 012017.

Takahashi, H.. "Strategic design under uncertain evaluations: structural analysis of design-build auctions." *RAND Journal of Economics*, Vol. 49 (2018), pp. 594-618.

Tibshirani, R., Walther, G., & Hastie, T.. "Estimating the number of clusters in a data set via the gap statistic." *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, Vol. 63 (2001), pp. 411-423.

Vuong, Q.. "Likelihood ratio tests for model selection and non-nested hypotheses." *Econometrica*, Vol. 57 (1989), pp. 307-333.

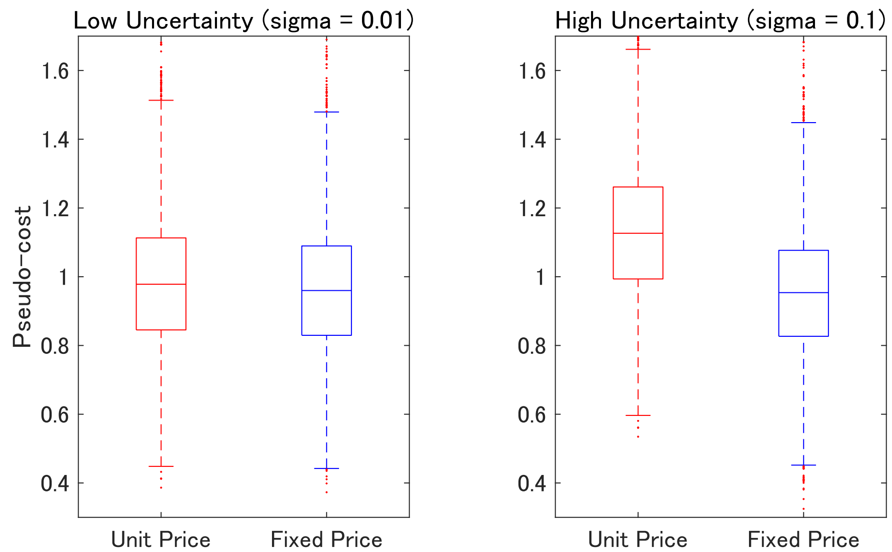

Figure 1: Pseudo-costs and Project risk in FP and UP Contracts

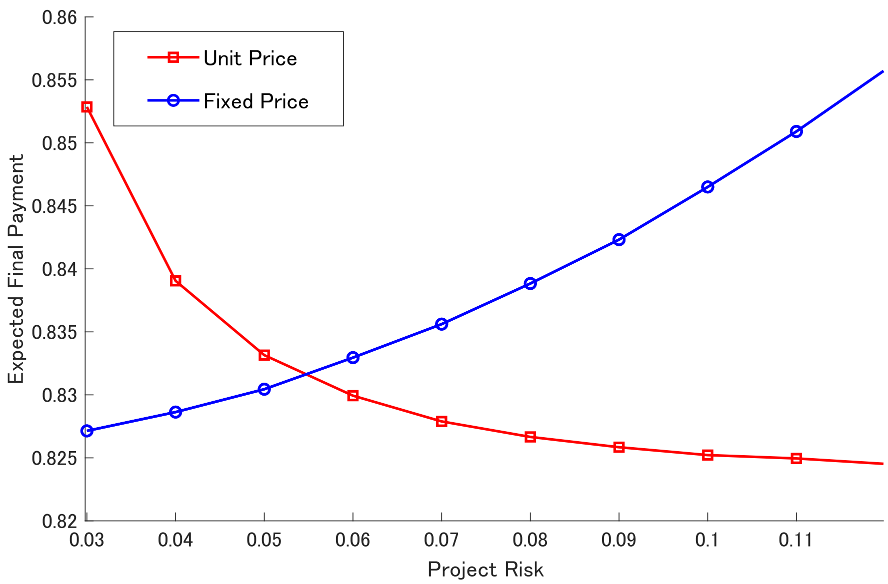

Figure 2: Expected Final Payment and Project Risk in FP and UP Contracts

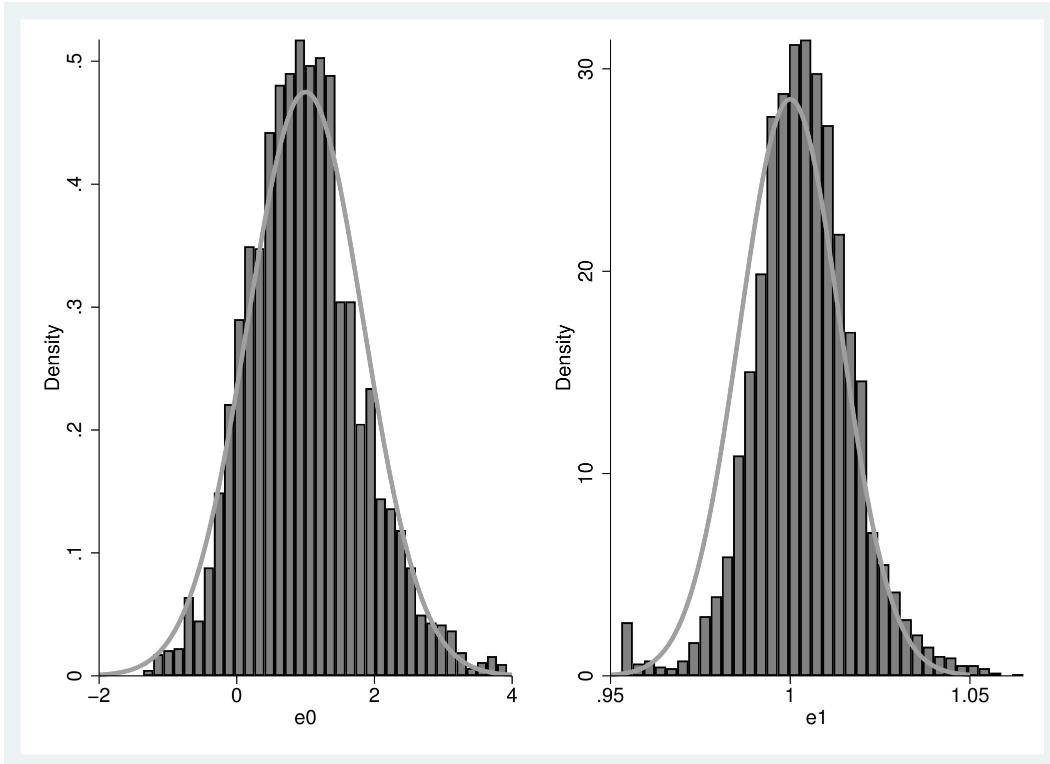

Figure 3: Estimated Distribution of Bidders' Efficiency Types (e_0, e_1)

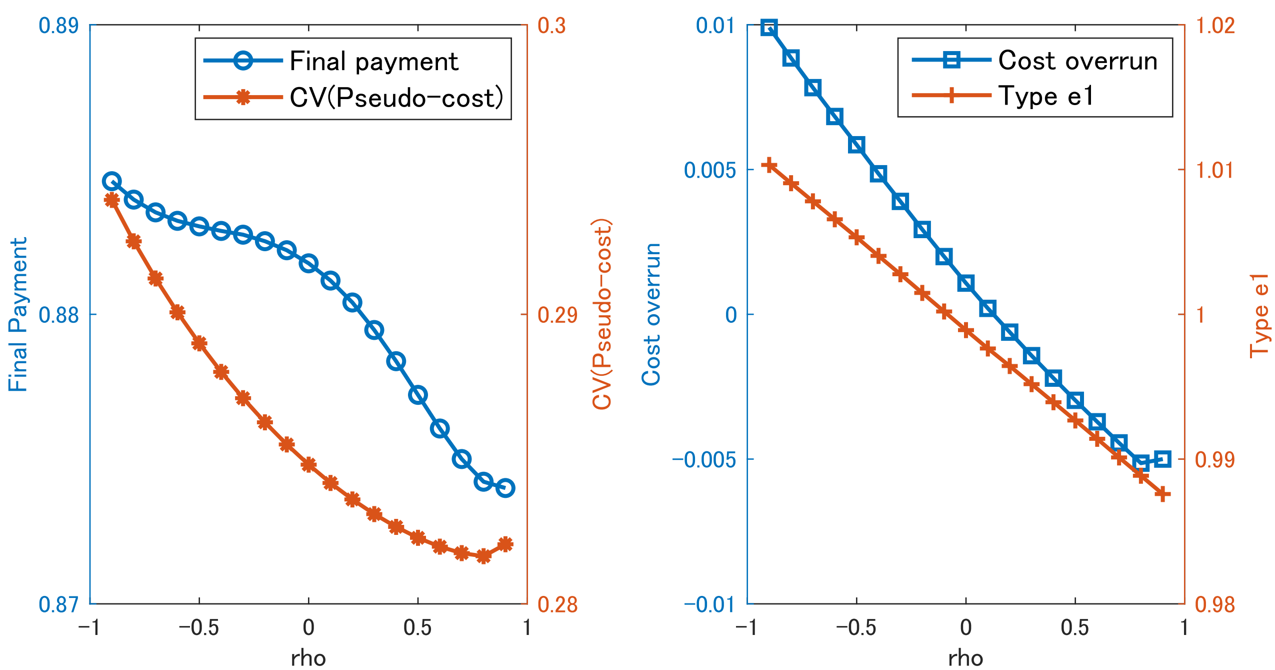

Figure 4: Role of Type Correlation ρ in UP Contracts ($\sigma \approx \widehat{\sigma}^H$)

Table 1: Summary Statistics of Fixed-Price and Unit-Price Contracts

	FP					UP				
Variable	**Mean**	**Std.**	**Min.**	**Max.**	**N**	**Mean**	**Std.**	**Min.**	**Max.**	**N**
Winning Score ($1,000s)	1601	2053	14.3	14500	628	3956	7510	7.51	148000	1260
Money on the Table	.102	.0945	.000687	.616	628	.0720	.0708	.000165	.532	1260
FDOT Cost Estimates ($1,000s)	1884	2321	23.3	16600	628	4774	9094	12.7	164000	1260
Final Payment to Contractor ($1,000s)	1601	2053	14.3	14400	628	4141	8095	7.50	159000	1260
Ex-Post Pay Adjustment ($1,000s)	50.9	177	-164	1851	628	184	750	-1999	11200	1260
# of Participating Bidders / Auction	4.32	2.39	1	15	628	4.98	2.67	1	19	1260
# of Potential Bidders / Auction	10.2	5.71	1	31	628	10.8	6.52	1	43	1260

Winning score is the winner's bid price for FP and the sum product of unit price and estimated quantity for UP, in thousands of dollars.

Money on the Table is the percentage difference between the lowest score and the second lowest score in a given auction.

*Ex-pos*t pay adjustments for FP contracts are non-zero due to adjustments on uncontracted items.

Table 2: OLS Comparison of Contract Formats, Bidder Behavior, and Auction Outcomes

Dependent Variable	Entry	Score (log)	Winner's Score (log)	Final Payment (log)
FP (=0 if UP, =1 if FP)	-.0159	-.0293	-.00824	.00961
	(.0081)	(.0080)	(.016)	(.017)
Engineer's Cost Estimate (log)	-.0480	.976	.996	1.01
	(.0027)	(.0029)	(.00650)	(.0068)
# of Participating Bidders		-.0217	-.0373	-.0386
		(.0013)	(.0034)	(.0036)
# of Potential Bidders	-.00621	-.00392	-.00548	-.00410
	(.00053)	(.00060)	(.0014)	(.0015)
R^2	.374	.975	.980	.977
N	20131	8984	1890	1890

Bidders who win less than one percent of the total value of projects are grouped together as fringe firms.

All specifications also include district FE, Year Trend, Month FE, and Bidder FE.

Standard errors are clustered at the project/auction level and presented in parentheses.

Table 3: Endogenous Switching Model: Estimation Results

Dependent Variable	$score_j$ (log)					
Specification	(1)		(2)		(3)	
Regime	FP	UP	FP	UP	FP	UP
ρ_f, ρ_u	-.690	.0872	-.653	.0673	-.649	.0760
	(.10)	(.070)	(.16)	(.060)	(.15)	(.066)
σ_f, σ_u	.352	.237	.340	.236	.337	.233
	(.030)	(.0081)	(.031)	(.010)	(.033)	(.0072)
Engineer's Cost Estimate (log)	1.02	.987	1.01	.988	1.01	.990
	(.015)	(.010)	(.016)	(.011)	(.014)	(.0077)
Bidder Backlog	1.28	.796	1.28	.778	1.57	1.96
	(.40)	(.19)	(.55)	(.15)	(.61)	(.28)
# of Participating Bidders	-.0199	-.0248	-.0200	-.0242	-.0189	-.0253
	(.0082)	(.0033)	(.0101)	(.0030)	(.0088)	(.0026)
Month FE	N	N	Y	Y	Y	Y
Bidder FE	N	N	N	N	Y	Y
Observations	8,977	8,977	8,977	8,977	8,977	8,977

Standard errors are clustered at the district-year level and given in parantheses.

District office backlog, district fixed effects, and year trends are controlled for in all specifications.

Bidders that have won less than one percent of the total value of projects are grouped together as fringe firms.

District office backlog is calculated as the total dollar value of incomplete projects at the time of project letting.

Table 4: Share of non-lumpsum bids and bidding strategy

Dependent variable	score (log)		win	
Non-lumpsum bid as a share of score	-.636	-.832	1.35	1.58
	(.030)	(.034)	(.10)	(.11)
Auction FE	Y	Y	Y	Y
Bidder FE	N	Y	N	Y
Observations	6,373	6,373	6,373	6,373

Standard errors given in parentheses.

Table 5: Structural Estimation Results

Parameter	α	σ^L	σ^H	θ_0	θ_1	σ_{e0}	σ_{e1}	ρ	μ_{ec}	σ_{ec}	P
Estimate	7.98	.0837	.0995	.237	.756	.982	.0140	.758	.0181	.0232	.449
Standard Error	(1.7)	(.0083)	(.010)	(.048)	(.074)	(.29)	(.0029)	(.038)	(.0036)	(.0049)	(.086)

Block-bootstrapped standard errors are given in parentheses.

Auction level characteristics include engineer estimates of project cost, which accounts for more than 90% of score variation.

The engineer's cost estimate is an estimate of the winning bid price, as predicted by an FDOT engineer prior to auction.

Table 6: Distribution of Actual Bids vs Simulated Bids

$\left(s^0_{u,ia}, b^0_{1,ia}\right)$	Actual bids		Simulated bids	
Number of bidders: n	**Mean**	**Std.**	**Mean**	**Std.**
$n = 3$	$(1.03, .809)$	$(.221, .256)$	$(1.08, .740)$	$(.185, .209)$
$n = 5$	$(1.01, .796)$	$(.215, .212)$	$(1.05, .740)$	$(.195, .209)$
$n = 7$	$(.973, .774)$	$(.194, .158)$	$(1.04, .740)$	$(.200, .209)$
$n = 9$	$(.953, .774)$	$(.241, .209)$	$(1.03, .740)$	$(.203, .209)$

Moments of homogenized score and non-lumpsum bids for a given n are presented in parentheses.

Table 7: Effect of switching from UP to FP on final payment

	State L (σ^L)	State H (σ^H)
Change in final payment without change in entry behavior	1.61%	2.82%
Change in final payment due to change in entry behavior	-.22%	-.34%
Total change in final payment	1.39%	2.48%

Table 8: Effect of reserve price on final payment in UP

	State L (σ^L)	State H (σ^H)
Change in final payment	-.20%	-.071%

Reserve price on non-lumpsum bids is set at $\hat{\theta}_1$.

Online Appendix to "Bidding for Contracts under Uncertain Demand: Skewed Bidding and Risk Sharing"

Yao Luo* Hidenori Takahashi†

September 1, 2022

Appendix A

This subsection contains additinal figures, tables and results in the order they appear in the main text.

*University of Toronto; yao.luo@utoronto.ca.
†Kyoto Institute of Economic Research, Kyoto University; takahashi.hidenori@kier.kyoto-u.ac.jp.

Examples of projects that may be good Lump Sum contracting candidates:

- Bridge painting
- Bridge projects
- Fencing
- Guardrail
- Intersection improvements (with known utilities)
- Landscaping
- Lighting
- Mill/Resurface (without complex overbuild requirements)
- Minor road widening
- Sidewalks
- Signing
- Signalization

Examples of projects that may not be good Lump Sum contracting candidates:

- Urban construction/reconstruction
- Rehabilitation of movable bridges
- Projects with subsoil earthwork
- Concrete pavement rehabilitation projects
- Major bridge rehabilitation/repair projects where there are many unknown quantities.

Figure A.1: Excerpt from The FDOT Project Guidelines

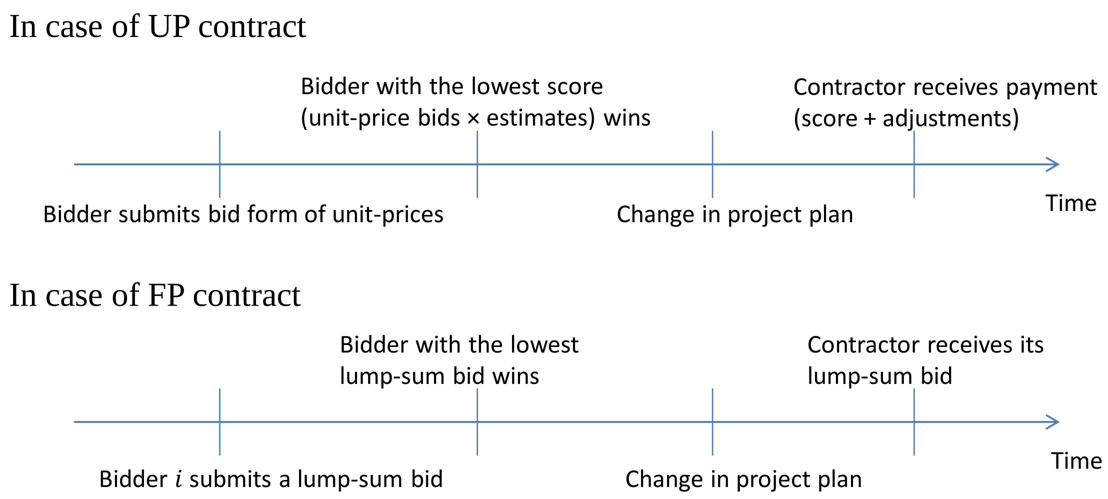

Figure A.2: Timeline of Events

Table A.1: Endogenous Switching Model: Relevance of Excluded Variables

Dependent Variable	FP (=1 if FP, =0 if UP)		
Specification	(1)	(2)	(3)
District Office Backlog	.844	.853	.884
	(.13)	(.14)	(.14)
District FE	y	y	y
Project Characteristics	y	y	y
Year Trend	y	y	y
Month FE	n	y	y
Bidder FE	n	n	y
N	1890	1890	1890

Standard errors are clustered at the district-year-month level. Project characteristics include engineer's estimate of project cost and number of plan holders. District office backlog is calculated as the total dollar value of incomplete projects at the time of project letting.

Table A.2: Endogenous Switching Model: without the Period of Stimulus Spending

Dependent Variable	$score_j$ (log)					
Specification	(1)		(2)		(3)	
Regime	FP	UP	FP	UP	FP	UP
ρ_f, ρ_u	-.759	.177	-.739	.0183	-.737	.0214
	(.11)	(.26)	(.13)	(.19)	(.13)	(.18)
σ_f, σ_u	.359	.214	.344	.210	.342	.207
	(.029	(.010)	(.027)	(.0093)	(.027)	(.0093)
Engineer's Cost Estimate (log)	.991	.991	.996	.996	.997	.997
	(.011	(.011)	(.0090)	(.0090)	(.0089)	(.0089)
Bidder Backlog	.122	.122	.0775	.0775	.843	.843
	(.19	(.19)	(.20)	(.20)	(.32)	(.32)
# of Participating Bidders	-.0142	-.0142	-.0145	-.0145	-.0155	-.0155
	(.0036	(.0036)	(.0033)	(.0033)	(.0033)	(.0033)
Month FE	n	n	y	y	y	y
Bidder FE	n	n	n	n	y	y
N	3933	3933	3933	3933	3933	3933

Standard errors are clustered at the district-year level.

District office backlog, district fixed effects, and year trends are controlled for in all specifications.

Bidders that have won less than one percent of the total value of projects are grouped together as fringe firms.

District office backlog is calculated as the total dollar value of incomplete projects at the time of project letting.

Table A.3: Test of Endogeneity of Excluded Variable

Dependent Variable	Time Overrun		
District Office Backlog	-.458	-.437	-.266
	(.37)	(.38)	(.38)
Bidder Backlog	y	y	y
Project Characteristics	y	y	y
District FE	y	y	y
Year Trend	y	y	y
Month FE	n	n	y
Bidder FE	n	n	n
N	1890	1890	1890

Standard errors are clustered at the district-year-month level.

Time overrun is defined as the log-difference in actual and expected contract days.

The test is conducted using the sample of 1,890 winning contractors.

Table A.4: Contract Type for Top 10 Items in UP contracts

Item Category	**Contractual Arrangement**	**Frequency**
Mobilization	Lumpsum	1241
Maintenance of Traffic	Lumpsum	1239
Work Zone Sign	Per Day	1217
Temporary Barricade	Per Day	1168
Advanced Warning / Arrow Board	Per Day	890
High Intensity Flashing Lights	Per Day	1200
Temporary Retro-reflective Pavement Marker	Each Unit	865
Portable Changeable Message Sign	Per Day	1004
Clearing & Grubbing	Lumpsum	1067
Painted Pavement Markings	Lumpsum	788

The means are calculated using the lowest bidder's unit-price bid from 1,341 unit-price auctions.

Quantities are estimated by FDOT prior to auction.

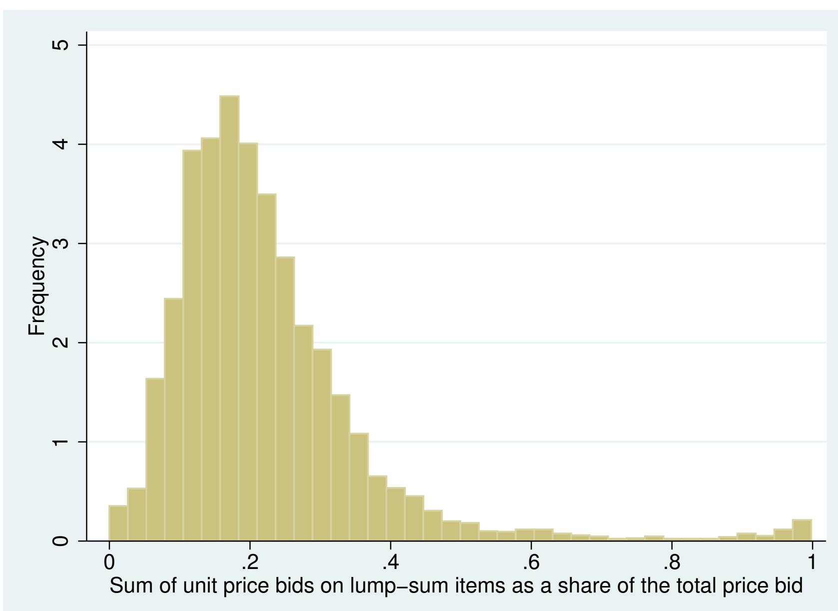

Figure A.3: Distribution of the sum of unit prices across lumpsum items as a share of bidder score

Table A.5: Variance Decomposition of Share of Non-Lumpsum Bids

	Std. Dev.	Percentage
Between-Auction	.130	70%
	(.0027)	
Within-Auction Between-Bidder	.0560	30%
	(.0005)	

Standard errors are given in parentheses.

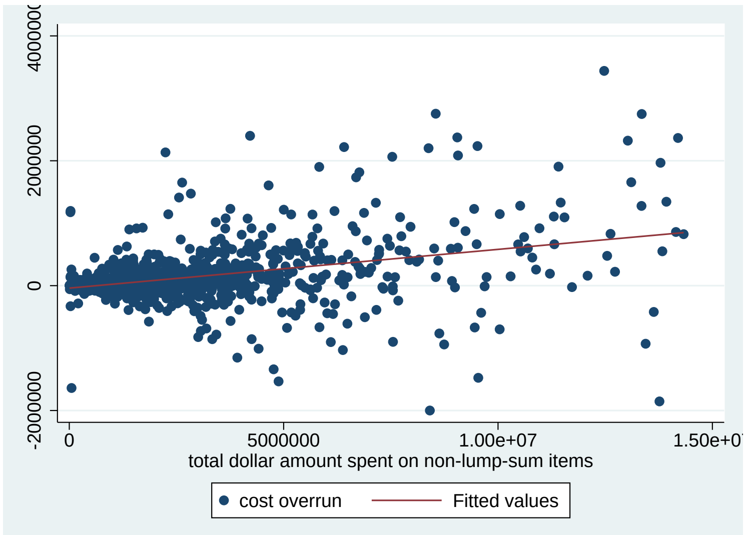

Figure A.4: Cost Overrun and Bids on Non-Lumpsum Items

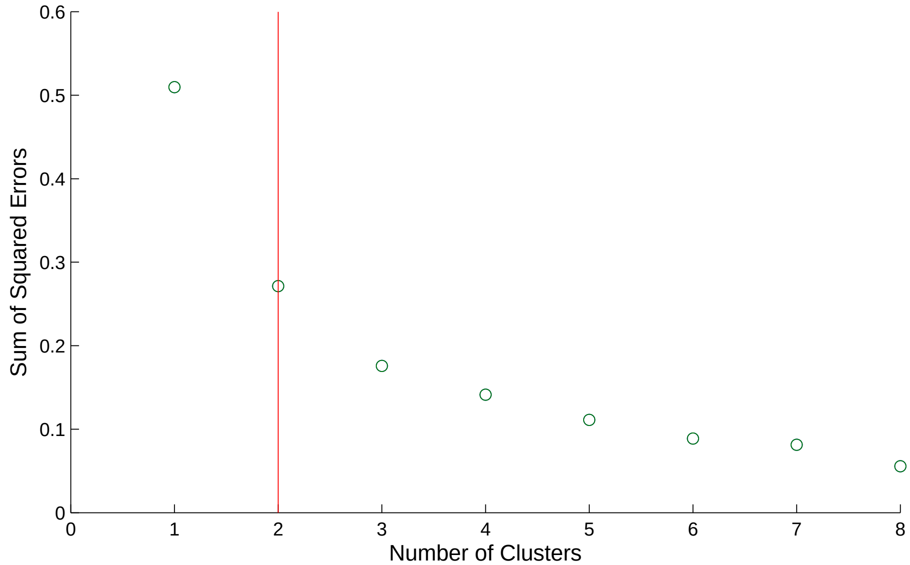

Figure A.5: Elbow Test on The Variance of Non-lumpsum Bids

Table A.6: OLS Comparison of Efficiency of Winning Bidders relative to Non-Winning Bidders

Dependent variable	e_0	e_1
Winner	-.473	-.00567
	(.033)	(.00056)

Standard errors are given in parentheses.

Appendix B: More Results on Contract Formats

There is also a large degree of heterogeneity in the use of these two contractual arrangements across FDOT district offices. Figure A.6 plots the varying levels of intensity in the use of FP relative to UP contracts for each of FDOT's seven district offices across time. As a district office procures multiple projects at a time, the intensity of FP use is measured by the share of all FP projects over the sum of FP and UP projects procured during a year.

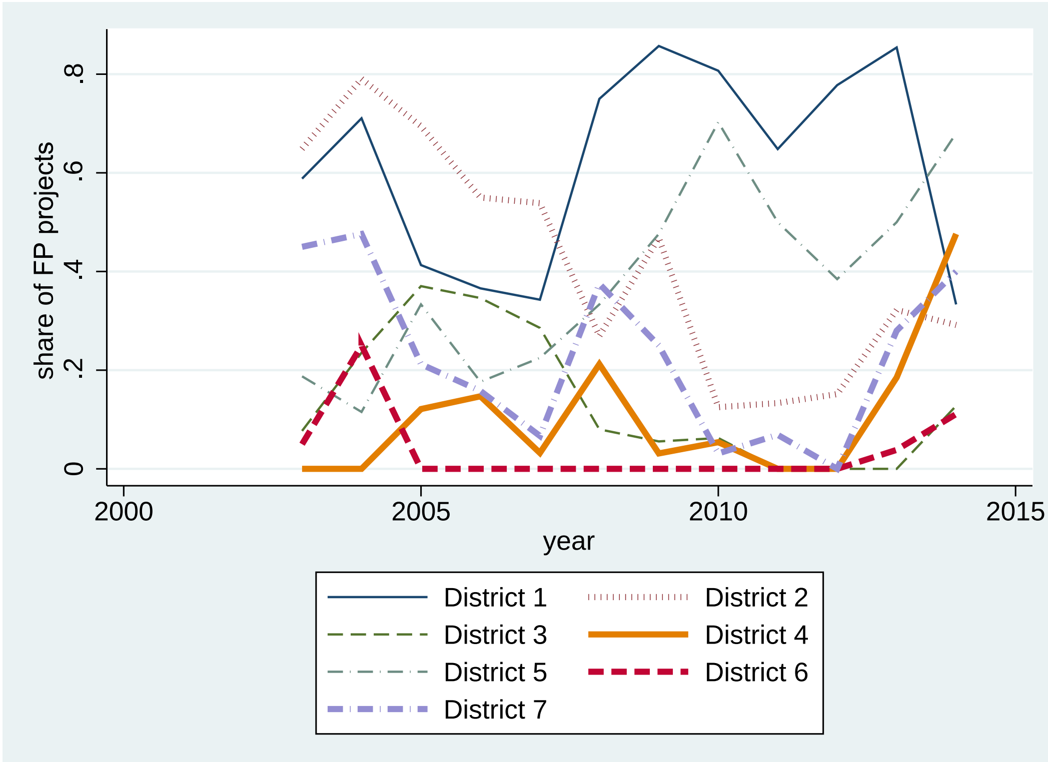

Figure A.6: Use of FP over UP at each FDOT district office

Two observations can be made from Figure A.6. First, there is state dependency in the use of FP over UP contracts while exhibiting much variation across time, which could be a product of turnover in project managers. Second, there is a common sharp increase in the use of FP over UP for the year following the financial crisis in 2008. In February 2009, the American Recovery and Reinvestment Act was signed into law. This stimulus package placed an emphasis on infrastructure investment, which raised the number of procurements significantly. If FDOT is capacity constrained, then FDOT may choose to procure those additional projects via FP. UP could involve higher transaction costs in order to estimate the quantity of each construction item, and to keep track of materials used. Indeed, FDOT engineers mention that the bulk of the administrative costs associated with UP comes from keeping track of materials used.

Table A.7: OLS Comparison of Contract Formats: Entry

Dependent Variable	Entry			
FP (=0 if UP, =1 if FP)	-.00342	-.0038	-.00427	.0151
	(.0098)	(.0097)	(.0098)	(.0085)
Engineer's Cost Estimate (log)	-.00481	-.00806	-.0058	-.0289
	(.0033)	(.0033)	(.0034)	(.003)
# of Potential Bidders	-.0109	-.0102	-.0105	-.00625
	(.00057)	(.00059)	(.00061)	(.00054)
District FE	y	y	y	y
Year Trend	n	y	y	y
Month FE	n	n	y	y
Bidder FE	n	n	n	y
R^2	.0623	.0632	.0654	.393
N	20131	20131	20131	20131

Bidders that win less than one percent of the total value of projects are grouped together as fringe firms.
Standard errors are clustered at the project/auction level and presented in parentheses.

Table A.8: OLS Comparison of Contract Formats: Score

Dependent Variable	Score (log)			
FP (=0 if UP, =1 if FP)	-.0512	-.0502	-.0471	-.027
	.0083	.0083	.0083	.0081
Engineer's Cost Estimate (log)	.985	.99	.989	.975
	.0026	.0027	.0027	.003
# of Participating Bidders	-.0199	-.0196	-.0199	-.0202
	.0013	.0013	.0013	.0014
# of Potential Bidders	-.00376	-.00502	-.00459	-.00563
	.00058	.00059	.00061	.00061
District FE	y	y	y	y
Year Trend	n	y	y	y
Month FE	n	n	y	y
Bidder FE	n	n	n	y
R^2	.969	.969	.97	.975
N	8984	8984	8984	8984

Bidders that win less than one percent of the total value of projects are grouped together as fringe firms.
Standard errors are clustered at the project/auction level and presented in parentheses.

Table A.9: OLS Comparison of Contract Formats: Winner's Score

Dependent Variable	Winner's Score (log)			
FP (=0 if UP, =1 if FP)	-.0489	-.0475	-.0436	-.00573
	.016	.016	.016	.017
Engineer's Cost Estimate (log)	1	1.01	1.01	.989
	.0055	.0057	.0057	.0069
# of Participating Bidders	-.0344	-.0343	-.0344	-.0336
	.0031	.0031	.0031	.0034
# of Potential Bidders	-.00585	-.00708	-.00662	-.00764
	.0013	.0013	.0013	.0014
District FE	y	y	y	y
Year Trend	n	y	y	y
Month FE	n	n	y	y
Bidder FE	n	n	n	y
R^2	.972	.972	.973	.981
N	1890	1890	1890	1890

Bidders that win less than one percent of the total value of projects are grouped together as fringe firms.
Standard errors are clustered at the project/auction level and presented in parentheses.

Table A.10: OLS Comparison of Contract Formats: Final Payment

Dependent Variable	Final Payment (log)			
FP (=0 if UP, =1 if FP)	-.0386	-.0375	-.0343	.012
	.016	.016	.017	.017
Engineer's Cost Estimate (log)	1.02	1.02	1.02	1
	.0058	.006	.006	.0071
# of Participating Bidders	-.0352	-.0351	-.0351	-.0347
	.0033	.0033	.0033	.0036
# of Potential Bidders	-.00479	-.0058	-.00525	-.00638
	.0013	.0014	.0014	.0015
District FE	y	y	y	y
Year Trend	n	y	y	y
Month FE	n	n	y	y
Bidder FE	n	n	n	y
R^2	.969	.969	.969	.979
N	1890	1890	1890	1890

Bidders that win less than one percent of the total value of projects are grouped together as fringe firms.
Standard errors are clustered at the project/auction level and presented in parentheses.

Table A.11: Top 10 Contractors for FP and UP Contracts

Top Contractors for FP	# of FP contracts	Top Contractors for UP	# of UP contracts
APAC-Southeast	73	Anderson Columbia Co.	103
Anderson Columbia Co.	70	Community Asphalt	101
AJAX Paving	47	APAC-Southeast	73
Lane Construction	33	Ranger Construction	72
Better Roads	31	Weekley Asphalt Paving	71
L-J Construction Co.	23	Hubbard Construction	51
C.W. Roberts Contracting	21	C.W. Roberts Contracting	47
Ranger Construction	19	General Asphalt Co.	38
Hubbard Construction	16	AJAX Paving	34
D.A.B. Constructors	14	P&S Paving	32

Appendix C: Derivation of (16)

Under the UP contract, a bidder's utility maximization problem with a pseudo-cost c_u is given by:

$$\max_{s_u} \quad [1 - G_n(s_{u,i}|X)]^{n-1}\, u\left(s_{u,i} - c_{u,i}|X\right),$$

where $u(.)$ is CARA utility.

The first-order optimality condition gives:

$$\frac{u(s_{u,i} - c_{u,i}|X)}{u'(s_{u,i} - c_{u,i}|X)} = \frac{1 - G_n(s_{u,i}|X)}{(n-1)g_n(s_{u,i}|X)}.$$

Rewriting the left-hand side of the above equation explicitly, we have:

$$\frac{u(s_{u,i} - c_{u,i}|X)}{u'(s_{u,i} - c_{u,i}|X)} = \frac{1}{\alpha(X)}\left(\exp\left\{\alpha(s_{u,i} - c_{u,i})\right\} - 1\right).$$

Rearranging the above first-order condition, we have:

$$s_{u,i} - \frac{1}{\alpha(X)} ln \left(1 + \alpha(X) \frac{1 - G_n(s_{u,i}|X)}{(n-1)g_n(s_{u,i}|X)}\right) \quad = \quad c_{u,i}.$$

Given we know that $b_i = \theta(X) + \frac{e_i - \iota}{\alpha(X)}\Sigma^{-1}$ and $c_{u,i} = \theta_0(X)e_{0,i} + \theta(X)\iota^T - \frac{1}{2\alpha(X)}(e_i - \iota)\Sigma^{-1}(X)(e_i - \iota)^T$, we have:

$$s_{u,i} - \theta(X)\iota^T - \frac{1}{\alpha(X)} ln \left(1 + \alpha(X) \frac{1 - G_n(s_{u,i}|X)}{(n-1)g_n(s_{u,i}|X)}\right) + \frac{\alpha(X)}{2}(b_i - \theta(X))\Sigma(X)(b_i - \theta(X))^T \quad = \quad \theta_0(X)e_{0,i}.$$

Therefore, we have:

$$E\left[s_{u,i} - \theta(X)\iota^T - \frac{1}{\alpha(X)} ln \left(1 + \alpha(X) \frac{1 - G_n(s_{u,i}|X)}{(n-1)g_n(s_{u,i}|X)}\right) + \frac{\alpha(X)}{2}(b_i - \theta(X))\Sigma(X)(b_i - \theta(X))^T | b_i, X\right] \quad = \quad \theta_0(X).$$

Appendix D: Bid Homogenization

We show that the unique equilibrium bidding strategies and cost overruns are multiplicatively separable in project characteristics X given the econometric specification in (18). To see this, let us make explicit the dependency of outcome variables on the primitives.

Let $b_{1,ia} := b_1\left(\theta_1(X_a), \sigma(X_a), \alpha(X_a), e_{1,ia}\right)$, $s_{u,ia} := s_u\left(\theta_0(X_a), \theta_1(X_a), \sigma(X_a), \alpha(X_a), e_{0,ia}, e_{1,ia}, n\right)$, and $\Delta_a := \Delta\left(\theta_1(X_a), \sigma(X_a), \alpha(X_a), e_{1,1a}, \epsilon_a\right)$. Define $b^0_{1,ia} := b_1\left(\theta_1(0), \sigma(0), \alpha(0), e_{1,ia}\right)$, $s^0_{u,ia} := s_u\left(\theta_0(0), \theta_1(0), \sigma(0), \alpha(0), e_{0,ia}, e_{1,ia}, n\right)$, and $\Delta^0_a := \Delta\left(\theta_1(0), \sigma(0), \alpha(0), e_{1,1a}, \epsilon_a\right)$ as "normalized" non-lumpsum score, normalized score, and normalized cost overrun, respectively. This multiplicative separability of project characteristics allows for the bid-homogenization approach in a setting with CARA bidders and reduces computational burden by reducing the number of auctions the econometrician has to solve.

Proposition. *Given the econometric specification above, the unique equilibrium non-lumpsum bidding strategy, scoring strategy, and cost overrun are all multiplicatively separable in project* *characteristics, such that:*

$$\begin{aligned} b_{1,ia} &= b_{1,ia}^0 \exp\{X_a\beta\}, \\ s_{u,ia} &= s_{u,ia}^0 \exp\{X_a\beta\}, \\ \Delta_a &= \Delta_a^0 \exp\{X_a\beta\}. \end{aligned}$$

First, consider non-lumpsum bidding strategy $b_{1,i} := b_{1,i}(\theta_1(X), \sigma(X), \alpha(X), e_{1,i})$. We know that:

$$\begin{aligned} b_{1,i}(\theta_1(X), \sigma(X), \alpha(X), e_{1,i}) &= \theta_1(X) + \frac{e_{1,i} - 1}{\alpha(X)\sigma(X)} \\ &= \left(\theta_1 + \frac{e_{1,i} - 1}{\alpha\sigma}\right) \exp\{X\beta\} \\ &= b_{1,i}^0 \exp\{X\beta\}, \end{aligned}$$

where the second line follows directly from the normalization assumption (18). Therefore, the non-lumpsum bidding strategy is multiplicatively separable in X.

Second, we show that the scoring strategy is multiplicatively separable in X. To see this, let us first consider the pseudo-cost $c_{u,i} := \theta_0(X)e_{0,i} + \theta_1(X) - \frac{1}{2\alpha(X)\sigma(X)}(e_{1,i} - 1)^2$ and $c_{u,i}^0 := c_{u,i}(0)$. We have:

$$\begin{aligned} c_{u,i} &= \left(\theta_0 e_{0,i} + \theta_1 - \frac{(e_{1,i} - 1)^2}{2\alpha\sigma}\right) \exp\{X\beta\} \\ &= c_{u,i}^0 \exp\{X\beta\}, \end{aligned}$$

and thus, pseudo-cost is multiplicatively separable in X. Now, conjecture that $s_{u,i} := s_{u,i}(\theta_0(X), \theta_1(X), \sigma(X), \alpha(X), e_{0,i}, e_{1,i}) = s_{u,i}^0 \exp\{X\beta\}$ constitutes an equilibrium scoring strategy. Consider the first-order condition with respect to score given by:

$$\begin{aligned}
s_{u,i} - \frac{1}{\alpha(X)} ln\left(1 + \alpha(X)\frac{1 - G_n(s_{u,i}|X)}{(n-1)g_n(s_{u,i}|X)}\right) &= c_{u,i}, \\
s_{u,i}^0 - \frac{1}{\alpha} ln\left(1 + \alpha\frac{1 - G_n(s_{u,i}^0|X=0)}{(n-1)g_n(s_{u,i}^0|X=0)}\right) \exp\{X\beta\} &= c_{u,i}^0 \exp\{X\beta\}, \\
s_{u,i}^0 - \frac{1}{\alpha} ln\left(1 + \alpha\frac{1 - G_n(s_{u,i}^0|X=0)}{(n-1)g_n(s_{u,i}^0|X=0)}\right) &= c_{u,i}^0,
\end{aligned}$$

where the second line follows because G_n is homogeneous of degree 0 while g_n is homogeneous of degree -1. Therefore, $s_{u,i} = s_{u,i}^0 \exp\{X\beta\}$ constitutes an equilibrium scoring strategy if $s_{u,i}^0$ is the equilibrium scoring strategy corresponding to pseudo-cost $c_{u,i}^0$. Because we know that the equilibrium is unique, $s_{u,i} = s_{u,i}^0 \exp\{X\beta\}$ is the unique equilibrium scoring strategy with $X \neq 0$.

Lastly, it is straightforward to see that $\Delta = \Delta^0 \exp\{X\beta\}$ from the cost overrun equation.

$$\begin{aligned}
\Delta &= b_{1,1}(e_{1,1} - 1 + \epsilon) \\
&= b_{1,1}^0(e_{1,1} - 1 + \epsilon) \exp\{X\beta\} \\
&= \Delta^0 \exp\{X\beta\}.
\end{aligned}$$

This completes the proof.