WINNING BY DEFAULT: WHY IS THERE SO LITTLE COMPETITION IN GOVERNMENT PROCUREMENT?

KARAM KANG AND ROBERT A. MILLER

Abstract. Government procurement contracts rarely have many bids, often only one. Motivated by the institutional features of federal procurement, this paper develops a principal-agent model where a buyer seeks sellers at a cost and negotiates contract terms with them. The model is identified and estimated with data on IT and telecommunications contracts. We find the benefits of drawing additional sellers are significantly reduced because the procurement agency can extract informational rents from sellers. Another factor explaining the small number of bids is that sellers are relatively homogeneous, conditional on observed project attributes. Administrative hurdles and corruption appear to play very limited roles.

1. Introduction

Procurement accounts for over 10 percent of U.S. federal government spending. Despite its vast size, the extent of competition for a procurement contract is not very intense: based on the data from the Federal Procurement Data System (FPDS), 44 percent of the procurement budget was paid to contracts only drawing a single bid during fiscal year 2015, for example. This paper seeks to quantify the factors determining the extent of competition by developing, identifying, and estimating a procurement model.

To conduct this analysis, we incorporate two important institutional features of federal procurement that have received attention from the literature but not yet studied

Date: June 28, 2021.
Kang (email: kangk@andrew.cmu.edu) & Miller (email: ramiller@cmu.edu): Tepper School of Business, Carnegie Mellon University. We would like to thank the editor, Áureo de Paula, anonymous referees, Decio Coviello, Francesco Decarolis, Navin Kartik, Kei Kawai, and Alessandro Lizzeri for helpful suggestions. The paper also benefited from comments by seminar and conference participants at ANU, Barcelona Summer Forum, Burton Conference at Columbia, Caltech, CIRPEE Political Economy Conference, Colombia IO Conference, CRES Applied Microeconomics Conference, Econometric Society Summer Meetings, Empirical Microeconomics Workshop in Banff, HKUST, IIES, IIOC, Korea University, LSE, NBER Summer Institute, Northwestern, Rice, SHUFE IO Mini Conference, SITE Summer Conference, Sogang, Stony Brook Center, TSE, UCL, UCLA, UNC Chapel Hill, UT Austin, U of Oklahoma, UPenn, UW Madison, and the Wallis Institute of Political Economy. Daniel Lee, Bridget Mensah, Manvendu Navjeevan, and Ana Rottaro provided excellent research assistance.

jointly. First, federal regulations allow a procurement agency (a buyer hereafter) a broad range of discretion to choose the extent to which a procurement project up for contracting will draw competitive bids. We study how competition is determined and quantify buyer preferences for the extent of competition, which may result from corruption, capture, administrative costs (Bajari and Tadelis, 2001; Bandiera et al., 2009), and noncontractible quality (Manelli and Vincent, 1995).

Second, the final contract price can differ from, and is often much larger than, the initially agreed upon price (Gagnepain et al., 2013; Bajari et al., 2014; Decarolis, 2014; Decarolis et al., 2020). We follow theoretical literature on optimal contracting in procurement (Laffont and Tirole, 1987; McAfee and McMillan, 1987; Riordan and Sappington, 1987) to analyze the detailed information on ex-post price and duration adjustments in the data. Jointly studying endogenous competition and price adjustments is important because competitive behavior affects initial contract terms and, hence, the final contract price. Section 2 further elaborates on these two important institutional details, delineates the institutional setting, explains the data sources, and presents empirical features that motivate our model.

The regulations give the buyer considerable discretion determining contract terms, as well as the extent of competition. However the data do not contain details about how negotiations on contract terms between the buyer and the sellers proceed, many of which could be informal; we only have details on procurement outcomes. For these reasons Section 3 models the procurement process as a two-stage noncooperative game where the buyer first chooses the extent of competition among sellers, and then negotiates contract terms.[1] The buyer is less informed than the sellers about their costs, and maximizes her expected payoff, which depends on the payment to the winning seller, effort she expends searching for additional bids if she permits competition, and her preference towards awarding the contract to a default seller rather than opening the process to competition.

We characterize optimal search and contracting when there are two types of sellers: low-cost and high-cost. In extract rent from low-cost sellers without deterring high cost sellers from bidding, while simultaneously economizing on the costs of attracting extra bidders, the buyer exploits differences between seller types in the probability distribution of contract outcomes, namely cost changes and duration adjustments. In equilibrium, sellers select a contract from a menu designed by the buyer, and the

[1]The alternative to negotiated acquisitions is a sealed bidding procedure. When only one seller is considered, sealed bidding is not possible; even when multiple sellers are considered, sealed bidding is rare in our data (less than 1 percent).

buyer chooses her preferred contract.[2] A typical contract in the menu specifies a base price and a mapping from contract outcomes to price adjustments. We prove the equilibrium menu separates the seller types, and includes a full insurance contract that low-cost sellers accept.

The data for our empirical analysis are sampled from the FPDS on procurement contracts in the IT and telecommunications sectors in the fiscal years 2004–2015. For each contract we observe whether the contract is competitively solicited, and if so, the number of sellers participating in the competition. We also observe the *contract type*, which specifies the conditions under which ex-post price adjustments can be made. A distinctive feature of the data is that they provide a full history of ex-post price and duration adjustments, along with the reasons for each adjustment. In addition, we observe various project attributes, the winning contractor, and the procurement agency.

The primitives in our structural econometric model include the distribution of seller costs for undertaking a project, sellers' risk preferences capturing the trade-off between receiving a fixed payment as opposed to an uncertain stream of payments, and costs the buyer incurs to solicit and intensify competitive bidding. Our data are likely to contain less information on seller costs than are available to the buyer, so we embed unobserved heterogeneity in the seller cost distribution, which both the buyer and sellers know. Specifically, the ex-ante probability that a seller is a low-cost type versus a high-cost one, denoted by π, is a project-specific random variable drawn from a probability distribution that depends on project and procurement agency attributes as well as the underlying extent of potential competition.

If there was only one bidder, then our model would predict the probability of observing a low-cost contract in the data is the unconditional mean of π. However more than 20 percent of our sample contracts have multiple bids, and in our model this implies the unconditional mean of π is less than the share of low-cost contracts. Since the buyer knows and conditions on π when designing a menu of contracts, the winning contract terms are determined by both π and the winning seller's cost type, neither of which are observed by us. This complicates identification and estimation, as

[2]Bajari and Tadelis (2001) argue that contract menus, such as Laffont and Tirole (1993), are not used for construction contracts, and mechanisms other than contract menus such as competitive bidding, reputation, and third-party bonding companies seem to be important in addressing adverse selection problems in procurement. In the contracts that we study, competition is not intense, most contractors do not win more than one contract, and performance and payment bonds are not required by federal acquisition regulations (FAR 28.103).

has been emphasized in the auction literature (Krasnokutskaya, 2011; Barkley et al., 2021).

Our semiparametric identification strategy, explained in Section 4, contributes to the literature on the identification of principal-agent models (Perrigne and Vuong, 2011; Gayle and Miller, 2015; An and Tang, 2019). We condition throughout on observed, exogenous contract attributes, and build upon the model's equilibrium conditions. Appealing to the separation property of the equilibrium, we directly infer the winning seller's cost type from the contract type reported in the data; this proves the probability distributions of observed contract outcomes for each seller type are identified. The sellers' risk preferences are identified from the buyer's first order condition for determining price adjustments, by exploiting assumptions that guarantee the base price of high-cost contracts are monotone in π. This leads to recovering the realizations of π for high-cost contracts, thus identifying the π distribution conditional on a high-cost seller winning. To identify the unconditional distribution of π, we use the model's predictions that in equilibrium a low-cost seller wins the contract unless all the bidders are high-cost, and that the low-cost contract is decreasing in π.

To identify seller costs, we exploit variation in the number of sellers, along with the equilibrium conditions that low-cost sellers are indifferent between the two contract types, and that high-cost sellers make no rents from winning the contract. Given the seller cost parameters, we partially identify the buyer's search costs as a function of π from the first order condition for her choice of search intensity, which determines the equilibrium number of bids. The probability of soliciting competition conditional on π helps identify the probability distribution of her solicitation costs.

Estimation, described in Section 5, follows the identification strategy, but due to the modest sample size, is parametric. Section 6 reports our empirical results. In the model when a buyer negotiates with a given number of sellers, rather than running a first-price sealed-bid auction, she extracts more rent and would benefit less from attracting extra sellers. We predict the expected equilibrium number of bids in an auction to be 4.3, almost tripling the expected number under negotiations, 1.6.

Aside from the format of the procurement mechanism that facilitates rent extraction by the buyer, several other factors help explain why there are so few bids. First, our estimates indicate the pool of sellers is relatively homogeneous. The average value of π in the sample is 0.94, whereas setting π to 0.5 for all projects sharply increases the expected number of bids to 6.5. We estimate that the average cost for a low-cost seller is \$360,870, which is \$40,910 lower than the average cost for a high-cost seller.

Doubling cost differences between two seller types increases the expected number of bids by 0.7. Second, halving the marginal search costs, estimated to be $1,700 per contract on average, increases the expected number by bidders by 0.6. Third, although our model cannot differentiate between the preferences of a social welfare maximizing buyer and a procurement agent with private interests, we find the buyer's cost of soliciting competitive bids averages only $60 per contract.

2. Institutional Background and Data

The data are drawn from the Federal Procurement Data System (FPDS), through usaspending.gov; it has also been used in recent studies by, for example, Warren (2014), Liebman and Mahoney (2017), and MacKay (ming). For each procurement contract, we observe the solicitation procedure, the number of bids, the contract type, and various attributes of the project and the winning contractor. We also construct the history of ex-post price and duration adjustments, based on the contracting officers' data entries. We augment this data with the federal human resources data (FedScope) from the U.S. Office of Personnel Management to incorporate the procurement agencies' attributes in the analysis, as well as the data on the number of establishments by industry from the County Business Patterns. This section describes the institutional background and the features of the data that are the most pertinent to our analysis.

2.1. **Scope of Analysis.** We analyze procurement contracts initiated in FY 2004–2015, focusing on those for information technology (IT) and telecommunications products (for example, computer hardware, software, and telecommunications equipment) and services (for example, IT strategy and architecture, programming, cyber security, and Internet service).[3] We study contracts that specify fixed schedules and quantities, such as definitive contracts and purchase orders.[4] A definitive contract is a mutually binding legal relationship, obligating the seller to provide the supplies or services for the procurement agency; a purchase order is an offer by the procurement agency to buy supplies or services, often using simplified acquisition procedures.

We further restrict our attention to contracts that satisfy the following six conditions. First, the *base maximal price*, defined as the total contract value including all

[3]Specifically, we study the contracts with a FPDS Product and Service code of Category 58 (Communication, Detection, and Coherent Radiation Equipment), 70 (Automatic Data Processing Equipment, Software, Supplies and Support Equipment), and D3 (IT and Telecommunications Service).

[4]Focusing on definitive contracts and purchase orders, we exclude indefinite delivery, indefinite quantity (IDIQ) contracts from our analysis.

options as agreed upon in the beginning of the contract, is below $1 million in 2010 CPI-adjusted dollars. Second, the *base price*, defined as the total amount of money that the government is obligated to pay in the beginning of the contract, is at least $150,000 in nominal dollars. The Federal Acquisition Regulations (FAR, 19.502) require the contracts with an anticipated value below $150,000 (and above $3,500) to be set aside for small businesses, and this paper does not study policies promoting small businesses. Third, the *base duration*, defined as the difference between the expected completion date, as agreed in the beginning of the contract, and its effective date, is at least 30 days and is no longer than 400 days. Fourth, the final contract end date, inferred from the contract entries, occurs before FY 2018. Fifth, we exclude the contracts performed outside of the U.S. because their cost structure could be very different. Lastly, we also exclude observations with missing or inconsistent information.[5] Appendix A.2 and Panel A of Table A2 provide more information on these sample selection criteria. There are 17,123 contracts that satisfy these six criteria, costing the government $6.2 billion (in 2010 dollars) in total.

2.2. **Competition and Solicitation Procedures.** Panel A of Table 1 presents summary statistics on the number of bids and the final contract price by the extent of competition, based the sample of the 17,123 contracts. *Full and open competition* is the default acquisition process, and federal regulations specify the circumstances under which a procurement agency is allowed to limit competition (FAR 6.2 and 6.3). For more than two thirds of the contracts in the sample, full and open competition was not employed. The reasons stated in the data can be categorized into three: (i) set-aside for small businesses due to statutory requirements, such as section 8(a) of the Small Business Act, (ii) unavailable for competition due to domestic statutes or international agreements, and (iii) not competed based on the procurement agency's *discretion*. The main reasons for discretionary restrictions are patent rights, copyrights, or brand (64 percent), follow-on contract (6 percent), and urgency (5 percent).

Panel B of Table 1 presents summary statistics by solicitation procedures. The most prevalent procedures are negotiation and simplified acquisition, and sealed bidding was rarely used (39 out of the sample in Table 1). Simplified acquisition is for contracts less than $150,000, or commercial items not exceeding $6.5 million.

If the negotiation procedure is employed, the procuring agency issues a request for proposal, upon which interested sellers submit their proposals. After receiving

[5]We conduct a sensitivity analysis using an expanded sample that includes 265 contracts with inconsistent information. Specification (11) in Table A13 shows our main results are unaffected.

TABLE 1. Competition for IT Contracts (FY 2004-2015)

	Obs.	Final price ($K)		Number of bids		
		Mean	SD	Mean	Median	Fraction one bid
Panel A: Competed or not						
Full and open competition	5,030	350.00	234.94	3.02	2	0.35
Set-aside for small business	2,534	343.04	232.24	4.11	3	0.27
No competition by regulation	3,376	423.60	293.81	1.03	1	0.99
No competition by discretion	6,183	359.37	228.49	1.00	1	1.00
Panel B: Solicitation procedures						
Negotiated proposal/quote	4,395	366.63	248.31	2.89	2	0.45
Simplified acquisition	5,964	344.70	229.29	2.49	1	0.58
Other procedures†	143	365.05	228.07	3.42	2	0.43
No solicitation	6,067	386.47	252.77	1.03	1	0.99
Not specified	554	393.12	322.07	1.82	1	0.80

Notes: This table provides summary statistics of all definitive contracts and purchase orders for IT and telecommunications products or services initiated during FY 2004–2015 and satisfy the six sample selection conditions as described in Section 2.1. *Final price* refers to the total amount of obligated money to the government in 2010 dollars. The categories of competition and solicitation procedures are based on four variables in the FPDS dataset,"extent competed," "reason not competed," "type of set aside," and "solicitation procedures," described in Appendix A.1.4. † Architect-engineer, basic research, and (two-step) sealed bids.

them, the agency determines the competitive range of the sellers and undertakes negotiations tailored to each seller, allowing the seller to revise his proposal regarding price, schedule, technical requirements, type of contract, or other terms of a proposed contract (FAR 15.3). After negotiations, the agency selects a winner based on the evaluation factors described in the solicitation.

2.3. **Final Sample and the Variables in Our Study.** Our analysis focuses on the contracts that are either competitively negotiated or awarded without competitive solicitation for discretionary reasons, in total of 6,981 contracts. To study the role of a buyer's discretion, we exclude contracts designated noncompetitive for statutory reasons. Our model is less suitable for analyzing sealed bidding or simplified acquisition procedure, where there is little scope for discretion (Bajari et al., 2008), and for studying procurement procedures related to basic research or professional services of an architectural and engineering nature. This yields a final sample of 2,375 competitive contracts and 4,606 noncompetitive ones, worth a total of $2.5 billion.[6] Table

[6]Of the 5,030 contracts in the "full and open competition" category in Panel A of Table 1, the negotiated proposal/quote procedure was employed for 2,375 contracts. The remainder, excluded from the analyses, consists of 2,402 contracts acquired through the simplified procedure; 83 through

2 provides the summary statistics of the various attributes of these contracts, and Appendix A.1 describes how each of the variables in the table are constructed.

We construct price and duration variables from the entries for each contract. The base price and the base duration, as defined in Section 2.1, are from the initial entry of a contract; the final price is the sum of all amounts of money that the government is obligated to pay across all entries; the final duration is the difference between the expected completion date as of the last entry and the initial effective date of the contract. The total price adjustment is the difference between the final and base price, the sum of three types of price adjustments. These depend on the reasons for adjustment: (i) work changes, such as new agreements for additional work, supplementary agreements, change orders, or termination; (ii) exercise of options or funding issues; (iii) administrative actions such as seller address changes. The duration adjustments are similarly defined.[7]

Table 2 shows the average final price is $363,710 in 2010 dollars, $26,960 (8 percent) higher than the average base price. The increase is mostly driven by the exercise of options and funding issues ($22,860), followed by work changes ($6,030). The average final duration is 297.6 days, 87.1 days (41 percent) longer than the average base duration. About half of the increase in duration is due to exercise of options and funding issues (42.8 days), and 30 percent due to administrative actions (26.5 days).

The FPDS dataset provides the number of bids, as recorded by the procurement agency.[8] Table 2 shows that the average number of offers is 1.64, and the average difference in the number of offers with and without competitive solicitation is 1.87. The most prevalent contract type is *firm-fixed-price* (96 percent). A firm-fixed-price contract provides for a price that is not subject to any adjustment on the basis of the contractor's cost experience in performing the contract (FAR 16.202). Price adjustments in a firm-fixed-price contract, however, are not uncommon (Table A5 and

uncommon procedures such as architect-engineer and basic research; and the rest through unspecified ones. Of the 6,183 contracts in the "no competition by discretion" category, 4,606 contracts are included in the final sample; 1,551 contracts acquired through the simplified procedure and 26 through uncommon procedures are excluded. See Appendix A.2 and Panel B of Table A2.

[7]Appendix A.1.3 explains how we construct the ex-post price and duration adjustment variables based on the entries in the FPDS data.

[8]Since we only observe contracts once they are awarded, we cannot account for how many times tendering for contracts goes unfilled, a shortcoming shared with many studies of auctions. In such cases the number of bidders are in effect undercounted if bidders in an unsuccessful auction fail to submit a bid in a subsequent auction for the same item(s). See Guerre and Luo (2019) for an analysis of first-price auctions when the number of bids is not observed.

TABLE 2. Summary Statistics of the Final Sample

	Mean	SD	Mean difference:	
	All		Competitively solicited vs. not	Firm-fixed vs. other
Price (in thousand 2010 dollars)				
Final	363.71	232.98	-9.43 (5.88)	-87.78 (14.58)
Base	336.75	188.77	-3.63 (4.77)	-23.83 (11.84)
Ex-post adjustments due to				
Work changes	6.03	65.01	-4.74 (1.64)	-25.02 (4.07)
Exercise of options and funding	22.86	106.82	-0.67 (2.70)	-47.04 (6.70)
Administrative actions	-1.94	39.51	-0.39 (1.00)	8.11 (2.48)
Duration (in days)				
Final	297.54	310.13	-28.73 (7.83)	-160.80 (19.36)
Base	210.44	130.97	-24.41 (3.30)	-39.23 (8.20)
Ex-post adjustments due to				
Work changes	17.79	101.45	-4.83 (2.56)	-19.92 (6.36)
Exercise of options and funding	42.84	183.58	3.42 (4.64)	-72.13 (11.49)
Administrative actions	26.46	152.22	-2.91 (3.85)	-29.52 (9.55)
Competitively solicited†	0.34	0.47	-	0.03 (0.03)
Number of bids	1.64	1.92	1.87 (0.04)	0.23 (0.12)
Contract type: Firm-fixed-price†	0.96	0.19	0.006 (0.005)	-
Project/procurement agency attributes				
Service (vs. product)†	0.26	0.44	-0.05 (0.01)	-0.51 (0.03)
Commercially available†	0.68	0.47	0.09 (0.01)	0.24 (0.03)
Definitive contract (vs. purchase order)†	0.49	0.50	-0.18 (0.01)	-0.11 (0.03)
Appropriations/Budget committee†	0.11	0.31	0.02 (0.01)	0.006 (0.02)
Department of Defense†	0.67	0.47	-0.02 (0.01)	0.18 (0.03)
Experienced contracting officers (CO)††	0.78	0.08	0.004 (0.002)	-0.03 (0.005)
Experience with similar contracts†	0.41	0.49	0.01 (0.01)	-0.05 (0.03)
Workload (number of contracts per CO)	4.86	3.08	0.25 (0.08)	-0.73 (0.19)
Potential competition				
Number of past winners	33.01	66.64	9.84 (1.68)	11.23 (4.18)
Number of establishments	696.12	1767.39	-164.8 (44.6)	-664.7 (110.6)

Notes: This table provides summary statistics of the variables used in our analysis for the final sample of 6,981 contracts. In the second last column, we provide the difference in sample means between the contracts competitively solicited and those not; in the last column, we provide the difference in sample means between firm-fixed-price contracts and others. See the text for the definition of each variable; †: indicator variables and ††: the fraction of contracting officers with 5 and more years of government experience in the procurement agency. The numbers in parentheses are standard errors.

A6 in Appendix B.3); for example, they may occur when there are ex-post changes in the nature of the work.

We construct ten variables to account for contract-specific observed heterogeneity. Four variables relate to the nature of the project. First, the project is for products (74 percent) or services, as designated by the FPDS Product and Service Code. Second, the product or service is either commercially available (68 percent) or not, as determined by the procurement agency. Third, about half of the contracts in our sample are definitive contracts, as opposed to purchase orders. Definitive contracts result from more intensive and specialized contracting, and the agency has little discretion over these two award types (Warren, 2014). Fourth, we look at the Congressional representation of the project location, focusing on the members of Congress who are in charge of the government budgeting and appropriations process: specifically, House Speakers, majority/minority leaders and whips, and chairmen or ranking members of the Committees on the Budget, Appropriations, and Ways and Means. The locations of 11 percent of the contracts were represented by such members.

Four variables capture observed heterogeneity in procurement agencies, which we aggregate to the level of the 15 cabinet executive departments or the 13 federal independent agencies. First, the Department of Defense (DoD) accounts for 67 percent of the contracts. The second variable is the fraction of the agency's contracting officers with at least 5 years of federal government experience. The third variable indicates whether the agency handled in the past three years a *similar* contract in the sense that Product and Service code, commercial availability, contract instrument (definitive contract or purchase order), and the state of the project location are the same. The fourth variable measures the amount of workload when the contract was signed, by the number of definitive contracts and purchase orders of size greater than $25,000 initiated during the fiscal year, per contracting officer of the agency.

The remaining two variables measure the extent of potential competition for each contract. First, we count the number of unique winners of the contracts that (i) are similar (as specifically defined above) to a given contract; (ii) were signed by the DoD (if the contract is also signed by that department) or other agencies (otherwise) in the past three years. The average number of such past winners is 33.01, but the distribution is skewed: 21 percent of contracts are associated with at most one past winner. Second, acknowledging that the first measure is likely to underestimate the level of potential competition by excluding losing contractors, we cast a wider net by computing the number of establishments that have the same North American Industry Classification System (NAICS) code and are located in the same state as the winner of a given contract during the year that the contract was signed.

2.4. **Endogenous Competition and Contract Type.** As discussed in Section 2.2, procurement agencies have discretion over whether to solicit competitive bids or not. Contracting officers must provide and certify the justification for not competitively soliciting bids. Approval by another official is required only if the contract size is over $0.7 million (FAR 6.3). We reviewed the justification documents associated with our sample, as available on the federal business opportunities website (`www.fbo.gov`).[9] Each document includes a section that provides qualitative reasons for not engaging in full and open competition (in 2.9 paragraphs on average). These documents sometimes acknowledge other sellers providing similar items.[10]

Procurement agencies also determine the extent to which they seek and exchange information with potential sellers, via pre-solicitation notices, requests for information, draft requests for proposals, public hearings, and market research, before issuing the actual solicitation. Furthermore, evaluating an additional bid incurs an extra administrative burden, and there is even anecdotal evidence that the risk of receiving a bid protest from losing sellers is nontrivial.[11]

These institutional features suggest that demand factors affect the number of bids. We regress the number of bids on contract attributes, and Column (2) of Table 3 shows the greater the procurement agency's workload, the fewer the bids.[12] Column (1) shows when more experienced contracting officers are employed in the agency, competitive solicitation is more likely. These findings are consistent with the notion that it is costly to acquire the market information and to wait for more bids.[13]

[9]We track the Justification and Approval (J&A) document for each contract by searching for public notices at `www.fbo.gov`. We match a public notice to a contract by the solicitation identifier, but that information is not required for contracting officers to provide for the FPDS dataset. As a result, we observe the identifier for only 40 noncompetitive contracts (1 percent); among that subset we identified public notices for 23 contracts, including 11 J&A documents in total.

[10]For example, the J&A document regarding VA11812Q0632 posted in September 2012 states: "Although other vendors provide similar imaging software, only iNtuition brand name software, through its use of the "thin client" server technology, meets this capability."

[11]Federal Times reported in July 2013 on how bid protests are slowing down procurements. The article quoted Mary Davie, assistant commissioner of the Office of Integrated Technology Services at the General Services Administration: "We build time in our procurement now for protests. We know we are going to get protested."

[12]In all the Table 3 regressions, we control for the ten contract attributes as described in Section 2.3, as well as fixed effects for four-digit Product and Service code; procurement agency; fiscal year and month contact is signed (Liebman and Mahoney, 2017); location of project by state.

[13]In addition, Table A4 in Appendix B.2 shows that using instruments eliminate the positive elasticity between price and the number of bids obtained in an OLS regression.

Table 3. Endogenous Competition

	Competitively solicited	Number of bids	Advertisement period	Log of num. bids
	(1)	(2)	(3)	(4)
Base duration $\geq$ 3 months	-0.083***	-0.532***	1.849	-0.191*
	(0.018)	(0.063)	(3.048)	(0.098)
Commercially available	0.046***	0.310***	-17.23***	0.329***
	(0.012)	(0.043)	(0.014)	(0.020)
Definitive contract	-0.045*	-0.173***	9.400**	0.056
	(0.022)	(0.059)	(3.990)	(0.110)
Agency's COs with 5+ years $\geq$ 80%	0.061**	0.037	-2.793	-0.0716
	(0.022)	(0.101)	(6.285)	(0.252)
Agency procured a similar contract	-0.004	0.008	-2.031	0.184
	(0.014)	(0.041)	(3.314)	(0.117)
Agency workload > 4.5	-0.006	-0.270**	0.638	-0.116
	(0.025)	(0.120)	(4.898)	(0.231)
Appropriations/Budget committees	0.047*	0.177	0.484	-0.116
	(0.025)	(0.120)	(6.974)	(0.169)
Number of past winners $\geq$ 2	0.020	0.127**	-8.455	0.280*
	(0.019)	(0.058)	(5.737)	(0.148)
Number of establishments $\geq$ 24	0.004	-0.032	3.713	-0.196
	(0.017)	(0.089)	(3.931)	(0.128)
Log (Advertisement period)				0.105***
				(0.051)
Product and Service Code FE	Yes	Yes	Yes	Yes
Procurement agency FE	Yes	Yes	Yes	Yes
State FE; Year FE; Month FE	Yes	Yes	Yes	Yes
N	6,981	6,981	388	388
R^2	0.158	0.131	0.552	0.420

Note: The dependent variables are: (1) a dummy variable indicating the contract was competitively solicited; (2) the number of bids; (3) the advertisement period; (4) the logarithm of the number of bids. The final sample is used for (1)–(2); those in the final sample with information from online public notices for (3)–(4). The standard errors are clustered at the 4-digit Product and Service Code level, and provided in parentheses; $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

For 394 contracts in our sample we augment solicitation information based on public notices available at `www.fbo.gov`.[14] We define the *advertisement period* as the number of days between the date of the first public notice, often for information acquisition before a solicitation, and the due date for the sellers to respond the solicitation. The advertisement period is 26.7 days on average, with the maximum of 194. Column (3)

[14]As discussed in Footnote 9, we use the solicitation identifier to match public notices with a contract, but the solicitation identifier is available for 712 contracts (10 percent). We found public notices for 394 of those contracts (55 percent). We observe when each notice was posted and seller responses are due. For 6 contracts, none of the related public notices require responses, so the number of observations in Columns (3)–(4) of Table 3 is 388.

of Table 3 presents the regression results explaining the advertisement period. They suggest that procurement agencies exert more search efforts on contracts that they expect to have a smaller pool of potential sellers: both commercial availability and purchase orders (as opposed to definitive contracts) are associated with more bids and shorter advertisement periods. Column (4) shows that, conditional on contract attributes, the advertisement period and the number of bids are positively correlated.

The regulations explicitly specify that the contract type is a matter for negotiation, recognizing the close relationship between final price and contract type (FAR 16.1).[15] Based on the 208 available solicitation documents, we find that (i) 26 percent of them do not specify a contract type; (ii) the contract type in the solicitation is not always identical to the actual type; (iii) even when the contract type is specified in the solicitation, the wording is not always definitive, stating that the government "intends to," "contemplates," or "anticipates" that the resulting contract will be a firm-fixed-price contract, for example.[16]

2.5. **Repeated Interaction.** We believe the scope for repeated interactions between the procurement agency and sellers is limited. First, Table 2 shows that for 59 percent of the contracts, the procurement agency does not have experience of procuring a similar contract to the contract in question within the past three years.[17] Second, Table 3 shows the procurement agency's experience of dealing with a similar contract is not correlated with the extent of competition.[18] Third, most sellers win only one contract during the period of study (Table A3 in Appendix B.1).

Our capacity to study collusion and reputation is limited; we observe the number of losing bids, but not their identities. However, the contracts in our sample tend to appear irregularly in terms of size and requirements. Coupled with the aforementioned point that most sellers win only once, these features make it difficult for sellers to maintain a collusive relationship (Porter and Zona, 1993). Although the data are

---

[15]FAR 16.103(a) states: "Selecting the contract type is generally a matter for negotiation and requires the exercise of sound judgement. Negotiating the contract type and negotiating prices are closely related and should be considered together."

[16]Among the 394 contracts that have public notices at `www.fbo.gov`, we retrieved the solicitation documents for only 208 contracts, mainly because the link to the documents was broken.

[17]In addition, a report of the US Government Accountability Office in 2009 (GAO-09-374) concludes that contracting officials are reluctant to rely more on past performance, partly because they are skeptical of the reliability of information and find it difficult to assess relevance to specific acquisition.

[18]On the flip side, Appendix B.1 shows that *repeat* sellers, those who have won contracts multiple times, do not necessarily face less competition than those who have not.

unsuitable for studying intertemporal incentives, we partially accommodate long-term relationships of buyer-seller pairs through buyer preferences for no competition.

3. Model

3.1. **Setup.**

The institutional features profiled in Section 2 guide our model. Suppose a buyer is assigned to administer a procurement process for a government project. There are two types of sellers, denoted by $k \in \{0, 1\}$.[19] The proportion of the second type in the population, denoted by $\pi \in (0, 1)$, is common knowledge to the buyer and the sellers. The total cost to a type k seller of completing the project is the sum of a type-specific initial cost, γ_k, plus an uncertain component. The latter component depends on contractible outcomes, denoted by $\mathbf{s}$, realized and observed by both parties after the project is completed, according to $f_k(\mathbf{s})$, a probability density function conditional on seller type. We denote the cost component determined by contractible outcomes by $c(\mathbf{s})$. The expected cost of a type k seller is denoted by c_k:

$$c_k \equiv \gamma_k + \int c(\mathbf{s}) f_k(\mathbf{s}) d\mathbf{s}.$$

The first seller type is designated *high-cost*, the second *low-cost*, and we assume

$$\gamma_1 < \gamma_0 \text{ and } \int c(\mathbf{s}) f_1(\mathbf{s}) d\mathbf{s} < \int c(\mathbf{s}) f_0(\mathbf{s}) d\mathbf{s}. \tag{1}$$

We assume γ_k is hidden information, known to the seller only, and therefore not contractible. We assume that $\mathbf{s}$ is informative but imperfect: $f_0(\mathbf{s}) \neq f_1(\mathbf{s})$ for some $\mathbf{s}$, but share a common support.

The solicitation rules described in Section 2.2 delegate responsibility to the buyer for deciding whether she will permit competition or not. If a buyer solicits competitive bids, as opposed to contracting with a default seller, there is a cost, η.[20] Regardless of whether she solicits competitive bids or not, the buyer designs a menu of contracts. Each contract in the menu is contingent on the number of sellers $n \in \{1, 2, \ldots\}$ who might bid. If she solicits competitive bids the buyer chooses how intensely to

[19] In the equilibrium menu derived in Theorem 3.1, there are as many seller types as there are contract types. As explained in Section 2.3, we partition contracts into one of two contract types, firm-fixed-price and other, to rationalize this assumption.

[20] The solicitation costs, η, incorporate the value to the buyer from the default seller compared to other sellers. In principle this value might arise from the default seller's level of specialization matching the specific needs of the buyer, concerns about noncontractible project quality from the other potential sellers, increased administrative costs incurred from engaging in a competitive solicitation process, as well as direct private benefits to the buyer from awarding the contract to the default seller, including bribery and corruption stemming from favoritism.

search for sellers if she permits competition, defined as the arrival rate of a Poisson distribution for the number of bids, $\lambda \in \mathcal{R}^+$, at the cost of $\kappa\lambda$. When a seller arrives, he selects and submits one contract from those listed on the menu. The buyer awards the project to a seller whose contract ranks the highest amongst total submissions, and ties are broken randomly.[21]

A typical contract denoted by $j \in \{0, 1, \ldots, J\}$ comprises a base price, which might depend on the number of sellers, n, we denote by p_{jn}, and a price adjustment, a mapping denoted by $q_{jn}(\mathbf{s})$. We assume there exists some fixed negative constant M that bounds the difference $q_{jn}(\mathbf{s}) - c(\mathbf{s})$ from below. In theory, this maximal penalty finesses situations where it might otherwise be optimal to achieve an outcome very close to first best, potentially achieved by imposing extremely steep penalties on low-cost winners for outcomes that would be very unlikely for high-cost sellers. In practice, M reflects limited liability and seller bankruptcy constraints.

The buyer is risk neutral. Denoting the winning contract by $\{p_{in}, q_{in}(\mathbf{s})\}$, the total cost of procurement is:

$$\begin{cases} p_{in} + q_{in}(\mathbf{s}) + \kappa\lambda + \eta & \text{if the buyer solicits competition with intensity } \lambda, \\ p_{i1} + q_{i1}(\mathbf{s}) & \text{if she contracts with a default seller.} \end{cases} \tag{2}$$

The seller can be risk averse. Liquidity concerns, or the cost of working capital, lead him to discount (enlarge) positive (negative) deviations from a contract that offers full insurance.[22] The payoff to a type k seller from winning $\{p_{in}, q_{in}(\mathbf{s})\}$ is:

$$p_{in} - \gamma_k + \psi\left[q_{in}(\mathbf{s}) - c(\mathbf{s})\right], \tag{3}$$

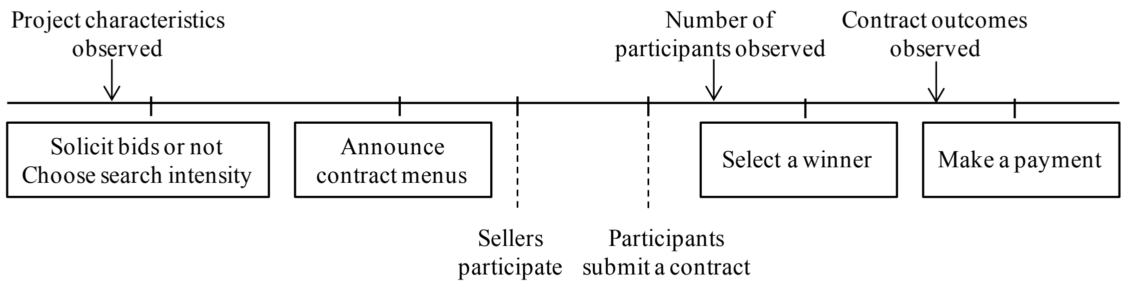
where $\psi(\cdot) : \mathcal{R} \to \mathcal{R}$ is continuous, with $\psi(0) = 0$, $\psi'(0) = 1$, and for any $r \in \mathcal{R}$, $\psi'(r) > 0$ and $\psi''(r) \leq 0$. Losing sellers receive a payoff of zero, as do sellers who opt out of the procurement process.

Summarizing the event sequence, first the buyer chooses whether to solicit competitive bids. At that time she also forms a contract menu, $\{p_{jn}, q_{jn}(\mathbf{s})\}_{j=0}^{J}$ including a

[21] An alternative model for negotiation is generalized Nash bargaining, which may be appropriate for a situation where there is a natural supplier with whom the government has an existing relationship based on past dealings. Given that in our data more than 50 percent of the winners only win once (Table A3 in Appendix B.1), this situation does not seem to apply to our data.

[22] The price adjustments can be costly, potentially due to adaptation costs (Crocker and Reynolds, 1993; Bajari and Tadelis, 2001; Bajari et al., 2014) and sellers' risk aversion (Baron and Besanko, 1987; Laffont and Rochet, 1998; Arve and Martimort, 2016). Arve and Martimort (2016) explicitly model firms' risk aversion in a procurement context. See pages 3240–3241 for their justifications, including imperfect risk management or diversification, bankruptcy or auditing cost of issuing debt, liquidity constraints, nonlinear tax systems, and internal agency problems.

Figure 1. Timeline of the Procurement Process



preference ordering over contracts on the menu. Contracts are contingent on the number of bidders n and the project outcomes $\mathbf{s}$, designed to screen seller types through their bids. If she does not solicit competitive bids there is only one bidder. If she solicits competitive bids, she chooses the level of search intensity, which stochastically determines the number of interested sellers. Sellers play a noncooperative game with a Bayesian equilibrium, each seller simultaneously making a bid through his selection of a contract. If there is more than one bid, the buyer follows her preference ordering to determine the winning contract. Payment is made on upon completion of the project, according to the specification of the winning contract, and the realization of contract outcomes $\mathbf{s}$. Figure 1 represents the timeline of the model.

3.2. **Designing the Contract Menu in Equilibrium.** If, contrary to the assumptions of our model, there was full information, the buyer would approach the low-cost seller, if there was one, and make an ultimatum offer to extract all the rent from the project. If sellers are risk neutral, the buyer could offer a lump sum payment of c_k to a type k seller; otherwise, the buyer could fully insure them with a contract that pays a base price of γ_k and a change of $c(\mathbf{s})$ induced by the outcome $\mathbf{s}$. When γ_k is private information to the seller, this simple arrangement is infeasible.

3.2.1. *Risk-neutral sellers.* Much of the intuition for the effects of private information about seller type on optimal contracting framework can be gleaned from a special case of the model, where there are no liquidity concerns, meaning $\psi(r) = r$.

First, the buyer can exploit precedence to induce sellers to separate into two contracts, when there are multiple sellers. To illustrate this point, consider a menu of two contracts of lump-sum payments, p_{0n} and p_{1n}, where $p_{1n} < p_{0n}$ and the low-priced contract, p_{1n}, is prioritized, that is ranked higher than the high-priced. In the noncooperative game following the menu determination, sellers do not participate unless their expected utility is weakly positive. So to guarantee the project is undertaken, $p_{0n} \geq c_0$. This inequality can be modeled as an individual rationality constraint on the buyer relating to high-cost sellers (IR_0), and Lemma A1 in Appendix C proves IR_0 binds: $p_{0n} = c_0$. Analogous reasoning motivates an individual rationality constraint for the low-cost sellers (IR_1), namely $p_{1n} \geq c_1$. Thus c_0 is offered to high-cost sellers, and buyer offers some lower price $p_{1n} \in [c_1, c_0)$ to low-cost sellers. To induce low-cost sellers to bid p_{1n} the expected value from doing so must be at least as great as the expected value from p_{0n}. Define ϕ_{1n}, the winning probability if he chooses p_{1n} when the other sellers follow the same equilibrium strategy, as:

$$\phi_{1n} \equiv \sum_{i=0}^{n-1} \binom{n-1}{i} \frac{\pi^i (1-\pi)^{n-1-i}}{i+1} = \frac{1}{n\pi} \sum_{i=1}^{n} \binom{n}{i} \pi^i (1-\pi)^{n-i} = \frac{1-(1-\pi)^n}{n\pi}. \quad (4)$$

If he chooses p_{0n} instead, the probability of winning is:

$$\phi_{0n} \equiv n^{-1}(1-\pi)^{n-1}. \quad (5)$$

Thus a low-cost seller prefers p_{1n} to p_{0n} if and only if:

$$\phi_{1n} (p_{1n} - c_1) \geq \phi_{0n} (c_0 - c_1). \quad (6)$$

We treat (6) as an incentive compatibility constraint for the low-cost seller (IC_1) that the buyer must respect when designing the menu. Note that IC_1 must bind when IR_1 does not; otherwise p_{1n} could be reduced without violating either constraint and reducing the expected amount of the buyer's payment to a winning seller. Making p_{1n} the subject of the resulting equality and simplifying:

$$p_{1n} = c_1 + \frac{\pi(1-\pi)^{n-1}}{1-(1-\pi)^n} (c_0 - c_1).$$

Thus p_{1n} declines in n, converging to c_1 and replicating a first-price sealed-bid auction with reservation price c_0. When $n = 1$, this menu reduces to a pooling equilibrium, but when $n > 1$, it is separating, $p_{1n} < c_0$, and hence the expected payment is strictly less than the pooling menu that satisfies IR_0, namely c_0.

Second, exploiting contract outcomes to further penalize the low-cost seller from deviating to the high-cost contract gives the buyer more leverage to extract rent from the low-cost seller. Intuitively, the contract for the high-cost seller is designed to discourage the low-cost seller from choosing it, by rewarding outcomes that are more likely to occur when a high-cost seller wins the project, and penalizing outcomes that are more likely if the low-cost seller had chosen the high-cost contract and won the project. For example, define:

$$r(\mathbf{s}) \equiv \begin{cases} (\gamma_0 - \gamma_1) / \int_{f_0(\mathbf{s}) \geq f_1(\mathbf{s})} [f_0(\mathbf{s}) - f_1(\mathbf{s})] \, d\mathbf{s} + M & \text{if } f_1(\mathbf{s}) \leq f_0(\mathbf{s}), \\ M & \text{otherwise,} \end{cases}$$

and set a menu of two contracts, consisting of $\{p_{1n}, q_{1n}(\mathbf{s})\} = \{c_1, 0\}$ and $\{p_{0n}, q_{0n}(\mathbf{s})\} = \left\{c_0 - \int [r(\mathbf{s}) + c(\mathbf{s})] f_0(\mathbf{s}) d\mathbf{s}, r(\mathbf{s}) + c(\mathbf{s})\right\}$. By inspection, the menu satisfies all constraints: IC_0 does not bind; IC_1 binds as does IR_1 and IR_0; the limited liability does not bind if $f_1(\mathbf{s}) \leq f_0(\mathbf{s})$ and binds otherwise. Under this menu, the buyer can extract all the seller surplus. Thus, given any number of sellers, the buyer offers a separating menu that exploits information from contract outcomes.

3.2.2. *Risk-averse sellers.* The intuition from the risk-neutral sellers can be extended to situations in which $\psi(r)$ is strictly concave. Some additional notation helps. Let $l(\mathbf{s}) \equiv f_1(\mathbf{s})/f_0(\mathbf{s})$ denote the likelihood ratio, and define the threshold likelihood ratio associated with the limited liability condition by:

$$\tilde{l}(\pi) \equiv \frac{1}{\pi} - \frac{1-\pi}{\pi \psi'(M)}. \tag{7}$$

Lemma A6 in Appendix C proves there is at most one root in $\pi \in (0,1)$ to the following expression:

$$\gamma_0 - \gamma_1 - \int \psi\left(\psi'^{-1}\left[\frac{1-\pi}{1-\pi l(\mathbf{s})}\right] \mathbb{1}\{l(\mathbf{s}) \leq \tilde{l}(\pi)\} + M \mathbb{1}\{l(\mathbf{s}) > \tilde{l}(\pi)\}\right) [f_0(\mathbf{s}) - f_1(\mathbf{s})] \, d\mathbf{s}. \tag{8}$$

We denote the root by $\tilde{\pi}$ when it exists, and otherwise set $\tilde{\pi} = 1$.

Theorem 3.1. *Let:*

$$r(\mathbf{s}) \equiv \begin{cases} \psi'^{-1}\left(\frac{1-\min\{\pi,\tilde{\pi}\}}{1-l(\mathbf{s})\min\{\pi,\tilde{\pi}\}}\right) & \textit{if } l(\mathbf{s}) \leq \tilde{l}(\min\{\pi,\tilde{\pi}\}), \\ M & \textit{if } l(\mathbf{s}) > \tilde{l}(\min\{\pi,\tilde{\pi}\}), \end{cases} \tag{9}$$

$$p_n \equiv \gamma_1 + \frac{\pi(1-\pi)^{n-1}}{1-(1-\pi)^n}\left(\gamma_0 - \gamma_1 - \int \psi[r(\mathbf{s})] \, [1 - l(\mathbf{s})] \, f_0(\mathbf{s}) d\mathbf{s}\right), \tag{10}$$

$$p \equiv \gamma_0 - \int \psi[r(\mathbf{s})] f_0(\mathbf{s}) d\mathbf{s} \tag{11}$$

To minimize her expected costs of procurement the buyer offers a menu of two contracts, given by $\{p_{1n}, q_{1n}(\mathbf{s})\} = \{p_n, c(\mathbf{s})\}$ *and* $\{p_{0n}, q_{0n}(\mathbf{s})\} = \{p, r(\mathbf{s}) + c(\mathbf{s})\}$*, ranking the former above the latter. This menu induces a separating equilibrium amongst the sellers: sellers of type* k *submit* $\{p_{kn}, q_{kn}(\mathbf{s})\}$*.*

Appendix C contains all the proofs. In the solution to the buyer's problem p_{1n} and p_{0n} solve two equations in terms of $q_{1n}(\mathbf{s})$ and $q_{0n}(\mathbf{s})$ that characterize IC_1 and IR_0, both of which bind. Low-cost sellers are offered a *full insurance contract*, where $q_{1n}(\mathbf{s}) = c(\mathbf{s})$. We show from (10), $p_{1n} < \gamma_0$, so IC_0 is not binding. Furthermore, IR_1 is satisfied for any π, and is binding when $\pi \geq \tilde{\pi}$ by (8). Substituting the solutions for p_{1n} and p_{0n} into the expression for the buyer's cost, we minimize the expected cost with respect to the remaining contract parameter, $q_{0n}(\mathbf{s})$, subject to the limited liability constraint.

The solution to the framework with risk-averse sellers share common features with its risk neutral analogue. First, there is no pooling equilibrium. Second, since $\psi'(0) = 1$ and its derivative is negative, it follows from (9) that $q_{0n}(\mathbf{s}) \gtreqless c(\mathbf{s})$ as $l(\mathbf{s}) \lesseqgtr 1$. In words, if a certain realized outcome of $\mathbf{s}$ is more (less) likely to be generated by a high-cost seller than a low-cost one, then $q_{0n}(\mathbf{s})$ over-compensates (under-compensates) cost changes so that low-cost sellers are incentivized not to mimic high-cost ones, as in the risk neutral case. Third, from (9) and (11), neither p_{0n} and $q_{0n}(\mathbf{s})$ depend on the number of bids, because IR_0 binds in both cases.[23]

The critical difference between the two scenarios is that when sellers are risk-averse, the buyer must compensate high-cost sellers with a sufficiently high risk premium for accepting contracts that do not offer full insurance. For some parameter values, IR_1 does not bind in the menu defined in Theorem 3.1. In that case, the expected contract price designed for low-cost sellers declines with the number of bids, converging to c_1, which can be seen by differentiating (10). This manifests the benefits of more competition in the risk averse case, and it also contrasts with the risk neutral case, where the only reason to attract more bidders is to increase the likelihood of attracting low-cost sellers, not to extract more rent from a low-cost winner.

Given n bids, let $T(n)$ denote the expected payment under the menu of Theorem 3.1; let $T_U(n)$ denote the minimal expected payment when the buyer is fully informed about seller type; and let $T_{FIC}(n)$ denote the minimal expected payment when she is constrained to offer only full insurance contracts. Corollary 3.1 implies $T_U(n) < T(n) < T_{FIC}(n)$.

[23]This result is similar to McAfee and McMillan (1987); Laffont and Tirole (1987); Riordan and Sappington (1987), where the distortions due to information asymmetry are invariant to the number of bids, though expected distortions and seller profits decline with the number of bids.

Corollary 3.1. *For any $n \in \{1, 2, \ldots\}$:*

$$T(n) = T_{FIC}(n) + (1-\pi)^{n-1}\,\Gamma, \tag{12}$$

$$T_{FIC}(n) = T_U(n) + (1-\pi)^{n-1}\,\pi\,(\gamma_0 - \gamma_1)\,, \tag{13}$$

$$T_U(n) = c_1 + (1-\pi)^n\,(c_0 - c_1)\,, \tag{14}$$

where:

$$\Gamma \equiv (1-\pi)\int \Big\{ r(\mathbf{s}) - \psi[r(\mathbf{s})] \Big\} f_0(\mathbf{s})d\mathbf{s} - \pi \int \psi[r(\mathbf{s})]\,[1 - l(\mathbf{s})]\,f_0(\mathbf{s})d\mathbf{s}. \tag{15}$$

From (12), note that $\Gamma = T(1) - T_{FIC}(1) < 0$. Moreover as n increases, the absolute value of the difference, $(1-\pi)^{n-1}\,\Gamma$, declines at a geometric rate. Intuitively, in her quest to extract rent from low-cost sellers when faced with the constraint of having to accept a high-cost seller as a last resort, the buyer uses $\mathbf{s}$ to discriminate between the two types, and that the value of discriminating declines with more bids.

3.3. **Soliciting Bids in Equilibrium.** Having solved the contract menu and the expected payments to a winning seller for a given number of bids, the expected total cost of competitive procurement with search effort λ is thus:

$$U(\lambda, \eta) \equiv \sum_{n=0}^{\infty} \frac{\lambda^n e^{-\lambda}}{n!} T(n+1) + \kappa\lambda + \eta, \tag{16}$$

where $T(n)$ is defined in (12). Because $U(\lambda, \eta)$ is convex in λ, it attains an unconstrained global minimum at its unique stationary point, denoted by $\tilde{\lambda}$, and we denote the optimal search intensity by $\lambda^o \equiv \max\{0, \tilde{\lambda}\}$. The expected total cost of noncompetitive procurement is $U(0, 0)$. Competitive bids are sought if and only if:

$$U(\lambda^o, \eta) \leq U(0, 0),$$

which is equivalent to $\eta \leq \Omega$, where

$$\begin{aligned} \Omega \;&\equiv\; U(0,0) - \sum_{n=0}^{\infty} \frac{(\lambda^o)^n e^{-\lambda^o}}{n!} T(n+1) - \kappa\lambda^o \\ &=\; (1 - e^{-\lambda^o \pi})\Big((1-\pi)(c_0 - c_1) + \pi(\gamma_0 - \gamma_1) + \Gamma \Big) - \kappa\lambda^o. \end{aligned} \tag{17}$$

Note that if $\lambda^o = 0$, then the choice reduces to the sign of η.

3.4. **Extensions.** Our model can incorporate entry or bid preparation costs borne by sellers to participate in the procurement process, denoted by κ_s.[24] As in the main model presented above, if the buyer decides to competitively solicit bids, then she determines the optimal search intensity, λ, at the cost of $\kappa\lambda$, and via the Poisson process with arrival rate λ, she gets in contact with n sellers. We assume each seller knows his type as well as the number of sellers that the buyer is in contact with. The buyer presents a menu to the sellers; each seller decides whether to pay κ_s or not, and if so, which item on the menu to select. The rest of the procurement proceeds as before: the buyer selects a winner, pays a base price when the project begins, and makes a price adjustment when the contract outcomes are revealed. Corollary 3.2 below solves an optimal menu for this extension.

Corollary 3.2. *Given an entry cost of κ_s and the buyer's search intensity λ, the equilibrium menu comprises two contracts, $\left\{p_n + \frac{\kappa_s}{\phi_{1n}}, c(\mathbf{s})\right\}$ and $\left\{p + \frac{\kappa_s}{\phi_{0n}}, r(\mathbf{s}) + c(\mathbf{s})\right\}$, where the former is ranked higher, ϕ_{kn} is defined in (4)–(5), and $(r(\mathbf{s}), p_n, p)$ is defined in (9)–(11).*

The explanation for this modified menu is straightforward. Sellers are not directly compensated for their entry costs, but when making a bid, they enter a lottery by paying κ_s. The lottery prize for winning the contract is κ_s/ϕ_{kn} for $k \in \{0, 1\}$, and the lottery is actuarially fair for either seller, appealing to (4)–(5). This form of compensation gives the appearance of padding initial costs, but is a way of efficiently managing entry, through the choice of λ, by internalizing the tension between compensating sellers for their entry costs and the beneficial effects from attracting a greater number of sellers bidding for the project.

These results add to the literature on endogenous entry in auctions where sellers pay entry costs (Bajari and Hortacsu, 2003; Hendricks et al., 2003; Li, 2005; Li and Zheng, 2009; Athey et al., 2011; Krasnokutskaya and Seim, 2011; Athey et al., 2013). In particular, Li and Zheng (2009) demonstrate that increasing the number of potential bidders can increase the price because a lower probability of winning reduces the chances of being compensated for entry costs, with such effects dominating the pressure to decrease the price through greater competition. There is no presumption in this literature that the equilibrium number of bids tendered is optimal from the

[24]We assume that the entry costs of sellers are independent of the cost of the project and its quality. Hence procurement of research and innovation, where sellers' (unverifiable) efforts prior to bidding may affect the quality (Taylor, 1995; Fullerton and McAfee, 1999; Che and Gale, 2003) is beyond the scope of the model. See Bhattacharya (ming) for an empirical study of R&D procurement contests in this context.

buyer's perspective. However, giving discretion to the buyer to set rules on how to determine the winner and the winning bid vests her with the power to internalize this congestion externality.

Another direction to extend the model is relaxing the assumption that the benefit from the project to the buyer does not depend on contract outcomes. To be explicit, we can express the benefits as a mapping $b(\mathbf{s})$. Denote the expected benefit from type k seller by $b_k \equiv \int b(\mathbf{s}) f_k(\mathbf{s}) d\mathbf{s}$. Then the ranking of seller types might not depend on their costs alone. If the expected benefits from a low-cost seller, b_1, are at least as good as a high-cost seller's, b_0, then the buyer ranks low-cost sellers over high-cost sellers and implements the menu of Theorem 3.1.

Corollary 3.3. *The menu defined in Theorem 3.1 is optimal if* $b_1 \geq b_0$.

Our model is limited to two seller types. We conjecture that the main properties of the model apply to extensions with more than two seller types: there is separation, precedence is inversely related to cost, the lowest cost seller is fully insured, and the individual rationality constraint for the highest cost seller binds. In this way the framework captures the essentials of a more general problem, but counterfactual predictions might be sensitive to the number of seller types.

One aspect left for future research is a role for moral hazard in this framework. Considering the simplest case, suppose there is hidden information about both seller type (high-cost or low-cost), and the agent's actions (work or shirk) affect the probability distribution of outcomes. Then, similar to Gayle and Miller (2015), necessary conditions for an optimal menu designed to induce both seller-types to work would be to respect additional incentive compatibility constraints that lead each seller-type to prefer working and announcing their true type to choosing alternative effort combination and pretending to be the other seller type. In equilibrium, price adjustments would reflect the effects of multiple likelihood ratios formed from the probability densities for contract outcomes with different seller types and effort choices. No contract would offer full insurance (because of the moral hazard aspect), but a characterization of even the qualitative properties would depend on a relatively detailed specification of the underlying outcome distributions. Complicating matters still further, our data does not include records of on-the-job monitoring or auditing.[25] For these reasons we

[25]Contracting officers in the agency have authority to enter into, administer, or terminate contracts (FAR 1.602), but they may delegate contract administration to another government agency (FAR 42.202). A government audit agency is responsible for analyzing the financial and accounting records of a contractor to determine the incurred and estimated costs and for reviewing the contractor's cost

do not pursue the analysis of a framework with both hidden information and hidden action components.

4. Identification

The distribution of contract outcomes, the risk preferences of sellers, the proportion of the low-cost type, the cost structure of both seller types, the buyer's search costs, and her preference for competitive contracting, comprise the primitives of the model. Rather than viewing π, the proportion of low-cost sellers, as a parameter to be estimated, we treat π as a project-specific unobserved random variable drawn from a probability distribution F_π, a nondecreasing and continuously differentiable mapping from $\Pi \subset (0,1)$ to $[0,1]$. Initial project costs depend on π through $\gamma_k(\pi)$, a differentiable mapping from Π to $\mathcal{R}^+$; likewise we model search costs $\kappa(\pi)$, as a continuous mapping from Π to $\mathcal{R}^+$. The density functions of $\mathbf{s} \in \mathcal{S}$, f_0 and f_1, belong to the set of continuous probability density functions, and the distribution function of the unobserved random variable η, is denoted by F_η, a nondecreasing function defined from $\mathcal{R}$ to $[0,1]$. Cost changes $c(\mathbf{s})$ are a mapping from $\mathcal{S}$ to $\mathcal{R}$. Risk preferences are represented by ψ, a twice differentiable concave function from $\mathcal{R}$ to $\mathcal{R}$ tangent to the identity function at the origin.

We assume the data generating process of the model records: whether the contract draws competitive bids, denoted by setting $y = 1$, or not (setting $y = 0$); the number of bids, n; the winning contract type, $k \in \{0,1\}$; contract outcomes, $\mathbf{s}$; the base price of the winning contract p_{kn}, and price adjustments $q_k(\mathbf{s})$, which depend on contract outcomes and the winning contract type.[26] We provide assumptions and notation, and establish three monotonicity results underpinning the identification. Then we describe an intuitive explanation of our identification strategy, followed by a step-by-step elaboration. Proofs not given in the text are provided in Appendix D.

4.1. **Assumptions and Notation.** To identify the model we assume:

A1.: $\mathbf{s}$, π, and η are mutually independent.

A2.: $F_\pi(\pi)$ is strictly increasing for all $\pi \in \Pi$.

A3.: $\Pi \subset (0,\tilde{\pi})$, and $l(\mathbf{s}) \leq \tilde{l}(\pi)$ for all $(\mathbf{s},\pi) \in \mathcal{S} \times \Pi$.

A4.: $\gamma_1(\pi)$ is non-increasing in $\pi \in \Pi$.

---

control systems (FAR 42.101). Furthermore, monitoring contractor compliance with contractual requirements must occur as part of the quality assurance procedures (FAR 46).

[26]We use the same notation k to denote the seller type and the contract type because the equilibrium is separating, which provides a one-to-one mapping between the seller type and the contract type. For this reason, we call $\{p_{1n}, q_{1n}\}$ a low-cost contract and $\{p_{0n}, q_{0n}\}$ a high-cost contract.

A5.: $\gamma_0(\pi) - \gamma_1(\pi)$ is non-increasing in $\pi \in \Pi$.
A6.: Either $\Psi_0(\pi) \leq \gamma_0'(\pi)$ for all $\pi \in \Pi$, or $\Psi_0(\pi) \geq \gamma_0'(\pi)$ for all $\pi \in \Pi$ where:

$$\Psi_0(\pi) \equiv \int \left(\psi'' \left[\psi'^{-1} \left(\frac{1-\pi}{1-\pi l(\mathbf{s})} \right) \right] \right)^{-1} \frac{(1-\pi)\,[l(\mathbf{s})-1]}{[1-\pi l(\mathbf{s})]^3} f_0(\mathbf{s}) d\mathbf{s}.$$

To facilitate the exposition we define $v(l,\pi)$ as the interior solution to r in the optimality condition given by (9):

$$\psi'(r) = \frac{1-\pi}{1-\pi l}. \tag{18}$$

Assuming **A3** implies from Theorem 3.1 that $v(l(\mathbf{s}),\pi) = q_{0n}(\mathbf{s}) - c(\mathbf{s})$ for all $\pi \in \Pi$. For notational convenience we also make explicit the dependence of the base price variables p and p_n on π by writing $p(\pi)$ and $p_n(\pi)$ respectively.

Assumption **A1** can be relaxed if suitable instruments are available. Our empirical implementation allows for correlation between π and η using an instrumental variables approach, and our approach to identification can be extended to account for such correlations.[27] We appeal to **A2** when connecting the probability distribution of p_n, conditional on n, with the probability distribution of π conditional on a low-cost seller winning. It is essentially a technical condition finessing situations where $f_\pi(\pi^*) = 0$ for some π^* and hence no observations exist for $p_n(\pi^*)$. **A3** means that neither IR_1 nor the limited liability constraint bind, implying (18) holds. Our parametric specification relaxes this assumption in estimation. Assumptions **A4** and **A5** bound the derivatives of base costs with respect to π, and include the notable specialization that initial costs do not depend on π. These bounds are not tight, and we do not impose them in the estimation. Our proof of identification also shows that if $\psi(r)$ is known, then the remaining parameters are over-identified from Assumptions **A1** through **A5** alone. Thus **A6** is a uniformity assumption jointly restricting the space of risk preferences and the distribution of outcomes, only used in the identification of $\psi(r)$. Summarizing, these assumptions are collectively sufficient but not necessary for identifying the primitives; they provide guidelines for estimation, and serve as a

[27]By way of contrast, we do not relax the assumption that $\mathbf{s}$ is independent of π and η. If the contract outcome distributions for each seller type $k = \{0, 1\}$ vary with (π, η) so that $f_k(\mathbf{s}|\pi,\eta) \neq f_k(\mathbf{s})$, then $f_k(\mathbf{s}|\pi,\eta)$ is not identified from data on contract outcomes and seller type alone because π and η are unobserved. Our approach is to identify $f_0(\mathbf{s})$ and $f_1(\mathbf{s})$ first from the observed contract outcomes conditional on seller type, and exploit this feature throughout. However if the distribution of s depends on (π, η), the buyer duly accounts for this dependence in her menu design. Ignoring it when aggregating across projects of different types could bias counterfactual predictions.

point of departure for restricting the parameter space along some dimensions in order to enlarge it on others, depending on the specificities of the dataset.

4.2. **Monotonicity.** The proof of identification exploits monotonicity properties. As π increases, there is a greater chance of selecting a low-cost seller and thus the buyer can reduce the base price for the low-cost contract if IR_1 does not bind already. We show that $\partial p_n(\pi)/\partial\pi < 0$ for all $n \in \{1, 2, \ldots\}$ given **A3**–**A5**. We show that to satisfy IC_1 while reducing $p_n(\pi)$ as π increases, the buyer increases the volatility of the high-cost contract, making it less attractive to low-cost sellers, which is to say $\partial |v(l, \pi)| / \partial\pi > 0$. Whether the increased volatility makes the high-cost contract more or less attractive to high-cost sellers depends on the other primitives; we provide conditions for monotonicity of $p(\pi)$ in π.

Lemma 4.1. *(i) If **A3** holds then* $\partial |v(l, \pi)| / \partial\pi > 0$. *(ii) If **A3**–**A5** hold then* $\partial p_n(\pi)/\partial\pi < 0$ *for all* $n \in \{1, 2, \ldots\}$. *(iii) If **A3** and **A6** hold then* $p(\pi)$ *is monotone.*

4.3. **Overview.** Because the equilibrium menu separates low-cost from high-cost sellers, the densities for contract outcomes, $f_1(\mathbf{s})$ and $f_0(\mathbf{s})$, are identified. Since the menu offers full-insurance to low-cost sellers, cost changes are identified from the price adjustments: $c(\mathbf{s}) = q_{1n}(\mathbf{s})$. Then we identify $\psi(r)$, sellers' risk preferences, using the optimality condition for the price adjustments, along with the monotonicity of $p(\pi)$, the base price for a high-cost contract. Rewriting (18) yields the realizations of π for high-cost contracts, which in turn identifies the distribution function of π conditional on (y, n) for high-cost contracts. From the model's prediction that $\Pr(k = 0|\pi, y, n) = (1 - \pi)^n$, and the fact that $\Pr(k = 0|y, n)$ is identified because (y, n, k) are observed, the density of π conditional on (y, n) for low-cost contracts is identified. The initial cost for the low-cost seller $\gamma_1(\pi)$ is now identified by using the monotonicity of $p_n(\pi)$ and exploiting variations in the number of sellers conditional on π, while the identification of $\gamma_0(\pi)$ is evident from rearranging the solution to $p(\pi)$. We establish identification of the equilibrium buyer search intensity, $\lambda(\pi)$, by appealing to Bayes' rule and $f_{\pi,y,n}(\pi, 1, n)$, identified in previous steps. The search cost parameter, κ, is set-identified from the buyer's first order condition determining search intensity. We partially identify F_η, the probability distribution function for the costs of soliciting competition, because the optimal rule for a buyer is characterized by an index identified in the previous steps crossing a threshold: the index depends on π, and so variation in π effectively traces out the distribution of η. Note there is observational equivalence between different combinations of sellers' initial project costs and entry costs; we set seller entry costs to zero.[28]

4.4. **Multistep Identification Strategy.**

4.4.1. *Contract Outcomes.* Since the equilibrium menu is separating, $f_0(\mathbf{s})$ and $f_1(\mathbf{s})$ are directly identified from the distributions of the contract outcomes, along the likelihood ratio $l(\mathbf{s})$. Furthermore for a winning low-cost seller, equilibrium price adjustments equal cost changes: $c(\mathbf{s}) = q_{1n}(\mathbf{s})$.

4.4.2. *Risk Preferences.* Risk preferences are identified from the optimality conditions that determine price adjustments for the high-cost seller. By Lemma 4.1, $p(\pi)$ is strictly monotone, and therefore has an inverse mapping, denoted by $\pi^*(p)$. Define the composite function $v^*(l,p) \equiv v[l, \pi^*(p)]$. It is evident that $\partial v(l,\pi')/\partial l = \partial v^*(l,p')/\partial l$ for all (l,π',p') satisfying $p' = p(\pi')$. Holding π constant, we totally differentiate (18) with respect to l, substitute the derivative $\partial v^*(l,p)/\partial l$ for $\partial v(l,\pi)/\partial l$ in the resulting equation, and rearrange to obtain:

$$\psi''(r) = \left[\frac{\partial v^*(l,p)}{\partial l}\right]^{-1} \frac{1-\psi'(r)}{1-l}\psi'(r). \tag{19}$$

Our assumptions guarantee that $v^*(l,p)$ is uniformly Lipschitz continuous in l for any p. Consequently the Picard–Lindelöf theorem applies, proving the differential equation (19) has a unique solution of $\psi'(r)$ given the normalizing constant $\psi'(0) = 1$. Furthermore $\psi(r)$ is solved from the other normalization, $\psi(0) = 0$ for any value of $p' = p(\pi')$ with $\pi' \in \Pi$. The identification of $\psi(r)$ now follows from the identification of $v^*(l,p)$ directly off the high-cost contracts.

4.4.3. *Distribution of the Fraction of Low-cost Sellers.* Identifying $f_\pi(\pi)$ follows from showing $f_{\pi|y,n}(\pi|y,n)$ is identified, because the distribution of (y,n) is identified off its empirical analogue. To prove $f_{\pi|y,n}(\pi|y,n)$ is identified, we draw upon two pieces of information. First, $f_{\pi|y,n,k}(\pi|y,n,0)$ is identified. Since $\psi(q)$ is identified, the

[28]In Appendix H, we estimate an extended model in Section 3.4, where entry costs are nonzero, and set the entry costs to be 1, 2, and 5 percent of the expected project costs, following the estimates from the literature. Using California highway procurement data, Krasnokutskaya and Seim (2011) estimate that the average entry cost is 2.2–3.9 percent of the engineering estimates (Table 9), similar to the estimates of Bajari et al. (2010). Appendix H.3 specifies the extended model and describes how it is estimated, and the results in Columns (12)–(14) in Table A13 show that our main findings are robust to allowing for entry costs.

realizations of π for high-cost contracts are identified. From (18):

$$\pi = \frac{1-\psi'\left[q_{0n}(\mathbf{s})-c(\mathbf{s})\right]}{1-\psi'\left[q_{0n}(\mathbf{s})-c(\mathbf{s})\right]l(\mathbf{s})}.$$

Second, in equilibrium the buyer resorts to high-cost contracts with probability $(1-\pi)^n$. Her selection links $f_{\pi|y,n,k}(\pi|y,n,0)$ with $f_{\pi|y,n,k}(\pi|y,n,1)$ as follows:

$$f_{\pi|y,n,k}(\pi|y,n,1) = \frac{\Pr(k=0|y,n)}{\Pr(k=1|y,n)}\frac{\left[1-(1-\pi)^n\right]}{(1-\pi)^n}f_{\pi|y,n,k}(\pi|y,n,0). \tag{20}$$

This in turn yields a formula for $f_{\pi|y,n}(\pi|y,n)$ in terms of $f_{\pi|y,n,k}(\pi|y,n,0)$.[29]

Lemma 4.2. *The density $f_{\pi|y,n}(\pi|y,n)$ is identified from:*

$$f_{\pi|y,n}\left(\pi|y,n\right) = \frac{f_{\pi|y,n,k}\left(\pi|y,n,0\right)}{(1-\pi)^n\int\left(1-\pi'\right)^{-n}f_{\pi|y,n,k}\left(\pi'\left|y,n,0\right.\right)d\pi'}. \tag{21}$$

Accordingly, $f_\pi(\pi)$ is identified.

4.4.4. *Seller Costs.* Turning to $\gamma_0\left(\pi\right)$ and $\gamma_1\left(\pi\right)$, let $G_{p_n|y}\left(p|y\right)$ denote the cumulative distribution function of p_n conditional on $y\in\{0,1\}$. By Lemma 4.1, p_n is strictly decreasing in π, and by **A2** the inverse of $F_\pi\left(\pi\right)$ exists. Therefore the inverse of $G_{p_n|y}\left(p|y\right)$ exists, leading us to conclude:

$$p_n\left(\pi\right)\equiv G^{-1}_{p_n|y}\left[1-F_{\pi|y,n,k}\left(\pi\left|y,n,1\right.\right)|y\right]. \tag{22}$$

for $y\in\{0,1\}$, where given π, by construction $p_n\left(\pi\right)$ solves for p_n.[30] Thus $p_n\left(\pi\right)$ is identified by Lemma 4.2, because $G_{p_n|y}\left(p|y\right)$ is identified directly off the data generating process. Also since the realizations of π associated with high-cost contracts are identified in **4.4.3**, $p\left(\pi\right)$ is identified. Substituting $p_n\left(\pi\right)$ for p_n in (10) and $p\left(\pi\right)$ for p in (11) and manipulating the resulting equations give the expressions for $\gamma_0\left(\pi\right)$ and $\gamma_1\left(\pi\right)$ in (23) below. Lemma 4.3 establishes the initial costs of sellers are identified.

Lemma 4.3. *$\gamma_1\left(\pi\right)$ and $\gamma_0\left(\pi\right)$ are identified, and for $n\in\{2,3,\ldots\}$:*

$$\begin{aligned}\gamma_1\left(\pi\right) &= \frac{1-\left(1-\pi\right)^n}{1-\left(1-\pi\right)^{n-1}}p_n\left(\pi\right)-\frac{\pi\left(1-\pi\right)^{n-1}}{1-\left(1-\pi\right)^{n-1}}p_1\left(\pi\right), \\ \gamma_0\left(\pi\right) &= p\left(\pi\right)+\int\psi\left(\psi'^{-1}\left[\frac{1-\pi}{1-\pi l\left(\mathbf{s}\right)}\right]\right)f_0(\mathbf{s})d\mathbf{s}.\end{aligned} \tag{23}$$

[29]See the proof of Lemma 4.2 in Appendix D for a derivation of (20).

[30]Note that Theorem 3.1 implies the base price of the low-cost contract does not depend on y, and therefore y does not appear as an argument in $p_n\left(\pi\right)$.

4.4.5. *Buyer Search Costs.* The first order condition for an interior solution to minimizing $U(\lambda, \eta)$ essentially identifies $\kappa(\pi)$, the buyer's search costs:

$$\kappa(\pi) = \pi e^{-\pi\tilde{\lambda}(\pi)} \left\{(1-\pi)\left[c_0(\pi) - c_1(\pi)\right] + \pi\left[\gamma_0(\pi) - \gamma_1(\pi)\right] + \Gamma(\pi)\right\}, \tag{24}$$

where we write $\Gamma(\pi)$ and $\tilde{\lambda}(\pi)$ for Γ and $\tilde{\lambda}$ to explicitly recognize their dependence on π. Let $\lambda^o(\pi) \equiv \max\left\{0, \tilde{\lambda}(\pi)\right\}$ denote the optimal search intensity conditional on soliciting competitive bids. Since we have already identified $\gamma_0(\pi) - \gamma_1(\pi)$ and the components of $c_0(\pi) - c_1(\pi)$ and $\Gamma(\pi)$, defined in (15), identifying $\kappa(\pi)$ mainly hinges on identifying $\lambda^o(\pi)$, proved in Lemma 4.4 below.

Lemma 4.4. *$\lambda^o(\pi)$ is identified for all $\pi \in \Pi$. If $\lambda^o(\pi) = 0$ then $\kappa(\pi)$ is set identified by a lower bound, $\pi\left\{(1-\pi)\left[c_0(\pi) - c_1(\pi)\right] + \pi\left[\gamma_0(\pi) - \gamma_1(\pi)\right] + \Gamma(\pi)\right\}$. If $\lambda^o(\pi) > 0$ then $\kappa(\pi)$ is identified from (24).*

4.4.6. *Soliciting Competition.* Replacing κ with (24) in the right hand side of (17), the buyer solicits competitive bids if and only if $\eta \leq \Omega(\pi)$, where:

$$\Omega(\pi) \equiv \left\{1 - \left[1 + \pi\lambda^o(\pi)\right] e^{-\lambda^o(\pi)\pi}\right\} \left\{(1-\pi)\left[c_0(\pi) - c_1(\pi)\right] + \pi\left[\gamma_0(\pi) - \gamma_1(\pi)\right] + \Gamma(\pi)\right\}. \tag{25}$$

Variation in π induces variation in $\Omega(\pi)$, partially identifying $F_\eta(\eta)$, because $F_\eta[\Omega(\pi)] = \Pr(y = 1|\pi)$, and both $\Pr(y = 1|\pi)$ and $\Omega(\pi)$ are identified from the previous results. For example when $\lambda^o(\pi) = 0$, implying $\Omega(\pi) = 0$, then $F_\eta(0)$ is identified.

Lemma 4.5. *$F_\eta(\eta)$ is identified on Υ, the range of $\Omega(\pi)$, defined:*

$$\Upsilon \equiv \left\{\widetilde{\eta} \in \mathcal{R} : \widetilde{\eta} = \Omega(\widetilde{\pi}) \text{ for some } \widetilde{\pi} \in \Pi\right\}.$$

The following theorem, a direct consequence of the lemmas and the discussion in the text, summarizes our results on identification.

Theorem 4.1. *Under Assumptions **A1**–**A6**, $f_k(\mathbf{s})$, $F_\pi(\pi)$, $\psi(r)$, $\gamma_k(\pi)$, $c(\mathbf{s})$, and $\lambda^o(\pi)$ are identified. If $\lambda^o(\pi) > 0$, then $\kappa(\pi)$ is identified; otherwise, its lower bound is identified. $F_\eta(\eta)$ is identified for any η such that there exists $\pi \in \Pi$ with $\Omega(\pi) = \eta$.*

5. Estimation

The identification analysis guides our estimation strategy, but due to the modest sample size and heterogeneity within our data, we parameterize the model. This section lays out our sequential estimation procedure.

5.1. **Matching Variables in the Model to the Data.** Our data on contracts comprise equilibrium objects, denoted by $\{y_i, n_i, p_i, q_i, k_i, \mathbf{s}_i\}$, and observed heterogeneity, $\{\mathbf{x}_i, \mathbf{z}_i\}$, for observations $i \in \{1, \dots, I\}$. The equilibrium objects are: $y_i = 1$ if there is a competitive solicitation, and 0 otherwise; n_i is the number of bids; p_i is the base price; q_i is the price adjustment; k_i represents the contract type, taking a value of 1 for a low-cost contract and 0 otherwise; $\mathbf{s}_i$ denotes contract outcomes.

As for observed heterogeneity, $\mathbf{x}_i$ represents project and procurement agency attributes. One subvector, denoted by $\mathbf{x}_{1i}$, consists of six dummy variables indicating that the base duration is greater than three months, the base maximal price is greater than \$300,000, the contract is to procure services, the item is commercially available, the procurement agency is the Department of Defense, and it is a definitive contract, respectively.[31] The remaining variables in $\mathbf{x}_i$ are four dummies that respectively indicate: the agency has a large fraction of experienced contracting officers; it procured a similar contract in the past three years; its annual contracting workload is big; the contract's location is represented by a key member of Congress for budgeting and appropriations. The measures of the underlying extent of potential competition for the contract, denoted by $\mathbf{z}_i$, are two variables indicating that there are more than one winner of similar items in the past three years, and the state has many establishments of the same NAICS code.

For estimation purposes, we equate a low-cost contract with a firm-fixed-price contract, and a high-cost contract with contract types other than firm-fixed-price (mostly cost-plus), for the following three reasons. First, the regulations prioritize firm-fixed-pricing (FAR 16.103).[32] Second, firm-fixed-price contracts tend to be cheaper than others, controlling for various project and agency attributes (Column (1) of Table A6 in Appendix B.3). Third, firm-fixed-price contracts are associated with smaller price adjustments than other contracts (Columns (3)–(5) of Table A6). This corresponds to the theoretical notion that while fluctuations in payments for high-cost contracts

[31] Acknowledging that the base maximal price might be endogenous, we estimate the model without controlling for that variable; Column (3) in Table A12 in the Appendix shows that the results are robust. In addition, to more flexibly control for heterogeneity, we focus on four different subsamples of the data, such as software contracts only, and find that the results, as presented in Columns (7)–(10) in Table A13 in the Appendix, are also robust.

[32] FAR 16.013(b) states that "A firm-fixed-price contract, which best utilizes the basic profit motive of business enterprise, shall be used when the risk involved is minimal or can be predicted with an acceptable degree of certainty. However, when a reasonable basis for firm pricing does not exist, other contract types should be considered, and negotiations should be directed toward selecting a contract type (or combination of types) that will appropriately tie profit to contractor performance."

are subject to uncertainty driven by two sources, screening and insurance, payments for low-cost contracts are subject to only the latter source.

Contractible outcomes are given by a six dimensional vector, $\mathbf{s} \equiv (\mathbf{s}_1, \mathbf{s}_2)$, where $\mathbf{s}_1 \equiv (s_{11}, s_{12}, s_{13})$ are cost changes, and $\mathbf{s}_2 \equiv (s_{21}, s_{22}, s_{23})$ measures duration adjustments. Each element s_{2h} is a duration adjustment divided by the length of the base contract duration, where $h \in \{1, 2, 3\}$ relates to one of the three categories of ex-post adjustments described in Section 2.3.[33] We allow for pairwise correlation in (s_{1h}, s_{2h}), but, due to sample size considerations, assume $(\mathbf{s}_{1h}, s_{2h})$ and $(\mathbf{s}_{1h'}, s_{2h'})$ for $h, h' \in \{1, 2, 3\}$ are independent. Whereas $\mathbf{s}_2$ is observed for all contracts, $\mathbf{s}_1$ is observed for low-cost contracts, but not for high-cost contracts. This is because costs are not directly observed, but in equilibrium (Theorem 3.1), price adjustments equal cost changes in low-cost contracts, although this is not the case for high-cost contracts.

Duration adjustments are considered part of contract outcomes for three reasons. First, the contracting officers record and track duration adjustments, sometimes leading to price adjustments (FAR 16.4 and 43.2). Second, we find that the duration adjustment distributions differ by contract type (Table A7 in Appendix B.3). Third, we find a positive correlation between delays and price adjustments (Table A8 in Appendix B.4).

5.2. **Estimation Strategy.** We assume that the data is generated by $\theta^* \equiv \big(\theta_s^*, \theta_\pi^*, \theta_c^*, \theta_\psi^*, M^*, \theta_\eta^*\big)$, an interior point of a closed convex subset in Euclidean space. First we separately estimate θ_s^* and θ_π^*, which characterize the probability density of some of the contract outcomes and the density for the proportion of low-cost sellers, respectively. Given parameter estimates $\widehat{\theta}_s$ and $\widehat{\theta}_\pi$, we draw upon Theorem 3.1, to estimate θ_c^*, the project costs, θ_ψ^*, which characterizes risk preferences, and M^*, the maximal penalty, by comparing realized values of the payments with the expected theoretical predictions. An estimate of the marginal search costs then follows directly from the first order condition choosing the estimated search intensity. The last step estimates θ_η^*, representing the distribution of solicitation costs, and exploits an inequality choosing whether or not to competitively solicit bids.

Our parametric approach gives us leeway to relax several assumptions made in the previous section. First, we relax the assumption that all contract outcomes are observed. As explained above, we observe the cost of the realized contract outcomes

[33]We also consider two categories of ex-post price and duration adjustments, consisting of work changes and the rest. Column (4) of Table A12 in Appendix H provides the estimation results under this categorization, and we find that our results are robust.

when a low-cost seller win, exploiting the equilibrium condition that $q_{1n}(\mathbf{s}) = c(\mathbf{s})$. If, however, a high-cost seller wins, we only observe duration adjustments, a sub-vector of outcomes, $\mathbf{s}_2$. In this way unobserved heterogeneity is not only embodied in π and η but also $\mathbf{s}_1$. Second, we relax the independence assumption, **A1**, by permitting correlation between the fraction of low-cost sellers, π, and solicitation costs, η, under the assumption that η is independent of $\mathbf{z}$, which measures the extent of potential competition. Third, we do not impose the monotonicity assumptions **A4** through **A6**. Fourth, we relax **A3** in estimation by removing the restriction on the support of π, allowing the IR_1 constraint to bind, and also permitting the limited liability constraint to bind. We define the parameterization and describe each estimation step; Appendix E further elaborates.[34]

5.2.1. *Contract Outcomes.* The joint density of contract outcomes $\mathbf{s}$ conditional on seller type k and project attributes $\mathbf{x}_1$, parameterized by $\theta_s \equiv (\theta_{s_1}, \theta_{s_2})$, is:

$$f_{k,\mathbf{s}}(\mathbf{s}|\mathbf{x}_1;\theta_s) = \prod_{h=1}^{3} f_{k,s_{1h}|s_{2h}}(s_{1h}|s_{2h},\mathbf{x}_1;\theta_{s_1}) f_{k,s_{2h}}(s_{2h}|\mathbf{x}_1;\theta_{s_2}). \tag{26}$$

Let $\Phi(\cdot)$ and $\phi(\cdot)$ denote the standard Normal distribution and density functions respectively. For each category $h \in \{1,2,3\}$ in (26), we define:

$$\theta_{s_{1h}} \equiv \left(\theta_{s_{1h,0}}, \theta_{s_{1h,d}}, \theta_{s_{1h,x}}, \theta_{s_{1h,1}}, \ldots, \theta_{s_{1h,4}}\right); \theta_{s_{2h}} \equiv \left(\theta_{s_{2h,0}}, \theta_{s_{2h,x}}, \theta_{s_{2h,1}}, \ldots, \theta_{s_{2h,4}}\right).$$

We parameterize $f_{k,s_{1h}|s_{2h}}(s_{1h}|s_{2h},\mathbf{x}_1;\theta_{s_1})$ by assuming that the probability of no ex-post cost increase due to reasons of category h is

$$\Pr(s_{1h} \leq 0|s_{2h},\mathbf{x}_1;\theta_{s_1}) = \Phi\left[(1-k)\theta_{s_{1h,0}} + \theta_{s_{1h,1}}\mathbb{1}\{s_{2h} > 0\} + \mathbf{x}_1\theta_{s_{1h,x}}\right], \tag{27}$$

and that the density of cost change conditional on being positive is

$$f_{k,s_{1h}|s_{2h}}(s_{1h}|s_{1h} > 0, s_{2h},\mathbf{x}_1;\theta_{s_1}) = \phi\left(\frac{s_{1h} - \theta_{s_{1h,1}} - k\theta_{s_{1h,2}}}{e^{\theta_{s_{1h,3}}\cdot + k\theta_{s_{1h,4}}}}\right). \tag{28}$$

Similarly, we parameterize $f_{k,s_{2h}}(s_{2h}|\mathbf{x}_1;\theta_{s_2})$ by assuming that the probably of no ex-post delay related to category h reasons is

$$\Pr(s_{2h} \leq 0|\mathbf{x}_1;\theta_{s_2}) = \Phi\left[(1-k)\theta_{s_{2h,0}} + \mathbf{x}_1\theta_{s_{2h,x}}\right], \tag{29}$$

and that the density of delay-to-base-duration ratio follows a Gamma distribution. Denoting by $g(\cdot|\zeta_1,\zeta_2)$ a Gamma probability density function with shape and scale

[34] We compute integrals over π and $\mathbf{s}$ numerically. Our results are robust to doubling the number of integration points (Specification (5) and (6) in Appendix H; Table A12).

parameters ζ_1 and ζ_2 respectively, we assume that for each category h:

$$f_{k,s_{2h}}(s_{2h}|s_{2h}>0,\mathbf{x}_1;\theta_{s_2}) = g\left(s_{2j}; e^{\theta_{s_{2h,1}}+k\theta_{s_{2h,2}}}, e^{\theta_{s_{2h,3}}+k\theta_{s_{2h,4}}}\right). \tag{30}$$

Limited information maximum likelihood (LIML) estimates for $\theta^*_{s_2}$ in (29) and (30) are obtained from data on $(k,\mathbf{x},\mathbf{s}_2)$. Based on cost changes that low-cost sellers incur, which we directly observe from price adjustments, we also obtain LIML estimates for all the elements of $\theta^*_{s_1}$ in (27) and (28), except for $\theta^*_{s_{1,0}} \equiv \{\theta^*_{s_{11,0}},\theta^*_{s_{12,0}},\theta^*_{s_{13,0}}\}$.

5.2.2. *Distribution of the Fraction of Low-cost Sellers.* We estimate the density of the fraction of low-cost sellers, π, for contracts won by a high-cost seller ($k=0$), conditional on observed competition (y,n) and contract attributes $(\mathbf{x},\mathbf{z})$. Let $\theta_{\pi,y,n} \equiv (\theta_{\pi,y,n,x},\theta_{\pi,y,n,z},\theta_{\pi,y,n,0})$. We assume $f_{\pi|y,n,k}(\pi|y,n,0,\mathbf{x},\mathbf{z};\theta_{\pi,y,n})$ is a Beta distribution with two shape parameters, $1+\exp(\mathbf{x}'\theta_{\pi,y,n,x}+\mathbf{z}'\theta_{\pi,y,n,z})$ and $1+\exp(\theta_{\pi,y,n,0})$.[35] We integrate (20) over π, rearrange terms to make $\Pr(k=0|y,n)$ the subject of the equation, and condition on $(\mathbf{x},\mathbf{z})$ to obtain:

$$\Pr(k=0|y,n,\mathbf{x},\mathbf{z};\theta_{\pi,y,n}) = \left(\int (1-\pi)^{-n} f_{\pi|y,n,k}(\pi|y,n,0,\mathbf{x},\mathbf{z};\theta_{\pi,y,n})\right)^{-1}. \tag{31}$$

Appealing to (31) we obtain $\widehat{\theta}_\pi \equiv \left\{\widehat{\theta}_{\pi,y,n}\right\}$ by maximizing:

$$\sum_i \left\{(1-k_i)\ln[\Pr(k=0|y_i,n_i,\mathbf{x}_i,\mathbf{z}_i;\theta_{\pi,y_i,n_i})] + k_i \ln[\Pr(k=1|y_i,n_i,\mathbf{x}_i,\mathbf{z}_i;\theta_{\pi,y_i,n_i})]\right\}.$$

Using (20), we estimate $f_{\pi|y,n,k}(\pi|y,n,1,\mathbf{x},\mathbf{z};\theta^*_{\pi,y,n})$ with:

$$\frac{\Pr(k=0|y,n,\mathbf{x},\mathbf{z};\widehat{\theta}_{\pi,y,n})}{\Pr(k=1|y,n,\mathbf{x},\mathbf{z};\widehat{\theta}_{\pi,y,n})}\frac{[1-(1-\pi)^n]}{(1-\pi)^n} f_{\pi|y,n,k}(\pi|y,n,0,\mathbf{x},\mathbf{z};\widehat{\theta}_{\pi,y,n}),$$

and then estimate $f_\pi(\pi|\mathbf{x},\mathbf{z};\theta^*_\pi)$ with:

$$\frac{\sum_i f_{\pi|y,n,k}(\pi|y_i,n_i,k_i,\mathbf{x}_i,\mathbf{z}_i;\widehat{\theta}_{\pi,y_i,n_i})\mathbb{1}\{(\mathbf{x}_i,\mathbf{z}_i)=(\mathbf{x},\mathbf{z})\}}{\sum_i \mathbb{1}\{(\mathbf{x}_i,\mathbf{z}_i)=(\mathbf{x},\mathbf{z})\}}.$$

[35]Given the scarcity of contracts with more than 4 bids (the fraction of such contracts is 6 percent in the sample), we restrict that for $n>4$, $f_{\pi|y,n,k}(\pi|1,n,0,\mathbf{x},\mathbf{z}) = f_{\pi|y,n,k}(\pi|1,4,0,\mathbf{x},\mathbf{z})$, or equivalently, $\theta_{\pi,y,n}=\theta_{\pi,y,4}$. Columns (1) and (2) of Table A12 in the Appendix present the results of the sensitivity analyses where we alternatively impose such restrictions for the number of bids greater than 3 and 5, respectively, instead of 4, showing the results are robust.

5.2.3. *Seller Costs and Risk Preferences.* Initial project costs, parameterized by $\theta_c \equiv (\theta_{c_1}, \theta_{c_0})$ with $\theta_{c_k} \equiv (\theta_{c_k,x}, \theta_{c_k,1}, \theta_{c_k,2})$, are now written as:

$$\gamma_1(\mathbf{x}_1, \pi; \theta_{c_1}) = \exp\left(\mathbf{x}_1\theta_{c_1,x} + \pi\theta_{c_1,1} + \pi^2\theta_{c_1,2}\right)$$
$$\gamma_0(\mathbf{x}_1, \pi; \theta_c) = \gamma_1(\mathbf{x}_1, \pi; \theta_{c_1}) + \exp\left(\mathbf{x}_1\theta_{c_0,x} + \pi\theta_{c_0,1} + \pi^2\theta_{c_0,2}\right).$$

Cost changes, $c(\mathbf{s})$, are assumed additive in $\mathbf{s}_1$:

$$c(\mathbf{s}) = s_{11} + s_{12} + s_{13}.$$

We parameterize risk preferences with:

$$\psi(r, \mathbf{x}_1; \theta_\psi) = \exp(\mathbf{x}_1\theta_\psi)\left\{1 - \exp\left[-r / \exp(\mathbf{x}_1\theta_\psi)\right]\right\}.$$

Substituting these parameterizations into (9) through (11) in Theorem 3.1, and substituting the parameter estimates obtained from the previous steps, we express the base price and the price adjustments, for each type of contract, as a function of $(n, \mathbf{x}_1, \mathbf{s})$ and parameters $(\theta_c, \theta_\psi, M, \theta_{s_{1,0}})$. We then estimate these parameters using an extremum estimator that minimizes the sum over observations $i \in \{1, \ldots, I\}$ of squared differences between the contract prices observed in the sample (p_i and q_i) and their theoretical expectations derived from the solution to the model.

5.2.4. *Buyer Search Costs.* Denoting the parameters in **5.2.1** through **5.2.3** by $\theta_\varphi \equiv (\theta_s, \theta_c, \theta_\psi, M)$, we exploit (24) to estimate $\kappa(\mathbf{x}, \mathbf{z}, \pi; \theta^*_\varphi, \theta^*_\pi)$, the empirical analogue of $\kappa(\pi)$. One of the expressions in $\kappa(\mathbf{x}, \mathbf{z}, \pi; \theta^*_\varphi, \theta^*_\pi)$ is the bid arrival rate, $\lambda^o(\mathbf{x}, \mathbf{z}, \pi; \theta^*_\pi)$, consistently estimated using the estimates obtained from **5.2.2**.

Lemma 5.1. *A consistent estimator for $\lambda^o(\mathbf{x}, \mathbf{z}, \pi; \theta^*_\pi)$ is:*

$$\widehat{\lambda}^o(\mathbf{x}, \mathbf{z}, \pi; \widehat{\theta}_\pi) = \frac{\sum_{i=1}^{I}(n_i - 1) f_{\pi|y,n,k}(\pi|1, n_i, k_i, \mathbf{x}_i, \mathbf{z}_i; \widehat{\theta}_\pi)\mathbb{1}\{(y_i, \mathbf{x}_i, \mathbf{z}_i) = (1, \mathbf{x}, \mathbf{z})\}}{\sum_{i=1}^{I} f_{\pi|y,n,k}(\pi|1, n_i, k_i, \mathbf{x}_i, \mathbf{z}_i; \widehat{\theta}_\pi)\mathbb{1}\{(y_i, \mathbf{x}_i, \mathbf{z}_i) = (1, \mathbf{x}, \mathbf{z})\}}.$$

Defining that the expected project cost for a type k seller given $(\mathbf{x}_1, \pi)$ as:

$$c_k(\mathbf{x}_1, \pi; \theta_\varphi) \equiv \gamma_k(\mathbf{x}_1, \pi; \theta_c) + \int c(\mathbf{s}) f_k(\mathbf{s}|\mathbf{x}_1; \theta_s)\, d\mathbf{s},$$

we summarize our estimator for $\kappa(\mathbf{x}, \mathbf{z}, \pi; \theta^*_\varphi, \theta^*_\pi)$ that applies when the first order condition for λ^o holds, and its lower bound when it doesn't:

$$\begin{aligned}\kappa(\mathbf{x}, \mathbf{z}, \pi; \widehat{\theta}_\varphi, \widehat{\theta}_\pi) \;=\; & \pi \exp\left[-\pi\widehat{\lambda}^o(\mathbf{x}, \mathbf{z}, \pi; \widehat{\theta}_\pi)\right]\left[\pi\left\{\gamma_0(\mathbf{x}_1, \pi; \widehat{\theta}_c) - \gamma_1(\mathbf{x}_1, \pi; \widehat{\theta}_c)\right\}\right. \\ & \left. +(1-\pi)\left\{c_0(\mathbf{x}_1, \pi; \widehat{\theta}_\varphi) - c_1(\mathbf{x}_1, \pi; \widehat{\theta}_\varphi)\right\} + \Gamma(\mathbf{x}_1, \pi; \widehat{\theta}_\varphi)\right], \quad (32)\end{aligned}$$

where $\Gamma(\mathbf{x}_1, \pi; \widehat{\theta}_\varphi)$ is a parameterized version of (15).[36]

5.2.5. *Competitive Solicitation Costs.* We assume that the costs of competitively soliciting bids, η, conditional on $(\pi, \mathbf{x})$, are normally distributed, independent of $\mathbf{z}$, with mean $\mathbf{x}\theta_{\eta x} + \pi\theta_{\eta 1} + \pi^2\theta_{\eta 2}$ and variance $\theta_{\eta v}^2$. It now follows that:

$$\Pr(y = 1|\mathbf{x}, \mathbf{z}) = \int \Phi\left(\frac{\Omega(\pi, \mathbf{x}, \mathbf{z}; \theta_\varphi) - \mathbf{x}\theta_{\eta x} - \pi\theta_{\eta 1} - \pi^2\theta_{\eta 2}}{\theta_{\eta v}}\right) f_{\pi|\mathbf{x},\mathbf{z}}(\pi|\mathbf{x}, \mathbf{z}; \theta_\pi) d\pi. \tag{33}$$

where $\Omega(\pi, \mathbf{x}, \mathbf{z}; \theta_\varphi)$ is the parameterized version of (25). To obtain a consistent estimate of $\theta_\eta \equiv (\theta_{\eta x}, \theta_{\eta 1}, \theta_{\eta 2}, \theta_{\eta v})$, we maximize the likelihood formed from (33) with respect to θ_η, after substituting in $\widehat{\theta}_\pi$ and $\widehat{\theta}_\varphi$.

6. Results

6.1. **Model Fit.** To evaluate goodness of fit, we compare moments describing the equilibrium in the model with their data analogues. The Data column in Table 4 shows sample averages on the extent of competition, contract type, and prices. The next column displays the model analogues, evaluated at the estimated parameter, $\widehat{\theta}$, computed using the closed-form solutions described in Appendix F.1 for each observation, integrated over the unobserved heterogeneity, and averaged over the sample. The main dissonance arises in predicting the proportion of firm-fixed-price contracts conditional on the number of bids when the buyer solicits competition: the model predicts fewer firm-fixed-price contracts when there is only one bidder and more when there are multiple bidders. Almost all the other moments in the data fall within the 95 percent confidence band, and the differences between the estimated predictions and their data analogues are small, both economically and when compared with the observed heterogeneity within the sample (evident from the means and standard deviations shown in Table 2). Table A10 in Appendix G presents the model fit based on moments conditional on the observed attributes.

Although there are too few observations on the advertisement period to include that variable in estimation, we use them to evaluate the estimates. Suppose the cost of attracting another seller is increasing in the elapse time between meeting sellers, defined as the quotient of the duration of the advertisement period, which we now denote by α, and the total number of participants, n. For example postponing the

[36] We find that for 10 percent of the observations in the final sample, $\widehat{\lambda}^o(\mathbf{x}_i, \mathbf{z}_i, \pi; \widehat{\theta}_\pi) = 0$ for some $\pi \in [0.01, 0.99]$. For these observations, we estimate a lower bound of $\kappa(\mathbf{x}, \mathbf{z}, \pi; \theta_\varphi^*, \theta_\pi^*)$, but the results of our counterfactual exercises are not affected by whether we include or exclude these observations.

TABLE 4. Model Fit

	Data	Model
Extent of competition		
Probability of competitive solicitation	0.340	0.348 [0.332, 0.360]
Expected number of bids	1.635	1.609 [1.453, 1.656]
Probability of a firm-fixed-price contract		
No competitive solicitation	0.960	0.961 [0.954, 0.965]
Competitive solicitation with one bid	0.958	0.940 [0.932, 0.953]
Competitive solicitation with multiple bids	0.971	0.988 [0.983, 0.991]
Contract price (in thousand 2010 USD)		
Final	363.7	363.4 [358.5, 371.8]
Base, firm-fixed-price, no solicitation	337.0	334.2 [330.6, 341.6]
Base, firm-fixed-price, solicitation with one bid	329.2	335.3 [332.1, 342.8]
Base, firm-fixed-price, solicitation with multiple bids	336.1	340.5 [329.6, 345.1]
Base, other	359.7	352.0 [335.4, 363.4]
Adjustments, firm-fixed-price	24.5	25.1 [21.8, 27.9]
Adjustments, other	88.5	55.9 [41.8, 120.1]

Notes: Numbers in brackets are 95 percent confidence intervals based on bootstrapping.

start of a project to attract more sellers also pushes back expected completion time. Under this interpretation κ would be a measure of the opportunity cost from delaying the project, positively related with α/n. Figure A4 and Table A11 in Appendix G show buyer marginal search cost estimates, after integrating out unobserved heterogeneity attributable to π, $\int \kappa(\mathbf{x}, \mathbf{z}, \pi; \widehat{\theta}_\varphi, \widehat{\theta}_\pi) f_\pi(\pi|\mathbf{x}, \mathbf{z}; \widehat{\theta}_\pi) d\pi$, are positively correlated with α/n, regardless of whether we control for observed heterogeneity $(\mathbf{x}, \mathbf{z})$ or not.

An attractive feature of this external validation exercise is that $\kappa(\mathbf{x}, \mathbf{z}, \pi; \theta^*_\varphi, \theta^*_\pi)$ is one of the last pieces to be estimated (in **5.2.4**) after estimating all seller-side primitives $(\theta^*_\varphi, \theta^*_\pi)$, and we do not impose any additional functional form assumptions on $\kappa(\mathbf{x}, \mathbf{z}, \pi; \theta^*_\varphi)$, drawing upon the buyer's first order condition (24). Notwithstanding unaccounted endogeneity issues that might arise from embedding the advertising period into the theory, these results lend support to our model.

6.2. **Structural Estimates.** To evaluate how important observed contract heterogeneity $(\mathbf{x}, \mathbf{z})$ is in characterizing seller and buyer costs, we define several random variables induced by the joint probability distribution of $(\mathbf{x}_i, \mathbf{z}_i)$, and characterize their distribution with sample analogues evaluated at the parameter estimates in Table 5. Table A9 in Appendix G reports the parameter estimates. For example, the

Table 5. Estimating the Role of Observed Heterogeneity

	All contracts			Mean differences:	
	Mean	Median	SD	Product vs. services	Commercially available vs. not
Fraction of low-cost sellers	0.940	0.963	0.065	0.097	0.031
	(0.004)	(0.004)	(0.004)	(0.008)	(0.006)
Project costs of low-cost sellers	360.87	244.69	141.81	-27.19	-11.23
	(3.54)	(4.78)	(2.04)	(6.80)	(5.38)
Project cost difference	40.91	20.37	46.55	-2.02	19.24
	(30.63)	(19.37)	(32.27)	(36.00)	(38.55)
Maximal benefits of competition†	4.51	1.16	13.17	-6.61	-0.46
	(1.12)	(0.72)	(5.09)	(2.56)	(1.91)
Marginal search costs	1.70	0.56	4.65	-3.73	-0.32
	(0.53)	(0.43)	(1.20)	(1.29)	(0.77)
Solicitation costs	0.06	0.06	0.02	-0.01	0.003
	(0.14)	(0.14)	(0.07)	(0.05)	(0.03)
Conditional soliciting costs	-0.01	-0.01	0.02	-0.01	0.01
	(0.06)	(0.23)	(0.14)	(0.06)	(0.03)

Notes: This table provides summary statistics of the distribution of the mean values of the fraction of low-cost sellers, sellers' project costs, and the buyer's search and solicitation costs, integrated over π and evaluated at each realization of $(\mathbf{x}_i, \mathbf{z}_i)$ and the estimated parameters. It also provides the mean differences between contracts for products and those for services, as well as the differences in means between contracts for commercially available versus unavailable products and services. All cost estimates are in thousand 2010 dollars. Numbers in parentheses are bootstrap standard errors. † See (34) for the definition.

expected project cost for a type k seller conditional on $(\mathbf{x}, \mathbf{z})$, integrated over π, is:[37]

$$\mathbb{E}_\pi(c_k|\mathbf{x}, \mathbf{z}; \theta^*_\varphi, \theta^*_\pi) \equiv \int c_k\left(\mathbf{x}_1, \pi; \theta^*_\varphi\right) f_\pi(\pi|\mathbf{x}, \mathbf{z}; \theta^*_\pi) d\pi.$$

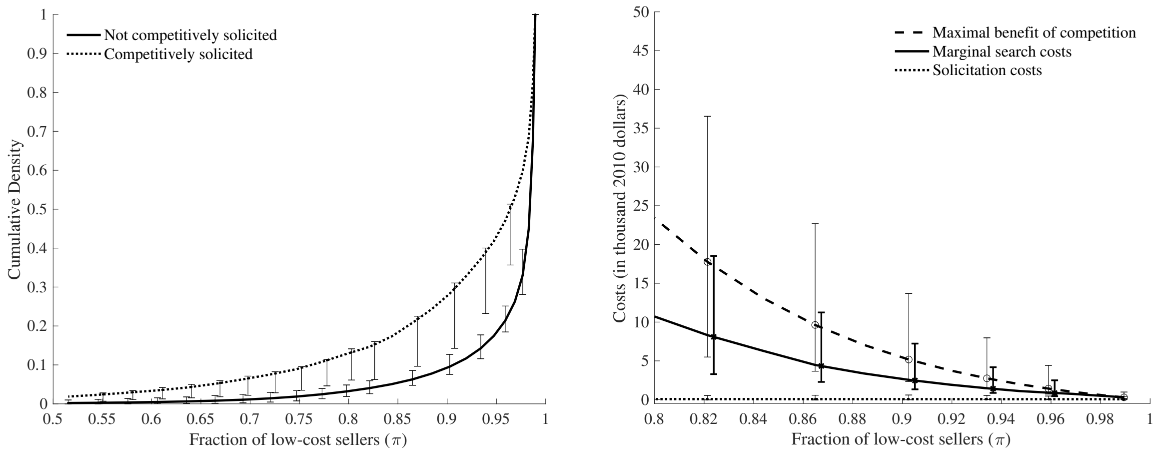
In Table 5, the mean of low-cost sellers' project costs is estimated by averaging $\mathbb{E}_\pi(c_1|\mathbf{x}_i, \mathbf{z}_i; \widehat{\theta}_\varphi, \widehat{\theta}_\pi)$ over the sample $i \in \{1, \ldots, I\}$.[38]

In addition, we show how the estimated primitives vary with π in Figure 2. Panel (A) of Figure 2 displays the estimated cumulative distribution function of π conditional on whether the contract is competitively solicited or not, after integrating out

[37]To clarify which variable the expectation is taken over, we use the subscript notation right next to the expectation operator. For example, $\mathbb{E}_\pi(\cdot)$ denotes the value of the term in parentheses integrated over the density of π.

[38]Bootstrap standard errors in Table 5 indicate the mean project cost differences and the mean solicitation costs are imprecisely estimated, but bootstrap confidence intervals in Table 6 are fairly tight. This apparent discrepancy may be explained by (i) our relatively precise parameter estimates of the π distribution and marginal search costs, key to the buyer's trade-off for extra bids; (ii) high-cost contracts comprising only 4 percent of the sample, yet providing an important source of variation for identification and estimation.

FIGURE 2. The Fraction of Low-cost Sellers and Procurement Costs



(A) Endogenous π Distributions (B) Buyer Costs

Notes: Based on the estimated parameters, Panel (A) shows the cumulative distribution function of π conditional on whether or not the contract is competitively solicited, averaged across sample observations, and Panel (B) provides the buyer's marginal search costs and solicitation costs, as well as an upper bound of the benefit of competition, as defined in (34). The error bars represent the 95% confidence intervals based on bootstrapping.

observed heterogeneity. It is the sample analogue of $\mathbb{E}_{\mathbf{x},\mathbf{z}}[F_{\pi|y}(\pi'|y', \mathbf{x}, \mathbf{z}; \theta_\pi^*)]$ computed for each π' in its support and $y' \in \{0, 1\}$, evaluated at $\widehat{\theta}_\pi$. Panel (B) of Figure 2 displays some of the benefits and costs of competition as a function of π.

From Table 5, the estimated average fraction of low-cost sellers in the population is 0.94. Thus the probability that a low-cost seller wins, $1 - (1 - \pi)^n$, is usually very high; as can be seen in Panel (A) of Figure 2, this is the case regardless of whether the buyer solicits extra bids or not. Panel (A) also shows the distribution of π for competitively solicited contracts is first-order dominated by the counterpart for contracts that are not. This implies procurement agencies are more likely to solicit competition when the probability of meeting a low-cost seller is relatively low.

The last two columns of Table 5 show that the expected mean value of π for procuring products is significantly higher than for services by 0.10. Similarly the fraction of low-cost sellers for commercially available items is significantly higher than for commercially unavailable ones. Thus contracts for services and commercially unavailable items tend to come from a pool with a greater fraction of high-cost sellers.

Project costs vary substantially with observed heterogeneity; the standard deviation of the expected project cost of a low-cost seller, \$141,810 in 2010 dollars, is about half its mean, \$360,870. Products on average are cheaper than services by \$27,190, and commercially available items are cheaper than those that are not by \$11,230.

The latter result might be anticipated: specialty items tend to cost than more standardized fare. In addition, the mean difference between high-cost and low-cost sellers is \$40,910, about 11 percent of the average project costs of a low-cost seller.

We define the maximal benefit of competition as the expected gain from eliminating exposure to high-cost sellers compared to the expected cost of randomly selecting a contractor from the population:

$$B(\mathbf{x}_1, \pi; \theta_\varphi^*) \equiv (1-\pi)\left[c_0\left(\mathbf{x}_1, \pi; \theta_\varphi^*\right) - c_1\left(\mathbf{x}_1, \pi; \theta_\varphi^*\right)\right]. \tag{34}$$

Table 5 provides summary statistics of the distribution of the consistent estimates of $\mathbb{E}_\pi[B(\mathbf{x}_1, \pi; \theta_\varphi^*)]$, obtained by taking its sample analogue evaluated at $\widehat{\theta}_\varphi$ and integrating it over π; Panel (B) of Figure 2 provides the estimates of $\mathbb{E}_\mathbf{x}[B(\mathbf{x}_1, \pi; \theta_\varphi^*)]$, the sample analogues computed for each π, evaluated at the parameter estimates.

Table 5 indicates that averaged over all projects, the estimated maximal benefits from competition are \$4,510 per contract. Panel (B) of Figure 2 shows they decline as π increases. Marginal search costs, $\kappa(\mathbf{x}, \mathbf{z}, \pi; \widehat{\theta}_\varphi, \widehat{\theta}_\pi)$, are substantial: the mean estimate is \$1,700, about 38 percent of the maximal benefits of competition. Furthermore, these costs decline with π: at $\pi = 0.8$, the estimated value of the expected marginal search costs, $\mathbb{E}_{\mathbf{x},\mathbf{z}}[\kappa(\mathbf{x}, \mathbf{z}, \pi = 0.8; \theta_\varphi^*, \theta_\pi^*)]$, is about half the maximal benefit of competition, but the differences vanish as π approaches to one.

Estimated solicitation costs are low, both unconditional and conditional on seeking alternatives to the default seller, and regardless of whether there is a relatively high proportion of low-cost sellers or not. Table 5 summarizes the distribution of the expected solicitation costs. Conditional on soliciting competition, the expected cost is -\$10; conditional on not soliciting extra bids competitively, \$90. Both estimates are not statistically different from zero and are a tiny fraction of both the average project amount in our data (\$363,710, Table 2) and the contracting officers' annual salary; their average salary during FY 2010, for example, is \$84,209, based on the FedScope data. This suggests that buyer preferences favoring the default seller play only a minor role in determining whether bids are solicited or not.

Despite these low solicitation costs, procurement agencies solicit competition only 34 percent of the time (Table 2). This is because our estimates indicate that the proportion of low-cost sellers is high and accordingly the maximal benefits from competition are low. They imply the buyer's problem often degenerates to extracting as much rent as possible from a low-cost default seller.

Table 6. Counterfactual Analyses

Panel A: Why so little competition?	Change in number of bids
Seller cost distribution	
Homogenous fraction of low-cost sellers (π)	
0.94 (Average in the sample)	+0.799 [0.654, 0.894]
0.5	+4.886 [4.783, 5.305]
0.25	+9.241 [9.010, 9.984]
Doubled cost differences ($c_2 - c_1$)	+0.664 [0.521, 0.747]
Buyer's ability to negotiate	
First-price sealed-bid auction	+2.728 [1.462, 3.375]
First-price sealed-bid auction with halved κ	+3.432 [1.989, 4.108]
Search and solicitation costs	
Halved κ	+0.577 [0.393, 0.679]
Halved η	+0.012 [0.004, 0.058]

Panel B: Effects of policies to mandate more competition

	Base	Minimum search intensity ($\lambda^o \geq 1$)	
		No	Yes
Number of bids	1.609 [1.453, 1.656]	+0.025 [0.010, 0.167]	+0.790 [0.773, 0.875]
Payments	363.38 [358.54, 371.75]	−0.01 [−0.10, −0.004]	−0.95 [−1.69, −0.61]
Search costs	0.66 [0.25, 1.02]	+0.01 [0.003, 0.07]	+1.34 [0.84, 2.34]
Solicitation costs	0.01 [-0.02, 0.04]	+0.05 [0.02, 0.39]	+0.05 [0.02, 0.39]

Note: Both counterfactual policies in Panel B mandate competitive solicitation; the first one requires no minimum search efforts, while the second one requires that search efforts are at least one so that the expected number of bids is two or more. All cost and payment estimates are in thousand 2010 dollars. Bootstrap 95 percent confidence intervals are provided in brackets.

6.3. **Why So Few Bids?** In our framework, procurement agencies manage competition mindful of the benefit and the cost of attracting extra bids. The former depends on the distribution of π, the differential between high and low-cost sellers, as well as how much rent the buyer can extract through negotiation. The latter includes up-front solicitation costs and marginal search costs. We quantify these factors using our parameter estimates. Panel A in Table 6 presents the model's predictions when the project cost distribution is less dispersed, heterogeneity amongst sellers is varied, the buyer loses her ability to negotiate, and search and solicitation cost decline.

The first exercise changes the level and dispersion of π throughout the population of projects, holding constant buyer and seller costs.[39] Although seller heterogeneity, conditional on observed characteristics $(\mathbf{x}, \mathbf{z})$, is maximized at $\pi = 0.5$, our results

[39]Recall both the seller and the buyer costs depend π in our estimated model. Holding costs fixed when varying π isolates the channel through which it affects the menu and competition.

show that as π declines, the number of expected bidders increases even beyond 9.2 extra bids at $\pi = 0.25$, before declining at values near zero. In addition, removing all dispersion of π over the population, and fixing the proportion of low-cost sellers for every project to $\mathbb{E}_{\mathbf{x},\mathbf{z},\pi}[\pi_i; \widehat{\theta}_\pi]$ increases the expected number of extra bidders, by 0.8. These findings show that the high average values of π and its dispersion help explain why there are so few bids for government procurement projects in this sector. Intuitively, when π is close to one, the buyer protects herself against a "lemon default seller," but when π is close to zero, she is "bargain hunting." Our estimates indicate the latter scenario generates more search in equilibrium than the former, yet contacting officers are much more likely to find themselves in the former scenario.

In our framework the buyer is cast as an effective negotiator that squeezes the profits of the high-cost seller to zero, and the profits of the low-cost seller to the amount necessary to induce truth-telling in this private information environment. This explains why the buyer needs to attract fewer bids than what an auction framework requires, to achieve the same outcome. To quantify the buyer's power to extract rent by limiting her discretion, we consider a *first-price sealed-bid* auction with a reserve price of γ_0.[40] In this auction, the contract type is set to be firm-fixed-price: sellers bid the base price, are liable for the initial project cost, and get reimbursed for uncertain cost changes. The equilibrium for this auction consists of two base prices, p_n'' and γ_0, where p_n'' takes precedence over γ_0 and p_n'' is defined:[41]

$$p_n'' \equiv \gamma_1 + \frac{\pi(1-\pi)^{n-1}}{1-(1-\pi)^n} (\gamma_0 - \gamma_1) . \tag{35}$$

Note that $p_n'' = \gamma_0$ when $n = 1$, decreasing in n to converge to γ_1 as $n \to \infty$. By Corollary 3.1, he expected total payment in this auction, $T_{FIC}(n)$, is higher than its negotiation counterpart, $T(n)$. Under this scenario, if solicitation and marginal search costs are held constant, it is optimal for the buyer to search more intensely, increasing the expected number of sellers by 2.73. This reduces the estimated expected payment by \$10 per contract, a small and statistically insignificant amount.

We speculate that conducting a first-price sealed-bid auction might be simpler than a negotiation process. Following that vein, consider a first-price sealed-bid auction where buyer search is half as costly for auctions compared to negotiations. Panel A of Table 6 shows that in such a scenario, the expected number of bids is 3.43 higher.

[40]Appendix F.2 describes how to implement this quantification exercise.

[41]Lemma A4 in the Appendix shows these prices form the optimal menu when the buyer is constrained to offer full insurance contracts. It is straightforward to establish, by a contradiction argument, that a first-price sealed bid scoring auction achieves these prices and allocation rule.

With more than twice the bids, total search costs are higher in the auction, but only a modest reduction in total payments is achieved, 0.25 percent or $895 per contract, for the reasons we explain above. It is not obvious an auction format is preferable even if attracting competitors is cheaper than in negotiations.

Turning to the buyer's costs, the solicitation costs, η, do not play a very important role in determining the optimal number of bids. Even if the value of η is halved, we estimate the expected number of bids would only increase by 0.01. On the other hand if marginal search costs, κ, are halved, we would expect 0.58 more bids. Although these estimates imply that the elasticity of bids with respect to marginal search costs is much greater than that with respect to solicitation costs, we cannot conclude that it is more cost-effective to invest in reducing marginal search costs than solicitation costs because on average κ is more than an order of magnitude greater that η.

6.4. **Policies to Mandate Competition.** To quantify the extent to which more competition can reduce the amount of payments to contractors, we consider two counterfactual policies. Both involve removing the buyer's discretion to forego competition and automatically award the project to a default seller. Thus the estimated distribution of solicitation costs, F_η, is not used for these counterfactual exercises, and since it is the final piece of the estimation procedure, our results on this segment are robust to misspecification of the distribution.

Under one policy, competitive solicitation is mandatory for all projects, but buyers have discretion in choosing their effort to attract more bids. The other policy requires the minimum amount of search efforts is one, so that the buyer attracts a greater number of bids than two in expectation.[42] Panel B of Table 6 shows these two policies would increase the average number of bids by 0.03 and 0.79, respectively, but the expected amount of payments to contractors would only decline by $10 and $950 per contract, less than 0.3 percent of the average payment size per contract under the current policy.[43]

These two alternative policies would decrease the size of the expected payments: increasing competition makes the selection of a low-cost seller more likely, thus reducing the project costs. However, Table 6 shows that these cost savings are more than

[42]For these two policies, the equilibrium search efforts, or equivalently the equilibrium number of bids, λ^o, are theoretically derived and calculated based on the estimates (Appendix F.3).

[43]These findings are consistent with Coviello et al. (2018). Based on a regression discontinuity design using data on public procurement in Italy, they show that increasing the buyer's discretion does not worsen procurement outcomes, and may even improve them. Using the Nigerian Civil Service data, Rasul and Rogger (2018) find that increasing bureaucrats' autonomy is positively associated with completion rates.

offset by an increase in the search and competitive solicitation costs. To the extent that the search costs reflect frictions in the market that are beyond the scope of a single buyer's responsibility (Kelman, 1990, 2005) and the costs of soliciting competitive bids represent a legitimate social cost (for example due to higher noncontractible quality of the default seller), both policies are suboptimal.

7. Conclusion

This paper is an empirical analysis of government procurement where procurement agencies have discretion about the extent of competition and contract terms. Our theory predicts that for any given number of bidders, procurement agencies can extract more rent from a winning seller when they negotiate, compared to running an auction. The agencies' ability to negotiate reduces their marginal value from promoting competition and attracting more bids. For example, we estimate that stripping the agencies of their discretion in designing and negotiating contracts would more than double the average number of bids, but hardly reduce the size of the payment to winning sellers. Allowing procurement agencies to exercise some discretion to use their knowledge of the supply side can reduce procurement costs, even if they simultaneously engage in some rent-seeking behavior. Broadly speaking, our findings are not very sensitive to the estimated costs of soliciting competition; agencies would, however, increase their search intensity and enlarge the pool of sellers if there was greater heterogeneity in the seller cost components. Our framework provides a template for analyzing other procurement auctions that attract only a modest number of bids.

References

An, Y. and X. Tang (2019). Specification and negotiation in incomplete contracts. *RAND Journal of Economics 50*(1), 57–92.

Arve, M. and D. Martimort (2016). Dynamic procurement under uncertainty: Optimal design and implications for incomplete contracts. *American Economic Review 106*(11), 3238–3274.

Athey, S., D. Coey, and J. Levin (2013). Set-asides and subsidies in auctions. *American Economic Journal: Microeconomics 5*(1), 1–27.

Athey, S., J. Levin, and E. Seira (2011). Comparing open and sealed bid auctions: Evidence from timber auctions. *Quarterly Journal of Economics 126*(1), 207–257.

Bajari, P., H. Hong, and S. P. Ryan (2010). Identification and estimation of a discrete game of complete information. *Econometrica 78*(5), 1529–1568.

Bajari, P. and A. Hortacsu (2003). The winner's curse, reserve prices, and endogenous entry: Empirical insights from ebay auctions. *RAND Journal of Economics 34*(2), 329–355.

Bajari, P., S. Houghton, and S. Tadelis (2014). Bidding for incomplete contracts: An empirical analysis of adaptation costs. *American Economic Review 104*(4), 1288–1319.

Bajari, P., R. McMillan, and S. Tadelis (2008). Auctions versus negotiations in procurement: An empirical analysis. *Journal of Law, Economics, & Organization 25*(2), 372–399.

Bajari, P. and S. Tadelis (2001). Incentives versus transaction costs: A theory of procurement contracts. *RAND Journal of Economics 32*(3), 387–407.

Bandiera, O., A. Prat, and T. Valletti (2009). Active and passive waste in government spending: Evidence from a policy experiment. *American Economic Review 99*(4), 1278–1308.

Barkley, A., J. R. Groeger, and R. A. Miller (2021). Bidding frictions in ascending auctions. *Journal of Econometrics 223*(2), 376–400.

Baron, D. P. and D. Besanko (1987). Monitoring, moral hazard, asymmetric information, and risk sharing in procurement contracting. *RAND Journal of Economics 18*(4), 509–532.

Bhattacharya, V. (forthcoming). An empirical model of R&D procurement contests: An analysis of the DOD SBIR program. *Econometrica*.

Bulow, J. and P. Klemperer (2002). Prices and the winner's curse. *RAND Journal of Economics 33*(1), 1–21.

Che, Y.-K. and I. Gale (2003). Optimal design of research contests. *American Economic Review 93*(3), 646–671.

Compiani, G., P. Haile, and M. Sant'Anna (2020). Common values, unobserved heterogeneity, and endogenous entry in U.S. offshore oil lease auctions. *Journal of Political Economy 128*(10), 3872–3912.

Coviello, D., A. Guglielmo, and G. Spagnolo (2018). The effect of discretion on procurement performance. *Management Science 64*(2), 715–738.

Crocker, K. J. and K. J. Reynolds (1993). The efficiency of incomplete contracts: An empirical analysis of air force engine procurement. *RAND Journal of Economics 24*(1), 126–146.

Decarolis, F. (2014). Awarding price, contract performance, and bids screening: Evidence from procurement auctions. *American Economic Journal: Applied Economics 6*(1), 108–132.

Decarolis, F., L. M. Giuffrida, E. Iossa, V. Mollisi, and G. Spagnolo (2020). Buyer competence and procurement outcomes. *Journal of Law, Economics, and Organization 36*(3), 537–597.

Fullerton, R. L. and R. P. McAfee (1999). Auctioning entry into tournaments. *Journal of Political Economy 107*(2), 573–605.

Gagnepain, P., M. Ivaldi, and D. Martimort (2013). The cost of contract renegotiation: Evidence from the local public sector. *American Economic Review 103*, 2352–2383.

Gayle, G.-L. and R. A. Miller (2015). Identifying and testing models of managerial compensation. *The Review of Economic Studies 82*(3), 1074–1118.

Guerre, E. and Y. Luo (2019). Nonparametric identification of first-price auction with unobserved competition: A density discontinuity framework. *mimeo*.

Hendricks, K., J. Pinkse, and R. H. Porter (2003). Empirical implications of equilibrium bidding in first-price, symmetric, common value auctions. *Review of Economic Studies 70*(1), 115–145.

Kelman, S. (1990). *Procurement and Public Management: The Fear of Discretion and the Quality of Government Performance*. The AEI Press.

Kelman, S. (2005). *Unleashing Change: A Study of Organizational Renewal in Government*. Brookings Institution.

Krasnokutskaya, E. (2011). Identification and estimation in procurement auctions under unobserved auction heterogeneity. *Review of Economic Studies 78*(1), 293–327.

Krasnokutskaya, E. and K. Seim (2011). Bid preference programs and participation in highway procurement auctions. *American Economic Review 101*, 2653–2686.

Laffont, J.-J. and J.-C. Rochet (1998). Regulation of a risk averse firm. *Games and Economic Behavior 35*(3), 149–173.

Laffont, J.-J. and J. Tirole (1987). Auctioning incentive contracts. *Journal of Political Economy 95*, 921–937.

Laffont, J.-J. and J. Tirole (1993). *A Theory of Incentives in Procurement and Regulation*. Cambridge, Mass.: MIT Press.

Lewis, G. and P. Bajari (2011). Procurement contracting with time incentives: Theory and evidence. *Quarterly Journal of Economics 126*, 1173–1211.

Lewis, G. and P. Bajari (2014). Moral hazard, incentive contracts and risk: Evidence from procurement. *Review of Economic Studies 81*, 1201–1228.

Li, T. (2005). Econometrics of first-price auctions with entry and binding reservation prices. *Journal of Econometrics 126*, 173–200.

Li, T. and X. Zheng (2009). Entry and competition effects in first-price auctions: Theory and evidence from procurement auctions. *Review of Economic Studies 76*(4), 1397–1429.

Liebman, J. B. and N. Mahoney (2017). Do expiring budgets lead to wasteful year-end spending? Evidence from federal procurement. *American Economic Review 107*(11), 3510–49.

MacKay, A. (forthcoming). Contract duration and the costs of market transactions. *American Economic Journal: Microeconomics*.

Manelli, A. M. and D. R. Vincent (1995). Optimal procurement mechanisms. *Econometrica 63*(3), 591–620.

McAfee, R. P. and J. McMillan (1987). Competition for agency contracts. *RAND Journal of Economics 18*(2), 296–307.

Perrigne, I. and Q. Vuong (2011). Nonparametric identification of a contract model with adverse selection and moral hazard. *Econometrica 79*, 1499–1539.

Pinkse, J. and G. Tan (2005). The affiliation effect in first-price auctions. *Econometrica 73*(1), 263–277.

Porter, R. H. and J. D. Zona (1993). Detection of bid rigging in procurement auctions. *Journal of Political Economy 101*(3), 518–538.

Rasul, I. and D. Rogger (2018). Management of bureaucrats and public service delivery: Evidence from the Nigerian civil service. *Economic Journal 128*(608), 413–446.

Riordan, M. H. and D. E. Sappington (1987). Awarding monopoly franchises. *American Economic Review 77*(3), 375–387.

Taylor, C. R. (1995). Digging for golden carrots: An analysis of research tournaments. *American Economic Review 85*(4), 872–890.

Warren, P. L. (2014). Contracting officer workload, incomplete contracting, and contractual terms. *RAND Journal of Economics 45*(2), 395–421.

Appendix A. Constructing the Dataset

A.1. **Definition of variables.**

A.1.1. *Contract price: Base and final.* The FPDS (Federal Procurement Data System) database provides three variables on the price of each contract action: (i) "base and all options value," the total contract value including all options including those not yet exercised; (ii) "base and exercised options value," the contract value for the base contract and any options that have been exercised; (iii) "action obligation," the amount that is obligated or de-obligated by the action. We define that the *final price* is the sum of all obligated amounts related to the contract; the *base price* is defined as the base and exercised options value as of the date that the contract was signed.

A.1.2. *Contract duration: Base and final.* The FPDS database provides four variables on the dates related to each contract action: (1) "date signed," the date that the action was signed; (ii) "effective date," the date that the parties agree will be the starting date for the contract requirements; (iii) "current completion date," the completion date of the base contract plus options that have been exercised; (iv) "ultimate completion date," the estimated or scheduled completion date including the base contract and all exercised and unexercised options. We define that the *start date* is the latter date of the date signed and the effective date in the initial entry; the *base duration* is the difference between the current completion date in the initial entry and the start date; the *final duration* is the difference between the current completion date as in the last entry and the start date. Note that we observe the expected completion date as in the last entry of a contract, not its actual completion date. Because further entries might occur after we retrieved the data from the FPDS (July 2018), we focus on contracts whose current completion date in the last contract entry lies before the end of FY 2017.

A.1.3. *Price and duration adjustments.* All contract actions, including the initial agreement and the subsequent adjustments, are recorded as entries in the FPDS database. Based on these entries, we construct the history of price and duration adjustments. Each contract action entry specifies the reason for the action, with the variable called "reason for modification." The variable value can take one of the reasons shown in Table A1, grouped into three categories: work changes, exercise of options and funding, and administrative actions. Using the "date signed" variable, we obtain the chronological order of all entries, and track the price and the duration adjustments based on the "action obligation amount" and the "current completion

Table A1. Price and Duration Adjustments

	Any (%)	Price ($K, 2010 USD)		Duration (days)	
		Mean	SD	Mean	SD
Work changes					
Additional work (new agreement)	1.69	116.56	224.68	114.09	177.01
Supplemental agreement for work within scope	9.65	39.66	118.80	113.48	208.78
Change order	5.51	27.40	119.50	89.31	252.40
Definitize change order or letter contract	0.27	153.85	196.82	41.68	86.18
Termination for convenience	0.72	-154.71	151.29	-9.72	110.62
Termination for cause	0.04	-49.02	58.80	0.00	0.00
Termination for default	0.04	-228.81	73.11	0.00	0.00
Legal contract cancellation	0.21	-218.12	172.07	-29.13	81.35
Options and funding					
Exercise of an option	6.49	261.60	224.88	450.57	401.21
Funding only	9.98	58.91	181.91	136.27	293.11
Administrative actions					
Close-out	8.97	-20.65	79.43	83.19	304.49
Vendor information change	0.33	2.17	10.63	21.64	96.40
Other administrative action	28.23	-0.36	59.10	66.43	220.94
Transfer or non-novated merger & acquisition	0.16	0.00	0.00	89.18	354.73
Novation agreement	0.37	2.55	12.99	8.92	79.93

Note: All contracts in the final sample are included. Column entitled as "Any" provides the fraction of the contracts with entries associated with a given reason. Conditional on having the respective entries, the average and standard deviation of the price adjustments (in thousand dollars, CPI-adjusted to 2010) and the duration adjustments (in days) are provided.

date" variables. Table A1 provides summary statistics of price and duration adjustments for each reason.

After the initial agreement on a contract, additional contract actions may be taken, relating to contract cost, schedule, fee, terms and conditions, and personnel. The need for such an action may arise due to changes in technologies, funding, and mission requirements. An "administrative" action applies when the substantive rights of either of the contracting parties are not affected by the action. An example of such an action is "close-out," which occurs when a contract has met all the terms of a contract and final payment has been made (FAR 4.804). Among the non-administrative contract actions, some (specifically, "additional work (new agreement)" and "supplemental agreement for work within scope") require both the contractor's and the contracting officer's signatures. Others do not require the contractor's signature because they are based on numerous clauses within the contract. The text for such clauses to be inserted in the contract, for example for change order, options, incremental funding, or termination, can be found in FAR 52.

A.1.4. *Extent of competition.* A contract in the category of *set-aside for small business* in Table 1 satisfies any of the following two conditions: (i) the "type of set aside" variable in the FPDS dataset takes a value other than "none"; or (ii) the "reason not competed" takes a value related to small business programs ("8AN," "HZS," "NZS," "SBA," and "BI"). For a contract to be labeled as *no competition by regulation*, its "reason not competed" variable must take "IA" (international agreement), "OTH" (authorized by statute), or "UT" (a regulated utility). If a contract doesn't belong to either of the above two categories and its "extent competed" variable takes either "A: Full and open competition" or "F: Competed under Simplified Acquisition Procedure (SAP)," it belongs to *full and open competition.* Those satisfying none of the above criteria fall into the category of *no competition by discretion.*

Note that in determining the four categories of the extent of competition, we do not use the "number of offers received" variable. All of the contracts that were not competed by regulation (3,376 contracts) or discretion (6,182 contracts) in Table 1, except 43 contracts and 1 contract respectively, received a single offer. This may reflect that limiting competition does not necessarily mean that only a single contractor is considered. However, in our final sample of the 6,981 contracts, all contracts that are categorized as not competed (by discretion) received a single offer.

In Panel B of Table 1, there are five categories of solicitation procedures, and these categories are directly from the FPDS variable entitled, "solicitation procedures." The procedures described in the variable include: "Negotiated proposal/quote", "Simplified acquisition," "No Solicitation (Only One Source)," as well as various other procedures such as "Sealed bid," "Two step," "Architect-Engineer," "Basic research" and "Multiple award fair opportunity."

A.1.5. *Contract type.* The FPDS dataset has the "type of contract" variable, and there are 16 different contract type codes for the variable, spanning from "Firm Fixed Price," "Fixed Price Incentive", "Fixed Price Award Fee," "Cost Plus Fixed Fee," "Cost Plus Incentive Fee," to "Time and Materials," and "Labor hours." All contract types are defined in FAR 16. A vast majority of the contracts in our final sample (6,717 out of 6,981) are "Firm Fixed Price," and the rest are mostly (212 out of 264) cost-plus contracts.

A.1.6. *Project attributes.* We construct the commercial availability variable based on two FPDS variables, "commercial item acquisition procedures" and "information technology commercial item category." The former designates whether the solicitation used the commercial item acquisition procedures. The latter is for computer hardware or services contracted or funded by the Department of Defense, and represents the commercial nature of the products or services. We define that the products or services are *commercial available* if the "commercial item acquisition procedures" variable is "Commercial Item" or the "information technology commercial item category" variable is "Commercial Available," "Other Commercial Item," "Non-developmental Item," or "Commercial Service."

The FPDS dataset has the "award type" variable, which can take four values: "Definitive Contract," "Purchase Order," "Delivery Order," and "BPA Call." Our study focuses on the first two types, and we construct a dummy variable indicating that a contract is a definitive contract.

Using on the "State: Place of Performance" and "Congressional District: Place of Performance" variables in the FPDS dataset, we identify the state and the Congressional district of the location where a contract is performed. We obtain the Congressional Committee assignment data, as collected by Charles Stewart III and Jonathan Woon: "Congressional Committees, Modern Standing Committees, 103rd-115th Congresses." The *Appropriations/Budget committee* variable indicates that the place of performance was represented, at the time of the signing the contract, by House Speaker, majority/minority leaders and whips, and chairmen or ranking members of the Committees on the Budget, Appropriations, and Ways and Means. The "Congressional District: Place of Performance" variable is not always available, especially for those in the FPDS dataset before 2007. For such contracts, we rely on the state information only, which is always available.

A.1.7. *Agency attributes.* By combining the FedScope Employment Cube with the FPDS data, we obtain the number and the government experience of the contracting officers hired by a procurement agency. For each agency, the FedScope data provides the number of employees by age, education, length of service, occupation, and pay plan/grade. The occupation code for contracting officers is 1102, and we obtain the number of all contracting officers in the agency and the numbers of such officers with at least 5 years of government service for each fiscal year. We then merge the data with the FPDS data, using the name of the government agency. Out of 235 agencies in the FPDS dataset, 196 are well-matched by the name, but the match for the rest is not clear. Given this, we use a larger unit of the government agency, or a parent agency, to merge the two datasets (69 parent agencies, such as the Department of Agriculture, the Department of Commerce, etc.), as opposed to a smaller unit (for example, Food Safety and Inspection Service, US Census Bureau, etc.). Given the agency-year-level data, we construct the *contracting officers with 5+ years* and *workload* variables.

A.1.8. *Measures of potential competition.* We construct two measures of potential competition, the *number of past winners* and the *number of establishments*. First, for a given contract, we look at all contracts in the FPDS dataset that were signed within three years and have the same values of Product and Service code, commercial availability, contract instrument (definitive contract or purchase order), state of the project location, and whether or not the Department of Defense is the procurement agency. We then count the number of unique contractors who won these contracts, based on the "Parent DUNS Number" variable, which is the identifier of the parent company of the winner. Second, based on the "NAICS" variable, which designates the principal North American Industry Classification System (NAICS) code for a contract, and the "State: Place of Performance" variable, we merge our dataset with the County Business Patterns dataset, which provides the number of establishments by industry, state, and year, to construct the *number of establishments* variable.

A.1.9. *Advertisement Period and Contract Types in Solicitations.* To obtain information on the procurement agency's actions to advertise and publicize solicitations, we combine the FPDS dataset with the information manually obtained from the federal business opportunity website (`www.fbo.gov`). This website provides all public notices regarding federal contract opportunities. To identify a public notice associated with a contract in the FPDS dataset, we use the "solicitation identifier" variable. The contracting officers are not required to report the solicitation identifier to the FPDS, and only 712 contracts in our sample (10 percent) have such information. Among them, we locate public notices for 394 contracts, and obtain the following: (i) the type as specified in the notice (pre-solicitation, sources sought, draft solicitation, request for information, request for proposal/quote, synopsis/solicitation, justification and approval, special notice, award, and cancellation); (ii) the date on which the notice was posted; (iii) the date by which a response by a contractor is requested. Whenever available, we obtain the solicitation and the justification and approval documents.

Figure A1 provides an excerpt of a webpage of a public notice for a solicitation. On the left panel, it provides the list of all public notices of the same strand, including the

FIGURE A1. An Excerpt of a Public Notice on FBO.GOV


FEDBIZOPPS.GOV Federal Business Opportunities

E·GOV USA.gov

Home | Getting Started | General Info | Opportunities | Agencies | Privacy

Buyers: Login | Register Vendors: Login | Register Accessibility

D--VISN 12 Consolidated LEC Services For Region 2: Indiana (IN), Illinois (IL), Michigan (MI), and Wisconsin (WI).

Solicitation Number: VA11814R0665
Agency: Department of Veterans Affairs
Office: VA Technology Acquisition Center
Location: VA Technology Acquisition Center

Notice Details | Packages | Interested Vendors List

Print Link

Complete View

Original Synopsis
Presolicitation
Sep 15, 2014
5:57 pm

Changed
Sep 23, 2014
1:50 pm
Solicitation

Return To Opportunities List

Solicitation Number:
VA11814R0665

Notice Type:
Solicitation

Synopsis:
Added: Sep 15, 2014 5:57 pm
The Department of Veterans Affairs (VA), Office of Acquisition Operations (OAO), Technology Acquisition Center (TAC), located at 23 Christopher Way, Eatontown, New Jersey, intends to enter into a contract on a basis of other than full and open competition for existing Local Exchange Carrier (LEC) services on the Region 2, Veterans Integrated Service Network (VISN) 12 Telecommunications Business Office (VISN 12 TBO) AT&T Global Services infrastructure. These LEC services consist of: plain old telephone service (POTS), Centrex service, Primary Rate Integrated Services Digital Network (PRI) (ISDN) service, Basic Rate ISDN (BRI) 2B+D Service, T-1 Digital Switched Service (DSS), Direct Inward Dialing (DID) numbers, Metro E-Service metropolitan-area Ethernet, or metro Ethernet network (MOE), Supertrunk to include Trunk Group and Port, Assured Private Branch Exchange (PBX) Trunk, Caller ID (name and number) feature (POTS Line and PRI Circuit (23B+D)), Three-Way Calling feature, Call Forward feature, Call Wait feature, Voicemail feature, Call Block feature, Call Hunting/Roll over feature, Call Redirect feature, Third Party Billing Block feature, Primary inter-LATA (Local access and transport area) Carrier (PIC/LPIC) provisioning, Telephone Service Priority (TSP), E-911 Private Switch / Automatic Location

ALL FILES

Attachment
Sep 15, 2014
VA118-14-R-0665 VA11...

Solicitation 1
Sep 23, 2014
VA118-14-R-0665 VA11...
VA118-14-R-0665 ATTA...
VA118-14-R-0665 Just...

GENERAL INFORMATION

Notice Type:
Solicitation

Original Posted Date:
September 15, 2014

Posted Date:
September 23, 2014

Response Date:
September 26, 2014

Original Response Date:
September 26, 2014

Archiving Policy:
Automatic, on specified date

Notes: This is a screenshot of a part of a webpage of a public notice for solicitation VA11814R0665 from `www.fbo.gov`, retrieved in August 2018.

pre-solicitation notice posted on September 15, 2014. In the middle panel, it specifies that the notice type as "solicitation," and a brief synopsis follows. On the right panel, there are links to the attached documents, followed by the information on dates: this notice was posted on September 23 and the response due date is September 26. The advertisement period in this case is 12 days (from September 15 to 26).

A.2. **Sample Selection.** There are 41,189 IT and telecommunications contracts with specified terms and conditions (definitive contracts or purchase orders) that were initiated in FY 2004–2015. Panel A of Table A2 shows summary statistics of the 17,123 contracts of Table 1 that satisfy all six sample selection criteria of Section 2.1, as well as those that do not meet each criterion, in the rows (A-1) to (A-6). Some contracts fail on multiple criteria. We sequentially drop observations, implying the sum of observations in rows (A-1) to (A-6) equals 41,189−17,123.

Table A2. Sample Selection

	Observations		Final price ($K, 2010)	
	Num.	Frac. (%)	Mean	SD
Panel A: All IT/telecommunications	41,189	100.0	3,028.49	33,243.8
Sample used in Table 1	17,123	41.6	366.87	246.74
Out of sample due to:				
(A-1) Base maximal price $\geq \$1M$ (real)	9,188	22.3	11,886.65	68,602.3
(A-2) Base price $\leq \$150K$ (nominal)	5,474	13.3	634.48	15,239.2
(A-3) Base duration < 30 or > 400 days	7,385	17.9	463.42	2,043.3
(A-4) Ended after the end of FY2017	228	0.6	2,084.9	13,680.4
(A-5) Performed outside of the U.S.	1,071	2.6	406.86	516.03
(A-6) Missing or inconsistent information†	720	1.8	1,996.1	2,924.8
Panel B: Sample used in Table 1	17,123	100.0	366.87	246.74
Final sample				
Fully competed, negotiated	2,375	13.9	357.49	237.23
Not competed by discretion, negotiated	4,606	26.9	366.91	230.72
Out of sample due to:				
(B-1) Not competed by rules	5,910	34.5	389.06	272.06
(B-2) Fully competed, other procedures	2,655	15.5	343.31	232.71
(B-3) Not competed by discretion, other proc.	1,577	9.2	337.36	220.48

Note: This table provides summary statistics of the final price of the contracts in the data, focusing on the IT and telecommunications contracts that initiated in FY 2004–2015, by the sample selection criteria discussed in Section 2.1 (Panel A) and Section 2.2 (Panel B). † We define price or duration information is *inconsistent* when (i) the final delay of the contract is greater than twenty times of the base duration (84 contracts); (ii) the final contract price is larger than three times of the base maximal price (524 contracts).

Panel B of Table A2 focuses on the sample used in Table 1, and presents summary statistics of the final sample and the remainders. In addition to the six criteria mentioned above, the contracts in the final sample satisfy two conditions: first, they were either fully competed or not competitively solicited for discretionary reasons; second, the contract terms were negotiated. The former rules out the 5,910 contracts, those in Row (B-1), which were not solicited by regulation or were set-aside for small business. The latter excludes the 2,655 contracts of the "full and open competition" category, those in Row (B-2), and the 1,577 contracts of the "no competition by discretion" category, those displayed in Row (B-3).

Appendix B. Further Evidence on the Assumptions

B.1. **Competition and Winning History.** Table A3 presents the summary statistics of our sample by the seller's history of winning contracts and three industries

Table A3. Non-repeat vs. Repeat Sellers

	Number of sellers	Number of contracts	Competitive solicitation	Number of bids	Final price ($K)
Communication Equipment (PSC: 58)					
Non-repeat sellers	1,012	1,012	0.37	1.69	351.0
			(0.02)	(0.06)	(7.02)
Repeat sellers (≤ 5)	348	927	0.25	1.44	360.3
			(0.01)	(0.06)	(7.17)
Repeat sellers (> 5)	55	614	0.21	1.24	364.6
			(0.02)	(0.04)	(8.27)
Automatic Data Processing Equipment, Software, Supplies (PSC: 70)					
Non-repeat sellers	1,180	1,180	0.37	1.84	347.2
			(0.01)	(0.08)	(6.56)
Repeat sellers (≤ 5)	397	1,043	0.37	1.63	335.3
			(0.01)	(0.05)	(6.07)
Repeat sellers (> 5)	45	517	0.62	2.38	341.8
			(0.02)	(0.11)	(8.3)
IT and Telecommunications Service (PSC: D3)					
Non-repeat sellers	1,105	1,105	0.28	1.51	413.1
			(0.01)	(0.05)	(8.4)
Repeat sellers (≤ 5)	241	597	0.31	1.46	394.1
			(0.02)	(0.05)	(11.6)
Repeat sellers (> 5)	16	136	0.32	1.30	409.7
			(0.04)	(0.09)	(22.2)

Notes: We divide the contracts in our sample based on the seller's history of winning any of the contracts in our sample: *non-repeat sellers*, *repeat sellers* with two to five contracts, and those with more than five. The numbers in parentheses are standard errors.

based on the two-digit Product and Service Code (PSC): 58 (communication equipment), 70 (automatic data processing equipment, software, and supplies), and D3 (IT and telecommunications service). The table shows that the correlation between the seller's winning history and the extent of competition varies by the industry. For PSC 58, the contracts won by repeat sellers tend to result from less competition, in terms of both competitive solicitation and the number of bids, than the contracts won by one-time sellers. On the other hand, completely opposite patterns are found for PSC 70; no statistically significant patterns for PSC D3.

B.2. **Competition and Price.** Columns (1) and (3) of Table A4 shows that more bids are associated with higher final and base prices, even after controlling for observed heterogeneity of each contract, including various fixed effects. When we instrument the number of bids using the two measures of potential competition, Columns (2) and (4) of the same table show the contract price is negatively correlated with the number

Table A4. Relationship between Competition and Price

Dependent variable:	Log of final price		Log of base price	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
Log (Number of bids)	0.028**	-0.791	0.025**	-0.066
	(0.011)	(0.631)	(0.0104)	(0.428)
Base duration $\geq$ 3 months	0.109***	-0.018	0.081***	0.066
	(0.024)	(0.096)	(0.025)	(0.078)
Commercially available	0.035*	0.116	0.010	0.019
	(0.019)	(0.071)	(0.015)	(0.046)
Definitive contract	0.159***	0.118***	0.106***	0.101***
	(0.014)	(0.033)	(0.015)	(0.031)
Agency's COs with 5+ years $\geq$ 80%	-0.025	-0.011	-0.031	-0.030
	(0.026)	(0.043)	(0.027)	(0.030)
Agency procured a similar contract	0.035***	0.043**	0.032**	0.032**
	(0.013)	(0.018)	(0.013)	(0.014)
Agency workload > 4.5	-0.045*	-0.096*	-0.029	-0.035
	(0.023)	(0.053)	(0.024)	(0.033)
Appropriations/Budget committees	-0.041	-0.002	-0.051**	-0.046
	(0.026)	(0.041)	(0.021)	(0.030)
Product and Service Code FE	Yes	Yes	Yes	Yes
Procurement agency FE	Yes	Yes	Yes	Yes
State FE; Year FE; Month FE	Yes	Yes	Yes	Yes
N	6,909	6,909	6,981	6,981
R^2	0.074	-	0.073	-

Note: Our final sample is used. The instruments are the number of the past winners of similar contracts, the number of the establishments sharing the NAICS code in the state, and the squared values of these two variables, respectively. The standard errors are clustered at the 4-digit Product and Service Code level, and provided in parentheses; $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

of bids, although the coefficients are not statistically significant. Absent unobserved heterogeneity, the equilibrium of standard auction models predicts that procurement price falls as the number of bids increases.[1]

B.3. **Firm-Fixed-Price Contracts vs. Others.** Table A5 shows the final price and the price adjustments, by contract type. We find that firm-fixed-price contracts are cheaper than other contracts on average. Price adjustments occur regardless of the contract type, but the price adjustments of firm-fixed-price contracts are smaller,

[1]In common value or affiliated private value auctions, a positive relationship between bids and the number of bidders may arise even in the absence of entry (Bulow and Klemperer, 2002; Pinkse and Tan, 2005; Compiani et al., 2020).

Table A5. Final Price and Price Adjustments

	Firm fixed	Other	Difference
Final price (thousand 2010 USD)	360.39	448.16	-87.78 (14.58)
Ratio of price adjustments to base price (%)			
Work changes	1.37	8.11	-6.73 (1.14)
Options and funding	8.03	26.11	-18.08 (2.58)
Administrative actions	-0.53	-2.63	2.10 (0.74)

Note: Our final sample is used. The standard errors are in parentheses.

Table A6. Final Price and Price Adjustments by Contract Type

Dependent variable:	Final	Adjustment	|Adjustment|×100/Base price		
			Work	Options	Admin.
	(1)	(2)	(3)	(4)	(5)
Firm-fixed-price	-38.31**	-27.02**	-2.857	-10.00***	-3.188*
	(18.50)	(11.69)	(2.278)	(3.197)	(1.870)
Contract attributes†	Yes	Yes	Yes	Yes	Yes
Product and Service Code FE	Yes	Yes	Yes	Yes	Yes
Procurement agency FE	Yes	Yes	Yes	Yes	Yes
State FE; Year FE; Month FE	Yes	Yes	Yes	Yes	Yes
N	6,981	6,981	6,981	6,981	6,981
R^2	0.080	0.096	0.060	0.096	0.050

Note: Results are based on our final sample. The standard errors are clustered at the 4-digit Product and Service Code level, and provided in parentheses; $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. †: Project and procurement agency attributes (other than number of bids and fixed effects) used in Table A4.

Table A7. Duration Adjustments by Contract Type

Dependent variable:	Any delay		Duration of delay	
	(1)	(2)	(3)	(4)
Firm-fixed-price	-0.267***	-0.187***	-121.6***	-58.16*
	(0.019)	(0.025)	(25.87)	(29.57)
Contract attributes†	No	Yes	No	Yes
Product and Service Code FE	No	Yes	No	Yes
Procurement agency FE	No	Yes	No	Yes
State FE; Year FE; Month FE	No	Yes	No	Yes
N	6,981	6,981	6,981	6,981
R^2	0.014	0.095	0.008	0.103

Note: Results are based on our final sample. The standard errors are clustered at the 4-digit Product and Service Code level, and provided in parentheses; $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. †: Project and procurement agency attributes (other than number of bids and fixed effects) used in Table A4.

controlling for the base price, than those of other contracts. Columns (1) and (2) of Table A6 show these patterns persist even after controlling for contract attributes.

Columns (3)–(5) of Table A6 show that price adjustments are less volatile for firm-fixed-price contracts than other contracts. The dependent variables are the ratio of the absolute value of the price adjustments, due to each of the three categories respectively, to the base price; hence, the larger the ratio is, the more volatile the price adjustments are. Column (4) shows that price adjustments associated with exercising options or funding issues tend to be 10 percent lower than the base price.

Lastly, Table A7 show that firm-fixed-price contracts are less likely to have delays, and conditional on having delays, the length is shorter, with or without controlling for contract attributes.

B.4. **Relationship between Price and Duration Adjustments.** Column (1) of Table A8 shows that price adjustments and delays are positively correlated. Contracts seemingly reward delays, at odds with time incentive contracts induced by moral hazard (Lewis and Bajari, 2011, 2014). This pattern may be driven by the contractual agreement to fully or partially "reimburse" project cost changes under various circumstances to manage the risk faced by the contractor. The financial and accounting records of the contractor, as well as the cost control systems, are reviewed by a government auditing agency to verify the claimed costs (FAR 42.101). Notably, this positive correlation is pronounced for the adjustments that are likely to involve cost changes, as shown in Columns (2)–(3), while it is reversed for the administrative adjustments. This illustrates the importance of decomposing price and duration adjustments for structural analysis.

Appendix C. Deriving the Optimal Contract Menu

Given a menu $\{p_{jn}, q_{jn}(\mathbf{s})\}_{j=0}^{J} \equiv \mathcal{J}$ we say individual rationality for a type k seller, denoted by IR_k, is satisfied if and only if:

$$\max_{j\in\mathcal{J}} \left\{ p_{jn} - \gamma_k + \int \psi[q_{jn}(\mathbf{s}) - c(\mathbf{s})] f_k(\mathbf{s}) d\mathbf{s} \right\} \equiv \max_{j\in\mathcal{J}} \{\omega_{jk}\} \equiv \omega_k \geq 0, \qquad \text{(A.1)}$$

where ω_{jk} is the expected utility to a type k from winning the procurement by choosing $\{p_{jn}, q_{jn}(\mathbf{s})\}$ from the menu. We say IR_k binds if $\omega_k = 0$. Without loss of generality we ignore contracts that neither seller type choose in equilibrium. In a pooling menu both seller types maximize their respective expected utilities by choosing all the contracts on the menu with positive probability, and it is straightforward to establish that the optimal pooling menu from the buyer's perspective is one full insurance

Table A8. Correlation between Price and Duration Adjustments

Dependent variable:	Price adjustment×100/Base Price			
	All (1)	Work (2)	Options (3)	Admin. (4)
Duration adjustments×100/Base duration†	0.958***	0.942***	4.765***	-0.224**
	(0.224)	(0.550)	(1.351)	(0.101)
Contract attributes††	Yes	Yes	Yes	Yes
Product and Service Code FE	Yes	Yes	Yes	Yes
Procurement agency FE	Yes	Yes	Yes	Yes
State FE; Year FE; Month FE	Yes	Yes	Yes	Yes
N	6,981	6,981	6,981	6,981
R^2	0.098	0.069	0.084	0.006

Note: Results are based on our final sample. The standard errors are clustered at the 4-digit Product and Service Code level, and provided in parentheses; $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. †: Duration adjustments associated with the respective category; namely, all duration adjustments for Column (1), work changes for (2), options and funding for (3), and administrative actions for (4). ††: Project and procurement agency attributes (other than number of bids and fixed effects) used in Table A4.

contract (FIC in short) taking the form $\{\gamma_0, c(\mathbf{s})\}$. In a separating menu each contract is only chosen by one seller type in equilibrium. Partition $\mathcal{J}$ by $\{\mathcal{J}_k\}_{k=0}^{1}$ where $\mathcal{J}_k$ denotes the set of contracts that a type k seller chooses with positive probability, and suppose ϕ_j is the probability of winning the procurement in equilibrium by choosing $\{p_{jn}, q_{jn}(\mathbf{s})\}$. Then incentive compatibility for a type k seller, abbreviated by IC_k, is satisfied in a Bayesian equilibrium if and only if for $k' \in \{0,1\}$:

$$\min_{j \in \mathcal{J}_k} \{\phi_j \omega_{jk}\} \geq \max_{j \in \mathcal{J}_{k'}} \{\phi_j \omega_{jk}\}. \tag{A.2}$$

A sequence of lemmas preface the proof to the theorem. Lemma A1 proves that in any optimal contract, IR_0 binds, a result used repeatedly in what follows. Then Lemma A2 proves that a separating menu giving precedence to contracts directed towards low-cost sellers is not optimal. Lemma A3 proves that an optimal menu contains a FIC directed towards low-cost sellers. Given these lemmas, we consider the optimal menu of contracts when the buyer is constrained to make only FIC offers in Lemma A4. Then Lemma A5 proves that offering FICs only is suboptimal. Combining Lemmas A2 to A5 together, we prove that an optimal menu must be a separating menu, consisting of FIC's directed towards low-cost sellers and non-FIC's directed towards high-cost sellers, that gives precedence to the former. Lemma A6 proves the claim about a unique root of (8) is correct, and thus demonstrates the menu presented in Theorem 3.1 is well defined. Lemma A7 proves that the menu of Theorem 3.1 is optimal *when only two contracts are permitted.* The proof of the theorem is completed by showing that the buyer's expected payment does not fall when extra contracts are permitted.

C.1. **Lemmas Preceding Theorem 3.1.**

Lemma A1. *IR_0 binds in any optimal menu of contracts.*

Proof. If neither IR_1 nor IR_0 bind, then reducing all payoffs by a small fixed amount leaves IR_k and IC_k satisfied for both $k \in \{0, 1\}$. The proposed adjustment does not affect the sellers' incentives, but does reduce the buyer's expected payment. Therefore IR_k binds for some $k \in \{0, 1\}$.

Consider the contrary hypothesis that IR_0 does not bind. Then IR_1 binds. If a high-cost seller faced a FIC, then a low-cost seller could switch and make positive profits. Therefore, a high-cost seller does not face a FIC. Moreover if IC_0 does not bind, then lowering the base price of the contract(s) to high-cost sellers would violate neither IC_1 nor IR_0, and reduce the buyer's expected payment. Therefore if IR_0 does not bind in an optimal menu, then both IR_1 and IC_0 bind.

The hypothesis implies a low-cost seller receives zero expected utility. Thus, a FIC of $\{\gamma_1, c(\mathbf{s})\}$ also satisfies both IR_1 and IC_1. Additionally, $c_1 \equiv \gamma_1 + \int c(\mathbf{s}) f_1(\mathbf{s}) d\mathbf{s}$ is the minimal payment to low-cost sellers satisfying IR_1. There are two cases to analyze, depending on whether sellers have liquidity concerns or not. First, when there are liquidity concerns, the expected payment of the FIC of $\{\gamma_1, c(\mathbf{s})\}$ is strictly lower than any contract directed towards low-cost sellers satisfying IR_1. Therefore, in an optimal menu, a low-cost seller faces the FIC. But this implies IC_0 does not bind because $\gamma_0 > \gamma_1$ by (1), contradicting an implication of the contrary hypothesis. Second, suppose there are no liquidity concerns. Consider replacing the contract(s) assigned to low-cost sellers with a FIC of $\{\gamma_1, c(\mathbf{s})\}$. This does not increase the buyer's expected payout to low-cost sellers, does not reduce their expected utility, satisfying IR_1 and IC_1. Now, however, IC_0 would not bind. Because neither IR_0 nor IC_0 bind, the buyer can reduce the amount offered to high-cost sellers without violating either IR_0 or IC_0. Thus, menus where IR_0 does not bind are not optimal. □

Lemma A2. *Separating menus giving precedence to contracts directed towards high-cost sellers are not optimal.*

Proof. If the expected payment conditional on a low-cost seller winning the procurement is no less than c_0, then the unconditional expected payment of the menu exceeds the expected payment of a one-contract pooling menu, $\{\gamma_0, c(\mathbf{s})\}$. This is because the pooling menu (i) minimizes the expected payment to a high-cost winner while meeting IR_0; (ii) reduces the expected payment to a low-cost winner by an amount exceeding

$$c_0 - \left[\gamma_0 + \int c(\mathbf{s}) f_1(\mathbf{s}) d\mathbf{s}\right] = \int c(\mathbf{s}) [1 - l(\mathbf{s})] f_0(\mathbf{s}) d\mathbf{s} > 0,$$

with the latter inequality held by (1); (iii) decreases the probability of expected payments greater than c_0. Therefore menus where the expected payment to a low-cost winner is larger than or equal to c_0 are not optimal.

Now consider the contrary hypothesis that the separating menu giving precedence to contracts directed towards high-cost sellers is optimal. Given our argument above, the expected payment to a low-cost winner must be less than c_0. This implies the expected payment if a low-cost wins is less than the expected payment if a high-cost seller wins, because the latter is bounded below by c_0, which can be achieved by offering $\{\gamma_0, c(\mathbf{s})\}$ in the menu. Therefore, the overall expected payment would be reduced by reversing precedence, providing the revised IR_k and IC_k are satisfied for $k \in \{0, 1\}$. Because the probability of a low-cost seller winning would increase, both IR_1 and IC_1 are weakened, and hence are satisfied. Also IR_0 does not change. This only leaves IC_0 to check. By Lemma A1 IR_0 binds. It now follows from IC_0, that the expected utility to a high-cost seller from choosing the contract directed at a low-cost seller, under either precedence rule, is bounded above by zero. Therefore IC_0 is also satisfied under the revised less costly menu that reverses precedence, contradicting the contrary hypothesis, and proving the lemma. □

Lemma A3. *Any optimal menu includes a FIC directed to low-cost sellers.*

Proof. Consider the contrary hypothesis that contracts other than FICs are directed to low-cost sellers, that is, a contract of $\{p, q(\mathbf{s})\}$, where $q(\mathbf{s}) \neq c(\mathbf{s})$ for some $\mathbf{s}$, is offered to low-cost sellers. Define:

$$p' \equiv p + \int \psi[q(\mathbf{s}) - c(\mathbf{s})] f_1(\mathbf{s}) d\mathbf{s}.$$

Replacing $\{p, q(\mathbf{s})\}$ with a FIC of $\{p', c(\mathbf{s})\}$ yields the same expected utility to low-cost sellers, satisfying IR_1 because under the contrary hypothesis $\{p, q(\mathbf{s})\}$ satisfies IR_1. It also reduces the buyer's expected payment to low-cost sellers, given our assumption that $\psi(r) < r$ for any $r \neq 0$:

$$\left[p + \int q(\mathbf{s}) f_1(\mathbf{s}) d\mathbf{s}\right] - \left[p' + \int c(\mathbf{s}) f_1(\mathbf{s}) d\mathbf{s}\right] = \int \left\{q(\mathbf{s}) - c(\mathbf{s}) - \psi[q(\mathbf{s}) - c(\mathbf{s})]\right\} f_1(\mathbf{s}) d\mathbf{s} > 0.$$

If $p' < \gamma_0$, then IC_0 is satisfied, contradicting the contrary hypothesis, since the proposed revision to the menu reduces the buyer's expected payment when a low-cost seller wins. If $p' \geq \gamma_0$, consider replacing the entire menu with a pooling contract of $\{\gamma_0, c(\mathbf{s})\}$. The pooling contract minimizes the buyer's expected payment to a high-cost winning seller, and it also minimizes the expected payment to a low-cost winning seller subject to the constraint that a low-cost seller obtains an expected utility of $\gamma_0 \leq p'$, while still meeting IR_1. This wholesale replacement reduces the buyer's expected payment when a low-cost seller wins, and does not increase the payout when a high-cost seller wins, thus showing that offering a low-cost seller a contract other than a FIC is not optimal. □

Lemma A4. *If the buyer can only make FIC offers and $n > 1$, then the optimal menu comprises two contracts, $\{p''_n, c(\mathbf{s})\}$ and $\{\gamma_0, c(\mathbf{s})\}$, where p''_n is defined in (35) and $\{p''_n, c(\mathbf{s})\}$ takes precedence over $\{\gamma_0, c(\mathbf{s})\}$, inducing a separating equilibrium. When $n = 1$ the menu collapses to the optimal pooling menu, $\{\gamma_0, c(\mathbf{s})\}$.*

Proof. The last statement in the lemma is verified by setting $n = 1$ in (35). Note that $\{\gamma_0, c(\mathbf{s})\}$ is the only contract offered to high-cost sellers on this menu satisfying IR_0, since it is the unique FIC in which IR_0 binds. Now consider a menu of two FIC's, $\{p_{1n}, c(\mathbf{s})\}$ and $\{\gamma_0, c(\mathbf{s})\}$. Clearly $p_{1n} < c_0$ otherwise IC_0 does not hold. To induce a low-cost seller to choose a FIC with a lower base price than γ_0, the buyer must give it precedence. Hence IC_1 simplifies to:

$$\phi_{1n}(p_{1n} - \gamma_1) \geq \phi_{0n}(\gamma_0 - \gamma_1), \tag{A.3}$$

where ϕ_{1n} and ϕ_{0n} are respectively defined by (4) and (5). Minimizing:

$$[1 - (1-\pi)^n](p_{1n} + c_1 - \gamma_1),$$

the only part of the buyer's expected payment that depends on p_{1n}, subject to (A.3) yields (35). Her expected payment from the menu of $\{p''_n, c(\mathbf{s})\}$ and $\{\gamma_0, c(\mathbf{s})\}$ is:

$$\begin{aligned} T_{FIC}(n) &= [1-(1-\pi)^n]\left[c_1 + \frac{\pi(1-\pi)^{n-1}}{1-(1-\pi)^n}(\gamma_0 - \gamma_1)\right] + (1-\pi)^n c_0 \qquad \text{(A.4)} \\ &= c_1 + (1-\pi)^{n-1}\left[\gamma_0 - \gamma_1 + (1-\pi)\int c(\mathbf{s})[1 - l(\mathbf{s})]f_0(\mathbf{s})d\mathbf{s}\right]. \end{aligned}$$

Note that when $n > 1$, it is smaller than the buyer's expected payment from the optimal pooling menu, $\{\gamma_0, c(\mathbf{s})\}$:

$$T_{POOL} = \pi\left[\gamma_0 + \int c(\mathbf{s})f_1(\mathbf{s})d\mathbf{s}\right] + (1-\pi)\left[\gamma_0 + \int c(\mathbf{s})f_0(\mathbf{s})d\mathbf{s}\right] = T_{FIC}(1) > T_{FIC}(n),$$

by the assumption of (1). Therefore, when $n > 1$, a pooling menu cannot be optimal.

Finally, suppose multiple fixed contracts are offered to low-cost sellers, which we now denote by $\left\{p_n^{(1)}, p_n^{(2)}, \ldots\right\}$. Also let Φ_i denote the probability of winning the contract by choosing $p_n^{(i)}$. Conditional on a low-cost seller winning the contract, the expected payment is $\sum_i \Phi_i p_n^{(i)} \equiv p_n^{(0)}$. By construction, offering $p_n^{(0)}$ instead of $\left\{p_n^{(1)}, p_n^{(2)}, \ldots\right\}$ is equally profitable for both low-cost sellers and the buyer. □

Lemma A5. *The menu defined in Lemma A4 is not optimal.*

Proof. We construct an alternative menu, comprising a preferred FIC $\{p_{1n}, c(\mathbf{s})\}$ plus a non-FIC $\{p_{0n}, q_{0n}(\mathbf{s})\}$, with a lower expected payment than $T_{FIC}(n)$, given in (A.4), thus proving the Lemma. By assumption $f_1(\mathbf{s}) \neq f_0(\mathbf{s})$ for some outcome $\mathbf{s}$, and hence for some $\epsilon > 0$, there exists $\tilde{S} \equiv \{\mathbf{s} : f_0(\mathbf{s}) - f_1(\mathbf{s}) > \epsilon\}$ and (μ_1, μ_0) such that:

$$0 < \mu_1 \equiv \int \mathbb{1}\{\mathbf{s} \in \tilde{S}\} f_1(\mathbf{s}) d\mathbf{s} < \int \mathbb{1}\{\mathbf{s} \in \tilde{S}\} f_0(\mathbf{s}) d\mathbf{s} \equiv \mu_0 < 1.$$

Noting that because $\psi(q)$ is monotonic its inverse exists, consider any δ satisfying

$$0 \leq \delta < \min\left\{\psi^{-1}\left[\frac{\beta(1-\mu_0)}{(\mu_0-\mu_1)}\right], \psi^{-1}\left[\frac{(1-\mu_0)}{\mu_0}|\psi(M)|\right]\right\}, \tag{A.5}$$

and define the differentiable mapping:

$$\mu(\delta) \equiv \psi^{-1}\left[-\mu_0 \psi(\delta)/(1-\mu_0)\right].$$

We define the base price of the alternative FIC as:

$$p_{1n} = \gamma_1 + \frac{\pi(1-\pi)^{n-1}}{1-(1-\pi)^n}\left\{\gamma_0 - \gamma_1 + \frac{\mu_1 - \mu_0}{1-\mu_0}\psi(\delta)\right\}, \tag{A.6}$$

and the other contract in the alternative menu is defined by:

$$p_{0n} = \gamma_0 \text{ and } q_{0n}(\mathbf{s}) = \begin{cases} c(\mathbf{s}) + \delta & \text{if } \mathbf{s} \in \tilde{S}, \\ c(\mathbf{s}) + \mu(\delta) & \text{if } \mathbf{s} \notin \tilde{S}. \end{cases}$$

A low-cost seller receives the following expected utility from choosing the FIC:

$$\phi_{1n}(p_{1n} - \gamma_1) = \frac{(1-\pi)^{n-1}}{n}\left[\gamma_0 - \gamma_1 + \frac{\mu_1 - \mu_0}{1-\mu_0}\psi(\delta)\right], \tag{A.7}$$

while his/her expected utility from choosing the non-FIC is:

$$\begin{aligned} &\phi_{0n}\left(p_{0n} - \gamma_1 + \int \psi[q_{0n}(\mathbf{s}) - c(\mathbf{s})] f_1(\mathbf{s}) d\mathbf{s}\right) \\ = \; &\frac{(1-\pi)^{n-1}}{n}\Big\{\gamma_0 - \gamma_1 + \mu_1\psi(\delta) + (1-\mu_1)\psi[\mu(\delta)]\Big\}, \end{aligned} \tag{A.8}$$

where ϕ_{1n} and ϕ_{0n} are defined in (4) and (5). From the definition of $\mu(\delta)$:

$$\mu_1\psi(\delta) + (1-\mu_1)\psi[\mu(\delta)] = \frac{\mu_1-\mu_0}{1-\mu_0}\psi(\delta). \tag{A.9}$$

Comparing $(A.7)$ with $(A.8)$ using $(A.9)$ demonstrates IC_1 is satisfied with equality. By $(A.5)$ and $(A.6)$, IR_1 is satisfied with strict inequality. Conditional on a high-cost seller winning the non-FIC contract, his expected payoff is

$$p_{0n} - \gamma_0 + \int \psi[q_{0n}(\mathbf{s}) - c(\mathbf{s})]f_0(\mathbf{s})d\mathbf{s} = 0,$$

implying IR_0 is satisfied with equality. From (A.6), IC_0 is satisfied with strict inequality because $\psi(\delta) > 0$ and $\mu_1 < \mu_0$, and by (A.5), the limited liability constraint is also satisfied. Therefore the proposed menu constitutes a direct revelation game. The expected payment, denoted by $\tilde{T}(n,\delta)$ to indicate its dependence on δ, is:

$$\begin{aligned}\tilde{T}(n,\delta) &= c_1 + (1-\pi)^{n-1}\Big\{\gamma_0 - \gamma_1 + (1-\pi)\int c(\mathbf{s})[1-l(\mathbf{s})]f_0(\mathbf{s})d\mathbf{s} \\ &\quad +\pi\frac{\mu_1-\mu_0}{1-\mu_0}\psi(\delta) + (1-\pi)\Big[\mu_0\delta + (1-\mu_0)\,\mu\,(\delta)\Big]\Big\}.\end{aligned}$$

Noting $\lim_{\delta\to 0}\mu(\delta) = 0$ and $\tilde{T}(n,0) = T_{FIC}(n)$, we show the derivative of $\tilde{T}(n,\delta)$ at $\delta = 0$ is negative:

$$\frac{\partial}{\partial\delta}\tilde{T}(n,0) = (1-\pi)^{n-1}\pi\frac{\mu_1-\mu_0}{1-\mu_0} < 0,$$

which completes the proof. □

Lemma A6. *There is at most one root in $\pi \in (0,1)$ to (8).*

Proof. Denote (8) as a real-valued mapping from $\pi \in (0,1)$, $H(\pi)$, and rewrite it as:

$$H(\pi) = \gamma_0 - \gamma_1 - \int \tilde{H}(\pi,\mathbf{s})f_0(\mathbf{s})d\mathbf{s},$$

where:

$$\tilde{H}(\pi,\mathbf{s}) \equiv \begin{cases}\psi\left(\psi'^{-1}\left[\frac{1-\pi}{1-\pi l(\mathbf{s})}\right]\right)[1-l(\mathbf{s})] & \text{if } l(\mathbf{s}) < \tilde{l}(\pi), \\ \psi(M)\,[1-l(\mathbf{s})] & \text{otherwise.}\end{cases}$$

If $l(\mathbf{s}) \geq \tilde{l}(\pi)$ then $\partial\tilde{H}(\pi,\mathbf{s})/\partial\pi = 0$. Otherwise:

$$\frac{\partial}{\partial\pi}\tilde{H}(\pi,\mathbf{s}) = -\left[\frac{1-\pi}{1-\pi l(\mathbf{s})}\right]\frac{[l(\mathbf{s})-1]^2}{[1-\pi l(\mathbf{s})]^2}\Big/\psi''\left[\psi'^{-1}\left(\frac{1-\pi}{1-\pi l(\mathbf{s})}\right)\right] > 0.$$

Taking the expectation of $\tilde{H}(\pi,\mathbf{s})$ with respect to $\mathbf{s}$ proves $H(\pi)$ is strictly decreasing in π. From (7) $\lim_{\pi\to 0}\tilde{l}(\pi) = \infty$, and $\psi'^{-1}(1) = 0$ by assumption; hence

$\lim_{\pi\to 0} H(\pi) = \gamma_0 - \gamma_1 > 0$ by (1). Therefore $H(\pi) > 0$ for all $\pi \in (0,1)$ or there exists a unique $\pi \in (0,1)$ solving $H(\pi) = 0$. □

Lemma A7. *Suppose menus are limited up to two contracts. Then the optimal menu is defined in Theorem 3.1 by (9)–(11).*

Proof. By Lemmas A4 and A5, there exist separating menus whose expected payment is strictly lower than the expected payment of the optimal pooling menu. By Lemmas A3 and A2, we consider the buyer's problem to minimize her expected payment by choosing a separating menu of a FIC directed to low-cost sellers, denoted by $\{p_{1n}, c(\mathbf{s})\}$, and a contract directed to high-cost sellers, denoted by $\{p_{0n}, q_{0n}(\mathbf{s})\}$ when she faces n sellers:

$$[1-(1-\pi)^n]\left[p_{1n} + \int c(\mathbf{s}) f_0(\mathbf{s}) d\mathbf{s}\right] + (1-\pi)^n\left[p_{0n} + \int q_{0n}(\mathbf{s}) f_0(\mathbf{s}) d\mathbf{s}\right], \quad \text{(A.10)}$$

subject to IR_k and IC_k for $k \in \{0,1\}$, as defined by (A.1) and (A.2), and the limited liability constraint:

$$q(\mathbf{s}) - c(\mathbf{s}) \geq M, \quad \text{(A.11)}$$

for all $\mathbf{s}$. From Lemma A1, IR_0 binds, implying:

$$p_{0n} = \gamma_0 - \int \psi\left[q_{0n}(\mathbf{s}) - c(\mathbf{s})\right] f_0(\mathbf{s}) d\mathbf{s}. \quad \text{(A.12)}$$

We show below that the solution to $r_{0n}(\mathbf{s}) \equiv q_{0n}(\mathbf{s}) - c(\mathbf{s})$ does not depend on n. Dropping the dependence of $q_{0n}(\mathbf{s})$ on n in $(A.12)$ yields $p_{0n} = p$ defined in (11). Substituting for p_{0n} and appealing to the definitions of ϕ_{1n} and ϕ_{0n} in (4) and (5), IC_1 simplifies to:

$$p_{1n} \geq \gamma_1 + \frac{\pi(1-\pi)^{n-1}}{1-(1-\pi)^n}\left(\gamma_0 - \gamma_1 - \int \psi[r(\mathbf{s})]\{1 - l(\mathbf{s})\} f_0(\mathbf{s}) d\mathbf{s}\right). \quad \text{(A.13)}$$

We show that the menu of Theorem 3.1 is the solution to minimizing (A.10) subject to IR_1, (A.12), (A.13), and the limited liability constraint. The remaining constraint, IC_0, simplified by:

$$\phi_{1n}\left(p_{1n} - \gamma_0\right) \leq \phi_{0n}\left(p + \int \psi[r(\mathbf{s})] f_0(\mathbf{s}) d\mathbf{s} - \gamma_0\right), \quad \text{(A.14)}$$

is automatically satisfied by the menu; the right hand side of $(A.14)$ is zero (because IR_0 binds), and from (10), $p_{1n} \leq \gamma_0$. There are two cases to consider, depending on whether or not IR_1 binds. If IR_1 does not bind, then IC_1 must bind, otherwise the base price of the fixed contract could be reduced, to the buyer's benefit. Solving for p_{1n} by strengthening (A.13) to an equality, and substituting the resulting expression for p_{1n} and p_{0n} using (A.12) into (A.10), we obtain the buyer's expected payment to a winning seller as:

$$[1-(1-\pi)^n]\left[\gamma_1+\frac{\pi(1-\pi)^{n-1}}{1-(1-\pi)^n}\left(\gamma_0-\gamma_1-\int\psi[r\left(\mathbf{s}\right)]\{1-l(\mathbf{s})\}f_0(\mathbf{s})d\mathbf{s}\right)\right.$$
$$\left.+\int c\left(\mathbf{s}\right)f_1(\mathbf{s})d\mathbf{s}\right]+(1-\pi)^n\left[\gamma_o-\int\psi\left[r\left(\mathbf{s}\right)\right]f_0(\mathbf{s})d\mathbf{s}+\int q\left(\mathbf{s}\right)f_0(\mathbf{s})d\mathbf{s}\right].$$

Simplifying the equation, we have:

$$c_1+(1-\pi)^{n-1}\Bigg[(1-\pi)(c_0-c_1)+\pi(\gamma_0-\gamma_1)+\Gamma\Bigg], \tag{A.15}$$

where Γ is defined by (15), which we reproduce here:

$$\Gamma\equiv(1-\pi)\int\Big\{r(\mathbf{s})-\psi[r(\mathbf{s})]\Big\}f_0(\mathbf{s})d\mathbf{s}-\pi\int\psi[r(\mathbf{s})]\left[1-l(\mathbf{s})\right]f_0(\mathbf{s})d\mathbf{s}.$$

The (scaled) Lagrangian for the cost minimization problem can now be expressed as:

$$\int\Bigg[(1-\pi)\Big\{r(\mathbf{s})-\psi[r(\mathbf{s})]\Big\}-\pi\psi[r(\mathbf{s})][1-l(\mathbf{s})]-\varkappa_1\left(\mathbf{s}\right)\left[r(\mathbf{s})-M\right]\Bigg]f_0(\mathbf{s})d\mathbf{s},$$

where $\varkappa_1\left(\mathbf{s}\right)\geq 0$ denotes the Kuhn Tucker multiplier for the limited liability constraint, (A.11). The first order condition with respect to $q(\mathbf{s})$ is:

$$(1-\pi)\left(1-\psi'[r(\mathbf{s})]\right)-\pi\psi'[r(\mathbf{s})][1-l(\mathbf{s})]-\varkappa_1\left(\mathbf{s}\right)=0.$$

Rearranging terms we obtain:

$$\psi'\left[r(\mathbf{s})\right]=\frac{1-\pi-\varkappa_1\left(\mathbf{s}\right)}{1-\pi l(\mathbf{s})}. \tag{A.16}$$

If $l(\mathbf{s})<\tilde{l}(\pi)$, then $r(\mathbf{s})=\psi'^{-1}\left[(1-\pi)/[1-\pi l(\mathbf{s})]\right]>M$ and hence $\varkappa_1\left(\mathbf{s}\right)=0$. If $l(\mathbf{s})\geq\tilde{l}(\pi)$, then $\varkappa_1\left(\mathbf{s}\right)>0$ and $r(\mathbf{s})=M$.

If IR_1 binds then $p_{1n}=\gamma_1$. Substituting for p_{1n} and p using (A.12), we obtain the buyer's expected payment, (A.10), as:

$$[1-(1-\pi)^n]\left[\gamma_1+\int c\left(\mathbf{s}\right)f_1(\mathbf{s})d\mathbf{s}\right]+(1-\pi)^n\left[\gamma_0+\int\Big\{-\psi\left[r\left(\mathbf{s}\right)\right]+q\left(\mathbf{s}\right)\Big\}f_0(\mathbf{s})d\mathbf{s}\right],$$

which can be further simplified as:

$$c_1+(1-\pi)^n\Bigg[(1-\pi)(c_0-c_1)+\pi(\gamma_0-\gamma_1)+\int\Big\{r(\mathbf{s})-\psi[r(\mathbf{s})]\Big\}f_0(\mathbf{s})d\mathbf{s}\Bigg].$$

Substituting for p_{1n} in $(A.13)$ yields:

$$\gamma_0 - \gamma_1 \leq \int \psi[r(\mathbf{s})]\{1 - l(\mathbf{s})\} f_0(\mathbf{s}) d\mathbf{s}. \tag{A.17}$$

Let $\varkappa_1(\mathbf{s}) \geq 0$ denote the Kuhn Tucker multiplier for the limited liability constraint, (A.11). If IC_1 does not bind, then the first order condition with respect to $r(\mathbf{s})$ for the Kuhn Tucker formulation is:

$$1 - \psi'[r(\mathbf{s})] = \varkappa_1(\mathbf{s}).$$

If $r(\mathbf{s}) > M$, then the complementary slackness condition requires $\varkappa_1(\mathbf{s}) = 0$, and hence $1 = \psi'[r(\mathbf{s})]$ implying $r(\mathbf{s}) = 0$. Therefore, either $r(\mathbf{s}) = M$ or $r(\mathbf{s}) = 0$. Let us define S_M as the set of contract outcomes such that $r(\mathbf{s}) = M$. The buyer's expected payment can now be written as:

$$c_1 + (1-\pi)^n \left\{ (1-\pi)(c_0 - c_1) + \pi(\gamma_0 - \gamma_1) + [M - \psi(M)] \int \mathbb{1}\{\mathbf{s} \in S_M\} f_0(\mathbf{s}) d\mathbf{s} \right\}. \tag{A.18}$$

By inspection $(A.18)$ is increasing in $\int \mathbb{1}\{\mathbf{s} \in S_M\} f_0(\mathbf{s}) d\mathbf{s}$, while setting $\int \mathbb{1}\{\mathbf{s} \in S_M\} f_0(\mathbf{s}) d\mathbf{s} = 0$ does not satisfy IC_1, $(A.17)$. This implies that when IR_1 binds, IC_1 does too; in other words (A.17) holds with equality. Now the (scaled) Lagrangian for the minimization problem can be written as:

$$\begin{aligned} &\int \left\{ \Big(r(\mathbf{s}) - \psi[r(\mathbf{s})] \Big) - \varkappa_1(\mathbf{s}) \left[r(\mathbf{s}) - M \right] \right\} f_0(\mathbf{s}) d\mathbf{s} \\ &+ \varkappa_2 \left\{ \gamma_0 - \gamma_1 - \int \psi[r(\mathbf{s})][1 - l(\mathbf{s})] f_0(\mathbf{s}) d\mathbf{s} \right\}, \end{aligned} \tag{A.19}$$

where $\varkappa_2$ denotes the Kuhn Tucker multiplier for (A.17). The first order condition with respect to $r(\mathbf{s})$ is:

$$1 - \psi'[r(\mathbf{s})] - \varkappa_1(\mathbf{s}) - \varkappa_2 \psi'[r(\mathbf{s})][1 - l(\mathbf{s})] = 0,$$

which can be expressed:

$$\psi'[r(\mathbf{s})] = \frac{1 - \varkappa_1(\mathbf{s})}{1 + \varkappa_2[1 - l(\mathbf{s})]}. \tag{A.20}$$

Since (A.19) does not depend on π, neither does $q(\mathbf{s})$ nor $\varkappa_1(\mathbf{s})$ and $\varkappa_2$. Noting that $\tilde{\pi}$ solves both first order conditions (A.16) and (A.20), we equate the two and deduce $\varkappa_2 = \tilde{\pi} / (1 - \tilde{\pi})$. Substituting for $\varkappa_2$ in (A.20), the solution for $r(\mathbf{s})$ follows by setting $\pi = \widetilde{\pi}$ in (9). It immediately follows from (10) that if $H(\pi) > 0$ then $p_n > \gamma_1$, but if $H(\pi) \leq 0$ then $p_n = \gamma_1$. Appealing to Lemma A6, we conclude if $\pi < \tilde{\pi}$, then $H(\pi) > 0$ and IR_1 not bind; otherwise $\pi \geq \tilde{\pi}$, then $H(\pi) \leq 0$ and IR_1 binds. □

C.2. **Proof of Theorem 3.1.** By Lemma A2 it is not optimal to offer a separating menu in which contracts directed to high-cost sellers are prioritized, that is ranked above low-cost sellers. By Lemma A3 it is optimal to offer low-cost sellers a FIC. Given Lemmas A4 and A7, the expected payment from offering a menu of FIC's to both seller types (including the optimal pooling menu when facing a single bidder), $T_{FIC}(n)$, exceeds $T(n)$. Then Lemma A7 establishes the optimal menu when the buyer is constrained to offer two-contract menus only.

We now show additional contracts are redundant. Noting that low-cost sellers are offered a FIC, exactly the same arguments used in the proof of Lemma A4 apply here. Therefore offering multiple full insurance contracts to low-cost sellers does not reduce the expected payment. Also every contract offered to high-cost sellers must individually satisfy IC_1 and IR_0, the latter with equality by Lemma A1. If any two contracts on the menu do not generate the same expected payment to a high-cost seller, then offering the more expensive one is suboptimal. This proves the first statement of the theorem. □

C.3. **Proof of Corollary 3.1.** To prove (14) note that the optimal strategy for a buyer with full information is to approach a low-cost seller if there is one, and offer the initial cost as a base price by setting $p_{kn} = \gamma_k$ plus full insurance $q_{kn}(\mathbf{s}) = c(\mathbf{s})$ for $k \in \{0, 1\}$, efficiently extracting all the project surplus. Thus:

$$T_U(n) = [1 - (1-\pi)^n] c_1 + (1-\pi)^n c_0 = c_1 + (1-\pi)^n (c_0 - c_1),$$

as required. From (A.4) and (14):

$$\begin{aligned}
& T_{FIC}(n) - T_U(n) \\
= \; & c_1 + (1-\pi)^n \left[c_0 - c_1 + \frac{\pi}{1-\pi} (\gamma_0 - \gamma_1) \right] - c_1 - (1-\pi)^n (c_0 - c_1) \\
= \; & \pi (1-\pi)^{n-1} (\gamma_0 - \gamma_1),
\end{aligned}$$

which proves (13). Finally appealing to (10) and (11) we can express $T(n)$ as (A.15). Thus, $T(n) = T_{FIC}(n) + (1-\pi)^{n-1}\Gamma$. By inspection $\Gamma < 0$ implying $T(n) < T_{FIC}(n)$ and $T_U(n) \leq T(n)$ since the cost minimization problem underpinning $T_U(n)$ imposes fewer constraints than the problem associated with $T(n)$. □

C.4. **Proof of Corollary 3.2.** In the extended model where sellers choose whether to pay the entry cost, κ_s, the individual rationality constraint as in (A.1) becomes:

$$\max_{j \in \mathcal{J}} \left\{ \omega_{jk} - \frac{\kappa_s}{\phi_{jn}} \right\} \equiv \omega_k^* \geq 0, \tag{A.21}$$

given a menu $\{p_{jn}, q_{jn}(\mathbf{s})\}_{j=0}^{J} \equiv \mathcal{J}$ and n sellers. Recall that ω_{jk} is the expected utility to a type k from winning the procurement by choosing $\{p_{jn}, q_{jn}(\mathbf{s})\}$ from the menu; ϕ_{jn} is the probability of winning the procurement when there are n sellers participating in the procurement process and a given seller chooses contract j. In contrast, the incentive compatibility applies after the entry costs have been paid, and hence remain unchanged from (A.2).

Lemmas A1–A6 can be adapted to this extended case with minimal notational changes. There is essentially no change to the proof of these lemmas, aside from replacing γ_k with $\gamma_{kn}^* \equiv \gamma_k + \kappa/\phi_{kn}$. Therefore the buyer's problem has the same representation as when sellers incur no entry costs, (A.10): given n sellers she minimizes her expected payment from choosing a separating menu of a full-insurance contract directed to low-cost sellers, now denoted by $\{p_{1n}^*, c(\mathbf{s})\}$, and a contract directed to high-cost sellers, denoted by $\{p_{0n}^*, q_{0n}^*(\mathbf{s})\}$, subject to IR_k^* and IC_k for $k \in \{0,1\}$, as defined by (A.21) and (A.2), plus the limited liability constraint (A.11).

Following the basic model, the solution $q_{0n}^*(\mathbf{s})$ does not depend on n, so we write $r^*(\mathbf{s}) \equiv q_{0n}^*(\mathbf{s}) - c(\mathbf{s})$, dropping the subscript n. Since IR_0 binds (Lemma A1):

$$p_{0n}^* = \gamma_{0n}^* - \int \psi\left[r^*(\mathbf{s})\right] f_0(\mathbf{s}) d\mathbf{s}. \tag{A.22}$$

Substituting for p_{0n}^*, IC_1 an be expressed as:

$$\phi_{1n}\left(p_{1n}^* - \gamma_1 - \frac{\kappa_s}{\phi_{1n}}\right) \geq \phi_{0n}\left(\gamma_{0n}^* - \int \psi[r^*(\mathbf{s})]\{1 - l(\mathbf{s})\} f_0(\mathbf{s}) d\mathbf{s} - \gamma_1 - \frac{\kappa_s}{\phi_{0n}}\right),$$

where ϕ_{kn} is defined in (4) and (5) for $k \in \{0,1\}$. Appealing to the definitions of γ_{kn}^* and ϕ_{kn} and simplifying:

$$p_{1n}^* \geq \gamma_{1n}^* + \frac{\pi(1-\pi)^{n-1}}{1-(1-\pi)^n}\left(\gamma_0 - \gamma_1 - \int \psi[r^*(\mathbf{s})]\{1 - l(\mathbf{s})\} f_0(\mathbf{s}) d\mathbf{s}\right). \tag{A.23}$$

The proof of the corollary is completed by obtaining the solution to minimizing (A.10) subject to IR_1^*, (A.22), (A.23), and the limited liability constraint. As before, the remaining constraint, IC_0^*, is automatically satisfied by the menu. The optimization problem determining $r^*(\mathbf{s})$ is identical to its analogue solving for $r(\mathbf{s})$, and hence they share the same solution. The remainder of the proof then runs parallel to the case where there are no entry costs borne by sellers. □

C.5. **Proof of Corollary 3.3.** Given n sellers, the expected benefits from using the menu of Theorem 3.1 are:

$$B(n) \equiv b_1 - (1-\pi)^n (b_1 - b_0).$$

The expected benefits from a menu with a separating equilibrium that prioritizes contracts a high-cost seller selects are:

$$B_1(n) \equiv b_0 + \pi^n (b_1 - b_0).$$

The expected benefits from randomly selecting a seller are:

$$B_2(n) \equiv b_1 - (1-\pi)(b_1 - b_0).$$

Since $b_1 \geq b_0$:

$$\begin{aligned} B(n) - B_1(n) &= [1 - \pi^n - (1-\pi)^n](b_1 - b_0) \geq 0, \\ B(n) - B_2(n) &= (1-\pi)\left[1 - (1-\pi)^{n-1}\right](b_1 - b_0) \geq 0. \end{aligned}$$

Let $T_1(n)$ denote the minimal expected cost of implementing a menu with a separating equilibrium that prioritizes contracts a high-cost seller selects, if such a menu exists; otherwise set $T_1(n) = \infty$. Let $T_2(n)$ denote the minimal cost of a menu that randomly selects a seller (a single item full insurance contract with base price γ_1). Then by definition $T(n) \leq \min\{T_1(n), T_2(n)\}$. Therefore $B(n) - T(n) \geq \max\{B_1(n) - T_1(n), B_2(n) - T_2(n)\}$. □

Appendix D. Proving Identification

D.1. **Proof of Lemma 4.1(i).** By **A3** $v(l,\pi)$ satisfies (18). Totally differentiating (18) with respect to π and making $\partial v(l,\pi)/\partial\pi$ the subject of the resulting equation:

$$\frac{\partial v(l,\pi)}{\partial \pi} = \frac{l-1}{\psi''(r)(1-\pi l)^2}. \tag{A.24}$$

By assumption $\psi''(r) < 0$, implying $\partial v(l,\pi)/\partial\pi \gtreqless 0$ when $l \gtreqless 1$. From (18) it follows that $v(l,\pi) \gtreqless 0$ when $l \gtreqless 1$. Combining both sets of inequalities $\partial v(l,\pi)/\partial\pi \gtreqless 0$ when $v(l,\pi) \gtreqless 0$, as claimed. □

D.2. **Proof of Lemma 4.1 (ii).** Rewriting (10) to make the dependence of p_n on π explicit:

$$\begin{aligned} p_n(\pi) &= \gamma_1(\pi) + \frac{\pi(1-\pi)^{n-1}}{1-(1-\pi)^n}\left[\gamma_0(\pi) - \gamma_1(\pi) - \int \psi\left(v\left[l(\mathbf{s}),\pi\right]\right)\left[1 - l(\mathbf{s})\right] f_0(\mathbf{s}) d\mathbf{s}\right] \\ &\equiv \gamma_1(\pi) + \Psi_{0,n}(\pi)\left[\gamma_0(\pi) - \gamma_1(\pi) - \Psi_1(\pi)\right], \end{aligned}$$

and hence:

$$p_n'(\pi) = \gamma_1'(\pi) + \Psi_{0,n}'(\pi)\left[\gamma_0(\pi) - \gamma_1(\pi) - \Psi_1(\pi)\right] + \Psi_{0,n}(\pi)\left[\gamma_0'(\pi) - \gamma_1'(\pi) - \Psi_1'(\pi)\right].$$

By definition $\Psi_{0,n}(\pi) > 0$, $\gamma_1'(\pi)$ by **A4**, and $\gamma_0'(\pi) - \gamma_1'(\pi) \leq 0$ by **A5**. By **A3** IR_1 does not bind, implying $\gamma_0(\pi) - \gamma_1(\pi) - \Psi_1(\pi) > 0$. Completing the proof, we now show that $\Psi_{0,n}'(\pi) \leq 0$ implying the second expression is nonpositive, and that $\Psi_1'(\pi) > 0$, implying the third expression is negative. With regards $\Psi_{0,n}'(\pi)$:

$$\frac{\partial}{\partial \pi} \ln\left[\Psi_{0,n}(\pi)\right] = \frac{1 - n\pi - (1-\pi)^n}{\pi(1-\pi)\left[1-(1-\pi)^n\right]}.$$

The derivative is zero at $n = 1$ and $-\pi^2$ at $n = 2$. Now suppose it is negative for all $n \in \{2, \ldots, \tilde{n}\}$. For $\tilde{n}+1$ the denominator is positive and the numerator is:

$$1 - (\tilde{n}+1)\pi - (1-\pi)(1-\pi)^{\tilde{n}} < \pi(1-\pi)^{\tilde{n}} - \pi < 0.$$

The first inequality follows from an induction hypothesis, and the second one from the inequalities $0 < \pi < 1$. Therefore $\Psi_{0,n}'(\pi) \leq 0$ for all (π, n). To sign $\Psi_1'(\pi)$:

$$\begin{aligned}
\Psi_1'(\pi) &= \int \psi'\left(v\left[l(\mathbf{s}), \pi\right]\right) \frac{\partial v\left[l(\mathbf{s}), \pi\right]}{\partial \pi}\left[1 - l(\mathbf{s})\right] f_0(\mathbf{s}) d\mathbf{s} \\
&= \int \left[\frac{1-\pi}{1-\pi l(\mathbf{s})}\right] \frac{\partial v\left[l(\mathbf{s}), \pi\right]}{\partial \pi}\left[1 - l(\mathbf{s})\right] f_0(\mathbf{s}) d\mathbf{s}.
\end{aligned}$$

Appealing to **A3**, the second equality uses (18) to substitute out $\psi'[v(\mathbf{s}, \pi)]$. Totally differentiating (18) with respect to π and making $\partial v(l, \pi)/\partial\pi$ the subject of the resulting equation:

$$\frac{\partial v(l, \pi)}{\partial \pi} = \frac{l - 1}{\psi''(r)(1-\pi l)^2}. \tag{A.25}$$

Using (A.25) to substitute out $\partial v(l, \pi)/\partial\pi$,

$$\Psi_1'(\pi) = \int \frac{(\pi - 1)\left[1 - l(\mathbf{s})\right]^2}{\psi''\left(v\left[l(\mathbf{s}), \pi\right]\right)\left[1 - \pi l(\mathbf{s})\right]^3} f_0(\mathbf{s}) d\mathbf{s} > 0.$$

The inequality follows from $\psi''(r) < 0$ and the assumption of an interior solution. □

D.3. **Proof of Lemma 4.1 (iii).** Let:

$$m(l, \pi) \equiv \psi'\left[v(l, \pi)\right] \frac{\partial v(l, \pi)}{\partial \pi}.$$

From (18) the first order condition for an interior solution can be rewritten as:

$$v(l, \pi) = \psi'^{-1}\left(\frac{1-\pi}{1-\pi l}\right), \tag{A.26}$$

and taking the derivative of $v(l,\pi)$ with respect to π:

$$\frac{\partial v(l,\pi)}{\partial \pi}=\left(\psi''\left[\psi'^{-1}\left(\frac{1-\pi}{1-\pi l}\right)\right]\right)^{-1}\frac{l-1}{(1-\pi l)^2}.$$

Therefore:

$$m(l,\pi)=\left(\psi''\left[\psi'^{-1}\left(\frac{1-\pi}{1-\pi l}\right)\right]\right)^{-1}\frac{(1-\pi)(l-1)}{(1-\pi l)^3}. \tag{A.27}$$

Totally differentiating with respect to π the base price for the high-cost contract defined in (11), and appealing to (A.27) yields:

$$\begin{aligned} p'(\pi) &= \gamma_0'(\pi)-\int m\left[l(\mathbf{s}),\pi\right]f_0(\mathbf{s})d\mathbf{s} \qquad \text{(A.28)}\\ &= \gamma_0'(\pi)-\int\left(\psi''\left[\psi'^{-1}\left(\frac{1-\pi}{1-\pi l(\mathbf{s})}\right)\right]\right)^{-1}\frac{(1-\pi)\left[l(\mathbf{s})-1\right]}{\left[1-\pi l(\mathbf{s})\right]^3}f_0(\mathbf{s})d\mathbf{s}\\ &\equiv \gamma_0'(\pi)-\Psi_0(\pi). \end{aligned}$$

It now follows that $p(\pi)$ is increasing in π if $\Psi_0(\pi)\le\gamma_0'(\pi)$ for all π, and decreasing in π if $\Psi_0(\pi)\ge\gamma_0'(\pi)$ for all π. □

D.4. **Proof of Lemma 4.2.** The joint probability that the contract type is fixed and $\pi\le\breve{\pi}$ can be expressed as:

$$\begin{aligned} \Pr\{\pi\le\breve{\pi},k=1\,|y,n\} &= F_{\pi|y,n,k}(\breve{\pi}\,|y,n,1)\Pr(k=1\,|y,n)\\ &= \int_{\pi=\underline{\pi}}^{\breve{\pi}} f_{\pi|y,n}(\pi\,|y,n)\left[1-(1-\pi)^n\right]d\pi. \end{aligned}$$

Taking the derivative with respect to $\breve{\pi}$ yields:

$$f_{\pi|y,n,k}(\breve{\pi}\,|y,n,1)\Pr(k=1\,|y,n)=f_{\pi|y,n}(\breve{\pi}\,|y,n)\left[1-(1-\breve{\pi})^n\right]. \tag{A.29}$$

Similarly:

$$\begin{aligned} \Pr\{\pi\le\breve{\pi},k=0\,|y,n\} &= F_{\pi|y,n,k}(\breve{\pi}\,|y,n,0)\Pr(k=0\,|y,n)\\ &= \int_{\pi=\underline{\pi}}^{\breve{\pi}} f_{\pi|y,n}(\pi\,|y,n)(1-\pi)^n\,d\pi, \end{aligned}$$

and taking the derivative with respect to $\breve{\pi}$ yields:

$$f_{\pi|y,n,k}(\breve{\pi}\,|y,n,0)\Pr(k=1\,|y,n)=f_{\pi|y,n}(\breve{\pi}\,|y,n)(1-\breve{\pi})^n. \tag{A.30}$$

Rearranging the quotient of (A.29) and (A.30) to make $f_{\pi|y,n,1}(\breve{\pi}\,|y,n,1)$ the subject of the resulting equation, and relabeling $\breve{\pi}$ as π, we obtain (20). Integrating (20) over

π:

$$1=\frac{\Pr(k=0|y,n)}{\Pr(k=1|y,n)}\int\frac{[1-(1-\pi)^n]}{(1-\pi)^n}f_{\pi|y,n,k}(\pi|y,n,0)d\pi. \tag{A.31}$$

Rearranging terms to make $\Pr(k=0|y,n)$ the subject of the equation:

$$\Pr(k=0|y,n)=\left(\int(1-\pi)^{-n}f_{\pi|v,n,k}(\pi|y,n,0)d\pi\right)^{-1}. \tag{A.32}$$

The identification of $f_{\pi|y,n}(\pi|y,n)$ and (21) now follow by expressing $f_{\pi|y,n,k}(\pi|y,n,1)$ and $\Pr(k=0|y,n)$ as functions of $f_{\pi|y,n,k}(\pi|y,n,0)$ using (20) and (A.32), and then appealing to the identity:

$$f_{\pi|y,n}(\pi|y,n)=f_{\pi|y,n,0}(\pi|y,n,0)\Pr(k=0|y,n)+f_{\pi|y,n,k}(\pi|y,n,1)\Pr(k=1|y,n).$$

Noting that $\Pr(y,n)$ is identified from the data and that both contracts in the separating menu occur with positive probabilities for any π in the support, $f_\pi(\pi)=f_{\pi|y,n}(\pi|y,n)\Pr(y,n)$ is also identified. □

D.5. **Proof of Lemma 4.3.** To prove the first equation in (23) set $n=1$ in (10) to obtain:

$$p_1(\pi)=\gamma_0(\pi)-\int\psi[r(\mathbf{s})][1-l(\mathbf{s})]f_0(\mathbf{s})d\mathbf{s}.$$

Subtract $\gamma_1(\pi)$ from both sides and substitute the right hand side of the resulting expression back into (10) to obtain:

$$p_n(\pi)=\gamma_1(\pi)+\frac{\pi(1-\pi)^{n-1}}{1-(1-\pi)^n}[p_1(\pi)-\gamma_1(\pi)].$$

The first equation in (23) follows. To prove the second equation in (23), we rearrange (18) using (A.26), substitute the expression into (11), and make $\gamma_0(\pi)$ the subject of the equation. □

D.6. **Proof of Lemma 4.4.** Lemma 4.2 identifies $f_{\pi|y,n}(\pi|y,n)$. Therefore, $\lambda^o(\pi)$ is identified from:

$$\lambda^o(\pi)=\sum_{n=1}^{\infty}(n-1)\Pr(n|\pi,y=1)=\frac{\sum_{n=1}^{\infty}(n-1)f_{\pi|y,n}(\pi|1,n)\Pr(n|y=1)}{\sum_{n=1}^{\infty}f_{\pi|y,n}(\pi|1,n)\Pr(n|y=1)}.$$

Given this, $\kappa(\pi)$ is identified for all values of π satisfying $\lambda^o(\pi)>0$ from (24) because $\Gamma(\pi)$, $c_0(\pi)-c_1(\pi)$, and $\gamma_0(\pi)-\gamma_1(\pi)$ are identified from previous steps. If $\lambda^o(\pi)=0$,

$$\kappa(\pi)\geq\pi\left\{\pi[\gamma_0(\pi)-\gamma_1(\pi)]+(1-\pi)[c_0(\pi)-c_1(\pi)]+\Gamma(\pi)\right\}.$$

thus establishing the identified lower bound. □

D.7. **Proof of Lemma 4.5.** Appealing to (17), the buyer solicits competitive bids if and only if $\eta \leq \Omega(\pi)$, implying $F_\eta[\Omega(\pi)] = \Pr(y = 1|\pi)$. We have previously identified all components of $\Omega(\pi)$, and hence $\Omega(\pi)$. Since $\Pr(y = 1|\pi) = f_{\pi|y}(\pi|y)\Pr(y)/f_\pi(\pi)$, and (y, n) are observed variables (implying their joint distribution is identified), $\Pr(y = 1|\pi)$ is identified from (21). Therefore $F_\eta(\widetilde{\eta})$ is identified on Υ. □

Appendix E. Estimation Procedure

This appendix elaborates on our sequential estimation procedure described in Section 5.2, and includes the proof of Lemma 5.1. As in the text, we assume the data is generated by θ^* and denote our estimates by $\widehat{\theta}$. For conciseness we abbreviate $(\mathbf{x}, \mathbf{z})$ with $\tilde{\mathbf{x}}$.

E.1. **Contract Outcomes and Distribution of π.** For each $h \in \{1, 2, 3\}$ the LIML estimator of $\theta^*_{s_{2h}}$, defined in (29) and (30), is:

$$\widehat{\theta}_{s_{2h}} = \arg\max_{\theta_{s_{2h}}} \sum_i k_i \log\left[f_{1,s_{2h}}(s_{2h}|\mathbf{x}_1; \theta_{s_{2h}})\right] + (1 - k_i)\log\left[f_{0,s_{2h}}(s_{2h}|\mathbf{x}_1; \theta_{s_{2h}})\right].$$

Noting that $f_{1,s_{1h}|s_{2h}}(s_{1h}|s_{2h}, \mathbf{x}_1; \theta_{s_{1h}})$ does not depend on $\theta_{s_{1h,0}}$ (to be estimated in the next step), the LIML estimator for all the elements $\theta^*_{s_{1h}}$ except $\theta^*_{s_{1h,0}}$ defined in (27) and (28), is:

$$\widehat{\theta}'_{s_{1h}} = \arg\max_{\theta'_{s_{1h}}} \sum_i k_i \log\left[f_{1,s_{1h}|s_{2h}}\left(s_{1h}|s_{2h}, \mathbf{x}_1; \theta'_{s_{1h}}\right)\right].$$

Following the procedure of **5.2.2**, we estimate θ^*_π and $f_\pi(\pi|\tilde{\mathbf{x}}; \theta^*_\pi)$.

E.2. **Seller Costs and Risk Preferences.** For notational convenience, let $\theta_\varphi \equiv (\theta_{\varphi_1}, \theta_{\varphi_2})$ where $\theta_{\varphi_1} \equiv \left(\theta'_{s_1}, \theta_{s_2}\right)$, estimated in a previous step, and $\theta_{\varphi_2} \equiv \{\theta_c, \theta_\psi, \theta_{s_{1,0}}, M\}$, the parameters remaining that characterize sellers costs. Following Lemma A6, let $\tilde{\pi}(\mathbf{x}, \pi; \theta_\varphi)$ uniquely solve:

$$\begin{aligned}\gamma_0(\mathbf{x}_1, \tilde{\pi}; \theta_c) - \gamma_1(\mathbf{x}_1, \tilde{\pi}; \theta_c) \quad = \quad & \int \Big[f_1(\mathbf{s}|\mathbf{x}_1, \theta_s) - f_0(\mathbf{s}|\mathbf{x}_1, \theta_s)\Big] \times \\ & \psi\left(\max\left\{-e^{\mathbf{x}_1\theta_\psi} \ln\left(\frac{1 - \tilde{\pi}}{1 - \tilde{\pi}l(\mathbf{s}|\mathbf{x}_1; \theta_s)}\right), M\right\}\middle|\mathbf{x}_1; \theta_\psi\right) d\mathbf{s}.\end{aligned}$$

Theorem 3.1 implies prices for the optimal menu in the parameterization are:

$$p_{1n}(\mathbf{x}_1,\pi;\theta_\varphi) = \gamma_1(\mathbf{x}_1,\pi;\theta_c) + \frac{\pi(1-\pi)^{n-1}}{1-(1-\pi)^n}\Big\{ [\gamma_0(\mathbf{x}_1,\pi;\theta_c) - \gamma_1(\mathbf{x}_1,\pi;\theta_c)] \tag{A.33}$$
$$- \int \psi\,[q_0(\mathbf{s},\mathbf{x}_1,\pi;\theta_\varphi) - c(\mathbf{s})|\mathbf{x}_1;\theta_\psi]\,[f_0(\mathbf{s}|\mathbf{x}_1;\theta_s) - f_1(\mathbf{s}|\mathbf{x}_1;\theta_s)]\,d\mathbf{s}\Big\},$$

$$q_0(\mathbf{s},\mathbf{x}_1,\pi;\theta_\varphi) = c(\mathbf{s}) + \max\left\{-e^{\mathbf{x}_1\theta_\psi}\ln\left(\frac{1-\min\{\pi,\tilde\pi(\mathbf{x}_1,\pi;\theta_\varphi)\}}{1-\min\{\pi,\tilde\pi(\mathbf{x}_1,\pi;\theta_\varphi)\}l(\mathbf{s}|\mathbf{x}_1;\theta_s)}\right), M\right\}.$$

We obtain $\widehat{\theta}_{\varphi 2}$ as follows:

$$\begin{aligned}
\hat\theta_{\varphi 2} \;=\; & \arg\min_{\theta_{\varphi_2}} \sum_i \Bigg\{ k_i\left[p_i - \int p_{1n}(\mathbf{x}_{1i},\pi;\widehat{\theta}_{\varphi_1},\theta_{\varphi_2}) f_{\pi|y,n,k}(\pi|y_i,n_i,1,\tilde{\mathbf{x}}_i;\widehat{\theta}_{\pi,y_i,n_i})d\pi\right]^2 \\
& +(1-k_i)\left[p_i - \int p_0(\mathbf{x}_{1i},\pi;\widehat{\theta}_{\varphi_1},\theta_{\varphi_2}) f_{\pi|y,n,k}(\pi|y_i,n_i,0,\tilde{\mathbf{x}}_i;\widehat{\theta}_{\pi,y_i,n_i})d\pi\right]^2 \\
& +(1-k_i)\left[q_i - \int q_0(\mathbf{s}_i,\mathbf{x}_{1i},\pi;\widehat{\theta}_{\varphi_1},\theta_{\varphi_2}) f_{\pi|y,n,k}(\pi|y_i,n_i,0,\tilde{\mathbf{x}}_i;\widehat{\theta}_{\pi,y_i,n_i})d\pi.\right]^2 \Bigg\}.
\end{aligned}$$

We compute integrals over π and $\mathbf{s}$ numerically: for the integration over π, we use Legendre-Gauss quadrature with 50 points from $[0.01, 0.99]$; for the integration over $\mathbf{s}$, we employ Monte Carlo simulations using 5,000 points of a six-dimensional Halton sequence.

E.3. **Buyer Search Costs and Solicitation Costs.** We obtain $\widehat{\lambda}^o(\tilde{\mathbf{x}},\pi;\widehat{\theta}_\pi)$, using the parameters estimated from a previous step and Lemma 5.1, and the proof of the lemma is below:

Proof. Note that:

$$\begin{aligned}
\lambda^o(\tilde{\mathbf{x}},\pi) &= \mathbb{E}[(n-1)|y=1,\tilde{\mathbf{x}},\pi] = \sum_{n=1}^{\infty}(n-1)\Pr(n|y=1,\tilde{\mathbf{x}},\pi) \\
&= \frac{\sum_{n=1}^{\infty}(n-1)\Pr(n,\pi|y=1,\tilde{\mathbf{x}})}{f_{\pi|y}(\pi|y=1,\tilde{\mathbf{x}})} \\
&= \frac{\sum_{n=1}^{\infty}(n-1)f_{\pi|y,n}(\pi|y=1,n,\tilde{\mathbf{x}})\Pr(n|y=1,\tilde{\mathbf{x}})}{\sum_{n=1}^{\infty}f_{\pi|y,n}(\pi|y=1,n,\tilde{\mathbf{x}})\Pr(n|y=1,\tilde{\mathbf{x}})} \\
&= \frac{\sum_{n=1}^{\infty}(n-1)\sum_{k=0}^{1}f_{\pi|y,n,k}(\pi|y=1,n,k)\Pr(n,k|y=1,\tilde{\mathbf{x}})}{\sum_{n=1}^{\infty}\sum_{k=0}^{1}f_{\pi|y,n,k}(\pi|y=1,n,k)\Pr(n,k|y=1,\tilde{\mathbf{x}})}.
\end{aligned}$$

A consistent estimator of $\Pr(n, k|y = 1, \tilde{\mathbf{x}})$ is:

$$\widehat{\Pr}(n, k|y = 1, \tilde{\mathbf{x}}) = \frac{\sum_{i=1}^{I} \mathbb{1}\{(n_i, k_i, y_i, \tilde{\mathbf{x}}_i) = (n, k, 1, \tilde{\mathbf{x}})\}}{\sum_{i=1}^{I} \mathbb{1}\{(y_i, \tilde{\mathbf{x}}_i) = (1, \tilde{\mathbf{x}})\}}. \tag{A.34}$$

If $f_{\pi|y,n,k}\,(\pi|1, n_i, k_i, \tilde{\mathbf{x}}_i)$ was known, a consistent estimator of $\lambda^o(\tilde{\mathbf{x}}, \pi)$ is:

$$\widehat{\lambda}^o(\tilde{\mathbf{x}}, \pi) = \frac{\sum_{n=1}^{\infty} \sum_{k=0}^{1} (n-1) f_{\pi|y,n,k}(\pi|1, n, k, \tilde{\mathbf{x}}) \widehat{\Pr}(n, k|y = 1, \tilde{\mathbf{x}})}{\sum_{n=1}^{\infty} \sum_{k=0}^{1} f_{\pi|y,n,k}(\pi|1, n, k, \tilde{\mathbf{x}}) \widehat{\Pr}(n, k|y = 1, \tilde{\mathbf{x}})}.$$

By substituting (A.34) for $\widehat{\Pr}(n, k|y = 1, \tilde{\mathbf{x}})$:

$$\begin{aligned}
\widehat{\lambda}^o(\tilde{\mathbf{x}}, \pi) &= \frac{\sum_{n=1}^{\infty} \sum_{k=0}^{1} (n-1) f_{\pi|y,n,k}(\pi|1, n, k, \tilde{\mathbf{x}}) \sum_{i=1}^{I} \mathbb{1}\{(n_i, k_i, y_i, \tilde{\mathbf{x}}_i) = (n, k, 1, \tilde{\mathbf{x}})\}}{\sum_{n=1}^{\infty} \sum_{k=0}^{1} f_{\pi|y,n,k}(\pi|1, n, k, \tilde{\mathbf{x}}) \sum_{i=1}^{I} \mathbb{1}\{(n_i, k_i, y_i, \tilde{\mathbf{x}}_i) = (n, k, 1, \tilde{\mathbf{x}})\}} \\
&= \frac{\sum_{i=1}^{I} (n_i - 1) f_{\pi|y,n,k}(\pi|1, n_i, k_i, \tilde{\mathbf{x}}) \mathbb{1}\{(y_i, \tilde{\mathbf{x}}_i) = (1, \tilde{\mathbf{x}})\}}{\sum_{i=1}^{I} f_{\pi|y,n,k}(\pi|1, n_i, k_i, \tilde{\mathbf{x}}) \mathbb{1}\{(y_i, \tilde{\mathbf{x}}_i) = (1, \tilde{\mathbf{x}})\}}. \qquad \text{(A.35)}
\end{aligned}$$

Substituting $f_{\pi|y,n,k}(\pi|1, n_i, k_i, \tilde{\mathbf{x}}_i; \widehat{\theta}_\pi)$ for $f_{\pi|y,n,k}(\pi|1, n_i, k_i, \tilde{\mathbf{x}}_i)$ proves the lemma. □

Then, we obtain $\hat{\kappa}(\tilde{\mathbf{x}}, \pi, \hat{\theta}_\varphi)$ from (32). With reference to (33), the estimator for θ_η^* is:

$$\widehat{\theta}_\eta = \arg\max_{\theta_\eta} \sum_i y_i \log \Pr(y = 1|\tilde{\mathbf{x}}_i; \theta_\eta, \widehat{\theta}_\varphi, \widehat{\theta}_\pi) + (1 - y_i) \log \Pr(y = 0|\tilde{\mathbf{x}}_i; \theta_\eta, \widehat{\theta}_\varphi, \widehat{\theta}_\pi),$$

where:

$$\Pr(y = 1|\tilde{\mathbf{x}}; \theta_\eta, \widehat{\theta}_\varphi, \widehat{\theta}_\pi) = \int \Phi\left(\frac{\widehat{\Omega}(\tilde{\mathbf{x}}, \pi; \widehat{\theta}_\varphi, \widehat{\theta}_\pi) - [\mathbf{x}\theta_{\eta x} + \pi\theta_{\eta_1} + \pi^2\theta_{\eta_2}]}{\theta_{\eta v}}\right) f_\pi(\pi|\tilde{\mathbf{x}}, \widehat{\theta}_\pi) d\pi,$$

and:

$$\begin{aligned}
\widehat{\Omega}(\tilde{\mathbf{x}}, \pi; \widehat{\theta}_\varphi, \widehat{\theta}_\pi) = &\Big\{1 - \exp\Big[\widehat{\lambda}^o(\tilde{\mathbf{x}}, \pi; \widehat{\theta}_\pi)\Big]\Big\} \Big[\pi\Big\{\gamma_0(\mathbf{x}_1, \pi; \widehat{\theta}_c) - \gamma_1(\mathbf{x}_1, \pi; \widehat{\theta}_c)\Big\} \\
&+ (1 - \pi)\Big\{c_0(\mathbf{x}_1, \pi; \widehat{\theta}_c) - c_1(\mathbf{x}_1, \pi; \widehat{\theta}_c)\Big\} + \Gamma(\mathbf{x}_1, \pi; \widehat{\theta}_\varphi)\Big] - \kappa(\tilde{\mathbf{x}}, \pi; \widehat{\theta}_\varphi, \widehat{\theta}_\pi)\widehat{\lambda}^o(\tilde{\mathbf{x}}, \pi; \widehat{\theta}_\pi).
\end{aligned}$$

Appendix F. Implementing Model Fit and Counterfactual Analyses

This section explains on how we calculate the extent of competition for the base and some of the counterfactual scenarios for Tables 4 and 6, given our model and the estimated parameters. We continue to abbreviate $(\mathbf{x}, \mathbf{z})$ with $\tilde{\mathbf{x}}$.

F.1. **Base Scenario.** For any given $(\tilde{\mathbf{x}}, \theta)$, the probability that the buyer chooses a competitive solicitation, as opposed to working with a default seller, denoted by

$\mathcal{Y}^o(\tilde{\mathbf{x}}, \pi; \theta)$, is:

$$\mathcal{Y}^o(\tilde{\mathbf{x}}, \pi; \theta) = \Phi\left(\frac{\Omega(\tilde{\mathbf{x}}, \pi; \theta_\varphi, \theta_\pi) - [\mathbf{x}\theta_{\eta x} + \pi\theta_{\eta 1} + \pi^2\theta_{\eta 2}]}{\theta_{\eta v}}\right).$$

The optimal search intensity is solved as:

$$\lambda^o\left(\tilde{\mathbf{x}}, \pi; \theta_\varphi, \theta_\pi\right) = \max\left[0, \frac{1}{\pi}\left(\ln\left\{\tilde{c}(\mathbf{x}_1; \theta_\varphi) + \Gamma(\mathbf{x}_1, \pi; \theta_\varphi)\right\} - \ln\kappa(\tilde{\mathbf{x}}, \pi; \theta_\varphi, \theta_\pi)\right)\right],$$

where

$$\tilde{c}(\mathbf{x}_1; \theta_\varphi) = \pi\{\gamma_0(\mathbf{x}_1; \theta_c) - \gamma_1(\mathbf{x}_1; \theta_c)\} + (1-\pi)\{c_0(\mathbf{x}_1; \theta_\varphi) - c_1(\mathbf{x}_1; \theta_\varphi)\}.$$

Then the expected number of bids is:

$$\mathcal{N}^o(\tilde{\mathbf{x}}, \pi; \theta) = 1 + \lambda^o\left(\tilde{\mathbf{x}}, \pi; \theta_\varphi, \theta_\pi\right)\mathcal{Y}^o(\tilde{\mathbf{x}}, \pi; \theta).$$

Table 4 presents the sample average of $\mathcal{Y}^o(\tilde{\mathbf{x}}, \pi; \theta)$ and $\mathcal{N}^o(\tilde{\mathbf{x}}, \pi; \theta)$ evaluated at the estimated parameter, $\widehat{\theta}$, integrated over π. For example, the predicted value for the expected number of bids in the table is:

$$\sum_i^I \int \mathcal{N}^o\left(\tilde{\mathbf{x}}_i, \pi; \widehat{\theta}\right) f_\pi\left(\pi|\tilde{\mathbf{x}}_i, \widehat{\theta}_\pi\right) d\pi\, /I.$$

F.2. **First-price Sealed-bid Auction.** If the buyer's ability to design contracts is limited so that she can offer full insurance contracts only, then the constrained optimal search intensity, $\lambda^{FIC}\left(\tilde{\mathbf{x}}, \pi; \theta, \kappa\right)$ is:

$$\lambda^{FIC}\left(\tilde{\mathbf{x}}, \pi; \theta_\varphi, \theta_\pi\right) = \max\left[0, \frac{1}{\pi}\left(\ln\tilde{c}(\mathbf{x}_1; \theta_\varphi) - \ln\kappa(\tilde{\mathbf{x}}, \pi; \theta_\varphi, \theta_\pi)\right)\right].$$

Section 3 has shown that $\Gamma < 0$, and therefore, $\lambda^{FIC}\left(\tilde{\mathbf{x}}, \pi; \theta, \kappa\right) > \lambda^*\left(\tilde{\mathbf{x}}, \pi; \theta, \kappa\right)$. The expected number of bids under this scenario, $\mathcal{N}^{FIC}(\tilde{\mathbf{x}}, \pi; \theta)$, is:

$$\mathcal{N}^{FIC}(\tilde{\mathbf{x}}, \pi; \theta) = 1 + \lambda^{FIC}\left(\tilde{\mathbf{x}}, \pi; \theta_\varphi, \theta_\pi\right)\Phi\left(\frac{\Omega^{FIC}(\tilde{\mathbf{x}}, \pi; \theta_\varphi, \theta_\pi) - [\mathbf{x}\theta_{\eta x} + \pi\theta_{\eta 1} + \pi^2\theta_{\eta 2}]}{\theta_{\eta v}}\right),$$

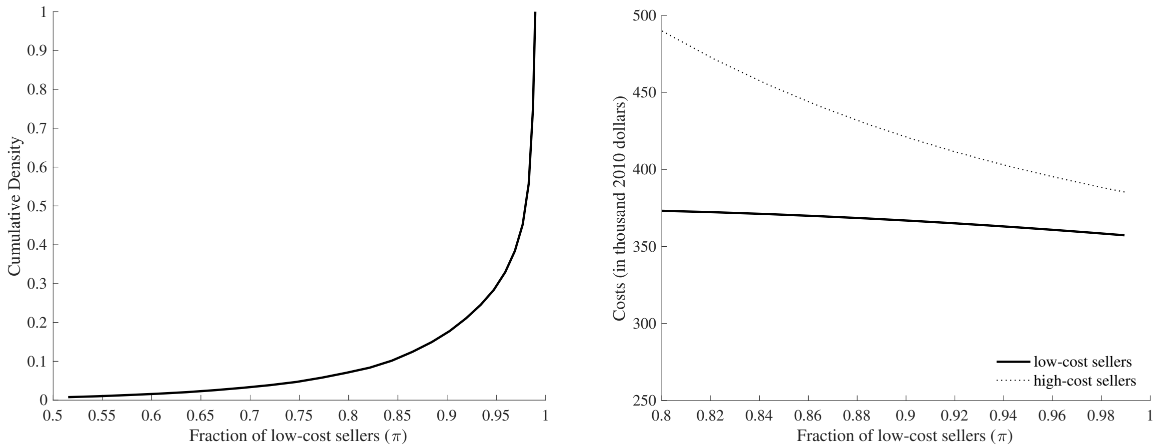
where

$$\Omega^{FIC}(\tilde{\mathbf{x}}, \pi; \theta_\varphi, \theta_\pi) \equiv \left\{1 - e^{-\lambda^{FIC}(\tilde{\mathbf{x}}, \pi; \theta_\varphi, \theta_\pi)\pi}\right\}\tilde{c}(\mathbf{x}_1; \theta_\varphi) - \kappa(\tilde{\mathbf{x}}, \pi; \theta_\varphi, \theta_\pi)\lambda^{FIC}\left(\tilde{\mathbf{x}}, \pi; \theta_\varphi, \theta_\pi\right).$$

Table 6 provides the following:

$$\sum_i \int \left[\mathcal{N}^{FIC}\left(\tilde{\mathbf{x}}_i, \pi; \widehat{\theta}\right) - \mathcal{N}^o\left(\tilde{\mathbf{x}}_i, \pi; \widehat{\theta}\right)\right] f_\pi\left(\pi|\tilde{\mathbf{x}}_i, \widehat{\theta}_\pi\right) d\pi\, /I.$$

Figure A2. The Estimates of the Model Primitives



(A) Distribution of π (B) Seller Costs

Notes: Based on the estimated parameters, Panel (A) shows the cumulative density function of π, averaged across sample observations. Panel (B) presents each seller type's expected project cost.

F.3. **Policies Mandating Competition.** When competitive solicitation is mandated, the equilibrium search intensity for the base scenario, λ^o, would be selected by the buyer. The expected number of bids under this scenario is:

$$\mathcal{N}^{MAN}(\tilde{\mathbf{x}}, \pi; \theta_\varphi, \theta_\pi) = 1 + \lambda^o (\tilde{\mathbf{x}}, \pi; \theta_\varphi, \theta_\pi).$$

If the search intensity must be at least 1, then the equilibrium search intensity would be $\max\{2, \lambda^o\}$, and the expected number of bids under this scenario is:

$$\mathcal{N}^{MIN}(\tilde{\mathbf{x}}, \pi; \theta, \theta_\varphi, \theta_\pi) = 1 + \max\left[1, \lambda^o (\tilde{\mathbf{x}}, \pi; \theta_\varphi, \theta_\pi)\right].$$

Table 6 provides the difference in the expected number of bids between the counterfactual scenarios and the base one. For example, for the first policy to mandate competition, the difference is:

$$\sum_i \int \left[\mathcal{N}^{MAN}\left(\tilde{\mathbf{x}}_i, \pi; \widehat{\theta}_\varphi, \widehat{\theta}_\pi\right) - \mathcal{N}^o\left(\tilde{\mathbf{x}}_i, \pi; \widehat{\theta}\right)\right] f_\pi\left(\pi|\tilde{\mathbf{x}}_i, \widehat{\theta}_\pi\right) d\pi \,/I.$$

Appendix G. Parameter Estimates and More Model Fit Results

Table A9 provides $\widehat{\theta}_\varphi$ and $\widehat{\theta}_\eta$. Instead of providing $\widehat{\theta}_\pi$, Figure A2 (A) presents the cumulative density function of π, averaged across the sample, for a range of π: $\sum_{i=1}^I F_\pi(\pi|\mathbf{x}_i, \mathbf{z}_i; \widehat{\theta}_\pi)/I$. Panel (B) shows how the expected project cost of each seller type varies with π: $\sum_{i=1}^I c_k(\mathbf{x}_{1i}, \pi)/I$.

Table A9. Parameter Estimates

Initial project costs: Low-cost seller		Initial project costs: Additional costs for high-cost seller	
$\theta_{c_1,x}$		$\theta_{c_0,x}$	
Constant	11.93 (0.319)	Constant	10.14 (1.395)
Base duration > 3 mo.	0.005 (0.012)	Base duration > 3 mo.	-0.674 (0.508)
Maximum size > $300K	0.826 (0.007)	Maximum size > $300K	2.627 (0.544)
Service	-0.083 (0.019)	Service	-1.332 (0.736)
Commercially available	-0.020 (0.013)	Commercially available	1.263 (0.547)
Department of Defense	0.011 (0.010)	Department of Defense	0.000 (0.561)
Complex	0.028 (0.012)	Complex	0.645 (0.490)
$\theta_{c_1,1}$	1.031 (0.801)	$\theta_{c_0,1}$	5.112 (4.022)
$\theta_{c_1,2}$	-0.714 (0.497)	$\theta_{c_0,2}$	-8.318 (3.727)
Risk preferences and Maximal penalty		**Solicitation costs**	
θ_{ψ}		$\theta_{\eta x}$	
Constant	20.11 (0.424)	Constant	-349.8 (3,365.4)
Base duration > 3 mo.	-0.508 (0.699)	Base duration > 3 mo.	7.207 (20.16)
Maximum size > $300K	0.546 (0.528)	Maximum size > $300K	8.388 (32.56)
Service	-0.535 (0.635)	Service	6.756 (92.52)
Commercially available	-1.084 (1.023)	Commercially available	2.639 (33.18)
Department of Defense	-0.325 (0.673)	Department of Defense	-13.78 (27.15)
Complex	2.068 (1.822)	Complex	24.17 (67.97)
M (in million USD)	-0.229 (15.67)	Experienced	-2.661 (16.44)
		Similar past contract	6.953 (37.49)
		Large workload	-9.592 (18.13)
		Represented in Congress	-1.790 (13.22)
		$\theta_{\eta 1}$	996.4 (8,013.8)
		$\theta_{\eta 2}$	-608.8 (4,695.2)
		$\theta_{\eta v}$	53.75 (165.9)
Cost changes by work changes ($h = 1$)		**Duration adjustments by work changes ($h = 1$)**	
$\theta_{s_{11,x}}$		$\theta_{s_{21,x}}$	
Constant	1.95 (0.075)	Constant	1.650 (0.067)
Base duration > 3 mo.	-0.127 (0.064)	Base duration > 3 mo.	-0.024 (0.049)
Maximum size > $300K	-0.146 (0.048)	Maximum size > $300K	-0.205 (0.047)
Service	-0.330 (0.058)	Service	-0.210 (0.051)
Commercially available	-0.126 (0.055)	Commercially available	-0.067 (0.049)
Department of Defense	-0.055 (0.055)	Department of Defense	0.026 (0.051)
Complex	0.060 (0.049)	Complex	-0.150 (0.045)
$\theta_{s_{11,0}}$	-0.707 (39.37)	$\theta_{s_{21,0}}$	-0.211 (0.113)
$\theta_{s_{11,d}}$	-1.857 (0.053)	$\theta_{s_{21,1}}$	-0.295 (0.056)
$\theta_{s_{11,1}}$ (in thousand USD)	49.23 (7.122)	$\theta_{s_{21,2}}$	0.133 (0.260)
$\theta_{s_{11,2}}$	-0.004 (0.068)	$\theta_{s_{21,3}}$	0.695 (0.118)
$\theta_{s_{11,3}}$	12.13 (0.081)	$\theta_{s_{21,4}}$	-0.084 (0.473)
$\theta_{s_{11,4}}$	10.12 (1.217)		

(Continued)

Table A9. Parameter Estimates (Continued)

Cost changes by options/funding ($h = 2$)		Duration adjustments by options/funding ($h = 2$)	
$\theta_{s_{12,x}}$		$\theta_{s_{22,x}}$	
Constant	2.081 (0.099)	Constant	2.360 (0.084)
Base duration > 3 mo.	-0.284 (0.077)	Base duration > 3 mo.	-0.425 (0.061)
Maximum size > $300K	-0.121 (0.053)	Maximum size > $300K	-0.379 (0.050)
Service	-0.506 (0.067)	Service	-0.598 (0.056)
Commercially available	-0.129 (0.062)	Commercially available	-0.161 (0.048)
Department of Defense	0.132 (0.061)	Department of Defense	-0.054 (0.053)
Complex	0.014 (0.060)	Complex	-0.208 (0.053)
$\theta_{s_{12,0}}$	0.935 (0.601)	$\theta_{s_{22,0}}$	-0.476 (0.080)
$\theta_{s_{12,d}}$	-3.408 (0.110)	$\theta_{s_{22,1}}$	0.128 (0.066)
$\theta_{s_{12,1}}$ (in thousand USD)	164.24 (8.644)	$\theta_{s_{22,2}}$	0.073 (0.239)
$\theta_{s_{12,2}}$	-0.005 (0.030)	$\theta_{s_{22,3}}$	0.554 (0.091)
$\theta_{s_{12,3}}$	12.41 (0.046)	$\theta_{s_{22,4}}$	-0.307 (0.249)
$\theta_{s_{12,4}}$	-12.38 (0.085)		
Cost changes by administrative actions ($h = 3$)		**Duration adjustments by administrative actions ($h = 3$)**	
$\theta_{s_{13,x}}$		$\theta_{s_{23,x}}$	
Constant	1.887 (0.086)	Constant	1.379 (0.068)
Base duration > 3 mo.	-0.171 (0.060)	Base duration > 3 mo.	-0.065 (0.049)
Maximum size > $300K	-0.131 (0.047)	Maximum size > $300K	-0.096 (0.039)
Service	-0.457 (0.044)	Service	-0.005 (0.053)
Commercially available	-0.155 (0.059)	Commercially available	0.041 (0.048)
Department of Defense	0.171 (0.010)	Department of Defense	-0.066 (0.047)
Complex	0.082 (0.055)	Complex	-0.120 (0.043)
$\theta_{s_{13,0}}$	0.292 (15.70)	$\theta_{s_{23,0}}$	-0.262 (0.087)
$\theta_{s_{13,d}}$	-1.091 (0.051)	$\theta_{s_{23,1}}$	-0.485 (0.048)
$\theta_{s_{13,1}}$ (in thousand USD)	-19.29 (5.691)	$\theta_{s_{23,2}}$	0.035 (0.174)
$\theta_{s_{13,2}}$	0.000 (0.025)	$\theta_{s_{23,3}}$	1.017 (0.077)
$\theta_{s_{13,3}}$	11.77 (0.143)	$\theta_{s_{23,4}}$	-0.188 (0.278)
$\theta_{s_{13,4}}$	-5.524 (0.828)		

Notes: Numbers in parentheses are bootstrap standard errors. See Section 5.2 for the parametric assumptions.

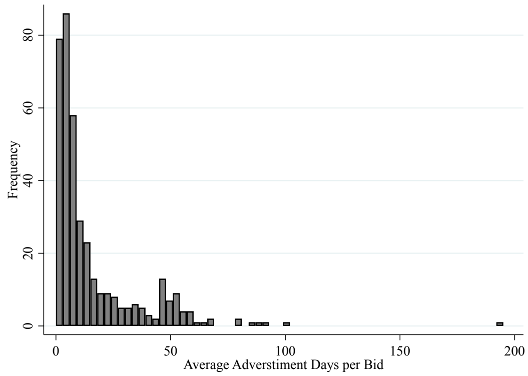
While Table 4 in Section 6 provides the model fit results unconditional on observed contract attributes, Table A10 provides the conditional model fit by running regressions of the actual and the predicted equilibrium outcomes on observed contract attributes and comparing the regression coefficients. The equilibrium outcomes we consider are whether or not a contract is competitively solicited, the number of bids, the contract type, and the final contract price. Specifically, for example, the

TABLE A10. Model Fit: Conditional on Observed Attributes

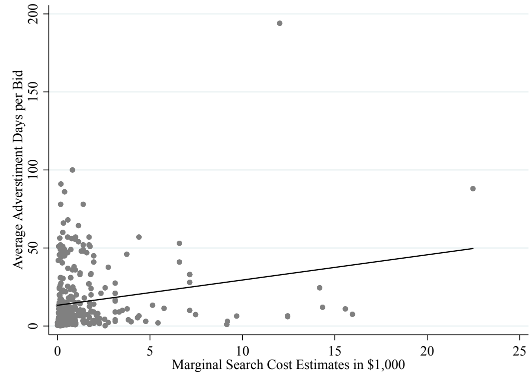
Dependent var.	Competitively solicited			Number of bids			Firm-fixed-price			Log(Final price)		
	Data		Model	Data		Model	Data		Model	Data		Model
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Duration > 3 mo.	-0.083	-0.117	-0.120	-0.532	-0.614	-0.611	0.002	0.003	0.005	0.032	0.035	0.034
	(0.017)	(0.021)	[0.015]	(0.063)	(0.070)	[0.074]	(0.006)	(0.006)	[0.003]	(0.010)	(0.010)	[0.012]
Size > $300K	0.0001	0.003	0.013	0.004	0.017	0.036	-0.005	-0.007	-0.007	0.829	0.831	0.807
	(0.011)	(0.013)	[0.014]	(0.049)	(0.048)	[0.058]	(0.005)	(0.005)	[0.004]	(0.009)	(0.010)	[0.008]
Service		-0.046	-0.026		-0.152	-0.155		-0.101	-0.082		0.055	0.036
		(0.024)	[0.019]		(0.077)	[0.060]		(0.012)	[0.007]		(0.014)	[0.016]
Commercial	0.046	0.053	0.045	0.310	0.312	0.306	0.048	0.043	0.032	0.025	0.019	-0.004
	(0.012)	(0.012)	[0.012]	(0.043)	(0.050)	[0.041]	(0.014)	(0.012)	[0.005]	(0.018)	(0.014)	[0.012]
Defense		-0.013	-0.010		-0.178	-0.198		-0.011	-0.007		0.010	0.011
		(0.020)	[0.017]		(0.101)	[0.067]		(0.015)	[0.005]		(0.022)	[0.011]
Complex	-0.045	-0.128	-0.129	-0.173	-0.266	-0.241	-0.025	-0.014	-0.011	0.062	0.058	0.047
	(0.025)	(0.026)	[0.014]	(0.058)	(0.069)	[0.063]	(0.012)	(0.011)	[0.005]	(0.010)	(0.011)	[0.012]
Experienced	0.061	0.014	0.018	0.037	0.076	0.080	0.002	-0.018	-0.012	-0.022	-0.004	0.005
	(0.022)	(0.017)	[0.014]	(0.101)	(0.052)	[0.048]	(0.008)	(0.007)	[0.004]	(0.012)	(0.010)	[0.003]
Past contract	-0.004	-0.024	-0.028	0.008	-0.069	-0.052	-0.017	-0.017	-0.011	0.019	0.021	0.007
	(0.014)	(0.014)	[0.014]	(0.041)	(0.045)	[0.061]	(0.009)	(0.008)	[0.005]	(0.009)	(0.010)	[0.003]
Large workload	-0.006	0.023	0.023	-0.270	0.003	-0.005	-0.007	-0.003	-0.001	-0.021	-0.015	0.001
	(0.025)	(0.016)	[0.013]	(0.121)	(0.054)	[0.058]	(0.012)	(0.009)	[0.005]	(0.013)	(0.009)	[0.002]
Budget committee	0.047	0.046	0.053	0.177	0.233	0.214	-0.005	-0.008	-0.009	0.018	-0.002	0.002
	(0.025)	(0.029)	[0.020]	(0.118)	(0.119)	[0.076]	(0.010)	(0.008)	[0.006]	(0.019)	(0.026)	[0.003]
Winners ≥ 2	0.020	0.046	0.035	0.127	0.158	0.141	-0.015	-0.011	-0.006	0.012	0.010	0.002
	(0.019)	(0.016)	[0.016]	(0.058)	(0.057)	[0.051]	(0.007)	(0.007)	[0.005]	(0.014)	(0.012)	[0.003]
Establishments ≥ 24	0.004	-0.016	0.009	-0.030	-0.023	-0.033	-0.023	-0.015	-0.012	0.010	-0.000	0.004
	(0.017)	(0.013)	[0.018]	(0.063)	(0.007)	[0.064]	(0.0057)	(0.006)	[0.003]	(0.018)	(0.015)	[0.003]
Constant	0.207	0.433	0.426	1.856	2.012	2.007	1.175	1.011	0.996	12.06	12.16	12.27
	(0.060)	(0.040)	[0.030]	(0.284)	(0.111)	[0.166]	(0.031)	(0.017)	[0.010]	(0.132)	(0.032)	[0.020]
PSC, Agency, State, Year, Month FE	Yes	No	No	Yes	No	No	Yes	No	No	Yes	No	No
R^2	0.158	0.052	0.275	0.131	0.048	0.172	0.125	0.069	0.637	0.558	0.546	0.998

Notes: Numbers in parentheses are standard errors clustered at the 4-digit product and service code level; all 6,981 observations in the final sample used; numbers in brackets are bootstrap standard errors.

FIGURE A4. Advertisement and the Search Cost Estimates



(A) Average Advertisement per Bid



(B) Advertisement vs. κ Estimates

Notes: Panel (A) presents the distribution of the average advertisement duration per bid, based on the 388 contracts with observations on the advertisement period. Panel (B) shows the scatter plot and the linear fit of the average advertisement duration per bid and the marginal search cost estimate.

dependent variable of Column (3) for each observation is computed as:

$$\int \mathcal{Y}^o(\mathbf{x}_i, \mathbf{z}_i, \pi; \widehat{\theta}) f_\pi(\pi|\mathbf{x}_i, \mathbf{z}_i, \widehat{\theta}_\pi) d\pi.$$

For the 388 contracts that we observe the advertisement period, we calculate the average duration of advertisement per bid—that is, the advertisement period in days divided by the number of bids. Panel (A) of Figure A4 shows the distribution of the average duration of advertisement per bid: the mean is 15.36 days per bid, with the median 7 and maximum 194. As can be seen in Panel (B) of Figure A4, the average duration of advertisement per bid is positively correlated with our marginal search cost estimates, $\mathbb{E}_\pi[\kappa(\mathbf{x}_i, \mathbf{z}_i; \widehat{\theta}_\varphi, \widehat{\theta}_\pi)|\mathbf{x}_i, \mathbf{z}_i; \widehat{\theta}_\pi]$. Table A11 shows that this correlation persists, even after controlling for the observed attributes used in the estimation. This is consistent with a notion that a lower meeting rate is a source of a higher marginal search cost.

APPENDIX H. SENSITIVITY ANALYSES

H.1. **Alternative Specifications of the Main Model.** Columns (1) and (2) of Table A12 are related to the parametric assumption on the equilibrium distribution of π for variable contracts, $f_{\pi|y,n,k}(\pi|y, n, 0, \mathbf{x}, \mathbf{z})$, as specified in Section 5.2. Given the scarcity of contracts with more than 4 bids in the data, the main specification

Table A11. External Validity of the Search Cost Estimates

Dependent variable:	Average advertisement per bid	
	(1)	(2)
Marginal search cost estimate	1.618***	1.196***
	(0.404)	(0.445)
Contract attributes	No	Yes
N	388	388
R^2	0.040	0.314

Notes: These regressions are based on the 388 contracts in our final sample that we observe the advertisement period. The marginal search cost estimate for each observation is $\mathbb{E}_\pi[\kappa(\mathbf{x}_i, \mathbf{z}_i; \widehat{\theta}_\varphi, \widehat{\theta}_\pi)|\mathbf{x}_i, \mathbf{z}_i; \widehat{\theta}_\pi]$, and Column (2) controls for the contract attributes used in the estimation. Numbers in parentheses are standard errors.

restricts that for $n > 4$,

$$f_{\pi|y,n,k}(\pi|1, n, 0, \mathbf{x}, \mathbf{z}) = f_{\pi|y,n,k}(\pi|1, 4, 0, \mathbf{x}, \mathbf{z}; \theta_{\pi,1,4}).$$

We consider alternative cutoffs, 3 and 5, instead of 4, and estimate the model and present the results in Columns (1) and (2), respectively. Column (3) is based on the specification where we do not use the indicator variable about the base maximal price being greater than \$300,000. In the specification for Column (4), we assume that contract outcomes, $\mathbf{s}$, consist of cost changes and duration adjustments that are associated with either (i) work changes or (ii) all other reasons. The results in Columns (5) and (6) show that further increasing the accuracy of the numerical integrations in the estimation does not change our results. As discussed in Appendix E, we use Legendre-Gauss quadrature with 50 points from $[0.01, 0.99]$ for integration over π; employ 5,000 points of Halton sequence for the Monte-Carlo integration over the contract outcomes $\mathbf{s}$. We use 100 points, instead of 50 points, for integration over π to produce the results of Column (5); we use 10,000 points, instead of 5,000 points, for integration over $\mathbf{s}$ in obtaining the results of Column (6).

H.2. **Alternative Samples.** Columns (7) through (10) in Table A13 display results based on four subsamples that are homogeneous in the observed variables. Column (7) reports on the 307 contracts with four-digit Product and Service Code (PSC) D304, "Telecommunications and Transmission Service"; Column (8) on the 1,156 contracts with PSC 7030, "Automatic Data Processing Software." In our data set these two PSC categories account for the largest number of observations within services and products, respectively. On average there are slightly fewer bids per project in these

Table A12. Sensitivity Analyses

(Costs in $ thousand)	Base	(1)	(2)	(3)	(4)	(5)	(6)
Table 5: Model primitives							
Fraction of low-cost sellers	0.940 (0.004)	0.937	0.943	0.939	0.940	0.939	0.940
Project costs of low-cost sellers	360.87 (3.54)	360.65	360.83	360.62	348.26	361.42	361.42
Project cost difference	40.91 (30.63)	49.02	42.59	41.09	31.04	23.29	37.90
Marginal search costs	1.70 (0.53)	1.70	1.71	1.83	1.59	1.26	1.43
Solicitation costs	0.06 (0.14)	0.04	0.13	0.15	0.07	0.01	0.05
Table 6: Why so little competition?							
Fraction of low-cost sellers = Avg.	+0.799 (0.075)	+0.78	+0.83	+0.82	+0.80	+0.85	+0.76
Fraction of low-cost sellers = 0.5	+4.886 (0.162)	+4.76	+5.05	+4.89	+4.88	+4.93	+4.89
Fraction of low-cost sellers = 0.25	+9.241 (0.294)	+9.00	+9.54	+9.23	+9.24	+9.35	+9.25
Doubled cost differences	+0.664 (0.063)	+0.67	+0.62	+0.61	+0.66	+0.73	+0.64
First-price sealed-bid auction	+2.728 (0.531)	+3.27	+2.44	+2.92	+1.26	+2.86	+3.64
Halved marginal search costs	+0.577 (0.085)	+0.60	+0.50	+0.49	+0.54	+0.67	+0.56
Halved solicitation costs	+0.012 (0.019)	+0.01	+0.03	+0.02	+0.01	+0.00	+0.01
Table 6: Effects of mandated solicitation							
Number of bids	+0.02 (0.049)	+0.02	+0.06	+0.04	+0.02	+0.01	+0.03
Payment	−0.01 (0.030)	−0.01	−0.03	−0.04	−0.02	−0.001	−0.01
Search costs	+0.01 (0.021)	+0.01	+0.02	+0.03	+0.01	+0.001	+0.01
Solicitation costs	+0.05 (0.140)	0.03	+0.12	+0.13	+0.06	+0.01	+0.04
Table 6: Effects of requiring minimum search efforts ($\lambda \geq 1$)							
Number of bids	+0.79 (0.032)	+0.80	+0.80	+0.80	+0.79	+0.79	+0.80
Payments	−0.95 (0.311)	−0.97	−0.98	−1.00	−0.92	−0.74	−0.82
Search costs	+1.34 (0.459)	+1.37	+1.37	+1.39	+1.27	+1.02	+1.16
Solicitation costs	+0.05 (0.140)	+0.03	+0.12	+0.13	+0.06	+0.01	+0.04
Number of observations	6,981	6,981	6,981	6,981	6,981	6,981	6,981

Note: The bootstrap standard errors are in parentheses. See Tables 5 and 6 for the model primitives and the counterfactual scenarios. Appendix H describes each specification of the sensitivity analyses.

TABLE A13. Sensitivity Analyses (Continued)

(Costs in $ thousand)	Base	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Table 5: Model primitives									
Fraction of low-cost sellers	0.940 (0.004)	0.867	0.959	0.961	0.927	0.929	0.940	0.940	0.940
Project costs of low-cost sellers	360.87 (3.54)	366.62	336.13	360.31	360.73	417.12	355.61	349.23	336.35
Project cost difference	40.91 (30.63)	37.46	135.91	44.27	38.13	48.23	36.45	38.37	34.37
Marginal search costs	1.70 (0.53)	4.16	5.42	1.70	1.94	4.90	0.92	0.71	0.47
Solicitation costs	0.06 (0.14)	0.01	0.08	0.15	0.30	0.06	0.10	1.54	1.26
Table 6: Why so little competition?									
Fraction of low-cost sellers = Avg.	+0.799 (0.075)	+1.43	+0.55	+0.73	+0.99	+0.85	−0.05	−0.06	−0.04
Fraction of low-cost sellers = 0.5	+4.886 (0.162)	+4.06	+5.12	+5.61	+4.85	+4.64	+1.06	+0.56	+0.07
Fraction of low-cost sellers = 0.25	+9.241 (0.294)	+7.37	+9.57	+10.57	+9.11	+8.75	+1.37	+0.62	+0.04
Doubled cost differences	+0.664 (0.063)	+1.21	+0.94	+0.63	+0.71	+0.64	+0.13	+0.11	+0.04
First-price sealed-bid auction	+2.728 (0.531)	+2.14	+2.33	+3.46	+1.56	+1.27	+1.32	+0.88	+0.31
Halved marginal search costs	+0.577 (0.085)	+1.18	+0.55	+0.47	+0.54	+0.55	+0.04	+0.02	+0.01
Halved solicitation costs	+0.012 (0.019)	+0.002	+0.02	+0.06	+0.07	+0.01	+0.00	+0.00	+0.00
Table 6: Effects of mandated solicitation									
Number of bids	+0.02 (0.049)	+0.005	+0.03	+0.11	+0.18	+0.04	+0.000	+0.002	+0.000
Payment	−0.01 (0.030)	−0.004	−0.03	−0.04	−0.21	−0.02	−0.002	−0.01	−0.001
Search costs	+0.01 (0.021)	+0.004	+0.03	+0.03	+0.17	+0.02	+0.002	+0.001	+0.000
Solicitation costs	+0.05 (0.140)	+0.01	+0.11	+0.15	+0.29	+0.05	+0.11	+2.35	+2.00
Table 6: Effects of requiring minimum search efforts ($\lambda \geq 1$)									
Number of bids	+0.79 (0.032)	0.86	+0.79	+0.84	+0.82	+0.81	+0.90	+0.94	+0.97
Payments	−0.95 (0.311)	−2.70	−3.27	−1.06	−1.23	−2.50	+0.83	+2.65	+8.15
Search costs	+1.34 (0.459)	+3.62	+5.04	+1.53	+1.56	+3.27	+0.76	+0.60	+0.41
Solicitation costs	+0.05 (0.140)	+0.01	+0.11	+0.15	+0.29	+0.05	+0.11	+2.35	+2.00
Number of observations	6,981	307	1,156	4,673	2,308	7,246	6,981	6,981	6,981

Note: The bootstrap standard errors are in parentheses. See Tables 5 and 6 for the model primitives and the counterfactual scenarios. Appendix H describes each specification of the sensitivity analyses.

subsamples, 1.31 and 1.60 respectively, than overall, 1.64. Comparing Columns (7) and (8), we find a larger pool of high-cost sellers and smaller project cost differences between the two seller types for the telecommunications/transmission service contracts than for the software contracts. Comparing these two subsamples with the main sample, the roles of seller heterogeneity and buyer search costs in explaining few bids differ somewhat, but the results are qualitatively similar across all three samples. Instead of pooling the Department of Defense (DoD) contracts and others as in our main estimation, we separately estimate the model using the 4,673 DoD contracts only for the results of Column (9), and use the remainders only for Column (10). Column (11) is based on our main sample plus the 265 contracts that we originally dropped due to inconsistent records in terms of price and duration (Appendix A.2). Our results in Section 6 are robust to using these alternative samples.

H.3. **Allowing for Entry Costs.** For Columns (12)–(14), we consider an extended model where sellers pay entry costs to participate, as discussed in Section 3.4. We assume that the entry cost per seller is a fraction of the expected project cost:

$$\kappa_s(\mathbf{x}_1, \pi; \theta_\varphi) = \alpha_\kappa \left[\pi c_1(\mathbf{x}_1, \pi; \theta_\varphi) + (1-\pi) c_0(\mathbf{x}_1, \pi; \theta_\varphi)\right].$$

Borrowing the estimates from the literature, we set $\alpha_\kappa = \{0.01, 0.02, 0.05\}$, respectively. As we allow for another source of market friction, the estimates of marginal search costs are smaller and mean solicitation costs are larger than the main estimates. Regardless, we find that the effects of mandating more competition are very similar, except that requiring minimum search efforts ($\lambda \geq 1$) would increase the expected payment. It is because the buyer would have to increase the amount of the reimbursement of entry costs to be included in the payment to a winning seller in order to induce sellers to participate when they expect more bids.

H.3.1. *Equilibrium when Sellers Pay Entry Costs.* We assume that sellers do not know their cost type before entry. Upon paying the entry cost, they learn their type. Assuming the sellers' belief on their type is based on the population distribution, the reimbursement of the entry cost to the winner, denoted as a, must be a fair lottery given the buyer's search intensity $\lambda > 0$:

$$\begin{aligned}\kappa_s &= a\sum_{j=0}^{\infty}\left[\pi\phi_{1,j+1}+(1-\pi)\phi_{0,j+1}\right]\frac{\lambda^j e^{-\lambda}}{j!}\\ &= a\sum_{j=0}^{\infty}\left[\pi\frac{1-(1-\pi)^{(j+1)}}{(j+1)\pi}+(1-\pi)\frac{(1-\pi)^j}{j+1}\right]\frac{\lambda^j e^{-\lambda}}{j!}\\ &= a\sum_{j=0}^{\infty}\frac{1}{j+1}\frac{\lambda^j e^{-\lambda}}{j!}=\frac{a}{\lambda}\sum_{j=0}^{\infty}\frac{\lambda^{j+1}e^{-\lambda}}{(j+1)!}=\frac{a}{\lambda}\sum_{j'=1}^{\infty}\frac{\lambda^{j'}e^{-\lambda}}{j'!}=\frac{a}{\lambda}(1-e^{-\lambda}),\end{aligned}$$

where the second equality results from plugging in the definitions of ϕ_{1n} and ϕ_{0n}, (5) and (6). Therefore, the reimbursement to the winner is $\kappa_s\lambda/(1-e^{-\lambda})$ if $\lambda > 0$ and κ_s otherwise. The expected payment to a winning seller when there are n participants under search intensity λ, denoted by $T^e(n)$, is:

$$T^e(n) = T(n) + \kappa_s\left(\mathbb{1}_{\{\lambda>0\}}\frac{\lambda}{1-e^{-\lambda}} + \mathbb{1}_{\{\lambda=0\}}\right),$$

where $T(n)$ is defined in (12). The expected total cost of competitive procurement with search effort λ and solicitation costs η, denoted by $U^e(\lambda,\eta)$, is:

$$U^e(\lambda,\eta) \equiv \sum_{n=0}^{\infty}\frac{\lambda^n e^{-\lambda}}{n!}T^e(n+1) + \kappa\lambda + \eta = U(\lambda,\eta) + \kappa_s\left(\mathbb{1}_{\{\lambda>0\}}\frac{\lambda}{1-e^{-\lambda}} + \mathbb{1}_{\{\lambda=0\}}\right),$$

where $U(\lambda,\eta)$ is defined in (16). If the optimal search intensity conditional on competition, denoted by λ^e, is positive, then it must satisfy the first order condition:

$$-\pi e^{-\lambda\pi}\big\{(1-\pi)(c_0-c_1)+\pi(\gamma_0-\gamma_1)+\Gamma\big\} + \kappa_s\left(\frac{1}{1-e^{-\lambda}} - \frac{\lambda e^{-\lambda}}{(1-e^{-\lambda})^2}\right) + \kappa = 0.$$

Denoting the root to the above equation by $\check{\lambda}$, $\lambda^e = \max\{0,\check{\lambda}\}$. There is competitive bidding if and only if $U^e(\lambda^e,\eta) \le U(0,0)$, or equivalently, $\eta \le \Omega^e$, where

$$\Omega^e = \Omega + \kappa_s\mathbb{1}_{\{\lambda^e>0\}}\left[1-\lambda^e/(1-e^{-\lambda^e})\right],$$

where Ω is defined in (17).

H.3.2. *Estimation when Sellers Pay Entry Costs.* The estimation procedures of **E.1** are identical to the estimation of the model when $\kappa_s = 0$. In addition, because the equilibrium search intensity estimates are based on $\widehat{\theta}_\pi$, $\widehat{\lambda}^e(\pi,\tilde{\mathbf{x}},\widehat{\theta}_\pi)$ is also the same as the estimates from the main specification. In implementing **E.2**, we use the following identities:

$$\begin{aligned}
\mathbb{E}[p|y,n,k=1,\tilde{\mathbf{x}}] &= \int \Bigg[p_{1n}(\mathbf{x}_1,\pi;\theta_\varphi)+\kappa_s(\mathbf{x}_1,\pi;\theta_\varphi)\Bigg(\mathbb{1}_{\{\lambda^e(\pi,\tilde{\mathbf{x}};\theta_\pi)>0\}}\frac{\lambda^e(\pi,\tilde{\mathbf{x}};\theta_\pi)}{1-e^{-\lambda^e(\pi,\tilde{\mathbf{x}};\theta_\pi)}} \\
&\qquad +\mathbb{1}_{\{\lambda^e(\pi,\tilde{\mathbf{x}};\theta_\pi)=0\}}\Bigg)\Bigg] f_{\pi|y,n,k}(\pi|y,n,1,\tilde{\mathbf{x}};\theta_\pi)d\pi, \\
\mathbb{E}[p|y,n,k=1,\tilde{\mathbf{x}}] &= \int \Bigg[p_{0}(\mathbf{x}_1,\pi;\theta_\varphi)+\kappa_s(\mathbf{x}_1,\pi;\theta_\varphi)\Bigg(\mathbb{1}_{\{\lambda^e(\pi,\tilde{\mathbf{x}};\theta_\pi)>0\}}\frac{\lambda^e(\pi,\tilde{\mathbf{x}};\theta_\pi)}{1-e^{-\lambda^e(\pi,\tilde{\mathbf{x}};\theta_\pi)}} \\
&\qquad +\mathbb{1}_{\{\lambda^e(\pi,\tilde{\mathbf{x}};\theta_\pi)=0\}}\Bigg)\Bigg] f_{\pi|y,n,k}(\pi|y,n,1,\tilde{\mathbf{x}};\theta_\pi)d\pi, \\
\mathbb{E}[q|y,n,k=0,\mathbf{s},\tilde{\mathbf{x}}] &= \int q_0(\mathbf{s},\mathbf{x},\pi;\theta_\varphi)f_{\pi|y,n,k}(\pi|y,n,0,\tilde{\mathbf{x}};\theta_\pi)d\pi,
\end{aligned}$$

where $p_{1n}(\mathbf{x},\pi;\theta_r)$, $p_0(\mathbf{x},\pi;\theta_r)$, and $q_0(\mathbf{s},\mathbf{x},\pi;\theta_r)$ are defined in (A.33). Given these identities, similarly estimate θ_{φ_2}, a subset of θ_φ, by minimizing the weighted sum of squared distances from the predicted and the actual values of the base prices and the price adjustments. In implementing **E.3**, the estimates of $\kappa(\tilde{\mathbf{x}},\pi;\theta_\varphi^*,\theta_\pi^*)$ and $\Omega^e(\tilde{\mathbf{x}},\pi;\theta_\varphi^*,\theta_\pi^*)$ are modified to:

$$\begin{aligned}
\kappa(\tilde{\mathbf{x}},\pi;\widehat{\theta}_\varphi,\widehat{\theta}_\pi) &= \pi e^{-\pi\widehat{\lambda^e}(\pi,\tilde{\mathbf{x}};\widehat{\theta}_\pi)}\Bigg[\pi\Big\{\gamma_0(\mathbf{x}_1,\pi;\widehat{\theta}_c)-\gamma_1(\mathbf{x}_1,\pi;\widehat{\theta}_c)\Big\} \\
&\quad +(1-\pi)\Big\{c_0(\mathbf{x}_1,\pi;\widehat{\theta}_\varphi)-c_1(\mathbf{x}_1,\pi;\widehat{\theta}_\varphi)\Big\}+\Gamma(\mathbf{x}_1,\pi;\widehat{\theta}_\varphi)\Bigg] \\
&\quad -\kappa_s(\mathbf{x}_1,\pi;\widehat{\theta}_\varphi)\mathbb{1}_{\left\{\widehat{\lambda^e}(\pi,\tilde{\mathbf{x}};\widehat{\theta}_\pi)>0\right\}}\left(\frac{1-e^{-\widehat{\lambda^e}(\pi,\tilde{\mathbf{x}};\widehat{\theta}_\pi)}[1+\widehat{\lambda}^e(\pi,\tilde{\mathbf{x}};\widehat{\theta}_\pi)]}{[1-e^{-\widehat{\lambda^e}(\pi,\tilde{\mathbf{x}};\widehat{\theta}_\pi)}]^2}\right),
\end{aligned}$$

and

$$\Omega^e(\tilde{\mathbf{x}},\pi;\widehat{\theta}_\varphi,\widehat{\theta}_\pi)=\Omega(\tilde{\mathbf{x}},\pi;\widehat{\theta}_\varphi,\widehat{\theta}_\pi)+\kappa_s(\mathbf{x}_1,\pi;\widehat{\theta}_\varphi)\mathbb{1}_{\left\{\widehat{\lambda^e}(\pi,\tilde{\mathbf{x}};\widehat{\theta}_\pi)>0\right\}}\left(1-\frac{\widehat{\lambda}^e(\pi,\tilde{\mathbf{x}};\widehat{\theta}_\pi)}{1-e^{-\widehat{\lambda^e}(\pi,\tilde{\mathbf{x}};\widehat{\theta}_\pi)}}\right).$$