Appendix (for Online Publication)

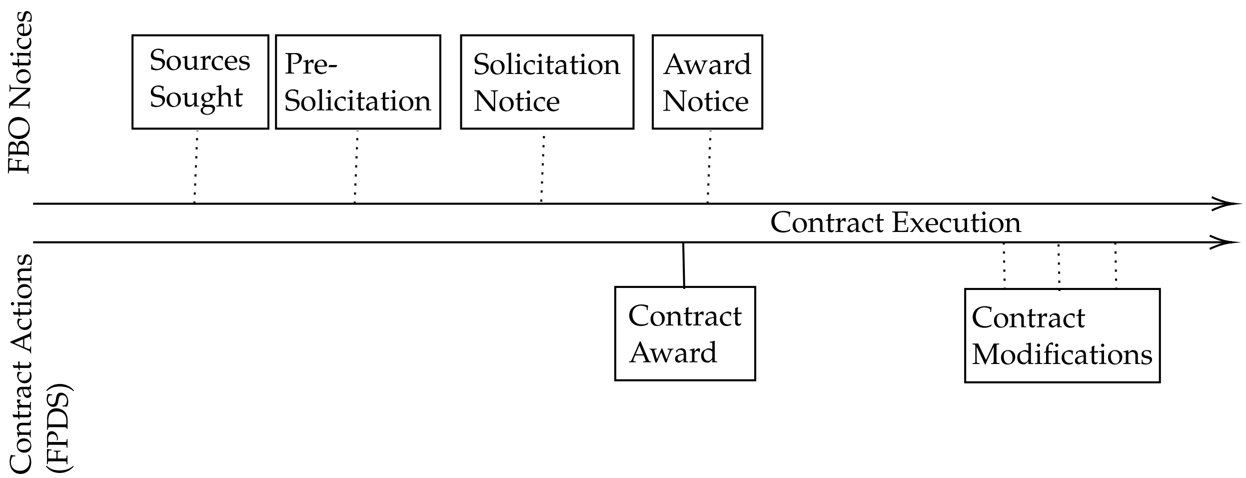
Competition Under Incomplete Contracts and the Design of Procurement Policies

Rodrigo Carril, Andres Gonzalez-Lira, and Michael S. Walker

Contents:

A Additional Figures

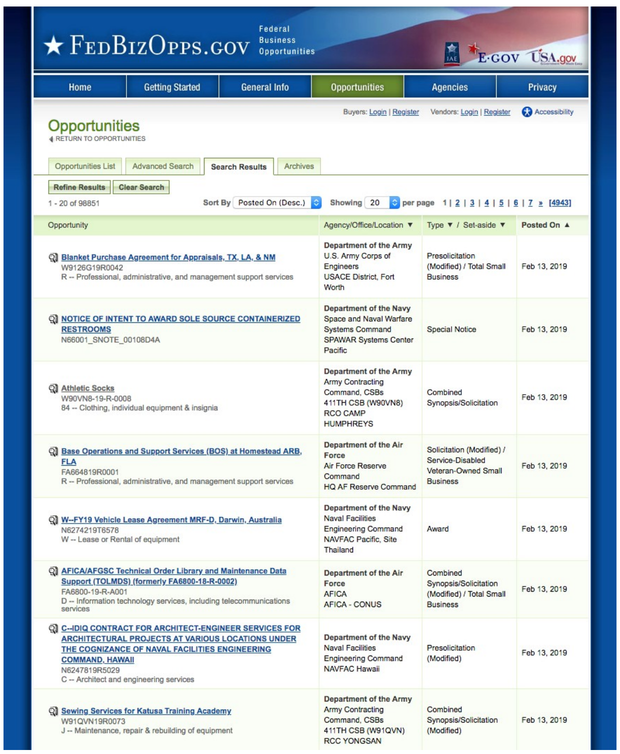
Figure A1: Contract Timeline and Data Sources



Notes: This figure presents a timeline of events associated with a typical contract. Milestones located above the arrows correspond to notices that are published on the government's point of entry (`fedbizopps.gov`). Milestones below the arrows generate information that is recorded on the Federal Procurement Data System (FPDS) - Next Generation.

Figure A2: FedBizzOpps

(a) List of Opportunities

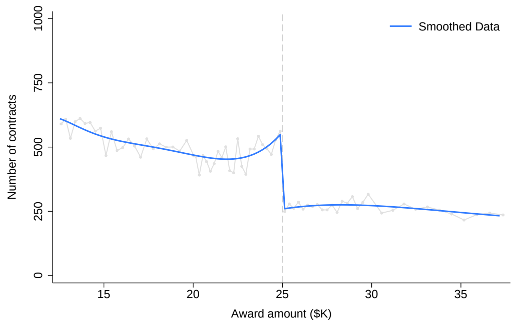


(b) Example Solicitation

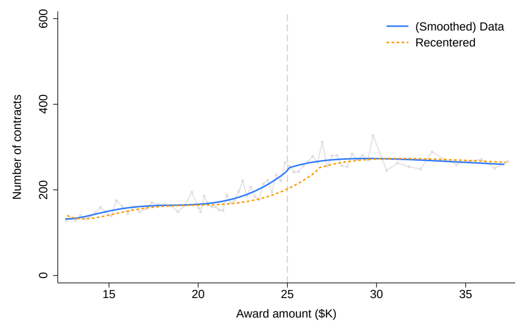
Notes: This figure shows two screenshots of FBO.gov.captured on Feb 13, 2019. Panel (a) shows a list of contract solicitations (opportunities). Panel (b) shows a particular solicitation for athletic socks, required by an Army procurement office.

Figure A3: Distribution of Contract Prices

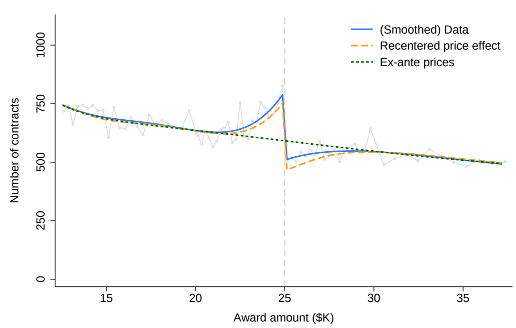
(a) Non-publicized contracts ($D = 0$)



(b) Publicized contracts ($D = 1$)



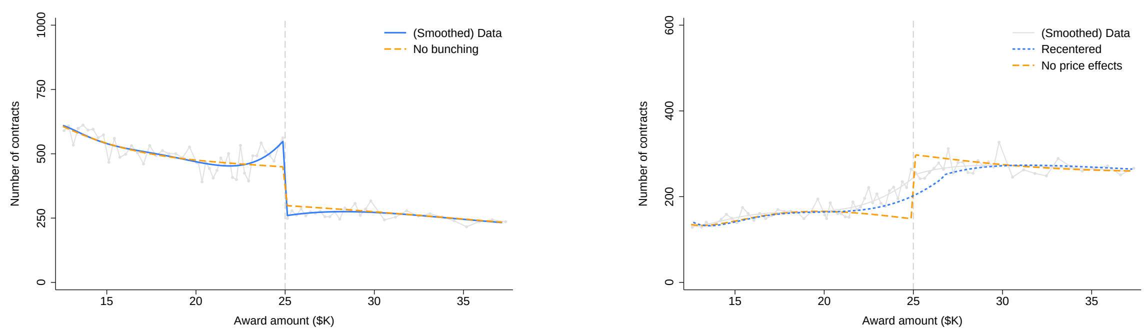
(c) All contracts



Notes: This figure shows the empirical distribution of the number of contracts at different price bins. Panel (a) shows the distribution of non-publicized contracts ($D = 0$). Panel (b) shows the distribution of publicized contracts ($D = 1$). Panel (c) displays the overall distribution, i.e., the sum of publicized and non-publicized contracts at every price. The blue line corresponds to a polynomial fit of degree five. The orange dashed lines in panels (b) and (c) represent the distribution of contract prices after re-centering publicized contracts by their price effect. The green dashed line in panel (c) represents the corresponding overall interpolation in the absence of price effects and bunching.

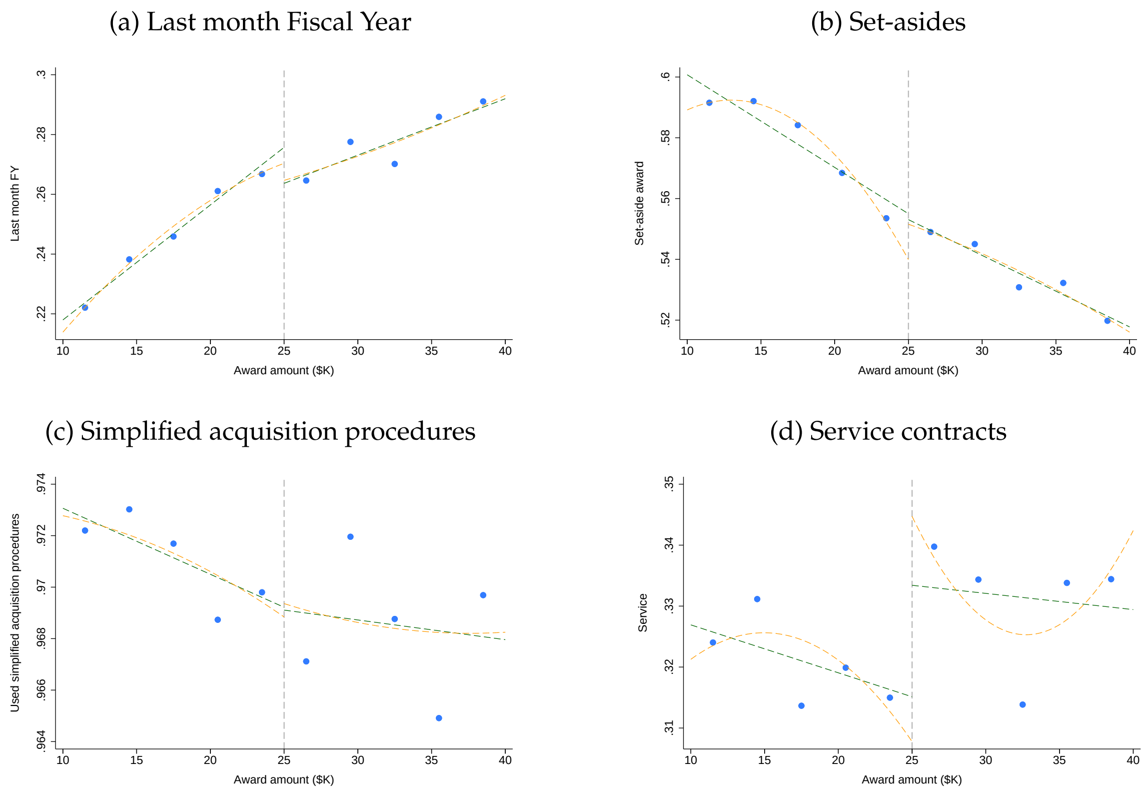
Figure A4: Distribution of Contract Prices

(a) Non-publicized contracts ($D = 0$) (b) Publicized contracts ($D = 1$)



Notes: This figure shows the empirical distribution of the number of contracts at different price bins. Panel (a) shows the distribution of non-publicized contracts ($D = 0$). Panel (b) displays the distribution of publicized contracts ($D = 1$). The blue line corresponds to a polynomial fit of degree five. The orange dashed lines in panels (b) and (c) represent the counterfactual distributions in the absence of price effects and bunching. The counterfactual distributions stem from the proposed framework. In panel (a), The comparison between the solid blue and the dashed orange lines provide a visual interpretation of the mass of bunched contracts. The comparison between the dashed blue and the dashed orange lines in panel (b) inform visually about the distribution of price effects.

Figure A5: Pre-award Characteristics Around the Threshold



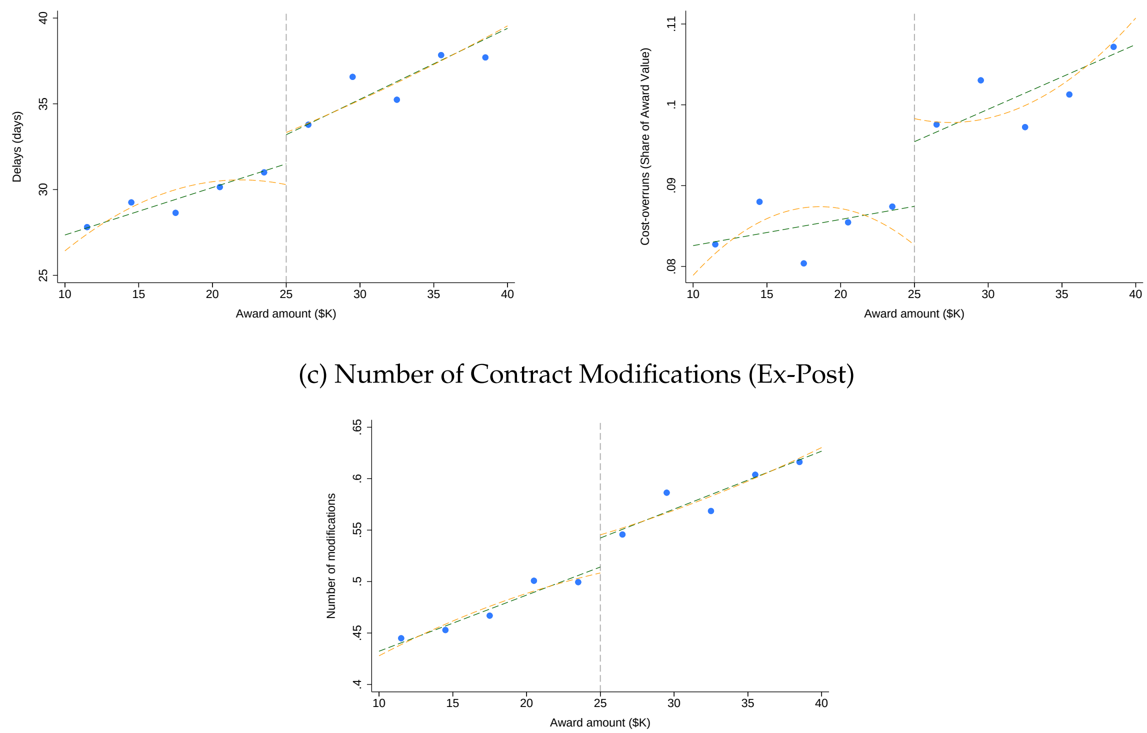
Notes: This figure presents four binned scatter plots, which depict an average pre-award characteristic by bins of award amounts, as well as linear and quadratic fits at each side of $25,000. The pre-award characteristic in each Panel is as follows: (a) an indicator equal to one if the contract was solicited the last month of the fiscal year (September); (b) an indicator equal to one if the contract was set-aside for a preferential group (e.g. small businesses); (c) an indicator equal to one if the contract was awarded using simplified acquisition procedures; (d) an indicator equal to one if the award is for a service contract. The data source is the Federal Procurement Data System-Next Generation. The sample consists of non-R&D definitive contracts and purchase orders, with award values between $ 10,000 and $ 40,000, awarded by the Department of Defense in fiscal years 2015 through 2019. Award amounts are discretized into right-inclusive bins of $3,000 dollars length.

Figure A6: Publicity Effects on Post-Award Contract Performance

(a) Delays (days)

(b) Cost-Overruns (Share of Award Value)

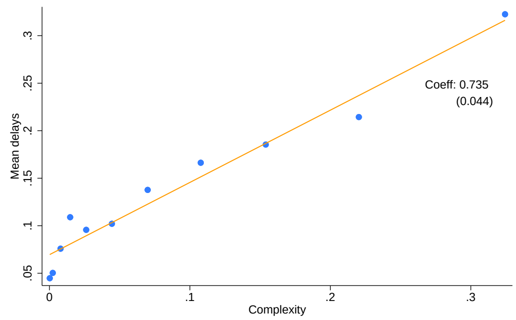
(c) Number of Contract Modifications (Ex-Post)



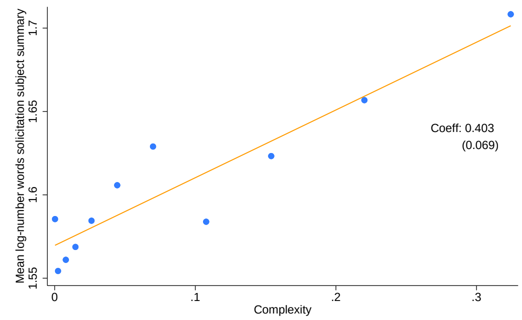
Notes: This figure presents three binned scatter plots, which depict an average post-award performance metric by bins of award amounts, as well as linear and quadratic fits at each side of $25,000. The outcomes in each Panel are as follows: (a) number of days of contract implementation delays; (b) cost-overruns as a share of award value; (c) number of modification to the original contract. The data source is the Federal Procurement Data System-Next Generation. The sample consists of non-R&D definitive contracts and purchase orders, with award values between $ 10,000 and $ 40,000, awarded by the Department of Defense in fiscal years 2015 through 2019. Award amounts are discretized into right-inclusive bins of $3,000 dollars length.

Figure A7: Correlation Complexity Degree with Other Variables

(a) Delays (days)

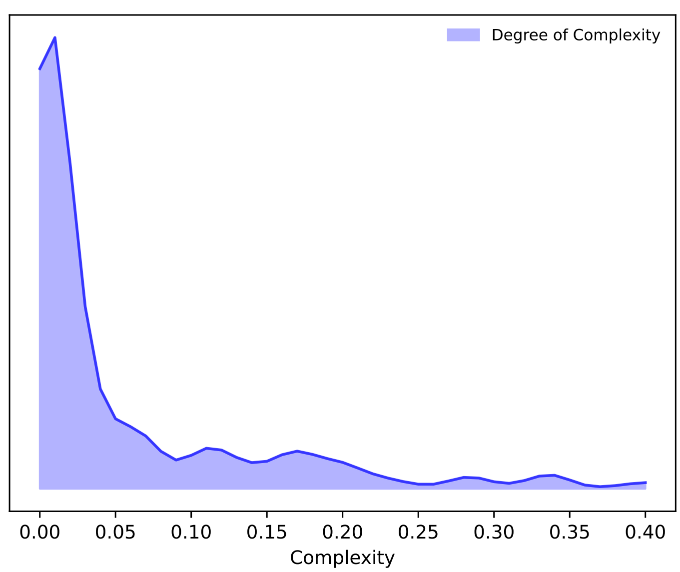


(b) Number of Words Solicitation



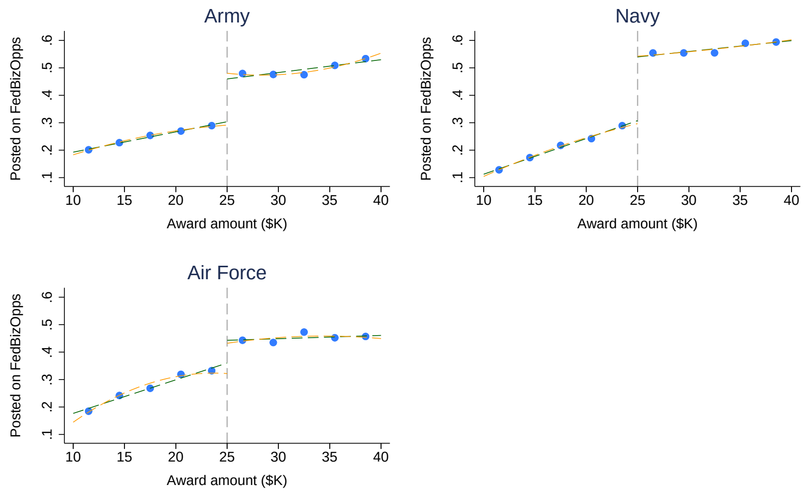
Notes: This figure displays the correlation between our measure of complexity (i.e., product-level average cost-overruns for contracts under $20K) with product-level average delays (Panel (a)) and product-level (log) average number of words contract synopsis from FBO. The number of words variable was residualized on office, type of solicitation, and year fixed effects, because the text often contains information specific to the office and the solicitation type. Every dot represents the mean of the Y-axis variable at different quantiles of the complexity measure. The orange line provides a (linear) regression fit at the product level. The slope coefficient (and SE) are presented in the graphs.

Figure A8: Complexity Distribution



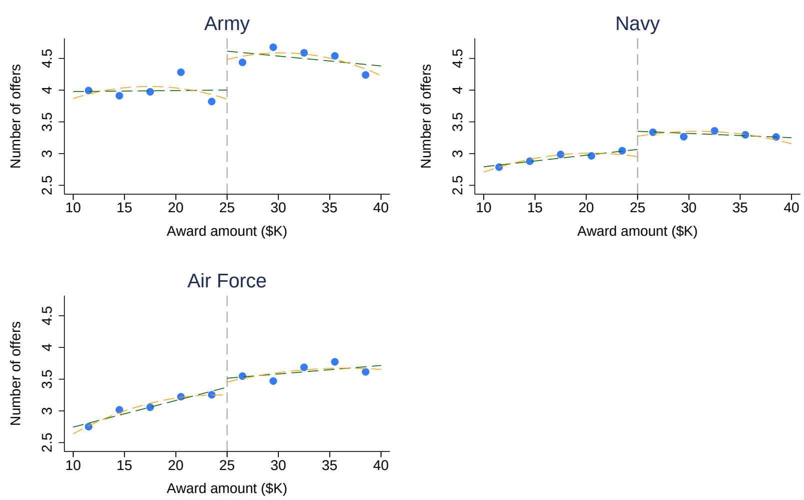
Notes: This figure presents the probability density function (PDF) of product complexity. Even though there's wide heterogeneity in the degree of complexity, the bulk of contracts in our sample have relatively low levels of complexity. The degree of complexity is defined as the log of the product's average overruns, and it is calculated on all contracts for the same product category that are below $20,000. The plotted distribution of log costs is smoothed using a kernel.

Figure A9: Heterogeneous publicity adoption by major departments



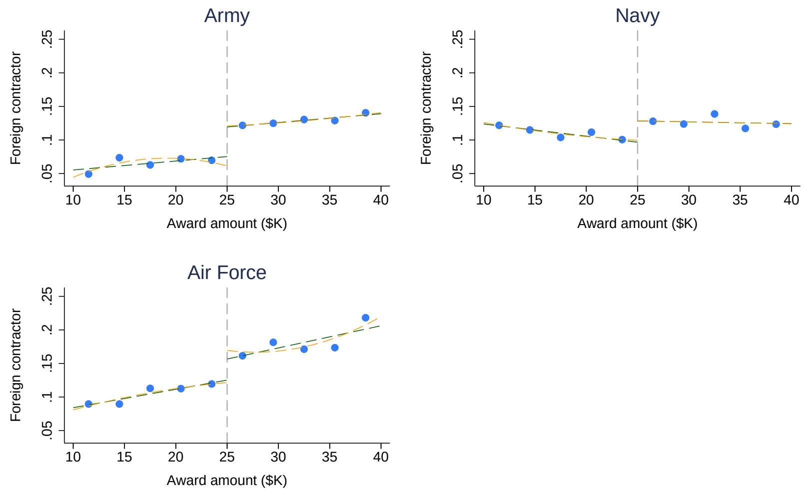
Notes: This figure presents three binned scatter plots, which depict the share of contracts publicized in FedBizzOpps by bins of award amounts, as well as linear and quadratic fits at each side of $25,000. The data source is the Federal Procurement Data System-Next Generation. The full sample consists of non-R&D definitive contracts and purchase orders, with award values between $ 5,000 and $ 45,000, awarded by the Department of Defense in fiscal years 2011 through 2017. Panel (a) restricts the sample to awards made by the Army. Panel (b) restricts the sample to awards made by the Navy. Panel (c) restricts the sample to awards made by the Air Force. Award amounts are discretized into right-inclusive bins of $2,500 dollars length.

Figure A10: Heterogeneous effects on competition by major departments



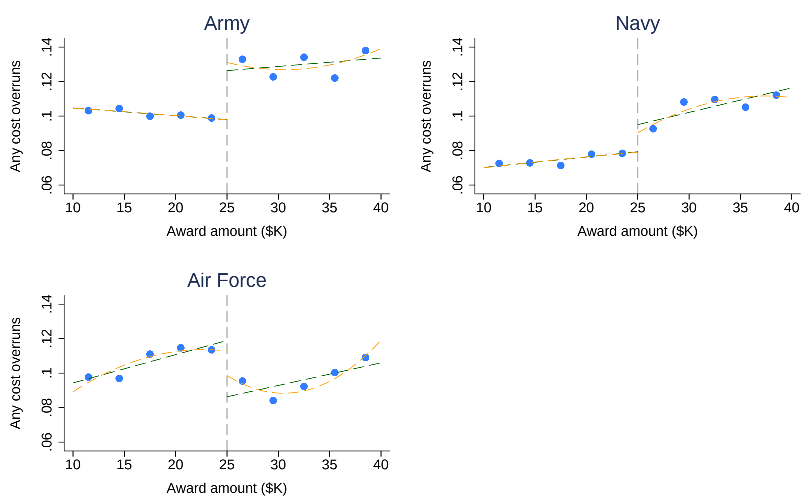
Notes: This figure presents three binned scatter plots, which depict the average number of offers received by bins of award amounts, as well as linear and quadratic fits at each side of $25,000. The data source is the Federal Procurement Data System-Next Generation. The full sample consists of non-R&D definitive contracts and purchase orders, with award values between $ 5,000 and $ 45,000, awarded by the Department of Defense in fiscal years 2011 through 2017. Panel (a) restricts the sample to awards made by the Army. Panel (b) restricts the sample to awards made by the Navy. Panel (c) restricts the sample to awards made by the Air Force. Award amounts are discretized into right-inclusive bins of $2,500 dollars length.

Figure A11: Heterogeneous effects on winner characteristics by major departments



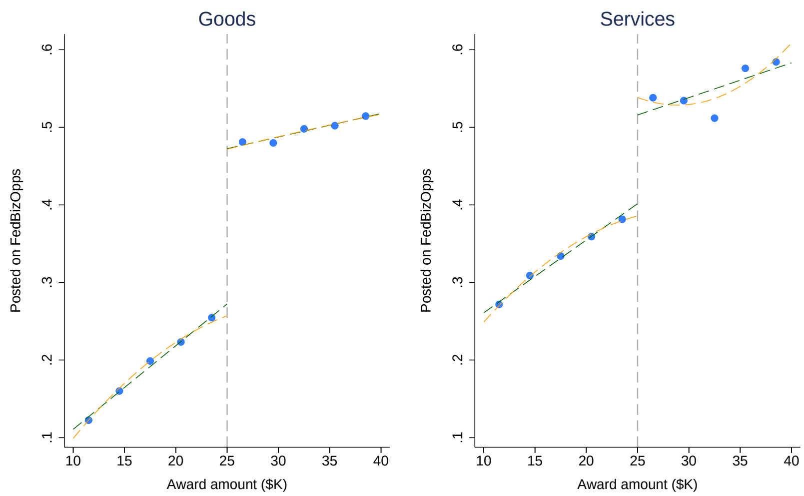
Notes: This figure presents three binned scatter plots, which depict the share of contracts awarded to a foreign firm by bins of award amounts, as well as linear and quadratic fits at each side of $25,000. The data source is the Federal Procurement Data System-Next Generation. The full sample consists of non-R&D definitive contracts and purchase orders, with award values between $ 5,000 and $ 45,000, awarded by the Department of Defense in fiscal years 2011 through 2017. Panel (a) restricts the sample to awards made by the Army. Panel (b) restricts the sample to awards made by the Navy. Panel (c) restricts the sample to awards made by the Air Force. Award amounts are discretized into right-inclusive bins of $2,500 dollars length.

Figure A12: Heterogeneous effects on performance by major departments



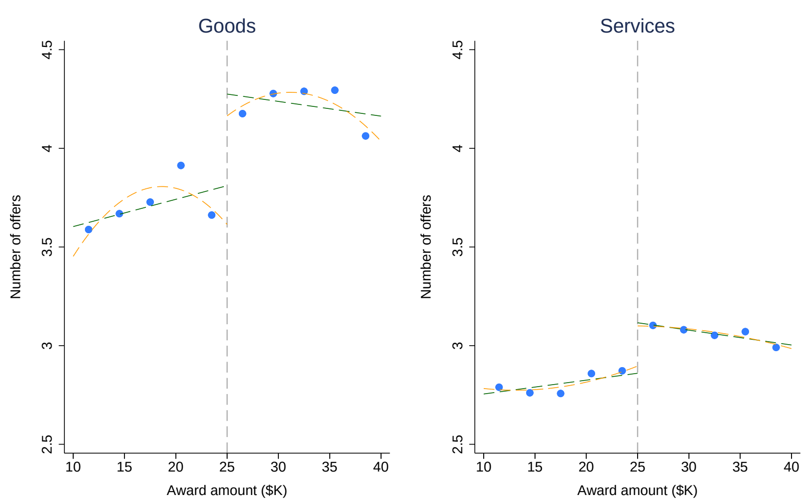
Notes: This figure presents three binned scatter plots, which depict average cost overruns by bins of award amounts, as well as linear and quadratic fits at each side of $25,000. Cost overruns are computed as the difference between actual obligated contract dollars and expected total obligations at the time of the award, divided by expected obligations. The data source is the Federal Procurement Data System-Next Generation. The full sample consists of non-R&D definitive contracts and purchase orders, with award values between $ 5,000 and $ 45,000, awarded by the Department of Defense in fiscal years 2011 through 2017. Panel (a) restricts the sample to awards made by the Army. Panel (b) restricts the sample to awards made by the Navy. Panel (c) restricts the sample to awards made by the Air Force. Award amounts are discretized into right-inclusive bins of $2,500 dollars length.

Figure A13: Heterogeneous publicity adoption: goods versus services



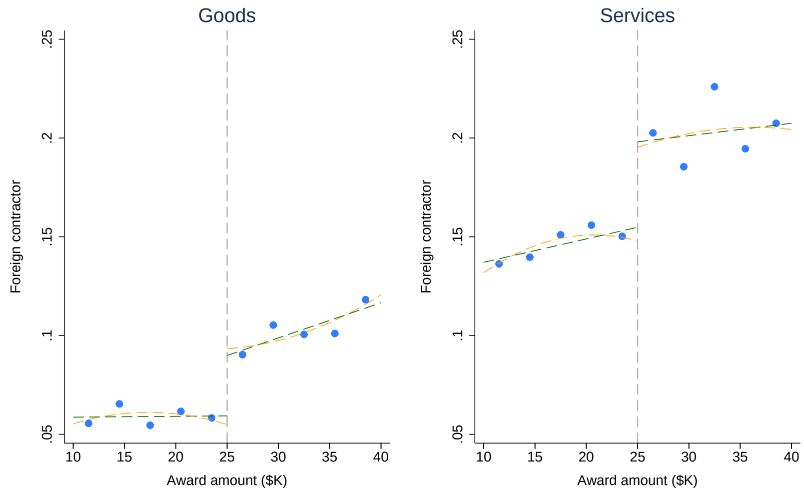
Notes: This figure presents two binned scatter plots, which depict the share of publicized contracts by bins of award amounts, as well as linear and quadratic fits at each side of $25,000. The data source is the Federal Procurement Data System-Next Generation. The full sample consists of non-R&D definitive contracts and purchase orders, with award values between $ 10,000 and $ 40,000, awarded by the Department of Defense in fiscal years 2015 through 2019. Panel (a) restricts the sample to awards for goods, while Panel (b) restricts the sample to service contracts. Award amounts are discretized into right-inclusive bins of $3,000 dollars length.

Figure A14: Heterogeneous effects on competition: goods versus services



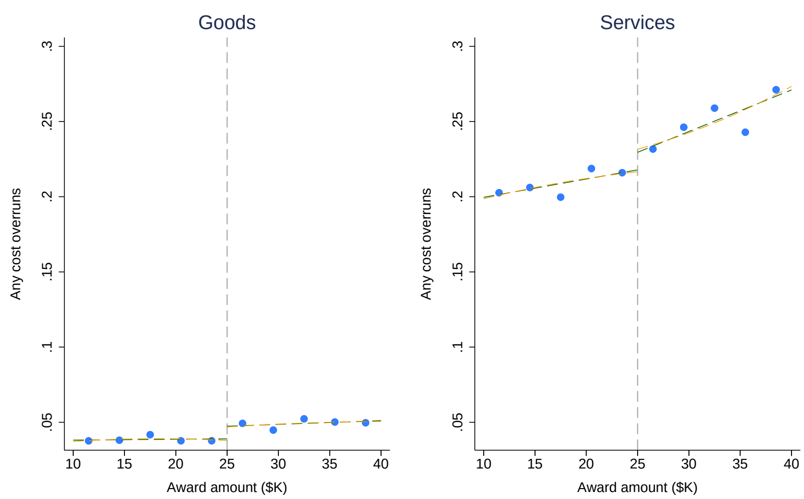
Notes: This figure presents two binned scatter plots, which depict the average number of offers received by bins of award amounts, as well as linear and quadratic fits at each side of $25,000. The data source is the Federal Procurement Data System-Next Generation. The full sample consists of non-R&D definitive contracts and purchase orders, with award values between $ 10,000 and $ 40,000, awarded by the Department of Defense in fiscal years 2015 through 2019. Panel (a) restricts the sample to awards for goods, while Panel (b) restricts the sample to service contracts. Award amounts are discretized into right-inclusive bins of $3,000 dollars length.

Figure A15: Heterogeneous effects on winner characteristics: goods versus services



Notes: This figure presents two binned scatter plots, which depict the share of contracts awarded to a foreign firm by bins of award amounts, as well as linear and quadratic fits at each side of $25,000. The data source is the Federal Procurement Data System-Next Generation. The full sample consists of non-R&D definitive contracts and purchase orders, with award values between $ 10,000 and $ 40,000, awarded by the Department of Defense in fiscal years 2015 through 2019. Panel (a) restricts the sample to awards for goods, while Panel (b) restricts the sample to service contracts. Award amounts are discretized into right-inclusive bins of $2,500 dollars length.

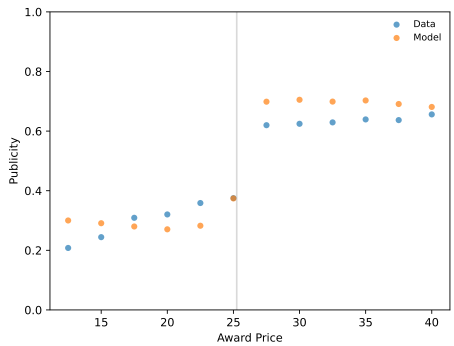
Figure A16: Heterogeneous effects on performance: goods versus services



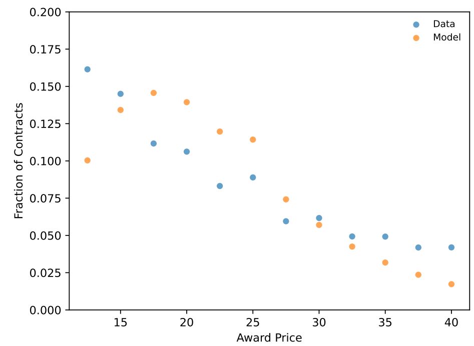
Notes: This figure presents two binned scatter plots, which depict share of contracts with cost overruns by bins of award amounts, as well as linear and quadratic fits at each side of $25,000. Cost overruns are computed as the difference between actual obligated contract dollars and expected total obligations at the time of the award, divided by expected obligations. The data source is the Federal Procurement Data System-Next Generation. The full sample consists of non-R&D definitive contracts and purchase orders, with award values between $ 10,000 and $ 40,000, awarded by the Department of Defense in fiscal years 2015 through 2019. Panel (a) restricts the sample to awards for goods, while Panel (b) restricts the sample to service contracts. Award amounts are discretized into right-inclusive bins of $3,000 dollars length.

Figure A17: Model Fit

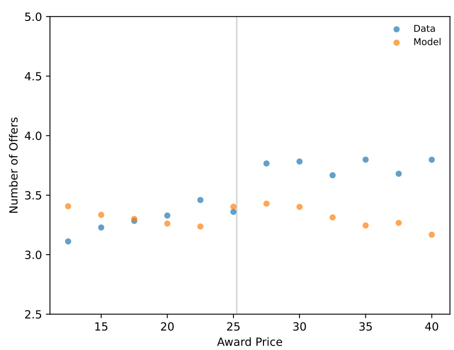
(a) Publicity Status



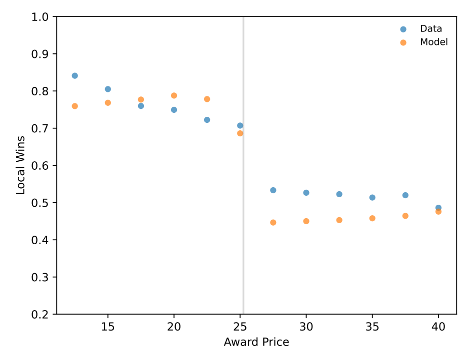
(b) Price Density



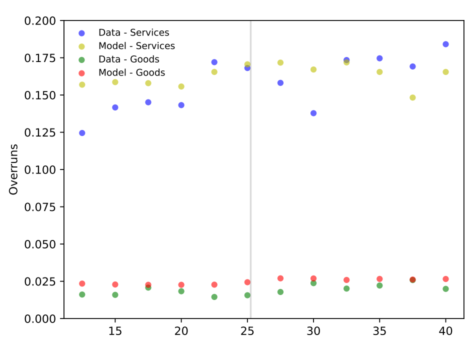
(c) Number of Bidders



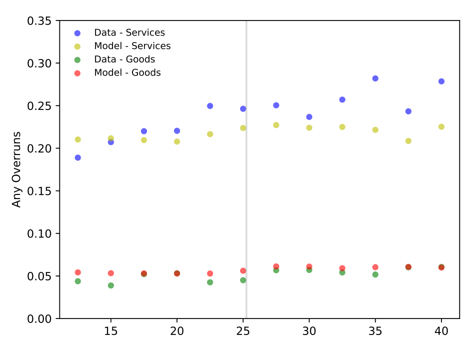
(d) Probability of a Local Winning



(e) Overruns

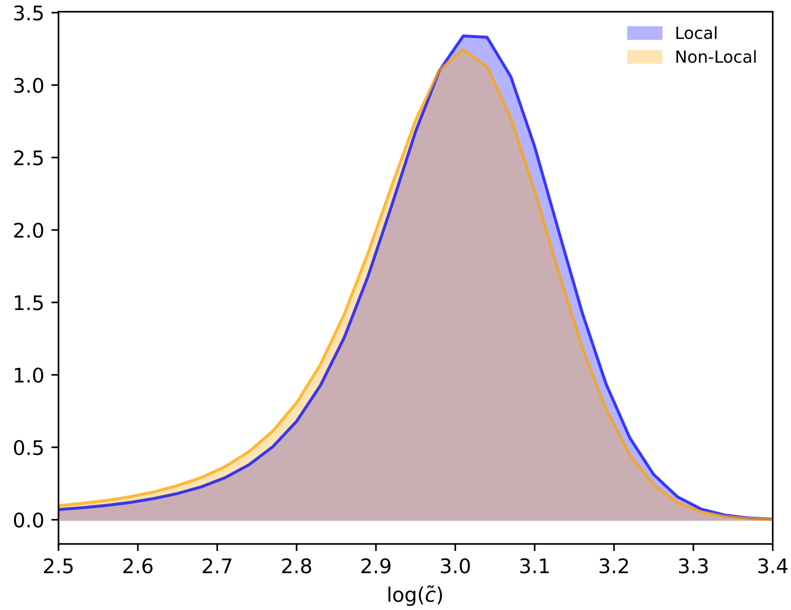


(f) Any Overruns



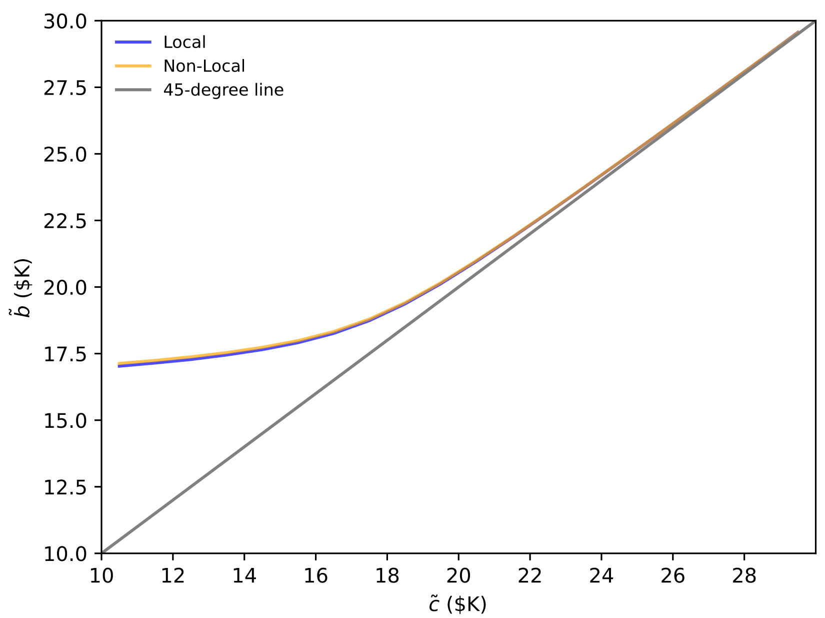
Notes: This figure presents the model fit, based on a simulated method of moments estimation. In each panel, relevant outcome variables are shown as a function of the awarding price. Actual data points are presented in blue, while model-based simulated data are presented in orange. Panel (a) presents the density of contract prices, Panel (b) the fraction of publicized contracts, Panel (c) the number of actual bidders, Panel (d) the fraction awarded to local contractors, Panel (e) average cost overruns, and Panel (f) the probability of having any overrun. The last two panels separate goods from services.

Figure A18: Estimated Production Cost Distributions



Notes: This figure shows the estimated probability density function (PDF) of log production costs for local and non-local contractors. This plot is estimated holding covariates fixed at their mean value and assuming $log(u) = 0$. The plotted distribution of log bids is smoothed using a kernel.

Figure A19: Bidding Function

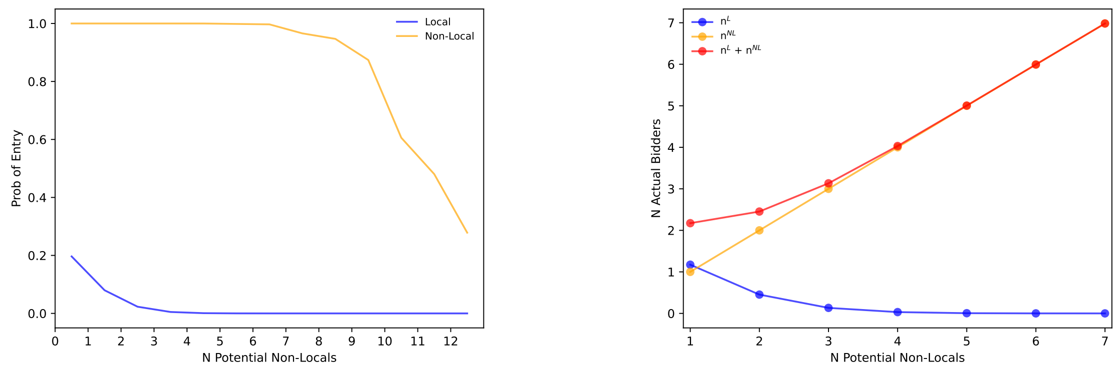


Notes: This figure displays the bidding function of local and non-local contractors. This plot is estimated holding covariates fixed at their mean value and assuming $log(u) = 0$. The plotted distribution of log bids is smoothed using a kernel.

Figure A20: Auction Entry and Winner Identity

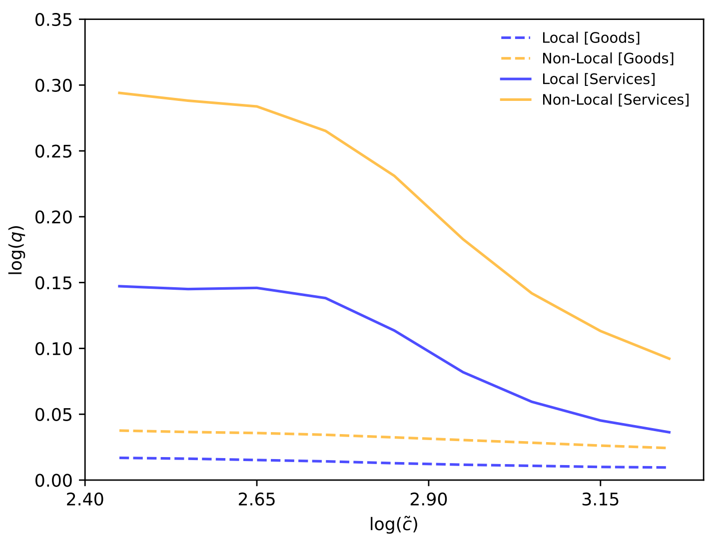
(a) Entry Probability

(b) Composition of Bidders



Notes: This figure presents participation decisions and subsequent winner identity as a function of the number of potential bidders. Panel (a) shows the number of actual bidders from each group, Panel (b) displays the average probability of awarding the contract to a local bidder. The higher the number of potential non-local contractors, the less likely that local contractors participate and win. These features connect directly with the fact that local contractors have substantially higher participation costs; thus, in equilibrium, reductions in predicted utility due to increased competition discourage their participation. Both figures were generated keeping constant (at the mean) the number of potential local contractors.

Figure A21: Relation between Production Costs and Cost Overruns



Notes: This figure shows the relation between production cost $\tilde{c}$ and overruns q. The orange line shows the relation for Non-Locals (orange) and for Locals (blue). It separates the relation for goods (dashed) and services (solid). The production cost $\tilde{c}$ is backed out from the simulated bids and the first order condition. The plot is generated for fixed covariates (estimation sample) and $\log(u) = 0$.

B Additional Tables

Table B.1: Summary Statistics

	Mean
Panel A: *Contracting Office*	
Navy	0.378
Army	0.441
Air Force	0.150
Other	0.031
Panel B: *Contract Characteristics*	
Award Amount (dollars)	20,807
Expected Duration (days)	54.10
Fixed-Price Contract	0.999
Set Aside Award	0.571
Simplified Procedure	0.971
Publicized on FedBizzOpps	0.299
Panel C: *Contract Competition*	
Number of Offers	3.542
One Offer	0.239
Panel D: *Contractor Characteristics*	
Foreign	0.099
Within-State Firm	0.690
Small Business	0.752
Woman-Owned Business	0.188
Panel E: *Contract Execution*	
Number of Modifications	0.439
Any Modifications	0.274
Cost-Overruns (Relative to Award Value)	0.076
Any Cost-Overruns	0.094
Delays (Relative to Expected Duration)	0.125
Any Delays	0.104
Sample Size	
No. of Contracts	85,661
No. of Contracting Offices	597
No. of Awarded Firms	29,641

Notes: This table presents summary statistics. The data source is the Federal Procurement Data System-Next Generation. The sample consists of non-R&D definitive contracts and purchase orders, with award values between $ 10,000 and $ 40,000, awarded by the Department of Defense in fiscal years 2015 through 2019. An observation is a contract, defined by aggregating all contract *actions* (initial award, modification, termination, etc.) associated with the same contract ID.

Table B.2: Top Product and Service Categories

	Goods		Services	
Rank	Name	N Contracts/year	Name	N Contracts/year
1	ADP Equipment and Software	1,374	Maintenance/Repair of Equipment	1,036
2	Laboratory Equipment	740	Utilities And Housekeeping	657
3	Medical Equipment and Supplies	685	Transport, Travel, Relocation	577
4	Electrical Equipment Compontents	653	Lease/Rent Equipment	534
5	Furniture	626	Support Services (Professional)	447
6	Communication/Coherent Radiation	530	ADP and Telecommunications	369
7	Power Distribution Equipment	320	Maintenance of Real Property	339
8	Ship And Marine Equipment	311	Education And Training	251
9	Hardware And Abrasives	295	Social Services	190
10	Construction And Building Material	291	Natural Resources Management	149

Notes: This table presents average annual counts of contracts in the most common product categories. The data source is the Federal Procurement Data System-Next Generation. The sample consists of non-R&D definitive contracts and purchase orders, with award values between $ 10,000 and $ 40,000, awarded by the Department of Defense in fiscal years 2015 through 2019. An observation is a contract, defined by aggregating all contract *actions* (initial award, modification, termination, etc.) associated with the same contract ID. A 4-digit alphanumeric code (PSC) is observed for each contract. The categories listed are constructed by aggregating PSC codes to two-digits for goods, and to a single digit (letter) for services.

Table B.3: Estimated Price Effect

Estimate / Sample	All	Goods	Services	Complexity Q1	Complexity Q2	Complexity Q3	Complexity Q4
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Mean (μ_γ)	0.0595	0.0498	0.0782	0.0400	0.0512	0.0613	0.0808
	(0.0193)	(0.0437)	(0.0355)	(0.0622)	(0.2020)	(0.1598)	(0.0946)
Standard Deviation (σ_γ)	0.0643	0.0670	0.0534	0.0746	0.0690	0.0678	0.0282
	(0.0073)	(0.0078)	(0.0210)	(0.0136)	(0.0261)	(0.0182)	(0.0194)

Notes: This table shows the estimates corresponding to the effect of publicity on contract prices. The estimates result from analyzing the observed contract price density distribution relative to a counterfactual distribution. The observed densities are generated using bins of width $250. The counterfactual distribution stems from a polynomial interpolation of degree 5. The standard deviation is calculated over the non-parametric distribution of γ. The standard errors are calculated through bootstrap. The subgroup analysis is performed independently for each group.

Table B.4: Reduced-form RDD: Baseline and "Donut-RD" specifications

Dependent Variable	OLS (1)	1K (2)	2K (3)	3K (4)	4K (5)	5K (6)	6K (7)
Number of offers	0.3569	0.3139	0.2887	0.2789	0.2703	0.3020	0.2708
	(0.0677)	(0.0709)	(0.0734)	(0.0760)	(0.0788)	(0.0819)	(0.0854)
Log distance firm-office	0.1392	0.1619	0.1508	0.1608	0.1663	0.1447	0.1497
	(0.0481)	(0.0502)	(0.0519)	(0.0536)	(0.0557)	(0.0578)	(0.0601)
Small business	-0.0277	-0.0260	-0.0251	-0.0289	-0.0325	-0.0286	-0.0278
	(0.0065)	(0.0068)	(0.0070)	(0.0072)	(0.0075)	(0.0078)	(0.0081)
Any cost-overrun	0.0135	0.0090	0.0094	0.0101	0.0113	0.0099	0.0097
	(0.0045)	(0.0047)	(0.0048)	(0.0050)	(0.0052)	(0.0054)	(0.0056)
Any delay	0.0130	0.0067	0.0085	0.0114	0.0146	0.0137	0.0138
	(0.0047)	(0.0049)	(0.0051)	(0.0052)	(0.0054)	(0.0056)	(0.0058)
Number of modifications	0.0375	0.0211	0.0208	0.0278	0.0347	0.0282	0.0254
	(0.0173)	(0.0181)	(0.0187)	(0.0193)	(0.0201)	(0.0208)	(0.0216)

Notes: This table shows Regression Discontinuity Design (RDD) estimates of the reduced-form relationship between a series of outcome variables and an indicator of whether a contract award price exceeds $25,000. Each estimate comes from a separate regression. Coefficients in column (1) use a linear fit above and below the discontinuity, and are identical to the corresponding estimates in the first column of Table 1. Coefficients in columns (2) through (7) use the same specification, but drop observations with a contract award value within a window of varying length around the $25,000 threshold. For example, column (3) drops contract awards between $24,500 and $25,500. Standard errors are shown in parentheses.

Table B.5: Complexity Measure: Top and Bottom Products

Rank	Product Category	Complexity
Top 10		
1	Meat, Poultry, and Fish	0.000
2	Fuel Oils	0.000
3	Food, Oils, and Fats	0.000
4	Miscellaneous Fire Control Equipment	0.000
5	Surgical Dressing Materials	0.000
6	Medical and Surgical Instruments, Equipment, and Supplies	0.000
7	Composite Food Packages	0.000
8	Ophthalmic Instruments, Equipment, and Supplies	0.000
9	Tool and Hardware Boxes	0.000
10	Electric Arc Welding Equipment	0.000
Bottom 10		
10	Facilities Operations Support	0.432
9	IT and Telecom-Internet	0.438
8	Laundry/Drycleaning	0.454
7	Lease of Office Machines and Text Processing Systems	0.470
6	Trash/Garbage Collection	0.505
5	Landscaping/Groundskeeping	0.653
4	Operation of Ships, Boats, and Floating Docks	0.712
3	Snow Removal/Salt	0.770
2	Custodial Janitorial	0.873
1	Operation Of Recreation Facilities - Non-Building	0.942

Notes: This table presents the top and bottom 10 product categories in terms of complexity index. The data source is the Federal Procurement Data System-Next Generation. The complexity index is calculated using non-R&D definitive contracts and purchase orders, with award values between $ 5,000 and $ 20,000, awarded by the Department of Defense in fiscal years 2015 through 2019. The complexity index is defined as the average cost overruns at the product or service category (PSC) level. Cost overruns are defined as the final contract price including all modifications, minus the award price, divided by the award price. PSCs correspond to a 4-digit alphanumeric code that is observed for each contract.

Table B.6: Model Estimation Sample Versus Full Sample

	Model Sample	Full Sample	Diff
Variables:			
Publicized in FBO	0.393	0.300	0.093
Award Amount	21.202	20.683	0.519
Number of Offers	3.416	3.310	0.106
Overruns (relative)	1.091	1.089	0.002
Service	0.300	0.312	-0.012
Mean Overruns Prod Cat	0.068	0.073	-0.005
Awarded in September	0.272	0.254	0.018
log Expected Duration (days)	3.880	3.811	0.069
Bidders' Classification			
Local is Awarded	0.697	-	-
N Potential Local Bidders	8.660	-	-
N Potential Non-Local Bidders	4.452	-	-
Number of Observations	28,330	84,389	

Notes: This table compares the sample use in the estimation of the model, compared with the full sample of contracts used in the reduced-form analysis. The first column shows the mean of selected variables using the model estimation sample. The second column shows the same means, but computed over the full sample. The third column shows the differences between these two means. The model estimation sample corresponds to the subset of contracts for which we could identify the number of potential local and non-local bidders. We restrict the analysis to buyer-product combinations that meet two conditions: at least four contracts were awarded between 2013 and 2019, and neither all nor none were publicized.

Table B.7: Complexity Measure: Top and Bottom Products

		Entry (Probit)		Bidding (Log Normal)		Execution (Log Normal)	
	baseline	Coef	SE	Coef	SE	Coef	SE
Panel A: Coefficients							
Constant	1.00	0.0038	0.0006	3.0668	0.0001	-1.9561	0.0016
Service	0.31	-0.0125	0.0004	0.0002	0.0001	0.0138	0.0022
DegreeOfComplexity	0.07	-1.3555	0.0026	-0.0715	0.0004	3.3885	0.0027
NonLocal		7.1005	0.0017	-0.0097	0.0001	0.1828	0.0024
NonLocalxComplexity		0.0457	0.0042	-0.0381	0.0008	0.0207	0.0054
LastMonth	0.27	-0.1209	0.0003				
ExpDurMedian	0.50					0.3099	0.0005
Nl	8.66	-0.0270	0.0000	-0.0017	0.0000		
Nnl	4.45	-0.5756	0.0001	-0.0037	0.0000		
Pabel B: Standard Deviation							
SigmaConstant				-4.6254	0.0007	-0.5361	0.0052
SigmaService				0.0250	0.0010	1.2891	0.0058
RhoConstant						-0.1415	0.0019
RhoNonLocal						-0.0104	0.0060
SigmaU				0.422	0.0054		
Pabel C: Buyer Preferences							
		Publicity Choice (Probit)					
		Coef	SE				
Constant		-0.2907	0.0017				
ExpPrice		-0.9707	0.0032				
ExpCostOverruns		-0.0960	0.0035				
ExpLocalWinning		0.4351	0.0018				
Above25K		1.1930	0.0022				

Notes: This table presents the top and bottom 10 product categories in terms of complexity index. The data source is the Federal Procurement Data System-Next Generation. The complexity index is calculated using non-R&D definitive contracts and purchase orders, with award values between $ 5,000 and $ 20,000, awarded by the Department of Defense in fiscal years 2015 through 2019. The complexity index is defined as the average cost overruns at the product or service category (PSC) level. Cost overruns are defined as the final contract price including all modifications, minus the award price, divided by the award price. PSCs correspond to a 4-digit alphanumeric code that is observed for each contract.

C Additional Details on the Setting

C.1 FedBizzOpps

FedBizOpps.gov (FBO) has been designed as a single government point of entry (GPE) for Federal buyers to publish and for vendors to find posted Federal business opportunities across departments and agencies. The FAR (part 5) regulates the publicity of contract actions. The goals of publicity policy (FAR 5.002) are (a) increase competition, (b) broaden industry participation in meeting Govt requirements (c) assist small businesses (and VO, VOSD, WO, HUBZone, etc.) in winning contracts and subcontracts. The FAR requires that contract actions expected to exceed $25,000 must be *synopsized* in the GPE. Contract actions under $25,000 must publicize "by displaying in a public place, or by any appropriate electronic means." The contracting officer is exempted to advertise in GPE (FAR 5.102(a)5 and 5.202), when "disclosure compromises national security, " "nature of the file (e.g., size) does not make it cost-effective or practicable," the "agency's senior procurement executive makes a written determination that it is not in the Government's interest," and several other special cases (see FAR 5.202).

Figure A2 displays screenshots to the website. Panel (a) shows the list of opportunities, Panel (b) includes the information contained a specific solicitation :

C.1.1 Types of FBO Notices

There are two broad types of FBO notices: *pre-award* and *post-award* notices. The *pre-award* notices are divided into four actions:[61]

- *Presolicitation:* The pre-solicitation notice makes vendors aware that a solicitation may follow. Vendors may add themselves to the Interested Vendors List, if the posting agency has enabled this feature. This helps government agencies determine if there are qualified vendors to perform the work scope and allows the contracting office to gather information on the interested vendors.

- *Combined Synopsis/Solicitation:* Most opportunities classified this way are open for bids from eligible vendors. These opportunities include specifications for the product or service requested and a due date for the proposal. The notice will specify bidding procedures in the details of the solicitation.

- *Sources Sought:* The Sources Sought notice is a synopsis posted by a government agency seeking possible sources for a project. It is not a solicitation for work or a request for proposal. For more information, see FAR 7.3 and OMB Circular A-76.

[61] Here we omit uncommonly used actions: *Sale of Surplus Property*, *Justification and Approval (J&A)*, *Fair Opportunity / Limited Sources Justification*, *Foreign Government Standard*, and *Intent to Bundle Requirements (DoD-Funded)*.

- *Special Notice:* Agencies use Special Notices to announce events like business fairs, long-range procurement estimates, pre-bid/pre-proposal conferences, meetings, and the availability of draft solicitations or draft specifications for review.

The post-award notices are essentially *award notices*:

- *Award Notice:* When a federal agency awards a contract in response to a solicitation, they may choose to upload a notice of the award to allow the interested vendors to view the vendor receiving the awarded contract, and amount agreed upon.

Figure A1 describes the life-cycle of a project and how different stages are linked to FBO actions.

C.2 Dataset Details

Our analysis combines data from two sources: Federal Procurement Data System - Next Generation (FPDS-NG) and data scrapped directly from FedBizzOpps.gov (FBO).

FPDS-NG. The FPDS-NG tracks the universe of federal awards that exceed $5,000.[62] The Federal Acquisition Regulation (FAR) requires Contracting Officers (COs) must submit complete reports on all contract actions. Thus, every observation corresponds to a contract action, representing either an initial award or a follow-on action, e.g., modification, termination, renewal, or exercise of options. For each observation, we observe detailed information, such as the dollar value of the funds obligated by the transaction; a four-digit product category code (PSC); six-digit Industry (NAICS) code; identification codes for the agency, sub-agency, and contracting office making the purchase; the identity of the private vendor (DUNS); the type of contract pricing (typically, fixed-price or cost-plus); the extent of competition for the award; characteristics of the solicitation procedure; the number of offers received; and the applicability of a variety of laws and statutes. We collapse all actions by contract ID. As a reference, 80% of awarded contracts are smaller than $50,000.

Our analysis contemplates overruns in terms of cost and time of completion. We define contract delays and cost overruns based on related literature (Decarolis et al., 2020a). We exclude outliers on both variables as they are likely associated with data entry issues. We cross-checked dates and amounts for contract award notices that appeared in FBO and found that mismatches are uncommon.

FBO Data. We use daily archives of all information posted in FBO. Every data row corresponds to a different notice action. Each action is associated with a unique URL. The two primary IDs to match FBO data with other datasets are "solicitation number" and "contract award number. The former identifies pre-award actions, whereas award notices are identified using "contract award number." A relevant fraction of the award-notices are not linked with any of the pre-award notices. FPDS data contain both IDs. Roughly, an annual database contains 300,000 notices.

[62] The data can be downloaded from `usaspending.gov`

The data preparation consists in three steps; first, we clean IDs and classify different actions associated with each ID. Second, we merge with FPDS data using contract number, then update solicitation number when both exist, finally merge and append unmatched observations using solicitation number. The last step is to collapse the data at the FPDS contract ID level. So the resulting dataset contains all the contract ids that also appeared in FBO.

We define that a contract appeared in FBO (treatment indicator) if the contract award has a solicitation number associated with at least one of the FBO pre-award actions described above.

D Empirical Framework for Estimating the Effects of Publicity on Contract Outcomes

This Section presents a detailed exposition of the empirical framework introduced in Section 3. Section D.1 presents our theoretical framework and the set of results that motivate the density analysis. Section D.2 explains the density analysis in detail, including all implementation details. Section D.3 discusses how to correct naive RDD estimates to account for price effects and potential measurement error. Section D.4 explains how we account for potential bunching responses in the RDD framework.

D.1 Empirical Model

D.1.1 Preliminaries

Consider a series of observed contract awards $t \in \{1, .., T\}$. Let $\tilde{p}_t$ be the *ex-ante award price* of contract t, which corresponds to the agency's estimate of what the contract price will be. Let p_t be the *observed award price* of contract t. $\tilde{p}_t$ and p_t are normalized relative to a policy threshold of \$25,000 and measured in logs. Therefore, negative (positive) values of $\tilde{p}_t$ and p_t are said to be below (above) the threshold for the purpose of the policy described below.

Prior to the award, the buyer decides whether to publicize the solicitation ($D_t = 1$) or not ($D_t = 0$). Let $p_t^d(\tilde{p}_t)$ be the potential price that we would observe for contract t, given an ex-ante estimate of $\tilde{p}_t$ and a publicity decision $D_t = d$, for $d \in \{0, 1\}$. There is a policy that encourages buyers to choose $D_t = 1$ for awards expected to exceed the threshold (i.e. for $\tilde{p}_t > 0$).

The buyer may choose to *strategically bunch* ($B_t = 1$), which means that she modifies the characteristics of the initial purchase in order to obtain an award price equal to $p_t^B(\tilde{p}_t)$, choosing $D_t = 0$ without being affected by the policy. $p_t^B(\tilde{p}_t)$ is equal to, or slightly below 0.

Therefore, observed prices can be written as:

$$p_t = p_t^0(\tilde{p}_t) + D_t \cdot \left[p_t^1(\tilde{p}_t) - p_t^0(\tilde{p}_t)\right] + B_t \cdot (1 - D_t) \cdot \left[p_t^B(\tilde{p}_t) - p_t^0(\tilde{p}_t)\right]$$

We assume the following:

A1 $\tilde{p}_t$ are i.i.d. draws from a distribution with smooth density $f_{\tilde{p}}(\cdot)$.

A2 $p_t^0(\tilde{p}_t) = \tilde{p}_t + \xi_t$, with $\xi_t \sim F_\xi(\cdot)$, $E[\xi_t] = 0$, and $\xi_t \perp \tilde{p}_t$.

A3 $p_t^1(\tilde{p}_t) = \tilde{p}_t + \gamma_t$, with $\gamma_t \sim F_\gamma(\cdot)$, $\gamma_t \perp \tilde{p}_t$, and $\gamma_t \perp \xi_t$.

A4 $\Pr(D_t = 1|\tilde{p}_t) \equiv \tilde{\pi}_D(\tilde{p}_t) = \tilde{\pi}_D^*(\tilde{p}_t) + \delta \cdot \mathbf{1}[\tilde{p}_t > 0]$, for a continuous function $\tilde{\pi}_D^*(\cdot)$.

A5 There exist $p_H > 0$ such that $B_t = 0$ for all $\tilde{p}_t > p_H$.

Note that here we present a slightly more general version of the model than in Section 3. In particular, **A2** allows for measurement error in agencies' ex-ante estimates.

D.1.2 Discretizing award values

Consider the division of the range of possible (normalized) award values into a set of equally-sized and right-inclusive bins around the threshold $b \in \{-R, (-R+1), ..., -1, 0, 1, ..., (R-1), R\}$. Note that bin $b = 0$ includes awards right at, or slightly below, the policy threshold.

Let $\{n_b^d\}_{b=-R}^R$ be the frequency distribution of observed awards conditional on treatment (publicity) status $D_t = d$, for $d \in \{0, 1\}$, so that n_b^d denotes the number of contracts with treatment status d and observed award value $p_t \in b$. Likewise, let $\{\tilde{n}_b^d\}_{b=-R}^R$ represent the (unobserved) frequency distribution of latent ex-ante prices. We also denote the distribution of *all* awards (both publicized and non-publicized) by simply omitting the superscript. That is, $n_b = n_b^0 + n_b^1$, and $\tilde{n}_b = \tilde{n}_b^0 + \tilde{n}_b^1$.

Consider also a *shifted* distribution of publicized contracts $\{n_b^{1,s}(\bar{\gamma})\}_{b=-R}^R$, which is obtained by subtracting a mean price effect $\bar{\gamma}$ to every publicized ($D_t = 0$) contract. That is, $n_b^{1,s}(\bar{\gamma})$ denotes the number of *publicized* contracts with award value p_t such that $(p_t + \bar{\gamma}) \in b$.

Finally, let Δ denote the discrete change in the number of publicized contracts at the discontinuity. Given **A4**, note that this is defined as $\Delta = \delta \cdot \sum_b n_b$.

D.1.3 Propositions

We now make a series of propositions that motivate our estimation method that we label "density analysis" in Section 3.

Proposition 1. *There exist some* $(\underline{b}^1, \bar{b}^1)$ *such that* $E[\tilde{n}_b^1] = E[n_b^{s,1}(\bar{\gamma})]$, *for* $\bar{\gamma} = E[\gamma_t]$, $b < \underline{b}^1 < 0$ *and* $b > \bar{b}^1 > 0$. *That is, far enough from the threshold, the distribution of* realized *award prices, appropriately shifted to cancel out mean price effects, coincides with the distribution of* ex-ante *award prices for publicized contracts.*

Proposition 2. *There exist some* $(\underline{b}^0, \bar{b}^0)$ *such that* $E[\tilde{n}_b^0] = E[n_b^0]$, *for* $b < \underline{b}^0 < 0$, *and* $b > \bar{b}^0 > 0$. *In other words, far enough from the threshold, the distributions of* ex-ante *and* realized *award prices for non-publicized contracts coincide.*

Corollary 1. $E[\tilde{n}_b] = E[n_b^0 + n_b^{s,1}(\bar{\gamma})]$, *for* $\bar{\gamma} = E[\gamma_t]$, $b < \underline{b} = \min\{\underline{b}^0, \underline{b}^1\} < 0$ *and* $b > \bar{b} = \max\{\bar{b}^0, \bar{b}^1\} > 0$.

Proposition 3. $\sum_{b \leq 0}(\tilde{n}_b - n_b) = \sum_{b > 0}(n_b - \tilde{n}_b)$. *This means that the excess mass below the threshold equals the missing mass above the threshold.*

Proposition 4. $\Delta \cdot F_{\gamma'}(x) = E[n_{b_x}^{1,s}(\bar{\gamma}) - \tilde{n}_{b_x}^1]$, *for* $x \in b_x$, $b_x \leq 0$, *and* $\gamma' = \gamma - \bar{\gamma}$.

D.1.4 Convolution of densities

The key to our propositions stems from characterizing the distribution of observed prices p_t, given the distributions of ex-ante estimates, price effects, and measurement error. Throughout this section, we normalize the price of publicized contracts by subtracting the mean of the price effects. This is for convenience so that we deal with a mean-zero price effect, but is without loss of generality, as the propositions appropriately adjust for $\bar{\gamma}$ when appropriate.

Consider first the density of publicized contracts, h_p^1. Because observed prices are given by the sum of two independent random variables, ex-ante estimates, and price effects (see **A3**), their density is given by the convolution of the densities $f_{\tilde{p}}^1 \equiv f_{\tilde{p}|D=1}$ and f_γ. That is:

$$h_p^1(p_t) = \int_{-\infty}^{\infty} f_{\tilde{p}}^1(p_t - \gamma_t) f_\gamma(\gamma) d\gamma \tag{14}$$

On the other hand, using Bayes' rule:

$$f_{\tilde{p}}^1(\tilde{p}_t) = \frac{\tilde{\pi}_D(\tilde{p}_t) \cdot f_{\tilde{p}}(\tilde{p}_t)}{\Pr(D_t = 1)} \tag{15}$$

So that (14) and (15) imply:

$$\begin{aligned} h_p^1(p_t) &= \int_{-\infty}^{\infty} \frac{\tilde{\pi}_D(p_t - \gamma) \cdot f_{\tilde{p}}(p_t - \gamma) \cdot f_\gamma(\gamma)}{\Pr(D_t = 1)} d\gamma \\ &= \int_{-\infty}^{\infty} \frac{(\tilde{\pi}_D^*(p_t - \gamma) + \delta \cdot \mathbf{1}[p_t - \gamma > 0]) \cdot f_{\tilde{p}}(p_t - \gamma) \cdot f_\gamma(\gamma)}{\Pr(D_t = 1)} d\gamma \\ &= \int_{-\infty}^{\infty} \frac{\tilde{\pi}_D^*(p_t - \gamma) \cdot f_{\tilde{p}}(p_t - \gamma) \cdot f_\gamma(\gamma)}{\Pr(D_t = 1)} d\gamma + \int_{-\infty}^{p_t} \frac{\delta \cdot f_{\tilde{p}}(p_t - \gamma) \cdot f_\gamma(\gamma)}{\Pr(D_t = 1)} d\gamma \end{aligned}$$

Or,

$$h_p^1(p_t) \equiv \int_{-\infty}^{\infty} f_{\tilde{p}}^{1*}(p_t - \gamma) \cdot f_\gamma(\gamma) \cdot d\gamma + \int_{-\infty}^{p_t} \Delta(p_t - \gamma) \cdot f_\gamma(\gamma) \cdot d\gamma \tag{16}$$

Consider $p_t \ll 0$, so that $f_\gamma(p_t) \approx 0$. In words, consider a price sufficiently below the threshold, so that the probability that the ex-ante estimate for this contract was above the threshold is negligible. In this case, the second term in Equation (16) is zero. On the other hand, $f_{\tilde{p}}^{1*}(p_t - \gamma) = f_{\tilde{p}}^1(p_t - \gamma)$ when $p_t < 0$, so that the first term is the convolution between the densities of $\tilde{p}$ and γ_t. If the former is sufficiently smooth, then adding a mean-zero price effect has no effect on the observed density, and $h_p^1(p_t) = f_{\tilde{p}}^1(p_t)$. It follows that the expected number of contracts with observed price p_t equals the expected number of contracts with ex-ante price estimate equal to p_t. Abandoning the normalization to allow for non-zero average price effects implies that this equality of expectations holds only once observed publicized prices are adjusted by adding the mean of γ. The first part of Proposition 1 follows: for sufficiently low $p_t \in \underline{b}$, $E[\tilde{n}_b^1] = E[n_b^{s,1}(\bar{\gamma})]$, for all $b \leq \underline{b}$.

As we move closer to the threshold from below, the second term in Equation (16) becomes positive. This corresponds to the excess mass of contracts relative to the counterfactual density of the first term. Intuitively, this term is given by the mass of contracts with ex-ante estimates to the right of the threshold that receive a sufficiently high price effect so as to end up at the left of it. This is what allows us to identify F_γ in Proposition 4. Consider $p_t = x$ closely below the threshold, so that $\Delta(x - \gamma) \approx \Delta$. With a constant Δ, it immediately follows that $\Delta \cdot F_\gamma(p_t) = h^1_p(p_t) - f^1_{\tilde{p}}(p_t)$.

A symmetric argument can be given for p_t closely above the threshold. In this case, the second term becomes the missing mass of the observed density $h^1_p(p_t)$, relative to the counterfactual density of $\tilde{p}$. Once we get to a high enough value of $p_t >> 0$, once again $f_\gamma(p_t)$ goes to zero, and this missing mass disappears. Observed and counterfactual densities converge, which completes Proposition 1: for sufficiently high $p_t \in \underline{b}$, $E[\tilde{n}^1_b] = E[n^{s,1}_b(\bar{\gamma})]$, for all $b > \overline{b}$.

The argument for non-publicized contracts is directly analogous. Observed awards are the sum of unobserved ex-ante estimates $\tilde{p}$ and a mean-zero error term ξ. This error term only generates a discrepancy between h^0_p and f^0_p when the latter is not smooth, which happens only at the threshold. Proposition 2 follows: for $p_t << 0$ and $p_t >> 0$, the two densities coincide.

All this discussion ignored the potential effect of bunching responses. However, strategic bunching does not affect any of the aforementioned results. This is because of **A5**: bunching responses occur only within a window around the threshold. Therefore, all of our arguments remain unchanged, as long as $b_H \leq \overline{b}$, where $p_H \in b_H$.

Finally, Proposition 3 follows directly from the fact that our model assumes no extensive margin responses. Contracting officers can avoid the mandate via bunching responses but still need to complete the purchase. We think this assumption is natural for this setting, so the overall number of observed and counterfactual contracts needs to coincide.

D.2 Density Analysis: Estimation of Price Effects and Counterfactual Densities

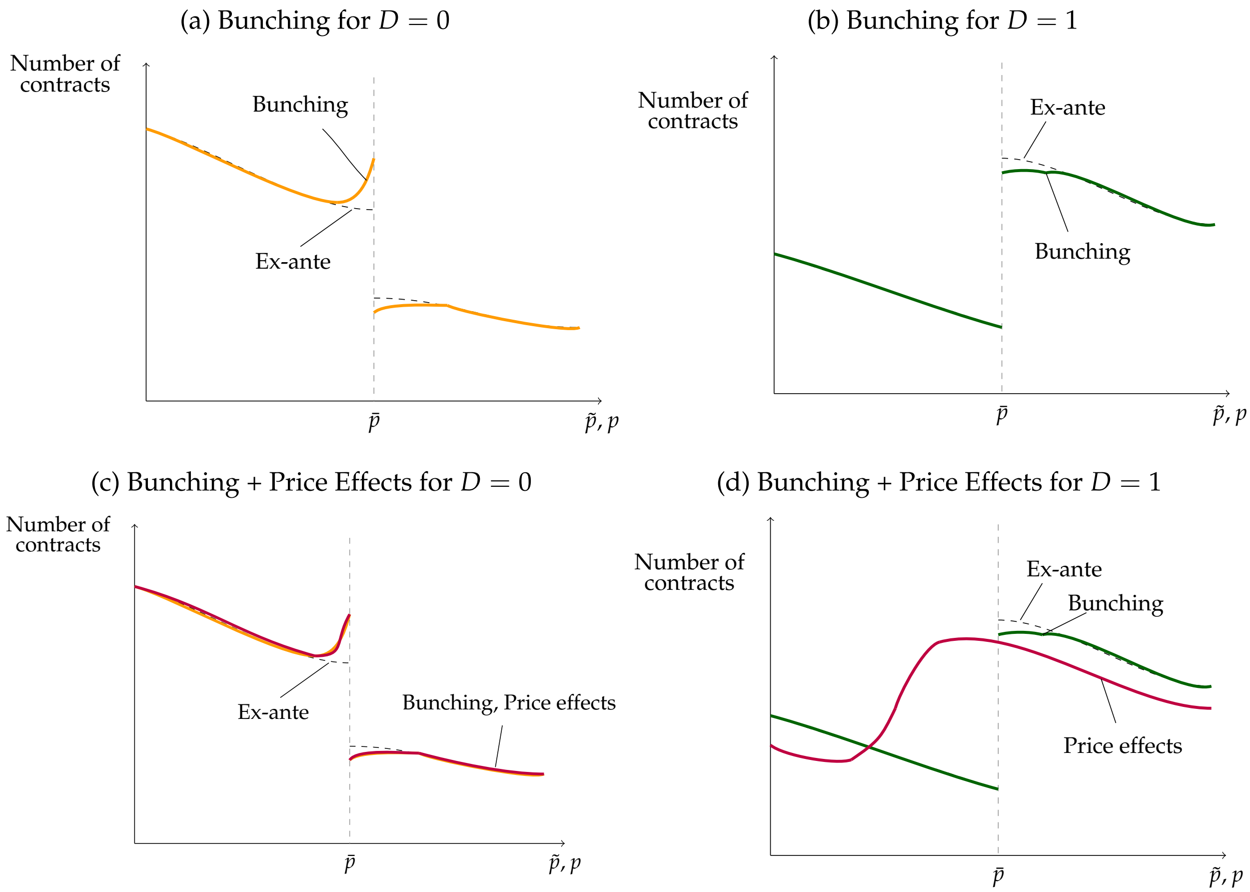
We know explain our density analysis estimation method in detail, building on the Propositions of the previous section.

Step 1

Our method starts from the observation that, relative to ex-ante prices, linear price effects will impact the distribution of publicized contracts in two ways: (i) they will shift the full distribution to the left by $E[\gamma_t]$; and (ii) they will smooth out the discontinuity in the distribution around the threshold, because of $V(\gamma_t)$ (see Figure A22 (d)).

Suppose that we knew the true value of mean price effects $E[\gamma_t] \equiv \bar{\gamma}$. From the observed frequency distribution of publicized contracts $\{n^1_b\}$, we can simply undo the first impact of price

Figure A22: Impact of Bunching and Price Effects on Award Distributions



Notes: This figure shows conceptually how the distributions of non-publicized and publicized awards are impacted by the existence of both strategic bunching responses and price effects due to increased competition. Panels (a) and (b) show, respectively for non-publicized and publicized contracts, the distributions of ex-ante award prices ($\tilde{p}$, in dashed black lines), as well as realized award prices (p, in solid orange and green lines) when we allow for strategic bunching responses. Panels (c) and (d) plot the additional effect of having price effects associated with publicity (in solid red lines).

effects by shifting this distribution back to the right. That is, we construct the *shifted* distribution $\{n_b^{1,s}(\bar{\gamma})\}$, which is obtained by adding the value of $\bar{\gamma}$ to the price award of every publicized contract. If the number of contracts is large, the shifted distribution should coincide with the unobserved distribution of ex-ante prices $\{\tilde{n}_b^d\}$, except near the threshold.

On the other hand, a similar argument can be made for non-publicized contracts, given the assumption that bunching responses are local to the threshold (**A4**). Except for a window around the threshold where bunching responses manifest, the observed distribution $\{n_b^0\}$ should coincide with the unobserved distribution $\{\tilde{n}_b^d\}$ (see Figure A22 (c)).

This intuition is supported by Propositions 1 and 2. Once we get "far enough" from the threshold, the distribution of non-publicized awards and the *appropriately shifted* distribution of publicly solicited awards should coincide with the latent distributions of ex-ante prices. In particular, we have that: $n_b^0 + n_b^{1,s}(\bar{\gamma}) \approx \tilde{n}_b^0 + \tilde{n}_b^1 = \tilde{n}_b$ for b sufficiently far from 0. On the contrary, close to the threshold, we have $n_b^0 + n_b^{1,s}(\bar{\gamma}) \neq \tilde{n}_b$ due to the effects of bunching and the variance in price effects.

Finally, because we know that the unobserved distribution $\{\tilde{n}_b\}$ should be smooth everywhere due to **A1**, we can use a standard bunching estimation procedure (Chetty et al., 2013; Kleven and Waseem, 2013) to infer the shape of it around the threshold. This means fitting a polynomial function through our constructed distribution $\{n_b^0 + n_b^{1,s}(\bar{\gamma})\}$, ignoring the contribution of the bins close to the threshold.

More concretely, we estimate the following specification:

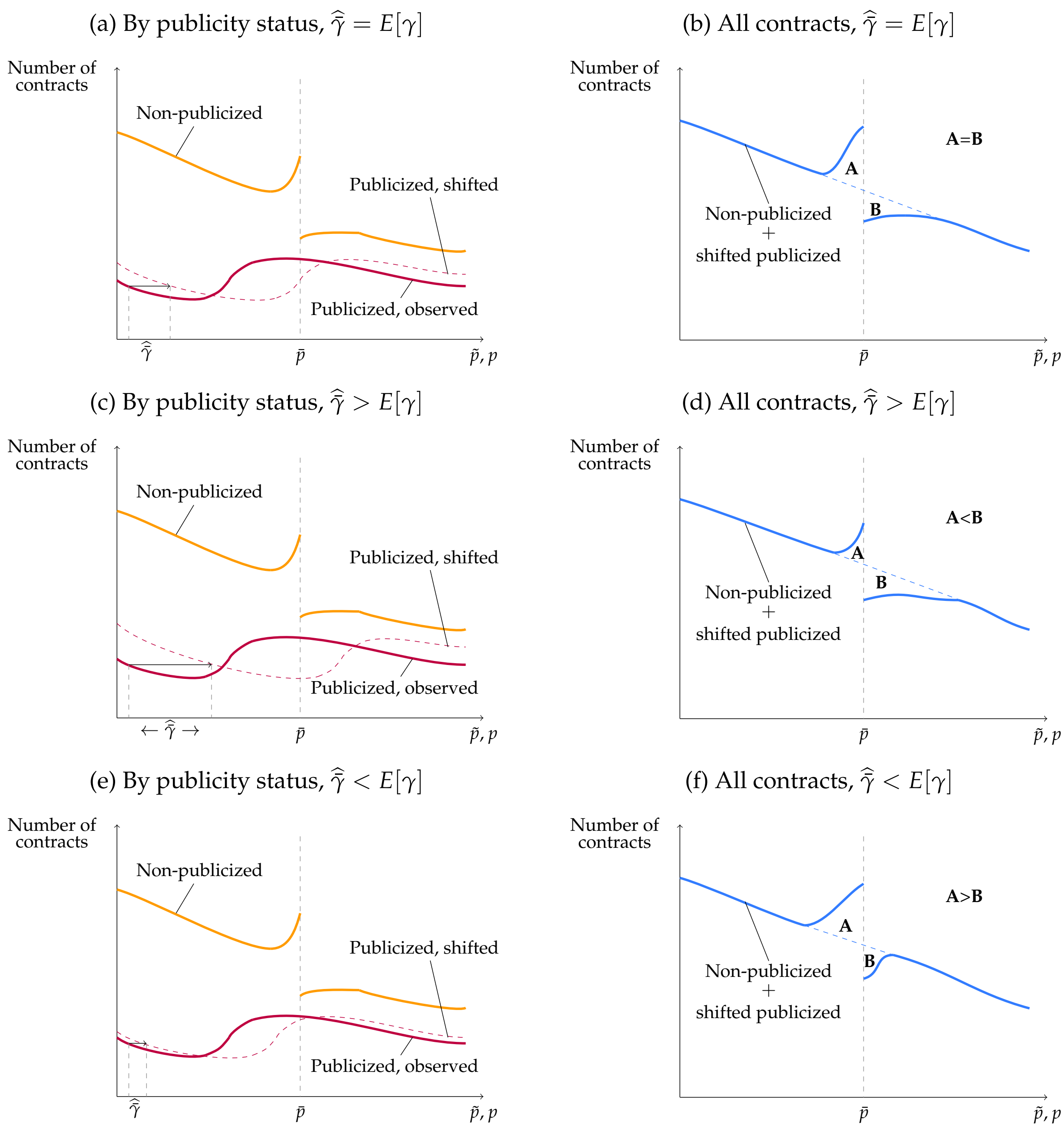
$$\left[n_b^0 + n_b^{1,s}(\widehat{\bar{\gamma}})\right] = \sum_{x=0}^{Q} \alpha_x \cdot b^x + \sum_{j=\underline{b}}^{\bar{b}} \gamma_j \cdot \mathbf{1}[b = j] + \nu_b, \qquad \text{for } b = \{-R, ..., R\} \tag{17}$$

and obtain fitted values:

$$\widehat{n_b} = \sum_{x=0}^{Q} \widehat{\alpha_x} \cdot b^x \qquad \text{for } b = \{-R, ..., R\}.$$

Now, this discussion started by *assuming* that we knew the value of the mean price effect $\bar{\gamma}$. Yet, in practice, this is the main unknown parameter that we seek to recover. So in order to estimate it, we rely on the integration constraint of Proposition 3: $\sum_{b=-R}^{R}(n_b^0 + n_b^{1,s}(\bar{\gamma})) = \sum_{b=-R}^{R} \widehat{\tilde{n}_b}$. As the intuition from Figure A23 shows, the integration constraints will bind only when we shift the distribution of publicized contracts according to the right value of $\bar{\gamma}$. We, therefore, start from an initial guess of $\widehat{\bar{\gamma}}$, and iterate until we find a value such that the constraint is satisfied.

Figure A23: Intuition of Method to Estimate Mean Price Effects



Notes: This figure provides (graphical) intuition of the procedure to estimate the mean price effect based on the integration constraint condition, i.e., the sum of excess of mass below the threshold equals the sum of missing masses above the threshold. Panels (a), (c), and (e) display distributions of publicized and non-publicized contracts. Panels (b), (d), and (f) show the corresponding overall distributions, i.e., the blue line in panel (b) corresponds to the sum of the yellow and red lines in panel (a). The key intuition is that the integration constraint condition is only met if the distribution of publicized contracts is re-centered by the correct mean of price effect, i.e., the resulting distribution has mean zero.

For the implementation, we choose the following parameters. We use a fifth-degree polynomial, i.e. $Q = 5$. We use bins of constant width of 0.01 log-points. This implies bins of roughly \$250 at the discontinuity. Indeed, bin $b = 0$ includes all contracts with price greater than \$24,751[63] and smaller than or equal to \$25,000. Our estimation is performed on a total set of 150 bins centered around zero, from -0.75 to 0.75. In dollar terms, this corresponds to contracts between \$11,809 and \$52,925. The excluded window for step 1 is symmetric, excluding 12 bins below zero and 12 bins above. In dollar terms, the excluded window consists of contracts between \$22,173 and \$28,187.

Step 2

The second step seeks to estimate separate counterfactual distributions by publicity status, i.e. $\{\widehat{\tilde{n}_b^0}\}$ and $\{\widehat{\tilde{n}_b^1}\}$. To do this, we can go back to the intuition from Figure A22, assuming that there are neither price effects nor bunching responses so that the distributions of ex-ante prices and observed realized prices coincide. In this case, the distributions for treated and control units should be continuous, except at the threshold, where we should see a discontinuous jump in publicized contracts mirrored by a discontinuous dip in non-publicized contracts. Suppose that we knew the size of this change, which we denote as Δ. Knowledge of Δ would allow us to undo these discontinuities by shifting the right part of each distribution vertically. Indeed, the distributions $\{n_b^0 + \Delta \cdot \mathbf{1}[b > 0]\}$ and $\{n_b^1 - \Delta \cdot \mathbf{1}[b > 0]\}$ should be continuous.

In the presence of bunching and price effects, these vertical shifts will not make the observed distributions continuous. However, just as in the discussion above, price effects and bunching should only affect the distributions within some window around the threshold. So, we use this logic again and use a polynomial interpolation to estimate the counterfactual distributions around the threshold.

First, we construct distributions that are vertically shifted above the threshold: $\{n_b^0 + \Delta \cdot \mathbf{1}[b > 0]\}_{b=-R}^{R}$ and $\{n_b^{1,s}(\widehat{\gamma}_b) - \Delta \cdot \mathbf{1}[b > 0]\}_{b=-R}^{R}$. We then apply the same interpolation method as before for each of the two distributions. That is, we separately estimate the following two specifications:

$$\left(n_b^0 + \Delta \cdot \mathbf{1}[b > 0]\right) = \sum_{x=0}^{Q} \alpha_x^0 \cdot b^x + \sum_{j=\underline{b^0}}^{\overline{b^0}} \gamma_j^0 \cdot \mathbf{1}[b = j] + \nu_b^0, \quad \text{for } b = \{-R, ..., R\} \tag{18}$$

$$\left(n_b^{1,s}(\widehat{\gamma}_b) - \Delta \cdot \mathbf{1}[b > 0]\right) = \sum_{x=0}^{Q} \alpha_x^1 \cdot b^x + \sum_{j=\underline{b^1}}^{\overline{b^1}} \gamma_j^1 \cdot \mathbf{1}[b = j] + \nu_b^1, \quad \text{for } b = \{-R, ..., R\} \tag{19}$$

and compute fitted values ignoring the contribution of the bins within the excluded window:

$$\widehat{n_b^{*0}} = \sum_{x=0}^{Q} \widehat{\alpha_x^0} \cdot b^x, \quad \text{for } b = \{-R, ..., R\}$$

[63] $\log(x) - \log(25,000) = 0.01 \iff x = 25,000 \cdot \exp(-0.01)$

$$\widehat{n_b^{*1}} = \sum_{x=0}^{Q} \widehat{\alpha_x^1} \cdot b^x, \quad \text{for } b = \{-R, ..., R\}$$

Finally, our estimates of the counterfactual distributions do incorporate the discontinuous effect of the policy. We estimate these by re-adding the shift that we originally removed:

$$\widehat{n_b^0} = \widehat{n_b^{*0}} - \Delta \cdot \mathbf{1}[b > 0] \quad \text{for } b = \{-R, ..., R\}$$

$$\widehat{n_b^1} = \widehat{n_b^{*1}} + \Delta \cdot \mathbf{1}[b > 0] \quad \text{for } b = \{-R, ..., R\}$$

Again, this exposition assumes that we know the value of Δ. Since, in practice, this is not directly observed, our method iterates over guesses of $\widehat{\Delta}$. The convergence criterion, in this case, is based on the fit of the interpolations outside the excluded window. Indeed, if the vertical shift we guess is too low or too high, the polynomial interpolation will fit poorly just outside of the excluded area. Figure A24 shows this intuition graphically.

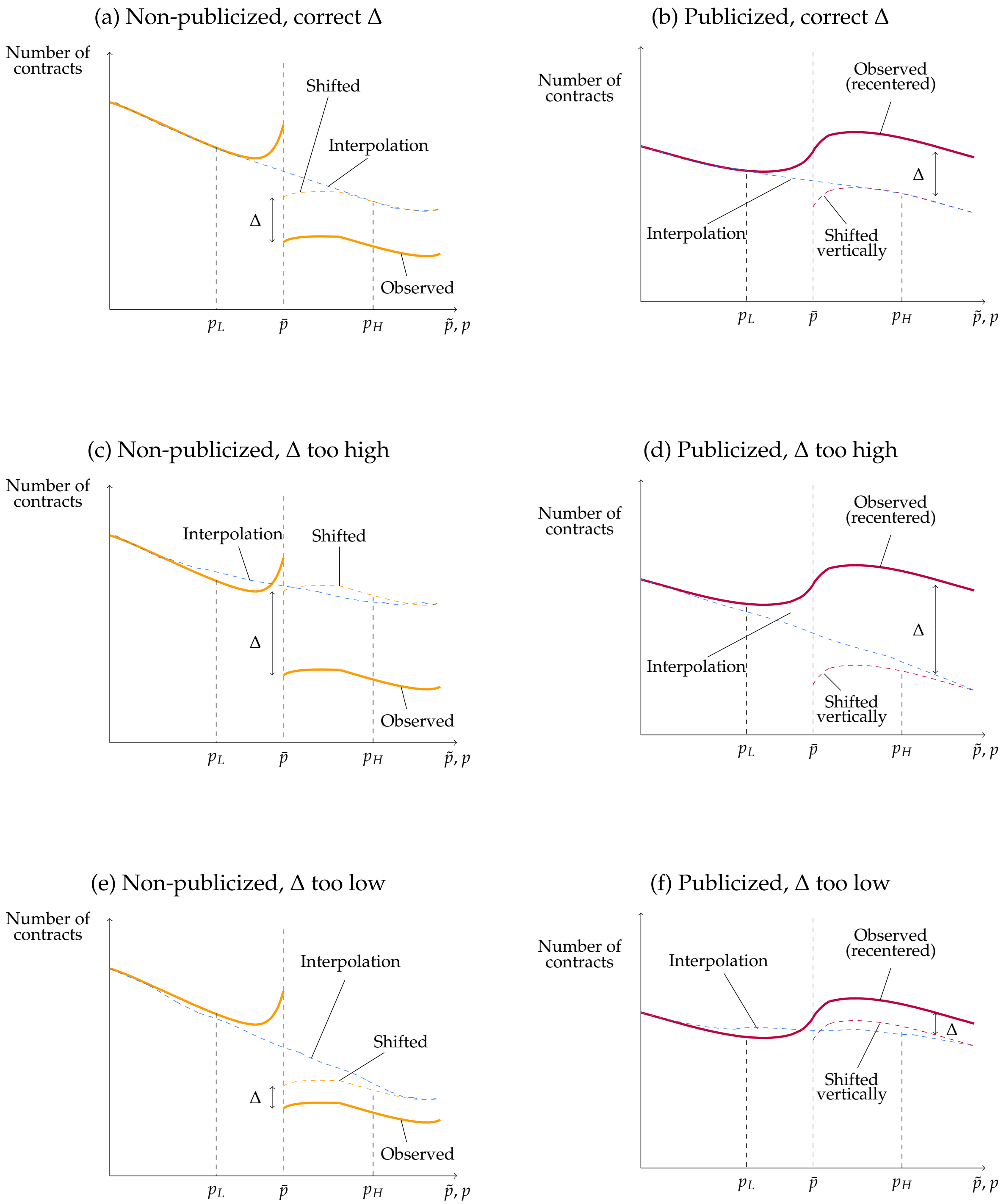
So, given a guess of $\widehat{\Delta}$, we compute the residuals for each of the two regressions (18) and (19). We then search over $\widehat{\Delta}$ to minimize:

$$W\left(\widehat{\Delta}\right) = 0.5 \cdot \sum_{b \neq Z^0} \widehat{\nu_b^0}\left(\widehat{\Delta}\right)^2 + 0.5 \cdot \sum_{b \neq Z^1} \widehat{\nu_b^1}\left(\widehat{\Delta}\right)^2 \quad ,$$

where $Z^0 = \{\underline{b^0}, ..., \overline{b^0}\}$ and $Z^1 = \{\underline{b^1}, ..., \overline{b^1}\}$ correspond to the excluded regions.

For step two, we keep the polynomial degree, binning, and range fixed as in step 1. However, we change the excluded region for the specification using non-publicized contracts (18). The justification for this is that we expect bunching to be concentrated closely below the threshold. Concretely, we choose 5 bins below the threshold and 12 bins above for Z^0 and keep the symmetric window of 12 bins above and below for Z^1.

Figure A24: Intuition of Method to Estimate Ex-Ante Price Distributions



Notes: This figure provides (graphical) intuition of the procedure to estimate the ex-ante price distribution. The method considers identifying the discrete change in the distribution of publicized contracts (Δ) that matches with the drop in the distribution of non-publicized contracts. Panels (a), (c), and (e) display distributions of non-publicized contracts. Panels (b), (d), and (f) show the distributions of publicized contracts. The procedure builds upon the general interpolation (dashed blue line) that relates the distributions of publicized and non-publicized contracts. We recover the Δ by identifying the vertical shift of the distributions that matches the counterfactual distribution.

Step 3

In step 3, we rely on the formula from Proposition 4 and use our estimates from above to compute:

$$\widehat{F_{\gamma'}}(x) = \frac{n^{1,s}_{b_x}(\widehat{\overline{\gamma}}) - \widehat{\tilde{n}^1_{b_x}}}{\widehat{\Delta}}$$

for $x \in b_x$, $b_x \in \{\underline{b}^1, ..., 0\}$, and $\gamma' = \gamma - \widehat{\overline{\gamma}}$. This is straightforward, given the implementation of steps 1 and 2. We obtain the $F_{\gamma'}$ evaluated at each bin on the lower half of the excluded region Z^1. For values $x < \underline{b}^1$, we impose $F_{\gamma'} = 0$, since below the excluded region, there is no longer any influence of price effects. Finally, we then obtain estimates for the rest of the CDF by imposing symmetry so that $F_{\gamma'}(x) = 1 - F_{\gamma'}(-x)$.

For all of our estimates, we compute standard errors via bootstrap. We sample with replacement from the original distribution of contracts and implement steps 1 through 3, obtaining a set of estimates $\hat{\theta}$. We repeat this process H times. The standard errors correspond to the empirical standard deviation of $\hat{\theta}^{(h)}$, for $h = \{1, 2, ..., H\}$.

D.3 RDD Correction for Price Effects and Measurement Error

Consider again the model described in Section D.1. Observed prices as a function of ex-ante prices are given by:

$$p_t = \tilde{p}_t + (1 - D_t) \cdot \xi_t + D_t \cdot \gamma_t \tag{20}$$

where p_t are observed normalized (i.e. logged and re-centered around 0) award prices, $\tilde{p}_t$ are normalized ex-ante prices, $D_t \in \{0, 1\}$ are publicity decisions, γ_t is the *price effect* of publicity, and ξ_t is *measurement error*. Let $\gamma_t \sim F_\gamma(\cdot)$, with $E[\gamma_t] = \mu_\gamma$ and $V[\gamma_t] = \sigma^2_\gamma$. Let $\xi_t \sim F_\xi(\cdot)$, with $E[\xi_t] = 0$ and $V[\xi_t] = \sigma^2_\xi$. Assume $\gamma_t \perp \xi_t \perp \tilde{p}_t$.

To assess the causal impact of D_t on outcomes of interest y_t, we assume a piece-wise linear relationship between expected outcomes and latent ex-ante prices. In particular:

$$E[y_t|\tilde{p}_t] = \mathbf{1}(\tilde{p}_t \leq 0) \cdot (\alpha_0 + \beta_0 \cdot \tilde{p}_t) + \mathbf{1}(\tilde{p}_t > 0) \cdot (\alpha_1 + \beta_1 \cdot \tilde{p}_t) \tag{21}$$

For simplicity, we focus on this reduced form relationship, but it would be straightforward to extend it to a two-equation model with a structural equation relating y_t and D_t, and a first-stage equation relating D_t and $\tilde{p}_t$. Our parameters of interest are $(\boldsymbol{\alpha}, \boldsymbol{\beta}) = (\alpha_0, \alpha_1, \beta_0, \beta_1)$. In particular, we focus on $(\alpha_1 - \alpha_0)$, the reduced form effect at the discontinuity.

The problem we face is that we do not observe a sample analog of $E[y_t|\tilde{p}_t]$, but rather of $E[y_t|p_t]$. Our "naive RDD" coefficients correspond to an estimate of $\left(\lim_{p \to 0^+} E[y_t|p] - \lim_{p \to 0^-} E[y_t|p]\right)$, which in general will not be equal to $(\alpha_1 - \alpha_0) = \left(\lim_{\tilde{p} \to 0^+} E[y_t|\tilde{p}] - \lim_{\tilde{p} \to 0^-} E[y_t|\tilde{p}]\right)$. Here, we propose an alternative estimator of $(\alpha_1 - \alpha_0)$ based on the following proposition.

Proposition 5. *Expected outcomes conditional on observed award prices $E[y_t|p_t]$ can be expressed as an explicit linear function of the structural parameters $(\boldsymbol{\alpha}, \boldsymbol{\beta})$, as well as other variables that we can directly observe or estimate. In particular:*

$$E[y_t|p_t] = \alpha_0 \cdot \psi_1(p_t) + \beta_0 \cdot \psi_2(p_t) + \alpha_1 \cdot \psi_3(p_t) + \beta_1 \cdot \psi_4(p_t) \quad ,$$

where $\psi_k(\cdot)$, $k \in \{1,2,3,4\}$ are explicit functions of observed prices (p_t), observed treatment probabilities at a given price $(\pi_D(p_t))$, and moments of the distributions of price effects and measurement error evaluated at a given price $(F_\gamma(p_t), F_\xi(p_t))$.

Below, we derive the explicit expressions for each ψ_k. We then compute these using our data and the estimate $\widehat{F_\gamma}(p_t)$ that we obtained from the density analysis. We also assume no measurement error, so that $\xi_t = 0$ for all t. However, the formulas we derive are general, allowing for any arbitrary distribution of measurement error. Once we compute these estimates $\widehat{\psi_k}(p_t)$, we use the equation in Proposition 5 to estimate $(\boldsymbol{\alpha}, \boldsymbol{\beta})$ by OLS. We are particularly interested in $(\hat{\alpha}_1^{OLS} - \hat{\alpha}_0^{OLS})$, which we then directly compare to the "naive RDD" reduced form coefficients.

D.3.1 Proof of Proposition 5

We now derive the explicit expression for $E[y_t|p_t]$. First, we use the Law of Total Probability to write:

$$E[y_t|p_t] = \underbrace{E[y_t|p_t, \tilde{p}_t \leq 0]}_{\Lambda_1} \cdot \underbrace{\Pr(\tilde{p}_t \leq 0|p_t)}_{\Lambda_2} + \underbrace{E[y_t|p_t, \tilde{p}_t > 0]}_{\Lambda_3} \cdot \underbrace{\Pr(\tilde{p}_t > 0|p_t)}_{\Lambda_4} \tag{22}$$

For each Λ_k, $k \in \{1,2,3,4\}$, we find an expression that depends only on magnitudes that we can directly observe or estimate.

We start with Λ_2:

$$\begin{aligned}
\Lambda_2 &= \Pr(\tilde{p}_t \leq 0|p_t) \\
&= \Pr(\tilde{p}_t \leq 0|p_t, D_t = 0) \cdot \Pr(D_t = 0|p_t) + \Pr(\tilde{p}_t \leq 0|p_t, D_t = 1) \cdot \Pr(D_t = 1|p_t) \\
&= \Pr(p_t - \xi_t \leq 0|p_t) \cdot [1 - \pi_D(p_t)] + \Pr(p_t - \gamma_t \leq 0|p_t, D_t = 1) \cdot \pi_D(p_t) \\
&= \left[1 - F_\xi(p_t)\right] \cdot [1 - \pi_D(p_t)] + [1 - F_\gamma(p_t)] \cdot \pi_D(p_t) \\
&\equiv \Lambda_2(p_t, \pi_D(p_t), F_\gamma(p_t), F_\xi(p_t), \boldsymbol{\alpha}, \boldsymbol{\beta})
\end{aligned} \tag{23}$$

Similarly for Λ_4:

$$\begin{aligned}
\Lambda_4 &= \Pr(\tilde{p}_t \geq 0|p_t) \\
&= \Pr(\tilde{p}_t \geq 0|p_t, D_t = 0) \cdot \Pr(D_t = 0|p_t) + \Pr(\tilde{p}_t \geq 0|p_t, D_t = 1) \cdot \Pr(D_t = 1|p_t) \\
&= \Pr(p_t - \xi_t \geq 0|p_t) \cdot [1 - \pi_D(p_t)] + \Pr(p_t - \gamma_t \geq 0|p_t, D_t = 1) \cdot \pi_D(p_t) \\
&= F_\xi(p_t) \cdot [1 - \pi_D(p_t)] + F_\gamma(p_t) \cdot \pi_D(p_t) \\
&\equiv \Lambda_4(p_t, \pi_D(p_t), F_\gamma(p_t), F_\xi(p_t), \boldsymbol{\alpha}, \boldsymbol{\beta})
\end{aligned} \tag{24}$$

For Λ_1 and Λ_3, the analysis is slightly more complicated. First, observe that:

$$\begin{aligned}
\Lambda_1 &= E[y_t|p_t, \tilde{p}_t \leq 0]) \\
&= E[\alpha_0 + \beta_0 \cdot \tilde{p}_t|p_t, \tilde{p}_t \leq 0] \\
&= \alpha_0 + \beta_0 \cdot E[\tilde{p}_t|p_t, \tilde{p}_t \leq 0] \\
&= \alpha_0 + \beta_0 \cdot \{E[\tilde{p}_t|p_t, \tilde{p}_t \leq 0, D_t = 1] \cdot \Pr(D_t = 1|p_t, \tilde{p}_t \leq 0) \\
&\qquad\qquad + E[\tilde{p}_t|p_t, \tilde{p}_t \leq 0, D_t = 0] \cdot \Pr(D_t = 0|p_t, \tilde{p}_t \leq 0)\} \\
&= \alpha_0 + \beta_0 \cdot \{E[p_t - \gamma_t|p_t, \tilde{p}_t \leq 0, D_t = 1] \cdot \Pr(D_t = 1|p_t, \tilde{p}_t \leq 0) \\
&\qquad\qquad + E[p_t - \xi_t|p_t, \tilde{p}_t \leq 0, D_t = 0] \cdot \Pr(D_t = 0|p_t, \tilde{p}_t \leq 0)\} \\
&= \alpha_0 + \beta_0 \cdot \{(p_t - E[\gamma_t|\gamma_t \geq p_t, p_t]) \cdot \Pr(D_t = 1|p_t, \tilde{p}_t \leq 0) \\
&\qquad\qquad + (p_t - E[\xi_t|\xi_t \geq p_t, p_t]) \cdot \Pr(D_t = 0|p_t, \tilde{p}_t \leq 0)\}
\end{aligned}$$

$\iff$

$$\begin{aligned}
\Lambda_1 = \alpha_0 + \beta_0 \cdot p_t + \beta_0 \cdot \{E[\gamma_t|\gamma_t \geq p_t, p_t]) \cdot \Pr(D_t = 1|p_t, \tilde{p}_t \leq 0) \\
- E[\xi_t|\xi_t \geq p_t, p_t]) \cdot \Pr(D_t = 0|p_t, \tilde{p}_t \leq 0)\}
\end{aligned} \tag{25}$$

Now, applying Bayes' rule to $\Pr(D_t = 0|p_t, \tilde{p}_t \leq 0)$:

$$\begin{aligned}
\Pr(D_t = 0|p_t, \tilde{p}_t \leq 0) &= \frac{\Pr(\tilde{p}_t \leq 0|D_t = 0, p_t) \cdot \Pr(D_t = 0|p_t)}{\Pr(\tilde{p}_t \leq 0|p_t)} \\
&= \frac{\Pr(\tilde{p}_t \leq 0|D_t = 0, p_t) \cdot \Pr(D_t = 0|p_t)}{\Lambda_2} \\
&= \frac{\Pr(p_t - \xi \leq 0|p_t) \cdot [1 - \pi_D(p_t)]}{\Lambda_2} \\
&= \frac{\left[1 - F_\xi(p_t)\right] \cdot [1 - \pi_D(p_t)]}{\Lambda_2}
\end{aligned} \tag{26}$$

And, therefore,

$$\Pr(D_t = 1|p_t, \tilde{p}_t \leq 0) = 1 - \Pr(D_t = 0|p_t, \tilde{p}_t \leq 0) \\ = \frac{[1 - F_\gamma(p_t)] \cdot \pi_D(p_t)}{\Lambda_2} \tag{27}$$

Combining (25), (26) and (27) implies:

$$\Lambda_1 = \alpha_0 + \beta_0 \left[p_t + \frac{E[\gamma_t|\gamma_t \geq p_t, p_t] \cdot [1 - F_\gamma(p_t)] \cdot \pi_D(p_t) - E[\xi_t|\xi_t \geq p_t, p_t] \cdot \left[1 - F_\xi(p_t)\right] \cdot [1 - \pi_D(p_t)]}{\Lambda_2} \right] \\ \equiv \Lambda_1(p_t, \pi_D(p_t), F_\gamma(p_t), F_\xi(p_t), \boldsymbol{\alpha}, \boldsymbol{\beta}) \tag{28}$$

Analogous calculations yield the following expression for Λ_3:

$$\Lambda_3 = \alpha_1 + \beta_1 \left[p_t + \frac{E[\gamma_t|\gamma_t \leq p_t, p_t] \cdot F_\gamma(p_t) \cdot \pi_D(p_t) - E\left[\xi_t|\xi_t \leq p_t, p_t\right] \cdot F_\xi(p_t) \cdot [1 - \pi_D(p_t)]}{\Lambda_4} \right] \\ \equiv \Lambda_3(p_t, \pi_D(p_t), F_\gamma(p_t), F_\xi(p_t), \boldsymbol{\alpha}, \boldsymbol{\beta}) \tag{29}$$

Finally, combining (22), (23), (24), (28), and (29), we obtain:

$$E[y_t|p_t] = \alpha_0 \cdot \psi_1(p_t) + \beta_0 \cdot \psi_2(p_t) + \alpha_1 \cdot \psi_3(p_t) + \beta_1 \cdot \psi_4(p_t)$$

where:

$$\psi_1(p_t) = \left[1 - F_\xi(p_t)\right] \cdot [1 - \pi_D(p_t)] + [1 - F_\gamma(p_t)] \cdot \pi_D(p_t)$$
$$\psi_2(p_t) = \psi_1(p_t) \cdot p_t + E[\gamma_t|\gamma_t \geq p_t, p_t] \cdot [1 - F_\gamma(p_t)] \cdot \pi_D(p_t) - E[\xi_t|\xi_t \geq p_t, p_t] \cdot \left[1 - F_\xi(p_t)\right] \cdot [1 - \pi_D(p_t)]$$
$$\psi_3(p_t) = F_\xi(p_t) \cdot [1 - \pi_D(p_t)] + F_\gamma(p_t) \cdot \pi_D(p_t)$$
$$\psi_4(p_t) = \psi_3(p_t) \cdot p_t + E[\gamma_t|\gamma_t \leq p_t, p_t] \cdot F_\gamma(p_t) \cdot \pi_D(p_t) - E\left[\xi_t|\xi_t \leq p_t, p_t\right] \cdot F_\xi(p_t) \cdot [1 - \pi_D(p_t)]$$

D.4 Accounting for Bunching

A standard test for the validity of the RDD framework consists of verifying the continuity of the density of the running variable around the threshold. If the running variable is not distributed smoothly around the cutoff, then it is said to be "manipulated". In recent work, Gerard, Rokkanen and Rothe (2020) shows that, while point identification of causal effects is infeasible in this case, it is possible to obtain sharp bounds on the effects of interest.

In their model, the extent of manipulation can be quantified as the excess bunching in the density of the running variable below the threshold. While one cannot identify which are the units below the threshold that are manipulating, the excess bunching π_B tells us what share of the observed units is in this group. Bounds on treatment effects are then computed by excluding a share π_B of the observations below the threshold in ways that yield the most extreme values for the estimate.

This process can be quite involved in general since one does not know the treatment assignment of the units that are manipulated. This transforms the computation of the bounds in an optimization problem, searching for the worst- and best-case scenarios in terms of how outcomes are distributed across treatment groups below the threshold.

However, our setting allows us to make a behavioral assumption that tremendously simplifies the problem. In particular, our model assumes that all units that manipulate the ex-ante price to bunch below the threshold successfully avoid the publicity mandate.Therefore, our model implies that the share π_B of units that manipulate all belong to the control group ($D_t = 0$). Bounds on treatment effects are straightforwardly obtained in this case by simply chopping the tails of the distribution of outcomes Y_t below the threshold for units in the control group.

In practice, we implement this procedure as follows. For each bin b closely below the threshold:

1. Compute the excess bunching in the control group, as $BUNCH_b = (n_b^0 - \widehat{\tilde{n}_b^0})$, obtained from our density analysis.

2. Sort control units according to the outcome variable Y_b^0.

3. Drop the $BUNCH_b$ units with the highest value of Y_b^0. Compute treatment effects. This yields the lower bound.

4. Drop the $BUNCH_b$ units with the lowest value of Y_b^0. Compute treatment effects. This yields the upper bound.

E Discussion on Modeling of Execution Performance

We measure execution performance by the magnitude of cost-overruns, which we model based on two important assumptions:

1. **The ex-post realization of q_t is not strategic, but a result of a type-specific shock**. This assumption is in line with related papers (Bajari et al., 2014; Eun, 2018; Ryan, 2020). It is also consistent with the reduced-form evidence discussed in Section 3.5, where we find that variation in the competitive environment does not generate changes in firm performance in terms of cost overruns or delays. We, therefore, think of contract execution as a stochastic realization that depends on a production technology that is fixed—at least in the short run—, and that cannot be modified after observing the competitive environment.

2. **The ex-post realization of q_t is fully passed through to the buyer**. This implies that cost overruns do not enter the utility function of the firm. Modelling choices in related papers are context-specific in this regard. For example, Bajari et al. (2014) and Eun (2018) study highway construction and consider that ex-post cost overruns negatively affect firms' utility as they involve costly re-negotiations and additional layers of bureaucracy. On the other hand, Ryan (2020) studies energy procurement and highlights that certain firms (e.g., politically connected) take advantage of these shocks to obtain better conditions.

   In our setting, contract ex-post modifications do not involve major bureaucratic hurdles beyond clarifying that the amendment is needed and that it involves unbudgeted costs that can be justified with invoices. This implies that the assumption that cost shocks are fully passed through resonates with the particularities of our institutional context. However, note that even if the model was misspecified, future overruns would only affect firm behavior in expectation due to risk neutrality. Moreover, if expected overruns do affect firms' utility, the estimated distributions of production and entry costs would be shifted by an (unknown) amount reflecting a "taste for expected overruns", i.e., $\hat{c}_{jt} = c_{jt} + \psi \cdot \mathbb{E}[q_{jt}]$, where ψ is a taste parameter that could be positive or negative. Importantly, if we did impose such a structure, there would be a limit to what we could identify. Related papers (e.g., Ryan (2020); Bajari et al. (2014)) are explicit about how ψ enters the utility function, yet they impose this structure at the expense of assuming that firms are symmetric. Instead, we allow for full flexibility in the asymmetry of all primitive distributions between locals and non-locals, but at the expense of being agnostic about ψ. We argue that our modeling choice in this regard takes better advantage of the variation available in our data and provides more flexibility to our counterfactual exercises.

F Model Identification

Lemma 1. *The expected k-th order statistic of B with n draws can be written in terms of the expected k-th and $(k+1)$-th order statistics with $n+1$ draws*

Proof. The probability density function of B is $g_B(b)$, then the k-th order statistic of B, $g_{B_k^{(n)}}(b)$, is:

$$\begin{aligned} g_{B_k^{(n)}}(b) &= k\binom{n}{k} g_B(b) G_B(b)^{k-1} \left[1 - G_B(b)\right]^{n-k} \\ &= \frac{n!}{(n-k)!(k-1)!} f_B(b) G_B(b)^{k-1} \left[1 - G_B(b)\right]^{n-k} \end{aligned}$$

Thus, the difference is expected k-th order statistics with n and $n+1$ actual competitors is expressed as follows:

$$\begin{aligned} &\mathbb{E}[B_k^{(n)}] - \mathbb{E}[B_k^{(n+1)}] = \int_{\underline{b}}^{\bar{b}} b g_{B_k^{(n)}}(b) db - \int_{\underline{b}}^{\bar{b}} b g_{B_k^{(n+1)}}(b) db \\ &= \int_{\underline{b}}^{\bar{b}} bk\binom{n}{k} g_B(b) G_B(b)^{k-1} \left[1 - G_B(b)\right]^{n-k} db - \int_{\underline{b}}^{\bar{b}} bk\binom{n+1}{k} g_B(b) G_B(b)^{k-1} \left[1 - G_B(b)\right]^{n+1-k} db \\ &= \int_{\underline{b}}^{\bar{b}} \left(\frac{n!(n+1-k) - (n+1)! \left[1 - G_B(b)\right]}{(k-1)!(n+1-k)!} \right) b g_B(b) G_B(b)^{k-1} \left[1 - G_B(b)\right]^{n-k} db \\ &= \int_{\underline{b}}^{\bar{b}} \left(\frac{(n+1)! G_B(b) - n!k}{(k-1)!(n+1-k)!} \right) b g_B(b) G_B(b)^{k-1} \left[1 - G_B(b)\right]^{n-k} db \\ &= \int_{\underline{b}}^{\bar{b}} \frac{(n+1)!}{(k-1)!(n+1-k)!} b g_B(b) G_B(b)^{k} \left[1 - G_B(b)\right]^{n-k} db \\ &\quad - \int_{\underline{b}}^{\bar{b}} \frac{n!k}{(k-1)!(n+1-k)!} b g_B(b) G_B(b)^{k-1} \left[1 - G_B(b)\right]^{n-k} db \\ &= \frac{k}{(n+1-k)} \left(\mathbb{E}[B_{k+1}^{(n+1)}] - \mathbb{E}[B_k^{(n)}] \right) \end{aligned}$$

Rearranging the terms, we get the expected k-th order statistic of n draws can be expressed as a simple weighted average of the k-th and $k+1$-th order statistic under $n+1$ draws:

$$\mathbb{E}[B_k^{(n)}] = \frac{k}{n+1} \mathbb{E}[B_{k+1}^{(n+1)}] + \frac{n+1-k}{n+1} \mathbb{E}[B_k^{(n+1)}] \tag{30}$$

□

F.1 Identification under Unobserved Heterogeneity

Below we show that identification can be achieved when only the winning bid and the number of (symmetric) bidders are observed as long as the number of bidders is exogenous. In particular, in our setting, bidders define bidding strategies without knowing the actual number of bidders, n, but based on beliefs about market conditions. Thus, n is exogenous conditional on (N, φ). We leverage variation in actual bidders to separately identify the private and the common cost components' distributions. To ease notation, we omit (N, φ) as conditions for exogeneity of n.

Proposition 6. *First price auctions with unobserved heterogeneity can be identified when only the winning bid and the number of bidders are observed as long as the number of active bidders is exogenous.*

Proof. The ratio of first-order statistics is identified by comparing observed winning bids for different values of n:

$$\frac{\frac{1}{T_{n,N}}\sum_t (B_{1,t}|n_t = n)}{\frac{1}{T_{n',N}}\sum_t (B_{1,t}|n_t = n')} \rightarrow \frac{\mathbb{E}[B_{1:n}]}{\mathbb{E}[B_{1:n'}]} = \frac{\mathbb{E}[\tilde{B}_{1:n}\cdot u]}{\mathbb{E}[\tilde{B}_{1:n'}\cdot u]} = \frac{\mathbb{E}[\tilde{B}_{1:n}]\cdot \mathbb{E}[u]}{\mathbb{E}[\tilde{B}_{1:n'}]\cdot \mathbb{E}[u]} = \frac{\mathbb{E}[\tilde{B}_{1:n}]}{\mathbb{E}[\tilde{B}_{1:n'}]} \tag{31}$$

where $(B_{1,t}|n_t = n)$ is auction's t observed winning bid with n active bidders. $\mathbb{E}[\tilde{B}_{1:n}]$ is the expected first order statistic normalized based on $u_t = 1$. Finally, u is assumed independent of the number of bidders and cancels out in the last identity. The normalization $\mathbb{E}[u] = 1$ pins down the scale of the first order statistics.

By contradiction; assume $(\hat{G}_{\tilde{b}}, \hat{H}_u)$ provide the same distribution observed in the data,

$$\begin{aligned} \tilde{B}_{1:n}u &\overset{d}{=} \hat{\tilde{B}}_{1:n}\hat{u} \\ \tilde{B}_{1:n'}u &\overset{d}{=} \hat{\tilde{B}}_{1:n'}\hat{u} \end{aligned}$$

Construct $\tilde{b}^*_{n'}, \hat{\tilde{b}}^*_{n'}\tilde{u}^*$, and $\tilde{\hat{u}}^*$ as random variables that are independent of and have the same conditional distributions as their asterisk-free counterparts. Then it follows that

$$\begin{aligned} (\tilde{B}_{1:n}u)\cdot\left(\hat{\tilde{B}}^*_{1:n'}\hat{u}^*\right) &\overset{d}{=} \left(\hat{\tilde{B}}_{1:n}\hat{u}\right)\cdot\left(\tilde{B}^*_{1:n'}u^*\right) \\ \implies \tilde{B}_{1:n}\cdot\hat{\tilde{B}}^*_{1:n'} &\overset{d}{=} \hat{\tilde{B}}_{1:n}\cdot\tilde{B}^*_{1:n'} \end{aligned} \tag{32}$$

Taking expectations on both sides:

$$\begin{aligned} \mathbb{E}[\tilde{B}_{1:n}]\cdot\mathbb{E}[\hat{\tilde{B}}_{1:n'}] &= \mathbb{E}[\hat{\tilde{B}}_{1:n}]\cdot\mathbb{E}[\tilde{B}_{1:n'}] \\ \frac{\mathbb{E}[\tilde{B}_{1:n}]}{\mathbb{E}[\tilde{B}_{1:n'}]} &= \frac{\mathbb{E}[\hat{\tilde{B}}_{1:n}]}{\mathbb{E}[\hat{\tilde{B}}_{1:n'}]} \end{aligned}$$

If $(\hat{G}_{\tilde{b}}, \hat{H}_u)$ rationalizes the data, it has a normalized distribution with the same ratio of first order statistics. Using, order statistic's recurrence relation (Lemma 1), we have that $\mathbb{E}[B_{1:n-1}] =$

$\frac{1}{n}\mathbb{E}[B_{2:n}] + \frac{n-1}{n}\mathbb{E}[B_{1:n}]$, we can link together these ratios when $n' = n - 1$:

$$\begin{aligned}
\frac{\mathbb{E}[\tilde{B}_{1:n}]}{\mathbb{E}[\tilde{B}_{1:n'}]} &= \frac{\mathbb{E}[\hat{\tilde{B}}_{1:n}]}{\mathbb{E}[\hat{\tilde{B}}_{1:n'}]} \\
\frac{\mathbb{E}[\tilde{B}_{1:n}]}{\frac{1}{n}\mathbb{E}[\tilde{B}_{2:n}] + \frac{n-1}{n}\mathbb{E}[\tilde{B}_{1:n}]} &= \frac{\mathbb{E}[\hat{\tilde{B}}_{1:n}]}{\frac{1}{n}\mathbb{E}[\hat{B}_{2:n}] + \frac{n-1}{n}\mathbb{E}[\hat{\tilde{B}}_{1:n}]} \\
\frac{\mathbb{E}[\tilde{B}_{1:n}]}{\mathbb{E}[\tilde{B}_{2:n}]} &= \frac{\mathbb{E}[\hat{\tilde{B}}_{1:n}]}{\mathbb{E}[\hat{\tilde{B}}_{2:n}]}
\end{aligned}$$

$\hat{G}_{\tilde{b}}$ has the same ratio of second-order statistics. With sequential values of $n \in \{2, \ldots, N\}$, we can iterate forward from the identified first-order and second-order statistics using the recursive relation between order statistics from Proposition 1. Therefore, $G_{\tilde{b}}$ and $\hat{G}_{\tilde{b}}$ are identical up to the first N order statistics from $\tilde{B}$ □

Corollary 2. *The distribution of the unobserved heterogeneity, H_u is obtained once $G_{\tilde{b}}$ is identified.*

Proof. By Independence of $\tilde{B}$ and u, leveraging basic properties of characteristic functions we can write $\psi_{log(B_{1:n})} = \psi_{log(\tilde{B}_{1:n})}\psi_{log(u)}$, where $\psi_{log(B_{1:n})}$ is the characteristic function of the log of observed winning bids under n active bidders. We can construct this characteristic function for different values of n. Once the characteristic function of $G_{\tilde{b}}$ is obtained, we can pin down H_u □

Corollary 3. *The distribution of normalized private costs, $F_{\tilde{c}}$ is identified once $G_{\tilde{b}}$ and equilibrium entry probabilities are obtained.*

This corollary follows from Guerre et al. (2000). If the distribution of $G_{\tilde{b}}$ is recovered, and the equilibrium entry probabilities are observed from entry choices. Then, we can use the first order and the boundary conditions to recover the latent distribution $F_{\tilde{c}}$.

G Model Estimation Details

G.1 Classifying Contractors' *Types*

Based on the patterns of contractor's participation, we identify two separate groups of firms: contractors who win awards without relying on publicity —which we refer to as *locals*—, and contractors that *only* win when contract solicitations are publicized —which we label *non-locals*. The logic is that, if a contractor wins without publicity, this indicates that the buyer informed her directly (e.g. through email or a phone call). The existence of direct communication reveals a buyer's preference for these contractors. Conversely, if a contractor requires a FedBizzOpps announcement to participate (and win), this suggests that there is no specific preference from that buyer for that contractor. This distinction came up frequently in conversations with procurement officers from several organizations.

To classify contractors empirically, we restrict the analysis to buyer-product combinations observed at least 4 times between 2013 and 2019 and with at least one —but not all— contracts publicized.[64] Table B.8 compares buyer-contractor distance and performance for contracts performed by local and non-locals. The third column shows the mean difference in performance between these two groups. As a reference, if the information source is irrelevant, locals and non-locals would have similar outcomes. However, we observe that contracts executed by *non-local* contractors experience 13.8 percentage points (240%) more cost-overruns and 13.7 percentage points (130%) more delays than locals.

Table B.8: Summary Statistics: Local vs. Non-Local Contractors

	Local	Non-Local	Diff
log Distance	3.283	3.421	-0.138
Located in the Same State	0.707	0.635	0.072
Overruns (relative)	0.057	0.195	-0.138
Delays (relative)	0.106	0.243	-0.137
Number of Modifications	0.435	0.721	-0.286

Notes: This table presents summary statistics for distance and execution variables for contracts performed by local and non-local contractors. The sample includes contracts between 10,000 and 40,000 dollars, and buyer-product combinations that appeared at least four times between 2013 and 2019. The need for observing multiple buyer-product observations stems from how we categorize these contractors. The variables "Overruns" and "Delays" are measured relative to dollars obligated and duration at the time of the award, respectively. The differences between the first two columns are all statistically significant at the 1% level.

[64] We noted that the Federal Procurement Data System (FPDS) sometimes misclassifies local buyers, assigning the same code to different branches that depend on a single (higher-level) office. This contrasts with the nature of most procurement officers' job, who typically contract within a particular area, leveraging their local market knowledge. We address this misclassification by defining a buyer based on the office code *and* the Metropolitan Statistical Area (MSA) of the purchase. As before, the definition of a product category is given by the 4-digit PSC code.

G.2 Estimation

Denote the target moments by m_n as a vector of moments from the data. The simulated moments are denoted by $m_s(\theta)$. The depends on the parameters $\theta \in \Theta \subset \mathbb{R}^P$. The estimator minimizes the standard distance metric:

$$\hat{\theta} = \underset{\theta}{\text{argmin}} \, (m_n - m_s(\theta))' \, W_n \, (m_n - m_s(\theta))$$

Where W_n is the weighting matrix, which is chosen using the standard two-step approach. Letting $M_s(\theta)$ be the $(P \times J)$ Jacobian matrix of the vector of simulated moments; under standard regularity assumptions, we have:

$$\sqrt{n}\,(\hat{\theta} - \theta_0) \xrightarrow{d} N\left(0, \left(1 + \frac{1}{s}\right)(M'WM)^{-1}M'W\Omega W'M(M'WM)^{-1}\right) \tag{33}$$

where W is the probability limit of W_n, M is the probability limit of $M_s(\theta_0)$, and Ω is the asymptotic variance of m_n (Pakes and Pollard, 1989). The vector of parameters is: $\theta = (\alpha^k, \nu^k, \tau^k, \gamma^k, \xi^k, \iota^k, \vec{\lambda}, \eta, \zeta, \sigma)$

G.2.1 Standard Errors

We compute standard errors using the asymptotic variance formula given by (33). The variance-covariance matrix of $\hat{\theta}$ is:

$$V(\hat{\theta}) = \frac{1}{n}\left(1 + \frac{1}{s}\right)(\hat{M}'W\hat{M})^{-1}\hat{M}'W\hat{\Omega}W'\hat{M}(\hat{M}'W\hat{M})^{-1}$$

Where $\hat{\Omega}$ is estimated via bootstrap: re-sampling contracts with replacement from the original data, and recompute the smoothed vector of moments, repeating this process 500 times. $\hat{\Omega}$ is the sample variance of these 500 vectors. $\hat{M}$ is the numeric derivative of the SMM objective function (11) evaluated at $\hat{\theta}$.

G.2.2 Minimization

We keep the underlying random draws constant throughout the minimization of the objective function. Nonetheless, the simulated objective is not continuous with respect to θ. Thus, we leverage the stochastic optimization algorithm *Differential Evolution* (Storn and Price, 1997) to perform the objective minimization. This algorithm does not rely on gradient methods, and given its heuristic approach for minimizing possibly nonlinear and non-differentiable continuous space functions, it is robust to poorly behaved objectives. Given the stochastic nature of the procedure, we estimated the model for 25 different seeds that generate a different vector of random draws and model parameters. We select the parameters that yield the minimum objective function.

G.3 Moments

We use three sets of target moments.

- First set of moments,
  - $\vec{m}_{11} = \mathbb{E}[\mathbf{x}_t^{(y)'} y_t]$ and $\vec{m}_{12} = \mathbb{E}[\mathbf{x}_t^{(y)'} y_t^2]$, where $y_t =$ *log winning bid, number of bidders, wins local, log overruns,* and *contract is publicized*, and $\mathbf{x}_t^{(y)}$ include a constant and covariates associated with outcome variable y
- Second set:
  - $\vec{m}_2 = \mathbb{E}[y_t | B_t \in (B^l, B^{l+1})]$, for $l \in \{1, \ldots, L-1\}$, where $y_t =$ *number of bidders, wins local, log overruns,* and *contract is publicized*. We separate these moments based on goods and services, and partition the domain of contract prices in bins of width $5,000
- Third set of moments:
  - $\vec{m}_3 = \mathbb{E}[\mathbb{1}\{b_t \in (b^l, b^{l+1})\}]$, for $l \in \{1, \ldots, L-1\}$. This set of moments correspond to the normalized frequencies on the relevant window of contract prices. The bin width is $5,000.

As a result we use 109 moments to estimate 35 parameters.

H Sensitivity of Parameter Estimates to Estimation Moments

We measure the sensitivity of our parameter estimates to estimation moments following the methodology and recommendations from Andrews, Gentzkow and Shapiro (2017). Following the notation introduced in Appendix G, sensitivity Λ is given by:

$$\Lambda = -(M'WM)^{-1}M'W$$

Since the units in our vector of moments are not directly comparable, we consider a normalized sensitivity matrix $\tilde{\Lambda}$ that scales each element in Λ by the standard deviation of the corresponding data moment:

$$\tilde{\Lambda}_{pj} = \Lambda_{pj}\sqrt{\Omega_{jj}}$$

where A_{ik} denotes the element in row i and column k of matrix A.

We construct an estimate of $\tilde{\Lambda}$ by directly plugging in our estimates of M, W, and Ω, which we compute as explained in Appendix G. The normalized sensitivity matrix $\tilde{\Lambda}$ provides a measure of the relative importance of each moment j for determining the value of each parameter p. Since $\tilde{\Lambda}$ is a very large matrix (dimension 109×35), the analysis that follows focuses on a few selected parameters to keep the discussion tractable. We choose parameters that involve different key components of our model, namely entry, ex-post performance, unobserved heterogeneity, and buyers' preferences.

H.1 Entry, Ex-post Performance, and Unobserved Heterogeneity

Our identification discussion in Section 4.3 implies that we should expect that parameters that govern entry are most sensitive to actual entry choices (i.e., number of actual bidders and probability of a local winner) and their interactions with market structure. Similarly, parameters that characterize firm performance should be most sensitive to moments that measure the existence and magnitude of cost overruns. Finally, the unobserved heterogeneity should be sensitive to the density of contract prices and to the number of potential and actual bidders.[65]

Following this logic, we classify certain estimation moments as "relevant" for each set of parameters based on this *a priori* reasoning,[66] and then contrast this with the estimated sensitivity.

[65] The distribution of unobserved heterogeneity is identified from the observed price and its sensitivity to variation in auction competition.

[66] Following the notation in Appendix Section G.3, for entry we select moments $\vec{m}_{11}$ for which the y_t is either the number of bidders or a dummy for a local winner. For cost overruns, we select moments $\vec{m}_{11}$ and $\vec{m}_2$ for which y_t is either the level of cost overruns, the log of cost overruns, or a dummy for any cost overruns. For the unobserved heterogeneity, we select moments $\vec{m}_{11}$ for which the y_t is the number of actual bidders and $\mathbf{x}_t^{(y)}$ is the number of potential bidders, as well as moments $\vec{m}_3$.

Figure A25 presents the absolute value of selected columns of $\tilde{\Lambda}$, ranked by magnitude from left to right, and highlighting the difference between (ex-ante) relevant moments and the rest. In each panel, we focus on a single parameter and plot the sensitivity to each of the 109 estimation moments. For entry (Panel (a)), we focus on the constant parameter τ^L in the entry probit specification, interpreted as a sort of baseline entry probability for local bidders. For cost overruns (Panel (b)), we focus on the constant γ^L parameter in the cost overruns specification, again a sort of baseline level of overruns for local firms. In Panel (c), we naturally focus on the only unknown parameter that governs the unobserved heterogeneity, i.e., its variance.

Across all panels, we see that the highlighted moments generate, on average, higher sensitivity than the rest of the moments. More importantly, the right tale of high sensitivity is completely dominated by moments that we ex-ante deemed as most relevant for identification. This means that, while not all of the ex-ante relevant moments end up mattering for the parameter estimates—something not completely surprising in an estimation procedure with so many moments—, virtually all of the moments that do significantly affect the estimate correspond to the relevant type. We take this as evidence that the sensitivity analysis is largely consistent with the identification discussion in Section 4.3.

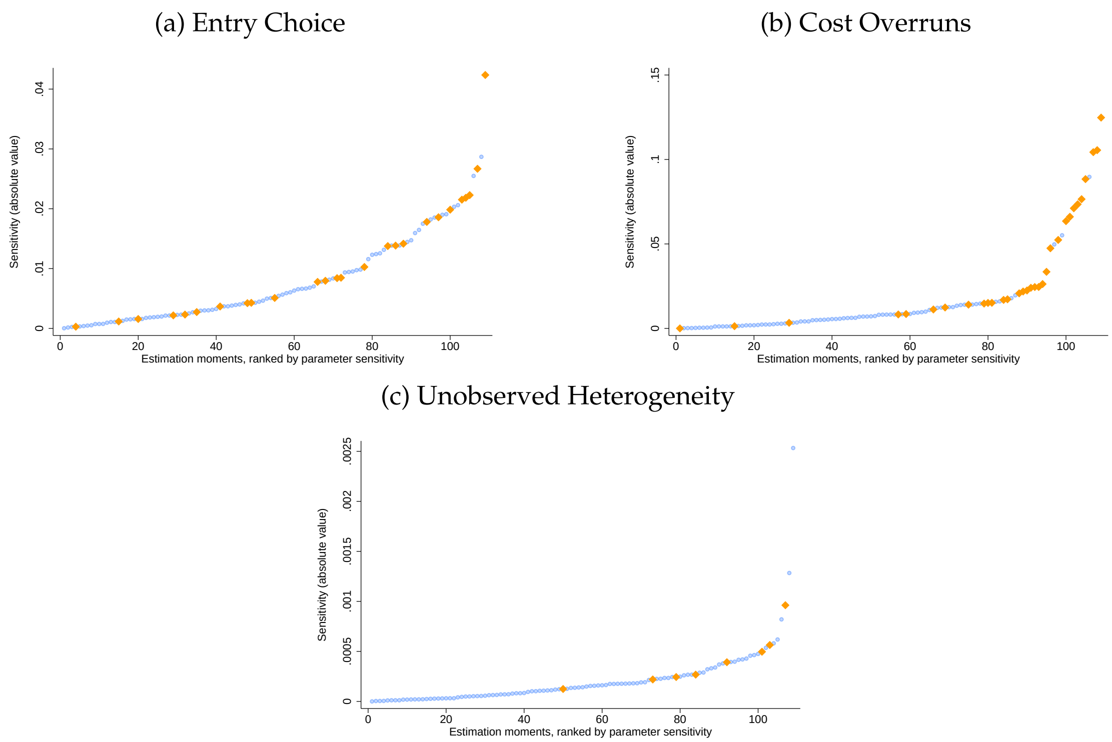
H.2 Buyer Preferences

For buyers' preferences, we focus on the parameter η, which is a measure of the disutility that buyers experience when going against the publicity regulation (i.e., not publicizing when exceeding the threshold). We choose η because it is an important parameter shaping buyers' choices in our setting, but also because it allows us to explore how the policy variation that we leverage in our reduced form analysis aids with the identification of the model.

In Section 4.3, we argue that η is identified from the discontinuous nature of the policy, following the logic of the RDD in Section 3. In particular, η is identified from the first stage of our RDD, i.e., the probability of publicizing a contract as a share of its expected price. In the context of the RDD, the size of the discontinuity at the policy threshold corresponds to the effect of the policy on buyers' *actions*. Our model imposes structure such that the effect of the policy on buyers' *preferences* is homogeneous across contract size (i.e., η is constant). Therefore, the identification of η comes from the difference in publicity levels below and above the threshold throughout the contract price range. This argument implies that moments measuring the share of publicized contracts below the threshold should contribute to reducing the estimate, whereas analogous moments above the threshold should increase it by the same amount.

Figure A26 shows the sensitivity of the parameter η to the share of publicized contracts at different price bins and separately for goods (Panel (a)) and services (Panel (b)). In both cases, we estimate an average negative sensitivity for moments below the threshold and a positive

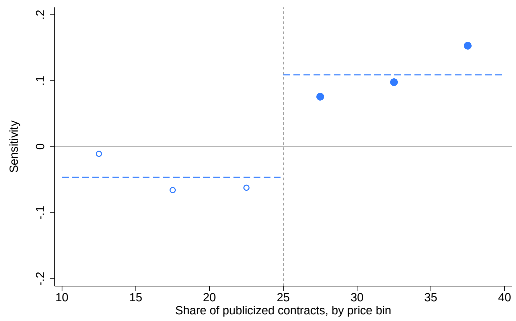
Figure A25: Sensitivity of Parameter Estimates to Estimation Moments



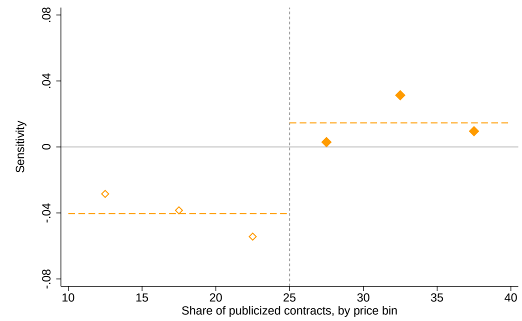
Notes: This figure presents estimates of the sensitivity ($\tilde{\Lambda}$) of three selected parameters estimates with respect to estimation moments. In Panel (a), the parameter is the constant on the entry probability specification for local bidders. In Panel (b), the parameter is the constant on the cost overruns specification for local bidders. In Panel (c), the parameter is the variance of the unobserved heterogeneity. In all panels, we plot the absolute value of the sensitivity of the relevant parameter with respect to all 109 estimation moments, ranked in magnitude from left to right. Moments that are deemed ex-ante relevant for the identification of each parameter are highlighted in orange.

Figure A26: Sensitivity of Buyers' Preferences for Publicity (η) to Estimation Moments Around the Threshold

(a) Good



(b) Services



Notes: This figure presents estimates of the sensitivity ($\tilde{\Lambda}$) of buyers' estimated preference for publicity (η) with respect to selected estimation moments. In Panel (a), the estimation moments are the share of publicized contracts for goods in six different bins of award price: $(\$10,000, \$15,000]$, $(\$15,000, \$20,000]$, $(\$20,000, \$25,000]$, $(\$25,000, \$30,000]$, $(\$30,000, \$35,000]$, $(\$35,000, \$40,000]$. In Panel (b), the estimation moments are analogous, but for service contracts. Dots and diamonds represent the point estimate of sensitivity. Dashed lines in each panel represent the average sensitivity for moments below and above the threshold.

sensitivity above the threshold. Consistent with our identification argument, the magnitude of both sensitivities is similar. These results show a clear connection between the policy variation and our model estimates and provide a bridge between our reduced form and structural analyses.

I The Role of Buyers' Preferences

In this section, we study the extent to which buyers' specific preference parameters explain contract outcomes. To do so, we leverage our model estimates and vary buyers' preferences, focusing on two hypothetical scenarios. First, we say that the buyer has "Cost-Oriented Preferences" if she puts equal weight on price reductions ex-ante and ex-post and has no idiosyncratic preference for local contractors. Second, we say that the buyer has "Local-Oriented Preferences" if they are geared toward favoring local contractors with no emphasis on costs. The specific preference parameters under each scenario are described in Table B.9. It is worth noting that these two benchmark scenarios are based on the estimated coefficients, but turn off specific taste parameters. Therefore, they can be seen as reference points for policies oriented to affect buyers' motives.

Table B.9: Buyers' Preferences

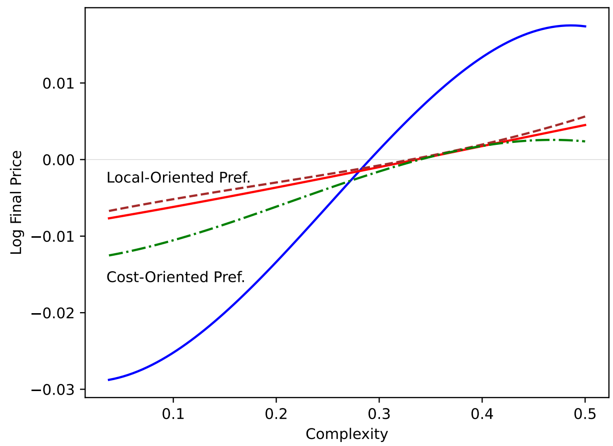
	Estimated Preference Parameters	Benchmarks	
		Cost-Oriented Preference	Local-Oriented Preference
λ^P	-0.971	-0.971	0
λ^Q	-0.096	-0.971	0
λ^L	0.435	0	0.435
Mean Pub.	0.275	0.393	0.263

Notes: This table shows estimates of buyer preferences parameters. The first column shows the estimated parameters for ex-ante prices, ex-post overruns, and awarding to local contractors. The second column shows the preference parameters associated with a buyer with cost-oriented preferences, i.e., with no idiosyncratic preference for local contractors. The third column shows preference parameters for a buyer that is fully oriented to local contractors, without a preference for prices ex-ante or ex-post. The last row describes the average use of publicity under each of these types of preferences.

Figure A27 shows changes in (log) final prices relative to a benchmark of no publicity as a function of the level of complexity of the purchase and for different counterfactual scenarios. We consider preference counterfactuals assuming full discretion (i.e., no threshold) and also compare these to the full publicity counterfactual discussed above. If buyers had "Cost-Oriented Preferences," they would exercise discretion to generate savings of roughly 0.5 percentage points relative to observed preferences across the full spectrum of product complexity. On the other hand, since "Local-Oriented" agents would seek to benefit local contractors, they would publicize infrequently, and, as a result, final prices would be higher than with no publicity for most of the complexity spectrum. If contracts are complex enough, the full publicity rule obtains prices that are (even) higher than those obtained by "Local-Oriented" buyers because favored local contractors tend to better execute these contracts, reducing cost overruns.

The existing literature on rules versus discretion in public procurement emphasizes that regulation can be an effective antidote to waste and abuse whenever these are pervasive. Yet, it can backfire if buyers are relatively aligned with the government's goals (Carril, 2022; Bosio et

Figure A27: Counterfactual Analysis II: Buyers' Preferences



Notes: This figure shows changes in log final prices as a function of product complexity, relative to a benchmark of no publicity, and for different counterfactual policies and assumptions on buyers' preferences parameters. The blue line is a counterfactual where all contracts are publicized and the red line represents the current policy (with a threshold at 25,000). The green and brown dashed lines represent counterfactuals where buyers have cost-oriented and local-oriented preferences, respectively. Each line corresponds to a flexible polynomial fit. The degree of complexity is defined as the log of the product category's average overruns for contracts below $20,000.

al., 2020). Our findings contribute to this literature by highlighting that this trade-off depends as well on the level of contract complexity. Publicity rules can be detrimental even when agents are misaligned since favoring local vendors has the positive effect of reducing cost overruns. On the other hand, strict publicity requirements may reduce procurement costs even when agents are aligned, provided that the transaction unit is sufficiently simple.[67]

[67] The intuition is that strict publicity requirements leverage the ex-ante price benefits of competition by removing the idiosyncratic variation in buyers' preferences that leads them not to publicize some contracts. At the same time, this is done at virtually no cost ex-post since simple contracts tend not to experience any overruns.

References

Aghion, Philippe and Jean Tirole, "Formal and real authority in organizations," *Journal of Political Economy*, 1997, *105* (1), 1–29.

Albano, Gian Luigi, Milo Bianchi, and Giancarlo Spagnolo, "Bid Average Methods in Procurement," *Rivista di Politica Economica*, January-F 2006, *96* (1), 41–62.

Andrews, Isaiah, Matthew Gentzkow, and Jesse M. Shapiro, "Measuring the Sensitivity of Parameter Estimates to Estimation Moments*," *The Quarterly Journal of Economics*, 06 2017, *132* (4), 1553–1592.

Andreyanov, Pasha, Francesco Decarolis, Riccardo Pacini, and Giancarlo Spagnolo, "Past Performance and Procurement Outcomes," Technical Report, Working paper 2023.

Asker, John and Estelle Cantillon, "Properties of scoring auctions," *RAND Journal of Economics*, 2008, *39* (1), 69–85.

_ and _, "Procurement when price and quality matter," *RAND Journal of Economics*, 2010, *41* (1), 1–34.

Athey, Susan, "Single crossing properties and the existence of pure strategy equilibria in games of incomplete information," *Econometrica*, 2001, *69* (4), 861–889.

_, Dominic Coey, and Jonathan Levin, "Set-asides and subsidies in auctions," *American Economic Journal: Microeconomics*, 2013, *5* (1), 1–27.

_, Jonathan Levin, and Enrique Seira, "Comparing open and sealed bid auctions: Evidence from timber auctions," *Quarterly Journal of Economics*, 2011, *126* (1), 207–257.

Bajari, Patrick, "Comparing competition and collusion: A numerical approach," *Economic Theory*, 2001, *18* (1), 187–205.

— **and Steven Tadelis**, "Incentives versus Transaction Costs: A Theory of Procurement Contracts," *RAND Journal of Economics*, 2001, *32* (3), 387–407.

— **, Robert McMillan, and Steven Tadelis**, "Auctions versus negotiations in procurement: An empirical analysis," *Journal of Law, Economics, and Organization*, 2009, *25* (2), 372–399.

— **, Stephanie Houghton, and Steve Tadelis**, "Bidding for Incomplete Contracts: An Empirical Analysis," *American Economic Review*, 2014, *104* (4), 1288–1319.

Bandiera, Oriana, Andrea Prat, and Tommaso Valletti, "Active and passive waste in government spending," *American Economic Review*, 2009, *99* (2009 Sept), 1278–1308.

— **, Michael Carlos Best, Adnan Qadir Khan, and Andrea Prat**, "The Allocation of Authority in Organizations: A Field Experiment with Bureaucrats*," *The Quarterly Journal of Economics*, 08 2021, *136* (4), 2195–2242.

Barreca, Alan I., Melanie Guldi, Jason M. Lindo, and Glen R. Waddell, "Saving Babies? Revisiting the effect of very low birth weight classification*," *The Quarterly Journal of Economics*, 10 2011, *126* (4), 2117–2123.

Best, Michael Carlos, Jonas Hjort, and David Szakonyi, "Individuals and Organizations as Sources of State Effectiveness," *American Economic Review*, August 2023, *113* (8), 2121–67.

Bhattacharya, Vivek, James W. Roberts, and Andrew Sweeting, "Regulating bidder participation in auctions," *The RAND Journal of Economics*, 2014, *45* (4), 675–704.

Bolotnyy, Valentin and Shoshana Vasserman, "Scaling Auctions as Insurance: A Case Study in Infrastructure Procurement," 2019.

Bosio, Erica, Simeon Djankov, Edward Glaeser, and Andrei Shleifer, "Public Procurement in Law and Practice," 2020.

Brendstrup, Bjarne and Harry J Paarsch, "Nonparametric Estimation of Dutch and First-Price , Sealed-Bid Auction Models With Asymmetric Bidders," 2003, (319).

Bresnahan, Timothy F. and Peter C. Reiss, "Entry and Competition in Concentrated Markets," *Journal of Political Economy*, 1991, *99* (5), 977–1009.

Bulow, Jeremy and Paul Klemperer, "Auctions Versus Negotiations," *American Economic Review*, 1996.

Burguet, Roberto, Juan José Ganuza, and Esther Hauk, "Limited liability and mechanism design in procurement," *Games and Economic Behavior*, 2012, *76* (1), 15–25.

Calonico, Sebastian, Matias D. Cattaneo, and Rocio Titiunik, "Robust Nonparametric Confidence Intervals for Regression-Discontinuity Designs," *Econometrica*, 2014, *82* (6), 2295–2326.

Calzolari, Giacomo and Giancarlo Spagnolo, "Relational Contracts and Competitive Screening," 2009.

Campo, Sandra, Isabelle Perrigne, and Quang Vuong, "Asymmetry in first-price auctions with affiliated private values," *Journal of Applied Econometrics*, 2003, *18* (2), 179–207.

Carril, Rodrigo, "Rules Versus Discretion in Public Procurement," *Mimeo.*, 2022, https://rcarril.github.io/website/carrilJMP.pdf.

Cattaneo, Matias D. and Rocío Titiunik, "Regression Discontinuity Designs," *Annual Review of Economics*, 2022, *14* (1), 821–851.

Chetty, Raj, John Friedman, and Emmanuel Saez, "Using Differences in Knowledge Across Neighborhoods to Uncover the Impacts of the EITC on Earnings : Web Appendix Sample and Variable De . . . nitions," *American Economic Review*, 2013, *103* (7), 2683–2721.

Chillemi, Ottorino and Claudio Mezzetti, "Optimal procurement mechanisms: bidding on price and damages for breach," *Economic Theory*, 2014, *55* (2), 335–355.

Compiani, Giovanni, Philip Haile, and Marcelo Sant'Anna, "Common Values, Unobserved Heterogeneity, and Endogenous Entry in US Offshore Oil Lease Auctions," *Journal of Political Economy*, 2020, *128* (10), 3872–3912.

Conley, Timothy G. and Francesco Decarolis, "Detecting Bidders Groups in Collusive Auctions," *American Economic Journal: Microeconomics*, 2016, *8* (2), 1–38.

Coviello, Decio and Mario Mariniello, "Publicity requirements in public procurement: Evidence from a regression discontinuity design," *Journal of Public Economics*, 2014, *109*, 76–100.

_ **and Stefano Gagliarducci**, "Tenure in office and public procurement," *American Economic Journal: Economic Policy*, 2017, *9* (3), 59–105.

_ **, Andrea Guglielmo, and Giancarlo Spagnolo**, "The Effect of Discretion on Procurement Performance," *Management Science*, 2018, *64.*

Davezies, Laurent and Thomas Le Barbanchon, "Regression discontinuity design with continuous measurement error in the running variable," *Journal of Econometrics*, 2017, *200* (2), 260–281.

Decarolis, Francesco, "Awarding Price, Contract Performance, and Bids Screening: Evidence from Procurement Auctions," *American Economic Journal: Applied Economics*, 2014, *6* (1 A), 108–132.

_ , "Comparing Procurement Auctions," *International Economic Review*, 2018, *59* (2), 391–419.

— , **Leonardo M. Giuffrida, Elisabetta Iossa, Vincenzo Mollisi, and Giancarlo Spagnolo**, "Bureaucratic Competence and Procurement Outcomes," *The Journal of Law, Economics, and Organization*, 2020, *No. 24201.*

— , **Raymond Fisman, Paolo Pinotti, and Silvia Vannutelli**, "Rules, Discretion, and Corruption in Procurement: Evidence from Italian Government Contracting," 2020.

Dini, Federico, Riccardo Pacini, and Tommaso Valletti, "Scoring rules," *Handbook of procurement*, 2006, pp. 293–321.

Espin-Sanchez, Jose-Antonio, Alvaro Parra, and Yuzhou Wang, "Equilibrium Uniqueness in Entry Games with Private Information," 2021.

Gerard, François, Miikka Rokkanen, and Christoph Rothe, "Bounds on treatment effects in regression discontinuity designs with a manipulated running variable," *Quantitative Economics*, 2020, *11* (3), 839–870.

Gourieroux, C., A. Monfort, and E. Renault, "Indirect inference," *Journal of Applied Econometrics*, 1993, *8* (1 S), S85–S118.

Guerre, Emmanuel, Isabelle Perrigne, and Quang Vuong, "Optimal nonparametric estimation of first-price auctions," *Econometrica*, 2000, *68* (3), 525–574.

Haile, Philip A and Yuichi Kitamura, "Unobserved Heterogeneity in Auctions," *The Econometrics Journal*, 2019, *22* (1), C1–C19.

Hong, Han and Matthew Shum, "Increasing Competition and the Winner ' s Curse : Evidence from Procurement," *Review of Economic Studies*, 2002, *69* (4), 871–898.

jae Eun, Dong, "Reducing ex-post adjustment by bid screening ex-ante : Evidence from procurement auctions for paving work," 2018.

Kang, Karam and Robert A Miller, "Winning by Default: Why is There So Little Competition in Government Procurement?," *The Review of Economic Studies*, 08 2021, *89* (3), 1495–1556.

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

Kleven, Henrik J and Mazhar Waseem, "Using Notches To Uncover Optimization Frictions And Structural Elasticities: Theory and Evidence from Pakistan," *The Quarterly Journal of Economics*, 2013, *128* (December), 669–723.

Krasnokutskaya, Elena, "Identification and Estimation of Auction Models with Unobserved Heterogeneity," *Review of Economic Studies*, 2011, *78* (1), 293–327.

— **and Katja Seim**, "Bid Preference Programs and Participation in Highway Procurement Auctions," *American Economic Review*, 2011, *101* (6), 2653–2686.

Krishna, Vijay, *Auction Theory* 2003.

Lebrun, Bernard, "First price auctions in the asymmetric N bidder case," *International Economic Review*, 1999, *40* (1), 125–142.

Lee, David S. and Thomas Lemieux, "Regression Discontinuity Design in Economics," *Journal of Economic Literature*, 2010, *20* (1), 281–355.

Levin, Dan and James L Smith, "Equilibrium in Auctions with Entry," *American Economic Review*, 1994, *84* (3), 585–599.

Lewis, Gregory and Patrick Bajari, "Procurement Contracting with Time Incentives Theory and Evidence," *Quarterly Journal of Economics*, 2011.

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

— **and** — , "Information acquisition and/or bid preparation: A structural analysis of entry and bidding in timber sale auctions," *Journal of Econometrics*, 2012, *168* (1), 29–46.

Liebman, Jeffrey B. and Neale Mahoney, "Do Expiring Budgets Lead to Wasteful Year-End Spending? Evidence from Federal Procurement Faculty Research Working Paper Series," *American Economic Review*, 2017, *107* (11), 3510–3549.

Lopomo, Giuseppe, Nicola Persico, and Alessandro T. Villa, "Optimal Procurement with Quality Concerns," *American Economic Review*, 2023, *113* (6), 1505–29.

MacKay, Alexander, "Contract duration and the costs of market transactions," *American Economic Journal: Microeconomics*, 2022, *14* (3), 164–212.

Macleod, W Bentley and James M Malcomson, "Implicit Contracts, Incentive Compatibility, and Involuntary Unemployment," *Econometrica*, 1989.

Malcomson, James M., "Relational incentive contracts," *The Handbook of Organizational Economics*, 2012, (508), 1014–1065.

— , "Relational Incentive Contracts," *The Handbook of Organizational Economics*, 2013.

Manelli, Alejandro M. and Daniel R. Vincent, "Optimal Procurement Mechanisms," *Econometrica*, 1995, *63* (3), 591–620.

Marmer, Vadim, Artyom Shneyerov, and Pai Xu, "What model for entry in first-price auctions? A nonparametric approach," *Journal of Econometrics*, 2013, *176* (1), 46–58.

Maskin, Eric and John Riley, "Asymmetric Auctions," *Review of Economic Studies*, 2003, *67* (3), 413–438.

— **and** — , "Equilibrium in Sealed High Bid Auctions," *Review of Economic Studies*, 2003, *67* (3), 439–454.

Mcfadden, Daniel, "A Method of Simulated Moments for Estimation of Discrete Response Models Without Numerical Integration," *Econometrica*, 1989, *57* (5), 995–1026.

Pakes, Ariel and David Pollard, "Simulation and the Asymptotics of Optimization Estimators," *Econometrica*, 1989, *57* (5), 1027–1057.

Pei, Zhuan and Yi Shen, "The devil is in the tails: Regression discontinuity design with measurement error in the assignment variable," *Advances in Econometrics*, 2017, *38* (October), 455–502.

Porter, Robert H and J Douglas Zona, "Detection of Bid Rigging in Procurement Auctions," *Journal of Political Economy*, 1993, *101* (3), 518–538.

Roberts, James W., "Unobserved heterogeneity and reserve prices in auctions," *RAND Journal of Economics*, 2013, *44* (4), 712–732.

Ryan, Nicholas, "Contract Enforcement and Productive Efficiency: Evidence From the Bidding and Renegotiation of Power Contracts in India," *Econometrica*, 2020, *88* (2), 383–424.

Samuelson, William F, "Competitive Bidding with Entry Costs," *Economics Letters*, 1985, *17*, 53–57.

Spagnolo, Giancarlo, "Reputation, competition, and entry in procurement," *International Journal of Industrial Organization*, 2012, *30* (3), 291–296.

Spulber, Daniel F, "Auctions and Contract Enforcement," *The Journal of Law, Economics, and Organization*, 1990, *6* (2).

Storn, Rainer and Kenneth Price, "Differential Evolution – A Simple and Efficient Heuristic for Global Optimization over Continuous Spaces," *Journal of Global Optimization*, 1997, pp. 341–359.

Sweeting, Andrew and Vivek Bhattacharya, "Selective Entry and Auction Design," *International Journal of Industrial Organization*, 2015, *43*, 189–207.

Szucs, Ferenc, "Discretion and Corruption in Public Procurement," 2020.

— , "Discretion and Favoritism in Public Procurement," *Journal of the European Economic Association*, 03 2023, *22* (1), 117–160.