Competition and Contract Performance: Evidence from US Defense Procurement

Rodrigo Carril* Andres Gonzalez-Lira† Michael S. Walker‡

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Abstract

We study the effects of increasing competition for public contracts through advertising. Publicizing contract opportunities promotes bidder participation, potentially leading to lower acquisition costs. Yet extensive advertising could also exacerbate the adverse selection of bidders on non-contractible quality dimensions. We study this trade-off in the context of procurement contracts for the U.S. Department of Defense. Our empirical strategy leverages a regulation that mandates agencies to publicize contract opportunities that exceed a certain threshold. We find that publicized contracts opportunities increases competition and leads to a different pool of vendors, which on average offer lower prices. However, we also find that the post-award performance of publicized contracts worsens, resulting in more post-award cost overruns and delays. The latter effect is driven by goods and services that are relatively more complex, highlighting the role of contract incompleteness. We show that for most product and service categories, the price gains ex-ante are modest relative to the increase in cost overruns ex-post. We conclude that publicizing contract opportunities in this context ends up "backfiring", leading to net increases in procurement costs.

*Department of Economics, Stanford University. Email: rcarril@stanford.edu

†Haas School of Business, UC Berkeley. Email: andres.gonzalez@berkeley.edu

‡US Department of Defense. Email: michael.s.walker110.mil@mail.mil

1. Introduction

Asymmetric information is a prominent feature of many market transactions. When procuring a good or service, a buyer often deals with two sources of uncertainty: sellers' production costs *ex-ante*, and the level of (non-contractible) quality experienced *ex-post* (Laffont and Tirole, 1990; Hart and Moore, 1988). Promoting competition between potential sellers is a common way of reducing *ex-ante* adverse selection for the buyer, as evidenced by the pervasive use of bidding procedures in public procurement. But how does competition affect the equilibrium provision of non-contractible quality? If low-cost suppliers also deliver superior quality, policies that promote competition in contracting will lead to cost savings *and* improved performance. Yet if this relationship operates in the opposite way, stronger competition may "backfire", leading to the selection of sellers that perform poorly *ex-post*.

We study the interplay of competition and contract outcomes in the context of US Department of Defense (DOD) procurement. In particular, we leverage a regulation that requires agencies to publicize contract opportunities that are expected to exceed $25,000 through a centralized online platform. We exploit the discontinuous nature of these publicity requirements to estimate the effect of enhanced information diffusion about contract opportunities on four sets of outcomes: the level of competition for the award, characteristics of the buyer-seller relationship, procurement costs, and post-award contractor performance. By providing evidence on all of these fronts, we quantitatively characterize the trade-off involved in broadly advertising contract opportunities with the goal of increasing competition. Furthermore, we exploit the rich heterogeneity in the types of contracts that the DOD awards to assess the role of contract incompleteness in explaining our results.

In principle, the sharp discontinuity in publicity requirements generates a convenient natural experiment. Contracts with an expected award amount around $25,000 should be similar on all dimensions, except for the differential regulatory requirements, which vary discontinuously at the threshold. However, a challenge with implementing this Regression Discontinuity Design (RDD) is that the requirement applies to *expected* pre-award amounts, a variable that we do not observe. In contrast, we observe *realized* actual award amounts, which may be partly affected by whether the contract solicitation was publicized. In other words, using actual award amounts as a running variable may be problematic, since it may partly reflect treatment effects, violating the assumptions of the standard RDD. This is likely to be the case if, as intended, publicizing solicitations increases competition and brings prices down.

The first part of our analysis proposes a method to estimate the magnitude of these effects on equilibrium award prices, by analyzing the densities of publicized and unpublicized contracts. Our method is robust to the existence of endogenous sorting below the threshold in order to avoid publicizing certain contracts. In fact, we are able to separately quantify the extent of strategic sorting[1] and the price effects of publicizing contracts. Intuitively, the identification argument relies

[1] In the Regression Discontinuity Design literature, this is typically referred to as "manipulation of the running variable", which results in bunching.

on the fact that while both effects might generate an excess mass of contracts in the area closely below the threshold, strategic sorting will be driven by unpublicized contracts, while price effects will be explained by publicized contracts.

Implementing our method, we find evidence that publicizing solicitations leads to lower contract prices. These effects are moderate, nonetheless, with an average saving of $470 at the threshold (roughly 2% of the total award). We also find evidence of some strategic sorting, which accounts for two-thirds of the excess mass observed below the threshold.

The second part of our analysis concerns estimating the effects of publicizing contract opportunities on three sets of outcomes: the level of competition, the characteristics of the selected vendors and their relationship to the specific buyers, and post-award performance. We implement an RDD on these non-price outcomes, and argue that we can use the results of the first part of the analysis to "correct" our estimates, accounting for price effects and strategic sorting. In practice, since both of these effects are estimated to be modest in magnitude, we still find a sharp and discrete jump in the likelihood of publicizing a contract as a function of its *realized* award value. This also implies that the quantitative effect of our proposed correction will be small.

We show that contract awards advertised in the government platform attract significantly more bids, therefore achieving the desired goal of increasing competition. We also show that these marginal participants are competitive, leading to changes in the characteristics of winning firms. In particular, awardees of publicized solicitations are more likely to have fewer past contracts with the awarding office and are more distant in terms of geographical location. Finally, advertised contracts result in worse ex-post performance, experiencing higher levels of cost overruns and delays. The latter results are driven by service contracts—as opposed to good purchases—, and by contracts that we ex-ante characterize as more complex. These heterogeneities highlight the role of contract incompleteness in explaining the effects of competition on post-award performance.

Taken together, our results indeed suggest that competition has mixed effects on contract outcomes. Ex-ante cost efficiencies are generated at the cost of an ex-post decrease in delivered quality. However, we show quantitatively that, for our setting, the former benefits are small relative to the latter costs. We illustrate this by comparing ex-ante price reductions with ex-post increases in cost overruns, which we can add up to compute net changes in acquisition costs. While there is a trade-off, in the sense that larger price reductions are associated with larger cost overruns, we find a net increase in total procurement costs for most product categories in our sample.

An implication of our results is that, at least in some cases, it might be convenient to restrict procurement competition to a limited number of bidders. Ultimately, the extent to which this is desirable depends on the buyers' specific preferences. In future work, we intend to combine our reduced form estimates with a discrete choice framework to recover buyers' valuations over different procurement outcomes, which will allow us to study how competition is endogenously determined. With the estimated parameters, we will empirically quantify the factors determining the extent of competition observed in the data. In particular, we can assess the relative weight that buyers put on competition, establishing sustained relationships with vendors, achieving ex-ante price reductions, and experiencing changes in ex-post performance. Recovering these preferences will allow us to speak to the severity of the agency problem in DOD procurement, and to evaluate the effects of alternative counterfactual policies related to advertising opportunities and competition.

Our paper relates to a series of studies that assess the effects of competition on contract outcomes, studying policies and rules oriented to increase (or restrict) competition in procurement (Athey, Coey, and Levin, 2013; Li and Zheng, 2009, 2012; Krasnokutskaya and Seim, 2011). We leverage variation in the intensity of competition that emerges from exogenous changes in the extent of information dissemination about contract opportunities, keeping fixed other characteristics of the institutional setting. In this respect, our paper is closely related to Coviello and Mariniello (2014), who study a similar policy in Italy.

The existing literature has also examined the role of buyers' characteristics and choices in procurement outcomes (Bandiera, Prat, and Valletti, 2009; Liebman and Mahoney, 2017; Coviello and Gagliarducci, 2017; Best, Hjort, and Szakonyi, 2017; Decarolis, Giuffrida, Iossa, Mollisi, and Spagnolo, 2018; Carril, 2020). By analyzing how public buyers endogenously promote competition, our contribution is closely related to Kang and Miller (2017), who study buyers' competition determination for IT contracts in the United States.

We also contribute to the large literature examining the role of incomplete contracts (Hart and Moore, 1988). One strand of this literature studies the design of procurement mechanisms to reduce the adverse effects of incomplete contracts, e.g., by studying auctions vs. negotiations (Bajari, McMillan, and Tadelis, 2009). Another set of studies have analyzed the role of repeated interactions as a potential tool to align incentives when contracts are difficult to fully specify (Banerjee and Duflo, 2000; MacLeod, 2007; Decarolis et al., 2020). Finally, there has been an attempt to connect these two strands, by explicitly studying the trade-off between competition and *ex-post* performance (Spulber, 1990; Bajari, Houghton, and Tadelis, 2014; Decarolis, 2014). Our main contribution is to study this tension across a rich set of heterogeneous goods and services, explicitly showing how the benefits and costs of competition depend on the degree of complexity of the purchase.

Finally, our method to identify price effects from the density of contracts follows the spirit of the estimators in the "bunching" literature (Saez, 2010; Kleven and Waseem, 2013; Kleven, 2016). We depart from the standard bunching design by proposing an empirical framework that recovers both contract manipulation (bunching) and potential treatment effects on the running variable.[2]

The rest of the paper proceeds as follows. Section 2 provides some background on the US procurement system and the data used in our analysis. In Section 3, we present our empirical framework for estimating the effects of publicizing contract opportunities. We present our results in Section 4. Section 5 contrasts the pre-award price effects with the post-award performance effects. Finally, Section 6 concludes, highlighting open questions for future work.

[2]In our setting, the effect of competition on contract prices.

2. Setting and Data

2.1. US Federal Procurement and Publicizing Requirements

Procurement is a large component of the US federal budget. In fiscal year 2018, federal contract awards totaled $835 billion, representing 20% of total federal outlays, and two-thirds of discretionary spending.[3] Contracts are awarded at highly decentralized levels, with more than 3,000 different contracting offices that are part of an executive or independent agency.[4] The workforce in charge of public contracting is made up of over 35,000 contracting officers whose primary role is to plan, carry out, and follow-up on purchases made by their units.

Contracting officers' scope of action is defined and limited by the Federal Acquisition Regulation (FAR). The FAR lays out policy goals and guiding principles, as well as a uniform set of detailed policies and procedures to guide the procurement process. Our analysis leverages a specific section of the FAR—Part 5 (*Publicizing Contract Actions*)—as a convenient natural experiment to study the effect of information diffusion.

FAR Part 5 requires publicizing contract opportunities in order to "increase competition", "broaden industry participation", and "assist small businesses (and other minority businesses) in obtaining contracts". Since October 1, 2001, contract actions expected to exceed $25,000 must be synopsized in an online government-wide platform which we will refer to as FedBizOpps (or FBO).[5] This implies uploading a request for quotes with a full description of the good or service being requested, and the instructions to submit the bids. We will refer to this synopsis document as a contract *solicitation*. Most of the contracts in this range are awarded to the lowest price quote that is technically acceptable according to the specifications.

Contracts that are not expected to exceed this threshold need not be publicized in FedBizOpps, although procurement officers should advertise the solicitation "by displaying [it] in a public place." This includes, for example, a physical bulletin board located at the contracting office. Of course, officers with contracts expected to fall below the threshold are still free to use FedBizOpps. On the other hand, the regulation allows for exemptions to the requirement above the threshold, as long as the procurement officer can properly justify it on grounds that it "compromises national security", that "the nature of the file does not make it cost-effective or practicable", or that "it is not in the government's interest". Therefore, while we expect that this policy may discretely affect the likelihood that a contract is publicized online around the $25,000 threshold, we anticipate that compliance may be far from perfect, given the voluntary nature of the rule below this value and the

[3]Discretionary spending excludes mandatory programs (such as Social Security and Medicare) and interest on debt.

[4]Executive agencies are headed by a Cabinet secretary, like the Department of Defense, the Department of State, or the Department of Health and Human Services. Independent agencies, which are not part of the Cabinet, include the Central Intelligence Agency, the Environmental Protection Agency, and the Federal Trade Commission.

[5]Throughout our period of analysis, this online platform—designated as the "government point of entry" by the FAR—was called Federal Business Opportunitites (FBO) and was available at: `fedbizopps.gov`. In late 2019 (after our sample period ends), the government point of entry migrated to `beta.sam.gov`, featuring significant changes to the user interface.

availability of exceptions above.

2.2. Data

We use two complementary sources of data. The first one consists of the historical files from FedBizOpps, which provides detailed information on pre-award notices (i.e. solicitations) posted on the platform. The second one is the Federal Procurement Data System - Next Generation (FPDS-NG), which tracks federal contracts from the time of their award and including all follow-on actions, such as modifications, terminations, renewals, or exercises of options.

We merge awards from FPDS-NG to notices on FedBizOpps using the solicitation number. Note, however, that while FPDS-NG contains the universe of federal awards, FedBizOpps only has the notices posted on the website. From this matching process, we construct a dummy variable that is equal to 1 if we are able to merge a contract with any pre-award notice on FedBizOpps, in which case we say the contract was *publicized*. Appendix Figure A1 describes the typical timeline of events surrounding the life-cycle of a contract, and the appropriate data source that records that information.

In addition, we observe detailed information for each contract award, including the dollar value of the funds obligated, a four-digit code describing the product or service, codes for the agency, sub-agency, and contracting office making the purchase, the identity of the private vendor, the type of contract pricing, the extent of competition in the award, characteristics of the solicitation procedure, the number of offers received, and the applicability of a variety of laws and statutes.

The analysis sample consists of all definitive contracts[6] with award values between $ 5,000 and $ 45,000, awarded in fiscal years 2011 through 2017 by the Department of Defense (DOD),[7] for products and services other than Research and Development (R&D).[8] Table 1 presents summary statistics of the sample. In total, there are roughly 240,000 contracts awarded by 760 contracting offices to almost 60 thousand distinct firms. Contract durations are expected to be 55 days on average and are awarded on a fixed-price basis. A noteworthy feature of this setting is that competition is very limited: more than a third of the awards are set-aside for a particular type of firm (typically, small business), and the average contract receives 2.4 offers, with the median contract receiving a single offer. The Department of the Navy and the Army each account for more than 40% of the contracts, with the rest being mostly awarded by the Air Force. Winning vendors are often geographically close to the contracting offices, with both located in the same state in 3 out of every 4 contracts. Finally, 62% of suppliers are characterized as small businesses.

We also observe rich information about the type of good and service that is contracted upon.

[6]Federal contracts can be broadly categorized into two types: definitive contracts (DCs) and indefinite delivery vehicles (IDVs). DCs are stand-alone one-time agreements with a single vendor for the purchase of goods or services under specified terms and conditions. See Carril (2020) for more details. We simplify the analysis by focusing exclusively on DCs, which are well-defined requirements involving a bilateral relationship within a single government unit and a private firm.

[7]The Department of Defense represents 55% overall federal spending and more than 60% in the restricted sample.

[8]R& D awards are subject to a whole set of special rules, see FAR Part 35.

Each award is classified into one of 1,918 possible standardized 4-digit alphanumeric codes. These can be aggregated into 101 broader 2-digit product categories, 77 goods and 24 services. Table 2 shows the top 10 most common 2-digit good and service categories. The most common product categories are ADP Equipment Software, Medical Equipment and Supplies and Maintenance and Repair Equipment.

Table 1: Summary statistics

	Mean
Contract Characteristics	
Expected Award Amount	22,070
Expected Duration (days)	55.15
Fixed-Price Contract	0.999
Competitively Awarded	0.614
Set Aside Award	0.357
Simplified Procedure	0.728
Competition	
Number of Offers	2.452
One Offer	0.530
Contracting Office Characteristics	
Navy	0.422
Army	0.402
Air Force	0.134
Other	0.043
Awarded Firm Characteristics	
Foreign	0.092
Within-State Firm	0.741
Small Business	0.620
Woman Owned Business	0.137
Sample	
No. of Contracts	240,514
No. of Contracting Offices	760
No. of Firms	59,697

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 $ 5,000 and $ 45,000, awarded by the Department of Defense in fiscal years 2011 through 2017. An observation is a contract, defined by aggregating all contract *actions* (initial award, modification, termination, etc.) associated with the same contract ID.

Table 2: Top product and service categories

	Goods		Services	
Rank	Name	N Contracts/year	Name	N Contracts/year
1	ADP Equipment and Software	3,005	Maintenance/Repair of Equipment	2,430
2	Medical Equipment and Supplies	2,998	Support Services (Professional)	1,187
3	Laboratory Equipment	1,643	Utilities And Housekeeping	1,096
4	Electrical Equipment Compontents	1,593	Transport, Travel, Relocation	854
5	Communication/Coherent Radiation	1,202	ADP and Telecommunications	806
6	Furniture	810	Lease/Rent Equipment	753
7	Power Distribution Equipment	697	Maintenance of Real Property	688
8	Ship And Marine Equipment	574	Education And Training	560
9	Hardware And Abrasives	530	Construct Of Structures/Facilities	335
10	Construction And Building Material	459	Social Services	286

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 \$ 5,000 and \$ 45,000, awarded by the Department of Defense in fiscal years 2011 through 2017. 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.

3. Empirical Framework

In this section, we propose a stylized model that captures some of the key aspects of the DOD procurement process, particularly in relation to publicizing decisions. We use this framework to motivate and explain our empirical approach.

3.1. Setup

A public buyer seeks to award a contract k to acquire a good or service. There is a set of potential suppliers $\mathcal{J}$. Each $j \in \mathcal{J}$ is characterized by a vector (c_{jk}, q_{jk}, ψ_j), which is private information, and where c_{jk} represents production costs, q_{jk} is a parameter that describes *expected* post-award performance, and ψ_j captures other contractor characteristics that are independent of the particular contract k.

If the buyer awards contract k to supplier j, then the buyer obtains contract outcomes $Y_{jk} = (p_{jk}, \tilde{q}_{jk}, \psi_j)$, where p_{jk} is the award price and $\tilde{q}_{jk}$ is the *realized* post-award performance. $\tilde{q}_{jk}$ is stochastic and is drawn from a distribution $\mathcal{F}(\cdot|q_{jk})$. The buyer evaluates contract outcomes according to a utility function $U(Y_{jk})$.

The buyer has a set of preferred or default suppliers $\mathcal{J}^0 \subset \mathcal{J}$, for which she knows (c_{jk}, q_{jk}, ψ_j). Let p_{0k} be the price at which the contract would be awarded, if she only solicits quotes from the default set $\mathcal{J}^0$. Alternatively, she can decide to post the solicitation on a public platform (i.e. FedBizOpps), in which case the set of potential bidders (weakly) expands to $\mathcal{J}^1 \subseteq \mathcal{J}^0$. Let p_{1k} be the price at which the contract would be awarded when solicited publicly through the platform.

There is a regulation that establishes that all contract awards expected to exceed $\bar{p}$ should be publicized on the platform. Nothing prevents buyers from using the platform if they expect not to exceed $\bar{p}$. They can also claim an exception to avoid the use of the platform even when they expect to be above $\bar{p}$. We assume that to claim such an exception, the buyer pays a utility cost of κ. Finally, if the award is expected to exceed the threshold, the buyer can also modify the contract characteristics (e.g. by reducing the scope of the contract), in order to reduce the quote obtained from the default set, and award $p_{0k} = \bar{p}$.

Appendix Figure A9 represents the model in a tree form, highlighting the timing of the game and the decision points at which the buyer moves. If the preferred quote p_{0k} does not exceed $\bar{p}$, then the buyer chooses between publicizing $(D_k = 1)$ and not $(D_k = 0)$, with award prices p_{1k} and p_{0k}, respectively. On the other hand, if $p_{0k} > \bar{p}$, then the buyer chooses between publicizing and awarding p_{1k}, not publicizing to award p_{0k} and pay the cost κ, or "bunching" at $\bar{p}$ by modifying the contract ($B_k = 1$).

With this structure, we can write the observed, *realized* award for contract k, as: $p_k = D_k \cdot p_{1k} + B_k \cdot \bar{p} + (1 - D_k - B_k) \cdot p_{0k}$, which we can rewrite as:

$$p_k = p_{0k} + D_k \cdot \underbrace{(p_{1k} - p_{0k})}_{\text{price effect}\equiv\delta_k} + B_k \cdot \underbrace{(\bar{p} - p_{0k})}_{\text{bunching}} \tag{1}$$

Now consider an empirical strategy that leverages the discontinuity in the FedBizOpps requirement to analyze the effect of publicizing contract solicitations on contract outcomes Y_k. Unable to observe the ex-ante expected awards, the implementation of this strategy would imply the use of realized award values p_k as a running variable in our RDD. Equation (1) makes clear the issues with this approach. On the one hand, the possibility of engaging in strategic bunching to avoid the publicity treatment would invalidate the standard design.[9] On the other hand, note that publicizing contracts, by leading to a different set of offerers, affects the equilibrium price at which the contract is awarded. This means that the treatment itself may have an effect on the running variable, again violating the assumptions of the standard RDD. Importantly, note that this price effect of publicizing contracts ($\delta_k \equiv p_{1k} - p_{0k}$) is not just a nuisance that we want to correct for, it is a magnitude of direct interest that we seek to quantify.

We propose a method to separately estimate δ_k from the confounding effect of strategic bunching. The argument is based on the fact that we observe both the density of publicized and unpublicized contracts, each of which is affected by only one of these unobserved effects. Moreover, once we estimate these magnitudes, we can use them to "correct" the estimation of the causal effects of publicizing contracts on another set of non-price outcomes, such as the intensity of competition, characteristics of the winning supplier, and post-award performance. Intuitively, these amended RDDs reweight observations to "shut down" the confounding effects of δ_k and bunching.

[9] This problem, known in the literature as "manipulation of the running variable", has been found in many contexts. In fact, Gerard, Rokkanen, and Rothe (2016) show that partial identification is still obtained in this case, and that the bounds converge to a point estimate as the amount of manipulation goes to zero.

3.2. Estimating Price Effects

We explain the logic of our method graphically in Figure 1. Suppose there is a large number of contracts, each of which has a preferred quote p_0. Panel (a) depicts a hypothetical distribution of these quotes, as well as separate densities of p_0 for publicized and unpublicized contracts. The policy generates a discontinuous jump in the share of publicized contracts right when p_0 crosses \$25,000. This is reflected by positive jump in the (latent) density of preferred quotes for publicized contracts, and a corresponding 1-to-1 drop in the density of p_0 for unpublicized contracts. Independently of publicizing choices, the aggregate density of p_0 is assumed smooth.

Now suppose that publicizing contracts has no effect on prices, so that $p_1 = p_0$, and that no bunching opportunities exist. Panel (b) shows in orange the densities of *observed* awards for each of the three categories (publicized, unpublicized, and total). These coincide exactly with the latent densities of p_0. For unpublicized contracts, this is by construction, since $p_k = p_0$. For publicized contracts, this is explained by the fact that $p_k = p_1$, and there are no price effects.

Panel (c) adds a constant price effect of $\delta_k = -2$. This means that every solicitation posted on FedBizOpps leads to a price p_1 that is \$2,000 lower than the preferred quote.[10] The price effects generates an excess mass below the threshold in the total density, compensated by a small decrease in the levels everywhere to the right of the threshold. These changes in the total density are explained by a leftward shift in the density of publicized contracts. Importantly, the density of unpublicized contracts is not affected by these price effects.

Panel (d) repeats the exercise in (c), assuming instead a constant *positive* price effect of \$2,000 from publicizing solicitations. While this might be irrelevant in practice (increasing the number of potential offerers is unlikely to increase award prices), a similar logic applies. This time, some missing mass to the right of the threshold appears in the total density, compensated by a small increase from that point to the right. Again, this comes entirely from the publicized density, and not from the unpublicized one.

Panel (e) depicts one more example of price effects, this time assuming $\delta_k \sim N(0, 1)$. In the total density, this generates a symmetric excess mass below the threshold and missing mass above it. Again, this comes from changes in the publicized density, not the unpublicized one. And in this case, the stochastic price effect smooths-out the jump at the threshold for the unpublicized density.

Finally, Panel (f) shuts down the price effect again ($\delta_k = 0$), but allows for some strategic bunching. This also generates excess mass below the threshold in the total density. Unlike in all of the above cases, however, this is explained by changes in the unpublicized density, while the publicized density remains unaffected.

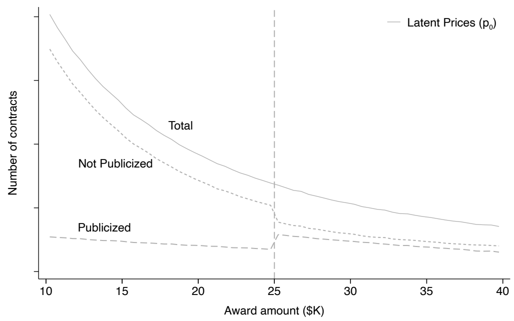
Because we observe the distribution of contract awards, as well as decisions to post on FedBizOpps, we can compute these two separate densities of publicized and unpublicized contracts. As Figure 1 illustrates, having these two sets of moments can help us to separately identify the two unobserved magnitudes of average price effects $\mathbb{E}[\delta_k]$ and the extent of bunching.

[10] We measure δ_k in thousand dollars.

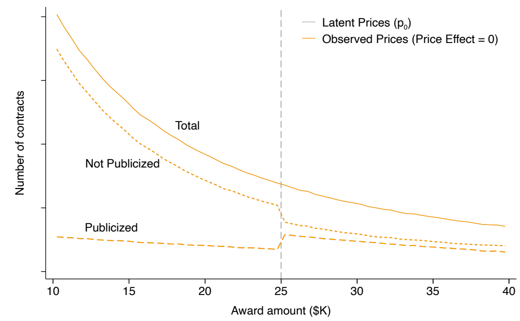
We believe that this argument is sufficiently powerful to enable the nonparametric identification of these objects under relatively mild assumptions. However, we leave that proof and its implementation for future work. Here, instead, we directly impose parametric assumptions on p_{0k}, δ_k, $\Pr(D_k = 1|p_0)$, and $\Pr(B_k = 1|p_0)$, and find parameters to maximize the fit of the model. The estimation details and results are presented in Section 4.1.

Figure 1: Distinguishing between price effects and strategic bunching

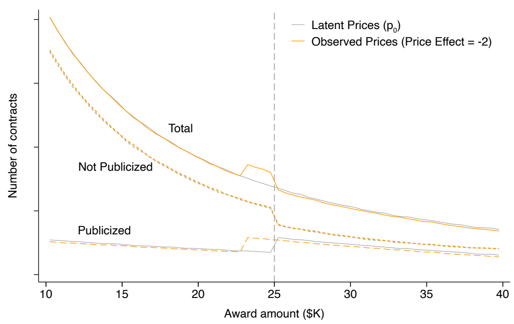
(a) Latent price densities



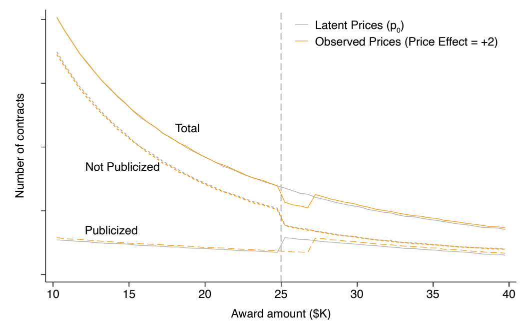
(b) No price effects



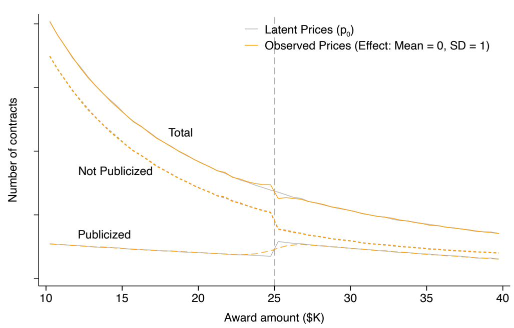
(c) Fixed negative price effects



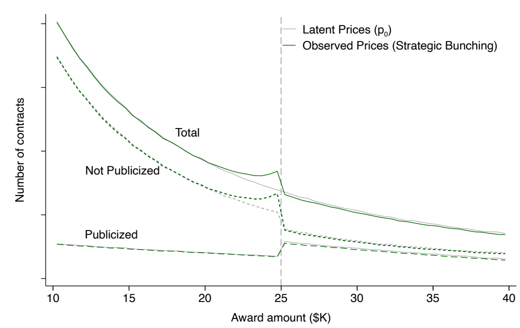
(d) Fixed positive price effects



(e) Stochastic normally distributed price effects



(f) Strategic bunching



Notes: This figure presents conceptual graphs to illustrate the identification of price effects and strategic bunching. Each of the graphs depicts contract densities, where the horizontal axis measures award amounts (in thousand dollars) and the vertical axis measures number of contracts. In each of the graphs, we show the density of publicized and unpublicized contracts, as well as the total density (the sum of these two). In Panel (a), the densities correspond to the latent expected awards p_0. In Panel (b), we add the observed densities for a hypothetical case of zero price effects and no strategic bunching. In Panel (c), we show the effect of a constant deterministic price effect of $-\$2,000$ on every publicized contract. Panel (d) repeats the exercise but with a $+\$2,000$ price effect. In Panel (e), we instead consider a stochastic, standard-normal price effect. Finally, Panel (f) shows a case with no price effects, but with strategic bunching.

3.3. Estimating Effects on Non-price Outcomes

The successful estimation of price effects and the extent of strategic bunching allows us to correct the biases that are introduced by using p_k as a running variable (instead of p_0) in an RDD applied to other outcomes. We are interested in specifications of the following form:

$$Y_k = \alpha + \beta \cdot D_k + g(p_{0k}) X_k' \delta + \epsilon_k \quad , \tag{2}$$

and we are interested in β, the causal effect of publicizing a solicitation on contract outcome Y_k. In the standard RDD, we obtain an estimate $\widehat{\beta}_{LATE}$ by instrumenting D_k with the discontinuity in publicity requirements. The first-stage of this IV procedure is of the form:

$$D_k = \lambda + \gamma \cdot \mathbf{1}[p_{0k} > \bar{p}] + g(p_{0k}) + X_k' \eta + \nu_k \quad , \tag{3}$$

for some smooth function $g(\cdot)$. A key advantage of this approach is that it is possible to provide compelling evidence on the existence of an effect by graphically showing the reduced form of this model, i.e.:

$$Y_k = \mu + \phi \cdot \mathbf{1}[p_{0k} > \bar{p}] + g(p_{0k}) + X_k' \pi + \xi_k \quad . \tag{4}$$

Again, the key challenge we face is that we observe p_k, but not p_{0k}. In terms of the price effect, it is easy to see why we can construct an unbiased estimate of the running variable for publicized contracts. At each observed price p_{1k}, we want to estimate $\mathbb{E}[p_{0k}|p_{1k}] = \mathbb{E}[p_{1k} - \delta_k|p_{1k}] = p_{1k} - \mathbb{E}[\delta_k|p_{1k}]$, where p_{1k} is observed and from the previous analysis we recover a consistent estimate of $\mathbb{E}[\delta_k|p_{1k}]$.

On the other hand, estimating the extent of bunching allows us to re-weight observations to appropriately reflect the average outcomes in the absence of this behavior. Using the results from Gerard, Rokkanen, and Rothe (2016), we can nonparametrically identify bounds on the treatment effects.

In this version of the paper, we do not implement these corrections, leaving them for future work. We will present in Section 4.2 the results from RDDs that use realized awards as the running variable, despite the interpretation caveats highlighted here.

However, it is important to consider that, in practice, the results presented below in Section 4.1 will show that both the price effects and the extent of bunching are very limited in our sample. That is an interesting result in and of itself, especially in terms of learning about the price effects of more intense competition through publicizing solicitations. However, they also imply that the aforementioned corrections of the RDDs will have at most modest effects. So while the estimates presented in Section 4.2 will not be definitive, we expect them to be highly informative of the true causal effects.

4. Results

4.1. Price Effects of Competition

4.1.1. Estimation Details: To implement the method described in Section 3.2, we make the following parametric assumptions. Unobserved preferred quotes are assumed log-normally distributed, $p_{0k} \sim \log N(\mu_p, \sigma_p^2)$. Price effects follow a normal distribution: $\delta_k \sim N(\mu_\delta, \sigma_\delta^2)$. Publicizing probabilities are characterized by a probit that depends quadratically on p_0 and is shifted by the noncompliance cost k. That is:

$$D_k = \alpha_0 + \alpha_1 \cdot p_{0k} + \alpha_2 \cdot p_{0k}^2 + \kappa \cdot \mathbf{1}[p_{0k} > \bar{p}] + \nu_k \quad , \tag{5}$$

where ν_k $N(0,1)$. Finally, and for simplicity, bunching probabilities are assumed constant for all preferred quotes above the threshold, i.e. $\Pr(B_k = 1|p_{0k}) = m_0 \cdot \mathbf{1}[p_{0k} > \bar{p}]$.

The model is then defined by a vector of nine parameters, $\theta = (\mu_p, \sigma_p^2, \mu_\delta, \sigma_\delta^2, \overrightarrow{\alpha}, \kappa, m_0)$. We follow Carril (2020) and estimate the parameters using simulated method of moments, matching smoothed versions of discretized densities for publicized and unpublicized contracts. We first define 60 right-inclusive bins of award amounts of \$500 width from \$10,000 to \$40,000.[11] Then we compute the normalized frequencies of publicized and unpublicized contracts at each bin, and fit a flexible polynomial with round-number corrections. The resulting 120 moments are used as targets for our simulated data.[12]

4.1.2. Results: Parameter estimates are presented in Table 3, both for the full sample, and separately for goods and services. The main finding is that the average price effect of publicizing contracts is -\$471. This means that, on average, posting a solicitation on FedBizOpps reduces the awarded price by roughly 2%.

The model fit is presented in Figure A10. Panels (a) and (b) present the densities of unpublicized and publicized contracts, respectively. Panel (c) presents the total density (the sum of (a) and (b)), and Panel (d) the share of publicized contracts at any given price level.

We then use the model to generate counterfactuals that allow us to shut down each of the effects, in order to quantify them. Figure 2 Panel (a) shows the density of publicized contracts, along with a counterfactual density in which price effects are eliminated. As we discussed in Section 3.2, price effects smooth-out this density at the threshold. The excess mass relative to the counterfactual that we see to the right of the threshold represents the set of contracts that had expected awards above the threshold, but were brought below it because of the competitive effect of publicizing the solicitations.

Panel (b) presents a second counterfactual, this time shutting down the possibility of bunching.

[11] That is, $(\$10K, \$10.5K], (\$10.5K, \$11K], ..., (\$39.5K, \$40K]$.

[12] See Carril (2020) for more details.

Table 3: Parameter estimates

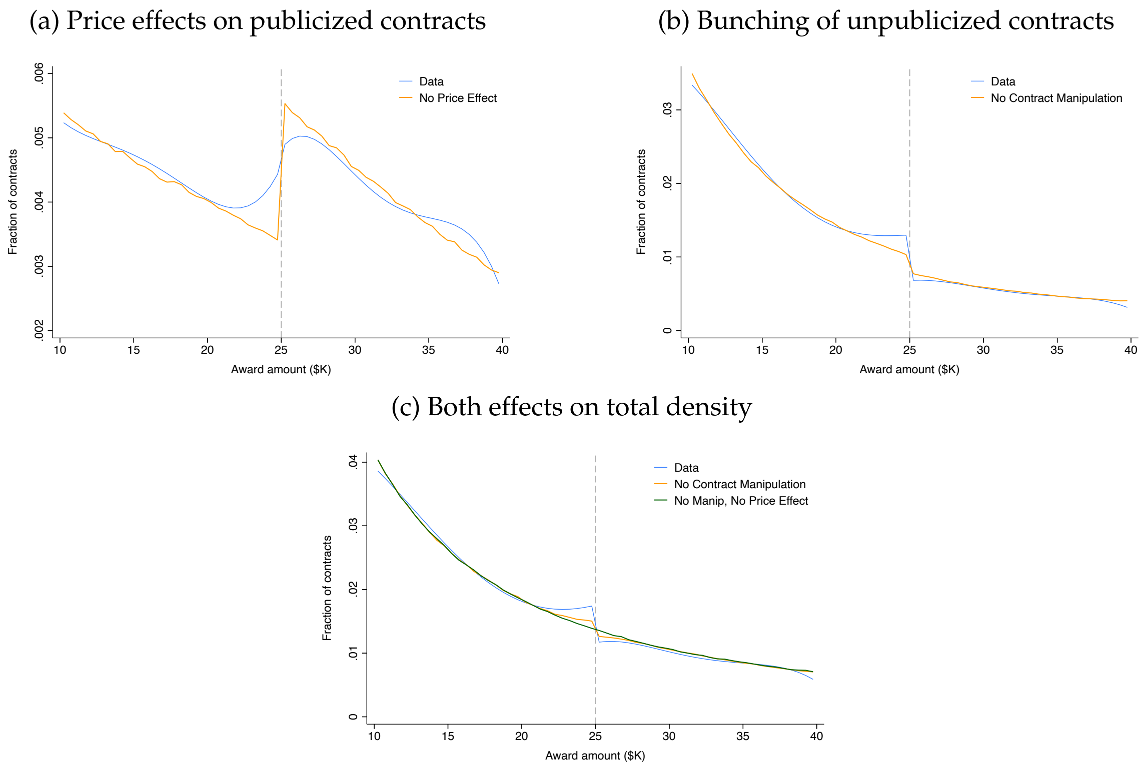
	Estimates		
Parameter	All Products	Goods	Services
Mean unpublicized price (μ_p^0)	2.128	2.133	2.097
S.d. unpublicized price (σ_p^0)	1.756	1.748	1.805
Mean price effect (μ_δ)	-0.471	-0.390	-0.539
S.d. price effect (σ_δ)	1.579	1.532	1.849
α_0	-1.655	-1.895	-1.295
α_1	0.064	0.075	0.050
α_2	-0.001	-0.001	-0.001
κ	0.475	0.552	0.346
m_0	0.026	0.028	0.021

Notes: This table presents model parameter estimates obtained via simulated method of moments. The estimation 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 2011 through 2017. The moments used in the estimation correspond to the smoothed fraction of publicized and unpublicized contracts, for each \$500-wide award bin between \$10,000 and \$40,000.

The effects are seen on the density of publicized contracts. Just like we anticipated in Section 3.2, some of the mass just below the threshold relocates to the right.

Finally, we present the effect of each of the above counterfactuals on the total density of contracts in Panel (c). Based on this analysis, we can conclude that one-third of the total excess mass below the threshold is due to price effects of competition, whereas the rest is explained by strategic bunching.

Figure 2: Counterfactuals



Notes: This figure shows model-based counterfactual estimates that seek to quantify the effects of price effects and strategic bunching. Panel (a) shows the smoothed density of publicized contracts in the data, compared to a simulated density assuming a price effect of zero for all contracts. In Panel (b), we plot the smoothed density of unpublicized contracts in the data, compared to a simulated density assuming no contract manipulation. Panel (c) shows the effects of both of these counterfactual simulations on the total density of contracts.

4.2. Contract Publicity, Competition and Outcomes

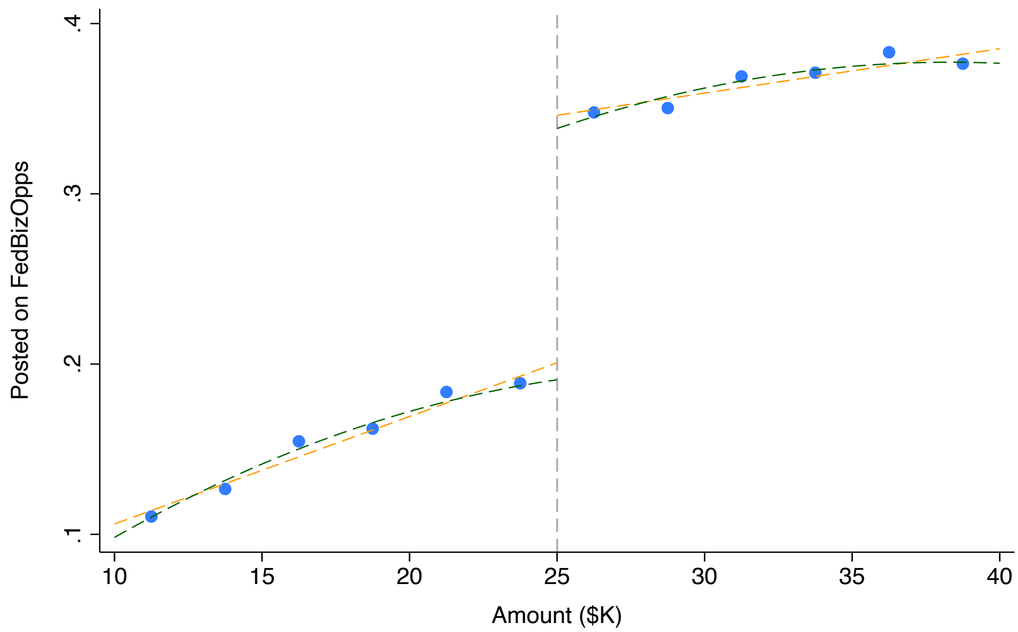
We estimate the effect of publicizing contract solicitations on procurement outcomes following the strategy described in Section 3.3, consisting of a set of three key specifications, Equation (2), Equation (3) and Equation (4). Recall that we estimate these regressions using actual award amounts (p_k) instead of ex-ante expected awards (p_0), leaving for future work an appropriate correction procedure. We consider linear and quadratic fits for the function $g(\cdot)$, and do not include controls X_k in our baseline specification.[13]

We start by estimating the first stage Equation (3). The results are presented graphically in Figure 3. We see that the use of FedBizOpps jumps sharply past the $25,000 threshold of realized award amounts. This is despite the theoretical concerns that price effects might have contributed to "erase" this sharp first stage, and is consistent with our results from Section 3.2, indicating that price

[13]Because of the preliminary nature of these estimates, we concentrate on providing compelling visual evidence in the form of RDD plots, and refer to the magnitudes implied by them. However, we leave the formal estimation of coefficient magnitudes and appropriate standard errors for when we implement the full adjusted RDD procedure.

effects are quantitatively small. The share of contracts that are publicly solicited in the government platform increases from roughly 18% at or slightly below $25,000, to 33% right past this threshold.

Figure 3: Publicizing requirement and use of FedBizOpps



Notes: This figure shows the fraction of contracts posted on FedBizOpps 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 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. Award amounts are discretized into right-inclusive bins of $2,500 dollars length.

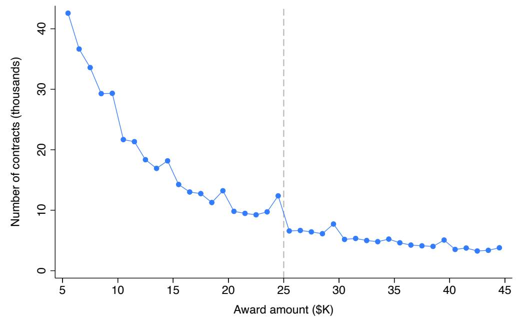
Another way to see that the role of selection in this context is small is to consider again the density of total awarded contracts. As Figure 4 shows, once we control for round number effects, the total excess mass below the threshold is small, limiting the scope for bias. Additionally, it is also reassuring that pre-award contract characteristics do not vary sharply at the threshold, as we show in Appendix Figure A2.

Reassured by all this evidence, we proceed to estimate reduced form effects (Equation (4)) of publicizing contracts on three sets of outcomes: the intensity of competition, winning vendor characteristics (including its relationship with the awarding office), and post-award performance. Most of the existing literature has studied these variables independently.[14] By studying them jointly, we are able to generate a comprehensive understanding of the mechanisms and implications of policies oriented to enhance competition.

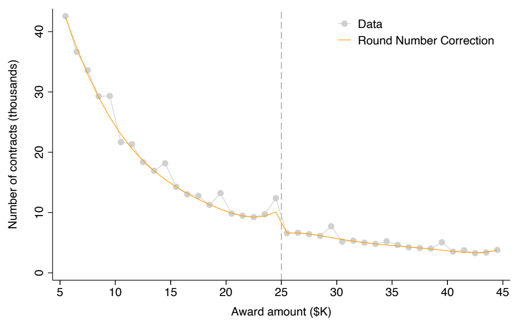
[14]See for example, Athey (2001); Li and Zheng (2009) (competition), Macleod and Malcomson (1989); Bajari et al. (2009); Malcomson (2012) (relations), and Bajari et al. (2014); Decarolis et al. (2018); Ryan (2020) (ex-post renegotiation and performance).

Figure 4: Contract award density

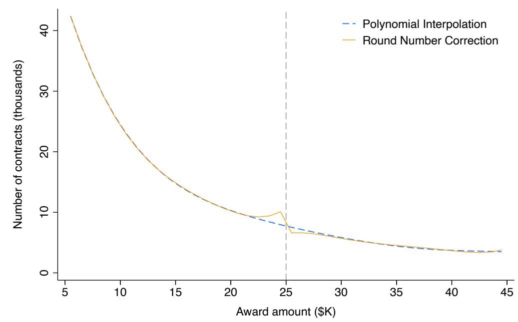
(a) Raw density



(b) Round number correction



(c) Polynomial interpolation

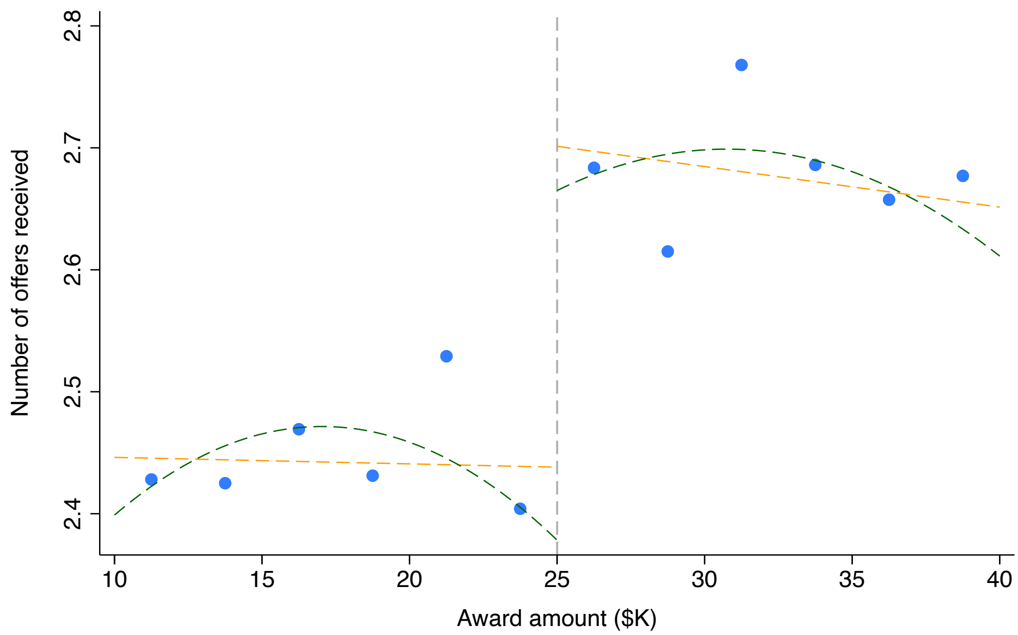


Notes: This figure shows the frequency distribution of contract awards as obtained from the data, as well as some non-parametric corrections. The data source is the Federal Procurement Data System-Next Generation. The sample consists of non-R&D definitive contracts and purchase orders, with award values between $ 5,000 and $ 45,000, awarded by the Department of Defense in fiscal years 2011 through 2017. Award amounts are discretized into right-inclusive bins of $1,000 dollars length. Panel (a) shows the raw frequency distribution. Panel (b) compares this with a smoothed function that corrects for round number effects at every $5,000 and $10,000 multiple, following the methodology from Kleven and Waseem (2013). Panel (c) compares the round number correction with a 5th-degree polynomial interpolation that excludes awards between $20,000 and $30,000.

4.2.1. Competition: Figure 5 shows how posting solicitations on FedBizOpps impacts the number of offers that a contract receives around the threshold. Contracts right above $25,000 (which are more likely to be publicly solicited), receive roughly 0.25 more bids. This effect is quite large for this context: the average contract receives less than 2.5 offers below the threshold, indicating a reduced form effect of more than 10%. Moreover, since the policy only changes the likelihood of a publicized solicitation by around 15p.p. (see Figure 3), this implies a causal effect of approximately 67%.

These results indicate that encouraging the public posting of solicitations leads to the stated goal of increasing competition, by attracting additional bids. However, an open question is whether these marginal new offers change the equilibrium allocation of the contract. We now turn to this question by analyzing the effects on the characteristics of the selected supplier.

Figure 5: Publicity and intensity of competition



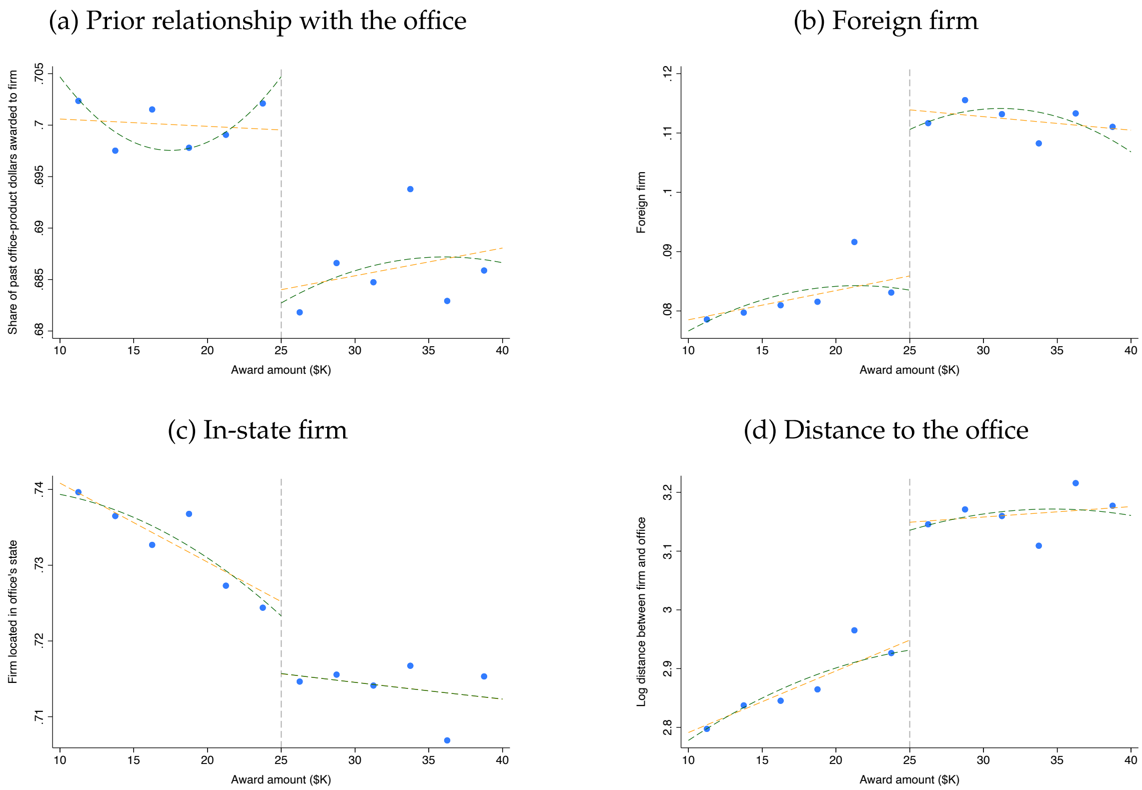
Notes: This figure shows the average number of offers received by bins of award amounts, as well as linear and quadratic fits at each side of $25,000. The data source is the Federal Procurement Data System-Next Generation. The sample consists of non-R&D definitive contracts and purchase orders, with award values between $ 5,000 and $ 45,000, awarded by the Department of Defense in fiscal years 2011 through 2017. Award amounts are discretized into right-inclusive bins of $2,500 dollars length.

4.2.2. Awarded Contractor Characteristics: Publicizing solicitations could attract marginal bidders that are not competitive, leaving the characteristics of the average selected supplier unchanged. However, Figure 6 shows that this is not the case. In Panel (a), we see that publicized contracts are awarded to vendors that have less prior contact with the office, as measured by the share of previous contract dollars for the same product category that were awarded to the firm. We also see in Panel (b) that publicized contracts are awarded to geographically more distant vendors, relative to the location of the contracting office. Along the same lines, Panel (c) and Panel (d) show that these selected contractors are more likely to be foreign and less likely to be in the same state as the buyer.

Taken together, these results suggest that marginal entrants attracted by the public solicitation do win awards with some positive probability. Furthermore, compared to the vendors of unpublicized contracts, they tend to have less previous contact with the contracting office and are further away from their physical location.

4.2.3. Performance: We now measure effects on post-award performance. We use two measures of contract performance that are commonly used in the literature: cost overruns and delays (e.g. Kang

Figure 6: Publicity and the characteristics of the winning firm

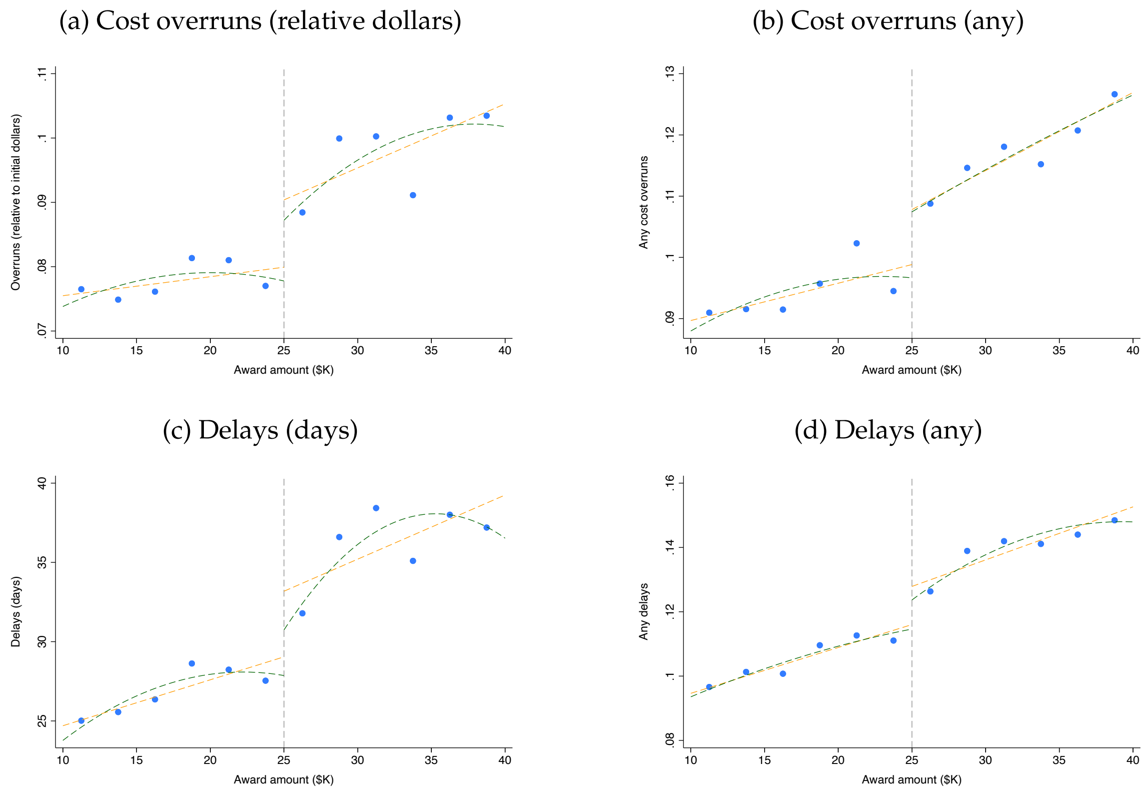


Notes: This figure presents four binned scatter plots, which depict an average outcome by bins of award amounts, as well as linear and quadratic fits at each side of $25,000. The outcome in each Panel is as follows: (a) the share of previous contract dollars by the same office and for the same product code, that had been awarded to the same winning firm; (b) an indicator equal to one if the contract is awarded to a foreign vendor; (c) an indicator equal to one if the contract is awarded to a firm in the same state as the contracting office; (d) the natural logarithm of the distance (in miles) from the contracting office's location and the vendor location. 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 $ 5,000 and $ 45,000, awarded by the Department of Defense in fiscal years 2011 through 2017. Award amounts are discretized into right-inclusive bins of $2,500 dollars length.

and Miller, 2017; Decarolis et al., 2018; Carril, 2020). For each of our two variables, we consider two continuous measures—overrun dollars as a share of the original award and days of delay relative to expected schedule—, and two dichotomic measures—any overruns or delays.

Figure 7 presents the results. We find an increase in all these four indicators of poor performance. The share of contracts with overruns and the share of contracts with delays both increase by 1p.p., which constitutes an effect of roughly 10%. Again, because the first-stage effect is around 15p.p., we expect the causal IV estimate to be in the order of 67%.

Figure 7: Publicity and post-award contract performance



Notes: This figure presents four binned scatter plots, which depict an average outcome by bins of award amounts, as well as linear and quadratic fits at each side of $25,000. The outcome in each Panel is as follows: (a) the difference between actual obligated contract dollars and expected total obligations at the time of the award (i.e. cost overruns), divided by the expected dollar obligations at the time of the award; (b) an indicator equal to one if the contract has positive cost overruns; (c) the difference between actual days of contract duration and expected days of duration at the time of the award (i.e. delays); (d) an indicator equal to one if the contract has positive delays. 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 $ 5,000 and $ 45,000, awarded by the Department of Defense in fiscal years 2011 through 2017. Award amounts are discretized into right-inclusive bins of $2,500 dollars length.

4.2.4. Heterogeneity Analysis: We now examine whether the results presented above vary systematically across important contract characteristics. We start by considering differential effects for each of the three main Departments within the DOD. We do this by re-estimating our RDD specifications separately for the Army, the Navy, and the Air Force. Appendix Figure A3, Appendix Figure A4, and Appendix Figure A5 present the results for the number of offers, the probability of a foreign contractor, and cost overruns, respectively. While the increase in the number of offers seems to be present across all three agencies, the effects on foreign contractors and cost overruns seem to be mostly driven by the Army.

We then consider heterogeneous effects for goods and services. Appendix Figure A6, Appendix Figure A7, and Appendix Figure A8 respectively present the same three outcomes: number of offers, probability of a foreign contractor, and cost overruns. We see that publicizing contracts increases competition for both goods and services by a similar amount, despite the lower overall number of offers received in service contracts. A similar pattern emerges from the effects on the share of foreign firms: both goods and services see an increase due to the publicity requirements, even though their baseline levels differ. Finally, we see a different pattern for the effects on post-award performance. We see no change at the threshold for goods, and a significant deterioration of performance for services.

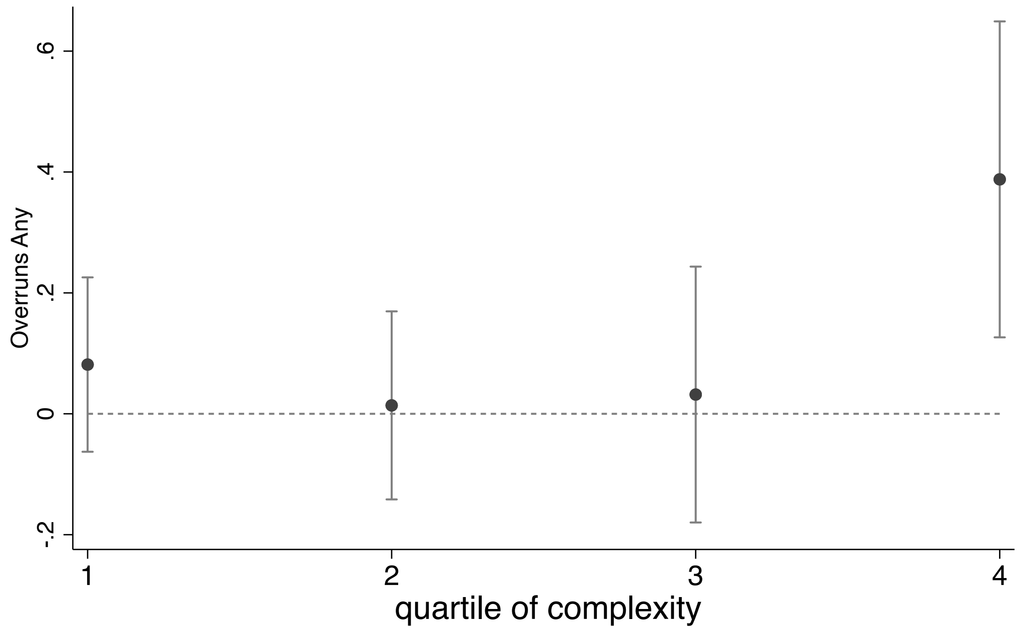
This last result is interesting, because it is consistent with the theory of contractual incompleteness, the foundation of most concerns about the negative effects of competition on post-award performance. Some transactions are easy to specify ex-ante, while others are more complex and involve countless possible contingencies. Writing down the precise terms for the purchase of a commodity (e.g., gasoline) is easier than to contract for an ad-hoc service, where post-award renegotiation and adaptation are likely to occur due to unspecified contingencies. Furthermore, bid evaluation for commodity contracts is likely a more straightforward endeavor than assessing the potential quality of bids for services. The results from Appendix Figure A8 are consistent with this intuition, finding that negative performance effects are driven by services and not goods.

To assess this mechanism more directly, we leverage the rich heterogeneity of our data, which features 1,918 distinct product categories. While some of them rarely experience performance issues ex-post, these are widespread for others. We use this fact to construct a proxy of complexity by product category. The proxy is based on the baseline level of post-award performance, which we define as the average performance experienced by contracts below \$20,000. Based on this measure, we divide product categories in quartiles, and estimate our RDDs separately for each of the four groups. If the contract incompleteness hypothesis is correct, then the negative impact of competition on post-award performance will be driven by those product categories that are more complex, defined as those that are exposed to negative performance even when not publicized.

Figure 8 supports this interpretation. We see that the average increase in overruns that we reported in Figure 7 is actually driven entirely by goods and services in the top quartile of complexity. In fact, we are unable to reject 0 for the lower three quartiles. These results are consistent with contract incompleteness being an important driver of our results.[15]

[15] An issue with this test is that it uses an outcome measure to define the different groups of analysis. We only use contracts below \$20,000 precisely to avoid any effect of the treatment on the classification, but the ideal measure would be based on pre-award characteristics of the contract. We are currently working on using data from the text of the solicitation to generate a better proxy of ex-ante complexity.

Figure 8: Heterogenous effects by contract complexity



Notes: This figure shows four regression coefficients and their 95% confidence intervals. Each coefficient is a regression discontinuity estimate of the reduced-form Equation (4), estimated separately on four subsamples of the data. The dependent variable is an indicator for any positive cost overruns. The subsamples are determined by the four quartiles of a proxy of contract complexity. The contract complexity proxy is constructed at the product category level, and is defined as the average cost overruns for contracts with awards below $15,000 in that category. 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 $ 5,000 and $ 45,000, awarded by the Department of Defense in fiscal years 2011 through 2017.

5. Comparing Pre-award and Post-award Effects

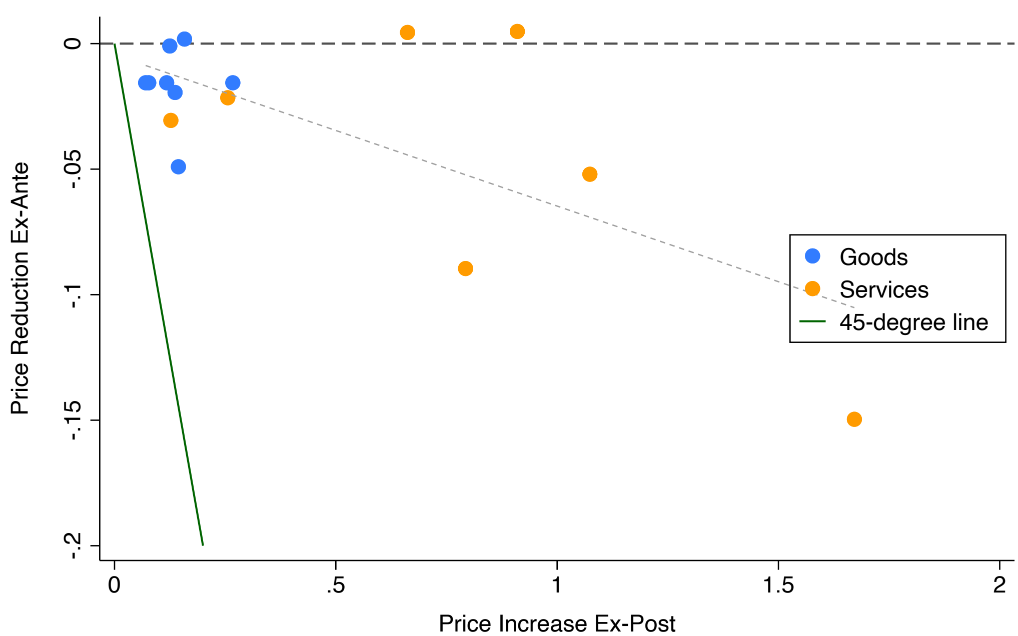
Taken together, the results presented in the previous section imply that there is a trade-off associated with increasing competition for contracts by publicly disseminating information about them. On the one hand, the competitive pressure leads to lower acquisition prices. On the other hand, selected suppliers are systematically different: they have less experience dealing with the contracting officer and they perform worse ex-post.

How to weigh these different components ultimately depends on how buyers value each dimension. This motivates future work to try to recover buyers' preferences from their observed choices. By imposing additional structure to the key primitives of the setup in Section 3.1, we hope to use the revealed choices of publicizing decisions along with the exogenous variation generated by the regulation to estimate these parameters. Measuring how buyers assess the different procurement outcomes will speak to the severity of agency problems across the DOD contracting units. Furthermore, it can help us evaluate the consequences of counterfactual policies that affect competition and solicitation transparency.

In the absence of this analysis, it may still be informative to compare different dimensions of this trade-off. In particular, we can compare the ex-ante price reductions with the ex-post increases in cost overruns, since both of these are measured in the same units (dollars of spending). We can then ask if, on average, cost savings associated with more intense competition justify additional disbursements after the award. We do this comparison separately for 14 product categories—7 goods and 7 services—that have at least 2,000 contracts in our sample. For each category, we estimate average price effects (ex-ante) and average overruns effects (ex-post).

Figure 9 presents the results. Two key points are worth highlighting. First, the negative slope of the average effects is consistent with the trade-off we have emphasized so far: larger price reductions ex-ante are associated with larger increases in overruns. Second, in terms of magnitudes, the ex-ante price reductions are small relative to the ex-post cost increases. For all the categories analyzed, the dots in Figure 9 fall to the right of the 45 degree line, indicating that the net cost changes (cost overruns effects - price effects) are all positive.

Figure 9: Comparing ex-ante price effects with ex-post cost overruns



Notes: This figure shows the relationship between estimates of price effects (vertical axis) and cost overruns (horizontal axis) for 14 product categories that have at least 2,000 contracts in our sample. Price effects estimates are discussed in Section 4.1, while cost overruns estimates are discussed in Section 4.2. The green 45-degree line represents points where the (ex-ante) price reductions are equal to the (ex-post) cost overruns. We depict estimates for goods categories in blue and for service categories in orange. The data source is the Federal Procurement Data System-Next Generation. The sample consists of definitive contracts and purchase orders in selected categories with more than 2,000 observations, with award values between $ 5,000 and $ 45,000, awarded by the Department of Defense in fiscal years 2011 through 2017.

Of course, these results do not provide a comprehensive assessment of the trade-off involved, because buyers may value other dimensions not included in this analysis. For example, publication of the offer on FedBizOpps may reduce the risk of a protested award by increasing transparency. However, the results constitute clear evidence that, at least in terms of resources spent in procurement, the policy seems to be backfiring: it generates modest cost savings at the time of the award that are more than compensated by later cost increases.

6. Conclusion

This paper studies the relationship between competition and public procurement outcomes. We do so by leveraging a regulation that generates quasi-experimental variation in the extent to which contract opportunities are broadly advertised to potential suppliers.

Our results emphasize that increasing competition via publicizing solicitations involves a trade-off for buyers. While the added competitive pressure results in lower acquisition prices, broader dissemination leads to a different pool of vendors, who on average perform worse ex-post. While a full evaluation of this trade-off requires more information about the government's preferences over different contract outcomes, we provide evidence that the publication requirement leads to increased procurement costs: price savings at the time of the award are smaller than observed increases in post-award cost overruns. We argue that the negative impact of competition on ex-post performance is explained by contract incompleteness. We do so by providing evidence that negative performance impacts are driven by contracts for goods and services that are relatively complex.

The analysis presented should be considered preliminary, leaving several open issues to be tackled in future work. First, we believe that it is feasible to propose an alternative estimation procedure for the price effects that relies less on parametric assumptions as the one formulated here. Second, we will formally implement the correction procedure for the RDD estimates, in order to account for the selection issues that we discuss in Section 3. Third, we will propose an explicit choice framework to explain how buyers make publication decisions in this context, in order to recover their preferences and evaluate policy-relevant counterfactuals.

An important lesson of our analysis is that the effects of policies that seek to increase competition may have highly heterogeneous effects depending on the specific characteristics of the purchase. This is somewhat at odds with the largely homogeneous set of rules contained in the Federal Acquisition Regulation. Our results suggest that having policies that explicitly recognize and accommodate this heterogeneity could yield large increases in the efficiency of the public procurement system.

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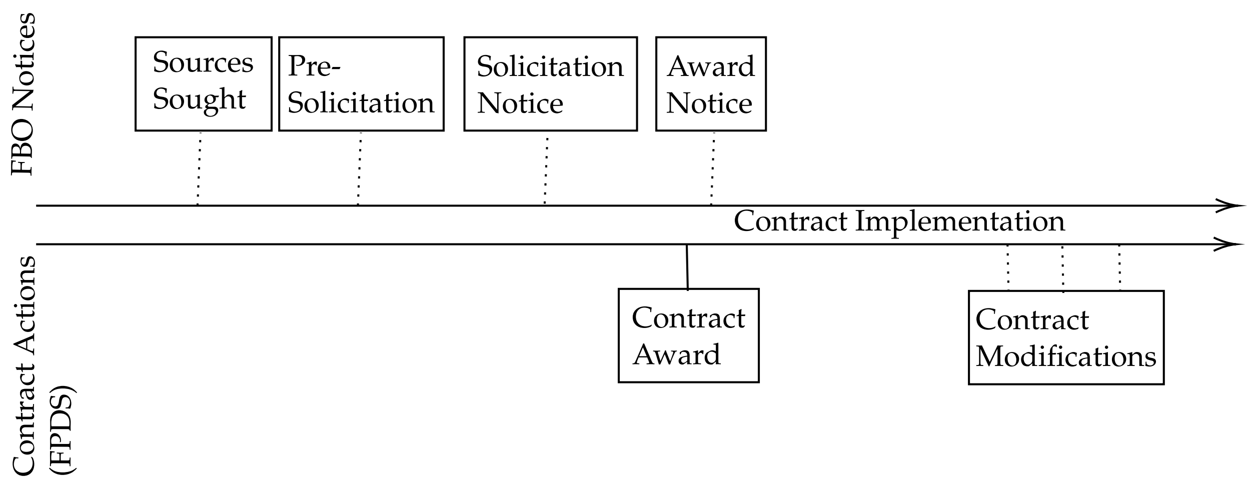
Appendix

A. Additional Figures

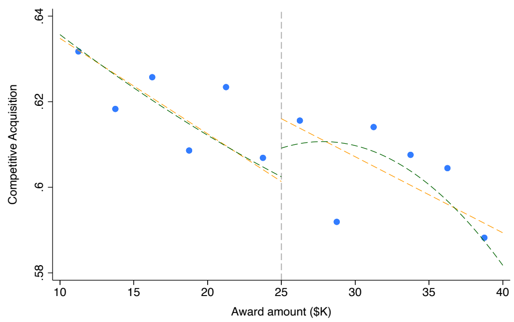
Figure A1: Contract Timeline and Data Sources



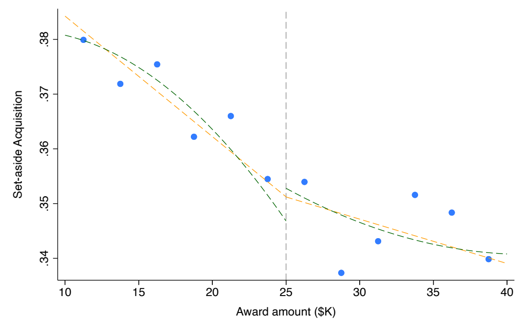
Notes: This figure presents a timeline of events associated with a typical contract. Milestones located above the arrows correspond to notices that are published on the government's point of entry (`fedbizopps.gov`). Milestones below the arrows generate information that is recorded on the Federal Procurement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

Figure A2: Pre-award characteristics around the threshold

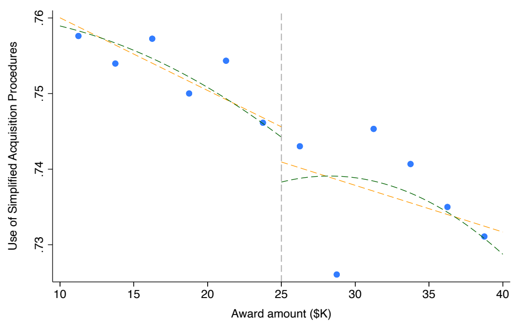
(a) Competitive award



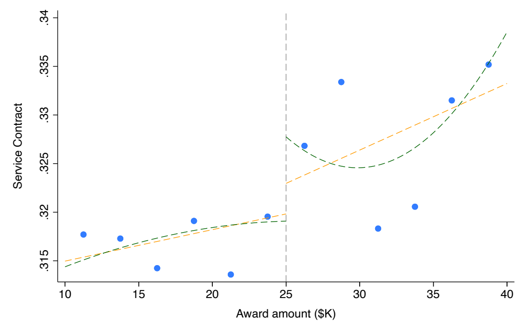
(b) Set-asides



(c) Simplified acquisition procedures

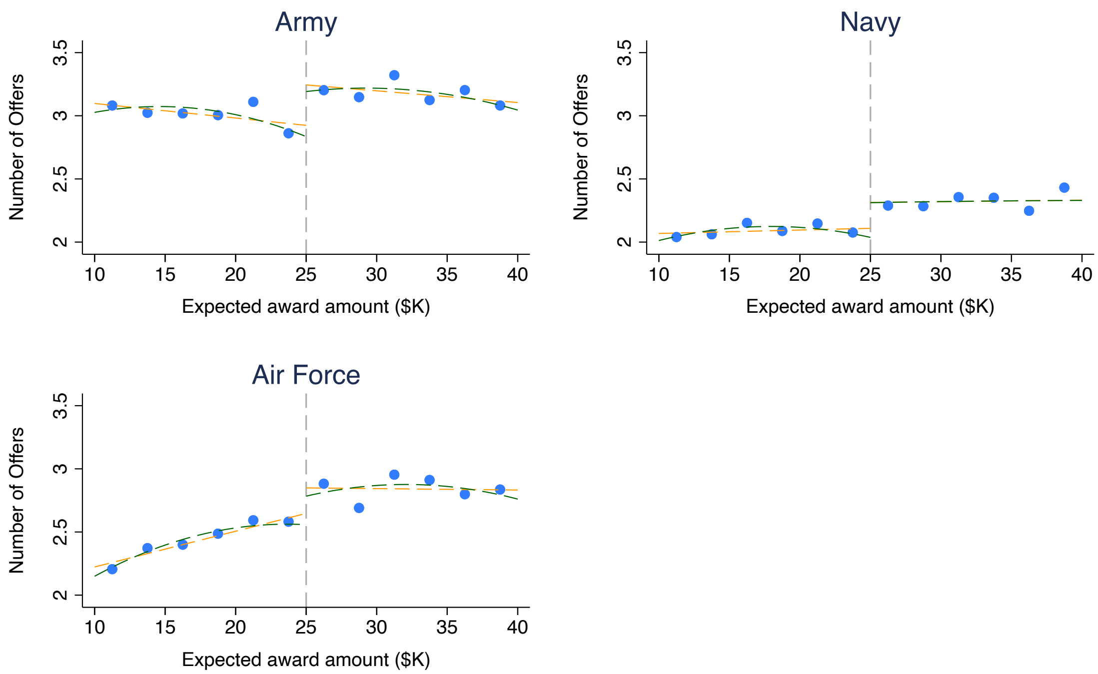


(d) Service contracts



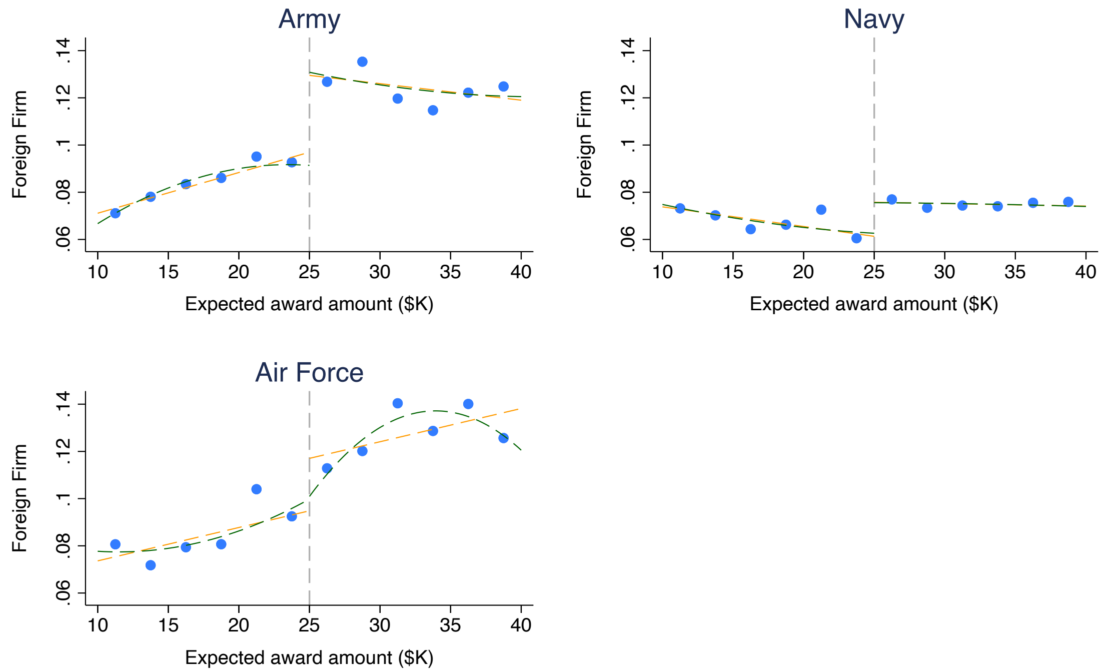
Notes: This figure presents four binned scatter plots, which depict an average pre-award characteristic by bins of award amounts, as well as linear and quadratic fits at each side of $25,000. The pre-award characteristic in each Panel is as follows: (a) an indicator equal to one if the contract was competitively solicited; (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 $ 5,000 and $ 45,000, awarded by the Department of Defense in fiscal years 2011 through 2017. Award amounts are discretized into right-inclusive bins of $2,500 dollars length.

Figure A3: Heterogeneous effects on competition by major departments



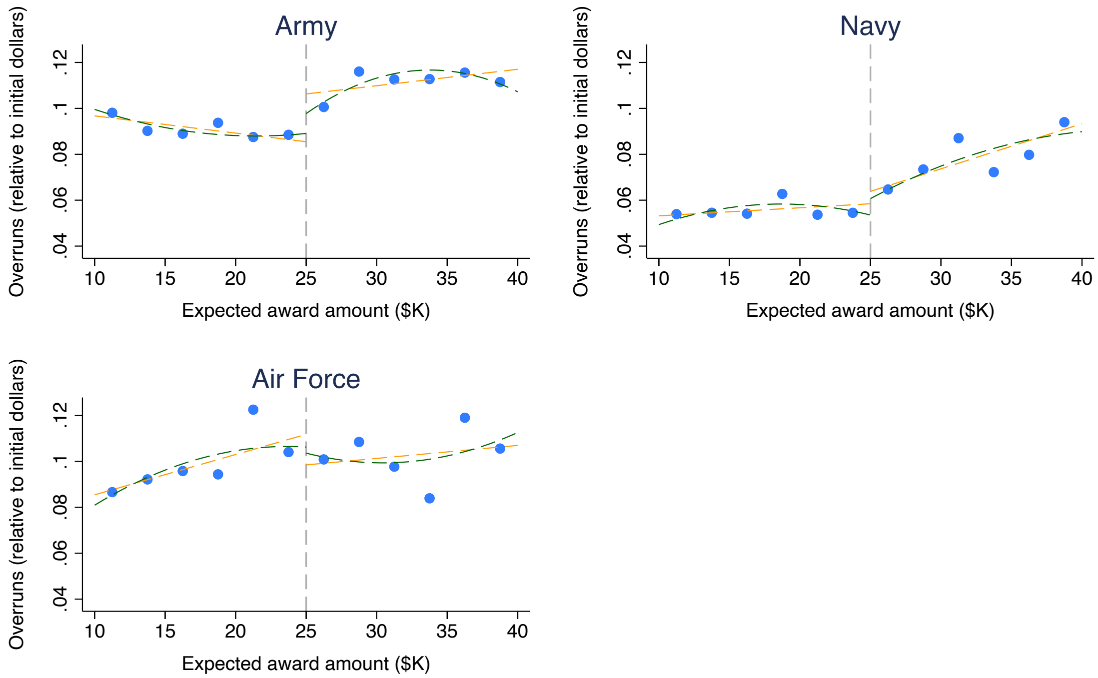
Notes: This figure presents three binned scatter plots, which depict the average number of offers received by bins of award amounts, as well as linear and quadratic fits at each side of $25,000. The data source is the Federal Procurement Data System-Next Generation. The full sample consists of non-R&D 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 A4: Heterogeneous effects on winner characteristics by major departments



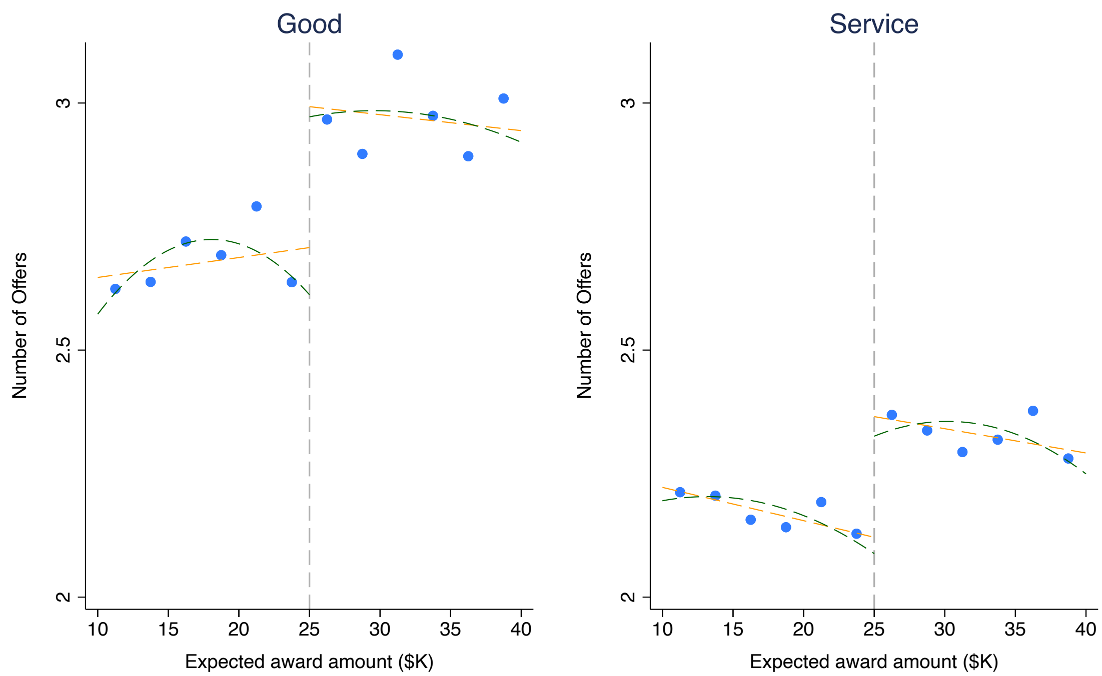
Notes: This figure presents three binned scatter plots, which depict the share of contracts awarded to a foreign firm by bins of award amounts, as well as linear and quadratic fits at each side of $25,000. The data source is the Federal Procurement Data System-Next Generation. The full sample consists 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 A5: Heterogeneous effects on performance by major departments



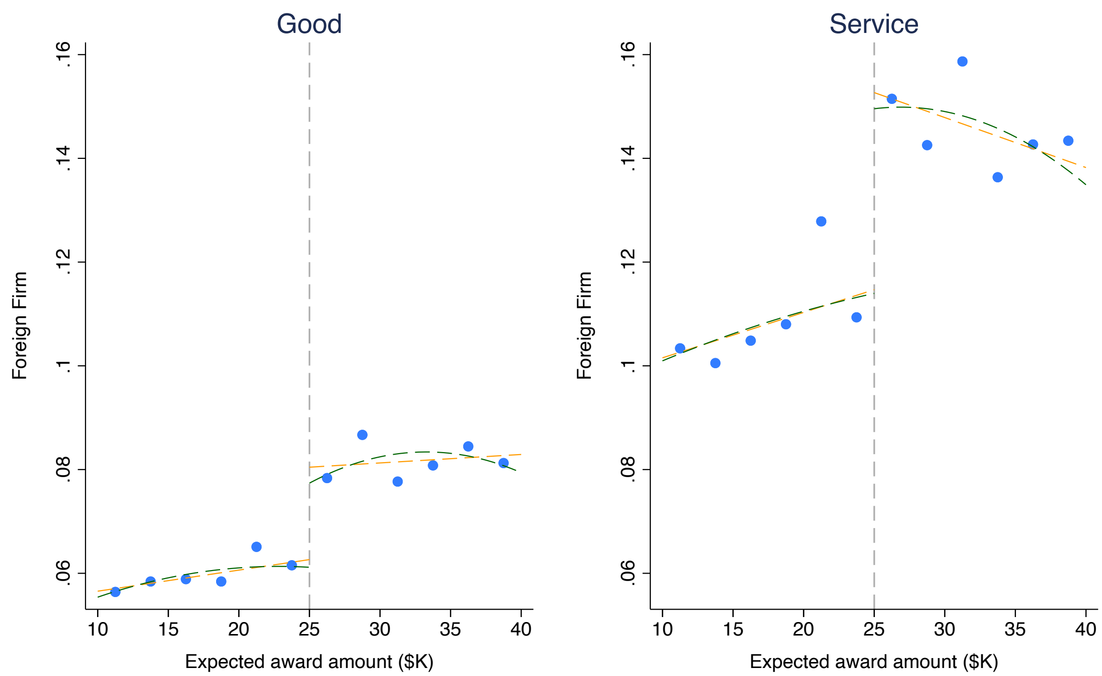
Notes: This figure presents three binned scatter plots, which depict average cost overruns by bins of award amounts, as well as linear and quadratic fits at each side of $25,000. Cost overruns are computed as the difference between actual obligated contract dollars and expected total obligations at the 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 A6: Heterogeneous effects on competition: goods versus services



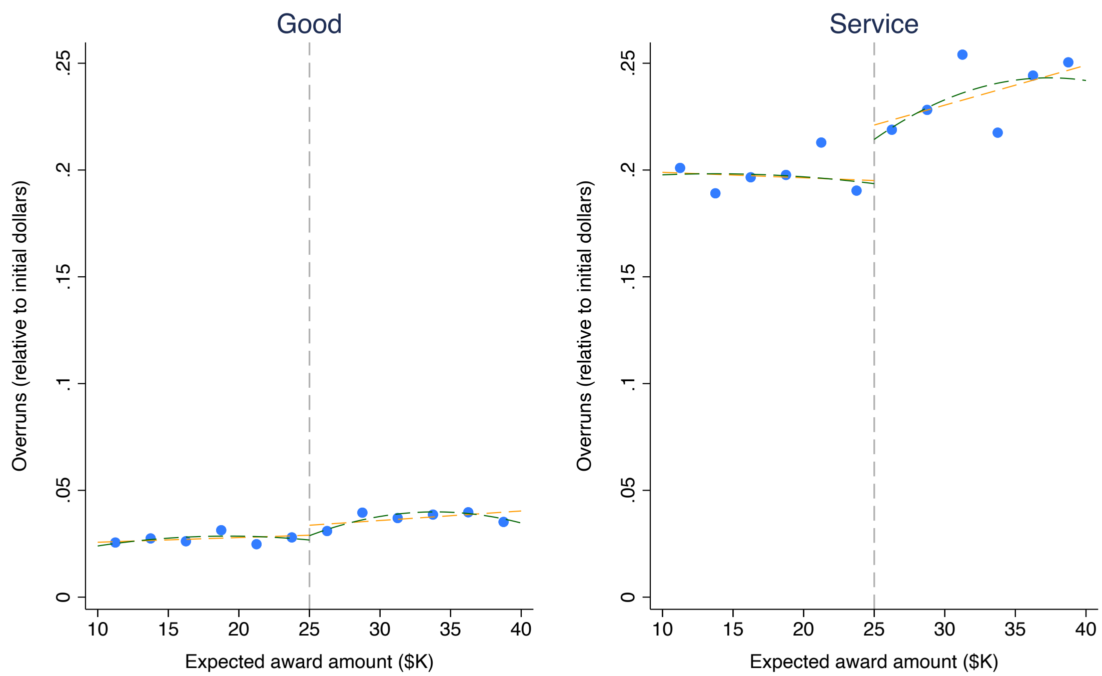
Notes: This figure presents two binned scatter plots, which depict the average number of offers received by bins of award amounts, as well as linear and quadratic fits at each side of $25,000. The data source is the Federal Procurement Data System-Next Generation. The full sample consists of non-R&D definitive contracts and purchase orders, with award values between $ 5,000 and $ 45,000, awarded by the Department of Defense in fiscal years 2011 through 2017. 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 A7: Heterogeneous effects on winner characteristics: goods versus services



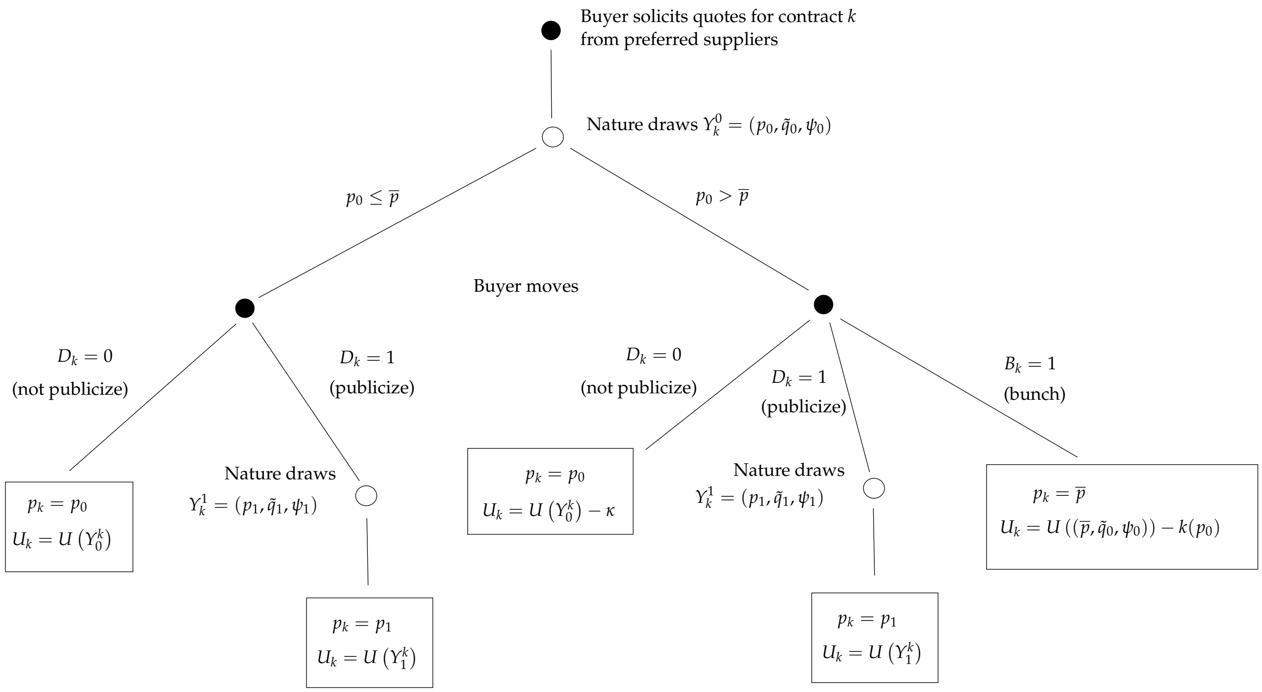
Notes: This figure presents two binned scatter plots, which depict the share of contracts awarded to a foreign firm by bins of award amounts, as well as linear and quadratic fits at each side of $25,000. The data source is the Federal Procurement Data System-Next Generation. The full sample consists of non-R&D definitive contracts and purchase orders, with award values between $ 5,000 and $ 45,000, awarded by the Department of Defense in fiscal years 2011 through 2017. 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 A8: Heterogeneous effects on performance: goods versus services



Notes: This figure presents two 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 for goods, while Panel (b) restricts the sample to service contracts. Award amounts are discretized into right-inclusive bins of $2,500 dollars length.

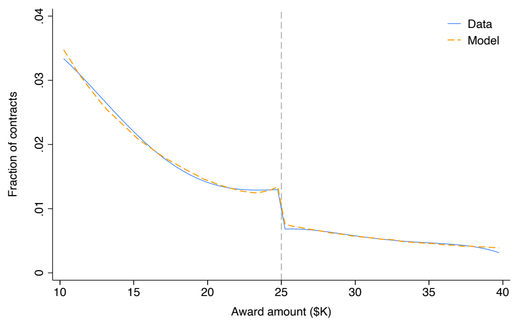
Figure A9: Model Tree



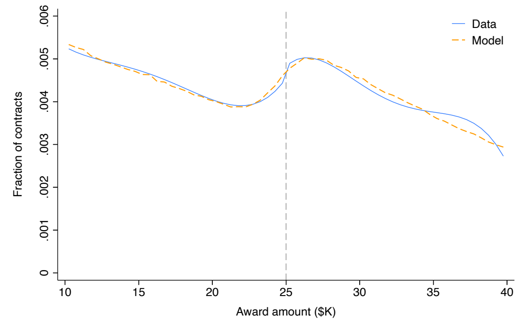
Notes: This figure presents a diagram of the model in Section 3 in the form of a tree. Filled nodes represent points where the buyer makes a choice. Hollow nodes represent moves by nature.

Figure A10: Model fit

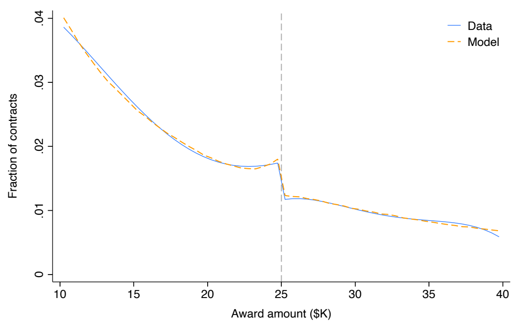
(a) Density of unpublicized contracts



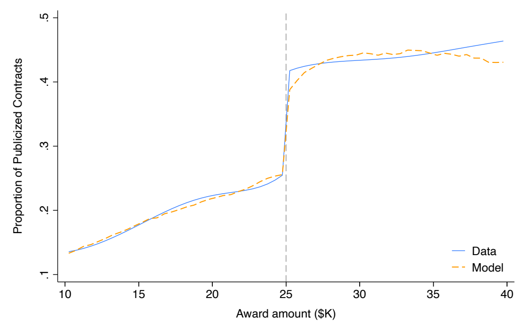
(b) Density of publicized contracts



(c) Density of all contracts



(d) Publicity compliance



Notes: This figure presents the model fit, based on a simulated method of moments estimation. In each panel, moments based on (smoothed) data are presented in solid blue lines, while model-based simulated moments are presented in dashed orange lines. Panel (a) presents the density of unpublicized contracts, Panel (b) the density of publicized contracts, Panel (c) the total density (the sum of (a) and (b)), and Panel (d) presents the share of publicized contracts at each award level.

B. Additional Tables