Competition under incomplete contracts and the design of procurement policies

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Abstract

We study the effects of intensifying competition for contracts in the context of U.S. Defense procurement. Conceptually, opening contracts up to bids by more participants leads to lower awarding prices, but may hinder buyers' control over non-contractible characteristics of prospective contractors. Leveraging a regulation that mandates agencies to publicize certain contract opportunities, we document that expanding the set of bidders reduces award prices, but deteriorates post-award performance, resulting in more cost overruns and delays. To further study the scope of this tension, we develop and estimate a model in which the buyer endogenously chooses the intensity of competition, invited sellers decide on auction participation and bidding, and the winner executes the contract ex-post. Model estimates indicate substantial heterogeneity in ex-post performance across contractors, and show that simple adjustments to the current regulation that account for adverse selection could provide 2 percent of savings in procurement spending, or $104 million annually.

JEL Codes: D22, D44, D73, H57, L13, L14.

1 Introduction

Buyer-seller transactions—concerning everything from standardized goods such as office supplies or fuels, to customized needs such as construction projects or consultancy services—are often governed by competitively-awarded procurement contracts. The pervasive use of competition to assign contracts stems from the notion that competitive bidding can be a powerful tool to reduce procurement prices (Bulow and Klemperer, 1996). Yet, expanding competition for contracts that involve customized obligations and deliverables could allow under-qualified contractors to win, leading to deficient execution ex-post. Therefore, the assessment of intensifying competition for procurement contracts should account both for potential benefits due to price reductions, as well as for potential adverse effects due to poor execution.

An empirical investigation of this trade-off is complicated, in part due to the need for comprehensive data on contract execution and a compelling research design. In this paper, we make progress in both of these fronts to study the equilibrium effects of enhancing competition for procurement contracts in acquisition prices and execution performance. We focus on U.S. Department of Defense (DOD) procurement, a setting of relevance given that it awards $500 billion in contracts per year, representing a sizable fraction of the U.S. economy. Moreover, this setting provides us with policy variation in the degree of contract competition, as well as with detailed administrative data throughout the life-cycle of each DOD contract, from design through execution.

Our empirical strategy exploits regulation that requires agencies to publicize contract opportunities that are expected to exceed $25,000 in value through a centralized online platform. Analyzing contract awards between $10,000 and $40,000, we exploit the discontinuous nature of the publicity requirements to estimate the effect of enhanced contract advertisement on four sets of outcomes: (i) the level of competition for the award, (ii) characteristics of the buyer-contractor relationship, (iii) procurement costs, and (iv) post-award contractor performance. By providing evidence on all of these fronts, we comprehensively characterize the consequences of changing the degree of competition for procurement contracts through this advertising channel. Furthermore, we exploit rich heterogeneity in the types of contracts that the DOD awards to assess the role of contract incompleteness in explaining our results.[1]

To estimate the price effects of contract publicity, we propose a method that recovers these effects from discontinuities in the conditional densities of publicized and non-publicized contracts. We then estimate the effects of publicizing contract opportunities on three sets of non-price outcomes—

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[1]Focusing on a window around the policy threshold implies that our sample does not include contracts related to major DOD acquisitions (e.g., fighter jets or weapon systems). However, the median contract awarded by the DOD is worth $19,800 and 68% of contracts obligate less than $40,000. Focusing on this range provides our results with a higher level of external validity, as contracts in our sample are much more similar to non-defense agencies and the private sector, compared to large-scale defense contracts. It is also worth noting that the volume of contracts impacted by the publicity regulation make its implications economically meaningful. In 2018 alone, the DOD publicized contract solicitations valued at $ 5.56 billion dollars via the online platform `FedBizzOpps.gov`.

the level of competition, the characteristics of the selected vendors, and post-award performance—using a Regression Discontinuity Design (RDD). We find that contract awards advertised through the government platform see an increase in the number of bids of roughly 60%, confirming that the policy translates into a substantial increase in participation. We show that these marginal participants are competitive, leading to changes in the characteristics of winning firms: awardees of publicized solicitations are, on average, 14% less likely to be small businesses, and are located 60% farther from the buying agency. Furthermore, we find that increased competition leads to contract price reductions: publicized contracts are, on average, awarded at 6% lower prices. However, advertised contracts result in worse ex-post performance: the probabilities of experiencing cost-overruns and delays in the implementation stage increase by 7% and 8%, respectively. The latter results are mostly driven by service contracts—as opposed to goods purchases—and by contracts that we ex-ante characterize as more complex. These results are stable across different estimation approaches and robustness checks that account for possible sources of bias.[2]

Taken together, our results suggest that promoting competition has mixed effects on contract outcomes: while it reduces the winning bid, it leads to worse outcomes at the execution stage. We find that suppliers' identity matters for explaining the variation in contract outcomes. Promoting competition hinders buyers' ability to restrict participation to qualified vendors, while attracting new participants who tend to perform poorly ex-post.

Motivated by this evidence, we develop and estimate an equilibrium model of competition for procurement contracts. The model allows us to estimate the underlying firm characteristics that shape adverse selection in this market. We also use the estimated parameters to study the role of buyer preferences in the decision to endogenously promote competition, and we evaluate the consequences of counterfactual policies aimed at reducing public spending.

Our model consists of four stages that cover the different phases of a procurement project. First, a buyer decides on the degree of competition by choosing whether to openly publicize the contract, or to invite only specific contractors. Second, firms that receive information about the contract simultaneously decide whether to prepare a bid. They do this by comparing the expected utility of participating with the idiosyncratic cost of preparing the bid, and decide to participate if the latter is sufficiently low. Third, each bidder submits a bid that depends on the realization of a production cost estimate, consisting of a private component and a common component, which accounts for unobserved heterogeneity (Krasnokutskaya, 2011; Haile and Kitamura, 2019).[3] The award mechanism is a first-price, sealed-bid auction. Fourth, the awarded contractor executes the contract. Execution performance depends on the existence and magnitude of cost-overruns, which stem from an idiosyncratic shock realized ex-post. The model incorporates the potential asymmetry

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[2]Our RDD setting is characterized by measurement error in the assignment variable. We address this concern directly, yet ultimately find that it has a quantitatively modest effect on the results.

[3]Controlling for unobserved heterogeneity is important since, in the procurement setting, bidders likely have more information about the auctioned contracts than the econometrician.

between bidders who are informed directly by the buyer and those who participate only when the contract is openly publicized. Moreover, the model does not impose restrictions on buyers' preferences over outcomes, and allows for idiosyncratic preferences for certain vendors that are uncorrelated with contract outcomes.

We estimate our model using data on publicity choices, auction participation, contract prices, and observed cost-overruns. We exploit variation in market structure and the publicity threshold to identify the model's parameters. Our estimates highlight an asymmetry between the sellers whom the buyer would invite directly in the absence of publicity and those who bid only when the solicitation is openly publicized. The added bidders have slightly lower production costs and substantially lower participation costs, which makes them more likely to participate *ceteris paribus*. They are also considerably more prone to experience cost-overruns in the execution stage. On the other hand, buyers show a preference for lower prices, lower cost-overruns, and incumbent suppliers.

By specifying the selection process that leads to buyers' publicity choices, the model allows us to extrapolate the local effects estimated at the policy discontinuity to the full sample. We then use our model parameters to estimate the effects of promoting competition through publicity under the current regulation, as well as under alternative policy scenarios. Overall, our findings are consistent with the estimated reduced-form effects. Increasing competition has heterogeneous effects, leading to cost reductions when the transaction unit is relatively simple. However, competition backfires when the contract involves a complex product category, as increases in cost-overruns exceed price reductions at the award stage.

Our results show that imposing regulation to promote bidder participation involves a risk of allowing under-qualified firms to bid. An alternative policy design is to rely on buyers (i.e. each local agency) to decide on whether to publicize each contract. Delegating this decision to the buyer involves a trade-off. On the one hand, more discretion allows the buyer to tailor decisions, mitigating the potential risks of intensifying competition. On the other hand, the buyer could use this added discretion opportunistically, restricting competition to favor specific contractors. We use our model to simulate equilibrium outcomes under a deregulated setting in which the buyer decides whether to publicize each contract. We find that delegating this decision to the buyer is welfare-enhancing when the transaction unit is complex: on average, the buyer achieves better outcomes than in regulated settings with either zero or full publicity. However, when the transaction unit is relatively simple, imposing full-publicity rules is convenient as the risks at the execution stage are minor.

We next use our model to identify improvements to the current policy design, which depart from uniform publicity requirements. Policies that regulate competition in most public procurement settings—including the one we study—are strikingly simple: they do not differ depending on whether the transaction involves a commodity or a highly customized service. This mismatch

between unsophisticated policies and a highly diverse set of transactions suggests meaningful room for improvement in policy design. We study the effects of introducing publicity requirements that are tailored to the complexity of the purchase, thus leveraging the benefits of intense competition for simple products, while limiting its adverse effects on complex products. We find that the cost-minimizing level of publicity for fully-specified products is 100%, whereas more complex product categories should require low use of publicity. We find that this reduces average defense procurement costs by 2 percent, or $104 million annually.

This paper contributes to several branches of the literature. First, it contributes to the literature on incentives in procurement. The procurement problem deals with two challenges stemming from asymmetric information: the ex-ante screening of vendors (Laffont and Tirole, 1993) and ex-post costly adaptations due to contract incompleteness (Williamson, 1976; Goldberg, 1977; Hart and Moore, 1988). Our paper examines these two asymmetries jointly and documents that increasing competition exacerbates adverse selection ex-ante, causing additional adaptation costs ex-post. Related papers study ex-ante and ex-post outcomes in procurement by manipulating either the awarding mechanism (Spulber, 1990; Bajari et al., 2009; Decarolis, 2014) or the flexibility of the contract structure (Crocker and Reynolds, 1993; Bajari and Tadelis, 2001). Instead, our setting provides exogenous variation in the intensity of competition, keeping fixed the awarding mechanism and contract design, which allows us to isolate the role of competition intensity on contract outcomes. Moreover, while existing papers typically focus on a single type of acquisition, our rich sample containing a wide range of product categories allows us to make a broader empirical contribution and show how the implications of promoting competition depend on the relative importance of adaptation costs.

Second, our paper contributes more specifically to a growing literature that evaluates policies aimed at promoting (or restricting) bidders' participation in procurement auctions. This literature emphasizes that expanding the pool of potential bidders may not necessarily translate into lower award prices if bidders' participation is endogenous, as their equilibrium bidding behavior can become less aggressive (Athey et al., 2011, 2013; Li and Zheng, 2009, 2012; Krasnokutskaya and Seim, 2011; Marmer et al., 2013; Bhattacharya et al., 2014; Sweeting and Bhattacharya, 2015).[4] We leverage variation in the number of potential bidders that stems from exogenous changes in publicity requirements. We model entry and bidding decisions and find that incumbents are indeed less likely to participate when they anticipate fiercer competition. However, in our setting, the effect of competition from new entrants dominates that of less aggressive bidding by incumbents, reducing the winning bid as a result. The source of variation in the number of potential bidders is closely related to Coviello and Mariniello (2014), who study a similar policy in Italy.

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[4]These ideas were initially introduced by Samuelson (1985) and Levin and Smith (1994). Li and Zheng (2009) provide an empirical framework highlighting that increasing the number of potential bidders within the independent private values (IPV) setting has ambiguous effects, since two counteracting effects occur in equilibrium: a "competition effect" and an "entry effect." The former tends to reduce prices, while the latter tends to increase them.

Third, this paper contributes to the growing literature that examines buyers' role as agents affecting market outcomes in procurement. This line of work highlights that buyers' actions can be motivated by objectives other than simple contract cost reductions (Bandiera et al., 2009; Liebman and Mahoney, 2017; Coviello and Gagliarducci, 2017; Best et al., 2017; Decarolis et al., 2020; Carril, 2019; Szucs, 2020). Our work is related to Kang and Miller (2021), who use IT procurement contracts in the United States to estimate a principal-agent model, where the buyer exerts costly effort to determine the degree of competition contracts receive. Our paper is also concerned with modelling how the level of competition is endogenously determined, but does not impose structure over a specific type of friction. Instead, it focuses on recovering preferences over the expected outcomes that drive buyers' choices.

The rest of the paper is organized as follows. Section 2 provides background on the U.S. DOD procurement system and the data we use for our analysis. In Section 3, we provide evidence on the effects of contract publicity on a range of relevant outcomes. In Section 4, we develop and estimate an equilibrium model of procurement competition, which we then use to study outcomes under counterfactual environments in Section 5. Section 6 concludes.

2   Setting and Data

2.1   US Federal Procurement and Publicizing Requirements

Public procurement is a large component of the US economy. In fiscal year 2019, federal contract awards totaled \$926 billion. Contracts are awarded at highly decentralized levels, with more than 3,000 different contracting offices that are part of an executive or independent agency.[5] 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 source of quasi-experimental variation 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 that exceed \$25,000 must be publicized in an online government-wide platform which we will refer to as FedBizOpps (or FBO).[6]

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[5]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.

[6]Throughout our period of analysis, this online platform—designated as the "government point of entry" by the FAR—was called Federal Business Opportunitites (FBO) available at: `fedbizopps.gov`. In late 2019 (after our sample

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*. Figure A2, in the Appendix, exhibits an example of FedBizOpps's interface.

Officers with contracts that are not expected to exceed this threshold are not required to publicize in FedBizOpps; however, they are still free to use it if they want to increase contract visibility.[7] The regulation also allows for exemptions to the requirement above the threshold, if doing so "compromises national security", if "the nature of the file does not make it cost-effective or practicable", or if "it is not in the government's interest". Therefore, while this policy discretely affects the likelihood of publicizing contracts around the threshold, compliance may be far from perfect given the voluntary nature of the rule below this value and the availability of exceptions above. Appendix C.1 presents additional details of the policy and the website.

The overwhelming majority of the contracts analyzed in this paper are allocated through so-called simplified acquisition procedures, and with vendors being selected according to the lowest price quote that is technically acceptable given the specifications.[8] This simple lowest-bid mechanism is in contrast with more sophisticated awarding procedures that are available for larger acquisitions, and which may consider attributes of the offer other than price. For example, the collection and use of past performance information from the Contractor Performance Assessment Reporting System (CPARS) is mandated for contracts with award values that largely exceed those considered in our analysis.[9]

2.2 Data

We use two complementary sources of data. The first consists of the historical files from FedBizOpps, which provide detailed information on pre-award notices (i.e. solicitations) posted on the platform. The second is the Federal Procurement Data System - Next Generation (FPDS-NG), which tracks federal contracts from the time of their award and includes 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

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period ends), the government point of entry migrated to `beta.sam.gov`, featuring minor changes to the user interface.

[7]Procurement officers with contracts with expected values below the threshold are only required to advertise the solicitation "by displaying [it] in a public place." This includes, for example, a physical bulletin board located at the contracting office.

[8]We conducted several interviews with contracting officers who confirmed that contract awards in this dollar-range are virtually always awarded to the lowest quote, and that there is little discretion to deem a particular offer as not acceptable. The most common reasons are a blatant omission of the solicitation specifications, or the fact that the contractor is barred from conducting business with the government based on past experience.

[9]For the DOD as of May 2021, the thresholds are $5,000,000 for Systems and Operations Support, $1,000,000 for Services and Information Technology, $750,000 for Construction, and $500,000 for Ship Repair and Overhaul. The only exception is Architect-Engineer contracts, with a threshold of $35,000, but these acquisitions represent less than 0.1% of our main analysis sample.

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 C.2 provides additional details on the construction of the dataset. 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. Furthermore, we observe the reason and the content of all contract modifications after the contract is awarded. These actions often involve extending the duration and/or increasing the dollar amount allocated to the vendor.

We use these modifications to compute two measures of contract execution performance that are commonly used in the literature: cost overruns and delays (e.g. Decarolis, 2014; Kang and Miller, 2021; Decarolis et al., 2020; Carril, 2019). Because the data contain the total sum of payments and completion date expected at the time of the award, we can construct measures of cost overruns and delays by comparing these expectations to the realized payments and duration.[10] A few considerations suggest that these are meaningful measures of performance. First, both overruns and delays are routinely collected for larger contracts and used to evaluate the execution of contractors. Furthermore, our interviews with contracting officers confirmed that staying on budget and on time is an important priority for the buyer. Finally, Carril (2019) shows that these execution measures are positively correlated with contract quality assessments based on objective product and service characteristics, using data from a sample of large IT contracts for which quality is systematically measured (Liebman and Mahoney, 2017).

The analysis sample consists of all competitively awarded definitive contracts[11] with award values between $ 10,000 and $ 40,000, awarded in fiscal years 2015 through 2019 by the Department of Defense (DOD), for products and services other than Research and Development (R&D).[12] Table B.1 presents summary statistics of the sample. In total, there are roughly 86,000 contracts awarded to almost 30,000 firms. These contracts are required by 597 contracting offices belonging to the Army, the Navy, or the Air Force. Contract durations are expected to be 54 days on average and are

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[10]The FPDS data records whether the modifications are in or out of contract scope. Our analysis does not restrict to a specific type of renegotiation, although *out-of-scope* modifications are extremely uncommon in our sample.

[11]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 (2019) for more details. We simplify the analysis by focusing exclusively on DCs, which are well-defined requirements involving a bilateral relationship between a single government unit and a private firm.

[12]The Department of Defense represents 58% of overall federal spending and more than 60% in the restricted sample. We exclude R&D awards because are subject to a unique set of acquisition rules, see FAR Part 35.

awarded on a fixed-price basis. A noteworthy feature of this setting is that competition is limited; an average contract receives 3.5 offers, with one out of four contracts receiving a single offer.[13] Winning vendors are often geographically close to the contracting offices, with both located in the same state in 2 out of every 3 contracts, and 75% of suppliers are characterized as small businesses. One out of every four contracts experiences modifications during the execution stage, leading to 7.6% of average cost overruns (i.e., excess cost relative to the original award value).

We also observe rich information about the type of good and service that is contracted upon. Each award is classified into one of 1,479 possible standardized 4-digit alphanumeric codes. These can be aggregated into 101 broader 2-digit product categories, 77 goods and 24 services. Table B.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.

3 The Effect of Competition on Contract Outcomes

In this section, we study the effects of publicizing procurement solicitations on contract outcomes. As described in Section 2.1, federal regulation introduces a publicity requirement at $25,000. We exploit this discontinuity to provide evidence of the effects of publicity on contract award price and other contract outcomes. These results will serve as the basis for the development of our model in Section 4.

3.1 Preliminaries

For each contract in our data, we observe agencies' decisions to publicly solicit a contract in *FedBizzOpps.gov* prior to its award (decision that we denote as $D \in \{0,1\}$). We leverage the variation introduced by the regulation, which discontinuously affects the likelihood of public solicitation at an arbitrary threshold ($\bar{p} = 25,000$) depending of the contract's *expected* award price ($\tilde{p}$). We do not observe ex-ante estimated prices $\tilde{p}$, but only ex-post realized prices p, which entails two empirical challenges. First, contracting officers know the policy threshold, so it may generate incentives to modify the purchase in a way that makes the ex-ante estimate fall below $\bar{p}$. This behavior would result in bunching on the distribution of ex-ante prices, generating an excess amount of contracts estimated to be at or slightly below $\tilde{p} = \bar{p}$. Second, since prices ex-post may differ from prices ex-ante, estimating effects at the discontinuity may be subject to measurement error biases. In our case, publicity may affect prices due to enhanced competition; thus, the error

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[13]More than half of the awards are set aside for a particular type of firm (typically, small business). Set-asides are a major factor of acquisition strategy in the DOD and contracting offices are required to meet specific set-aside goals. Even though they affect contract competition, we abstract away from that feature as we do not condition nor restrict our sample based on that margin. Importantly, set-aside requirements do not vary within the range of contract values that we study.

distribution may differ depending on the publicity status of the contract.

These empirical challenges are discussed in detail by Carril and Gonzalez-Lira (2021), who propose a method that uses the distribution of observed awards p and publicizing decisions D to (nonparametrically) recover information about the distribution of $\tilde{p}$, the distribution of the effects of publicity on price, and the extent of "manipulation".[14] Intuitively, the method hinges on comparing the observed empirical distributions of award prices with estimated counterfactual distributions stripped of the confounding influence of bunching and competitive price effects. Carril and Gonzalez-Lira (2021) combine existing density analyses approaches aimed at recovering behavioral parameters (Kleven, 2016), estimating policy effects (Chernozhukov et al., 2013; Jales and Yu, 2017) and correcting for measurement error (Schennach, 2020). Below, we use this framework to estimate price effects and correct (and bound) RDD estimates on non-price outcomes accounting for the aforementioned confounds. It is worth mentioning, however, that these corrections end up having a modest effect in our results, which is why we leave most details to Supplementary Material G and Carril and Gonzalez-Lira (2021).

Section 3.2 discusses the price effects of publicity that are obtained from the density analysis approach. Section 3.3 describes the estimation of publicity effects on non-price outcomes relying on corrected RDD methods. Sections 3.4, 3.5 and 3.6 provide interpretation of the estimated effects.

3.2 Analysis of Contract Price Distributions

Let $p_t(\tilde{p}_t|D_t)$ be the *potential* log-price that we would have observed for contract t, as a function of ex-ante estimates $\tilde{p}_t$ and a publicity decision of $D_t \in \{0, 1\}$. We assume that publicizing solicitations leads to a (log-)linear random price effect for contract t: i.e., $p_t(\tilde{p}_t|D_t = 1) = \tilde{p}_t - \gamma_t$, with $\gamma_t \sim F_\gamma(\cdot)$.

We estimate $E[\gamma_t]$ from the observed distributions of publicized and non-publicized contracts. The intuition of our method is based on three observations. First, relative to a counterfactual with no price effects of publicity (i.e., $\gamma_t = 0$ for all t), the observed distribution of publicized contracts should be shifted horizontally by $E[\gamma_t]$. Second, by definition, the distribution of non-publicized contracts is not affected by publicity effects γ_t. Third, we expect the counterfactual price distribution of the *total* number of contracts (the sum of those with and without publicity) to be smooth around the discontinuity, even though the threshold regulation generates discontinuities on each conditional distribution. These three observations motivate our method. We pick a value for $\widehat{E[\gamma_t]}$ and "undo" the price effects of publicity by shifting the distribution of publicized contracts, which we then add to the non-publicized contracts. The "right" value of $\widehat{E[\gamma_t]}$ will satisfy smoothness of the overall distribution and an integration constraint.

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[14]By manipulation we mean any decision ex-ante that modifies the requirement with the sole purpose of arriving at a different price estimate. The term follows the literature on Regression Discontinuity, which refers to this as manipulation of the running variable. However, it is noteworthy that this behavior need not involve any wrongdoing.

Figure 1: Distribution of Price Effects

| (a) Full Distribution | (b) Good vs. Service | (c) Quartile of Complexity |
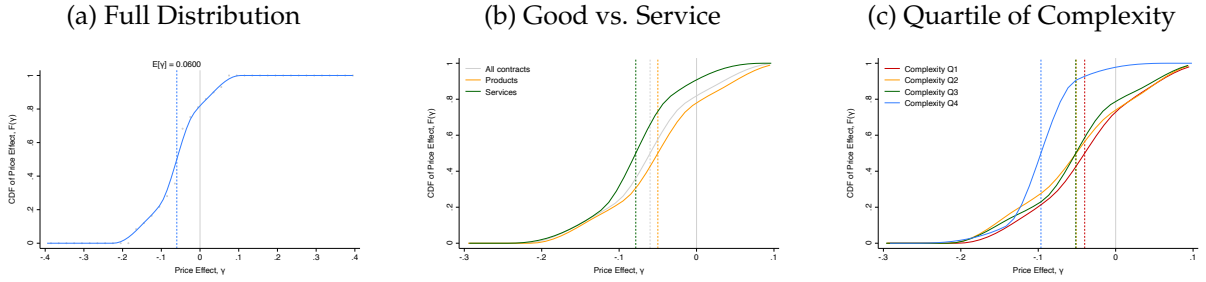
Notes: Notes: This figure presents the estimated cumulative distribution function (CDF) of the price effects of publicity (γ). Panel (a) shows the cumulative CDF of all contracts in the sample. Every gray dot shows actual point estimates given a discretization of the support of γ. The blue line corresponds to a kernel fit. The dashed vertical line corresponds to the estimated mean effect. Panel (b) shows the CDF of price effects separating contracts for goods and services. Panel (c) shows the CDF of price effects by quartile of complexity.

Carril and Gonzalez-Lira (2021) further show that if F_γ is symmetric, then the logic can be extended to nonparametrically identify the full CDF given the observed distributions of realized prices conditional on publicity status, $f(p_t|D_t = 0)$ and $f(p_t|D_t = 1)$. Moreover, the analysis is robust to having strategic bunching in the distribution of non-publicized awards, and the extent of this behavior is also identified using similar arguments. The key is that strategic bunching affects only the distribution of non-publicized awards, so that price effects and bunching are separately identified from the two observed distributions.

Figure 1(a) depicts the (nonparametric) estimate of the CDF of γ_t, along with a local polynomial smoothing. We find that publicity leads to an average reduction in award price of 0.06 log-points (SE: 0.02), equivalent to \$ 1,456 at the discontinuity. From the full distribution, we see that publicizing contract opportunities reduces award prices for 83% of the contracts. Table B.3 in the Appendix provides more details about the mean and variance of price effects and displays sub-group analyses. We find that price effects are higher for services, and the effects are larger for contracts that are more complex. [15]

Figure A4 shows the density distributions of both publicized and non-publicized contracts, stripped down from price effects and strategic bunching responses. From the distribution of non-publicized awards (Panel (a)), we can directly compute the excess bunching below the threshold, explained by agencies' desire to avoid the publicity mandate. We estimate that the excess mass right below the discontinuity equals 12% of the value of the density at the threshold. This magnitude will be used to account for the effects of this manipulation on our RDD estimates in Section 3.3. However, we can already infer that, since the extent of bunching is arguably modest, its impact on our estimates will be limited as well.

Finally, in Panel (b), we compare the empirical distribution to the sharply discontinuous

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[15]By complexity, we refer to the average cost-overrun for all contracts in the product category valued under \$20,000. This is discussed later in the paper.

distribution of publicized awards that would be observed if $\gamma_t = 0$ for all t. It is evident how the distribution of γ_t smooths out the discontinuity in the density of publicized contracts. As noted by existing literature, observing the assignment variable with error biases the estimated effects towards zero in the RDD setting (Lee and Lemieux, 2010; Davezies and Le Barbanchon, 2017; Pei and Shen, 2017). We leverage the estimated distribution of γ_t to correct for this factor in Section 3.3.

3.3 Regression Discontinuity Design: Estimating Effects on Non-price Outcomes

In this section, we leverage the discontinuous nature of the publicity requirements to gauge the effects of publicity on a set of other relevant outcomes, including the level of competition, characteristics of the winning bidder, and post-award contractor performance. We use the estimates of price effects and bunching to adjust the RDD estimates accounting for these factors.

3.3.1 Empirical Framework

Consider specifications of the following form:

$$Y_t = \alpha + \tau \cdot D_t + f(\tilde{p}_i) + X_t'\zeta + \epsilon_t \quad , \tag{1}$$

where the coefficient of interest is τ, the effect of publicizing a solicitation on contract outcome Y_t. In the standard Regression Discontinuity Design (RDD), we obtain an estimate of $\widehat{\tau}_{IV}$ by instrumenting D_t with the discontinuity in publicity requirements. The first-stage of this IV procedure is of the form:

$$D_t = \kappa + \delta \cdot \mathbf{1}[\tilde{p}_t > \bar{p}] + h(\tilde{p}_t) + X_t'\eta + \nu_t \quad , \tag{2}$$

for some smooth function $h(\cdot)$. 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.:

$$Y_t = \mu + \phi \cdot \mathbf{1}[\tilde{p}_t > \bar{p}] + g(\tilde{p}_t) + X_t'\psi + \xi_t \quad . \tag{3}$$

Consider first a naive RDD, described by versions of Equation (1), Equation (2), and Equation (3), where we simply replace ex-ante prices $\tilde{p}_t$ by realized observed prices p_t. The estimates obtained from this analysis will be identical to the true RDD if there are neither price effects ($\gamma_t = 0$ for all t) nor bunching responses. The larger these effects are, the more the estimates from the naive RDD will differ from the true parameters. Given this, we take the naive RDD as our baseline and sequentially implement corrections to account for price effects and bunching responses, to transparently show how these elements affect the estimation.

In Supplementary Material G.1.6, we describe in detail the first of such corrections, namely a method to recover the causal parameters of interest in the presence of price effects γ_t. The key result

is that, under our modelling assumptions, we can write the conditional expectation of contract outcomes given *observed* prices $E[Y_t|p_t]$ as an explicit linear function of the causal parameters that we seek to recover, plus objects that we can directly observe or estimate. This function depends on observed prices p_t, observed treatment probabilities π_D, and moments of the distributions of price effects F_γ (which we obtained from the density analysis). We then use this result to estimate the causal parameters using OLS.[16]

On the other hand, we can account for the effect of bunching responses by following the results from Gerard, Rokkanen, and Rothe (2020). These authors derive sharp bounds on treatment effects for the RDD in the presence of bunching. The simple argument is that, if one can estimate the extent of "manipulation in the running variable", which in our case corresponds to the excess mass below the threshold among untreated units (non-publicized contracts), then one can derive bounds on treatment effects by assuming that these units are the ones with either the highest or the lowest values of the outcome variable Y_t. Intuitively, these are computed under the "worst" and "best" case scenarios in terms of how selection can influence RDD estimates. In Supplementary Material Section G.1.8, we explain in detail how to derive these bounds in our setting, and how to calculate them using our estimate of excess bunching obtained in our density analysis.

3.3.2 Effects on Non-Price Outcomes

Baseline RDD Results. We start with our baseline results—which ignore the possible influence of price effects or bunching—, and then sequentially apply corrections to account for the specific issues present in our setting. We estimate Equation (1), Equation (2), and Equation (3), assuming that $\tilde{p}_t = p_t$. In our baseline specifications, we use a simple linear fit for $g(\cdot)$ and no controls X_t, but also present results from the robust local polynomial approach proposed by Calonico, Cattaneo, and Titiunik (2014). We present these RDD results visually, by plotting binned scatters of Equation (2) and Equation (3). In the next section we explicitly assess how these baseline estimates change as we consider the impact of price effects and (or) bunching responses.[17]

The results for the first stage Equation (2) are presented graphically in Figure 2(a). We see that the use of FedBizOpps jumps sharply past the \$25,000 threshold of award amounts. The share of contracts that are publicly solicited in the government platform increases from roughly 30% at or slightly below \$25,000, to 50% right above this threshold.

The reduced form specifications (Equation (3)) are estimated on three sets of outcomes: the intensity of competition, winning vendor characteristics (including its relationship with

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[16]We also show in Supplementary Material G.1.6 that this logic can be easily extended to accommodate measurement error in ex-ante prices, so that $\tilde{p}$ is only an unbiased but not necessarily perfect forecast of $p^0(\tilde{p})$.

[17]Appendix Figure A5 presents RDD plots for baseline variables. We find that baseline contract design characteristics are balanced around the threshold, with the exception of goods vs. services. There are more services right above the threshold. The difference is noisy and against possible selection patterns. All of our baseline estimates are robust to the inclusion of a service dummy as control.

Figure 2: Publicizing Requirement and Intensity of Competition

(a) Use of FedBizOpps

(b) Number of Offers Received
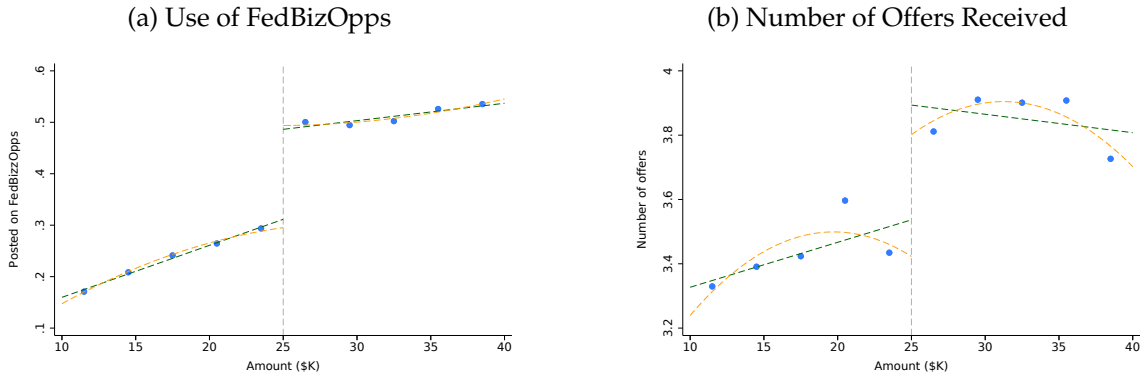
Notes: Panel (a) and Panel (b) respectively show the fraction of contracts posted on FedBizOpps and the number of offers received, as a function of award amounts. Blue dots represent average outcomes by bins of award amounts. Colored dashed lines represent linear and quadratic fits at each side of the $25,000 threshold. The data sources are FBO.gov and the Federal Procurement Data System-Next Generation. The sample consists of competitive, 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.

the awarding office), and post-award performance. Most of the existing literature has studied these variables independently.[18] By studying them jointly, we can generate a comprehensive understanding of the mechanisms and implications of policies oriented to enhance competition.

Figure 2(b) 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 0.4 more bids. The magnitude of the increase in the number of offers is considerable given that the policy only changes the likelihood of a publicized solicitation by around 20 p.p.

These results indicate that encouraging the public posting of solicitations leads to the stated goal of increasing competition by attracting additional bids. However, it does not necessarily imply that these new offers affect the equilibrium allocation of the contract, since new marginal bidders may not be competitive. Figure 3 shows that this is not the case. In Panel (a), we see that publicized contracts are awarded to vendors that are relatively larger, as measured by a reduction of the probability of awarding the contract to a small firm.[19] This "penalty" for small businesses is interesting because it goes against the stated goals of the publicity regulation (FAR Part 5). Panel (b) and Panel (c) show that publicized contracts are more likely to be awarded to foreign firms or firms that are geographically more distant from the contracting office location. These results suggest that marginal entrants attracted by the public solicitation do win awards with a positive probability.

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[18]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. (2020); Ryan (2020) (ex-post renegotiation and performance).

[19]The Small Business Administration (SBA) defines size standards by NAICS Industry. These standards depend on the number of employees and/or annual revenue. As a reference, the revenue standard for *building cleaning services* (NAICS code 561720), a common category in the sample, is $ 19.5 million per year.

Figure 3: Publicity and the Characteristics of the Winning Firm

(a) Contractor is a Small Business   (b) Foreign Firm   (c) Distance to the Office
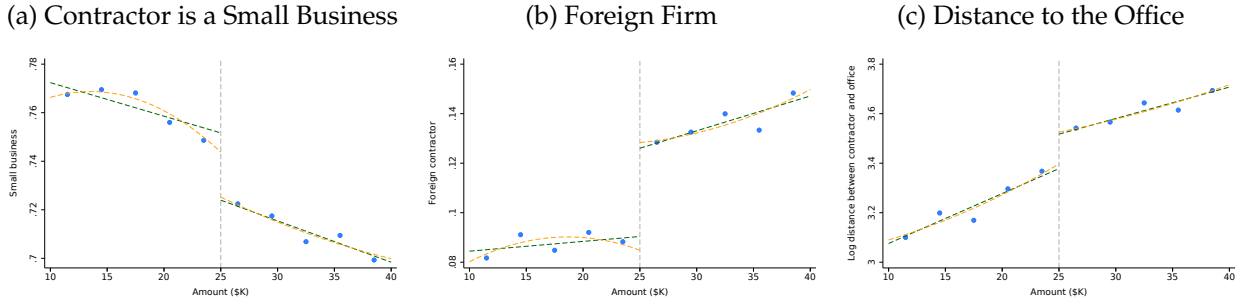
Notes: Panel (a), Panel (b) and Panel (c) respectively show the fraction of awarded contractors that are small businesses, the fraction of awarded contractors that are foreign, and the natural logarithm of the distance (in miles) between the contracting office's location and the contractor location, as a function of award amounts. Blue dots represent average outcomes by bins of award amounts. Colored dashed lines represent linear and quadratic fits at each side of the $25,000 threshold. The data sources are FBO.gov and the Federal Procurement Data System-Next Generation. The sample consists of competitive, 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.

To measure the impact on post-award contract performance, we use two measures that are commonly used in the literature: cost overruns and delays. We compute these as the difference between the ex-post realized sum of payments and duration of the project, and the expected value of these variables at the time of the award. Figure 4 presents the results. We find that the share of contracts with overruns and the share of contracts with delays increase by 2 p.p. and 1.5 p.p., respectively. These differences are statistically and economically significant considering the magnitude of the first stage. These results show that the execution of publicized contracts tends to result in poorer performance outcomes, including ex-post costs. Figure A6 in the Appendix shows effects on additional performance-related variables; the number of post-award contract modifications, cost-overrun dollars as a share of the original award; and days of delay relative to expected schedule. These results align with the findings presented in Figure 4: publicized contracts experience more problems during the execution stage. In Supplementary Material F.1 we provide figures illustrating how these effects vary by agency and type of product requested.

Adjusted RDD Results. In this section, we present a series of refinements to our baseline RDD results. First, we explore robustness to our baseline linear specification with the estimator proposed by Calonico, Cattaneo, and Titiunik (2014), which uses robust local polynomial fits. Second, building upon the results of our density analysis in Section 3.2 and further explained in Supplementary Material G and Carril and Gonzalez-Lira (2021), we adjust the baseline RDD estimates to account for the observed running variable (award price) being subject to both treatment effects (price effects of publicity) and potential manipulation (bunching).
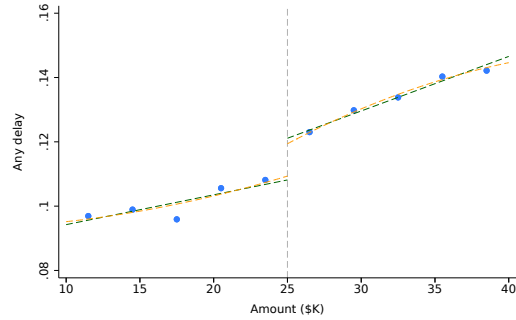
Table 1 presents reduced-form estimates for each relevant outcome variable. The first column

Figure 4: Publicity and Post-award Contract Performance

(a) Share of Contracts Experiencing Cost-overruns
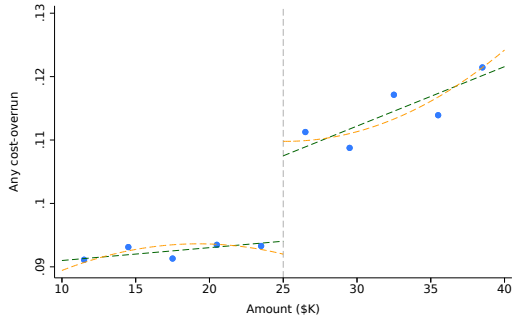
(b) Share of Delayed Contracts

Notes: Panel (a) and Panel (b) respectively show the fraction of contracts experiencing cost-overruns and the fraction of contracts experiencing delays, as a function of award amounts. Cost-overruns are measured as the difference between total obligated dollars and obligated dollars at the time of the award. Delays are measured as the difference between total duration of the contract and expected duration at the time of the award. Blue dots represent average outcomes by bins of award amounts. Colored dashed lines represent linear and quadratic fits at each side of the $25,000 threshold. The data sources are FBO.gov and the Federal Procurement Data System-Next Generation. The sample consists of competitive, 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.

shows the coefficient of our naive linear RDD using ordinary least squares (OLS). These results replicate the RDD plots discussed earlier. Column (2) presents Calonico et al. (2014)'s local polynomial estimates with robust bias-corrected standard errors. Overall, non-linear estimates are similar in magnitude and significance to simple OLS estimates. The third column present estimates that account for price effects in the treatment group (i.e. publicized contracts), following the method explained in Supplementary Material G.1.6. The correction for price effects is relatively modest, and in most cases tends to amplify the baseline results. This is consistent with the fact that the price effects smooth-out the discontinuity for the treatment group: under naive estimation, some publicized contracts are observed below the threshold when their original (ex-ante) price was above it.

The next two columns present partial identification estimates that account for bunching responses. Column (4) shows lower and upper bounds without accounting for price effects, while the fifth column shows bounds that do adjust for price effects. Notably, since the magnitude of bunching is modest in our context, the bounds presented are relatively narrow, which tells us that bunching does not pose a serious threat to the interpretation of our results. Interestingly, the lower bounds in Column (5) tend to be very close to our baseline estimates. This implies that the downward bias introduced by price effects on the naive estimates of Column (1) is of similar magnitude than the worst-case upward bias introduced by bunching responses.

Taken together, these results imply that the strong visual evidence presented in Figures 2(a)

Table 1: Reduced-form RDD Estimates and Corrections

Dependent Variable	OLS (1)	CCT (2)	Price Effect Adjustment (3)	Manipulation Bounds (4)	Price Effect + Manip. Bounds (5)
Number of offers	0.3569 (0.0677)	0.5447 (0.1053)	0.3526	[0.2762 , 0.5344]	[0.3073 , 0.4506]
One offer	-0.0191 (0.0064)	-0.0235 (0.0108)	-0.0204	[-0.0272 , 0.0052]	[-0.0248 , -0.0070]
Log distance firm-office	0.1392 (0.0481)	0.1199 (0.0817)	0.1909	[0.0290 , 0.2688]	[0.1304 , 0.2619]
Foreign firm	0.0357 (0.0045)	0.0508 (0.0078)	0.0375	[0.0328 , 0.0520]	[0.0358 , 0.0465]
New firm	0.0175 (0.0075)	0.0185 (0.0126)	0.0247	[0.0023 , 0.0350]	[0.0164 , 0.0344]
Small business	-0.0277 (0.0065)	-0.0295 (0.0110)	-0.0265	[-0.0523 , -0.0195]	[-0.0399 , -0.0220]
Any cost-overrun	0.0135 (0.0045)	0.0246 (0.0077)	0.0144	[0.0103 , 0.0263]	[0.0127 , 0.0216]
Cost-overruns (relative dollars)	0.0095 (0.0058)	0.0161 (0.0100)	0.0127	[0.0053 , 0.0179]	[0.0104 , 0.0174]
Any delay	0.0130 (0.0047)	0.0151 (0.0080)	0.0143	[0.0094 , 0.0270]	[0.0123 , 0.0222]
Delays (days)	2.3262 (2.0388)	4.0361 (3.4935)	2.7491	[1.2278 , 5.3554]	[2.1492 , 4.4660]
Number of modifications	0.0375 (0.0173)	0.0619 (0.0300)	0.0395	[0.0204 , 0.0926]	[0.0300 , 0.0701]

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. Coefficients in column (1) use a linear fit above and below the discontinuity. Coefficients in column (2) correspond to the robust local polynomial method proposed by Calonico, Cattaneo, and Titiunik (2014). Column (3) applies a correction to the estimates in column (1), accounting for the existence of price-effects, following the method proposed in Appendix G.1.6. Column (4) shows bounds on the reduced-form coefficient in column (1), accounting for the possibility of "running variable manipulation" (i.e. bunching), following the method proposed in Appendix G.1.8. Column (5) shows bounds on the adjusted reduced-form coefficient in column (4), accounting for both the existence of price-effects and the possibility of "running variable manipulation" (i.e. bunching). Standard errors for the coefficients in columns (1) and (2) are shown in parentheses.

through 4 is robust to fully accounting for the potentially confounding influence of price effects and strategic bunching by the buyer.

3.4 The Role of Contract Complexity

Our analysis includes a wide variety of transactions, from standardized goods to customized services. A procurement contract aims to regulate the nature of a expected transaction. Nevertheless, specifying possible contingencies is easier if the purchase involves a standardized product rather than an *ad-hoc* service. Thus, the more difficult it is to specify the need in a contract, the more variable will be the post-award performance. This explains why some product categories rarely experience execution issues ex-post, while others present ex-post modifications for most contracts.

Similarly, the effects of expanding competition on award prices are also likely to vary depending on the good or service's underlying complexity. For example, if bidders of relatively complex products are more heterogeneous in production costs, additional offers would lower contract prices more than when contractors are homogeneous. Thus, there are reasons to believe that the degree of contract complexity affects both prices ex-ante and ex-post.

To assess these mechanisms more directly, we leverage rich heterogeneity in our data, which features 1,918 distinct product categories. Using this information, we proxy the degree of complexity at the product category level based on the baseline level of execution performance. In particular, we define a category's degree of complexity as the average cost-overruns experienced by all contracts in that category with an award below \$20,000.[20] This leads to an intuitive classification, as shown in Appendix Table B.5, which lists the complexity measure associated with the top and bottom product categories. Contracts for easy-to-specify purchases—like fuel, lumber, or medical supplies—receive the lowest complexity score. In contrast, contracts for more customized needs—e.g., medical services, facility operation, and housekeeping—are associated with higher degrees of complexity.

We divide the contracts in our sample into quartiles of complexity, and re-estimate both price effects and RDDs on performance, separately for each of the four groups.[21] Appendix Table B.3 shows estimates for the mean and standard deviation of price effects γ_t, separately for the full sample (column 1), goods versus services (columns 2 and 3), and each of the four quartiles of complexity (columns 4 through 7). Similarly, Figure 1 shows the CDFs of price effects for each of these groups. Although estimates become noisier as we divide the sample, we see suggestive evidence that large price effects are more concentrated among the most complex contracts. Our point estimates indicate that, on average, publicity reduces the prices of goods by 5% and of services by 7.8%. This effect corresponds to 4% for the least complex quartile, versus 9.6% for the top quartile of complexity.

The results are qualitatively similar for the impact of publicity on post-award performance. Figure 5 shows that the increase in overruns and delays that we reported in Figure 4 is driven by goods and services in the *top* quartile of complexity. We are unable to reject the null for the lower three quartiles.[22] Overall, it is noteworthy that both counteracting effects of competition—price reductions ex-ante and overruns ex-post—are more pronounced for complex contracts. In section

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[20]There are multiple ways of characterizing product complexity. We implemented different approaches, including using the standard deviation in performance, indexing multiple performance variables, and counting the number of words in the solicitation's description. These classifications lead to roughly the same rank of products categories, and thus varying the definition does not threaten the general results. We present correlations between some of these measures in Figure A7. We use the mean of cost-overruns because it is transparent and easy to interpret. We get around the issue of classifying contract categories based on an outcome by focusing on awards below \$20,000.

[21]We also consider the more simple heterogeneity of effects between goods and services.

[22]Figure SM8 in the Supplementary Material shows RD plots for cost-overruns separating for goods and services. Note that cost-overruns increase for both types of contracts. However, both the baseline level and the magnitude of the jump are substantially larger for services.

Figure 5: Effects of Publicity on Post-award Performance by Degree of Complexity

(a) Cost-overruns   (b) Delays
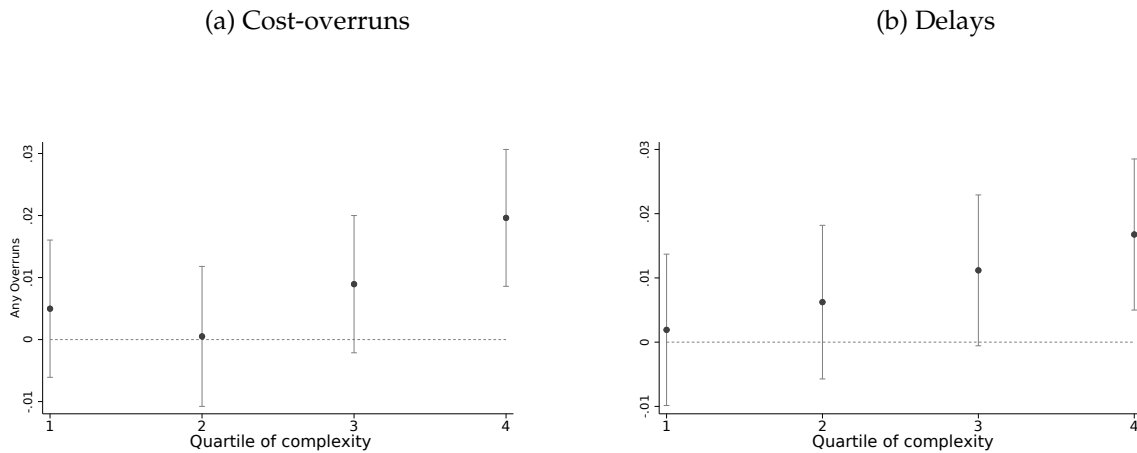
Notes: This figure shows four regression coefficients and their 95% confidence intervals. Each coefficient is an estimate of a RDD reduced-form coefficient in Equation (3), per sub-group, estimated using (interacted) OLS. The dependent variable in Panel (a) and Panel (b) are indicators for any positive cost-overruns and delays, respectively. The subgroups are determined by 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 \$20,000 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 \$ 10,000 and \$ 40,000, awarded by the Department of Defense in fiscal years 2015 through 2019.

4, we zoom in on the drivers of these effects.

3.5 Evidence of Adverse Selection

Our results show that increasing the pool of bidders through publicity generates changes to contract prices and subsequent contract execution. Overall, there are two classes of explanations through which we can rationalize the connection between publicity and contract outcomes: *moral hazard* and *adverse selection*.[23] The first explanation implies that contractors modify their behavior depending on the publicity status of the contract. This could be rationalized by suppliers behaving differently depending on the buyer. For example, if a vendor receives contract information directly from the buyer, she could decide to absorb potential overruns to make sure she gets direct information again in the future. The second explanation implies that publicity allows the participation of suppliers that are "different," an that their performance capacity is unrelated to the identity of the buyer or contract's advertising.

To elucidate between these mechanisms, we leverage the fact that buyers often require the same product categories repeatedly over time, allowing us to observe multiple contracts for the same buyer-product combination, with variation in the size of the award and other dimensions. Moreover, from the supplier's side, we observe most contractors executing more than one contract,

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[23] Again, note that publicizing contracts in FBO.gov impacts neither the contract's design nor the selection mechanism. Being posted in FedBizOpps.gov solely affects the diffusion of information.

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for one or more different buyers. This variation allows us to test how much of the observed variation is due to contractor's "types," relative to variation "within" contractor. To do this, we re-estimate the RDD analysis on post-award performance including contractor fixed-effects. In Appendix Table B.4, we show that the changes in performance disappear once we include contractor fixed-effects, with the point estimates shrinking substantially and the size of the standard errors remaining stable. This implies that most of the effects of publicity on contract performance is explained by variation across contractors, as opposed to within contractors. We interpret this as strong evidence in favor of adverse selection (i.e., publicity brings in different vendors), as opposed to moral hazard (i.e., publicity induces the same firms to change their behavior).

3.6 Discussion

To summarize, promoting vendor participation through publicity increases contract competition, as the average number of offers received rises substantially. The added competition translates into reductions in contract prices, but we also find that publicized contracts result in more cost-overruns and delays. Taken together, our results show that promoting contract competition for contracts that are (at least partially) incomplete involves a trade-off: it reduces contract award prices at the cost of exacerbating adverse selection, leading to contractors that are characterized by lower execution performance. Furthermore, we find that this trade-off is heterogeneous, with both price effects and performance effects depending on the degree of contract complexity.

While this policy analysis is informative of the effects of promoting competition on contract outcomes, it also presents some limitations. First, the estimated effects are local to the policy threshold of $25,000, so they may not be informative of the impacts for the rest of sample. Second, they do not provide a clear representation of the mechanisms by which buyers' and sellers' characteristics and behavior shape market outcomes. Finally, our reduced-form analysis does not allow us to evaluate equilibrium conditions under alternative policy designs. To complement the previous analysis, we therefore develop and estimate an equilibrium model of public procurement competition.

4 A Model of Competition Promotion, and Firms' Participation and Bidding Decisions

We develop and estimate an equilibrium model of publicity selection, firm participation, and bidding decisions in our public procurement setting. The ultimate goal is to estimate the model's primitives and study the implications of policy counterfactuals. We make modeling assumptions based on the setting's key features, aiming to transition from a theoretical model to an empirical one that can be estimated using the data available. Furthermore, we leverage the same variation

highlighted in Section 3—namely, the discontinuous nature of the publicity requirement—, along with additional variation in market structure, to identify the model's parameters. Section 4.1 introduces the theoretical model and discusses the auction's entry and bidding equilibrium strategies. Section 4.2 describes the empirical implementation of the model. In Section 4.3, we discuss the key variation in the data that we use for identification. The estimation approach is presented in Section 4.4 and results are discussed in Section 4.5.

4.1 Model

A buyer offers a single and indivisible contract to N potential contractors. Each potential contractor j must incur an entry cost $\omega_j > 0$ to learn her private cost to complete the task $c_j \in [\underline{c}, \overline{c}] \subset \mathbb{R}_+$ and bid for the contract. Both ω_j and c_j are assumed to be independent random draws from specific distributions. We model the potential bidders' choices in two stages. First, knowing the number of potential competitors N, each potential bidder decides whether to incur the entry cost. After the entry stage, the $n \leq N$ firms that incurred entry costs learn their costs of completing the project and submit their bids. The awarding mechanism is a first-price sealed-bid auction. The quality of the contract execution q_j is observed once the contract is finished.

Our analysis considers asymmetry between potential contractors. In particular, there are two types of firms, locals (L) and non-locals (NL). These firms differ in their distributions of entry costs G_ω^k, the cost of completing the project F_c^k, and the execution quality F_q^k, where $k(j) \in \{L, NL\}$ denotes group affiliation of bidder j. We assume that project and bid preparation costs are private information of each firm and are distributed independently across all firms and identically within group.

The contract publicity status determines the set of potential participants as follows: if the contract solicitation is openly publicized, both *local* and *non-local* contractors learn about the contract opportunity; conversely, if the contract is not advertised, only *local* contractors receive the information. Hence, our model allows the buyer to endogenously determine the set of potential contractors through the publicity choice, which is made considering the likelihood that a contractor of each group is awarded the contract, the expected price, and the expected execution performance in terms of cost overruns.

4.1.1 Equilibrium in the Bidding Stage

We start by characterizing the bidding stage and then use these results to analyze the participation stage. Our analysis focuses on a group-symmetric equilibrium where bidders of group k follow the same bidding strategy $\beta_k(\cdot)$, mapping project cost c_j, into a bid b_j. We assume that c_j is drawn independently from a type-specific continuous distribution $F_c^k(\cdot)$, with density $f_c^k(\cdot)$ and common support $[\underline{c}, \overline{c}] \subset \mathbb{R}_+$. The distributions of entry and production costs, and the number of potential

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bidders of each type are common knowledge. Nevertheless, we assume that bidders do not observe the number of actual competitors of each group n_t^k, as in Krishna (2003) and Li and Zheng (2009).

Our setting considers two possible scenarios: with and without publicity. If the contract solicitation is publicized, then both *local* and *non-local* firms can participate. In this case, the expected utility of bidder j with cost realization c_j and group membership $k(j)$ depends on the number of bidders from each group:

$$\mathbb{E}\left[\pi_j(c_j)\right] = \left(b_j - c_j\right) \left(\sum_{l=2}^{N^{k(j)}} \rho_l^{k(j)} \left(1 - F_c^{k(j)}\left(\beta_{k(j)}^{-1}(b_j)\right)\right)^{l-1}\right) \left(\sum_{l'=1}^{N^{-k(j)}} \rho_{l'}^{-k(j)} \left(1 - F_c^{-k(j)}\left(\beta_{-k(j)}^{-1}(b_j)\right)\right)^{l'}\right)$$

where $\rho_l^{k(j)}$ is the probability that the number of actual bidders is equal to l, and $-k(j)$ denotes the other group of potential contractors. The optimal bidding requires solving a system of differential equations corresponding to the first order conditions for both types of bidders, as follows:[24]

$$
\begin{aligned}
\frac{1}{b_j - c_j} &= f_c^{k(j)}\left(\beta_{k(j)}^{-1}(b_j)\right) \frac{\partial \beta_{k(j)}^{-1}}{\partial b_j} \left[\frac{\sum_{l=2}^{N^{k(j)}} \rho_l^{k(j)}(l-1)\left(1 - F_c^{k(j)}\left(\beta_{k(j)}^{-1}(b_j)\right)\right)^{l-2}}{\sum_{l=1}^{N^{k(j)}} \rho_l^{k(j)}\left(1 - F_c^{k(j)}\left(\beta_{k(j)}^{-1}(b_j)\right)\right)^{l-1}}\right] \\
&+ f_c^{-k(j)}\left(\beta_{-k(j)}^{-1}(b_j)\right) \frac{\partial \beta_{-k(j)}^{-1}}{\partial b_j} \left[\frac{\sum_{l'=1}^{N^{-k(j)}} \rho_{l'}^{-k(j)} l'\left(1 - F_c^{-k(j)}\left(\beta_{-k(j)}^{-1}(b_j)\right)\right)^{l'-1}}{\sum_{l'=1}^{N^{-k(j)}} \rho_{l'}^{-k(j)}\left(1 - F_c^{-k(j)}\left(\beta_{-k(j)}^{-1}(b_j)\right)\right)^{l'}}\right]
\end{aligned}
\tag{4}
$$

If a contract solicitation is not publicized, only *local* firms can bid, i.e., the number of potential *non-local* contractors is zero. In this case, the bidding problem is symmetric as there is only one group involved. Local suppliers observe the contracts' publicity status and hence the number of potential competitors.

4.1.2 Equilibrium of the Entry Stage

Firms compare the *ex-ante* expected profit conditional on entry to their entry cost ω_j, where ω_j is independently drawn from a type-specific continuous distribution $G_\omega^k(\cdot)$ with common support $[\underline{\omega}, \overline{\omega}]$. Firms with entry costs below their expected profit decide to incur the entry fee to learn about their cost of completing the project. The *ex-ante* (expected) profits from participating are given by:

$$\bar{\pi}^k(\varphi^k, \varphi^{-k}) = \int_{\underline{c}}^{\overline{c}} \left(\sum_{n_k-1, n_{-k} \subset N_k-1, N_{-k}} \pi^k(c|n^k - 1, n^{-k}) Pr\left(n^k - 1, n^{-k}|N^k, N^{-k}\right)\right) dF_c^k(c) \tag{5}$$

where φ^k and φ^{-k} are the entry probabilities of each group. Because entry decisions are made

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[24]As noted by previous research on asymmetric auctions (Lebrun, 1999; Bajari, 2001; Maskin and Riley, 2003a,b), the Lipschitz conditions are not satisfied in this case. The bidding strategies cannot be solved analytically, but require numerical methods. Campo, Perrigne, and Vuong (2003) and Brendstrup and Paarsch (2003) discuss non-parametric identification of cost functions in this setting.

simultaneously, the equilibrium condition is characterized by a group-specific entry cost threshold $\bar{\omega}_k$, such that firms whose entry cost is below their group-specific threshold participate.[25] Finally, when the contract is not publicized, only locals can participate, and thus the participation problem becomes symmetric. Therefore, for a given contract t, the local group's participation threshold differs depending on whether the contract was publicized.

4.2 Empirical Model

Based on equilibrium conditions of the general model, we proceed to describe its implementation based on the empirical setting. A contract solicitation t is characterized by (x_t, z_t, u_t, N_t). The vector x_t corresponds to baseline characteristics of the contract, z_t are entry-cost shifters, and u_t captures unobserved project heterogeneity reflecting project attributes not included in the data but that impact firms' bidding behavior. In the empirical implementation below, x_t includes the product or service category required, its associated complexity measure, the expected duration of the contract, and the location of the contract. On the other hand, for z_t we use variables related to the timing of the solicitation and, in particular, whether it was required at the end of the fiscal year.[26] Finally, $N_t = (N_t^L, N_t^{NL})$ denotes the number of potential contractors of each group.[27] The model proceeds in four stages, which are depicted in the Figure 6. The stages are:

T = 0: *Publicity Decision.* The buyer observes (x_t, z_t, u_t, N_t) and decides whether to publicize the contract, $D_t \in \{0,1\}$, in order to maximize expected utility. Contract publicity status determines the set of potential bidders.

T = 1: *Entry Decision.* Each firm that learns about the contract opportunity observes (x_t, z_t, u_t, N_t). They draw individual and private realizations of entry cost, and they simultaneously decide

---

[25]In equilibrium, the entry probabilities are defined by the system of equations:

$$\varphi^L = G_\omega^L \left[\bar{\omega}_L(\varphi^L, \varphi^{NL}) \right]$$
$$\varphi^{NL} = G_\omega^{NL} \left[\bar{\omega}_{NL}(\varphi^L, \varphi^{NL}) \right]$$

Group-specific equilibria exist by Brouwer's Fixed Point Theorem. We numerically verified uniqueness of the equilibrium entry probabilities within our estimation routine (Krasnokutskaya, 2011; Roberts, 2013). Espin-Sanchez et al. (2021) discuss sufficient condition for equilibrium uniqueness in entry games with private information.

[26]As documented by Liebman and Mahoney (2017), the volume of contracting activity at the end of the fiscal year is disproportionally high, which may reduce the attention that any given vendor can devote to each solicitation.

[27]Identifying the potential number of bidders is not trivial (Athey, Levin, and Seira, 2011; Krasnokutskaya and Seim, 2011; Mackay, 2020). We combine two methodologies. First, using the procedure described in Appendix section E.1, we classify and count the suppliers that ever won a contract for every buyer-product combination. The second method considers the maximum number of actual bidders for buyer-product auctions. This method is discussed by Athey, Levin, and Seira (2011); Roberts (2013). It is rooted in the theoretical idea that if all potential bidders decide whether to enter simultaneously, with enough observations, the maximum number of observed bidders across observations will be equal to the total number of potential bidders. The maximum number of bidders of auctions that weren't publicized informs about the number of potential *local* bidders. In contrast, the maximum number of bidders of advertised contracts approximates the sum of *local* and *non-local* potential bidders. Finally, we define the number of potential bidders for every buyer-product as the maximum of both approaches. Combining these two methods alleviates potential weaknesses of each of them. The median number of potential *local* and *non-local* bidders is six and three, respectively.

whether to participate.

T = 2 *Bid Decision.* Active bidders draw a realization of the production cost and decide the magnitude of their bid. The contract price equals the lowest bid submitted.

T = 3 *Execution Stage.* Once the contract is finalized, the performance of the selected contractor is observed and corresponds to the realization of an execution shock in terms of cost overruns.

Figure 6: Timing of the Model
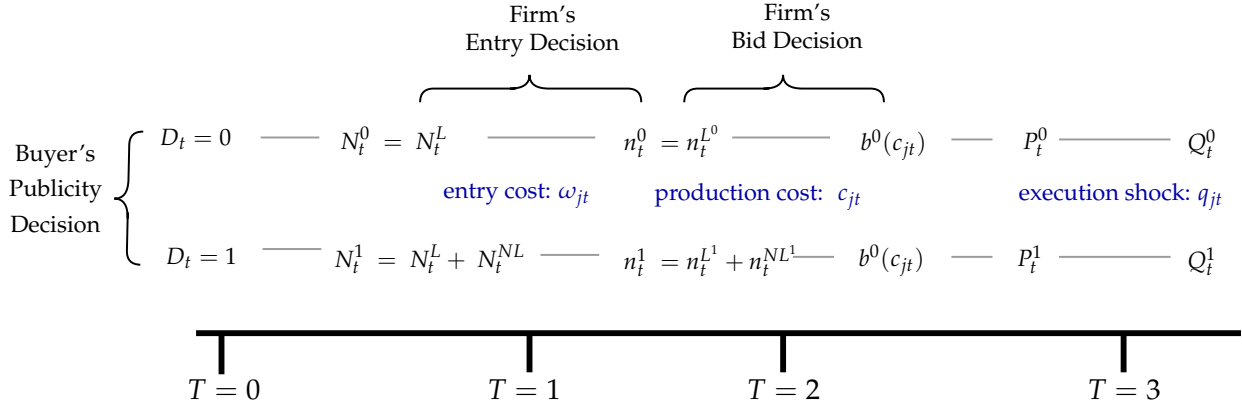
4.2.1 Model Specification

Publicity Decision. We assume that the buyer is risk-neutral, forms unbiased beliefs, and derives utility from expected contract outcomes linearly:

$$
\begin{aligned}
U_t^D &= U(\bar{P}_t^D, \bar{Q}_t^D, \bar{L}_t^D) \\
&= \lambda^P \bar{P}_t^D + \lambda^Q \bar{Q}_t^D + \lambda^L \bar{L}_t^D + \varepsilon_t^D,
\end{aligned}
$$

where $\bar{P}_t^D$, $\bar{Q}_t^D$ and $\bar{L}_t^D$ are, respectively, the expectation of the log awarding price, log cost overruns, and likelihood that a local contractor wins. These expected outcomes are objects that depend on realizations of (x_t, z_t, u_t, N_t) and the publicity status $D_t \in \{0,1\}$. The terms $\bar{P}_t^D$ and $\bar{Q}_t^D$ are in log-dollar units, while $\bar{L}_t^D$ is a probability. Finally, ε_t^D is an idiosyncratic utility shock.

The publicity regulation kicks in when the expected award price without publicity is higher than \$25,000. This introduces a utility shift, η, which translates into a discrete jump on the probability of advertisement at the threshold. Intuitively, η captures the intensity of regulation enforcement above the threshold:[28]

$$
D_t = 1 \quad \Longleftrightarrow \quad U(\bar{P}_t^1, \bar{Q}_t^1, \bar{L}_t^1) + \eta \mathbb{1}\left(\bar{P}_t^0 > \log(25)\right) \geq U(\bar{P}_t^0, \bar{Q}_t^0, \bar{L}_t^0)
$$

---

[28]Since we have documented that contract "manipulation" (i.e., strategic bunching of price estimates) is unimportant in this setting, for simplicity we abstract away from this action in the model.

23

Entry and Bidding Decision. Bidder j's execution cost for contract t is multiplicative: $c_{jt} = \tilde{c}_{jt} \cdot u_t$, where $\tilde{c}_{jt}$ is a firm-specific cost component that is private information of firm j, and u_t represents a common cost component that is known to all bidders but is unobserved by the researcher (Haile and Kitamura, 2019). The distribution of the firm-specific cost component for group-k firms is given by $F_{\tilde{c}}^k(\cdot|x_t)$, and each draw $\tilde{c}_{jt}$ is independent across j and t conditional on observables. The unobserved project heterogeneity is given by $u_t \sim H(\cdot)$, and is independent from project characteristics (x_t), entry-cost shifters (z_t), and the number of potential bidders (N_t).

We assume that bidders are risk neutral. Thus, the Bayes-Nash equilibrium bid function for group k is multiplicative: $\beta_k(c_{jt}|x_t, u_t, N_t) = u_t \cdot \tilde{\beta}_k(\tilde{c}_{jt}|x_t, N_t)$.[29] Each bidder submits a bid of $b_{jt} = \tilde{b}_{jt} u_t$, where $\tilde{b}_{jt} = \tilde{\beta}_k(\tilde{c}_{jt}|x_t, N_t)$ represents the bid for bidder j when u_t is one. Therefore, $\log(b_{jt}) = \log(\tilde{b}_{jt}) + \log(u_t)$, and the log of the unobserved heterogeneity component acts as an additive mean shifter to the conditional distribution of log bids.

Finally, we assume that entry costs ω_{jt} are independent across j and t conditional on observed project characteristics x_t. In equilibrium, firms' participation behavior is characterized by group-specific thresholds, $\bar{\omega}_t^{k*}$. Thus, the number of actual bidders n_t^k from group $k \in \{L, NL\}$ distributes binomial with an individual entry probability of $\varphi^{k*}(x_t, z_t, u_t, N_t)$ and N_t^k trials, where $\varphi^{k*}(x_t, z_t, u_t, N_t) = G_\omega^k(\bar{\omega}^{k*}(x_t, z_t, u_t, N_t))$. Our model considers entry shifters z_t, which capture market-level conditions that affect entry decisions.[30]

Contract Execution. Contract execution is observed ex-post and corresponds to a draw from the group-specific distribution $F_q^k(\cdot|x_t)$. We focus on one direct measure of performance, which is the magnitude of cost overruns. This variable is convenient as it can be directly benchmarked against the contract's awarded dollar value. Of course, this convenience comes at the cost of abstracting away from other (context-specific) execution costs.[31] The contractor does not derive utility from changes on cost-overruns ex-post. This connects directly to the evidence provided in Section 3, where we document that contractors do not seem to behave strategically in this regard, but rather transfer the excess cost to the buyer.

Equilibrium is characterized by the buyer choosing a contract's publicity status that maximizes her expected utility, and informed potential contractors entering and bidding optimally if expected profits exceed their entry costs. Finally, contract execution is revealed once the contract concludes.

---

[29]This formulation is discussed by Krasnokutskaya (2011), Proposition 1. The author shows that when the cost function is multiplicative with unobserved heterogeneity, Bayes-Nash equilibrium bidding strategies are also multiplicative.

[30]For a given vector of observables x_t, the entry shifters expand the range of combinations of auction entrants. Relying only on changes in the number of potential bidders combine counteracting "entry" and "competition" effects discussed by Li and Zheng (2009).

[31]For example, Lewis and Bajari (2011) study the welfare gains associated with reducing delays on highway construction.

4.3 Identification

We aim to identify the type-specific distributions of ω_{jt}, $\tilde{c}_{jt}$ and q_{jt}, the distribution of the unobserved heterogeneity u_t, and the parameters that govern the buyer's utility function. For every contract t, we observe in the data a set of model *inputs* (x_t, z_t, N_t) and *outputs* $(D_t, n_t, P_t, Q_t, L_t)$. The model is identified based on three main assumptions:

(i) Contract and market characteristics (x_t, z_t, N_t) are exogenous.

(ii) Idiosyncratic components of entry cost shocks are (conditionally) independent from production cost and quality shocks, i.e., $\omega_{jt} \perp (c_{jt}, q_{jt})|x_t$.

(iii) Unobserved heterogeneity u_t is independent across t with $\mathbb{E}[u_t|x_t, z_t, N_t] = \mathbb{E}[u_t] = 1$.

    Identification in our model involves pinning down primitive distributions of the two types of bidders (locals and non-locals). In our setting, the contract's publicity status determines the composition of participating bidders. The data from non-publicized contracts inform about the distributions of local contractors, while non-local contractors are only observed on publicized contracts. Identification of these two distributions requires that the sample of publicized and non-publicized contracts be selected at random, yet buyers' publicity choices are driven by observables, unobservables, and utility shocks. In the spirit of the RDD discussed above, we leverage the discrete nature of the publicity requirement to obtain quasi-experimental variation on publicity adoption, and thus identify type-specific distributions separately. We now discuss identification more specifically for the different components of the model.[32]

Bidding. The empirical challenge involves separately identifying $F_{\tilde{c}}$ from H_u. The identification argument relates to Mackay (2020) and builds upon exogenous variation on the number of bidders.[33] In our setting, bidders observe auction characteristics and the set of *potential* competitors, N_t, but do not know the set *actual* competitors, n_t. Equilibrium bidding strategies depend on the information they have in hand: auction bidders that form the same beliefs about the competitive environment would set the same bidding strategies. Thus, the number of *actual* competitors $(n_t|x_t, z_t, N_t)$ would depend on realizations of (random) individual entry cost shocks.

    Exogenous variation in the number of entrants allows for identifying $N - 1$ expected order statistics of the bidding distribution for each (x_t, z_t, N_t) combination. Since u_t is assumed

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[32]In what follows we omit the distinction depending $D_t \in \{0,1\}$, because it is taken as given by the bidders. To ease notation, when a contract t is publicized, the set of bidders has two dimensions: i.e., $N_t^1 = (N_t^L, N_t^{NL})$ and $n_t^1 = (n_t^L, n_t^{NL})$.

[33]Alternative strategies to identify models with unobserved heterogeneity involve either stringent assumptions on auction participation or observing the full distribution of bids. Compiani et al. (2020) assumes the number of active bidders can be characterized by an (equilibrium) reduced-form relation, $n_t = \eta(x_t, z_t, u_t, N_t)$ that is weakly increasing in u_t, thus a realization of n_t inform about (unobservable) realizations of u_t. Roberts (2013) provides a similar identification argument but leveraging variation in auctions' reserve price. Alternatively, Krasnokutskaya (2011) follows a measurement error approach and builds upon deconvolution methods to separately identify the distribution of unobserved heterogeneity and individual costs functions. The latter requires observing at least two bids per auction.

independent, one additional competitor under the same bidding strategy is equivalent to one additional draw from the distribution of normalized bids, $G_{\tilde{b}}^k(\cdot)$. Restrictions over expected order statistics approximate the quantiles of $G_{\tilde{b}}^k(\cdot)$, and if $N \to \infty$, $G_{\tilde{b}}^k(\cdot)$ is exactly identified. The underlying cost distribution $F_{\tilde{c}}^k(\cdot)$ is pinned down from the distribution of $G_{\tilde{b}}^k(\cdot)$ (Guerre et al., 2000; Campo et al., 2003). See Appendix D.1 for more identification details and proofs.

Entry. Potential bidders set a threshold for realizations of entry costs. They pay ω_{jt} and enter auction t only if the realization ω_{jt} is smaller than the expected profit of participating in the auction, i.e., $\omega_{jt} < \bar{\omega}_t^k$. Since the probability of participating enters into the expected utility function which defines the cutoff, the (fixed-point) equilibrium entry cutoff is characterized by a type-specific entry probability $\varphi_t^{k*} = G_\omega^k(\bar{\omega}_t^{k*})$. Identifying $G_\omega^k(\cdot|x_t)$ from the data entails three steps. First, we observe the *realized* fraction of potential bidders that decide to enter each auction t, which implies that, with enough observations per combination of (x_t, z_t, N_t), we can estimate $\varphi^{k*}(x_t, z_t, N_t)$. Then, we use Equation (5) to back-up the expected utility of entering, conditional on (x_t, z_t, N_t). The final step leverages variation in (z_t, N_t) to construct combinations of $(\varphi^{k*}, \bar{\omega}^{k*}|x_t)$ that pin down $G_\omega^k(\cdot|x_t)$.

Execution. Contract execution performance (cost overruns) is given by (conditionally) independent random shocks. Thus, the observed distribution of cost overruns directly reveals $F_q^k(\cdot|x_t)$.

Buyer's Preference Parameters. The buyer's taste parameters for price, overruns, and local contractors are identified from variation in contract and market characteristics (x_t, z_t, N_t). In particular, variation in the set of potential bidders determines the effects of publicity on price and on having a local winning the auction. The degree of complexity of the transaction helps pin down the potential scope for overruns ex-post. Intuitively, keeping other factors fixed, if a transaction involves a fully specified product, there will be no differences in performance ex-post, which shuts down that factor in the decision.

4.4 Estimation Approach

We make functional form assumptions to characterize equilibrium conditions of each stage and take the model to data:[34]

- *Bidding Stage:* We specify that the log of individual bids $\log(\tilde{b}_{jt})$ is distributed normal with mean $\mathbb{E}[\tilde{b}_t^k | x_t, N_t] = [x_t, N_t]' \alpha^k$ and variance $\mathbb{V}[\tilde{b}_t^k | x_t] = \left(\exp(x_t' v^k)\right)^2$. We further assume that $\log(u_t)$ is distributed normal with mean zero and variance σ_u^2.

- *Entry Stage:* The equilibrium entry choices are characterized by type-specific probabilities, $\varphi_t^k(x_t, z_t, N_t)$. We assume $\varphi_t^k(x_t, z_t, N_t) = \Phi\left([x_t, z_t^e, N_t]' \tau^k\right)$, where $\Phi(\cdot)$ denotes the

---

[34]Our parametric assumptions are linked to related literature (Krasnokutskaya and Seim, 2011; Hong and Shum, 2002; Porter and Zona, 1993). Moreover, Krasnokutskaya (2011) indicates that the distribution of firm-specific components and unobserved heterogeneity closely resembles log-normality. Overall, our results are not sensitive to adding additional covariates or variations to the functional form. Our data provide enough variation for identifying these distributions independent from the specific functional form.

cumulative distribution of the standard normal distribution, and z_t are entry-cost shifters. The number of participating bidders $n_t^k(\cdot)$ is distributed binomial with N_t^k independent draws with probability of success $\varphi_t^k(\cdot)$.[35]

- *Execution Stage:* Given that most contracts stay right on budget, we adopt the same specification as Eun (2018), and censor at zero the observed distribution of cost overruns. We assume that $\log(q_t^k)$ is the latent distribution, while we only observe $Q_t^k = \max\{0, \log(q_t^k)\}$, where $\log(q_t^k)$ distributes normal with mean $\mathbb{E}[q_t^k | x_t^q] = x_t^{q\prime}\gamma^k$ and variance $\mathbb{V}[q_t^k | x_t] = \left(exp\{x_t^{q\prime}\xi^k\}\right)^2$.

- *Publicity Choice:* We specify that the difference of buyers' utility shocks $(\varepsilon_t^0 - \varepsilon_t^1)$ distributes standard normal, so that $Pr(D_t = 1) = \Phi\left(\lambda^P \tilde{P}_t + \lambda^Q \tilde{Q}_t + \lambda^L \tilde{L}_t + \eta \mathbb{1}(\bar{P}_t^0 > 25) + x_t'\zeta\right)$, where $\left(\tilde{P}_t, \tilde{Q}_t, \tilde{L}_t\right)$ are the *change* in expected outcomes associated with publicity, leaving no publicity as the omitted category.[36] We include agency fixed-effects as well as $\mathbb{1}(\bar{P}_t^0 > 25)$ to indicate whether the expected price without publicity is above the regulation threshold.

Our specification provides flexibility to allow all distributions to differ across locals and non-locals. Moreover, we interact all of our covariates with indicators of non-local bidders.

Estimating Dataset. The data used to estimate the model is the same one used in previous sections, except for one adddional restriction. In order to classify local and non-local vendors, we require buyer-product combinations to appear at least four times in the full database between 2013-2019, at least one of which should appear in FBO. This restriction rules out products that are purchased less often. Table B.7 compares summary statistics for the relevant variables between this selected sample and the full sample used in Section 3. Overall, given that the sample selection involves the buyer contracting the same product multiple times, the selected sample includes contracts for categories that are, on average, less durable (i.e., it over-represents services). Finally, and consistent with the rest of the analysis, we estimate the model using contracts around the regulation threshold, i.e., between 10 and 40 thousand dollars.

Estimation Procedure. Our empirical model yields predictions about equilibrium conditions for suppliers' participation, bidding, and ex-post execution, with and without publicity. We also characterize the buyer's publicity decision. Our estimation strategy proceeds using simulated method of moments (Mcfadden, 1989; Pakes and Pollard, 1989). That is, we choose a vector of parameters θ to generate simulated moments that closely resemble key moments from the data. Using the parametrized primitives discussed previously, we simulate four sets of moments:

---

[35]Related papers either assume parametric distributions for the entry costs, which paired with the expected utility of entering map into well-defined group-specific entry probabilities (Krasnokutskaya and Seim, 2011; Mackay, 2020); or make functional form assumptions on the entry probabilities, which combined with expected utilities allow for recovering entry costs (Athey et al., 2011, 2013). We follow the latter approach.

[36]Our estimation does not restrict the set of values for parameters λ^P, λ^Q, and λ^L. However, in general, we should expect that buyers dislike paying higher prices or experiencing overruns, so we expect λ^P and λ^Q to be negative.

participation decisions, bidding strategies, quality delivered, and publicity decisions.

Our simulation procedure starts with a set of data inputs (x_t, z_t, N_t) of size T. Then, from every observation we generate S random draws of u_t. Finally, our setting contemplates that the buyer decides based on expectations, which are formed conditional on (x_t, z_t, N_t) and u_t, integrating over Monte Carlo simulated distributions of award price, overruns, and the likelihood of a local winning. This method, although computationally involved, is useful to circumvent integrating over potentially non-linear functions, and provides enough flexibility to match theoretical moment functions that cannot be evaluated directly.

Formally, denote the target m_n as a vector of moments from the data. The analogous moments generated by simulating observations are denoted by $m_s(\theta)$. Note that this vector depends on the parameters $\theta \in \Theta \subset \mathbb{R}^P$. The estimator minimizes the standard distance metric:

$$\hat{\theta} = \operatorname*{argmin}_{\theta} \left(m_n - m_s(\theta) \right)' W_n \left(m_n - m_s(\theta) \right) \tag{6}$$

where W_n is the weighting matrix, which is chosen using the standard two-step approach: the quasi-optimal weight matrix W_n is derived in the first stage, and the parameters are estimated in the second stage (Gourieroux, Monfort, and Renault, 1993). The vector of parameters corresponds to: $\theta = (\alpha^k, \nu^k, \tau^k, \gamma^k, \xi^k, \vec{\lambda}, \zeta, \sigma)$.

We use three sets of target moments. The first set of moments are a vector of means and variances of the outcome variables, as well as its interaction with the relevant covariates. The relevant outcome variables are the auction price, the number of bidders, local winner, the magnitude of cost-overruns, an indicator of any cost-overrun, and publicity choices. The second set of moments consists of means of these same outcome variables conditional on partitions of the domain of contract prices, and are estimated separately for goods and services. Finally, the third set of moments corresponds to a vector of normalized observation frequencies on the relevant window of contract prices. Stacking together these three vectors, we obtain the vector m_n of 357 moments that we seek to match with the model. We use the stochastic optimization algorithm *Differential Evolution* (Storn and Price, 1997) to perform the objective minimization.[37] The details of the estimation procedure are discussed in the Appendix E.

4.5 Estimation Results

We estimate the model's parameters of publicity selection, entry, bidding, and execution, and combine these estimates with model equilibrium conditions to recover the primitive distribution of production and entry costs for locals and non-locals. These estimates are inputs for the policy counterfactuals in Section 5.

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[37]This algorithm performs a (parallel) direct search approach; it does not rely on gradient methods for minimizing possibly nonlinear and non-differentiable continuous space functions.

4.5.1 Estimates

To facilitate the interpretation of coefficients, Table 2 shows the marginal effects on the relevant outcomes for the set of coefficients associated with the bidding stage. Appendix Table B.8 displays the underlying coefficient estimates with their corresponding standard errors.[38]

Several findings are worth highlighting. First, bidders are less prone to participate if the contract involves a service or a relatively complex product. Thus, auctions for these types of products are less competitive. In line with the evidence presented in Section 3.5, non-local contractors are 72 p.p. more likely to participate than locals. This is consistent with the fact bidders reduce their probability of entering if they observe more potential non-local competitors: one additional non-local contractor reduces the entry by 7.4 p.p.

Second, bids from non-locals are slightly lower than locals; they bid 4 p.p. lower prices. Another relevant feature is that unobserved heterogeneity is important in our data. Most of the variation in bidding is explained by common factors instead of variation between bidders within auction. The standard deviation of (log) unobserved heterogeneity is 27 times larger than the bids' standard deviation when $\log(u_t) = 0$.

Third, the execution shock depends on the transacted product: the mean of log-overruns shocks is substantially higher for services. In line with the reduced-form results, the difference in execution quality between locals and non-locals is substantial: non-locals have a mean shock that is 23 p.p. higher. Interestingly, the difference between these two groups is relatively stable over different degrees of product complexity.

Panel C of Table 2 shows that if buyers anticipate that publicity leads to a 10% reduction in awarding price, they increase their likelihood of publicizing by 2.4 p.p. However, a 10% increase in cost overruns reduces the probability of advertising by only 1 p.p. This asymmetry in the taste parameters for (log) dollars at the award stage and cost-overruns ex-post is interesting. One possible explanation is that buyers may underestimate the value of contract execution when they do not deal directly with the contractor during the execution stage.[39]

Buyers have a preference for local vendors: if they anticipate a 10 p.p. reduction in the likelihood of a local contractor winning, buyers reduce the probability of publicity by 2.3 p.p. The preference for locals captures any form of favoritism that is not related to award price or execution performance. In this sense, we remain agnostic about the specific nature of this preference—which could reflect anything from convenience, to path dependence, to corruption— and focus on the impacts on total procurement spending. We find that the preference for locals is meaningful in magnitude: the buyer is indifferent between increasing the probability of a local winner by 10%

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[38]Although the model is estimated altogether, Table 2 and Table B.8 present estimates in different columns to facilitate visual interpretation. The procedure to estimate standard errors is discussed in Appendix E.2.1.

[39]In interviews with procurement officers, we noted that some agencies separate the tasks of contract award and contract management.

Table 2: Model Estimates: Marginal Effects

	$\bar{x}$	Δx	Entry $\Delta\varphi/\Delta x$	Bidding $\Delta\tilde{b}/\Delta x$	Execution $\Delta q/\Delta x$	$\Delta(q>0)/\Delta x$
Panel A: Marginal Effects						
Service	0.38	1	-0.024	0.000	0.075	0.013
Degree of Complexity	0.09	0.1	-0.028	0.000	0.163	0.030
Non-Local		1	0.721	-0.040	0.235	0.039
Non-Local×Complexity		0.1	0.001	-0.003	0.009	0.001
Last Month	0.25	1	-0.333			
Exp. Duration > Median	0.50	1			0.127	0.021
N^L	6.08	1	0.000	-0.002		
N^{NL}	3.34	1	-0.074	0.010		
Panel B: Standard Deviation						
Estimated ($\hat{\sigma}$)					0.076	1.035
Unob. Het. (σ_u)				2.168		

	Δx	Publicity $\Delta Pub/\Delta x$
Panel C: Marginal Effects		
Exp. Price	0.1	-0.0243
Exp. Cost-Overruns	0.1	-0.0095
Exp. Local Winning	0.1	0.0228
Above $25K	1	0.3263
Number of Observations	24,135	

Notes: This table shows model estimates of marginal effects. Panel A shows the marginal effects of different covariates on the main dependent variables related to bidders' actions. Covariates are listed in the first column. Marginal effects are computed at the mean of each covariate, shown in column two. The third column shows the change in the covariate used to estimate the marginal effect. Columns four through seven show the value of the marginal effects on different dependent variables: the probability of entry, the level of the bid, the amount of cost overruns, and the probability of any positive overruns. Panel B shows the estimated standard deviation of the normalized bids and the estimated standard deviation of the unobserved heterogeneity component. Panel C displays the marginal effects of four variables on the probability of publicizing the contract solicitation in *FBO.gov*. The variables are: expected log-award price, expected log-cost-overruns, expected probability of a local contractor winning, and being above $25K in expected award price without publicity. These coefficients are jointly estimated using Simulated Method of Moments (SMM).

and reducing the award price by roughly 10%. Finally, predicting that the price without advertising will exceed $25,000 increases the likelihood of publicity by 32 p.p. This in line with the estimates from Section 3.

Model Fit. Overall, the model closely replicates the key empirical patterns in the estimation sample. Appendix Figure A9 compares the distribution of model-simulated equilibrium outcome variables with actual data. The simulated data resembles actual publicity choices, prices, number of bidders, and the share of contracts assigned to local contractors. Panels (e) and (f) separate cost-overruns by products and services. We find that, for services, the model slightly under-predicts the probability of having any (positive) cost-overrun, but over-predicts the magnitude of cost-overruns. This

Figure 7: Estimated Cost Distributions

(a) Production Cost   (b) Entry Cost
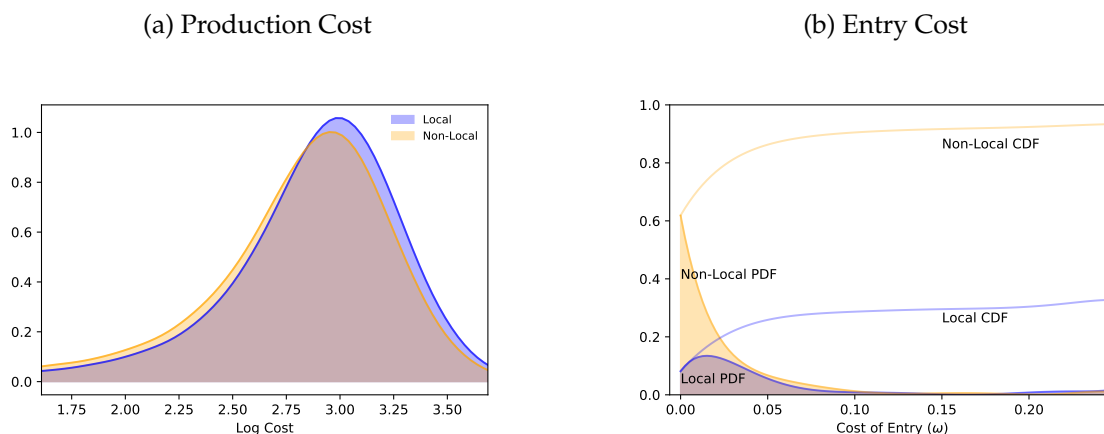
Notes: Panel (a) shows the estimated probability density function (PDF) of log production costs for local and non-local contractors. Panel (b) shows the estimated entry cost probability and cumulative density distributions (CDFs). The CDFs are estimated comparing the entry probability at different levels of predicted (log) utilities. The PDFs are computed as the numerical derivatives of the CDFs, using bins with a width size of 0.025. Both plots are estimated for covariates fixed at sample averages and $\log(u) = 0$. The plotted distribution of log costs in panel (a) is smoothed using a kernel. The raw distributions of entry costs in panel (b) are smoothed using a 7-degree polynomial fit. Zero is the minimum expected utility consistent with entry.

dichotomy suggests that buyers may face frictions when introducing contract modifications ex-post that our model does not account for.

4.5.2 Recovering the Project Cost Distribution

We recover the distribution of project costs leveraging the methodology introduced by Guerre, Perrigne, and Vuong (2000), and Campo, Perrigne, and Vuong (2003). This method combines the first-order conditions (Equation 4)—subject to boundary conditions—with estimated equilibrium bids to recover the inverse bid function. In our setting, the first-order condition depends on the probabilities of different combinations of local and non-local bidders. These probabilities are formed from simulations based on the model's participation parameters. Finally, strict monotonicity between the bid and the inverse bid functions enables us to to obtain an estimate of project costs from estimated distribution of bids.

Figure 7(a) shows the probability density function of log costs $\log(\tilde{c}_{jt})$ for both groups. Local bidders have slightly higher costs than non-locals. Appendix Figure A11 displays the mean $\log(\tilde{b}_j(\tilde{c}))$ as a function of the log cost. As expected, markups decrease with higher cost draws.

4.5.3 Recovering Entry Costs

We recover group-specific entry-costs using the equilibrium conditions for optimal entry behavior discussed in Section 4.1.2. A potential bidder compares the draw from the entry-cost distribution

G_ω^k with the expected utility of entering, i.e., $\varphi^k(x_t, z_t, N_t) = G_\omega^k \left(\bar{\pi}^k(x_t, N_t, z_t) \right)$. Our estimated cost distributions $F_{\hat{c}}^k(c)$ allow us to estimate the (*ex-ante*) predicted utility of participating (Equation 5) and compare it to observed entry behavior (Athey, Levin, and Seira, 2011).

Figure 7(b) displays estimated entry cost distributions, and shows that they differ substantially across groups. On the one hand, roughly 60% of non-local firms face zero entry cost (i.e., they enter with probability one), and 90% enter of the entry cost is less than 0.1 log units. On the other hand, local contractors face substantially higher entry costs. Indeed, with a 60% chance, they would *not* enter for any of the values included in the estimated range of existing expected utilities. The estimated entry-cost asymmetry shapes the composition of actual bidders and, subsequently, the winning bid conditions.

Appendix Figure A10 shows how the composition of actual competitors (and the identity of the winner) depends on the number of potential non-local contractors. The number of actual bidders decreases as the number of potential non-local bidders increases. This is consistent with the fact that reductions on predicted utility due to increased competition discourage local bidders' participation, making it substantially more likely that a non-local contractor wins.

4.6 Effects of Increasing Competition through Publicity

Having estimated the primitives of the model as a function of observable characteristics, we can replicate the policy evaluation discussed in Section 3. Furthermore, the model allows us to evaluate contract outcomes with and without publicity, not only for contracts around the threshold, but throughout the range of awards included in our sample.

Figure 8 displays the variation on contract outcomes as a function of the expected price. We compare the observed regime with three alternative scenarios: one with no publicized contracts, one with all publicized contracts, and one where officers are free to choose throughout the expected price range (i.e., no threshold regulation). Results are in line with our reduced-form analysis. Publicizing contract solicitations allows the participation of non-local bidders, which are more prone to experience overruns and have substantially lower participation costs, discouraging locals' participation. Thus, enhancing contract participation through publicity reduces prices ex-ante, yet increases prices ex-post.

We consider the following definition of the *final price* $p_{F,t}^D$ that takes into account both effects:

$$p_{F,t}^D = p_{I,t}^D (1 + q_t^D)$$

where $D_t \in \{0, 1\}$ denotes contract t's publicity status, $p_{I,t}^D$ is the log award price, and q_t^D is the share of cost-overruns *ex-post*.

Figure 9 compares contract award prices, cost overruns, and final prices, with and without

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Figure 8: Policy Evaluation Using Model Estimates

(a) Number of Bidders

(b) Local Wins

(c) Log Prices

(d) Overruns
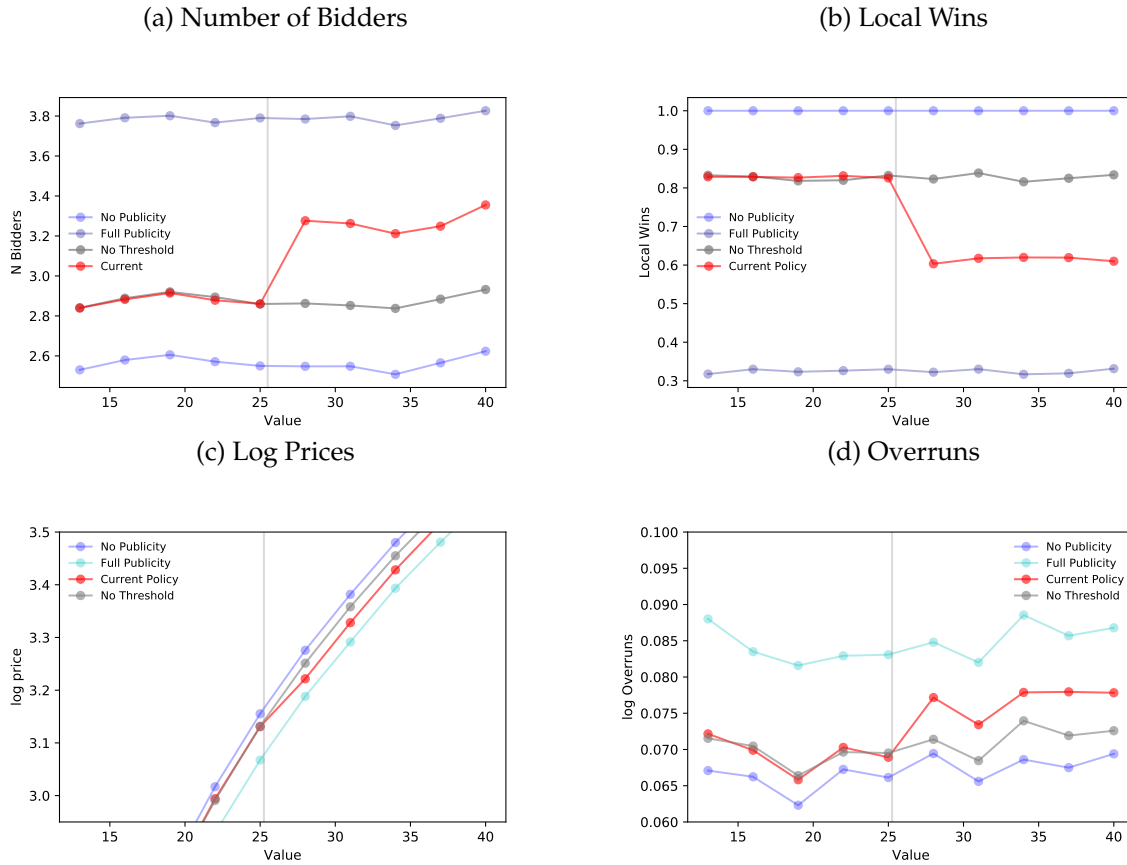
Notes: This figure shows different outcome variables around the threshold, for different counterfactual policies. Panel (a) shows the number of bidders, Panel (b) the probability of awarding to a local vendor, Panel (c) the log award price, and Panel (d) log overruns. The x-axis in every graph is the expected award value of the contract without publicity. In every graph, we compare the current policy design (red line) with counterfactual regulations mandating full and zero publicity. We also include a counterfactual policy of no threshold, implying that the buyers may freely choose whether to publicize contracts throughout the expected award range.

publicity, for different levels of complexity. The gray line at zero marks the no-publicity benchmark. The orange and green lines show results that are consistent with the motivating evidence: both the effect of publicity on award prices and on cost overruns is more pronounced for complex contracts. The empirical model sheds additional light on the mechanisms behind the first result: contracts that require complex contracts have a higher variance in bid functions and face lower participation levels. The former increases the support of possible price reductions from additional bidders, while adding one more bidder to an auction with low participation has a higher effect than adding one to an auction that already has many competitors. Finally, the blue line shows the combined effect of ex-ante price reductions and ex-post price increases. Publicity reduces total prices for contracts with low levels of complexity, but increases them for more complex acquisitions.

These findings align with and extend our reduced form results. They also provide quantitative

Figure 9: Effects of Publicity on Ex-ante, Ex-post, and Final Prices
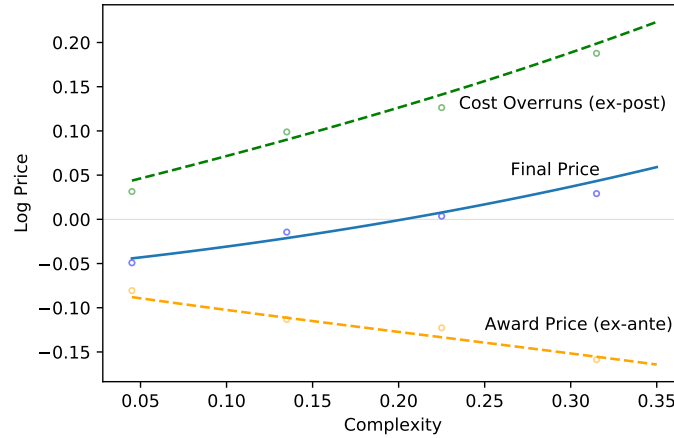
Notes: This figure shows the effect of publicity on (log) award prices, (log) cost overruns, and (log) final prices, as a function of product complexity. Effects are measured relative to a benchmark of no publicity, represented in the horizontal line at zero. Circles represent the mean effect by complexity bin. 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.

evidence consistent with the idea introduced by seminal papers on incomplete contracting: there exist a degree of transaction complexity beyond which promoting competition may backfire. When there's a high number of possible contingencies during the execution stage, ensuring adequate performance *ex-post* may be more important than reducing prices *ex-ante*. (Williamson, 1976; Bajari and Tadelis, 2001; Bajari et al., 2014; Bolotnyy and Vasserman, 2019).

5 Counterfactual Analysis

We use our model to evaluate the implications of counterfactual policies. Our counterfactuals build upon the fact that the buyer endogenously influences how much competition a contract gets, conditional on complying with publicity rules. We focus on the two aspects that shape competitive outcomes in this setting: buyer preferences and rules design. In the first counterfactual exercise, we analyze the consequences of removing publicity rules, allowing the buyer to decide whether to advertise the solicitation in an unrestricted way. The second exercise studies the effects of alternative regulation designs.

5.1 The Strategic Value of Delegating Competition Promotion to the Buyer

What are the implications of allowing the buyer to choose whether to openly publicize a contract, as opposed to mandating rules that constraint buyer's discretion? This trade-off pertains to the more general problem of the delegation of authority within organizations (Aghion and Tirole, 1997), and

has been frequently analyzed in the context of public procurement.[40]

Conceptually, the publicity requirement acts as a discontinuous jump in the cost of not publicizing. Below the threshold, buyers choose whether to advertise the contract solicitation with full discretion; above the threshold, regulation forces them to publicize more often than desired. Using the estimated model parameters, we simulate buyers' hypothetical decisions in a *no threshold* situation, with full discretion over publicity decisions for the whole range of contracts in our sample. We benchmark this counterfactual against the current policy design, a baseline of no publicity for any contract, and a *full publicity* regulation, where all contracts are publicized regardless of their size.
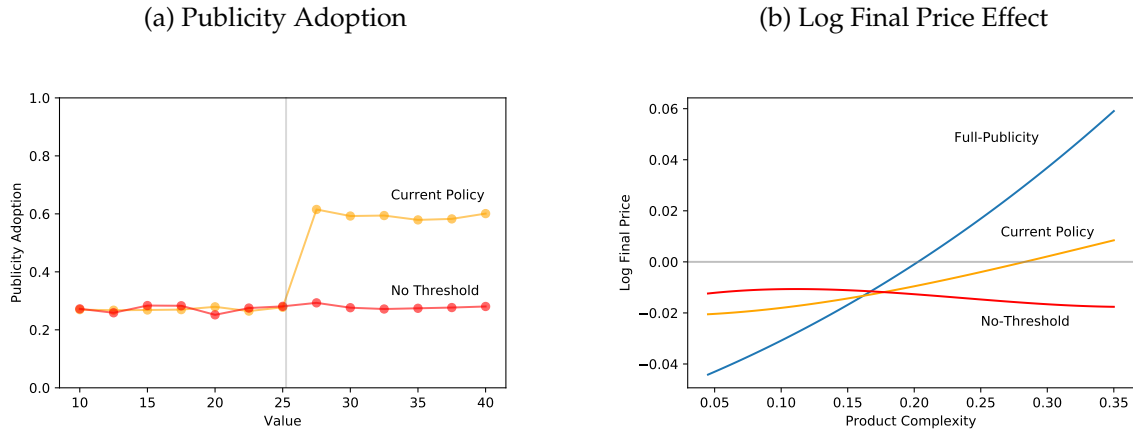
Figure 10 displays the results. Panel (a) shows the fraction of publicized contracts as a function of award values. Panel (b) shows changes in log final prices as a function of product complexity. Several things are worth noting. First, relative to no publicity (the benchmark gray line at zero), full discretion (no threshold) leads to lower contracting costs regardless of the contract's complexity. This highlights the value of letting buyers take advantage of their knowledge about the local market and of contract specifics. Relative to full publicity, however, the effects become ambiguous. For low degrees of complexity, full publicity delivers larger cost savings than discretion, yet for highly complex transactions discretion leads to lower final prices. The current regulation can be thought of as a combination of these two counterfactuals, providing discretion below the threshold and nudging higher levels of publicity above it. The key take-away of this exercise is that the value of discretion depends on—and, in particular, increases with—the transaction's underlying degree of complexity.

The Role of Buyers' Preferences. In our setting, the buyer affects the level of contract competition motivated by interests that are not necessarily aligned with those of the organization. Thus, this agency problem hinges on the degree of *misalignment* between the buyer's (agent) and the organization's (principal) objectives. Indeed, an extensive theoretical literature has studied the design of incentives to increase the alignment between the agent's actions and the organization's (principal) objectives (Laffont and Tirole, 1993) varying the scope of rationality and completeness of contract menus.

To shed light on this agency problem, we study the extent to which buyers' specific preference parameters explain contract outcomes. To do so, we leverage our model estimates and vary the degree of "alignment" in buyers' preferences in two particular ways. 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 towards favoring local contractors with no emphasis on costs. The specific preference parameters under each scenario are described in Table 3. It is worth

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[40]See Kelman (1990); Coviello et al. (2018); Carril (2019); Szucs (2020); Bandiera et al. (2021); Bosio et al. (2020); Decarolis et al. (2020).

Figure 10: Counterfactual Analysis I: Delegation of Publicity Decision to the Buyer

(a) Publicity Adoption

(b) Log Final Price Effect

Notes: Panel (a) shows the share of publicized contracts as a function of expected award value in the absence of publicity. The orange line displays the current policy with a regulation threshold at $25,000. The red line describes a counterfactual with no regulation threshold, meaning that each buyer can freely decide whether to publicize contracts throughout the expected award range. Panel (b) shows changes in log final prices as a function of product complexity, relative to a benchmark of no publicity, and for different counterfactual policies. The blue line is a counterfactual where all contracts are publicized, the orange line represents the current policy (with a threshold at 25,000), and the red line shows the no regulation threshold counterfactual. 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.

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.
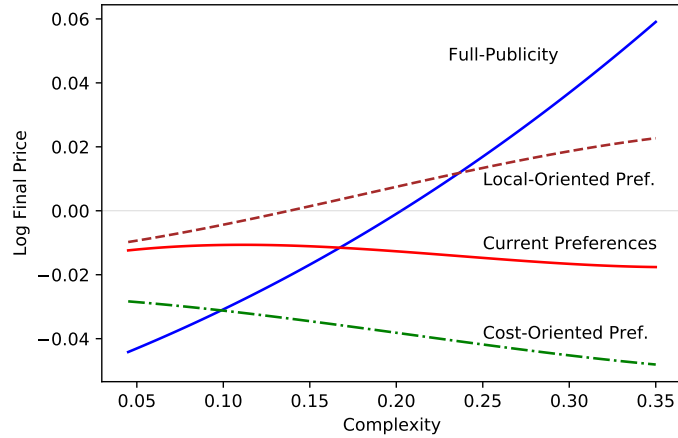
Table 3: Buyers' Preferences

	Estimated	Benchmarks	
	Preference Parameters	Cost-Oriented Preference	Local-Oriented Preference
λ^P	-0.636	-0.636	0
λ^Q	-0.245	-0.636	0
λ^L	0.588	0	0.588
Mean Pub.	0.274	0.408	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 11 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 1.5 percentage points

Figure 11: 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.

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. Interestingly, full publicity achieves higher prices than "Local-Oriented" buyers when contracts are sufficiently complex, because favored local contractors tend to be better at executing 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, 2019; Bosio et al., 2020). Our findings contribute to this literature by highlighting that this trade-off may also depend 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.[41]

5.2 Complexity-Based Publicity Requirements

We now take the estimated preferences as given and vary the regulation design depending on the level of contract complexity. The proposed exercise contemplates identifying the cost-minimizing

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[41]This effect stems from the fact that strict publicity requirements for easy-to-specify contracts leverage the gains of competition removing the idiosyncratic variation on buyers' preferences that leads them to not publicize some contracts.

level of publicity requirements for each degree of complexity. This exercise refers to publicity requirements as the share of contracts that buyers must publicize. Even though other, more sophisticated regulatory tools can enhance procurement efficiency, in practice the design of procurement rules faces a constraint on their level of intricacy. Therefore, we choose to analyze counterfactual complexity-based requirements considering that they would represent relatively minor modifications to the current environment and thus could be realistically implemented.[42] We show that even this minor regulatory change may result in substantial procurement cost savings.

We proceed in three steps. First, we simulate contract outcomes under different levels of product-specific publicity requirements that buyers are mandated to meet. Second, we estimate the final price under each of these requirements. Finally, we identify the publicity requirement that yields the lowest final price at each complexity level.

Figure 12 summarizes this procedure. Panel (a) shows the change in final price relative to no publicity, as a function of contract complexity, and for different levels of publicity requirements. Panel (b) illustrates the publicity requirement that minimizes final price at different complexity levels. Panel (c) replicates Panel (a), but shows the effect of tailored publicity requirements. The latter is depicted as the brown-dashed line in Panel (c), and corresponds to the lower contour of the price effects for different requirement levels in Panel (a). The tailored publicity requirements alter the span of the buyer's actions. In particular, when the unit of purchase is simple, it removes the buyer's discretion entirely to leverage the benefits of enhanced competition. However, it provides more discretion when contracts are more complex in order to attenuate the negative consequences on contract implementation ex-post.

5.3 Comparing Policy Counterfactuals

Table 4 consolidates the visual evidence presented in Figures 10, 11, and 12, and compares the mean changes in final prices under each of these scenarios, relative to a baseline of no publicity for any contract. The current policy design, which introduces publicity requirements at $ 25,000, reduces, on average, the final price by 1.6%. If the publicity choice was delegated to the buyer, this mean reduction would be 1.3%. A uniform full-publicity rule would reduce contract costs by 3%. Finally, the counterfactual policy that tailors the publicity requirements to the purchase's degree of complexity outperforms all the other regulations, reducing average prices by 3.6%. The 2 percentage point difference in cost savings between the current regime and the complexity-based

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[42]The current version of FAR Part 5 (Publicizing Contract Actions) allows buyers to apply for exemptions if they prefer not to publicize a contract. The proposed policy design could be implemented by simply varying the set of exemptions that different product categories are allowed to invoke. For example, if the contract solicitation involves a well-defined product for which the product category's cost-minimizing level of publicity requirement is 100%, then there would be no exemption to be invoked. Conversely, if the solicitation requires a relatively complex product, the buyer could have more (or total) discretion to file exemptions.

Figure 12: Counterfactual Analysis III: Complexity-based Requirements

(a) Publicity Adoption   (b) Log Final Price Effect   (c) Log Final Price Effect
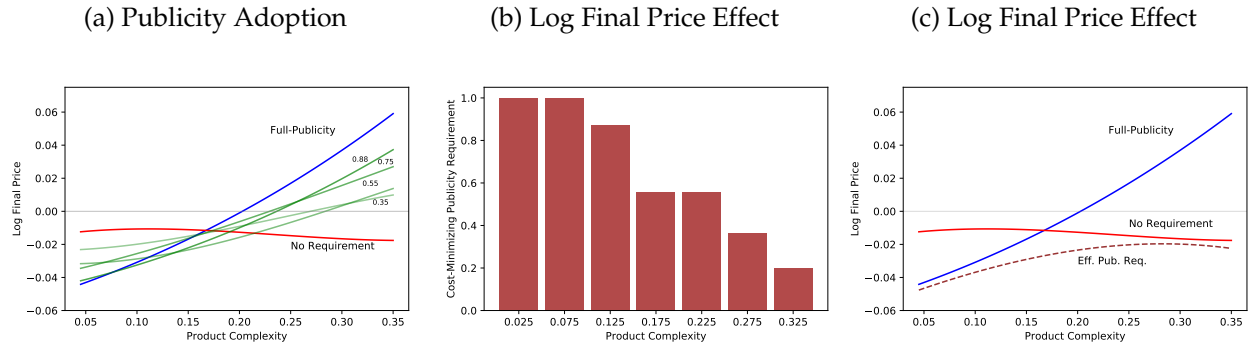
Notes: Panel (a) shows changes in log final prices as a function of product complexity, relative to a benchmark of no publicity, and for different counterfactual policies. The blue line is a counterfactual where all contracts are publicized, the red line shows the no regulation threshold counterfactual, and each of the green lines correspond to counterfactuals where some share of contracts (displayed as a label) are required to be publicized. Panel (b) shows the level of publicity requirement that yields the minimum final prices for different levels of complexity. Panel (c) is analogous to Panel (a), but instead of the various green lines with fixed shares of publicity requirements, it depicts the cost-minimizing policy that requires different levels of publicity at each degree of complexity. The price effects of this policy are shown as the brown-dashed line, which corresponds to the lower envelope of all possible green lines illustrated in Panel (a). 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.

design corresponds to $104 million per year.[43]

Finally, we also benchmark the consequences of these policy designs with the hypothetical situation in which the buyer has Cost-Oriented preferences. We find that the complexity-based publicity requirement achieves better outcomes than having Cost-Oriented Buyers. This is a significant result from a policy standpoint, since it implies that arguably modest improvements to the regulation design achieve, on average, larger cost savings than any incentive mechanism aimed at aligning buyers' objectives.

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[43]This amount is calculated extrapolating to all competitively awarded contracts from the Department of Defense in 2018 with values between $10,000 and $150,000 (i.e., below the Simplified Acquisition Threshold).

Table 4: Effects of Counterfactual Scenarios

	Mean	95 Perc C. I.
Current Policy	-0.0164	[-0.0195 , -0.0133]
Delegate the Decision to the Buyer		
Current Preferences	-0.0136	[-0.0161 , -0.0111]
Buyer with Price-Oriented Pref.	-0.0304	[-0.0335 , -0.0271]
Buyer with Local-Oriented Pref.	-0.0068	[-0.0092 , -0.0043]
Alternative Regulation Designs		
Full Publicity	-0.0306	[-0.0357 , -0.0256]
Complexity-Based Publicity Req.	-0.0367	[-0.0412 , -0.0323]

Notes: This table reports mean equilibrium effects on log final prices under different counterfactual scenarios. All effects are measured relative to a benchmark with no publicity. The first row describes the current policy, with a threshold at $ 25,000. The middle set of rows shows a counterfactual without publicity requirements, leaving publicity decisions to the buyer. This is computed under different assumptions regarding buyers' preferences. The bottom two rows show counterfactual scenarios with alternative regulation designs, specifically one with full publicity and one with cost-minimizing publicity requirements that depend on the level of complexity of the product. Confidence intervals are constructed via bootstrap.

6 Conclusion

This paper studies the relationship between competition and procurement contract outcomes. Even though procurement contracts represent a key component of the economy, there is minimal evidence on the implications of policies oriented to expand competition, considering not only the award price but also the post-award contract execution. We provide extensive evidence on the effects of increasing competition through publicity, using data and policy variation from U.S. Department of Defense procurement.

Our identification strategy leverages a regulation that generates quasi-experimental variation in the extent to which contract opportunities are broadly advertised to potential suppliers. We find that contract publicity increases contract competition. The added competitive pressure results in lower acquisition prices; however, broader dissemination leads to a different pool of vendors, who perform worse ex-post. We further explore the implications of the key trade-off between price reductions ex-ante and worse contract execution ex-post. Our analysis shows that the degree of contract complexity determines the extent of this trade-off. Promoting competition reduces total contract costs only for simple transactions, as relatively complex ones are more exposed to cost overruns and delays in the execution stage.

Motivated by this evidence, we develop and estimate an equilibrium model of competition for

procurement contracts. The model allows us to estimate the underlying firms' characteristics that shape adverse selection in this market and buyers' objectives when promoting competition through advertising. We also use our estimates to evaluate relevant counterfactual policies. Our results show that delegating competition promotion to the buyer is only beneficial when the transaction unit is complex: on average, the buyer achieves better outcomes than in regulated settings with either zero or full publicity. However, when the transaction unit is relatively simple, imposing full-publicity rules is preferred to delegation, as the risks at the execution stage are relatively minor. Moreover, we use our model to engineer improvements to the current policy design by introducing publicity requirements that are tailored to the degree of complexity of the purchase. We find that departing from a uniform regulation would significantly reduce procurement costs.

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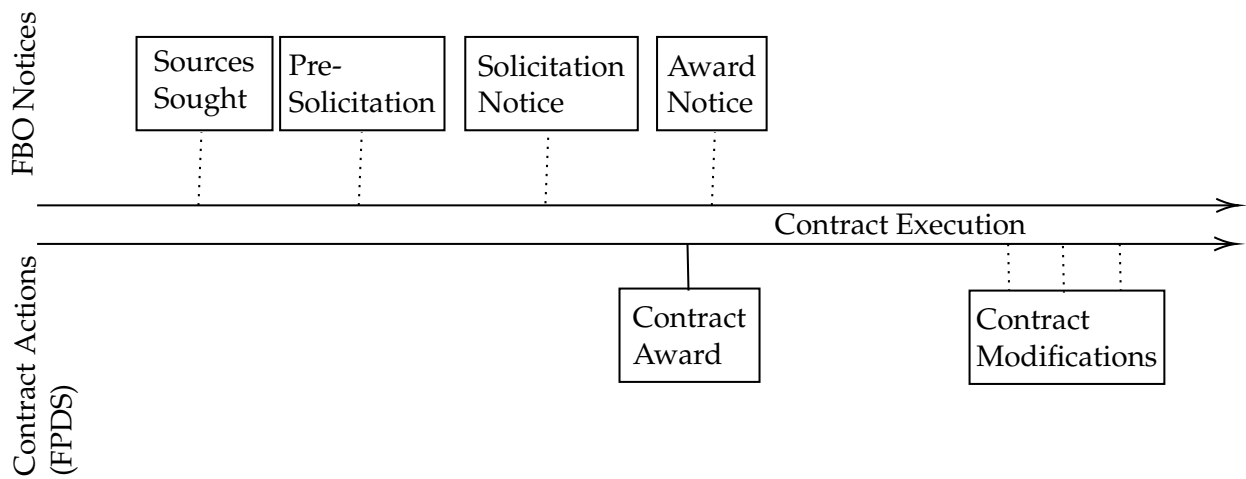
Online Appendix

Competition Under Incomplete Contracts and the Design of Procurement Policies

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

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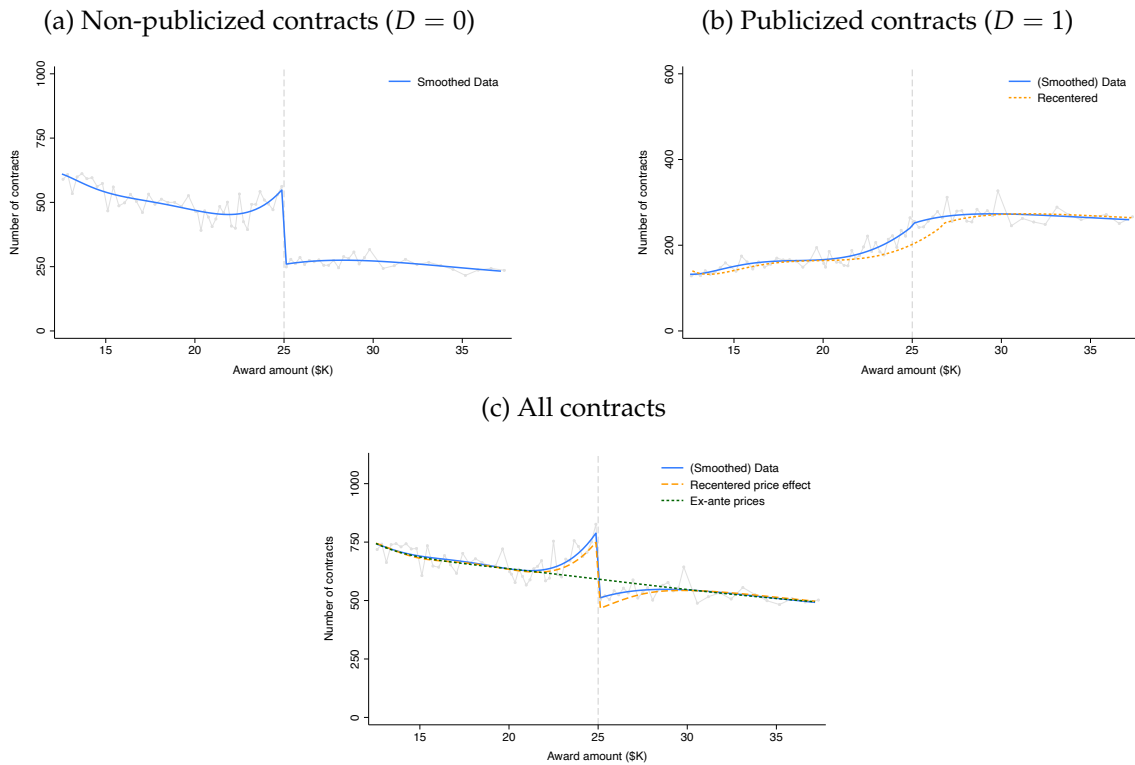
(a) Non-publicized contracts ($D = 0$)

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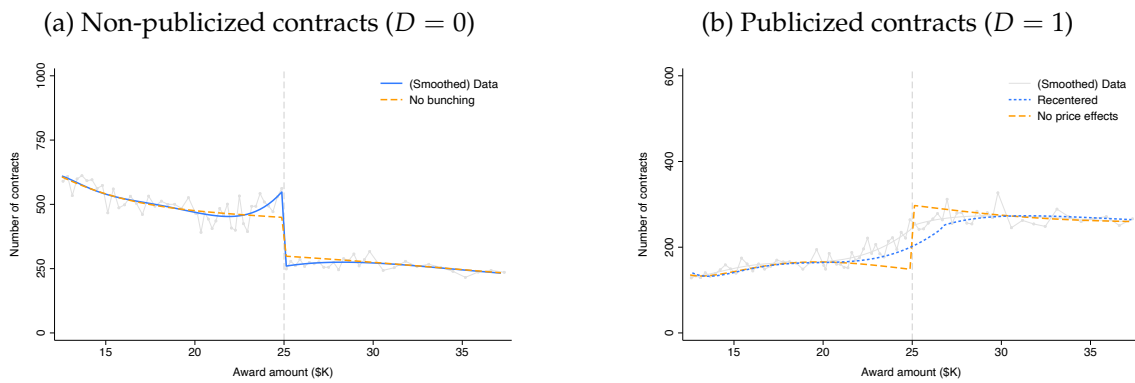
(a) Non-publicized contracts ($D = 0$)

(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

(a) Last month Fiscal Year

(b) Set-asides

(c) Simplified acquisition procedures

(d) Service contracts
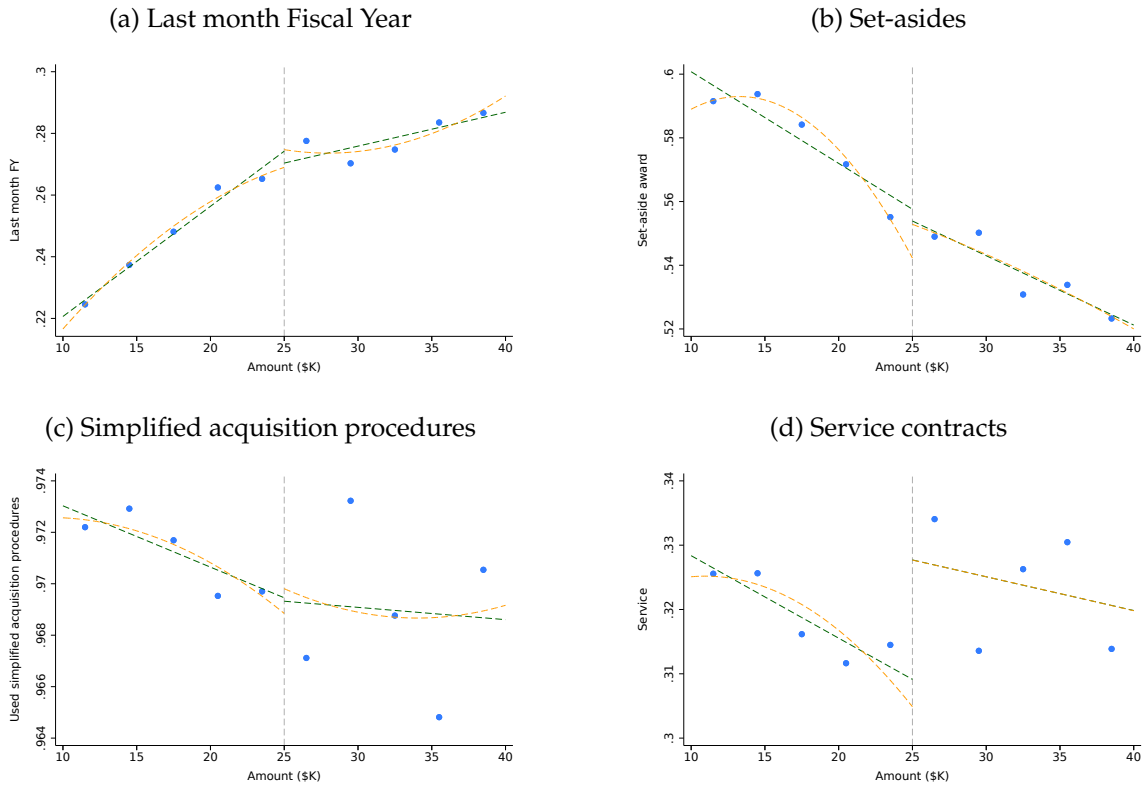
Notes: This figure presents four binned scatter plots, which depict an average pre-award characteristic by bins of award amounts, as well as linear and quadratic fits at each side of $25,000. The pre-award characteristic in each Panel is as follows: (a) an indicator equal to one if the contract was solicited 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)
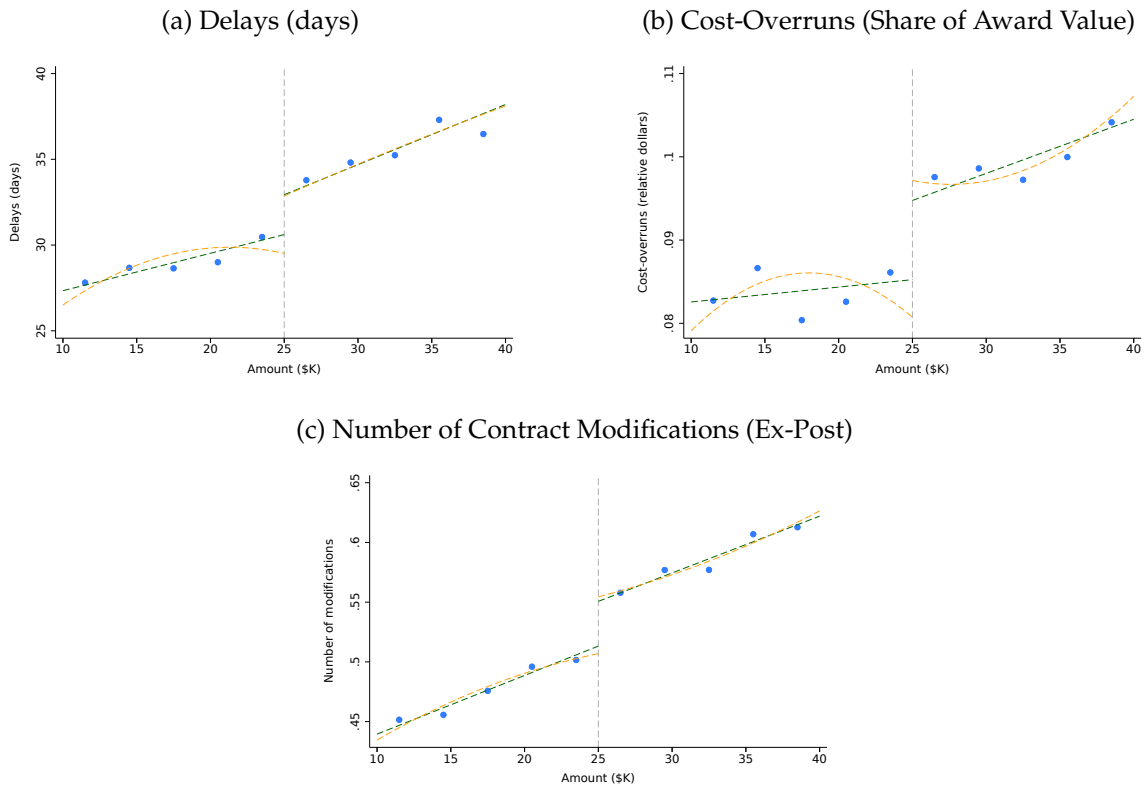
Notes: This figure presents three binned scatter plots, which depict an average post-award performance metric by bins of award amounts, as well as linear and quadratic fits at each side of $25,000. The outcomes in each Panel are as follows: (a) number of days of contract implementation delays; (b) cost-overruns 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
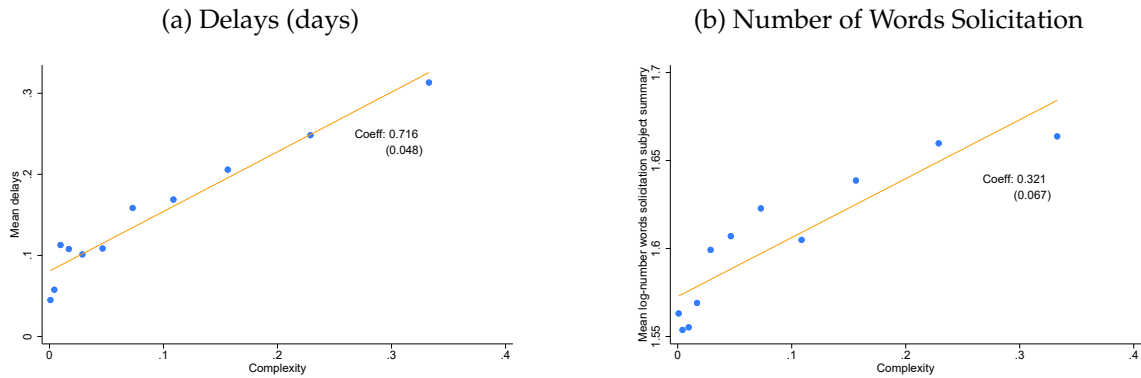
Notes: This figure displays the correlation between our measure of complexity (i.e., product-level average cost-overruns for contracts under $20K) with product-level average delays (Panel (a)) and product-level (log) average number of words contract synopsis from FBO. The number of words variable was 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
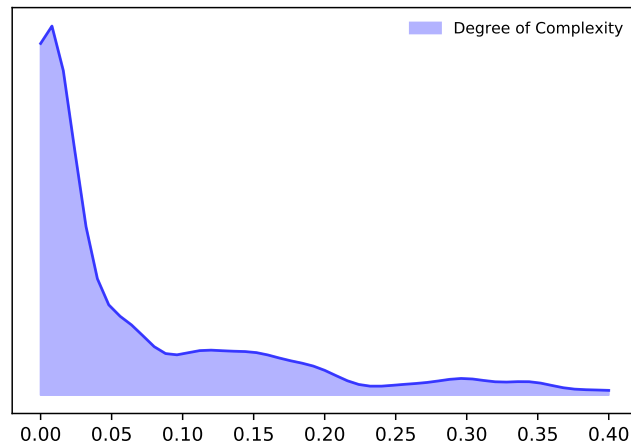
Notes: This figure presents the probability density function (PDF) of product complexity. Even though there's wide heterogeneity in the degree of complexity, the bulk of contracts in our sample have relatively low levels of complexity. The degree of complexity is defined as the log of the product's average 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: Model Fit

(a) Publicity Status

(b) Price Density

(c) Number of Bidders

(d) Probability of a Local Winning

(e) Overruns

(f) Any Overruns
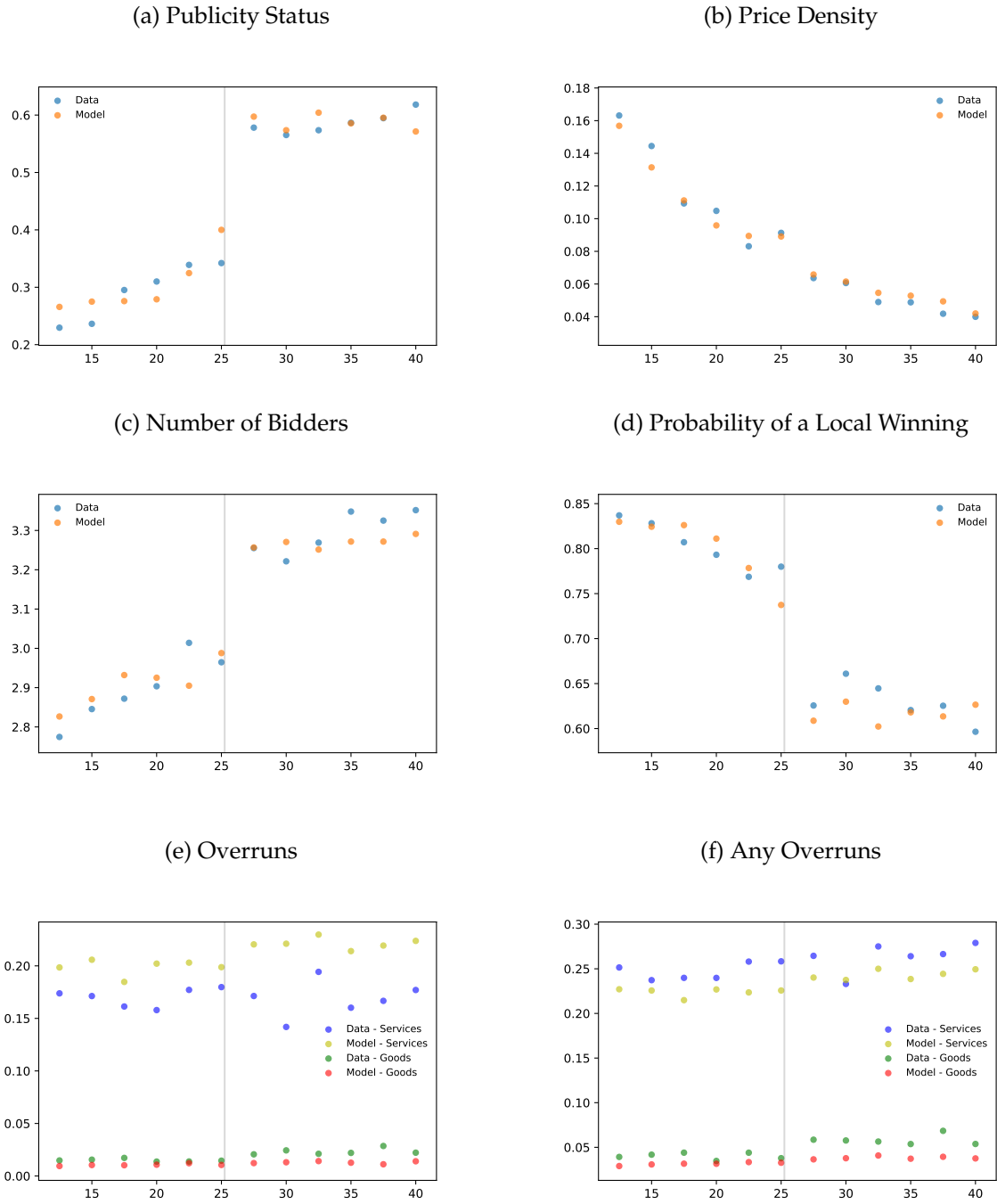
Notes: This figure presents the model fit, based on a simulated method of moments estimation. In each panel, relevant outcome variables are shown as a function of the awarding price. Actual data points are presented in blue, while model-based simulated data are presented in orange. Panel (a) presents 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 A10: Auction Entry and Winner Identity

(a) Composition of Bidders

(b) Identity of the Winner
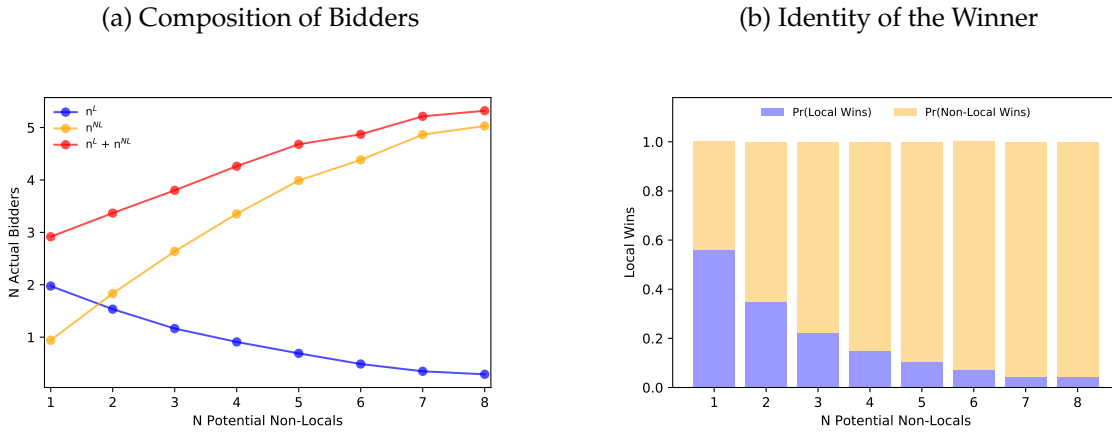
Notes: This figure presents participation decisions and subsequent winner identity as a function of the number of potential bidders. Panel (a) shows the number of actual bidders from each group, Panel (b) displays the average probability of awarding the contract to a local bidder. The higher the number 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 A11: Bidding Function
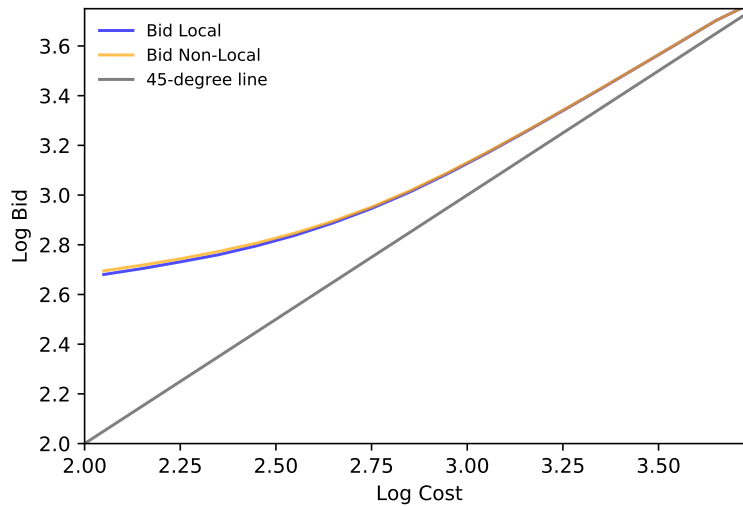
Notes: This figure displays the bidding function of local and non-local contractors. This plot is estimated holding covariates fixed at their mean value and assuming $log(u) = 0$. The plotted distribution of log bids is smoothed using a kernel.

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
Womam 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	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 $ 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	Q2	Q3	Q4
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Mean (μ_γ)	0.0595	0.0498	0.0782	0.0397	0.0505	0.0510	0.0962
	(0.0201)	(0.0622)	(0.0596)	(0.0475)	(0.1692)	(0.1908)	(0.0920)
Standard Deviation (σ_γ)	0.0643	0.0670	0.0534	0.0669	0.0739	0.0680	0.0369
	(0.0075)	(0.0084)	(0.0202)	(0.0140)	(0.0760)	(0.0295)	(0.0280)

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: Effect on Cost-Overruns Controlling for Firm-FE

| | Share with Cost Overruns | | | |
	(1)	(2)	(3)	(4)
Estimate	0.076	0.099	0.022	0.044
S. E.	(0.027)	(0.042)	(0.029)	(0.035)
Estimation Method	IV	CCT	IV	CCT
Firm Fixed Effect Included	No	No	Yes	Yes
Number of Observations	69296	69296	69296	69296

Notes: This table shows the instrumental variable estimates for appearing in FedBizzOpps. The dependent variable is an indicator of having any positive cost-overrun. Columns 1 and 3 are linear IV estimates. Columns 2 and 4 show fuzzy RD estimates using robust-local polynomial regression (CCT - Cataneo et al. 2014). Columns 3 and 4 include firm fixed effects to control for the average performance of the contractors. The sample consists of observations from contractors that appear more than once in the data; otherwise, they are naturally dropped from fixed effect regression. Column 4 is estimated using a residualized outcome variable. Cost overruns are computed as the difference between actual obligated contract dollars and expected total obligations at the award time. 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.

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

Rank	Product Category	Complexity
Bottom 10 - Least Complex		
1	Medical Equipment and Supplies	0.000
2	Musical Inst/Phonograph/Home Radio	0.000
3	Photographic Equipment	0.000
4	Furniture	0.000
5	Pipe, Tubing, Hose, and Fittings	0.001
6	Recreational/Athletic Equipment	0.001
7	Hand Tools	0.001
8	Lumber, Millwork, Plywood, Veneer	0.001
9	Ship and Marine Equipment	0.001
10	Fuels, Lubricants, Oils, Waxes	0.001
Top 10 - Most Complex		
10	Lease/Rent Equipment	0.158
9	Professional Support Services	0.164
8	Quality Control, Test, Inspection	0.177
7	Natural Resources Management	0.194
6	Maintenance/Repair of Equipment	0.213
5	ADP and Telecommunications	0.249
4	Social Services	0.270
3	Medical Services	0.296
2	Utilities and Housekeeping	0.380
1	Operation Of Govt Owned Facility	0.771

Notes: This table presents the top ten and bottom ten product categories in terms of their 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 (i.e., the final contract price including all modifications, minus the award price, divided by the award price) at the product or service category (PSC) level. PSCs correspond to a 4-digit alphanumeric code that is observed for each contract. The categories listed in the table are constructed by aggregating PSC codes to two-digits for goods and to a single digit (letter) for services.

Table B.6: Summary Statitistics: Local vs. Non-Local Contractors

	Local	Non-Local	Diff
log Distance	3.471	4.554	-1.083
Located in the Same State	0.695	0.501	0.194
Overruns	0.078	0.236	-0.158
Delays	0.130	0.275	-0.145
Number of Modifications	0.548	0.880	-0.332

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 the way 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 columnds are all statistically significant at the 1% level.

Table B.7: Model Estimation Sample Versus Full Sample

	Model Sample	Full Sample	Diff
Variables:			
Publicized in FBO	0.373	0.274	0.099
Award Amount	21.178	20.627	0.551
Number of Offers	3.002	3.098	-0.096
Overruns (relative)	0.117	0.088	0.029
Service	0.375	0.308	0.067
Mean Overruns Prod Cat	0.089	0.071	0.018
Awarded in September	0.249	0.262	-0.013
log Duration	3.976	3.811	0.165
Bidders' Classification			
Local is Awarded	0.754	-	-
N Potential Local Bidders	6.078	-	-
N Potential Non-Local Bidders	3.339	-	-
Number of Observations	24,135	103,899	

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.8: Estimated Parameters of Entry, Bidding and Execution

	$\bar{x}$	Entry (Probit) Coeff	S.E.	Bid Distribution (Log Normal) Coeff	S.E.	Execution (Log Normal) Coeff	S.E.
Panel A: Coefficients							
Constant		0.0048	(0.00057)	3.0517	(0.00025)	-1.7041	(0.00038)
Service	0.375	-0.0598	(0.00014)	0.0000	(0.00030)	0.0751	(0.00026)
Degree of Complexity	0.089	-0.7367	(0.00071)	-0.0005	(0.00037)	1.6284	(0.00066)
Non-Local		2.1651	(0.00040)	-0.0402	(0.00037)	0.2354	(0.00069)
Non-Local×Complexity		0.0299	(0.00026)	-0.0308	(0.00063)	0.0868	(0.00082)
Last Month	0.249	-0.8826	(0.00077)				
Exp. Duration > Median	0.5					0.1273	(0.00025)
N^L	6.078	0.0002	(0.00010)	-0.0023	(0.00027)		
N^{NL}	3.339	-0.1876	(0.00028)	0.0099	(0.00024)		
Panel B: Standard Deviation							
Constant				-2.6132	(0.00081)	-0.4102	(0.00048)
Service				0.0996	(0.00031)	1.1854	(0.00048)
S.D. Unob. Het. (σ_u)				2.1683	(0.00087)		

Panel C: Buyer Preferences

		Publicity Choice (Probit)	
Constant		-0.2584	(0.00059)
Exp. Price (λ^P)		-0.6361	(0.00043)
Exp. Cost-Overruns (λ^Q)		-0.2457	(0.00058)
Exp. Local Winning (λ^L)		0.5879	(0.00069)
Above \$25K		0.8542	(0.00037)
Number of Obs.	24,135		

Notes: This table displays estimated coefficients and their corresponding standard errors obtained with the model. Panel A describes the coefficients associated with key covariates on the three model stages that concern bidders: entry probability, mean of (log) bids, and mean of (log) execution shocks. Covariates are listed in the first column and their sample mean is listed in column two. Panel B displays the estimates associated with the standard deviation of (log) bids, unobserved heterogeneity, and (log) cost-overruns. Panel C shows the coefficients associated with the publicity choice by the buyer. Agency and year fixed effects are omitted in this table. These coefficients are estimated jointly using Simulated Method of Moments (SMM). Log-bids and the log of the unobserved project heterogeneity are assumed to be normally distributed. The entry and publicity choices are modelled as a Probit. The standard deviation of log-bids and log-overruns shocks are estimated as $\sigma = exp(b_0 + b_1 \mathbb{1}(Service))$, where $\mathbb{1}(Service)$ indicates a contract for a service.

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:[44]

- **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.

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[44]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.[45] 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., 2020). 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.

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[45]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   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:

$$
\mathbb{E}[B_k^{(n)}] = \frac{k}{n+1} \mathbb{E}[B_{k+1}^{(n+1)}] + \frac{n+1-k}{n+1} \mathbb{E}[B_k^{(n+1)}] \tag{7}
$$

□

D.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 1. *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:

$$\frac{\frac{1}{T_{n,N}}\sum_t (B_{1,t}|n_t = n)}{\frac{1}{T_{n',N}}\sum_t (B_{1,t}|n_t = n')} \rightarrow \frac{\mathbb{E}[B_{1:n}]}{\mathbb{E}[B_{1:n'}]} = \frac{\mathbb{E}[\tilde{B}_{1:n} \cdot u]}{\mathbb{E}[\tilde{B}_{1:n'} \cdot u]} = \frac{\mathbb{E}[\tilde{B}_{1:n}] \cdot \mathbb{E}[u]}{\mathbb{E}[\tilde{B}_{1:n'}] \cdot \mathbb{E}[u]} = \frac{\mathbb{E}[\tilde{B}_{1:n}]}{\mathbb{E}[\tilde{B}_{1:n'}]} \tag{8}$$

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,

$$\tilde{B}_{1:n}u \stackrel{d}{=} \hat{\tilde{B}}_{1:n}\hat{u}$$

$$\tilde{B}_{1:n'}u \stackrel{d}{=} \hat{\tilde{B}}_{1:n'}\hat{u}$$

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

$$(\tilde{B}_{1:n}u) \cdot \left(\hat{\tilde{B}}^*_{1:n'}\hat{u}^*\right) \quad \stackrel{d}{=} \quad \left(\hat{\tilde{B}}_{1:n}\hat{u}\right) \cdot \left(\tilde{B}^*_{1:n'}u^*\right)$$

$$\implies \quad \tilde{B}_{1:n} \cdot \hat{\tilde{B}}^*_{1:n'} \quad \stackrel{d}{=} \quad \hat{\tilde{B}}_{1:n} \cdot \tilde{B}^*_{1:n'} \tag{9}$$

Taking expectations on both sides:

$$\mathbb{E}[\tilde{B}_{1:n}] \cdot \mathbb{E}[\hat{\tilde{B}}_{1:n'}] = \mathbb{E}[\hat{\tilde{B}}_{1:n}] \cdot \mathbb{E}[\tilde{B}_{1:n'}]$$

$$\frac{\mathbb{E}[\tilde{B}_{1:n}]}{\mathbb{E}[\tilde{B}_{1:n'}]} = \frac{\mathbb{E}[\hat{\tilde{B}}_{1:n}]}{\mathbb{E}[\hat{\tilde{B}}_{1:n'}]}$$

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 $n' = n - 1$:

$$\frac{\mathbb{E}[\tilde{B}_{1:n}]}{\mathbb{E}[\tilde{B}_{1:n'}]} = \frac{\mathbb{E}[\hat{\tilde{B}}_{1:n}]}{\mathbb{E}[\hat{\tilde{B}}_{1:n'}]}$$

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

$$\frac{\mathbb{E}[\tilde{B}_{1:n}]}{\mathbb{E}[\tilde{B}_{2:n}]} = \frac{\mathbb{E}[\hat{\tilde{B}}_{1:n}]}{\mathbb{E}[\hat{\tilde{B}}_{2:n}]}$$

$\hat{G}_{\tilde{b}}$ 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 1. *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 2. *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 $F_{\tilde{c}}$.

E   Model Estimation Details

E.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 that are observed at least 4 times between 2013 and 2019, and which had at least one —but not all— contracts publicized.[46] Table B.6 compares buyer-contractor distance and performance for contracts performed by local and non-locals. The third column shows the mean difference of 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 16 percentage points (200%) more cost-overruns and 14.5 percentage points (110%) more delays than locals.

E.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:

---

[46]We noted that the Federal Procurement Data System (FPDS) sometimes missclassifies 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.

$$\sqrt{n}\left(\hat{\theta}-\theta_0\right) \xrightarrow{d} N\left(0,\left(1+\frac{1}{s}\right)(M'WM)^{-1}M'W\Omega W'M(M'WM)^{-1}\right) \tag{10}$$

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: $\theta = (\alpha^k, \nu^k, \tau^k, \gamma^k, \xi^k, \vec{\lambda}, \zeta, \vec{\sigma})$.

E.2.1 Standard Errors

We compute standard errors using the asymptotic variance formula given by (10). 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 (6) evaluated at $\hat{\theta}$.

E.2.2 Minimization

We keep constant the underlying random draws 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.

E.3 Moments

We use three sets of target moments.

- First set of moments,
  - $\vec{m}_{11} = \mathbb{E}[x_t^{(y)\prime}y_t]$ and $\vec{m}_{12} = \mathbb{E}[x_t^{(y)\prime}y_t^2]$, where $y_t = $ *log winning bid, number of bidders, wins local, log overruns,* and *contract is publicized,* and $x_t^{(y)} = (1, \vec{x}_t^{(y)})$ = 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 \$1,000

- 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 \$1,000.

As a result we use 357 moments to estimate 37 parameters.

Supplementary Material for:

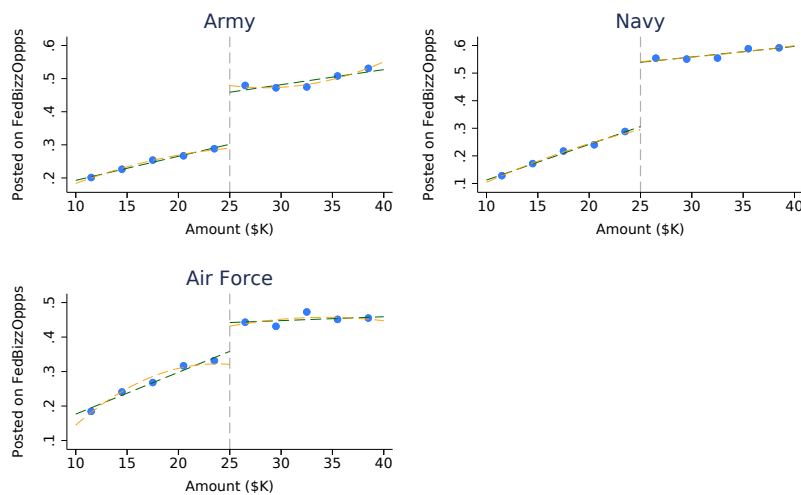# Competition Under Incomplete Contracts and the Design of Procurement Policies

(Not for Publication)

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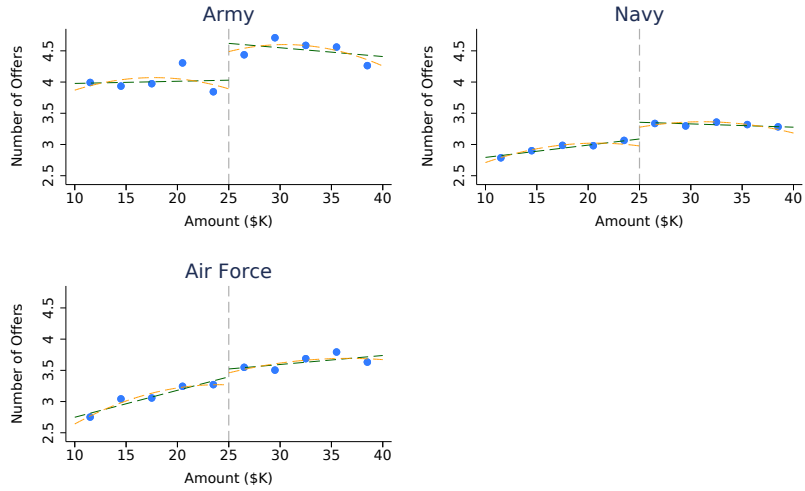
F   Additional Figures

F.1   Heterogeneous Effects of Publicity

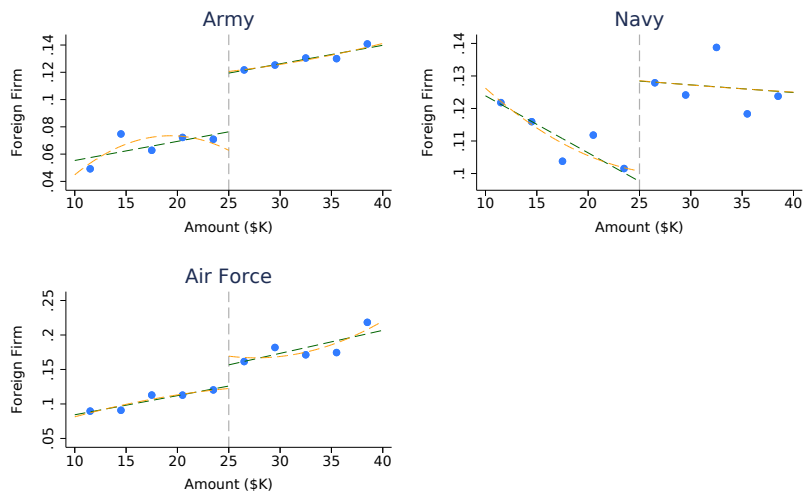Figure SM1: Heterogeneous publicity adoption by major departments

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 SM2: 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 SM3: 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 SM4: Heterogeneous effects on performance by major departments
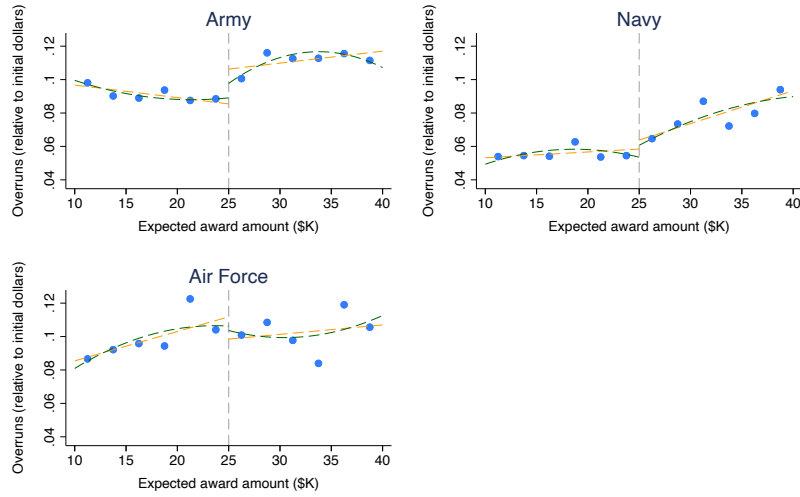
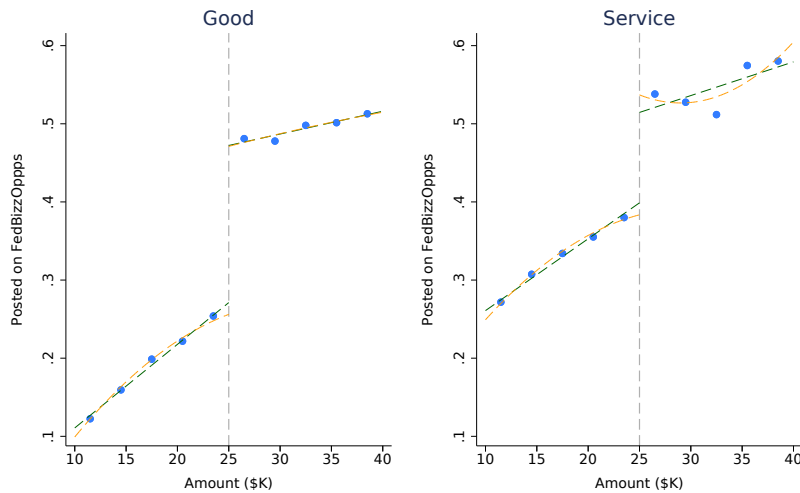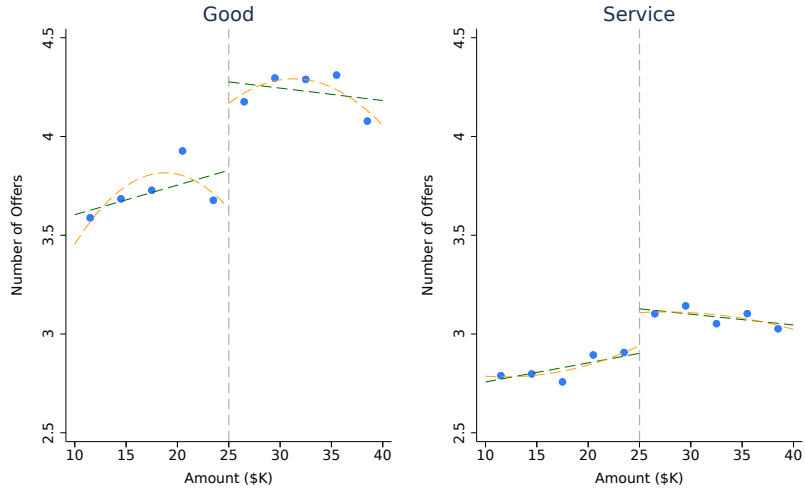Notes: This figure presents three binned scatter plots, which depict average cost overruns by bins of award amounts, as well as linear and quadratic fits at each side of $25,000. Cost overruns are computed as the difference between actual obligated contract dollars and expected total obligations at the 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 SM5: 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 SM6: 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 SM7: Heterogeneous effects on winner characteristics: goods versus services
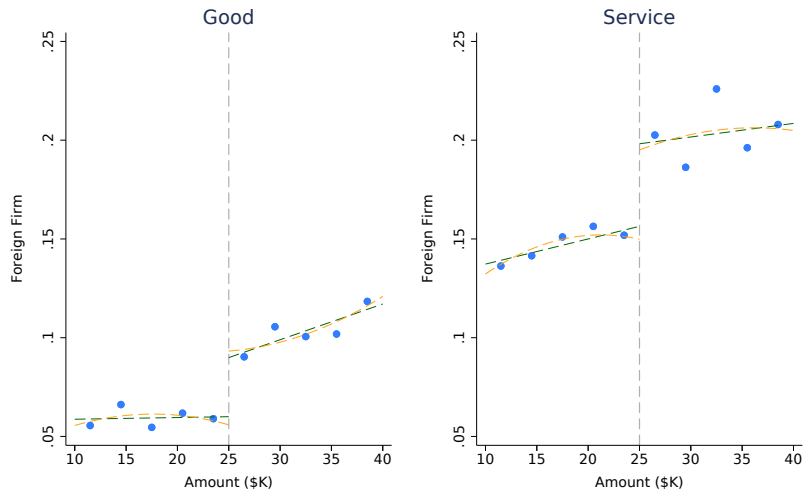
Notes: This figure presents two binned scatter plots, which depict the share of contracts awarded to a foreign firm by bins of award amounts, as well as linear and quadratic fits at each side of $25,000. The data source is the Federal Procurement Data System-Next Generation. The full sample consists 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 SM8: Heterogeneous effects on performance: goods versus services
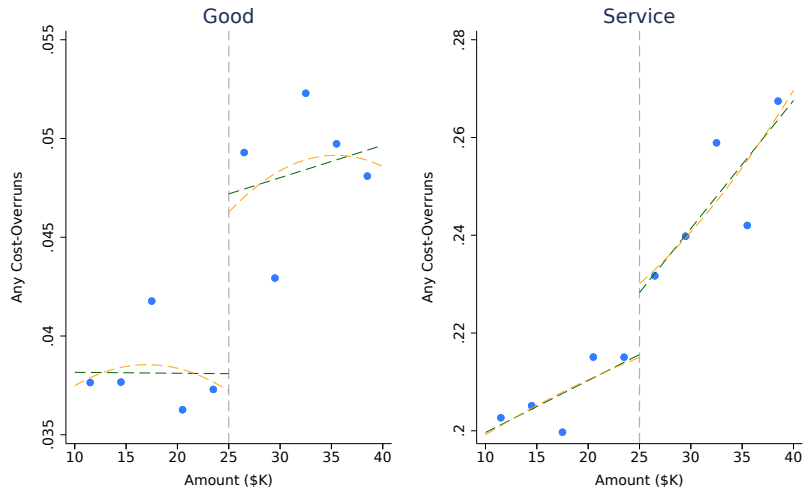
Notes: This figure presents two binned scatter plots, which depict share of contracts with cost overruns by bins of award amounts, as well as linear and quadratic fits at each side of $25,000. Cost overruns are computed as the difference between actual obligated contract dollars and expected total obligations 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.

G   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 G.1 presents our theoretical framework and the set of results that motivate the density analysis. Section G.1.5 explains the density analysis in detail, including all implementation details. Section G.1.6 discusses how to correct naive RDD estimates to account for price effects and potential measurement error. Section G.1.8 explains how we account for potential bunching responses in the RDD framework. Each section is discussed in detail by Carril and Gonzalez-Lira (2021).

G.1   Empirical Model

G.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 that in Section 3. In particular, **A2** allows for measurement error in agencies' ex-ante estimates.

G.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 $\Delta = \delta \cdot \sum_b n_b$.

G.1.3 Propositions

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

Proposition 2. *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 3. *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 3. $E[\tilde{n}_b] = E[n_b^0 + n_b^{s,1}(\bar{\gamma})]$, *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 4. $\sum_{b \leq 0}(\tilde{n}_b - n_b) = \sum_{b > 0}(n_b - \tilde{n}_b)$. *This means that the excess mass below the threshold equals the missing mass above the threshold.*

Proposition 5. $\Delta \cdot F_{\gamma'}(x) = E[n_{b_x}^{1,s}(\bar{\gamma}) - \tilde{n}_{b_x}^1]$, *for* $x \in b_x$, $b_x \leq 0$, *and* $\gamma' = \gamma - \bar{\gamma}$.

G.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:

$$h_p^1(p_t) = \int_{-\infty}^{\infty} f_{\tilde{p}}^1(p_t - \gamma_t) f_\gamma(\gamma) d\gamma \tag{11}$$

On the other hand, using Bayes' rule:

$$f_{\tilde{p}}^1(\tilde{p}_t) = \frac{\tilde{\pi}_D(\tilde{p}_t) \cdot f_{\tilde{p}}(\tilde{p}_t)}{\Pr(D_t = 1)} \tag{12}$$

So that (11) and (12) 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,

$$h_p^1(p_t) \equiv \int_{-\infty}^{\infty} f_{\tilde{p}}^{1*}(p_t - \gamma) \cdot f_\gamma(\gamma) \cdot d\gamma + \int_{-\infty}^{p_t} \Delta(p_t - \gamma) \cdot f_\gamma(\gamma) \cdot d\gamma \tag{13}$$

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 (13) 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 2 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 (13) 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 estimate 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 5. Consider $p_t = x$ closely below the threshold, so that $\Delta(x - \gamma) \approx \Delta$. With a constant Δ, it immediately follows that $\Delta \cdot F_\gamma(p_t) = h_p^1(p_t) - f_{\tilde{p}}^1(p_t)$.

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 $h_p^1(p_t)$, 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 2: for sufficiently high $p_t \in \underline{b}$, $E[\tilde{n}_b^1] = E[n_b^{s,1}(\bar{\gamma})]$, for all $b > \bar{b}$.

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_p^0 and f_p^0 when the latter is not smooth, which happens only at the threshold. Proposition 3 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 $b_H \leq \bar{b}$, where $p_H \in b_H$.

Finally, Proposition 4 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 that the overall number of observed and counterfactual contracts needs to coincide.

G.1.5 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 SM9 (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 $\{n_b^1\}$, we can simply undo the first impact of price

Figure SM9: Impact of Bunching and Price Effects on Award Distributions

(a) Bunching for $D = 0$

(b) Bunching for $D = 1$

(c) Bunching + Price Effects for $D = 0$

(d) Bunching + Price Effects for $D = 1$
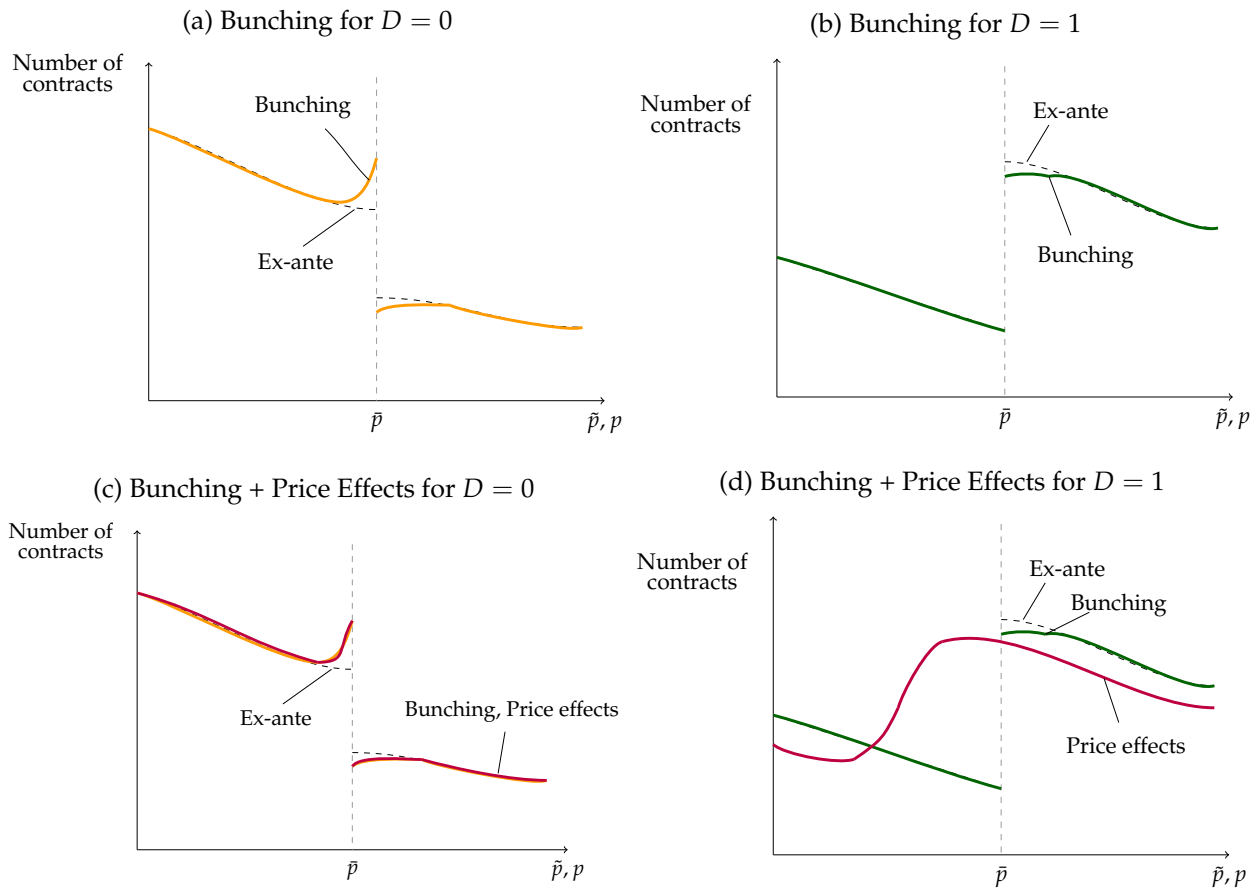
Notes: This figure shows conceptually how the distributions of non-publicized and publicized awards are impacted by the existence of both strategic bunching responses and price effects due to increased competition. Panels (a) and (b) show, respectively for non-publicized and publicized contracts, the 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 SM9 (c)).

This intuition is supported by Propositions 2 and 3. 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.

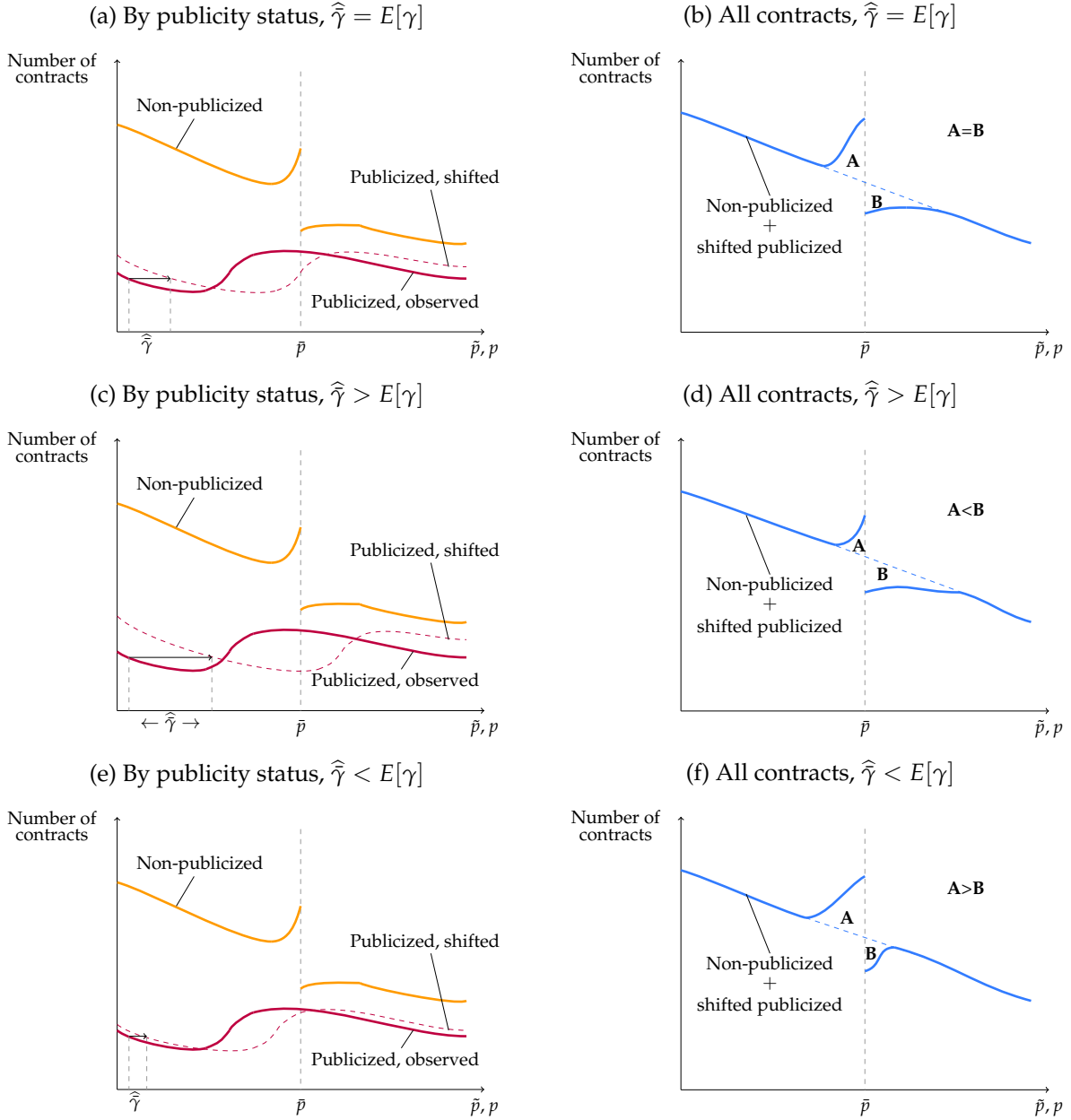More concretely, we estimate the following specification:

$$\left[n_b^0 + n_b^{1,s}(\widehat{\gamma})\right] = \sum_{x=0}^{Q} \alpha_x \cdot b^x + \sum_{j=\underline{b}}^{\bar{b}} \gamma_j \cdot \mathbf{1}[b=j] + \nu_b, \quad \text{for } b = \{-R, ..., R\} \tag{14}$$

and obtain fitted values:

$$\widehat{n}_b = \sum_{x=0}^{Q} \widehat{\alpha}_x \cdot b^x \quad \text{for } b = \{-R, ..., R\}.$$

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 4: $\sum_{b=-R}^{R}(n_b^0 + n_b^{1,s}(\bar{\gamma})) = \sum_{b=-R}^{R} \widehat{n}_b$. As the intuition from Figure SM10 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 $\widehat{\gamma}$, and iterate until we find a value such that the constraint is satisfied.

Figure SM10: Intuition of Method to Estimate Mean Price Effects

(a) By publicity status, $\widehat{\widehat{\gamma}} = E[\gamma]$

(b) All contracts, $\widehat{\widehat{\gamma}} = E[\gamma]$

(c) By publicity status, $\widehat{\widehat{\gamma}} > E[\gamma]$

(d) All contracts, $\widehat{\widehat{\gamma}} > E[\gamma]$

(e) By publicity status, $\widehat{\widehat{\gamma}} < E[\gamma]$

(f) All contracts, $\widehat{\widehat{\gamma}} < E[\gamma]$

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[47] 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 SM9, 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 $\{n_b^{1,s}(\widehat{\tilde{\gamma}}_b) - \Delta \cdot \mathbf{1}[b > 0]\}_{b=-R}^R$. We then apply the same interpolation method as before for each of the two distributions. That is, we separately estimate the following two specifications:

$$\left(n_b^0 + \Delta \cdot \mathbf{1}[b > 0]\right) = \sum_{x=0}^{Q} \alpha_x^0 \cdot b^x + \sum_{j=\underline{b^0}}^{\overline{b^0}} \gamma_j^0 \cdot \mathbf{1}[b = j] + v_b^0, \quad \text{for } b = \{-R, ..., R\} \tag{15}$$

$$\left(n_b^{1,s}(\widehat{\tilde{\gamma}}_b) - \Delta \cdot \mathbf{1}[b > 0]\right) = \sum_{x=0}^{Q} \alpha_x^1 \cdot b^x + \sum_{j=\underline{b^1}}^{\overline{b^1}} \gamma_j^1 \cdot \mathbf{1}[b = j] + v_b^1, \quad \text{for } b = \{-R, ..., R\} \tag{16}$$

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

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

---

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

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

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 SM11 shows this intuition graphically.
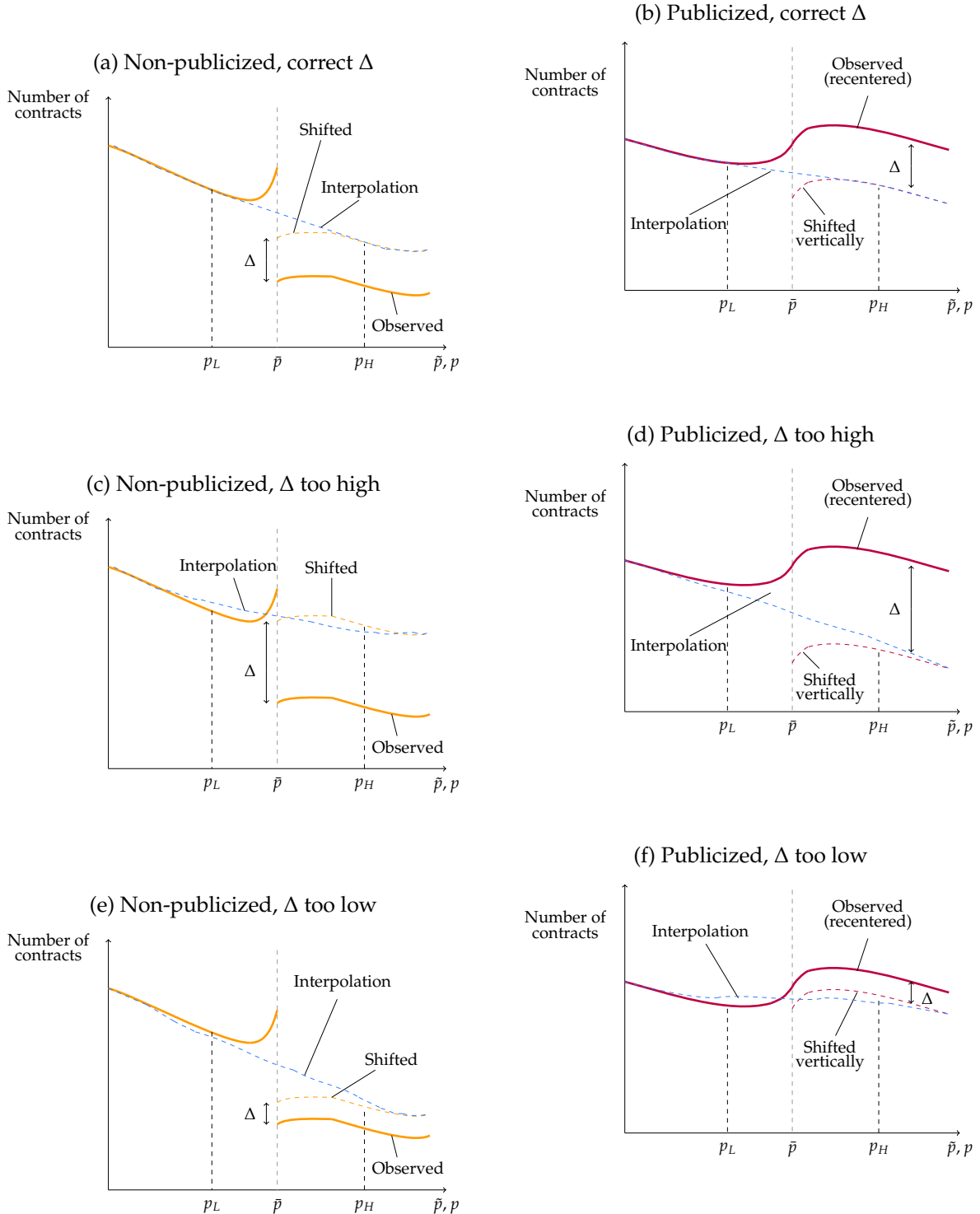
So, given a guess of $\widehat{\Delta}$, we compute the residuals for each of the two regressions (15) and (16). We then search over $\widehat{\Delta}$ to minimize:

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

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 fixed, binning and range fixed as in step 1. However, we change the excluded region for the specification using non-publicized contracts (15). The justification of 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 SM11: Intuition of Method to Estimate Ex-Ante Price Distributions

(a) Non-publicized, correct Δ

(b) Publicized, correct Δ

(c) Non-publicized, Δ too high

(d) Publicized, Δ too high

(e) Non-publicized, Δ too low

(f) Publicized, Δ too low

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 5 and use our estimates from above to compute:

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

for $x \in b_x$, $b_x \in \{\underline{b}^1, ..., 0\}$, and $\gamma' = \gamma - \widehat{\widehat{\gamma}}$. This is straightforward given 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 $h = \{1, 2, ..., H\}$.

G.1.6 RDD Correction for Price Effects and Measurement Error

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

$$p_t = \tilde{p}_t + (1 - D_t) \cdot \xi_t + D_t \cdot \gamma_t \tag{17}$$

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 $V[\gamma_t] = \sigma_\gamma^2$. Let $\xi_t \sim F_\xi(\cdot)$, with $E[\xi_t] = 0$ and $V[\xi_t] = \sigma_\xi^2$. 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:

$$E[y_t | \tilde{p}_t] = \mathbf{1}(\tilde{p}_t \le 0) \cdot (\alpha_0 + \beta_0 \cdot \tilde{p}_t) + \mathbf{1}(\tilde{p}_t > 0) \cdot (\alpha_1 + \beta_1 \cdot \tilde{p}_t) \tag{18}$$

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 6. *Expected outcomes conditional on observed award prices $E\left[y_t|p_t\right]$ 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:*

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

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 6 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.

G.1.7 Proof of Proposition 6

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

$$E[y_t|p_t] = \underbrace{E[y_t|p_t, \tilde{p}_t \leq 0])}_{\Lambda_1} \cdot \underbrace{\Pr(\tilde{p}_t \leq 0|p_t)}_{\Lambda_2} + \underbrace{E[y_t|p_t, \tilde{p}_t > 0]}_{\Lambda_3} \cdot \underbrace{\Pr(\tilde{p}_t > 0|p_t)}_{\Lambda_4} \tag{19}$$

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:

$$
\begin{aligned}
\Lambda_2 &= \Pr(\tilde{p}_t \leq 0|p_t) \\
&= \Pr(\tilde{p}_t \leq 0|p_t, D_t = 0) \cdot \Pr(D_t = 0|p_t) + \Pr(\tilde{p}_t \leq 0|p_t, D_t = 1) \cdot \Pr(D_t = 1|p_t) \\
&= \Pr(p_t - \xi_t \leq 0|p_t) \cdot [1 - \pi_D(p_t)] + \Pr(p_t - \gamma_t \leq 0|p_t, D_t = 1) \cdot \pi_D(p_t) \\
&= \left[1 - F_\xi(p_t)\right] \cdot \left[1 - \pi_D(p_t)\right] + \left[1 - F_\gamma(p_t)\right] \cdot \pi_D(p_t) \\
&\equiv \Lambda_2(p_t, \pi_D(p_t), F_\gamma(p_t), F_\xi(p_t), \boldsymbol{\alpha}, \boldsymbol{\beta})
\end{aligned}
\tag{20}
$$

Similarly for Λ_4:

$$\Lambda_4 = \Pr(\tilde{p}_t \geq 0|p_t)$$

$$= \Pr(\tilde{p}_t \geq 0|p_t, D_t = 0) \cdot \Pr(D_t = 0|p_t) + \Pr(\tilde{p}_t \geq 0|p_t, D_t = 1) \cdot \Pr(D_t = 1|p_t)$$

$$= \Pr(p_t - \xi_t \geq 0|p_t) \cdot [1 - \pi_D(p_t)] + \Pr(p_t - \gamma_t \geq 0|p_t, D_t = 1) \cdot \pi_D(p_t) \qquad (21)$$

$$= F_\xi(p_t) \cdot [1 - \pi_D(p_t)] + F_\gamma(p_t) \cdot \pi_D(p_t)$$

$$\equiv \Lambda_4(p_t, \pi_D(p_t), F_\gamma(p_t), F_\xi(p_t), \boldsymbol{\alpha}, \boldsymbol{\beta})$$

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

$$\Lambda_1 = E[y_t|p_t, \tilde{p}_t \leq 0])$$

$$= E[\alpha_0 + \beta_0 \cdot \tilde{p}_t|p_t, \tilde{p}_t \leq 0]$$

$$= \alpha_0 + \beta_0 \cdot E[\tilde{p}_t|p_t, \tilde{p}_t \leq 0]$$

$$= \alpha_0 + \beta_0 \cdot \{E[\tilde{p}_t|p_t, \tilde{p}_t \leq 0, D_t = 1] \cdot \Pr(D_t = 1|p_t, \tilde{p}_t \leq 0)$$

$$+ E[\tilde{p}_t|p_t, \tilde{p}_t \leq 0, D_t = 0] \cdot \Pr(D_t = 0|p_t, \tilde{p}_t \leq 0)\}$$

$$= \alpha_0 + \beta_0 \cdot \{E[p_t - \gamma_t|p_t, \tilde{p}_t \leq 0, D_t = 1] \cdot \Pr(D_t = 1|p_t, \tilde{p}_t \leq 0)$$

$$+ E[p_t - \xi_t|p_t, \tilde{p}_t \leq 0, D_t = 0] \cdot \Pr(D_t = 0|p_t, \tilde{p}_t \leq 0)\}$$

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

$$+ (p_t - E[\xi_t|\xi_t \geq p_t, p_t]) \cdot \Pr(D_t = 0|p_t, \tilde{p}_t \leq 0)\}$$

$$\Longleftrightarrow$$

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

$$- E[\xi_t|\xi_t \geq p_t, p_t]) \cdot \Pr(D_t = 0|p_t, \tilde{p}_t \leq 0)\} \qquad (22)$$

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

$$\Pr(D_t = 0|p_t, \tilde{p}_t \leq 0) = \frac{\Pr(\tilde{p}_t \leq 0|D_t = 0, p_t) \cdot \Pr(D_t = 0|p_t)}{\Pr(\tilde{p}_t \leq 0|p_t)}$$

$$= \frac{\Pr(\tilde{p}_t \leq 0|D_t = 0, p_t) \cdot \Pr(D_t = 0|p_t)}{\Lambda_2}$$

$$= \frac{\Pr(p_t - \xi \leq 0|p_t) \cdot [1 - \pi_D(p_t)]}{\Lambda_2} \qquad (23)$$

$$= \frac{[1 - F_\xi(p_t)] \cdot [1 - \pi_D(p_t)]}{\Lambda_2}$$

And, therefore,

$$\Pr(D_t = 1 | p_t, \tilde{p}_t \leq 0) = 1 - \Pr(D_t = 0 | p_t, \tilde{p}_t \leq 0)$$
$$= \frac{[1 - F_\gamma(p_t)] \cdot \pi_D(p_t)}{\Lambda_2} \tag{24}$$

Combining (22), (23) and (24) implies:

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

$$\tag{25}$$

Analogous calculations yield the following expression for Λ_3:

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

$$\tag{26}$$

Finally, combining (19), (20), (21), (25), and (26), 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:

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

G.1.8 Accounting for Bunching

A standard test for the validity of the RDD framework consists on 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) show 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 are 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 manipulate. 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.