Competition under Incomplete Contracts and the Design of Procurement Policies[*]

Rodrigo Carril[†] Andres Gonzalez-Lira[‡] Michael S. Walker[§]

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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 significant savings in procurement spending.

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[†]Universitat Pompeu Fabra and Barcelona School of Economics. Email: rodrigo.carril@upf.edu.

[‡]Pontificia Universidad Católica de Chile, Business School. Email: andresgonzalezlira@uc.cl.

[§]US Department of Defense. Email: michael.s.walker110.mil@mail.mil.

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, more intense 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 competition promotion should account for both potential benefits due to contract price reductions and possible adverse effects due to poor execution.

An empirical investigation of this trade-off is complicated due to the need for comprehensive data on contract execution and a compelling research design. In this paper, we make progress on both 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 more than half of federal procurement spending. Moreover, this setting provides us with policy variation in the degree of contract competition, as well as 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. Publicity increases competition by expanding the set of potential bidders informed about the auction. Analyzing contract awards between $10,000 and $40,000, we exploit the discontinuous nature of the publicity requirements to estimate its effects on four sets of outcomes: (i) the actual number of bids received, (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.

[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 makes its implications economically meaningful. In 2018 alone, the DOD publicized contract solicitations valued at $5.56 billion via the online platform `FedBizzOpps.gov`.

We then estimate the effects of publicizing contract opportunities on three sets of non-price outcomes—the number of bids received, 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, 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 probability of experiencing cost overruns and delays in the implementation stage increases by 7% and 8%, respectively. Performance results are driven mainly by service contracts—as opposed to goods purchases—and by contracts that we ex-ante characterize as more complex. Finally, we find that these patterns are primarily accounted for by variation across firms (consistent with adverse selection) and not by within-firm responses to changes in the competitive environment.

Our reduced-form 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. Suppliers' identities matter for explaining this variation in contract outcomes. Overall, promoting competition hinders buyers' ability to restrict participation to qualified vendors while attracting new participants who tend to perform poorly ex-post. These results are stable across different estimation approaches and robustness checks that account for possible sources of bias.[2]

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 and the role of buyer preferences in the decision to promote competition. Furthermore, we use the model to 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. 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,

[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.

the awarded contractor executes the contract. Execution performance depends on the existence and magnitude of cost overruns stemming from an idiosyncratic shock realized ex-post. The model allows for a correlation between pre-award production cost realizations and post-award performance shocks, and incorporates the potential asymmetry 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. For both types of bidders, we estimate a negative correlation between production cost realizations and cost overrun shocks, implying that winning more competitive auctions will be associated with lower bids and higher overruns. Still, most of the negative effects of publicity on performance are quantitatively accounted for by the differential selection of bidders, not by within-type changes in the distribution of overrun realizations. Finally, we estimate that buyers have 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 impact 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 regulations to promote bidder participation involves a risk of allowing under-qualified firms to bid. An alternative policy design may rely on buyers (i.e., each local agency) to decide 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 where the buyer decides whether to publicize each contract. We find that the effects of discretion are ambiguous and critically depend on the degree of complexity of the purchase. Relative to no-publicity or full-publicity rule benchmarks, discretion yields lower contract costs for an intermediate range of complexity values, suggesting ample space to improve the current regulation.

We use our model to identify improvements to the current policy design, which depart from uniform publicity requirements. Many policies that regulate competition in 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 tailored to the complexity of the purchase, thus leveraging the benefits of intense competition for simple products while limiting its adverse impact on complex products. We find that the cost-minimizing level of publicity for fully-specified products is close to 100%, whereas more complex product categories should require low use of publicity. This reduces average defense procurement costs by 1.5% percent, or $104 million annually.

This paper contributes to the literature studying the classic problem of procurement in the presence of noncontractible quality concerns. Many papers have theoretically emphasized the shortcomings of standard (price-only) auctions and have studied the properties of alternative mechanisms (e.g. Spulber, 1990; Bajari, 2001; Calzolari and Spagnolo, 2009; Decarolis, 2018), including the derivation of optimal mechanisms in models with adverse selection (Manelli and Vincent, 1995; Lopomo, Persico and Villa, 2023) and moral hazard (Burguet, Ganuza and Hauk, 2012; Chillemi and Mezzetti, 2014).[4] This paper relates to the empirical literature showing that awarding mechanisms aimed at promoting price competition can be outperformed by less competitive alternatives (e.g., Bajari, McMillan and Tadelis, 2009; Decarolis, 2014; Conley and Decarolis, 2016; Coviello, Guglielmo and Spagnolo, 2018). Unlike most previous work, our setting offers a source of exogenous variation in the intensity of competition while keeping the awarding mechanism and contract design fixed. This 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.

Our reduced-form analysis builds on closely related work by Coviello and Mariniello (2014), who use an analogous threshold-based publicity requirement policy in Italy to study its effects on similar outcomes as the ones we consider. They find that publicity leads to an increase in the number of bids, a significant reduction in prices, and no effect on post-award performance as

[4] Asker and Cantillon (2008) and Asker and Cantillon (2010) study cases where quality is contractible and can, therefore, be explicitly incorporated into the awarding rule. Dini, Pacini and Valletti (2006) provides an overview of these theoretical arguments and discusses the issues related to the practical implementation of scoring rules. In our setting, even if some non-price components were contractible, buyers are constrained by regulation to use price-only auctions.

measured by delays. While there are many similarities between our settings—most significantly, the policy variation and the fact that auctions are sealed-bid and price-only—, two important differences may limit the direct comparability of both sets of results. First, the mechanism used to award contracts in their setting is not a first-price auction but the so-called average bid auction (ABA).[5] Since the ABA does not select the lowest bidder but a bid that tends to be close to the average bid, we need not expect the same type of competitive effects of publicity. The authors acknowledge that the effect of increased participation in equilibrium ABA bids is theoretically ambiguous, even absent endogenous entry considerations.[6] Furthermore, by eliminating very low bids, the effect of competition on post-award performance also becomes more subtle.[7] A second relevant difference is that the size of the "treatment" in both settings differs substantially. Empirically, while publicity requirements in their setting increase the number of bidders by 3.3 from a mean of 36, we find an increase of 2.3 bids from a mean of 3.5.[8] This suggests that the shock to competition may be more pronounced in our context (Bresnahan and Reiss, 1991).

We also contribute 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 may 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).[9] We explore this issue by explicitly modeling entry and bidding decisions and leveraging variation in the number of potential bidders that stems from exogenous changes in publicity requirements. We indeed find that incumbents are less likely to participate when anticipating fiercer competition. However, the competitive effect from new entrants dominates that of less aggressive bidding by incumbents, reducing the winning bid as a result.

Finally, this paper belongs to the literature that examines buyers' discretion on public procurement outcomes. This line of work has focused on the incentives that buyers face and highlights that their actions can be motivated by objectives other than simple contract cost reductions (Bandiera, Prat and Valletti, 2009; Liebman and Mahoney, 2017; Coviello and

[5] The ABA awards the contract to the lowest bidder *only after* excluding bids that are deemed to be "too low" (Albano, Bianchi and Spagnolo, 2006). Decarolis (2018) describes the selection rule as follows: "*Disregard the top and bottom 10% of the bids; calculate the average of the remaining bids (call it A1); then calculate the average of all the bids strictly above the disregarded bottom 10% and strictly below A1 (call this average A2); the first price above A2 wins the contract and is paid his own price bid to complete the work.*"

[6] Decarolis (2018) shows that this type of mechanism features multiple symmetric Bayesian-Nash equilibria and that equilibrium bids may increase and converge to the reserve price as the number of bidders grows large.

[7] The authors can replicate their key findings in a small sample of contracts awarded through first-price auctions, yet all the baseline analysis is conducted on contracts awarded through ABA.

[8] This is the instrumental variables estimate (see Table 2 column 5). The reduced form effect is 0.36 (Table 1 column 1).

[9] 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.

Gagliarducci, 2017; Coviello, Guglielmo and Spagnolo, 2018; Best, Hjort and Szakonyi, 2023; Decarolis, Giuffrida, Iossa, Mollisi and Spagnolo, 2020a; Carril, 2022; Szucs, 2023). Our contribution to this literature is to emphasize how buyers' actions impact sellers' endogenous decisions to participate in procurement markets. In this respect, our work is related to Kang and Miller (2021), who use IT procurement contracts in the United States to estimate a principal-agent model in which the buyer exerts costly effort to determine the degree of competition that contracts receive. Our paper is also concerned with modeling how the level of competition is endogenously determined, but rather than emphasizing a trade-off between the price benefits of competition and the costly effort of promoting it, we highlight the tension between price competition ex-ante and deteriorated performance ex-post.

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 over 3,000 different contracting offices that are part of an executive or independent agency.[10] The workforce in charge of public contracting comprises over 35,000 contracting officers whose primary role is to plan, carry out, and follow up on purchases made by their units. The Federal Acquisition Regulation (FAR) defines and limits the contracting officers' scope of action. The FAR lays out policy goals, guiding principles, and 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.

FAR Part 5 requires publicizing contract opportunities 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 on an online government-wide platform, which we will refer to as FedBizOpps (or FBO).[11] This

[10]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.

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

implies uploading a request for quotes with a complete 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*. Appendix Figure A2 exhibits an example of FedBizOpps's interface.

Officers with contracts not expected to exceed this threshold are not required to publicize in FedBizOpps; however, they are still free to use it to increase contract visibility.[12] 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. Importantly, no other relevant regulations vary at this same threshold value. Appendix C.1 presents additional policy and website details.

The overwhelming majority of the contracts analyzed in this paper are allocated through so-called simplified acquisition procedures, with vendors being selected according to the lowest price quote that is technically acceptable given the specifications.[13] This simple lowest-bid mechanism contrasts with more sophisticated awarding procedures available for larger acquisitions, 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) are mandated for contracts with award values that largely exceed those considered in our analysis.[14]

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. However, while FPDS-NG contains the universe of federal awards, FedBizOpps only has the notices posted on the website. From this matching process, we construct a dummy variable equal to 1

[12]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.

[13]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 unacceptable. The most common reasons are a blatant omission of the solicitation specifications or the fact that the contractor is debarred from conducting business with the government based on past experience.

[14]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.

if we can 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 data set. Appendix Figure A1 describes the typical timeline of events surrounding the life-cycle of a contract and the appropriate data source that records that information.

In addition, we observe detailed information for each contract award, including the dollar value of the funds obligated, a four-digit code describing the product or service, codes for the agency, sub-agency, and contracting office making the purchase, the identity of the private vendor, the type of contract pricing, the extent of competition in the award, characteristics of the solicitation procedure, the number of offers received, and the applicability of a variety of laws and statutes. Furthermore, we observe the reason for and 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., 2020a; Carril, 2022). Because the data contain the total sum of payments and the 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.[15] 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.[16] Furthermore, our interviews with contracting officers confirmed that staying on budget and on time is an important priority for the buyer. Finally, Carril (2022) 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).[17]

The analysis sample consists of all competitively awarded definitive contracts[18] 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).[19]

[15]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.

[16]For example, the *IT dashboard*—which tracks the performance of large IT projects—scores projects based on a series of considerations, two of which are deviations with respect to budgeted cost and scheduled delivery. Similarly, the DOD is required to periodically report to Congress on the cost and schedule status of all Major Defense Acquisition Programs.

[17]For a sample of FPDS contracts merged to IT projects in the *IT dashboard*, Carril (2022) shows that overruns and delays as computed here correlate positively and significantly with officers' evaluations, which need to be based on objective performance metrics such as, e.g., "percent of the time that the system is available", "percent of servers reduced as a result of virtualization", "number of repeat customers using system", etc.

[18]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 (2022) 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.

[19]The Department of Defense represents 58% of overall federal procurement spending and more than 60% in the

Appendix Table B.1 presents summary statistics of the sample. In total, roughly 86,000 contracts have been awarded to almost 30,000 firms. These contracts are awarded by 597 contracting offices belonging to the Army, the Navy, or the Air Force. The expected contract duration is 54 days on average, and all contracts are 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.[20] Winning vendors are often geographically close to the contracting offices, with both located in the same state in two out of every three contracts. 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 goods and services that are 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. Appendix 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

This section studies 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 interpret these requirements as an exogenous increase in the level of competition for the award: they increase the set of potential participants who are aware of the auction. This is the relevant measure of the competitive environment for bidders, as they place their bids without knowing the set of actual participants. We exploit the $25,000 threshold to provide evidence of the effects of promoting competition on contract award price and other contract outcomes. These results will be the basis for 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* before its award (a decision that we denote as $D \in \{0,1\}$). We leverage the variation introduced by the regulation, which discontinuously affects the likelihood of public

restricted sample. We exclude R&D awards because they are subject to a unique set of acquisition rules; see FAR Part 35.

[20]More than half of the awards are set aside for a particular type of firm (typically, small business). Set-asides are a major factor in the acquisition strategy of 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.

solicitation at an arbitrary threshold ($\bar{p} = 25,000$) depending on 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, which may generate incentives to modify the purchase to make the ex-ante estimate fall below $\bar{p}$. This behavior would result in bunching on the distribution of ex-ante prices, generating excess 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 distribution may differ depending on the publicity status of the contract.

To tackle these empirical challenges, we 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".[21] 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. We use this framework to estimate price effects and correct (and bound) RDD estimates on non-price outcomes accounting for the aforementioned confounds. Since these corrections ultimately have a modest effect on our final results, we leave most details about the method to Appendix D.[22]

Section 3.2 discusses the price effects of publicity 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 the unconditional distribution of potential contract prices is smooth and 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 $\gamma_t \sim F_\gamma(\cdot)$.

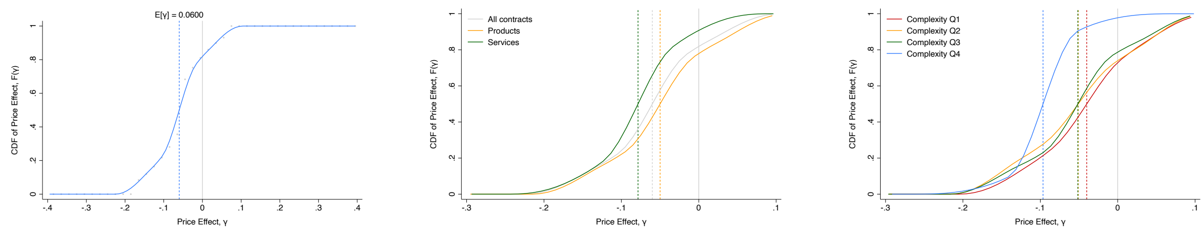
We estimate $E[\gamma_t]$ from the observed distributions of publicized and non-publicized contracts. The intuition of our method is based on three observations. First, relative to a counterfactual with no price effects of publicity (i.e., $\gamma_t = 0$ for all t), the observed distribution of publicized 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

[21] 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.

[22] The key intuition for why these corrections are unimportant in our case can be better understood using a standard "donut-RD" logic: since both sources of measurement error would be most pronounced right around the discontinuity cutoff, then RDD estimates should be sensitive to the exclusion of small subsets of observations around the threshold. In contrast, we show below that baseline estimates are quite robust to excluding windows around $25,000.

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.

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 the smoothness of the overall distribution and an integration constraint.

Appendix D shows how this logic can be extended to nonparametrically identify the full CDF of price effects γ_t 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 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. The full distribution shows that publicizing contract opportunities reduces award prices for 83% of the contracts. Appendix Table B.3 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 more complex contracts.[23]

Appendix 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

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

magnitude will be used to account for the effects of this manipulation on our RDD estimates in Section 3.3. However, we can infer that since the extent of bunching is arguably modest, its impact on our estimates will also be limited.

Finally, in Panel (b), we compare the empirical distribution to the sharply discontinuous 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 toward 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 number of bids, 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, showing how these elements affect the estimation transparently.

In Appendix D.3, 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 modeling assumptions, we can write the conditional expectation of contract outcomes given *observed* prices $E\left[Y_t|p_t\right]$ 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.[24]

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 regarding how selection can influence RDD estimates. In Appendix D.4, we explain in detail how to derive these bounds in our setting and 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 we 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.[25]

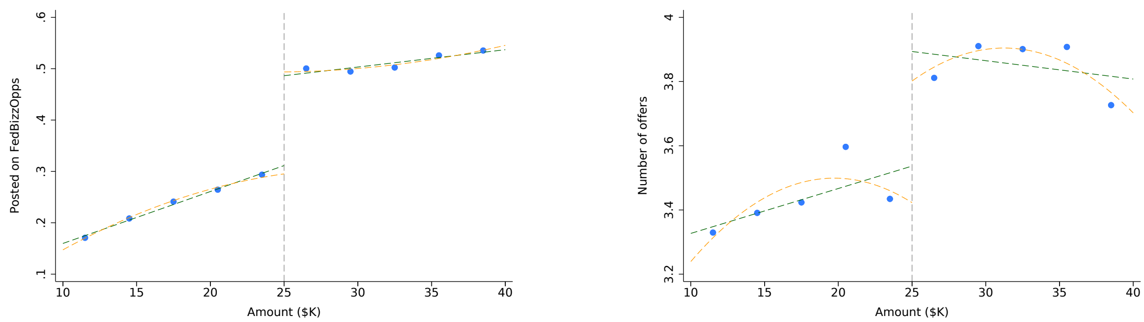
The results for the first stage Equation (2) are presented graphically in Figure 2(a). We see that the use of FedBizOpps jumps sharply past the $25,000 threshold of award amounts. The share of publicly solicited contracts in the government platform increases from roughly 30% at or slightly

[24] We also show in Appendix D.3 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 $p^0(\tilde{p})$.

[25] Appendix Figure A5 presents RDD plots for baseline variables. We find that baseline contract design characteristics are balanced around the threshold, except for a small difference in the share of goods vs. services. All of our baseline estimates are robust to including a service dummy as a 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.

below $25,000 to 50%

The reduced form specifications (Equation (3)) are estimated on three sets of outcomes: the number of bids received, winning vendor characteristics (including its relationship with the awarding office), and post-award performance. Most of the existing literature has studied these variables independently.[26] By studying them jointly, we can comprehensively understand the mechanisms and implications of policies oriented to enhance competition.

Figure 2(b) shows how posting solicitations on FedBizOpps impacts the number of offers 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.

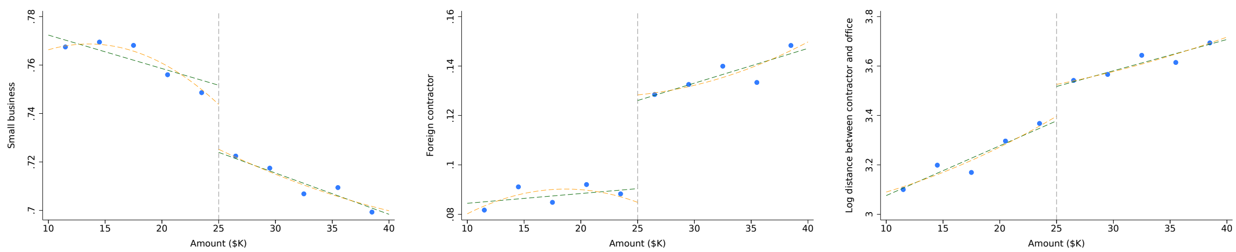
These results indicate that expanding the set of *potential* bidders through the public posting of solicitations leads to the desired goal of increasing the number of *actual* participant bidders. However, it does not necessarily imply that these new offers affect the equilibrium allocation of the contract 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.[27] This

[26] 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. (2020a); Ryan (2020) (ex-post renegotiation and performance).

[27] 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.

"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 public solicitation do win awards with a positive probability.

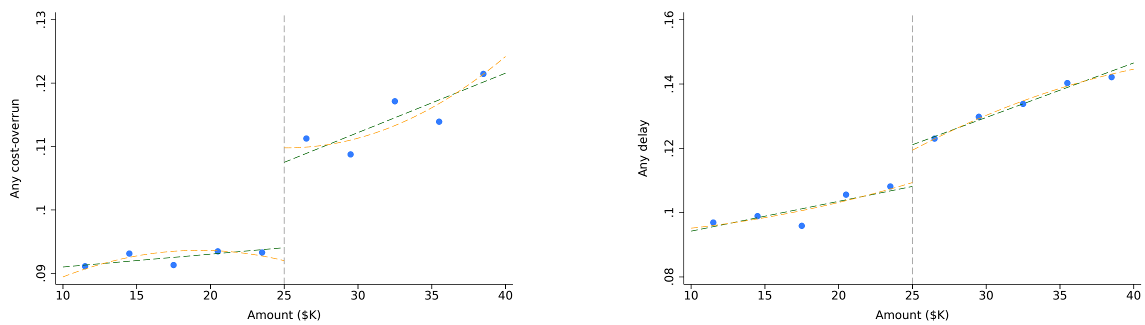
To measure the impact on post-award contract performance, we use two measures that are commonly used in the literature: cost overruns and delays. We compute these as the difference between the ex-post realized sum of payments and duration of the project, and the expected value of these variables at the 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. Appendix Figure A6 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 the expected schedule. These results align with the findings presented in Figure 4: publicized contracts experience more problems during the execution stage. Appendix Figures A10 through A16 illustrate how these effects vary by agency and type of purchased product.

Adjusted RDD Results. In this section, we present a series of refinements to our baseline RDD results. First, we explore the robustness of our baseline linear specification with the estimator proposed by Calonico, Cattaneo and Titiunik (2014), which uses robust local polynomial fits.

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.

Second, building upon the results of our density analysis in Section 3.2 and further explained in Appendix D, 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 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 presents estimates that account for price effects in the treatment group (i.e., publicized contracts), following the method explained in Appendix D.3. 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 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

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	[-0.0273 , 0.0051]	[-0.0249 , -0.0071]
Log distance firm-office	0.1392 (0.0481)	0.1199 (0.0817)	0.1909	[0.0290 , 0.2688]	[0.1303 , 0.2619]
Foreign firm	0.0357 (0.0045)	0.0508 (0.0078)	0.0375	[0.0328 , 0.0519]	[0.0358 , 0.0465]
New firm	0.0175 (0.0075)	0.0185 (0.0126)	0.0247	[0.0022 , 0.0350]	[0.0164 , 0.0344]
Small business	-0.0277 (0.0065)	-0.0295 (0.0110)	-0.0265	[-0.0523 , -0.0195]	[-0.0399 , -0.0219]
Any cost-overrun	0.0135 (0.0045)	0.0246 (0.0077)	0.0144	[0.0103 , 0.0262]	[0.0127 , 0.0216]
Cost-overruns (relative dollars)	0.0095 (0.0058)	0.0161 (0.0100)	0.0127	[0.0053 , 0.0179]	[0.0103 , 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	[1.2300 , 5.3639]	[2.1504 , 4.4703]
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. Each estimate comes from a separate regression. 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 D.3. 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 D.4. 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.

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 a similar magnitude to the worst-case upward bias introduced by bunching responses.

Taken together, these results imply that the strong visual evidence presented in Figures 2(a) through 4 is robust to the potentially confounding influence of price effects and strategic bunching by the buyer. Intuitively, the reason is that our estimates are not overly reliant on data that is very close to the discontinuity. As it is visually apparent from the figures and corroborated in Table 1, simple linear estimates that rely on a wider window of data are not too different from estimates that give a higher weight to the data very near the cutoff. This is important because the potential influence of price effects and strategic bunching would most strongly affect this area of the distribution. Hence, if these confounds were empirically relevant, the RDD estimates would be highly sensitive to excluding data points very close to $25,000. In contrast, Appendix Table B.4 implements a series of "donut-RD" specifications (Barreca et al., 2011; Cattaneo and Titiunik, 2022), and shows that our baseline linear estimates are robust to the exclusion of a window of varying width around the cutoff: for all window sizes considered, coefficients are statistically indistinguishable from the baseline.

3.4 The Role of Contract Complexity

Prior literature on incomplete contracts in procurement has emphasized the link between the underlying complexity of a transaction—an exogenous characteristic of the product being procured—and the level of costly ex-post adaptation (Bajari and Tadelis, 2001; Bajari, McMillan and Tadelis, 2009; Bajari, Houghton and Tadelis, 2014). Since the difficulty of specifying several possible contingencies varies across contracts, we should observe less variability in post-award performance if the purchase involves, e.g., a standardized product rather than an *ad-hoc* service. This may explain why some product categories in our data rarely experience execution issues ex-post, while others present post-award modifications for most contracts. It may also imply that the effects on post-award performance that we documented above are heterogeneous across goods or services with different underlying complexity. Similarly, the impact of expanding competition on award prices is also likely to vary with complexity. For example, if bidders of relatively complex products are more heterogeneous in production costs, additional offers would lower contract award prices more than when contractors are homogeneous. Thus, the degree of contract complexity may shape how competition affects both prices ex-ante and performance 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.[28] This leads to an intuitive

[28] 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

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 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. 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 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.[29] Overall, it is noteworthy that both counteracting effects of competition—price reductions ex-ante and overruns ex-post—are more pronounced for complex contracts.[30] In Section 4, we return to this trade-off and zoom in on the drivers of these effects.

3.5 Evidence of Adverse Selection

Our results show that increasing the pool of potential bidders through publicity generates changes to contract prices and subsequent contract execution. There are two classes of explanations through which we can rationalize the connection between publicity and contract performance: within-contractor and cross-contractor changes in performance. The within-contractor variation would imply that the same firm may perform systematically differently depending on the publicity status of the contract. This could stem from contractors' strategic choices (i.e., moral hazard) or features

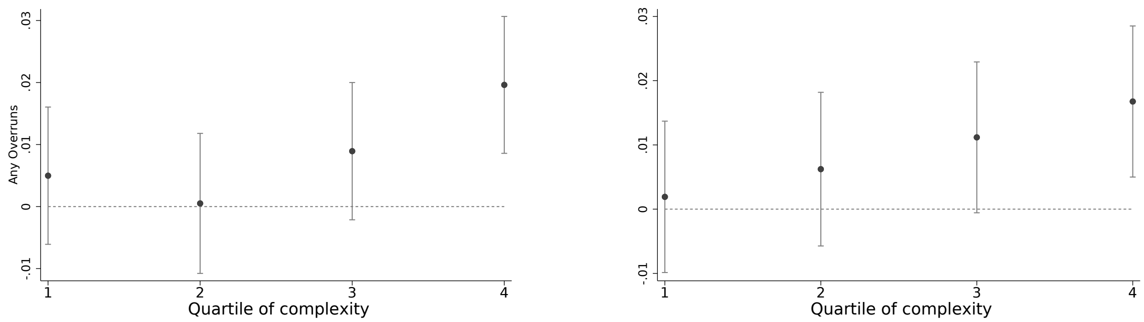
words in the solicitation's description. These classifications lead to roughly the same rank of product categories, and thus, varying the definition does not threaten the general results. We present correlations between some of these measures in Appendix Figure A7. We use the mean of cost overruns because 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.

[29] Appendix Figure A16 shows RD plots for cost overruns separating 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.

[30] Because the publicity effects on award price and overruns are estimated using different methodologies—namely, density analysis and RDD—, it is not straightforward to combine the two. This is why we leave a thorough analysis of the effects of publicity on the final price (i.e., award price plus overruns) for the model in Section 4. Having said this, the evidence presented so far suggests: (i) adding the two effects implies an impact of publicity on final prices that is heterogeneous on complexity; (ii) given the estimated null effects on overruns for the least complex products, publicity likely reduces the final price for that group; and (iii) the trade-off is more nuanced for more complex contracts.

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.

of the production technology. The cross-contractor variation would imply that publicity allows the participation of suppliers that are "different" and that their performance ability is unrelated to the contract's advertising (i.e., adverse selection).

To elucidate between these mechanisms, we leverage the fact that buyers often purchase 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 characteristics of the contract. Moreover, on the supply side, we observe most contractors executing more than one contract for one or more different buyers. This variation allows us to test how much of the observed variation is due to contractors' "types," relative to variation "within" contractor.

Table 2 presents the results of this exercise, where we re-estimate RDD specifications assessing the effects of including contractor fixed effects. To make the different coefficients comparable, we constraint the sample in all columns to the set of firms for which we can estimate the fixed-effects specifications.[31] Columns 1 and 3 display the baseline IV estimates of the changes in performance induced by publicity, showing that the share of contracts experiencing overruns and delays jumps by 7.6 and 5.0 percentage points, respectively. Columns 2 and 4 show that incorporating contractor fixed effects shrinks the absolute value of the estimates substantially (to 2.2 and -1.3 percentage points, respectively), making both of them statistically indistinguishable from zero. Importantly, while there is no effect of publicity on performance when we look within contractors, columns

[31]This leaves us with 81% of the contracts in the full sample (number of observations is 69,296, whereas Appendix Table B.1 reports 85,661 contracts), and 41% of the firms (12,240 firms out of 29,641 firms reported in Appendix Table B.1).

5 and 6 show that the actual competitive environment is indeed changing when we cross the threshold: the IV estimate of publicity on the number of offers barely changes with the introduction of contractor fixed-effects, moving from 2.3 to 2.1 additional offers, both statistically different from zero and statistically indistinguishable from each other.

This evidence implies that most of the effects of publicity on contract performance are explained by variation *across* contractors, as opposed to *within* contractors. Conditional on the selected firm, performance does not significantly change when we cross the threshold, even though competition does increase substantially. We interpret these results as strong evidence in favor of adverse selection (i.e., that publicity brings in different vendors) as opposed to publicity inducing the same firms to change their behavior.

Table 2: IV-RD Estimates Controlling for Firm Fixed-Effects

	Any Cost Overrun		Any Delay		Number of Offers	
	(1)	(2)	(3)	(4)	(5)	(6)
Estimate	0.076	0.022	0.050	-0.013	2.312	2.091
S. E.	(0.027)	(0.029)	(0.028)	(0.032)	(0.436)	(0.470)
Firm Fixed Effects	No	Yes	No	Yes	No	Yes
Number of Observations	69,296	69,296	69,296	69,296	69,296	69,296

Notes: This table shows instrumental variable estimates of the effect of appearing in FedBizzOpps on contract outcomes using a regression discontinuity design. The instrument corresponds to a dummy indicating whether the award value exceeds $25,000. The dependent variable in columns 1 and 2 is an indicator of having any positive cost overruns. The dependent variable in columns 3 and 4 is an indicator of having any positive delays. The dependent variable in columns 5 and 6 is the number of offers received. Columns 2, 4, and 6 include firm fixed effects. Cost overruns are computed as the difference between actual obligated contract dollars and expected total obligations at the award time. Delays are computed as the difference between the actual duration of the contract and the expected duration 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.

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. Our results show that promoting contract competition for (at least partially) incomplete contracts involves a trade-off: it reduces contract award prices at the cost of exacerbating adverse selection, leading to contractors characterized by lower execution performance. Furthermore, this trade-off is heterogeneous, with both price 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 the 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 present and estimate a 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, and in Section 4.3 we discuss 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 potential contractors. Each potential contractor j must incur an entry cost $\omega_j \geq 0$ 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. We model the potential bidders' choices in two stages. First, knowing the set of potential competitors $\mathbf{N}$, each potential bidder decides whether to incur the entry cost. After the entry stage, the $\mathbf{n} \subseteq \mathbf{N}$ firms that incurred entry costs privately learn their costs of completing the project and submit their bids b_j. The awarding mechanism is a first-price sealed-bid auction. The winner of the auction becomes the contractor, and its execution performance, q_j, is publicly observed once the contract is awarded.

Our analysis considers asymmetry between potential contractors: there are two types of firms, locals (L) and non-locals (NL). These firms differ in their production technology, which is characterized by the distribution of entry costs $H^k(\omega)$ and the joint distribution of project completion costs and execution performance $F^k(c,q) \equiv F^k_c(c) \cdot F^k_{q|c}(q|c)$, where $k(j) \in \{L, NL\}$ denotes bidder j's type. We assume that entry and project completion costs are private information and are distributed independently and identically within a type.

Contract Execution: Cost Overruns. Throughout our analysis, we measure contractors' performance by the magnitude of cost overruns, which correspond to ex-post realizations of unbudgeted costs. 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.[32]

We assume that contractors draw q_j at the execution stage and fully pass through this cost shock to the buyer, leaving the utility of the contractor unchanged. Thus, potential differences in execution performance across contractors are explained by differences in production technologies that we take as given (i.e., types), rather than by strategic aspects. By estimating the primitive joint distributions $F^k(c, q)$ that capture these underlying production technologies, we will allow the data to inform us about the relationship between costs and performance.[33] This modeling choice is motivated by the evidence presented in Section 3.5.

Publicity Choice. 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. Our model allows the buyer to endogenously determine the set of potential contractors through the publicity choice, which is made taking into consideration (i) the likelihood that a contractor of each type is awarded the contract, (ii) the expected award price, and (iii) the expected execution performance in terms of cost overruns.

4.1.1 Equilibrium in the Bidding Stage

Our analysis focuses on a type-symmetric equilibrium where bidders of type 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 bidders of each type are common knowledge. Nevertheless, we assume that bidders do not observe the number of actual competitors of each type 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 payoff of bidder j, with type $k(j)$, cost realization c, and market composition $\mathbf{N} = \left(N^{k(j)}, N^{-k(j)}\right)$ is:

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

[33] In Appendix E, we further discuss the implications and limitations of our modeling assumptions.

$$\Pi_j(b, c|\mathbf{N}) \quad = \quad (b-c)\,\mathbf{P}_j(b|\mathbf{N}), \tag{4}$$

where $\mathbf{P}_j(b|\mathbf{N})$ is the probability that bidder j wins the auction when bidding b. Given that the bidders don't observe the composition of actual competitors in the auction, the probability of winning depends on the entry probabilities of the other potential bidders:

$$\mathbf{P}_j(b|\mathbf{N}) \quad = \quad \left(\sum_{l=2}^{N^{k(j)}} \rho_l^{k(j)} \left(1 - G^{k(j)}(b)\right)^{l-1}\right)\left(\sum_{l'=1}^{N^{-k(j)}} \rho_{l'}^{-k(j)} \left(1 - G^{-k(j)}(b)\right)^{l'}\right), \tag{5}$$

where $G^k(b)$ is the distribution of equilibrium bids of type-k bidders, ρ_l^k is the probability that the number of actual bidders of type k is equal to l, and $-k$ denotes the other type of potential contractors. The optimal bidding is obtained from the usual first-order condition:[34]

$$(b-c)\mathbf{P}'_j(b|\mathbf{N}) + \mathbf{P}_j(b|\mathbf{N}) = 0 \quad . \tag{6}$$

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 only one type is involved. Local suppliers observe the contracts' publicity status and, hence, the number of potential competitors.[35]

4.1.2 Equilibrium in the Entry Stage

We focus on type-symmetric entry equilibrium strategies, φ^L, φ^{NL}. 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 $H^k(\omega)$ with common support $[\underline{\omega}, \overline{\omega}]$. Firms with entry costs below their expected profit decide to incur the entry cost to learn about their cost of completing the project. The *ex-ante* (expected) profits from participating are given by:

[34] 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. Bidding strategies cannot be solved analytically; they require numerical methods. Campo, Perrigne and Vuong (2003) and Brendstrup and Paarsch (2003) discuss non-parametric identification of cost functions in this setting.

[35] Thus, the probability of winning a contract that is not publicized is:

$$\mathbf{P}_j(b|\mathbf{N}) \quad = \quad \sum_{l=2}^{N^{k(j)}} \rho_l^{k(j)} \left(1 - G^{k(j)}(b)\right)^{l-1} \tag{7}$$

$$\overline{\Pi}^k(\varphi^k, \varphi^{-k}) = \int_{\underline{c}}^{\bar{c}} \left(\sum_{n^k-1, n^{-k} \subset N^k-1, N^{-k}} \pi^k(c|n^k-1, n^{-k}; \mathbf{N}) Pr\left(n^k-1, n^{-k}|\mathbf{N}\right) \right) dF_c^k(c) \quad , \tag{8}$$

where $\pi^k(c|n^k-1, n^{-k})$ denotes the expected profit of potential entrant with type k in an auction where the set of participants includes n^k-1 and n^{-k}, and participants use equilibrium bid strategies $\beta_k(\cdot)$ and $\beta_{-k}(\cdot)$, respectively. The terms φ^k and φ^{-k} are the entry probabilities of each type. Because entry decisions are made simultaneously, the equilibrium condition is characterized by a type-specific entry cost threshold $\bar{\omega}_k$, such that firms whose entry cost is below their type-specific threshold participate.[36] Finally, when the contract is not publicized, only locals can participate, and thus the participation problem becomes symmetric. Therefore, for a given contract, the local type's participation threshold differs depending on whether the contract was publicized.

4.2 Empirical Model

Based on the equilibrium conditions of the general model, we proceed to describe its implementation in the empirical setting. A contract solicitation t is characterized by $(\mathbf{x}_t, \mathbf{z}_t, u_t, \mathbf{N}_t)$, $\mathbf{x}_t$ corresponds to a set of baseline characteristics of the contract, $\mathbf{z}_t$ 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, $\mathbf{x}_t$ includes the contract's good or service category, associated complexity measure, expected duration, and location. On the other hand, for $\mathbf{z}_t$, we use variables related to the timing of the solicitation, particularly whether it was awarded at the end of the fiscal year.[37] Finally, $\mathbf{N}_t = (N_t^L, N_t^{NL})$ denotes the number of potential contractors of each type.[38] The model proceeds in four stages, depicted in Figure 6. The stages are:

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

$$\begin{aligned} \varphi^L &= H^L\left[\bar{\omega}_L(\varphi^L, \varphi^{NL})\right] \\ \varphi^{NL} &= H^{NL}\left[\bar{\omega}_{NL}(\varphi^L, \varphi^{NL})\right] \end{aligned}$$

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

[37] 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.

[38] Identifying the potential number of bidders is not trivial (Athey, Levin and Seira, 2011; Krasnokutskaya and Seim, 2011; MacKay, 2022). We combine two methodologies. First, using the procedure described in Appendix section G.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. We define the number of potential bidders for every

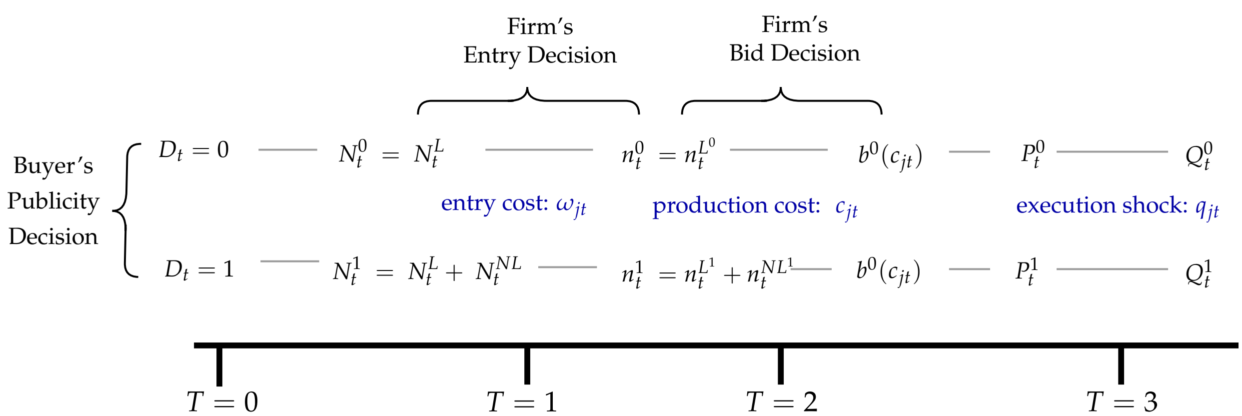
T = 0: *Publicity Decision.* The buyer observes $(\mathbf{x}_t, \mathbf{z}_t, u_t, \mathbf{N}_t)$ and decides whether to publicize the contract, $D_t \in \{0, 1\}$, in order to maximize expected utility. Contract publicity status determines the set of potential bidders.

T = 1: *Entry Decision.* Each firm that learns about the contract opportunity observes $(\mathbf{x}_t, \mathbf{z}_t, u_t, \mathbf{N}_t)$. They draw individual and private realizations of entry costs and simultaneously decide 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 Specification

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

$$\begin{aligned} U_t^D &= U(\bar{P}_t^D, \bar{Q}_t^D, \bar{L}_t^D) \\ &= \lambda^P \bar{P}_t^D + \lambda^Q \bar{Q}_t^D + \lambda^L \bar{L}_t^D + \varepsilon_t^D, \end{aligned} \tag{9}$$

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 $(\mathbf{x}_t, \mathbf{z}_t, u_t, \mathbf{N}_t)$ 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. The parameters λ^P and λ^Q capture standard price sensitivity.

buyer-product as the maximum of both approaches. Combining these two methods alleviates each of their potential weaknesses. The median number of potential *local* and *non-local* bidders is six and three, respectively.

λ^L captures any form of favoritism unrelated to award price or execution performance.[39] 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 in the probability of advertisement at the threshold. Intuitively, η captures the intensity of regulation enforcement above the threshold:[40]

$$D_t = 1 \quad \Longleftrightarrow \quad U(\bar{P}_t^1, \bar{Q}_t^1, \bar{L}_t^1) + \eta\, \mathbb{1}\left(\bar{P}_t^0 > \log(25)\right) \geq U(\bar{P}_t^0, \bar{Q}_t^0, \bar{L}_t^0) \tag{10}$$

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 type-k firms is given by $F_{\tilde{c}}^k(\cdot|\mathbf{x}_t)$, and each draw $\tilde{c}_{jt}$ is independent across j and t conditional on observables. The unobserved project heterogeneity is given by $u_t \sim K(\cdot)$, and is independent from project characteristics ($\mathbf{x}_t$), entry-cost shifters ($\mathbf{z}_t$), and the set of potential bidders ($\mathbf{N}_t$).

We assume that bidders are risk-neutral. Thus, the Bayes-Nash equilibrium bid function for type k is multiplicative: $\beta_k(c_{jt}|\mathbf{x}_t, u_t, \mathbf{N}_t) = u_t \cdot \tilde{\beta}_k(\tilde{c}_{jt}|\mathbf{x}_t, \mathbf{N}_t)$.[41] Each bidder submits a bid of $b_{jt} = \tilde{b}_{jt} \cdot u_t$, where $\tilde{b}_{jt} = \tilde{\beta}_k(\tilde{c}_{jt}|\mathbf{x}_t, \mathbf{N}_t)$ 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.[42] [43]

Finally, we assume that entry costs ω_{jt} are independent across j and t conditional on observed project characteristics $\mathbf{x}_t$. In equilibrium, firms' participation behavior is characterized by type-specific thresholds, $\bar{\omega}_t^{k*}$. Thus, the number of actual bidders n_t^k from type $k \in \{L, NL\}$ distributes binomial with an individual entry probability of $\varphi^{k*}(\mathbf{x}_t, \mathbf{z}_t, u_t, \mathbf{N}_t)$ and N_t^k trials, where $\varphi^{k*}(\mathbf{x}_t, \mathbf{z}_t, u_t, \mathbf{N}_t) = H^k\left(\bar{\omega}^{k*}(\mathbf{x}_t, \mathbf{z}_t, u_t, \mathbf{N}_t)\right)$. Our model considers entry shifters $\mathbf{z}_t$, which capture market-level conditions that affect entry decisions.[44]

[39] 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.

[40] 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.

[41] 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.

[42] We assume that the buyer sets a shadow reserve price at the 99th percentile of the cost function of local contractors. Establishing a shadow reserve price acknowledges that the buyer is not necessarily forced to accept unreasonably high bids and allows us to discard equilibria in which firms bid infinity due to the chance of being the only bidder. This way, the reserve price is scaled by x_t and u_t, and is almost never binding in compliance with necessary conditions for identification (Krasnokutskaya, 2011). Related papers either rule out data from auctions with only one bidder or assume that in the case of a single bid, the buyer operates as a second bidder (Li and Zheng, 2009; Athey et al., 2011; Krasnokutskaya and Seim, 2011).

[43] Note that the buyer's utility function is linear on the log-winning bid, so an auction's $\log(u_t)$ is an additive term on both sides of Equation (10), implying that it cancels out in the buyer's publicity choice.

[44] In the absence of entry shifters, variation in actual entrants would still be obtained from changes in potential bidders

Contract Execution. Contract execution is observed ex-post and corresponds to the magnitude of cost overruns, drawn from the distribution $F^k_{q|c}(\cdot|\mathbf{x}_t)$. Thus, $F^k_{q|c}(\cdot|\mathbf{x}_t)$ is type-dependent, varies by observables $\mathbf{x}_t$ and is directly observed in the data.

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.

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* $(\mathbf{x}_t, \mathbf{z}_t, \mathbf{N}_t)$ and *outputs* $(D_t, \mathbf{n}_t, P_t, Q_t, L_t)$. The model is identified based on three main assumptions:

(i) Contract and market characteristics $(\mathbf{x}_t, \mathbf{z}_t, \mathbf{N}_t)$ are exogenous.

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

(iii) Unobserved heterogeneity u_t is independent across t with $\mathbb{E}[u_t|\mathbf{x}_t, \mathbf{z}_t, \mathbf{N}_t] = \mathbb{E}[u_t] = 1$.

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 randomly selected. 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 in publicity adoption and thus identify type-specific distributions separately. We now discuss identification more specifically for the different components of the model.[45]

Bidding. The empirical challenge involves separately identifying $F_{\tilde{c}}(\tilde{c})$ from $K(u)$. The identification argument relates to MacKay (2022) and builds upon exogenous variation in the number of bidders,

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$\mathbf{N}_t$. So while the entry-cost shifters $\mathbf{z}_t$ are not strictly necessary for identification, they generate additional variation in the number of actual entrants $\mathbf{n}_t$ for a given vector of observables $\mathbf{x}_t$. This is useful since the pass-through from $\mathbf{N}_t$ to $\mathbf{n}_t$ may be small and potentially ambiguous due to counteracting "entry" and "competition" effects (Li and Zheng, 2009). Now, note that $\mathbf{z}_t$ provides additional variation only if it is uncorrelated with production costs. In our estimation, $\mathbf{z}_t$ is a dummy that takes value one if the contract was solicited in the last month of the fiscal year. The reasoning is that the timing of the auction affects entry costs (e.g., due to short solicitation notice) but is independent of contract costs. The latter is equivalent to assuming that the distribution of project cost is constant over time.

[45] In what follows, we omit the distinction between $D_t \in \{0, 1\}$ 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., $\mathbf{N}_t = (N^L_t, N^{NL}_t)$ and $\mathbf{n}_t = (n^L_t, n^{NL}_t)$. If a contract is not publicized, only locals could participate: $\mathbf{N}_t = (N^L_t, 0)$ and $\mathbf{n}_t = (n^L_t, 0)$

$\mathbf{n}_t$.[46] In our setting, bidders observe auction characteristics and the set of *potential* competitors, $\mathbf{N}_t$, but do not know the set of actual competitors, $\mathbf{n}_t$. 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 $(\mathbf{n}_t|\mathbf{x}_t, \mathbf{z}_t, \mathbf{N}_t)$ 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 $(\mathbf{x}_t, \mathbf{z}_t, \mathbf{N}_t)$ combination. Since u_t is assumed independent, one additional competitor under the same bidding strategy is equivalent to one additional draw from the distribution of normalized bids, $G^k(\tilde{b})$. Restrictions over expected order statistics approximate the quantiles of $G^k(\tilde{b})$, and if $N \to \infty$, $G^k(\tilde{b})$ is exactly identified. The underlying cost distribution $F^k_{\tilde{c}}(\tilde{c})$ is pinned down from the distribution of $G^k(\tilde{b})$ (Guerre et al., 2000; Campo et al., 2003). See Appendix F.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., $\omega_{jt} < \bar{\omega}^k_t$. 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 $\varphi^{k*}_t = H^k(\bar{\omega}^{k*}_t)$. Identifying $H^k(\cdot|\mathbf{x}_t)$ from the data entails three steps. First, we observe the *realized* set of potential bidders that decide to enter each auction t, which implies that, with enough observations per combination of $(\mathbf{x}_t, \mathbf{z}_t, \mathbf{N}_t)$, we can estimate $\varphi^{k*}(\mathbf{x}_t, \mathbf{z}_t, \mathbf{N}_t)$. Then, we use Equation (8) to back out the expected utility of entering, conditional on $(\mathbf{x}_t, \mathbf{z}_t, \mathbf{N}_t)$. The final step leverages variation in $(\mathbf{z}_t, \mathbf{N}_t)$ to construct combinations of $(\varphi^{k*}, \bar{\omega}^{k*}|\mathbf{x}_t)$ that pin down $H^k(\omega)(\cdot|\mathbf{x}_t)$.

Execution. Contract execution performance (cost overruns) is given by (conditionally) independent random shocks. Thus, the observed distribution of cost overruns directly reveals $F^k_{q|c}(\cdot|\mathbf{x}_t)$. The joint distribution of $F^k(\tilde{c}, q|\mathbf{x}_t)$ is obtained from $F^k_{q|\tilde{c}}(q|\mathbf{x}_t) \cdot F^k_{\tilde{c}}(\tilde{c}|\mathbf{x}_t)$.

Buyer's Preference Parameters. The buyer's taste parameters for price, overruns, and local contractors are identified from variation in contract and market characteristics $(\mathbf{x}_t, \mathbf{z}_t, \mathbf{N}_t)$. 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. Finally, the disutility from avoiding the publicity regulation is identified from the publicity choices below and above the threshold. Following the logic of the

[46] 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 cost functions. The latter requires observing at least two bids per auction.

RDD in Section 3, the difference in publicity intensity below and above the threshold directly informs about the "bite" of the policy, which reveals its effects on buyers' utilities.

4.4 Estimation Approach

We make functional form assumptions to characterize equilibrium conditions of each stage and take the model to data:[47]

- *Bidding and execution.* We specify normalized equilibrium bids as a linear function of covariates, $\mathbf{x}_t$, and the set of potential bidders, $\mathbf{N}_t$:

$$\log(\tilde{b}_{jt}) = [\mathbf{x}_t, \mathbf{N}_t]'\alpha^k + \varepsilon^{\tilde{b}}_{jt}$$

  We further assume that $\log(u_t)$ is normally distributed with mean zero and variance σ_u^2. The observed distribution of cost overruns is censored at zero to accommodate the fact that most contracts stay right on budget (Eun, 2018): $Q_t^k = \max\{0, \log(q_t^k)\}$, where $log(q_{jt})$ is a linear function of observables:

$$\log(q_{jt}) = \mathbf{x}_t'\gamma^k + \varepsilon^q_{jt}$$

  We specify the joint distribution of bid and execution shocks as a bivariate normal:

$$\begin{pmatrix} \varepsilon^{\tilde{b}}_{jt} \\ \varepsilon^{q}_{jt} \end{pmatrix} \sim N \begin{pmatrix} 0 & \sigma^2_{\tilde{b}} & \rho\sigma_{\tilde{b}}\sigma_q \\ 0 , & \rho\sigma_{\tilde{b}}\sigma_q & \sigma^2_q \end{pmatrix}$$

  where $\sigma^2_{\tilde{b}} = \exp\{\mathbf{x}_t'\nu^k\}$, $\sigma^2_q = \exp\{\mathbf{x}_t{}'\xi^k\}$, and ρ specifies the correlation between bidding and execution shocks. Intuitively, $\rho < 0$ implies that vendors with negative bid shocks (who bid low due to low cost draws) tend to experience more cost overruns ex-post. We specify $\rho = \mathbf{x}_t{}'\iota^k$.

- *Entry.* The equilibrium entry choices are characterized by type-specific probabilities, $\varphi_t^k(\mathbf{x}_t, \mathbf{z}_t, \mathbf{N}_t)$. We assume $\varphi_t^k(\mathbf{x}_t, \mathbf{z}_t, \mathbf{N}_t) = \Phi\left([\mathbf{x}_t, \mathbf{z}_t, \mathbf{N}_t]'\tau^k\right)$, where $\Phi(\cdot)$ denotes the cumulative distribution of the standard normal distribution, and $\mathbf{z}_t$ are entry-cost shifters. Since the entry decisions are independent and simultaneous, the number of participating bidders $n_t^k(\cdot)$ follows a binomial distribution with N_t^k independent draws with a probability of success $\varphi_t^k(\cdot)$.[48]

[47] 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 to identify these distributions independently from the specific functional form.

[48] Related papers either assume parametric distributions for the entry costs, which paired with the expected utility of

- *Publicity choice.* We specify that the difference of buyers' utility shocks $(\varepsilon_t^0 - \varepsilon_t^1)$ in equation (9) distributes standard normal, so that $Pr(D_t = 1) = \Phi\left(\lambda^P \tilde{\bar{P}}_t + \lambda^Q \tilde{\bar{Q}}_t + \lambda^L \tilde{\bar{L}}_t + \eta \mathbb{1}(\bar{P}_t^0 > 25) + \mathbf{x}_t' \zeta\right)$, where $\left(\tilde{\bar{P}}_t, \tilde{\bar{Q}}_t, \tilde{\bar{L}}_t\right)$ are the *change* in expected outcomes associated with publicity, leaving no publicity as the omitted category.[49] 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 our main 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 additional restriction. To classify local and non-local vendors, we require buyer-product combinations to appear at least four times in the full database between 2013 and 2019, at least one of which should appear in FBO. This restriction rules out products that are purchased less often. Appendix Table B.6 compares summary statistics for the relevant variables between this selected sample and the full sample used in Section 3. Overall, the model sample is broadly representative of the full sample in terms of observables. However, given that the selection involves the buyer contracting the same product multiple times, the selected sample includes contracts for categories that are, on average, less durable, with a slightly higher probability of being publicized in FBO (0.39 vs. 0.3). 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 the simulated method of moments (Mcfadden, 1989; Pakes and Pollard, 1989). 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: participation decisions, bidding strategies, cost overruns, and publicity decisions.

Our simulation procedure starts with a set of data inputs $(\mathbf{x}_t, \mathbf{z}_t, \mathbf{N}_t)$ 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 $(\mathbf{x}_t, \mathbf{z}_t, \mathbf{N}_t)$ and u_t, integrating over Monte Carlo simulated distributions of award price, overruns, and the likelihood of a local winning. Although computationally involved, this method is useful to circumvent integrating over potentially nonlinear 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

entering map into well-defined type-specific entry probabilities (Krasnokutskaya and Seim, 2011; MacKay, 2022); or make functional form assumptions on the entry probabilities, which combined with expected utilities allow for recovering entry costs (Athey et al., 2011, 2013; Compiani et al., 2020). We follow the latter approach.

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

generated by simulating observations are denoted by $m_s(\theta)$. This vector depends on the parameters $\theta \in \Theta \subset \mathbb{R}^P$. The estimator minimizes the standard distance metric:

$$\hat{\theta} = \underset{\theta}{\operatorname{argmin}} \left(m_n - m_s(\theta)\right)' W_n \left(m_n - m_s(\theta)\right) \tag{11}$$

where W_n is the weighting matrix.[50]

The vector of parameters is: $\theta = (\alpha^k, \nu^k, \tau^k, \gamma^k, \xi^k, \iota^k, \vec{\lambda}, \eta, \zeta, \sigma)$. We use three sets of target moments. The first set of moments is a vector of means and variances of the outcome variables and their interaction with the relevant covariates. The outcome variables are the auction price, the number of bidders, an indicator for a local winner, the magnitude of cost overruns, an indicator for 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 these three vectors, we obtain the vector m_n of 109 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.[51] The details of the estimation procedure are discussed in Appendix G.

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.

4.5.1 Estimates

To facilitate the interpretation of coefficients, Panel A in Table 3 presents marginal effects. Although the coefficients are estimated jointly, the marginal effects are presented in three different columns for each decision (entry, bidding, and execution). Appendix Table B.7 displays the underlying coefficient estimates with their corresponding standard errors.[52] Panel B shows the estimates associated with standard deviations and correlations, and Panel C describes buyers' preference parameters in terms of marginal effects.

Several findings are worth highlighting. First, bidders are less prone to participate if the contract

[50] The quasi-optimal weighting matrix, W_n, is obtained previously from a set of candidate parameters (Gourieroux, Monfort and Renault, 1993)

[51] 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.

[52] The procedure to estimate standard errors is discussed in Appendix G.2.1.

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 more likely to participate than locals, and bidders reduce their probability of entering if they expect more competition (i.e., face a higher number of potential bidders). As expected, one additional potential non-local competitor has a higher effect on entry than a local one.

Table 3: Model Estimates: Marginal Effects

			Entry	Bidding	Execution	
	$\bar{x}$	Δx	$\Delta\varphi/\Delta x$	$\Delta\tilde{b}/\Delta x$	$\Delta q/\Delta x$	$\Delta(q>0)/\Delta x$
Panel A: Marginal Effects						
Service	0.31	1	-0.004	0.000	0.014	0.002
Degree of Complexity	0.07	0.1	-0.046	-0.007	0.339	0.052
Non-Local		1	0.971	-0.010	0.183	0.021
Non-Local×Complexity		0.1	0.002	-0.004	0.002	0.000
Last Month	0.27	1	-0.042			
Exp. Duration > Median	0.50	1			0.310	0.035
N^L	8.66	1	-0.009	-0.002		
N^{NL}	4.45	1	-0.165	-0.004		
Panel B: Standard Deviation						
Standard Deviation ($\hat{\sigma}$)				0.099	0.934	
Correlation Local ($\hat{\rho}^L$)				-0.142		
Correlation Non-Local ($\hat{\rho}^{NL}$)				-0.152		
St. Dev. Unob. Het. (σ_u)				0.422		
			Publicity Choice			
Panel C: Marginal Effects		Δx	$\Delta Pub/\Delta x$			
Exp. Price		0.1	-0.037			
Exp. Cost-Overruns		0.1	-0.004			
Exp. Local Winning		0.1	0.017			
Above $25K		1	0.431			
Number of Observations	28,330					

Notes: This table shows model estimates. 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 the second column. 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 bid level, the amount of cost overruns, and the probability of any positive overruns. Panel B shows the estimated standard deviation of the normalized log-bids, overruns, and the estimated standard deviation of the unobserved cost heterogeneity component. Also, it shows the estimated correlation between normalized log bids and overruns. 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 the Simulated Method of Moments (SMM).

Second, bids from non-locals are 1 p.p. lower than bids from locals, and more potential competitors reduce the equilibrium bids. 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 an auction. The standard deviation of (log) unobserved heterogeneity is 4.3 times larger than the bids' standard deviation when $\log(u_t) = 0$.[53]

Third, the execution shock depends on the transacted product: the mean of log-overrun shocks is substantially higher for more complex products. In line with the reduced-form results, the difference in cost overruns between locals and non-locals is sizable, with non-locals having a mean shock of 18 p.p. higher. Interestingly, the difference between these two groups is relatively stable over different degrees of product complexity. Additionally, we find that shocks to cost overruns and bids are negatively correlated: the estimated correlation for local contractors is -0.142, while for non-locals it is -0.152. These correlations emphasize the possible drawbacks of promoting too much competition for contracts, as lower bid draws are more likely to produce higher overruns.

Panel C of Table 3 shows that if buyers anticipate that publicity leads to a 10% reduction in awarding price, they increase their likelihood of publicizing by 3.7 p.p. However, a 10% increase in cost overruns reduces the probability of advertising by only 0.4 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.[54]

Buyers have a preference for local vendors. Anticipating a 10 p.p. reduction in the likelihood of a local contractor winning leads buyers to reduce the probability of publicity by 1.7 p.p. This coefficient is meaningful in magnitude: the buyer is indifferent between increasing the probability of a local winner by 10% and reducing the award price by roughly 4.6 p.p. Finally, predicting that the price without advertising will exceed $25,000 increases the likelihood of publicity by 43 p.p.

Model Fit. Overall, the model replicates the key empirical patterns in the estimation sample. Appendix Figure A17 compares the distribution of model-simulated equilibrium outcome variables with actual data. The simulated data resembles actual publicity choices, prices, the 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 the model slightly over-predicts the jump in publicity at the threshold, which leads to a slight over-prediction of the dip in the probability of a local winning the contracts. Also, for services, the model slightly under-predicts the probability of having any (positive) cost overrun but over-predicts the magnitude of cost overruns. This dichotomy suggests that buyers may face frictions when introducing contract modifications ex-post that our model does not account for.

Sensitivity. In Appendix H, we explore the sensitivity of our parameter estimates to the estimation

[53] It is not surprising that the unobserved heterogeneity term captures a sizable proportion of the price variance, considering that in our data the contract price corresponds to the total awarded value, not distinguishing between the required quantity and unit price. Thus, the unobserved heterogeneity term may capture important quantity differences across contracts. Other unobserved relevant factors are the travel costs between the place of delivery or execution and the bidders' location.

[54] In interviews with procurement officers, we noted that some agencies separate personnel in charge of the contract award and contract management phases of the procurement process.

moments, following the approach proposed by Andrews, Gentzkow and Shapiro (2017). Results are consistent with our identification arguments in Section 4.3. Focusing on a few parameters as examples, we show that these are most sensitive to the moments deemed *a priori* as important for identification.

4.5.2 Recovering Cost Distributions

Project Costs. We recover the distribution of project costs by leveraging the methodology introduced by Guerre, Perrigne and Vuong (2000) and Campo, Perrigne and Vuong (2003). This method combines the first-order conditions (Equation 6)—subject to boundary conditions—with estimated log bids (net of unobserved heterogeneity) to recover the costs that generated these bids. In our setting, the first-order condition depends on the probabilities of different combinations of the number of local and non-local bidders. These probabilities are formed from simulations based on the model's participation parameters. Appendix Figure A18 shows the probability density function of log costs $\log(\tilde{c}_{jt})$ for both types. Local bidders have slightly higher costs than non-locals. Appendix Figure A19 displays the mean relation between $\tilde{b}_j$ and $\tilde{c}_j$. As expected, markups decrease with higher cost draws.

Entry Costs. We recover type-specific distributions of 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 $H^k(\omega)$ with the expected utility of entering, i.e., $\varphi^k(\mathbf{x}_t, \mathbf{z}_t, \mathbf{N}_t) = H^k\left(\overline{\Pi}^k(\mathbf{x}_t, \mathbf{z}_t, \mathbf{N}_t)\right)$. Our estimated project cost distributions $F_c^k(c)$ allow us to form (*ex-ante*) expected utility of participating, $\overline{\Pi}^k(\mathbf{x}_t, \mathbf{z}_t, \mathbf{N}_t)$, in Equation 8, and relate it to observed entry behavior (Athey, Levin and Seira, 2011).

The entry decisions differ substantially across types. On the one hand, non-local firms enter with probability 1 for a range of combinations of $(\mathbf{x}_t, \mathbf{z}_t, \mathbf{N}_t)$. Entry choices, combined with the expected utility of entry, yield that non-locals face (near) zero entry costs for over 80% of contracts, and virtually all entry cost draws are smaller than one thousand dollars. On the other hand, local firms are substantially less likely to enter. Indeed, we find that their entry costs are greater than zero for all their contracts and, with an 80% chance, they would *not* enter for any of the values in the estimated range of expected utilities. This estimated entry-cost asymmetry shapes the composition of actual bidders and, subsequently, the winning bids. Appendix Figure A20(a) shows the probability of entry as a function of the number of non-local potential entrants: locals' modest entry probability shrinks rapidly to zero as competition from non-locals increases, whereas non-locals enter with very high probability unless they expect several (> 6) potential rivals. Appendix Figure A20(b) shows how these entry probabilities translate into the composition of actual competitors (and the winner's identity) as a function of the number of potential non-local contractors.

4.5.3 Relationship Between Project Costs and Cost Overruns

Our modeling structure allows project costs $\tilde{c}$ and cost overruns q to be correlated. We achieve this in our estimation by allowing for a correlation between bid shocks and cost overrun shocks, which we can estimate from the inversion of simulated bids and cost overruns. Appendix Figure A21 shows mean cost overruns for different levels of project costs, separately for locals and non-locals, and by product type (goods vs. services). Both locals and non-locals feature a relatively flat relationship between overruns and project costs for goods, but the relationship is negative for services, meaning that lower cost draws are associated with higher cost overruns. Relative to locals, non-locals exhibit a more pronounced negative relationship between cost overruns and project costs and higher levels of cost overruns for any given cost. In terms of magnitudes, a 30 p.p. lower cost draw (equivalent to the 25-to-5th percentile gap) is partially offset by a 7 p.p. increase in cost overruns for service contracts by non-locals. We return to the implications of these patterns in Section 5.1.1.

5 Counterfactual Analysis

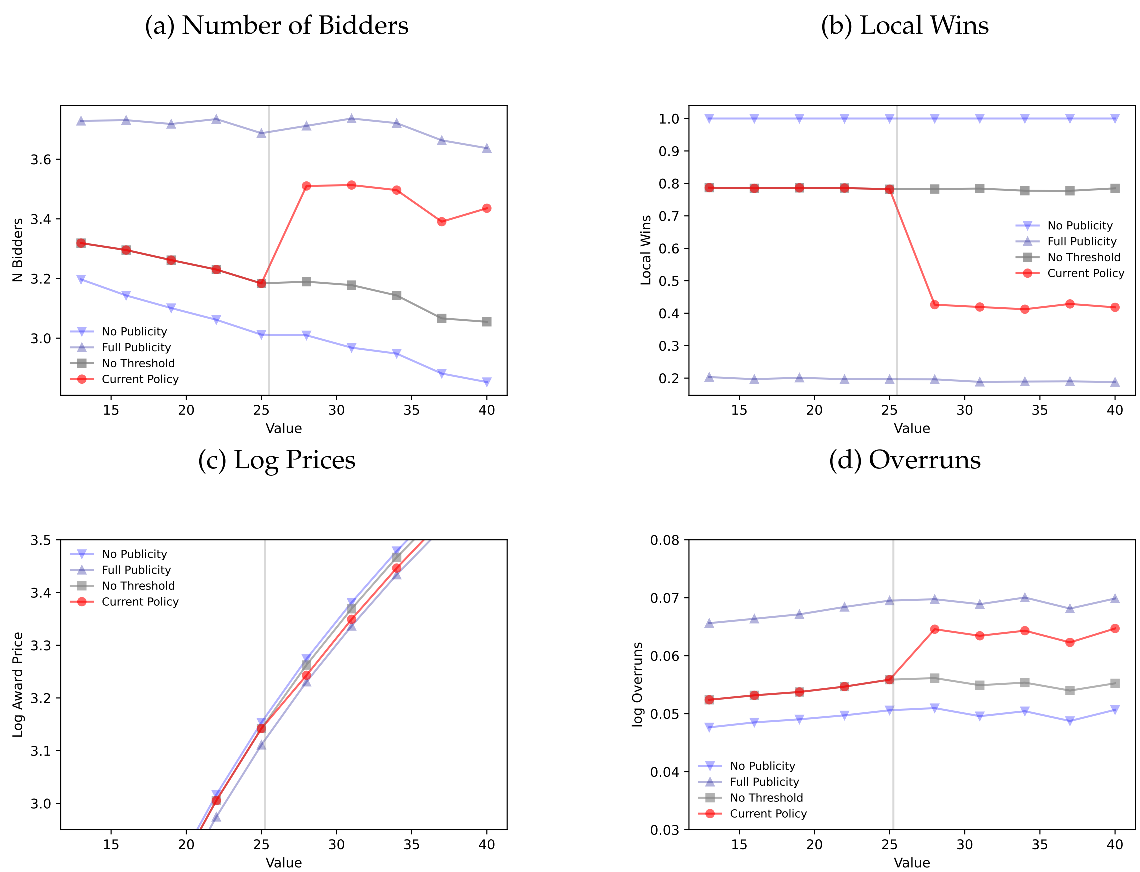
We use our model to evaluate the implications of counterfactual scenarios. In the first counterfactual exercise, we gauge the effects of increasing competition through publicity on contract outcomes. This exercise extends and complements the reduced form estimates obtained in Section 3 and allows us to assess quantitatively the mechanisms that drive the effects we observe in the data. The second and third counterfactuals evaluate the implications of modifying publicity rules. In the second counterfactual, we analyze the consequences of removing publicity altogether, allowing every buyer to decide whether or not to advertise the solicitation. The third exercise studies the effects of an alternative regulatory design that makes publicity requirements a function of the underlying contract complexity.

5.1 Effects of Increasing Competition through Publicity

Our model estimates allow us to replicate and extend the results from Section 3. Using the model, we can evaluate contract outcomes with and without publicity throughout the range of awards in our sample, not only for contracts around the threshold. Indeed, relative to the reduced form Local Average Treatment Effects (LATE) presented before, the estimated model allows us to measure publicity effects over the complete sample, i.e., estimate the Average Treatment Effect (ATE) of publicity.

Figure 7 shows a series of outcomes as a function of the expected contract price. For the current policy (red line), results are broadly in line with our reduced-form analysis: the number of bidders jumps at the threshold under the current policy (Panel (a)), allowing non-locals to participate and win at higher rates (Panel (b)), slightly reducing award prices (Panel (c)), and

Figure 7: Policy Evaluation Using Model Estimates



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.

increasing cost overruns (Panel (d)). Our model allows us to benchmark the observed regime with three alternative scenarios: one with no publicized contracts (*no publicity*), one with all publicized contracts (*full publicity*), and one where officers are free to choose throughout the expected price range (*no-threshold* regulation). Intuitively, the no-threshold regulation is equivalent to the current policy below the threshold and extends this regime to awards expected to exceed it, eliminating the discontinuities. On the other hand, full publicity and no publicity represent bounds on the extent to which the regulator can leverage publicity to affect outcomes. Full publicity maximizes the number of bidders and minimizes the share of local winners, leading to the lowest prices and the highest overruns. The opposite is true for no publicity.

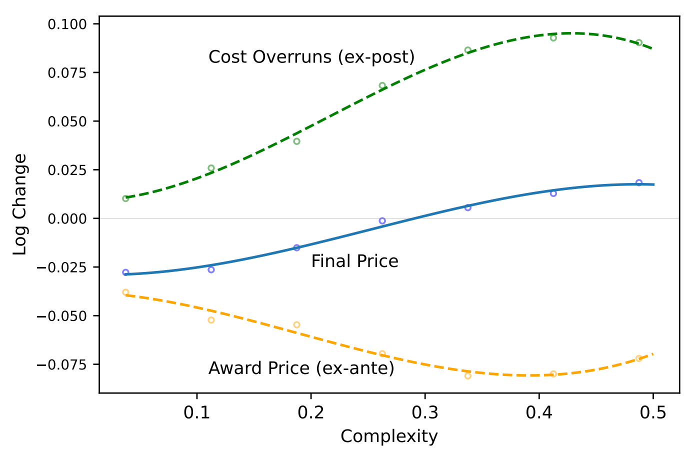
To assess whether ex-ante price effects or ex-post cost overruns effects dominate, we consider the *final* price $P^D_{F,t}$:

$$P_{F,t}^{D} = P_{I,t}^{D}(1 + Q_t^{D}) \tag{12}$$

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

Figure 8 compares contract award prices, cost overruns, and final prices, with and without publicity, for different levels of complexity. The gray line at zero marks the no-publicity benchmark. The orange dashed line shows the effects of publicity on award price, and the green dashed line shows the effect on cost overruns. Both effects are more pronounced for complex contracts. This is intuitive for cost overruns but less obvious for award prices and is explained by two factors. First, auctions that require complex contracts have a higher variance in bid functions, which increases the support of possible price reductions from additional bidders. Second, auctions for complex contracts have lower participation, meaning that the effect of an extra bidder is higher than when there are fewer competitors. The blue solid 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.

Figure 8: 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. Note that from the final price definition (12), we have that $log(P_{F,t}^{D}) = log(P_{I,t}^{D}) + log(1 + Q_t^{D})$, so the effect on log final price is the addition of the effect on log award price and the effect on log overruns. The figure presents the effects of publicity relative to a benchmark of no publicity, represented in the horizontal line at zero. Circles exhibit 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.

These findings provide quantitative evidence consistent with the idea introduced by seminal papers on incomplete contracting: there exists a degree of transaction complexity beyond which promoting competition may backfire. When there is 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).

5.1.1 Breaking Down the Effects on Contract Performance

In Section 4.5.3, we show that our estimates imply a negative relationship between contract completion costs and cost overruns and that the strength of this relationship is type-dependent. This fact suggests that the effects of competition on performance arise due to a combination of *within-type* and *cross-type* effects. Within-type effects occur since winners in more competitive auctions tend to draw costs from the lower part of the cost distribution, and the estimated negative correlation implies that this will lead to higher cost overruns. Cross-type effects instead come from the increased participation of non-local firms, which tend to draw worse performance shocks.

We leverage the model estimates to disentangle these effects quantitatively. Two aspects of this exercise are worth highlighting. First, this investigation is related to the reduced form analysis presented in Section 3.5, where we show that the effects of publicity on contract performance were primarily driven by cross-firm rather than within-firm variation. Second, the results may be informative about the plausibility of some of our modeling choices. Finding a large role for within-type effects could indicate model misspecification reflecting, for example, that our parametrization of heterogeneity into two groups is too restrictive or that strategic considerations that we have shut down by assumption may be relevant in practice. Instead, finding that most of the influence of competition on performance is due to cross-type effects would be reassuringly consistent with the reduced form evidence and our simplifying assumptions regarding the source of performance differences.

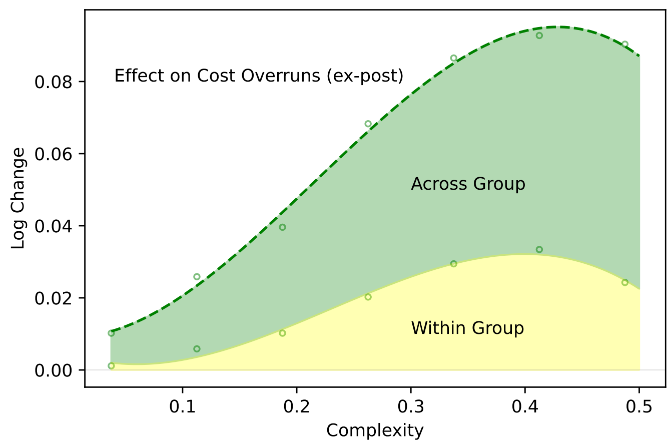
We consider the following decomposition:

$$\underbrace{log(1+Q_t^1) - log(1+Q_t^0)}_{\text{Total effect}} = \underbrace{log(1+Q_t^1) - log(1+Q_t^{1L})}_{\text{Cross-type effect}} + \underbrace{log(1+Q_t^{1L}) - log(1+Q_t^0)}_{\text{Within-type effect}}, \qquad (13)$$

where Q_t^0 corresponds to the level of cost overruns if contract t is not publicized, Q_t^1 is the level of cost overruns if the contract is publicized, and Q_t^{1L} is the level of cost overruns if the contract is publicized and we force the firm that executes the contract to draw overrun shocks from the distribution of locals, keeping all other factors constant. The cross-type effect captures changes in overruns due to changes in the contractor's group affiliation, while the within-type effect captures changes in overruns within the group of locals. Note that when a publicized contract is won by a local, the cross-type effect is mechanically zero ($Q_t^1 = Q_t^{1L}$), and the full effect is due to changes within a type.

We implement this decomposition and find that 77% of the increase in overruns is explained by cross-type effects. This implies that if we shut down cross-type effects, enhanced competition would induce less than one-fourth of the increase in overruns we observe in the data. Moreover, we find that the relative contribution of these effects is heterogeneous, with cross-type effects accounting for 89% and 70% of the total effects for goods and services, respectively. Figure 9 shows the decomposition of the impact on overruns for different degrees of contract complexity. Even though the contribution of cross-type effects slightly decreases with complexity, it remains the main factor explaining the increase in overruns. We interpret these results as broadly consistent with our reduced form evidence and supportive of our key modeling assumptions regarding performance effects.

Figure 9: Decomposition of the Effects of Publicity on Cost Overruns



Notes: This figure shows the effect of publicity on (log) cost overruns, as a function of product complexity. The total effect of publicity compares the level of log overruns with publicity relative to a benchmark of no publicity, represented in the horizontal line at zero. The Within-type and Across-type decomposition follows (13). Circles exhibit 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.

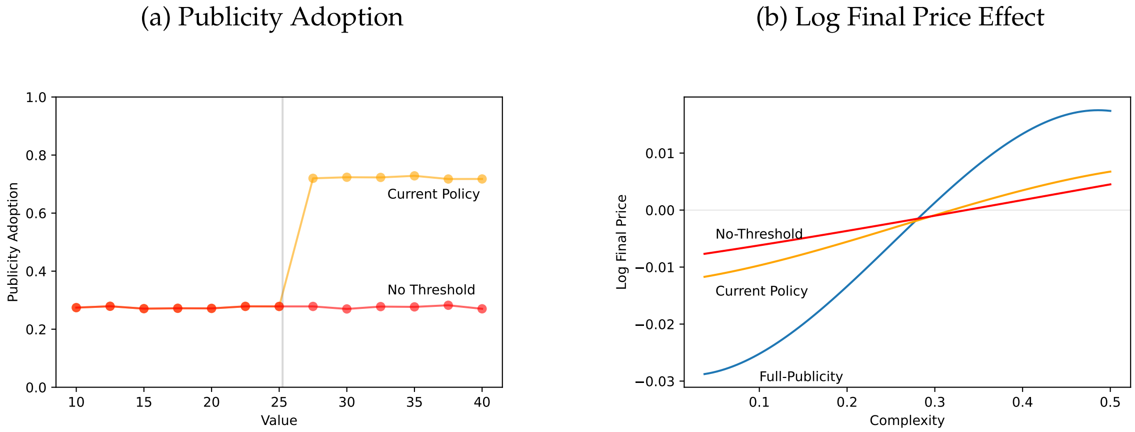
5.2 The Value of Delegating Competition Promotion to the Buyer

We now assess the implications of allowing the buyer to choose whether to openly publicize a contract, as opposed to mandating rules that constrain the 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.[55]

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*

[55]See, e.g., Kelman (1990); Coviello et al. (2018); Carril (2022); Szucs (2020); Bandiera et al. (2021); Bosio et al. (2020); Decarolis et al. (2020b).

Figure 10: Delegation of Publicity Decision to the Buyer



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.

situation, with full discretion over publicity decisions for the whole range of contracts in our sample. Like before, we benchmark this counterfactual against the current policy design, a scenario without 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 relative to no publicity (the benchmark gray line at zero) and as a function of product complexity. We find that the effects of discretion are ambiguous compared to no publicity or full publicity. On the one hand, relative to no publicity, discretion (no threshold) leads to lower final contracting costs for contracts with a degree of complexity below 0.34 –as a reference, 0.34 corresponds to the complexity of contracts for "Housekeeping- Laundry/Drycleaning." A no-publicity rule outperforms discretion for more complex contracts because the buyer underweights overruns relative to the award price. On the other hand, a full publicity rule delivers larger cost savings than discretion for contracts with sufficiently low levels of complexity. Finally, for an intermediate range of complexity values, discretion yields lower contract costs than the two extreme scenarios. These results suggest ample space for improvements to the current regulation, as the value of discretion heavily depends on the transaction's underlying degree of complexity. Appendix I discusses the role of buyer preference parameters in shaping contract outcomes.

5.3 Complexity-Based Publicity Requirements

We now consider varying the regulation design depending on the level of contract complexity. The proposed exercise contemplates identifying the cost-minimizing level of publicity requirements for each degree of complexity. By publicity requirements, we mean the share of contracts that buyers must publicize. Even though other, more sophisticated regulatory tools may enhance procurement efficiency, the design of real-world procurement rules faces a constraint on the 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.[56] 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 11 summarizes this procedure. Panel (a) illustrates the publicity requirement that minimizes the final price at different complexity levels. Panel (b) shows the effect of complexity-based publicity requirements on final prices (brown-dashed line), relative to a benchmark of no publicity, and compares it with the effects of full discretion (no threshold) and full publicity. The cost-minimizing publicity requirements are close to 100% for low-complexity products, and the optimal share of publicity requirements falls gradually as complexity increases. Panel (b) shows this yields final price reductions relative to the other counterfactual scenarios. When the product purchased is simple, the tailored publicity requirements remove buyers' discretion entirely to leverage the benefits of enhanced competition. However, it provides more discretion when contracts are more complex to attenuate the negative consequences of contract implementation ex-post.

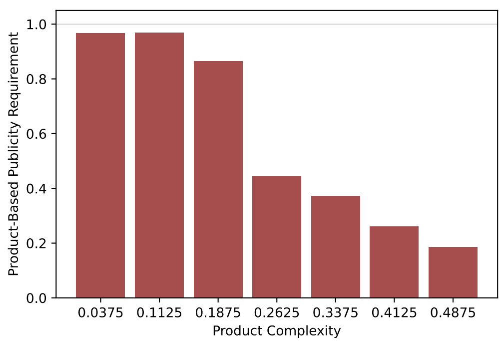
Relative to a baseline of no publicity for any contract, the current policy design with publicity requirements at $ 25,000 reduces, on average, the final price by 0.94%. The counterfactual policy of tailoring the publicity requirements to the degree of complexity outperforms all the other considered regulations, reducing average prices by 2.39%. The 1.45 percentage point difference in cost savings between the current regime and the complexity-based design corresponds to $103.5 million per year.[57]

[56]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.

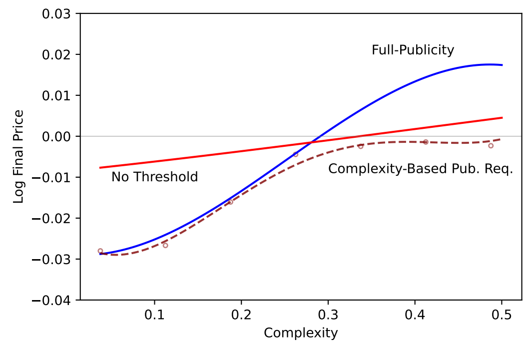
[57]This amount is calculated extrapolating to all competitively awarded definite contracts from the Department of Defense in 2019 with values below the Simplified Acquisition Threshold (i.e., $250,000).

Figure 11: Counterfactual Analysis III: Complexity-based Requirements

(a) Log Final Price Effect



(b) Log Final Price Effect



Notes: Panel (a) shows the level of publicity requirement that yields the minimum final prices for different levels of complexity. Panel (b) shows the effects on final cost relative to the no-publicity benchmark at each degree of complexity. The blue line is a counterfactual where all contracts are publicized, the red line shows the no regulation threshold counterfactual, and the brown-dashed line corresponds to the price effect under the cost-minimizing publicity requirement. Each line corresponds to a flexible polynomial fit. The brown dots correspond to the mean at different complexity bins. The degree of complexity is defined as the log of the product category's average overruns for contracts below $20,000.

5.4 Discussion

While the main regulatory counterfactual we explore is slightly more sophisticated than the current uniform policy, it is still remarkably simple and keeps most institutional features unchanged. We do this purposely to emphasize the nontrivial cost savings of even a minor, easy-to-implement change. While estimating the impact of more involved policy reforms exceeds the scope of this study, two alternative policy designs are worth mentioning.

The first is to change the auction design to account for adverse selection. Various approaches have been proposed in the literature. One recent example is Lopomo, Persico and Villa (2023), who show that the optimal mechanism in the presence of non-contractible quality concerns features both a price ceiling and, more surprisingly, a price floor. The mechanism, which the authors call a lowball lottery auction (LoLA), uses the price floor to reduce the advantage of cheap suppliers, limiting the extent to which they can bid aggressively. In our setting, a price floor in more complex product categories may reduce total costs by reducing the likelihood of a low-performance winner.

A second approach would be explicitly including past performance measures in the awarding mechanism.[58] Our results suggest that considering past performance may counteract some of the negative performance effects we document since they may help screen out low-cost, low-performance contractors. Still, the full effects of this approach may be more subtle since its impact on bidding strategies will depend on the interplay between costs and performance and their heterogeneity (Andreyanov et al., 2023). Finally, using past performance may act as a reputational

[58]Past performance is recorded and used in DOD procurement to evaluate proposals in awards exceeding the simplified acquisition threshold (currently, $250,000). The evaluations for these awards are recorded in the Contractor Performance Assessment Reporting System (CPARS).

incentive in settings where moral hazard is a dominating force (Calzolari and Spagnolo, 2009; Malcomson, 2013; Spagnolo, 2012). For example, Coviello, Guglielmo and Spagnolo (2018) find evidence that the use of discretion by public buyers in Italy increases the probability of repeated winners and that this credible commitment to possible repeated contracting disciplines suppliers into having high performance.

6 Conclusion

This paper studies the relationship between competition and procurement contract outcomes. Even though procurement represents a significant share of the economy, there is limited evidence on the implications of policies oriented to expand competition, considering not only the effects on award prices but also on post-award contract execution. Using data and policy variation from U.S. Department of Defense procurement, we provide extensive evidence on the effects of increasing competition through publicity.

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 the number of participating bidders and that this added competitive pressure results in lower acquisition prices. However, broader advertisement leads to a different pool of vendors, who perform worse 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 competitive bidding 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 use our estimates to evaluate relevant counterfactual policies. Our results show that delegating competition promotion to the buyer has ambiguous effects. For an intermediate range of complexity values, discretion yields lower contract costs than simple rules of zero or mandatory publicity, which suggests ample space for improvements to the current threshold-based publicity rules. Thus, we use our model to engineer improvements to the current policy design by introducing publicity requirements tailored to the degree of complexity of the purchase. We find that departing from a uniform regulation would significantly reduce procurement costs.

While our empirical analysis focuses on Department of Defense procurement, our results have wider applicability. The highly specific nature of defense acquisitions is readily apparent for major contracts involving fighter jets or weapons systems. Yet our sample of contracts below $40,000 is composed of products and services similar to those procured by civilian agencies and the private sector, including software and computers, medical supplies, furniture, maintenance services, and utilities and housekeeping.[59] Moreover, while small awards represent a modest share of all federal procurement spending, they do reflect the typical contracting activity of the federal government.[60] Therefore, we expect the tension between price competition and contract performance that we study in this paper will be relevant in many other procurement settings.

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[59] See Table B.2.

[60] In fiscal year 2017, 71% of the contracts awarded by non-DOD federal agencies were valued at $40,000 or less.

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Appendix (for Online Publication)

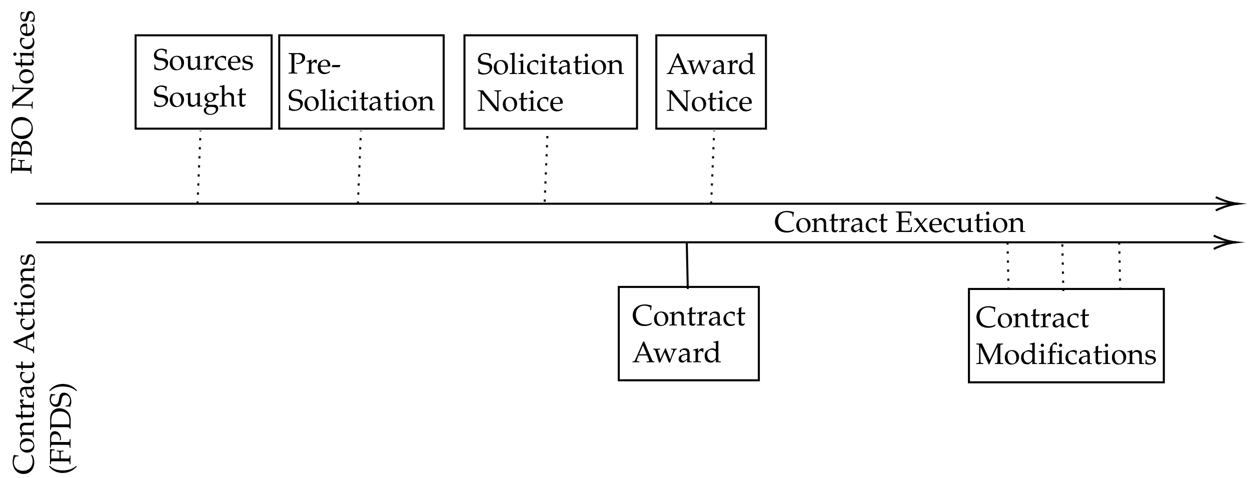
Competition Under Incomplete Contracts and the Design of Procurement Policies

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

Contents:

A Additional Figures

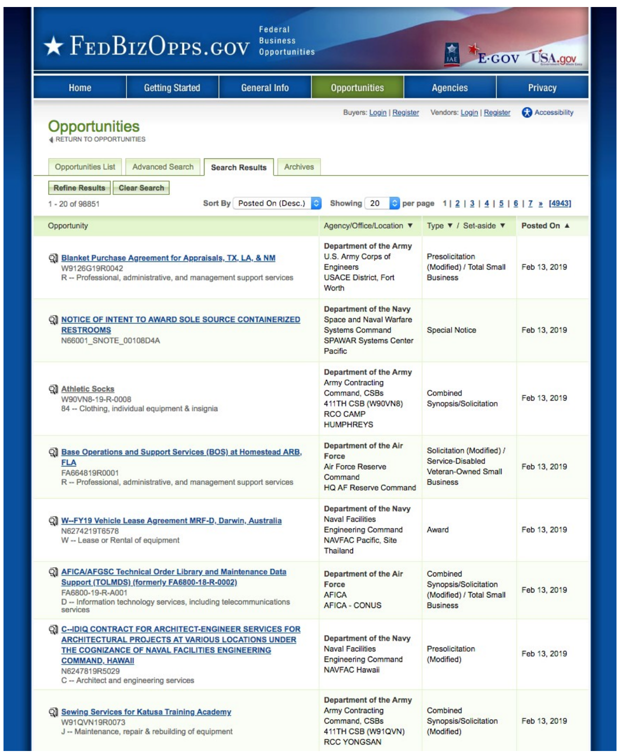
Figure A1: Contract Timeline and Data Sources



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

Figure A2: FedBizzOpps

(a) List of Opportunities

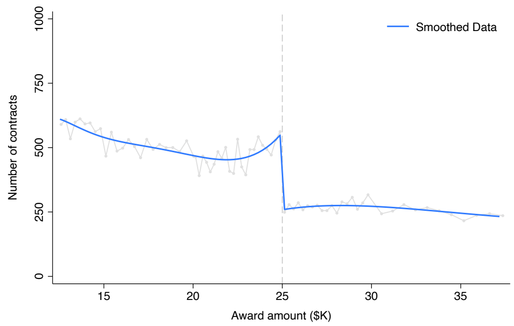


(b) Example Solicitation

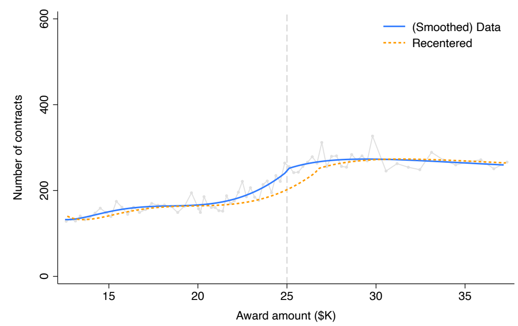
Notes: This figure shows two screenshots of FBO.gov.captured on Feb 13, 2019. Panel (a) shows a list of contract solicitations (opportunities). Panel (b) shows a particular solicitation for athletic socks, required by an Army procurement office.

Figure A3: Distribution of Contract Prices

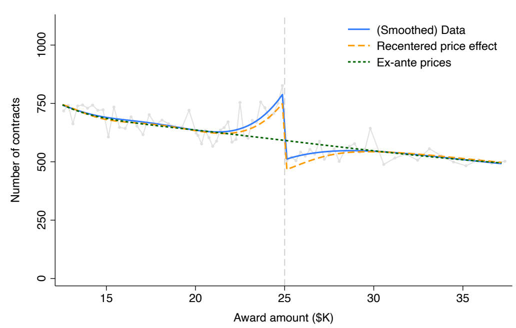
(a) Non-publicized contracts ($D = 0$)



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



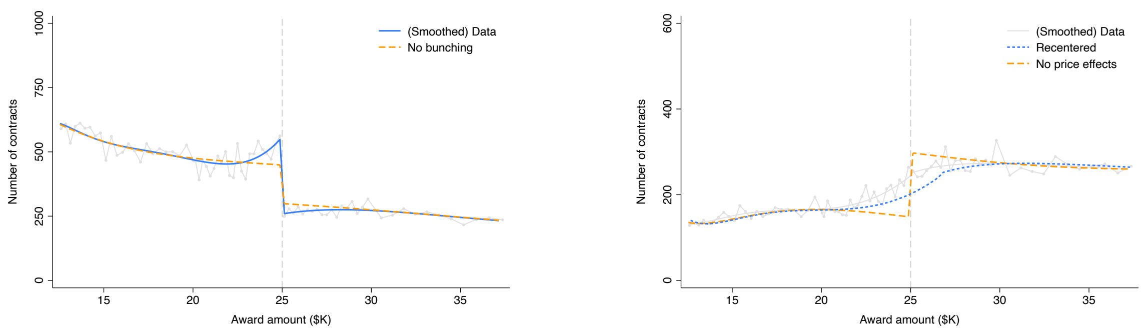
(c) All contracts



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

Figure A4: Distribution of Contract Prices

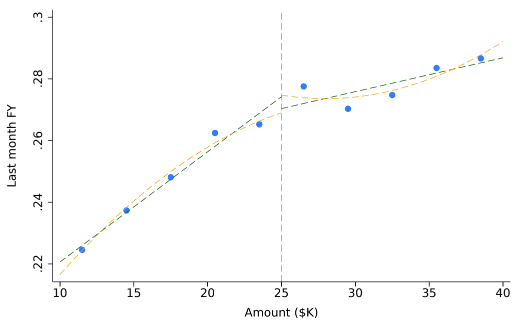
(a) Non-publicized contracts ($D = 0$) (b) Publicized contracts ($D = 1$)



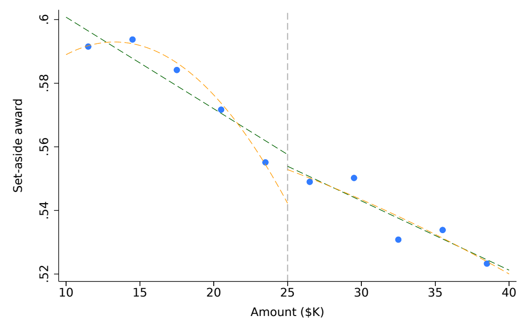
Notes: This figure shows the empirical distribution of the number of contracts at different price bins. Panel (a) shows the distribution of non-publicized contracts ($D = 0$). Panel (b) displays the distribution of publicized contracts ($D = 1$). The blue line corresponds to a polynomial fit of degree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

Figure A5: Pre-award Characteristics Around the Threshold

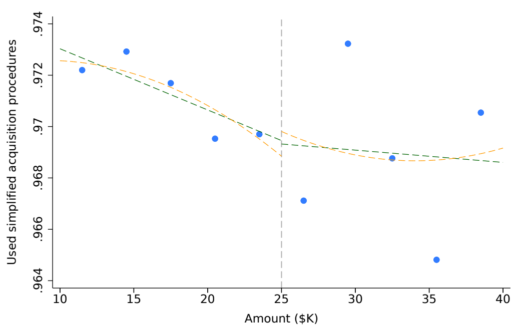
(a) Last month Fiscal Year



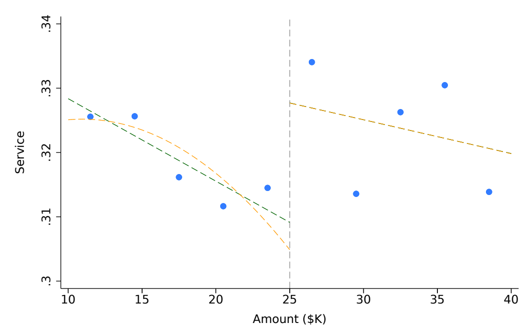
(b) Set-asides



(c) Simplified acquisition procedures



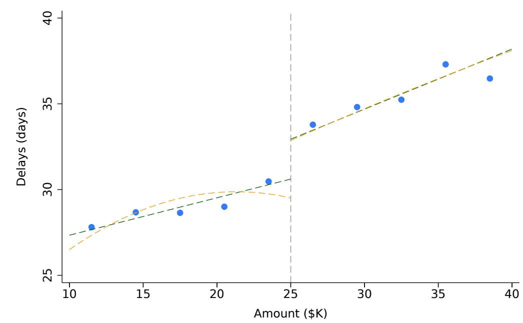
(d) Service contracts



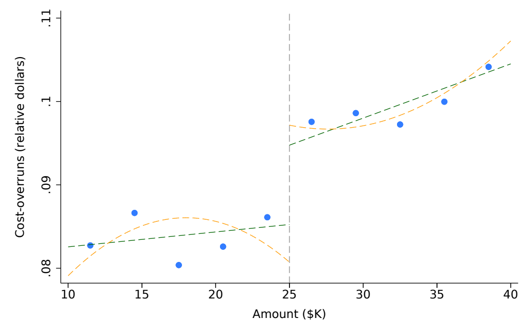
Notes: This figure presents four binned scatter plots, which depict an average pre-award characteristic by bins of award amounts, as well as linear and quadratic fits at each side of $25,000. The pre-award characteristic in each Panel is as follows: (a) an indicator equal to one if the contract was solicited 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

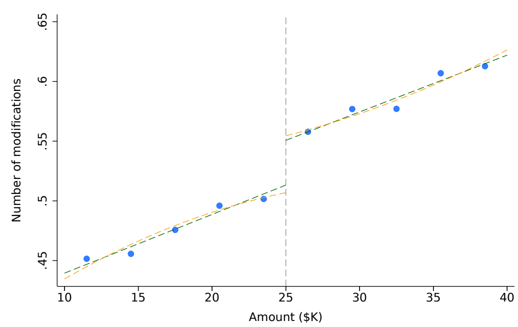
(a) Delays (days)



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



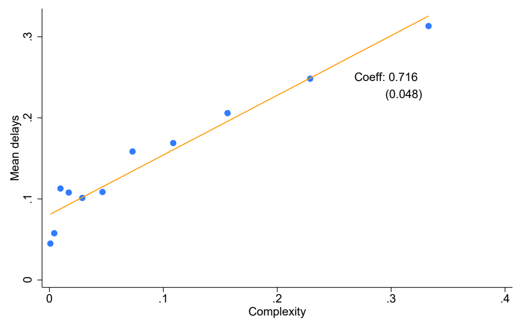
(c) Number of Contract Modifications (Ex-Post)



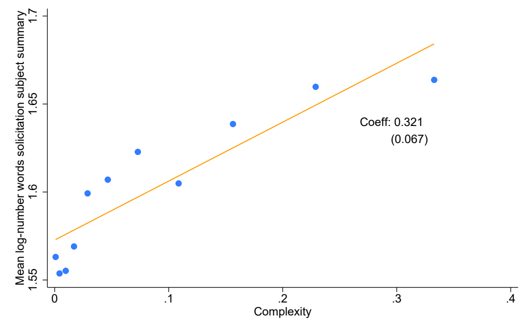
Notes: This figure presents three binned scatter plots, which depict an average post-award performance metric by bins of award amounts, as well as linear and quadratic fits at each side of $25,000. The outcomes in each Panel are as follows: (a) number of days of contract implementation delays; (b) cost-overruns 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)

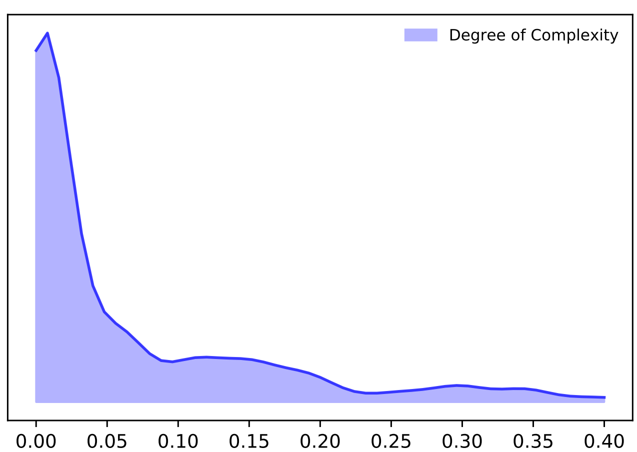


(b) Number of Words Solicitation



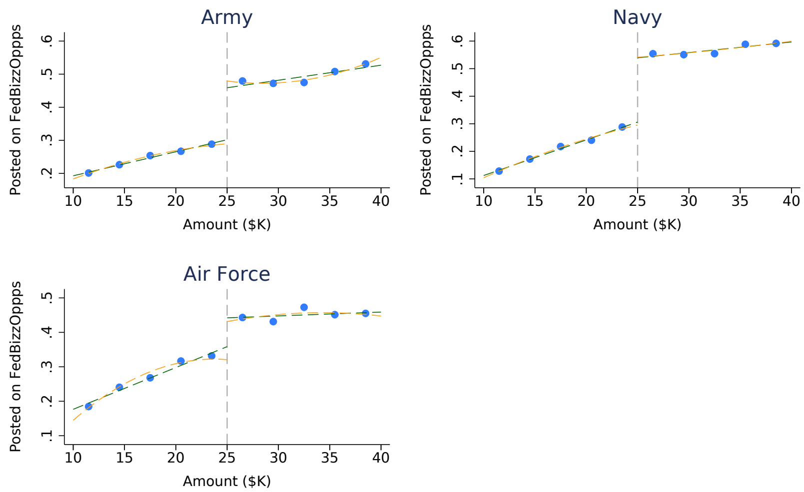
Notes: This figure displays the correlation between our measure of complexity (i.e., product-level average cost-overruns for contracts under $20K) with product-level average delays (Panel (a)) and product-level (log) average number of words contract synopsis from FBO. The number of words variable was 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



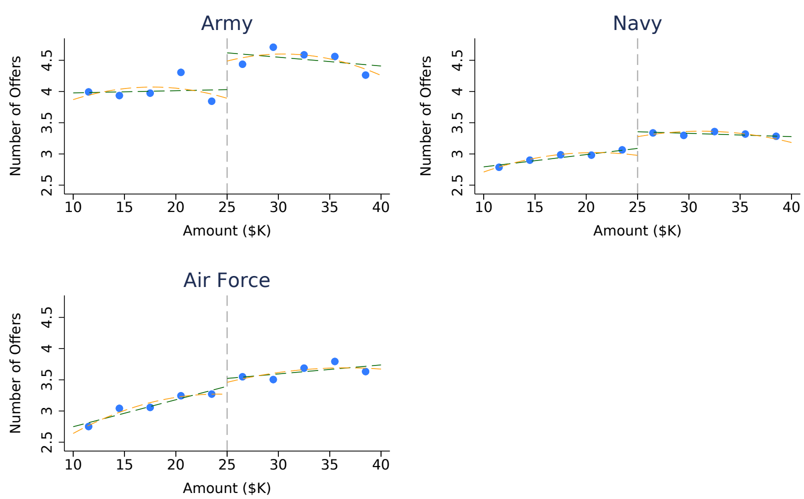
Notes: This figure presents the probability density function (PDF) of product complexity. Even though there's wide heterogeneity in the degree of complexity, the bulk of contracts in our sample have relatively low levels of complexity. The degree of complexity is defined as the log of the product's average 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: Heterogeneous publicity adoption by major departments



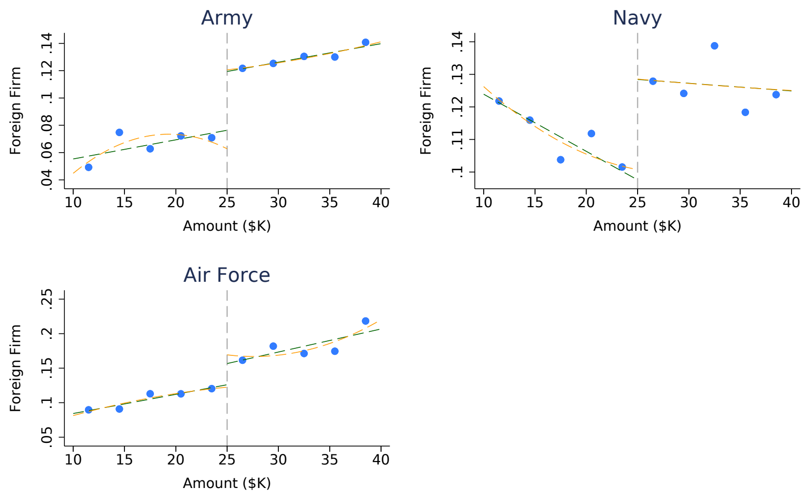
Notes: This figure presents three binned scatter plots, which depict the share of contracts publicized in FedBizzOpps by bins of award amounts, as well as linear and quadratic fits at each side of $25,000. The data source is the Federal Procurement Data System-Next Generation. The full sample consists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

Figure A10: Heterogeneous effects on competition by major departments



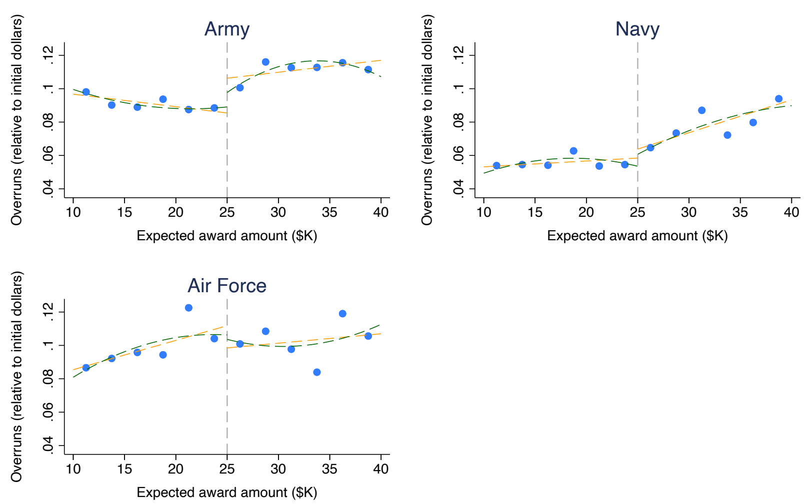
Notes: This figure presents three binned scatter plots, which depict the average number of offers received by bins of award amounts, as well as linear and quadratic fits at each side of $25,000. The data source is the Federal Procurement Data System-Next Generation. The full sample consists of non-R&D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

Figure A11: Heterogeneous effects on winner characteristics by major departments



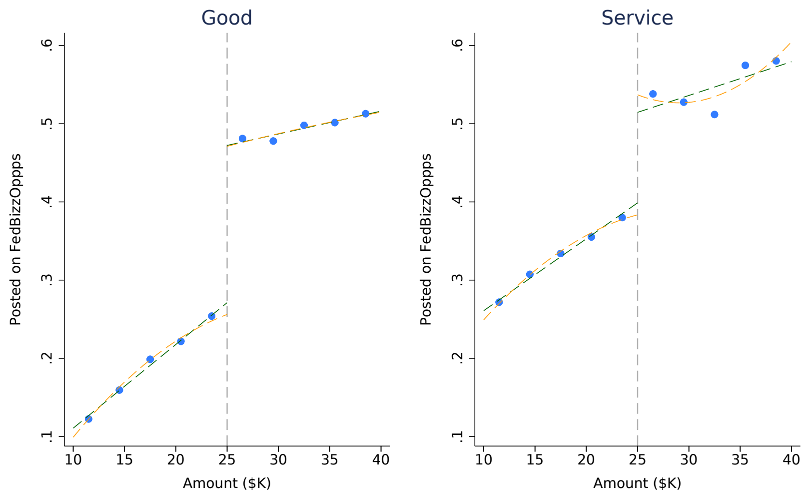
Notes: This figure presents three binned scatter plots, which depict the share of contracts awarded to a foreign firm by bins of award amounts, as well as linear and quadratic fits at each side of $25,000. The data source is the Federal Procurement Data System-Next Generation. The full sample consists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

Figure A12: Heterogeneous effects on performance by major departments



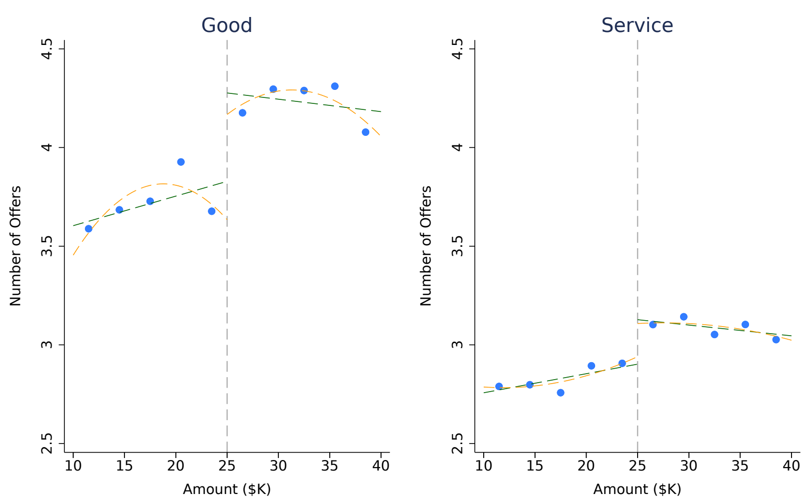
Notes: This figure presents three binned scatter plots, which depict average cost overruns by bins of award amounts, as well as linear and quadratic fits at each side of $25,000. Cost overruns are computed as the difference between actual obligated contract dollars and expected total obligations at the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

Figure A13: Heterogeneous publicity adoption: goods versus services



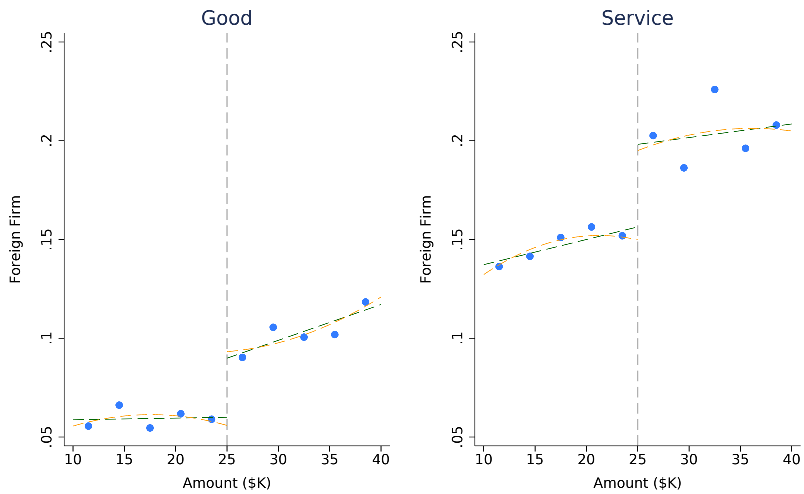
Notes: This figure presents two binned scatter plots, which depict the share of publicized contracts by bins of award amounts, as well as linear and quadratic fits at each side of $25,000. The data source is the Federal Procurement Data System-Next Generation. The full sample consists of non-R&D definitive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

Figure A14: Heterogeneous effects on competition: goods versus services



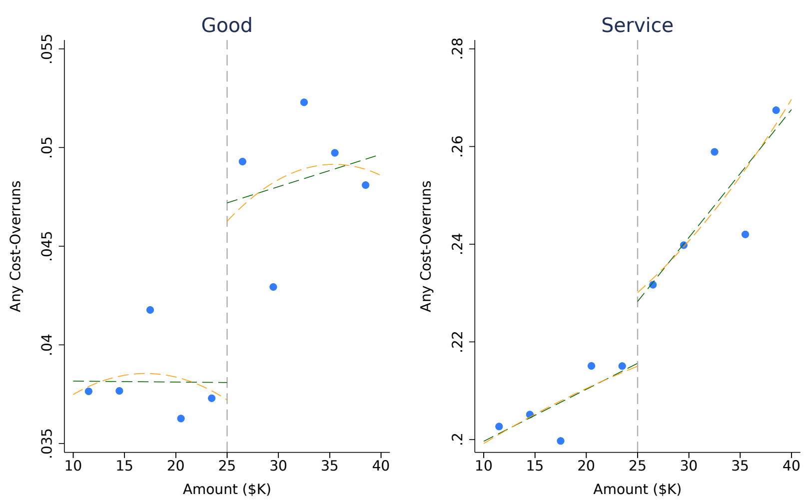
Notes: This figure presents two binned scatter plots, which depict the average number of offers received by bins of award amounts, as well as linear and quadratic fits at each side of $25,000. The data source is the Federal Procurement Data System-Next Generation. The full sample consists of non-R&D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

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



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

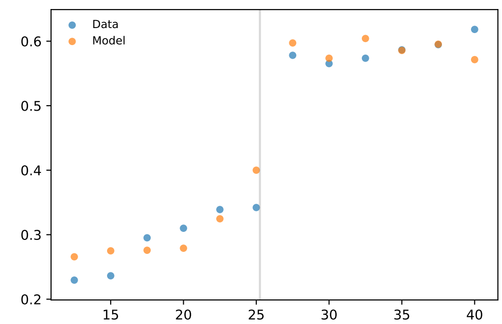
Figure A16: Heterogeneous effects on performance: goods versus services



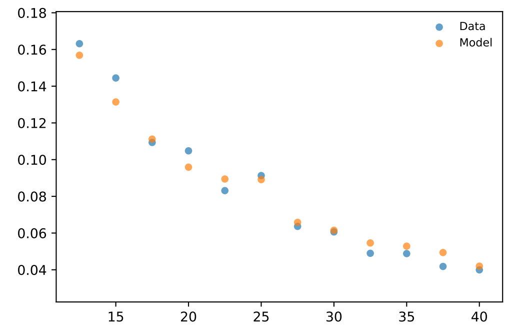
Notes: This figure presents two binned scatter plots, which depict share of contracts with cost overruns by bins of award amounts, as well as linear and quadratic fits at each side of $25,000. Cost overruns are computed as the difference between actual obligated contract dollars and expected total obligations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

Figure A17: Model Fit

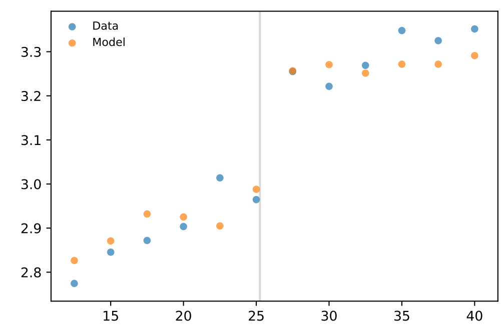
(a) Publicity Status



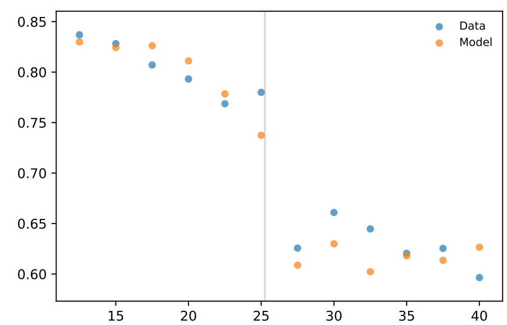
(b) Price Density



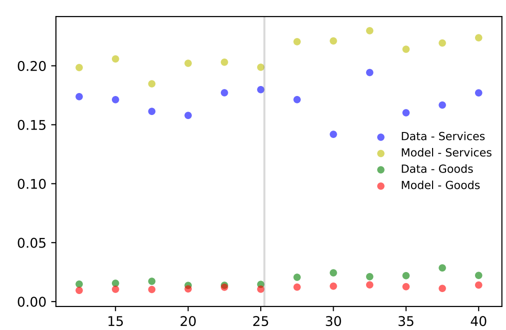
(c) Number of Bidders



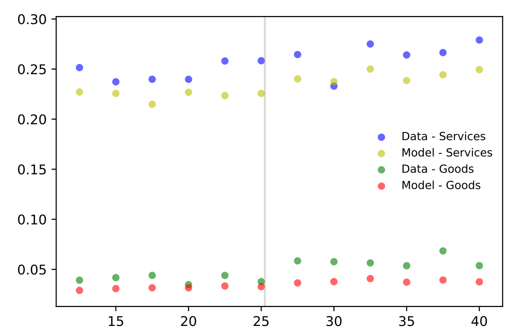
(d) Probability of a Local Winning



(e) Overruns

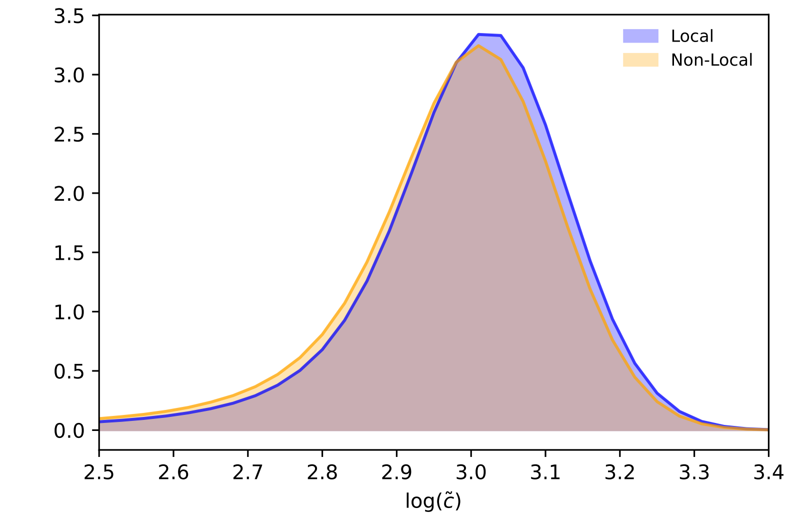


(f) Any Overruns



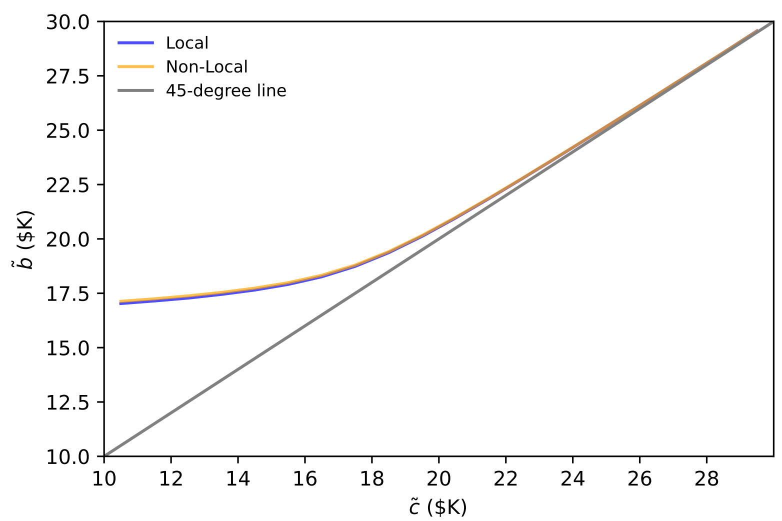
Notes: This figure presents the model fit, based on a simulated method of moments estimation. In each panel, relevant outcome variables are shown as a function of the awarding price. Actual data points are presented in blue, while model-based simulated data are presented in orange. Panel (a) presents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

Figure A18: Estimated Production Cost Distributions



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

Figure A19: Bidding Function

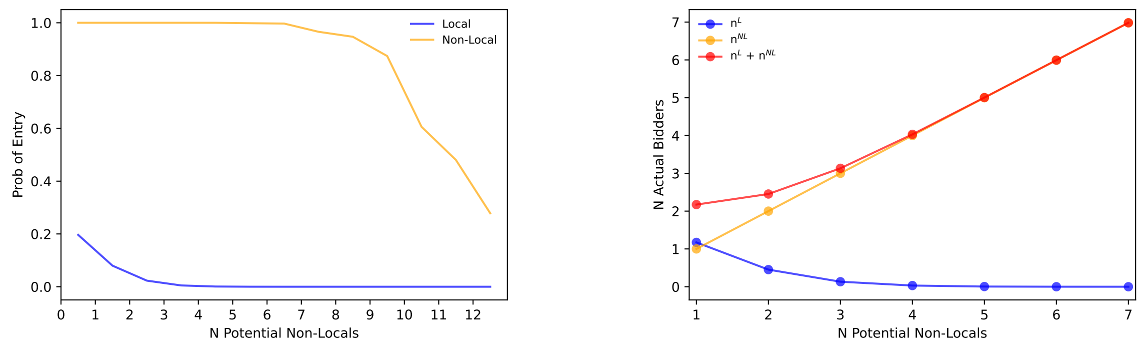


Notes: This figure displays the bidding function of local and non-local contractors. This plot is estimated holding covariates fixed at their mean value and assuming $log(u) = 0$. The plotted distribution of log bids is smoothed using a kernel.

Figure A20: Auction Entry and Winner Identity

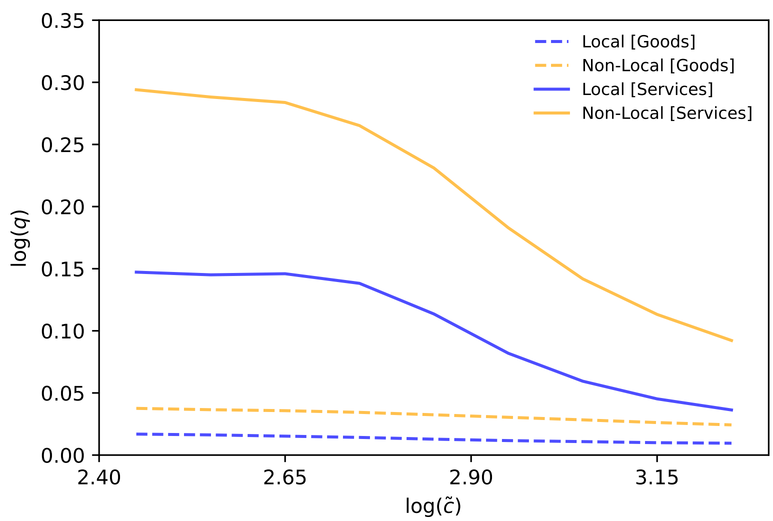
(a) Entry Probability

(b) Composition of Bidders



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

Figure A21: Relation between Production Costs and Cost Overruns



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

B Additional Tables

Table B.1: Summary Statistics

	Mean
Panel A: *Contracting Office*	
Navy	0.378
Army	0.441
Air Force	0.150
Other	0.031
Panel B: *Contract Characteristics*	
Award Amount (dollars)	20,807
Expected Duration (days)	54.10
Fixed-Price Contract	0.999
Set Aside Award	0.571
Simplified Procedure	0.971
Publicized on FedBizzOpps	0.299
Panel C: *Contract Competition*	
Number of Offers	3.542
One Offer	0.239
Panel D: *Contractor Characteristics*	
Foreign	0.099
Within-State Firm	0.690
Small Business	0.752
Women-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	Complexity Q2	Complexity Q3	Complexity 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: Reduced-form RDD: Baseline and "Donut-RD" specifications

Dependent Variable	Baseline OLS (1)	Donut-RD with Varying Window Size $500 (2)	$1000 (3)	$1500 (4)	$2000 (5)	$2500 (6)	$3000 (7)
Number of offers	0.3569	0.3139	0.2887	0.2789	0.2703	0.3020	0.2708
	(0.0677)	(0.0709)	(0.0734)	(0.0760)	(0.0788)	(0.0819)	(0.0854)
Log distance firm-office	0.1392	0.1619	0.1508	0.1608	0.1663	0.1447	0.1497
	(0.0481)	(0.0502)	(0.0519)	(0.0536)	(0.0557)	(0.0578)	(0.0601)
Small business	-0.0277	-0.0260	-0.0251	-0.0289	-0.0325	-0.0286	-0.0278
	(0.0065)	(0.0068)	(0.0070)	(0.0072)	(0.0075)	(0.0078)	(0.0081)
Any cost-overrun	0.0135	0.0090	0.0094	0.0101	0.0113	0.0099	0.0097
	(0.0045)	(0.0047)	(0.0048)	(0.0050)	(0.0052)	(0.0054)	(0.0056)
Any delay	0.0130	0.0067	0.0085	0.0114	0.0146	0.0137	0.0138
	(0.0047)	(0.0049)	(0.0051)	(0.0052)	(0.0054)	(0.0056)	(0.0058)
Number of modifications	0.0375	0.0211	0.0208	0.0278	0.0347	0.0282	0.0254
	(0.0173)	(0.0181)	(0.0187)	(0.0193)	(0.0201)	(0.0208)	(0.0216)

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

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

Rank	Product Category	Complexity
Top 10		
1	Fuel Oils	0.000
2	Food, Oils and Fats	0.000
3	Tool and Hardware Boxes	0.000
4	Composite Food Packages	0.000
5	Surgical Dressing Materials	0.000
6	Medical and Surgical Instruments, Equipment, and Supplies	0.000
7	Meat, Poultry, and Fish	0.000
8	Games, Toys, and Wheeled Goods	0.000
9	Ophthalmic Instruments, Equipment, and Supplies	0.000
10	Miscellaneous Fire Control Equipment	0.000
Bottom 10		
10	IT and Telecom- Internet	0.411
9	Medical, Dental, and Veterinary Equipment and Supplies	0.418
8	Laundry/Drycleaning	0.471
7	Lease of Office Machines, and Text Processing Systems	0.479
6	Trash/Garbage Collection	0.516
5	Insect/Rodent Control	0.618
4	Landscaping/Groundskeeping	0.628
3	Snow Removal/Salt	0.765
2	Custodial Janitorial	0.860
1	Operation Of Recreation Facilities - Non-Building	0.943

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

Table B.6: Model Estimation Sample Versus Full Sample

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

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

Table B.7: Model Estimatess

	$\bar{x}$	Entry (Probit)		Bid Distribution (Log Normal)		Execution (Log Normal)	
		Coeff	S.E.	Coeff	S.E.	Coeff	S.E.
Panel A: Coefficients							
Constant		0.0038	(0.00068)	3.0668	(0.00020)	-1.9561	(0.00571)
Service	0.311	-0.0125	(0.00056)	0.0002	(0.00044)	0.0138	(0.00597)
Degree of Complexity	0.072	-1.3555	(0.00355)	-0.0715	(0.00095)	3.3885	(0.00739)
Non-Local		7.1005	(0.00249)	-0.0097	(0.00025)	0.1828	(0.01014)
Non-Local×Complexity		0.0457	(0.01595)	-0.0381	(0.00175)	0.0207	(0.01044)
Last Month	0.270	-0.1209	(0.00034)				
Exp. Duration > Median	0.500					0.3099	(0.00058)
N^L	8.660	-0.0270	(0.00009)	-0.0017	(0.00001)		
N^{NL}	4.452	-0.5756	(0.00026)	-0.0037	(0.00003)		
Panel B: Standard Deviation							
Contant				-4.6254	(0.00451)	-0.5361	(0.05709)
Service				0.0250	(0.01067)	1.2891	(0.07639)
Correlation Bid-Overruns (ρ):							
Contant						-0.1415	(0.01204)
Non-Local						-0.0104	(0.02040)
S.D. Unob. Het. (σ_u)				0.4222	(0.00005)		
Panel C: Buyer Preferences							
		Publicity Choice (Probit)					
		Coeff	S.E.				
Constant		-0.2907	(0.0040)				
Exp.Price		-0.9707	(0.0241)				
Exp. Cost-Overruns		-0.0960	(0.0185)				
Exp. Local Winning		0.4351	(0.0054)				
Above $25K		1.1930	(0.0061)				
Number of Obs.		28,330					

Notes: This table displays estimated coefficients and their corresponding standard errors obtained with the model. Panel A describes the coefficients associated with 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, (log) cost overruns, and the correlation between log bids and 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 the 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 modeled as a Probit. The standard deviation of log-bids and log-overruns shocks are estimated as $\sigma^2 = exp(b_0 + b_1 \mathbb{1}(Service))$, 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:[61]

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

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

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

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

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

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

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

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

C.2 Dataset Details

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

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

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

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

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

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

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

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

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

D.1 Empirical Model

D.1.1 Preliminaries

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

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

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

Therefore, observed prices can be written as:

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

We assume the following:

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

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

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

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

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

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

D.1.2 Discretizing award values

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

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

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

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

D.1.3 Propositions

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

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

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

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

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

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

D.1.4 Convolution of densities

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

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

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

On the other hand, using Bayes' rule:

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

So that (14) and (15) imply:

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

Or,

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

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

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

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

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

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

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

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

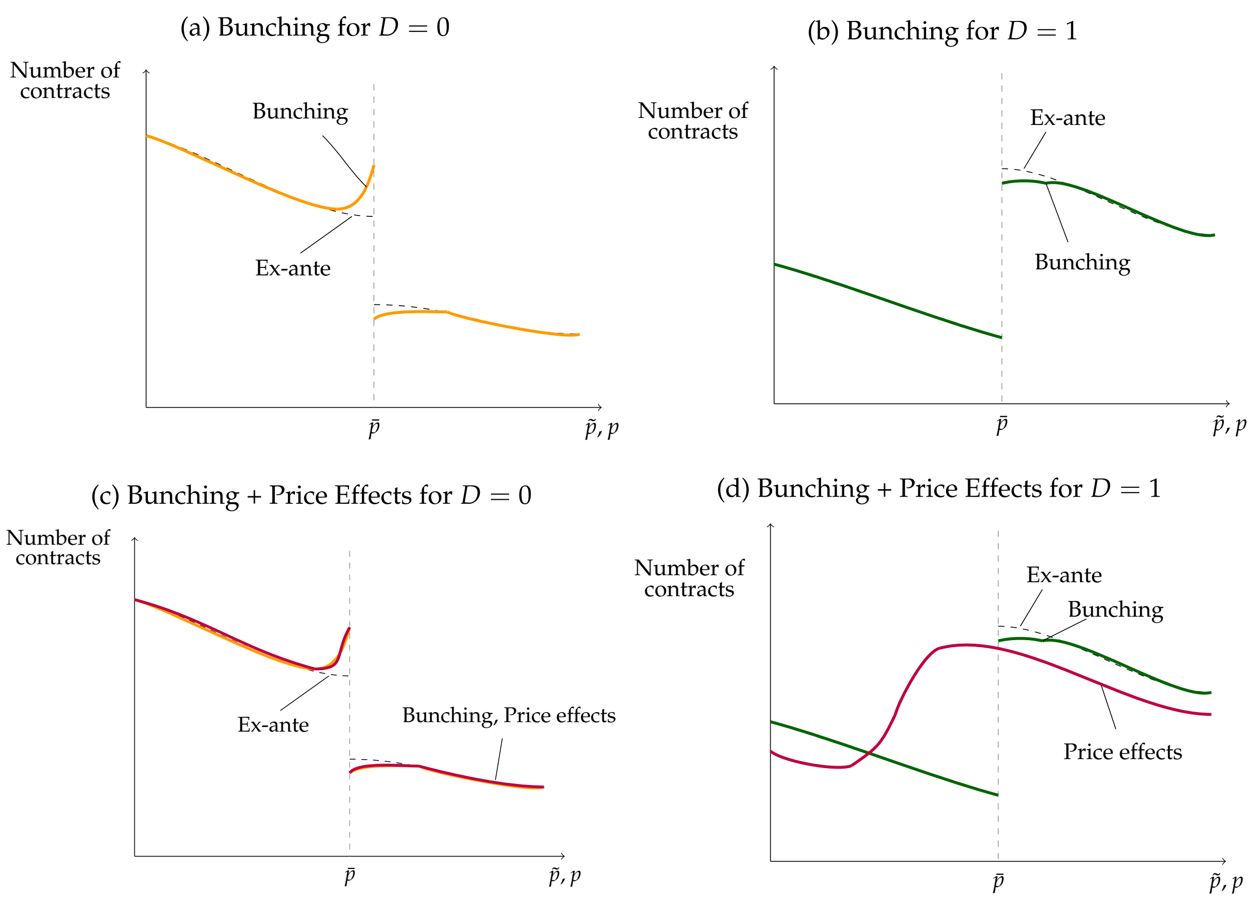
We know explain our density analysis estimation method in detail, building on the Propositions of the previous section.

Step 1

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

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

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



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

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

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

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

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

More concretely, we estimate the following specification:

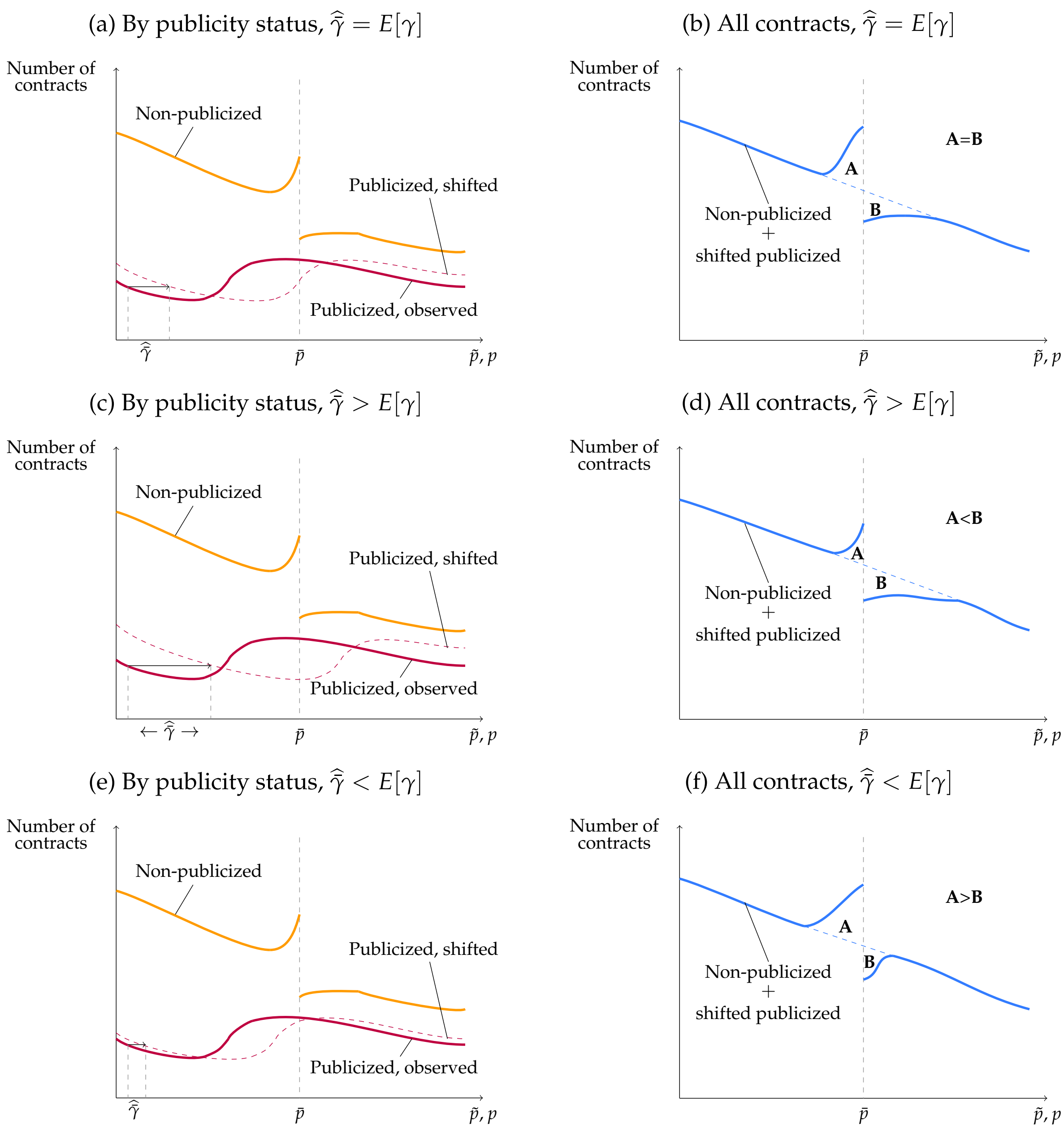
$$\left[n_b^0 + n_b^{1,s}(\widehat{\bar{\gamma}})\right] = \sum_{x=0}^{Q} \alpha_x \cdot b^x + \sum_{j=\underline{b}}^{\bar{b}} \gamma_j \cdot \mathbf{1}[b=j] + \nu_b, \qquad \text{for } b = \{-R, ..., R\} \tag{17}$$

and obtain fitted values:

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

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

Figure A23: Intuition of Method to Estimate Mean Price Effects



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

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

Step 2

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

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

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

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

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

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

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

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

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

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

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

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

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

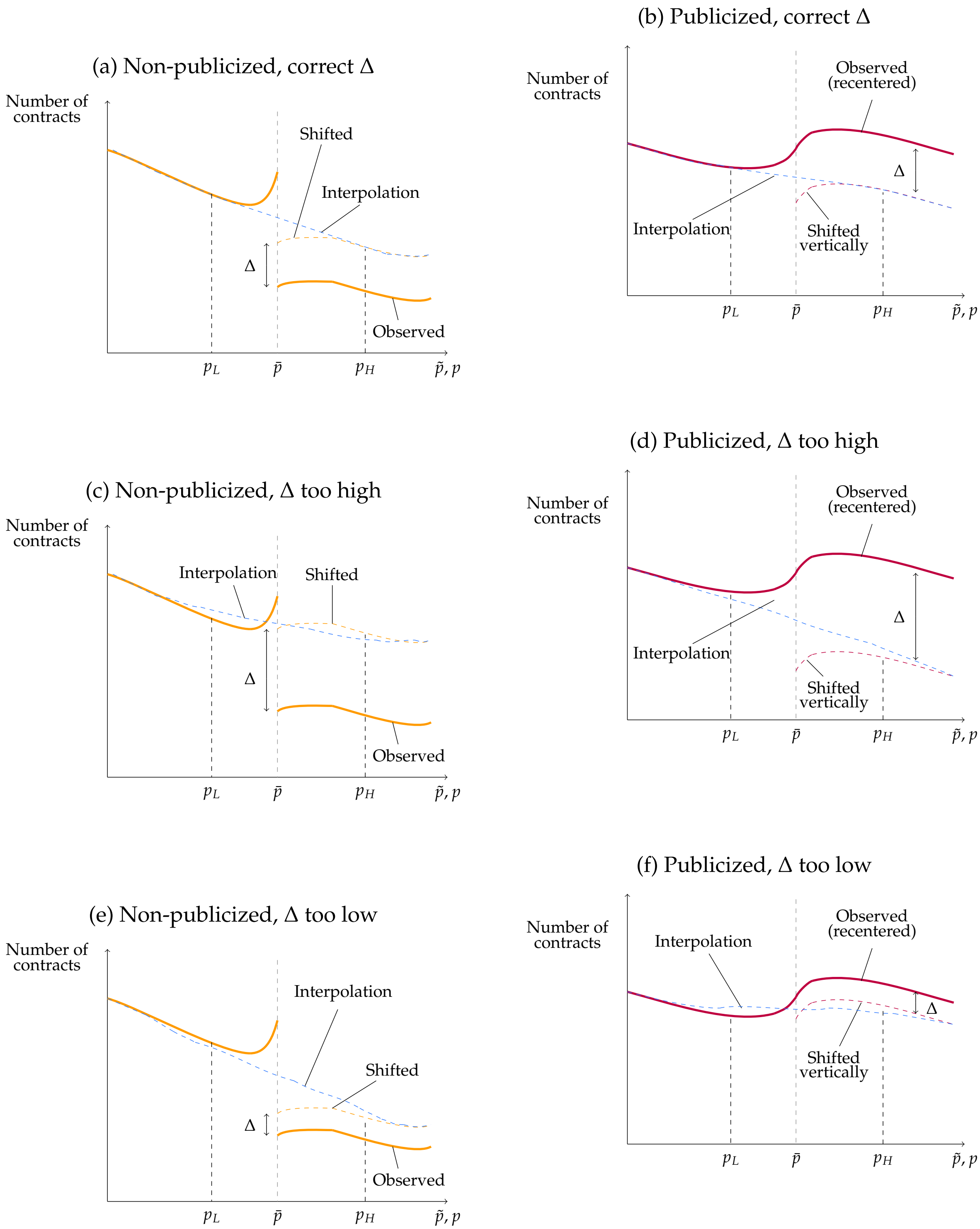
So, given a guess of $\widehat{\Delta}$, we compute the residuals for each of the two regressions (18) and (19). We then search over $\widehat{\Delta}$ to minimize:

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

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

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

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



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

Step 3

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

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

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

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

D.3 RDD Correction for Price Effects and Measurement Error

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

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

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

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

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

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

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

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

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

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

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

D.3.1 Proof of Proposition 5

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

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

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

We start with Λ_2:

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

Similarly for Λ_4:

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

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

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

$\Longleftrightarrow$

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

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

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

And, therefore,

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

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

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

Analogous calculations yield the following expression for Λ_3:

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

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

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

where:

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

D.4 Accounting for Bunching

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

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

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

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

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

1. Compute the excess bunching in the control group, as $BUNCH_b = (n_b^0 - \widehat{\tilde{n}_b^0})$, obtained from our density analysis.
2. Sort control units according to the outcome variable Y_b^0.
3. Drop the $BUNCH_b$ units with the highest value of Y_b^0. Compute treatment effects. This yields the lower bound.
4. Drop the $BUNCH_b$ units with the lowest value of Y_b^0. Compute treatment effects. This yields the upper bound.

E Discussion on Modeling of Execution Performance

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

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

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

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

F Model Identification

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

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

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

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

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

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

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

□

F.1 Identification under Unobserved Heterogeneity

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

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

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

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

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

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

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

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

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

Taking expectations on both sides:

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

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

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

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

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

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

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

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

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

G Model Estimation Details

G.1 Classifying Contractors' *Types*

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

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

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

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

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

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

G.2 Estimation

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

$$\hat{\theta} = \underset{\theta}{\operatorname{argmin}} \left(m_n - m_s(\theta)\right)' W_n \left(m_n - m_s(\theta)\right)$$

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

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

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

G.2.1 Standard Errors

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

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

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

G.2.2 Minimization

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

G.3 Moments

We use three sets of target moments.

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

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

H Sensitivity of Parameter Estimates to Estimation Moments

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

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

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

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

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

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

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

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

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

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

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

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

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

H.2 Buyer Preferences

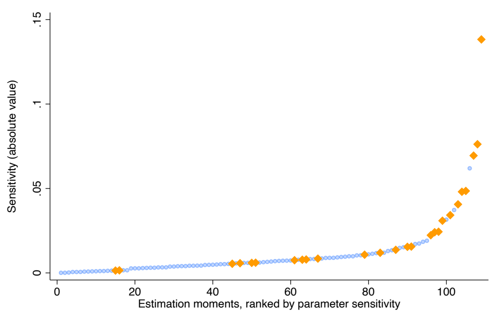
For buyers' preferences, we focus on the parameter η, which is a measure of the disutility that buyers experience when going against the publicity regulation (i.e., not publicizing when exceeding the threshold). We choose η because it is an important parameter shaping buyers' choices in our setting,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

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

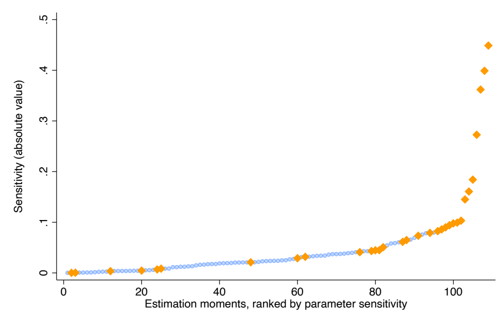
Figure A26 shows the sensitivity of the parameter η to the share of publicized contracts at different price bins and separately for goods (Panel (a)) and services (Panel (b)). In both cases, we estimate an average negative sensitivity for moments below the threshold and a positive

Figure A25: Sensitivity of Parameter Estimates to Estimation Moments

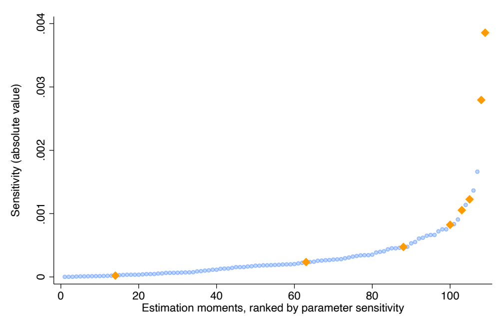
(a) Entry Choice



(b) Cost Overruns

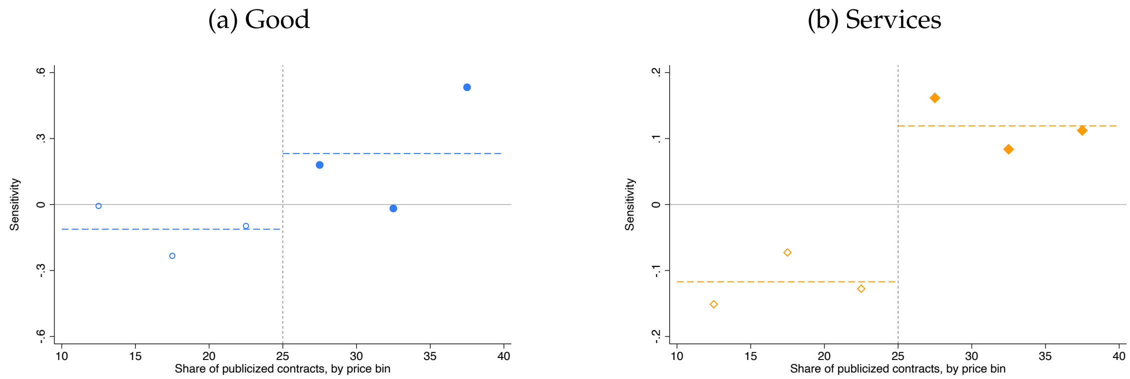


(c) Unobserved Heterogeneity



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

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



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

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

I The Role of Buyers' Preferences

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

Table B.9: Buyers' Preferences

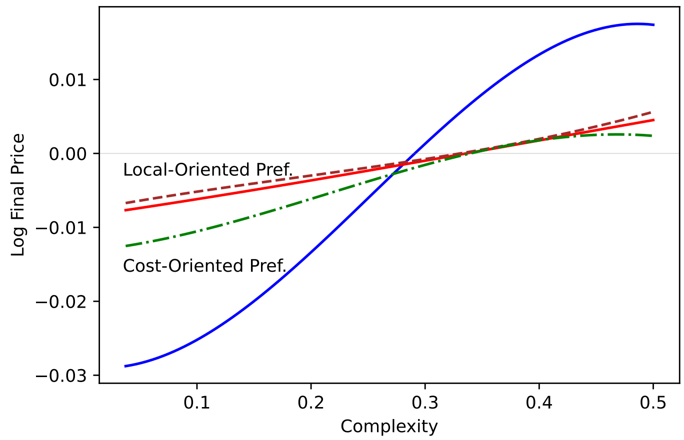
	Estimated	Benchmarks	
	Preference Parameters	Cost-Oriented Preference	Local-Oriented Preference
λ^P	-0.971	-0.971	0
λ^Q	-0.096	-0.971	0
λ^L	0.435	0	0.435
Mean Pub.	0.275	0.393	0.263

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

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

The existing literature on rules versus discretion in public procurement emphasizes that regulation can be an effective antidote to waste and abuse whenever these are pervasive. Yet, it

Figure A27: Counterfactual Analysis II: Buyers' Preferences



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

can backfire if buyers are relatively aligned with the government's goals (Carril, 2022; Bosio et al., 2020). Our findings contribute to this literature by highlighting that this trade-off depends as well on the level of contract complexity. Publicity rules can be detrimental even when agents are misaligned since favoring local vendors has the positive effect of reducing cost overruns. On the other hand, strict publicity requirements may reduce procurement costs even when agents are aligned, provided that the transaction unit is sufficiently simple.[67]

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