

Imperfect Competition and Rents in Labor and Product Markets: The Case of the Construction Industry*

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Abstract

The primary goal of our paper is to quantify the importance of imperfect competition in the U.S. construction industry by estimating the size of rents earned by American firms and workers. To obtain a comprehensive measure of the total rents and to understand its sources, we take into account that rents may arise both due to markdown of wages and markup of prices. Our analyses combine the universe of U.S. business and worker tax records with newly collected records from U.S. procurement auctions. We first examine how firms respond to a plausibly exogenous shift in product demand through a difference-in-differences design that compares first-time procurement auction winners to the firms that lose, both before and after the auction. Motivated and guided by these estimates, we next develop, identify, and estimate a model where construction firms compete with one another for projects in the product market and for workers in the labor market. The firms may participate both in the private market and in government projects, the latter of which are procured through first-price sealed-bid auctions. We find that American construction firms have significant wage- and price-setting power. This imperfect competition generates a considerable amount of rents, two-thirds of which is captured by the firms. Lastly, we use the estimated model to perform counterfactual analyses which reveal how increases in the market power of firms, in the product market or the labor market, would affect the outcomes and behavior of workers and firms in the construction industry.

JEL Codes: J31, J42, D44, L11

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1 Introduction

Researchers and policymakers are keenly interested in measuring the degree of imperfect competition in the U.S. economy and in understanding how it affects the outcomes of workers and firms. In the labor market, firms may exploit their market power to markdown the wages of workers below their marginal products, with important implications for earnings inequality, employment, and the labor share of gross domestic product. In the product market, firms may use their market power to markup prices above costs, thereby increasing profits, potentially at the cost of consumer welfare, investment, and innovation.

To draw inferences about imperfect competition in these two markets, it is natural to measure the size of rents earned by employers and workers, where rents refer to the excess return over that required to change a decision, as in Rosen (1986). However, rents are not directly observed and recovering them from data has proved elusive for several reasons. On the worker side, observationally equivalent workers could be paid differentially because of unobserved skill differences, not markdown of wages. On the firm side, profits may vary across observationally equivalent firms because of unobserved productivity, not markup of prices.

The primary contribution of our paper is to address these and other empirical challenges to accurately measure, and to understand the mechanisms behind, the size and sharing of the rents earned by firms and workers in the context of the American construction industry. To obtain a comprehensive measure of the total rents and to understand its sources, we take into account that rents may arise both due to markdown of wages and markup of prices. By comparison, existing empirical work on imperfect competition typically focuses on either the labor market or the product market in isolation, which may give a limited or misleading picture of the total rents earned by firms and workers.

As described in Section 2, our analyses are based on a matched employer-employee panel data set, which is constructed by combining the universe of U.S. business and worker tax records for the period 2001-2015. The firm data contain information on sales, profits, and intermediate inputs, as well as industry codes. The worker data give us information about the number of (new and incumbent) workers and their wage bill. We merge the employer-employee panel data set with a new data set on U.S. procurement auctions that we constructed primarily by scraping bidding websites. The resulting data set covers billions of dollars in procurement contracts awarded to thousands of firms. Importantly, we observe the bid of each firm, not only that of the winner.

In Sections 3 and 4, we use the panel data set to estimate the effects of winning a procurement auction. As described in Section 3, we use a difference-in-differences (DiD) design that compares first-time procurement auction winners to the firms that lose, both before and after the auction. The inclusion of firm and year fixed effects helps mitigate the natural concern that firms that win are likely to differ from those that lose, even in the absence of winning the auction. For example, in the standard model of first-price sealed-bid auctions with private information on costs, firms bid monotonically in costs, so low-cost firms are more likely to win. This suggests there are likely systematic differences in the composition of auction winners and losers, which motivates the DiD design.

Although the DiD design adjusts for differences across firms in levels, one could still be concerned that firms in the treated group may have different underlying trends as compared to firms in the control group. For example, firms with different cost functions may experience different changes in market conditions. We take several steps to make the firms even more comparable and, thus, more likely to satisfy the identifying assumption of common trends. One of these is to restrict the control group to firms that are close to winning the auction in a cardinal sense. These are firms that place bids within a certain threshold of the winning bid in dollar value. Another is to restrict the control group to firms that are close to winning the auction in an ordinal sense. These are firms that place bids lower than other bidders in the auction, but still higher than the winner's bid. Though stricter sample restrictions reduce sample size and thus lead to less precise estimates, it is reassuring to find that our results do not materially change across these various specifications.

Section 4 presents the estimates from the DiD design. Winning a procurement auction – which corresponds to a \$2.7 million procurement contract on average – increases sales by 17 percent, expenditure on intermediate inputs by 15 percent, and the wage bill by 10 percent. The total increase in sales is slightly larger than the payments received from the government procurement project, pointing to a small crowd-in of production in the private market. The 10 percent increase in the wage bill is due to an 8 percent increase in the number of employees and a 2 percent increase in earnings per employee. This finding is consistent with the firm bidding up wages to attract more workers, which would be the case if it faces an upward-sloping labor supply curve and, therefore, has wage-setting power in the labor market. One potential concern with this interpretation is that the increase in offered wages may be due to the firm hiring workers of higher quality. However, this explanation is at odds with our empirical evidence. We find no evidence of changes in the quality of the workers as a result of winning a procurement auction. Furthermore, the estimated increase in earnings per worker does not change if we restrict the sample to workers that are employed by the same firm before and after it wins the auction.

Motivated and guided by these findings, Section 5 develops a model where construction firms compete with one another for projects in the product market and for workers in the labor market. Importantly, we allow (but do not impose) that firms have wage-setting power in the labor market, or price-setting power in the product market, or both. The model serves several purposes. First, it offers an economic interpretation of the estimated treatment effects of winning a procurement auction. Without a model, it would be hard to gauge the size of these treatment effects and difficult to understand the responses to the procurement-induced changes in product demand. Second, the model makes explicit the assumptions needed to recover the parameters that govern the behavior of firms and workers in the construction industry. This includes the firm's technology as well as the labor supply and product demand curves it faces. Third, the model lets us quantify the size and sharing of rents in the construction industry, with a particular focus on whether government spending on infrastructure projects creates rents for firms, for workers, or for both. Fourth, the model makes it possible to perform counterfactuals to explore how increases in the market power of firms, in the product market or the labor market, affect the outcomes and behavior of workers and firms in the construction industry.

The labor market side of the model builds on work by Rosen (1986), Boal and Ransom (1997),

Bhaskar et al. (2002), Manning (2003), Card et al. (2018), and Lamadon et al. (2019). Competitive labor market theory requires firms to be wage-takers so that labor supply facing a given firm is perfectly elastic. The evidence that winning a procurement auction causes the firm to bid up wages and hire more workers is at odds with this theory. To allow the firm-specific labor supply curve to be imperfectly elastic, we let workers have heterogeneous preferences over the non-wage job characteristics or amenities that firms offer. Since we allow these amenities to be unobserved to the analyst, they can include a wide range of characteristics, such as distance of the firm from the worker's home, flexibility in the work schedules, the type of tasks performed, the effort required to perform these tasks, the social environment in the workplace, and so on (Hameross, 1999; Pierce, 2001; Mas and Pallais, 2017; Wiswall and Zafar, 2017; Maestas et al., 2018). We assume that firms do not observe the idiosyncratic taste for amenities of any given worker. This information asymmetry implies that employers cannot price discriminate with respect to workers' reservation wages. Instead, if a firm faces higher demand for its products and wants to hire more labor, it needs to offer higher wages to all workers. As a result, the equilibrium allocation of workers to firms creates rents to inframarginal workers and, moreover, some or all the gains from a firm winning a procurement auction may fall on its workers.

The firm side of the model consists of two types of product markets in which the construction firms may participate: projects in the private market and government projects, the latter of which are procured through auctions. The firm's behavior is specified as a two-stage problem, which we solve backwards. In the first stage, firms submit a bid for a government project that is procured through a first-price sealed-bid auction. The project specifies the amount of output that must be produced. At the end of the first stage, firms learn the outcome of the auction. If a firm wins the auction, it receives the winning bid amount as revenue and commences production. In the second stage, the firm chooses inputs to maximize profit from total production, taking as given the outcome of the procurement auction. A firm may earn rents in the private market due to price-setting power and in the government projects because of a limited number of bidders in the auction. Production in both private and procurement projects occur simultaneously at the end of the second stage.

In Section 6, we take the model to the data. We prove identification of the model parameters, before presenting and economically interpreting the parameter estimates. The identification argument forges a direct link between our model in Section 5 and the treatment effects analyses in Section 4. For example, the rents earned by workers can be measured using the elasticity of the firm's labor supply curve. This elasticity can be recovered from the DiD estimates of the effect of winning a procurement auction on the wage bill compared to the effect on the number of workers. To identify the technology parameters, we use data on the firm's choice of intermediate inputs and labor and, especially, the DiD estimates of how it changes these inputs in response to winning a procurement auction. The identification argument for the product demand curve builds on Ackerberg et al. (2015), who show the conditions under which one can use the intermediate input demand function to control for unobserved productivity across firms.

The estimates of the model parameters yield four key findings. First, firms have significant wage-setting power with an estimated firm-specific labor supply elasticity of about 4.1. The estimate indicates that, if an American construction firm aims to increase the number of employees by 10

percent, it needs to increase wages by around 2.4 percent. Second, firms have significant price-setting power in the private market with an estimated product market elasticity of 7.3. The estimate suggests that, in order for a firm to increase output by 7.3 percent in the private market, it must reduce the price of its product by 1 percent. Third, workers are, on average, willing to pay 20 percent of their wage to stay in their current firms. Comparing these worker rents to those earned by firms suggests that two-thirds of the total rents are captured by firms. Only 13 percent of the total rents come from government spending on procurement auctions, a quarter of which is captured by workers. Fourth, the estimated return to scale (over capital and labor) is slightly above one, consistent with the findings of Levinsohn and Petrin (2003). Despite increasing return to scale, the firms curtail production in order to earn rents from their wage- and price-setting power.

In Section 7, we use the estimated model to perform counterfactual analyses. We present two sets of counterfactuals. The first considers the consequences of increasing a firm's wage-setting power in the labor market by rotating the labor supply curve it faces, whereas the second explores the impact of increasing a firm's price-setting power in the private market by rotating the firm-specific product demand curve. Taken together, the results from these counterfactuals reveal how increases in the market power of firms, in the product market or the labor market, would affect the outcomes and behavior of workers and firms in the construction industry.

Our paper is primarily related to a large literature on imperfect competition, rents, and inequality in the labor market, reviewed by Manning (2011) and Card et al. (2018). A number of studies show that trends in wage dispersion closely track trends in productivity dispersion across industries and workplaces (Barth et al., 2016; Dunne et al., 2004; Faggio et al., 2010). While this correlation might reflect that some of the productivity differences across firms spill over to wages, it could also be driven by changes in the degree to which workers of different quality sort into different firms (Murphy and Topel 1990; Gibbons and Katz 1992; Abowd et al. 1999; Gibbons et al. 2005). To address the sorting issue, a growing body of work has taken advantage of panel data on workers and firms to control for time-invariant firm and worker heterogeneity in the estimation of the pass-through of changes in the value added of a firm to the wages of its workers (Card et al., 2018). For example, using panel data on the universe of American workers and firms, Lamadon et al. (2019) estimate that a 10 percent increase in the value added of a firm leads to a 1.4 percent increase in the earnings of incumbent workers. This estimate translates into a firm-specific labor supply elasticity of about 4.6, and suggests that workers are, on average, willing to pay 14 percent of their wage to stay in their current jobs.

Our paper contributes to this literature in several ways. First, we recover the labor supply curve and the worker rents from how an observable shifter of product demand affects wages as compared to employment, not from how changes in the value added of a firm passes through to the wages of the workers.¹ In particular, our DiD design allows us to credibly identify the causal links from

¹A few other studies have examined the pass-through of firm-specific, observable changes. For example, Van Reenen (1996) studies how innovation affects firms' profits and workers' wages. He also investigates patents as a source of variation, but finds them to be weakly correlated with profits. Building on this insight, Kline et al. (2019) study the incidence of patents that are predicted to be valuable. Our paper differs in that we study the pass-through of an exogenous change in product demand, instead of using innovation or patents as a shifter of the total factor productivity of the firm. A related literature on skill-biased technical change has examined the wage and productivity effects of adoption of new technology in firms (see Akerman et al., 2015, and the references therein).

winning a procurement auction to workers' wages as well as to the firms' sales, employment, and use of intermediate inputs.² By comparison, the panel data estimates of pass-through rates require assumptions about how the latent productivity of firms and workers evolve over time.

Second, we study a particular market, the construction industry. By comparison, much of the existing work is trying to measure pass-through rates and rents in the entire labor market, paying little attention to the large heterogeneity in technology and market structure across industries. Our focus on a particular industry allows us to pay closer attention to the structure and the functioning of the relevant markets. For example, many construction firms participate simultaneously in the private market, where output and prices are endogenously chosen by firms, and in government projects, which are procured through auctions where firms choose how much to bid but not how much to produce. As explained in detail later, this institutional feature is essential both for our identification argument, for understanding and modeling the behavior of firms, and for accurately predicting the profits the firms make if they win the auction.

Third, we identify and estimate the model parameters, not only the pass-through rates. This allows us to not only measure the current size and sharing of the rents earned by firms and workers, but also to understand the underlying mechanisms and to quantify how the rents and rent-sharing would change if market power changes. The closest study to ours is Lamadon et al. (2019), who also identify and estimate the model parameters to draw inference about imperfect competition and rents. Our paper complements this analysis by explicitly incorporating how rents may also arise from price-setting power in the product market and by using an observable shifter of product demand for identification.

Our paper also makes several contributions to the empirical work on auctions, reviewed by Athey and Haile (2007). Our modeling of auctions differs in that we consider incomplete information in unobserved productivity rather than unobserved costs. By modeling bidding as a function of productivity, we allow for a flexible relationship between the probability of winning the auction and other firm outcomes that depend on productivity, such as employment and output (Foster et al., 2008; Ackerberg et al., 2015). Moreover, we take the auction model to the data by estimating productivity directly from information on inputs and output. In contrast, most existing work only observe the auction-related activities, and therefore choose to estimate the auction model by inverting the equilibrium mapping between costs and bids (e.g., Guerre et al. 2000). Our paper also differs from existing work by allowing for heterogeneity in the value of the outside option, which we pin down from data on the private market activity of firms that lose auctions. By doing so, we are able to quantify how winning a procurement auction affects the firm's total production and whether it crowds-in or crowds-out activity in the private market. In comparison, existing empirical work either normalizes the value of the outside option to be zero for all firms (Athey and Haile, 2007) or models the outside option as (dynamic) participation in future auctions (Jofre-Bonet and Pesendorfer, 2003). Our work also complements existing papers on auctions by taking into account that firms may have

²A small number of papers have used a similar research design comparing winners and losers of procurement auctions. They estimate how government purchases affect employment during an economic crisis (Gugler et al., 2020) and firm dynamics and growth (Ferraz et al., 2015, Hvide and Meling, 2019). None of these studies use the procurement auctions to draw inference about imperfect competition or rents. Nor do they use these quasi-experiments to identify and estimate an economic model of the behaviors of firms and workers.

market power both in the labor market and in the private market. Both sources of market power affect the firm's bidding behavior in and profits from the auction.

The remainder of the paper proceeds as follows. Section 2 describes the institutional context, the procurement auction records, and the linking of auction records to tax records. Section 3 develops our research design based on a DiD framework. Section 4 presents the estimates of the causal effect of being awarded a procurement auction on the outcomes of interest. Sections 5 develops and Section 6 identifies and estimates the economic model of the behavior of firms and workers. Section 7 uses the estimated model to perform counterfactual analyses that allow us to infer how imperfect competition affects the outcomes and behavior of workers and firms in the construction industry. The final section concludes.

2 Data

Our empirical analyses are based on a matched employer-employee panel data set with information on the characteristics and outcomes of U.S. workers and firms linked to procurement auction records. The employer-employee data cover the years 2001-2015. The data set is constructed by first linking U.S. Treasury corporate tax returns to worker-level tax returns, and then merging this linked data set with procurement auction records. The tax returns cover nearly all firms and workers in the private sector, whereas the procurement auction records cover hundreds of thousands of auctions. Below, we briefly describe data sources, sample selection, and key variables. Additional details on the sample and variable definitions are provided in Online Appendix B.1.

The corporate tax returns include balance sheet and other information from Forms 1120 (C-corporations), 1120S (S-corporations), and 1065 (partnerships). We then link the corporate tax returns to worker-level W-2 (direct employee) tax returns and 1099 (independent contractor) tax returns, defining the highest-paying firm in a given year as the worker's primary employer. Our baseline set of workers consists of prime-aged W-2 employees with annual earnings from the primary employer greater than the annualized full-time minimum wage in the year. Because firms sometimes use part-time workers or contracted labor, we also consider a broader measure of the workforce that includes any worker to whom the firm reports payments on a W-2 or 1099 tax record.

The key variables that we draw on from the corporate tax returns are sales, intermediate input costs, and the NAICS industry code. We define two measures of profits. The first measure is sales minus intermediate input costs and wage bill (hereafter, "sales net of costs"). The second measure of profits is earnings before interest, taxes, and depreciation (hereafter, "EBITD"), which we construct following Kline et al. (2019). The key variables we draw from the worker tax returns are the number of employees and their wage bill for the primary sample of workers. We also consider the number of employees and wage bill for the broader sample that includes part-time workers and independent contractors. Using the panel structure of the employer-employee data, we define three measures of mean earnings: mean earnings among all workers; mean earnings among stayers, which we define as workers employed at the bidding firm consistently from 2 years prior to the procurement auction until 2 years after; and the past earnings of new hires at their previous firm, which we define as the mean earnings at $t - 1$ of workers who become primarily employed by a new firm at t .

	Sample Size	Share of the Construction Sector	
Number of Firms	7,876		0.9%
Workers per Firm	46		11.7%
	Value Per Firm (\$ millions)	Mean of the Log	Share of the Construction Sector (%)
Sales	19.927	15.061	12.1%
EBITD	9.159	14.075	9.6%
Intermediate Costs	14.661	14.719	12.4%
Wage bill	2.737	13.549	13.4%

Table 1: Sample Characteristics

Notes: This table displays 2010 descriptive statistics for the sample of firms that place bids in that year. In the third column, we compare aggregates for our sample to all firms in the construction sector in the tax records.

We obtain the new data set on procurement auctions by scraping the website of Bid Express, a service that facilitates the bidding process online for a number of states, scraping state-specific bidding websites, and through FOIA requests to state governments. The procurements broadly involve the construction and landscaping of local roads, bridges, and highways. In total, we recover the auction records from the Department of Transportation (DOT) in 28 states. Online Appendix B.2 provides the details on how we obtained the auction records. Construction firms often bid in auctions in other states, so our auction sample includes construction firms from nearly every state. An observation in this data set is at the auction-firm level, with variables on firm's name and address as well as the firm's bid and the date of the auction. Importantly, we observe the bid of each firm for a given auction, not only the winner. The resulting data set covers billions of dollars in procurement contracts awarded to thousands of firms through hundreds of thousands of auctions.

To merge the auction data to the tax records, we use a fuzzy matching approach based on the firm's name and location. For six states, we were able not only to obtain the name and address but also the federal Employer Identification Number (EIN) of the firm, allowing us to perform an exact match to tax records. We trained the algorithm on these six states before applying it to the other 22 states. Online Appendix B.3 explains how we trained and validated the linking algorithm used to merge the auction records to the tax returns. It also provides an out-of-sample validation analysis in which we tested the performance of the matching algorithm on publicly available pension data tax filings, finding that it performs well. Furthermore, Online Appendix Figure A.6 shows in the bars labeled "Known EIN" that our main results do not change materially if we restrict the sample to the six states for which we match records exactly using EINs.

Table 1 displays the sample sizes of firms and workers that participate in auctions in 2010. In 2010, our sample includes almost 8,000 unique firms that generate over \$150 billion in annual revenues and employ about 360,000 full-time workers. Nearly all the firms are recorded as being in the construction industry (i.e. the firms have NAICS codes beginning with 23). As a share

of the national construction sector (as recorded in the tax records in 2010), our sample of 8,000 firms accounts for 12 percent of sales, 12 percent of employment, 10 percent of EBITD, 12 percent of intermediate input costs, and 13 percent of wage payments. The state-specific sample size and share of the local economy represented by auction participants linked to tax records is displayed in Online Appendix Table A.4. California, Michigan, and Texas are the states with the most bidding firms, while Iowa, Kansas, and Montana are the states in which bidders employ the greatest share of workers in the construction sector.

3 Institutional Setting and Research Design

3.1 Procurement Auctions in the US

The procurement auctions studied in this paper are administered by the Department of Transportation (DOT) in 28 states. Construction firms often bid in auctions in other states, so our auction sample includes construction firms from nearly every state. Our data show that these 28 DOTs allocated \$383 billion through 155,768 distinct auctions involving 16,697 bidders in 2010. The procurements broadly involve the construction and landscaping of local roads, bridges, and highways. The DOTs are responsible for determining the nature of the project, including the blueprints, detailed list of tasks to be performed or items to be constructed, quality guidelines and standards, and expected or required time to completion. This information is publicly available in the solicitation for bidders posted by each DOT.

The awarding of a contract has two steps. The first step is qualification. In order to submit a bid, a firm must be pre-qualified by the DOT to ensure sufficient experience, equipment, and competence to carry out the tasks involved.³ Once approved, the firm is awarded a license to bid. The second step is the auction. In the first-price sealed-bid auction, a qualified firm submits a bid without observing the bidding behavior of other firms, and the contract is awarded to the firm with the lowest bid. Importantly, we observe the bids of every participant in the auction, not only the winner.

3.2 Research Design

To estimate the effects of winning a procurement auction, we use a difference-in-differences (DiD) research design. The idea is to compare first-time winners of a procurement auction to the firms that lose the auction, both before and after the auction.

To be concrete, consider an auction that occurs in year c (“cohort”) and let t denote the number of years since the auction occurred. For notational convenience, we omit the firm subscript on all variables. Denote a firm’s observed outcome by $Y_{c,t}$. Let $D_c = 1$ if the firm wins its first auction at c , and $D_c = 0$ if it bids in an auction at c but loses.⁴ Let $Y_{c,t}(1)$ and $Y_{c,t}(0)$ represent the realization

³The DOT may choose to further restrict bidder participation. For example, in California, projects labeled “business development initiatives” can only be bid on by local small or disadvantaged contractors.

⁴To account for left-censoring, we do not define a win as a “first win” unless there are at least two observed years of data during which the firm could have won but did not win an auction. For example, if a state provides auction records for 2001-2015, and a firm is first observed winning in 2001 or 2002, we do not consider this firm a first-time

of $Y_{c,t}$ that would have been experienced by the firm had its win status been exogenously set to 1 or 0, respectively. The relationship between observed and potential outcomes is given by

$$Y_{c,t} = D_c Y_{c,t}(1) + (1 - D_c) Y_{c,t}(0)$$

The parameter of interest is $\mathbb{E}[Y_{c,t}(1) - Y_{c,t}(0)|D_c = 1]$, which is the cohort-specific average treatment effect on the treated (ATT), t years after the auction among firms winning their first auction in cohort c . In the empirical analysis, we average the estimates of these cohort-specific ATTs across cohorts.

The key identification challenge is to recover the average potential outcome among auction winners if they had lost, $\mathbb{E}[Y_{c,t}(0)|D_c = 1]$. A natural control group for the treated firms that won their first auction at c is the set of firms that also had never won an auction before c and placed a bid at c but lost. Let $X_c = 1$ indicate firms that belong to this control group. Given this control group, one possibility is to use a matching estimator that infers the average potential outcome of the winners if they had lost the auction, $\mathbb{E}[Y_{c,t}(0)|D_c = 1]$, from the observed outcome of the control group that did lose the auction, $\mathbb{E}[Y_{c,t}(0)|D_c = 0, X_c = 1]$. However, matching is unlikely to perform well in our setting. In the standard model of optimal bidding in first-price auctions with private information on costs, firms bid monotonically in costs, so low-cost firms are more likely to win. This implies there are likely to be differences in the composition of auction winners and losers, even after conditioning on $X_c = 1$.

To account for such differences, we consider a cohort-specific DiD estimator of the form,

$$\mathbb{E}[Y_{c,t} - Y_{c,s}|D_j = 1] - \mathbb{E}[Y_{c,t} - Y_{c,s}|D_j = 0, X_c = 1] \quad (1)$$

for a given pre-period $s < 0$. The data must satisfy two conditions in order for the DiD to recover the ATT. The first condition is *parallel trends*,

$$\mathbb{E}[Y_{c,t}(0) - Y_{c,s}(0)|D_j = 1] = \mathbb{E}[Y_{c,t}(0) - Y_{c,s}(0)|D_c = 0, X_c = 1]$$

whereas the second condition is *no anticipation*,

$$\mathbb{E}[Y_{c,s}(1)|D_j = 1] = \mathbb{E}[Y_{c,s}(0)|D_j = 1]$$

Under parallel trends and no anticipation, it is straightforward to show that the DiD estimator in equation (1) recovers the ATT. Intuitively, compositional differences between the winners and losers (such as differences in costs) are differenced out by comparing changes over time for the treated and control groups.

Although the DiD estimator adjusts for differences across firms in levels, one could still be concerned that firms in the treated group may have different underlying trends as compared to firms in the control group. For example, firms with different cost functions may experience different changes in market conditions. To make the firms even more comparable and, thus, more likely to

winner, but if the firm is first observed winning in 2003 or later, we consider it a first time winner. The results do not materially change if we use all years of the data.

satisfy the parallel trends condition, it may be useful to place stronger restrictions on X_c . In our empirical analysis, we make several such restrictions. One of these is to restrict the control group to firms that are close to winning the auction in a cardinal sense. These are firms that place bids within a certain threshold of the winning bid in dollar value. Another is to restrict the control group to firms that are close to winning the auction in an ordinal sense. These are firms that place bids lower than other bidders in the auction, but still higher than the winner's bid. Though stronger sample restrictions reduce sample size and thus lead to less precise estimates, it is reassuring to find that the main estimates do not materially change across these various specifications.

Another potential concern is that the winners might anticipate that they are relatively likely to win an upcoming auction and change their behavior even prior to the outcome of the procurement auction. To investigate this concern, we directly assess the pre-trends. If such anticipation occurs, we can change the timing of the before and after contrast to avoid the periods in which anticipation is likely. Our evidence indicates that winning firms may be adjusting their behavior in the year just before the outcome of the auction. If we were to use $s = -1$ as the omitted relative time, this anticipatory behavior may create bias in the DiD estimates. However, there is no evidence of anticipatory behavior in earlier time periods. Thus, our baseline DiD specification contrasts the outcomes in the post-treatment periods to those in the pre-treatment periods $s < -1$.

A final possible concern is that firm composition may change over time due to differential firm survival between winning and losing firms. We investigate this explicitly by defining a firm death indicator and estimating survival probabilities for the treated and control group, finding a relatively precisely estimated zero effect on differential survival.

3.3 Graphical Evidence

Before presenting our main results, we provide graphical evidence on the effects of winning an auction for the first time. We consider as the treated group the firms that win their first procurement auction in year c . The control group is the set of firms that have not won an auction before c and placed a bid at c but lost. Letting j denote a firm and considering each relative time $t = -4, \dots, 4$, we consider the regression,

$$Y_{j,c,t} = \underbrace{\sum_{t' \neq s} 1\{t' = t\} \mu_{c,t'}}_{\text{relative time fixed effect}} + \underbrace{\sum_{j'} 1\{j' = j\} \psi_{j',c}}_{\text{firm fixed effect}} + \underbrace{\sum_{t' \neq s} 1\{t' = t\} D_{j,c} \tau_{c,t'}}_{\text{treatment status by relative time}} + \underbrace{\epsilon_{j,c,t}}_{\text{residual}} \quad (2)$$

where the empirical counterpart to $\tau_{c,t}$ is the DiD estimand defined in equation (1). We use the regression implementation to make it easier to include additional covariates and calculate the standard errors (which are clustered at the firm level j to account for serial correlation).⁵

Online Appendix Figure A.2 presents estimates from equation (2) for two outcomes from the procurement auctions: Subfigure (a) plots the share of firms that are first-time winners of a procurement auction, and subfigure (b) plots the share of firms that win a procurement auction in the relative year. Mechanically, both treated and control units have no wins prior to $t = 0$, so the effect

⁵We estimate $\tau_{c,t}$ for all c and t and then average across c , using the delta method to compute standard errors.

is zero on $t < 0$ for both subfigures. At $t = 0$, the treated group wins a contract for the first time and the control group bids for a contract but loses, so the treatment effect is mechanically one for both subfigures. The mean winnings for first-time winners at $t = 0$ are \$2.7 million. On $t > 0$ in subfigure (a), we see that some control units win auctions, with around 15 percent of control units winning their first auction at $t = 1$ and around 5 percent at $t = 4$. This means the losers continue to bid and partially catch up to the winners. However, as shown in subfigure (b), treated units are more likely than control units to win any procurement auction on $t > 0$. Treated firms are around 21 percent more likely to win at least one auction at $t = 1$ and 14 percent more likely at $t = 4$.

In Online Appendix Figure A.1, we plot pre-trends and post-trends at annual frequency from the estimates of the treatment effect for 12 outcomes of interest. Four patterns stand out. First, in the pre-treatment relative times -4 to -2, there is no evidence of differential trends between the winners and losers. This is consistent with the auction winners at relative time 0 being similar before they begin differentially winning procurement contracts. Second, at relative time -1, there is suggestive evidence of winners changing behavior as compared to losers, though the estimates are only a small fraction of the effects at relative times 0 and onward.⁶ This is reassuring given our DiD strategy. If we were to use $s = -1$ as the omitted relative time, this anticipatory behavior may create bias in the DiD estimates. However, there is no evidence of anticipatory behavior in earlier time periods. Thus, our baseline DiD specification contrasts the outcomes in the post-treatment periods to those in the pre-treatment periods $s < -1$. Third, at relative times 0 to 2, the contract has been awarded and the outcomes of treatment firms jump in an economically and statistically significant manner relative to control firms. At relative times 3 to 4, the differences show some evidence of fading out, as the control group begins to catch up to the treatment group, though the difference is economically and statistically significant.

Based on the patterns observed at annual frequency, our main estimates of the effects of winning a procurement contract on winners relative to losers classifies relative times $\{-4, -3, -2\}$ as the pre-treatment period (“Before”), and relative times $\{0, 1, 2\}$ as the post-treatment period (“After”). One sometimes sees empirical studies restrict the behavior of the control group in the post-period by requiring that the control group remains untreated long after the event. Though such a restriction helps to clarify the counterfactual, it risks biasing the estimate by conditioning on an endogenous outcome. As a robustness check, we nevertheless restrict the control group to firms that do not win an auction during the “After” interval. As evidenced by Online Appendix Figure A.6 (bars labeled “Non-winner”), the main patterns are unchanged, though the point estimates become slightly larger.

Furthermore, one may worry that our results depend strongly on our choice of “Before” and “After” time intervals. As a robustness check, Online Appendix Figure A.6 (bars labeled “All Time Periods”) considers including all of the pre-periods $\{-4, -3, -2, -1\}$ in the “Before” interval and all of the post-periods $\{0, 1, 2, 3, 4\}$ in the “After” interval, finding that the estimates are very similar.

⁶The evidence of a partial effect at relative time -1 may be driven in part by the fact that fiscal years of firms can differ from calendar years, and relative time is defined based on calendar years. For example, a firm may report its activity from the second half of relative time -1 and the first half of event year 0 as the calendar year corresponding to relative time -1.

4 Effects of Winning Procurement Auctions

4.1 Main Estimates

Balance Sheet Outcomes

Figures 1(a)-1(e) present the main estimates of the effects of winning an auction on five outcomes constructed from the firm balance sheet data, where “Before” refers to relative times $\{-4, -3, -2\}$ and “After” refers to relative time $\{0, 1, 2\}$. The “Before” effects are small in magnitude and are not statistically different from zero (all p -values above 0.10). This is consistent with the graphical evidence presented in the previous section indicating no differential pre-trends between auction winners and losers on the balance sheet outcomes, among firms bidding at the same time.

The “After” effects in Figure 1 provide our main results on balance sheet outcomes. We find the largest effect on sales, which increase by 17 percent for winners relative to losers (p -value below 0.01). Removing the procurement contract value from the measure of sales allows us to study private market activity. A negative estimate on sales net of procurements would indicate that public expenditure “crowds-out” revenues from the private market, but we find no evidence of crowd-out. Instead, the effect on sales net of procurements remains positive at 6 percent (p -value below 0.10), suggesting a small crowd-in effect. In Section 6, our economic model shows how the evidence of crowd-in can be informative about firm technology and market power.

Next, we estimate the effects on two distinct measures of profits that accrue to firms: sales net of costs (on intermediate inputs and labor), and EBITD (earnings before interest, taxes, and depreciation). Both measures show that profits increase by over 14 percent (p -values around 0.01). In Section 6, our economic model uses this estimate to assess the economic incidence of winning a procurement contract on firms.

Lastly, we estimate the effect of winning a procurement contract on intermediate input costs, finding an increase of 15 percent (p -value below 0.01). In Section 6, our economic model clarifies that the ratio between the effects of winning an auction on intermediate inputs and on labor is informative about the firm technology.

Employment and Earnings Outcomes

Figures 1(f)-1(l) present the main estimates of the effects of winning an auction on seven outcomes constructed from the worker earnings data. The “Before” effects are small in magnitude and are not statistically different from zero (all p -values above 0.10). This is consistent with the graphical evidence presented in the previous section indicating no differential pre-trends between auction winners and losers on employment and earnings outcomes, among firms bidding at the same time.

The “After” effects in Figure 1 provide our main results on employment and earnings outcomes. We find that winning a procurement auction leads to a 10 percent increase in the wage bill, an 8 percent increase in the number of employees, and a 2 percent increase in earnings per employee (all p -values below 0.01). We also estimate effects on the broader measure of the firm’s workforce that includes part-time and contracted labor. Like Kline et al. (2019), we find larger effects for this

broader measure of the firm’s workforce, with a 14 percent increase in wage bill, 10 percent increase in number of workers, and 4 percent increase in mean earnings (all p -values below 0.01).

The evidence that winning a procurement auction causes the firm to bid up wages and hire more workers is at odds with the textbook model in which the labor supply curve facing the firm is perfectly elastic. Instead, it suggests that firms face upward-sloping labor supply curves and, therefore, have wage-setting power in the labor market. In Section 5, we recover the slope of the firm-specific labor supply curve, and thus the degree of imperfect competition in the labor market, from the employment and earnings impacts of the procurement win. The estimated 2 percent increase in earnings per worker relative to an 8 percent increase in employment is consistent with firms facing an imperfectly elastic labor supply curve.

One potential concern with this interpretation of the estimated effects on labor outcomes is that firms might engage in skill-upgrading in response to winning the auction. In other words, the increase in earnings per worker may arise from composition changes from low-skill to high-skill labor, not movement along the labor supply curve. To investigate this, we perform two checks. First, we consider earnings at previous firms as a proxy for worker quality of new hires. We estimate the DiD regression using this proxy as the outcome. As evidenced from Figure 1(l), we find that the average previous earnings of new hires does not experience a statistically significant change in response to winning a procurement auction (p -value about 0.5). This suggests firms do not engage in skill-upgrading, as the new hires are not significantly different before and after winning the auction.

The second way we check whether or not the observed increase in earnings per worker is due to skill-upgrading is to condition on the sample of workers that do not change firms. Mechanically, conditioning on stayers ensures we look at earnings for the same set of workers before and after the auction. In the baseline stayers estimates, we consider workers employed by the same firm during relative times (-2,...,2). This point estimate is virtually identical to the result for the full sample, finding in Figure 1(k) that earnings per incumbent worker increases by just over 2 percent. In Online Appendix Figure A.3(a), we vary the definition of a stayer by expanding and contracting the stayer window, always finding an increase of around 2 percent across definitions. In the analysis of the stayers sample, one may be concerned with conditioning on the potentially endogenous outcome of staying in the same firm after the auction outcome. This motivates the exercise in Online Appendix Figure A.3(b), where we condition on workers who have been employed at the firm for a certain number of years prior to the auction (“tenure”), but do not condition on the workers remaining in the firm after the auction. Thus, if the worker moves to a new firm, we use the earnings at the new firm as their outcome. We find a consistent 2 percent increase in earnings per worker, regardless of tenure.

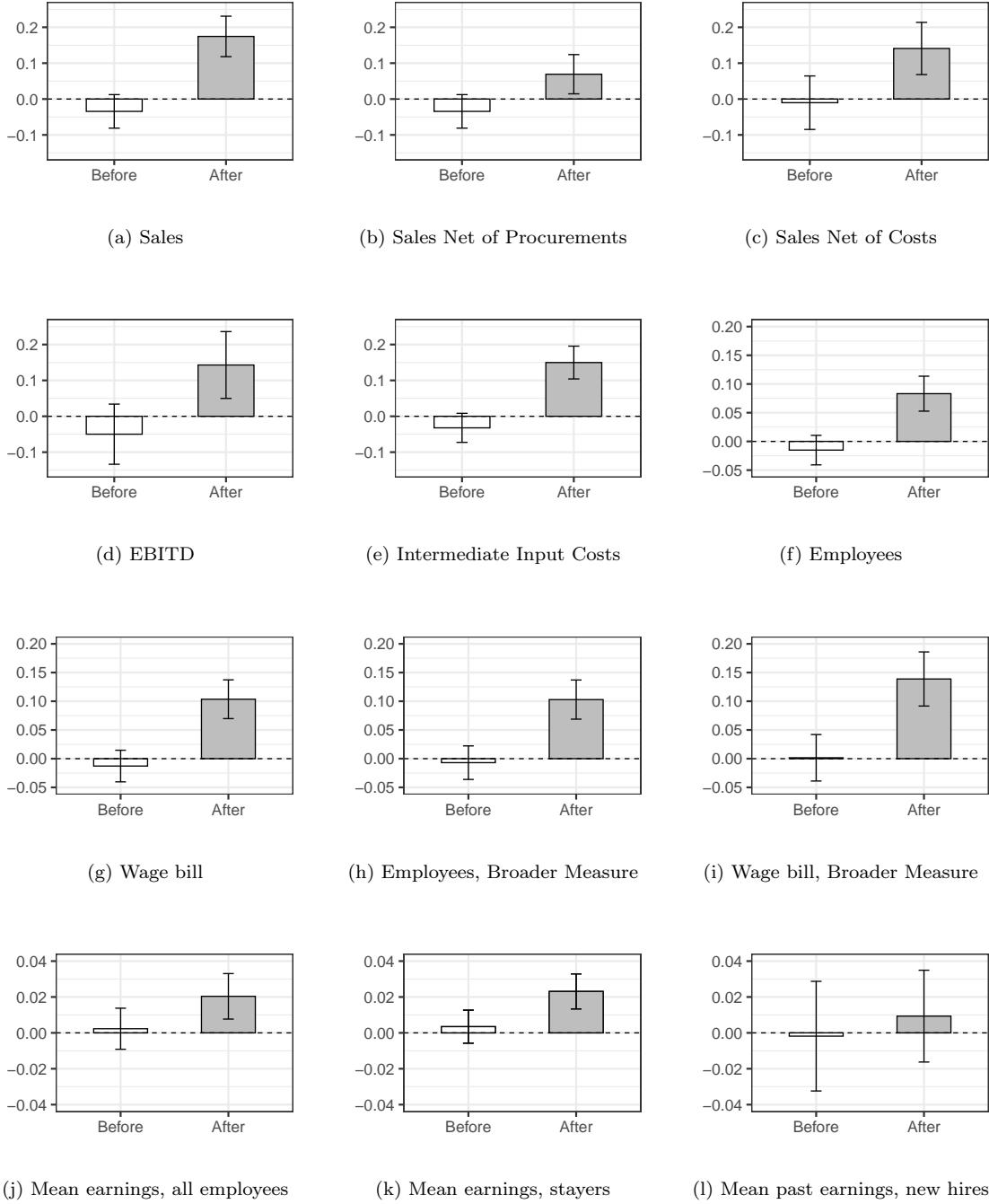


Figure 1: Effects of Winning Procurement Auctions

Notes: This figure presents average treatment effect on the treated estimates using the difference-in-differences specification defined in the text. All outcomes are in log units. All results include firm fixed effects. “Before” refers to relative times $\{-4, -3, -2\}$ and “After” refers to relative times $\{0, 1, 2\}$. Control firms are restricted to those that place a bid in a procurement auction in the same year that the reference treatment cohort wins. The omitted relative time is -2 . 90 percent confidence intervals are displayed, clustering on firm.

4.2 Robustness Checks

As discussed in the previous section, the key concern with comparing outcomes of those who win and lose is that control firms may differ from treated firms in time-invariant characteristics. Our baseline specification addresses this concern by including firm fixed effects to capture time-invariant differences, and by verifying that there are no differential pre-trends in event years -4 to -2 (see the results in the “Before” bars). We do not use relative time -1 in the before and after contrast to ensure it cannot create bias in the DiD estimates. For completeness, in Online Appendix Figure A.6 (bars labeled “All Time Periods”), we nevertheless examine results when including -1 and later time periods, finding that the estimates are very similar. In Online Appendix Figure A.6 (bars labeled “Non-winners”), we consider restricting the control group to firms that do not win any auctions throughout the “After” time interval, again finding the same patterns with slightly stronger effects. In Online Appendix Figure A.6 (bars labeled “Known EIN”), we provide main estimates when restricting to the subsample of firms from the six states that provided the EIN. For this subsample of firms, we link auction records to tax records exactly instead of relying on a fuzzy matching algorithm. The results are nearly identical, suggesting that the fuzzy matching algorithm recovers the same main estimates as exact matching.

To make the firms even more comparable and thus more likely to satisfy common trends, it may be useful to place stronger restrictions on the control group. In Online Appendix Figure A.4, we restrict to firms that are close to winning the auction in a cardinal sense. These are firms that place bids within a certain threshold of the winning bid in dollar value. In Online Appendix Figure A.5, we restrict to firms that are close to winning the auction in an ordinal sense.⁷ These are firms that place bids lower than other bidders in the auction, but still higher than the winner’s bid. Though stronger sample restrictions weaken the precision of the estimator by reducing sample size, it is reassuring to find that the estimates are materially unchanged across these various alternatives.

Our main specification controls for differences in the composition of treated and control firms through firm fixed effects. This removes any time-invariant characteristics of firms, subsuming the identity of the auctions in which they participate at time c . However, these fixed effects are included in an additive fashion. As a robustness check, we re-estimate the DiD estimator separately for each auction, then average the treatment effect estimates across auctions. Standard errors are calculated using the block bootstrap, where a block is taken to be an auction. Results are displayed in Online Appendix Figure A.6 (bars labeled “Within Auction”). It is reassuring to find that the estimates do not depend on whether we include additive fixed effects or estimate the model separately for each auction.

5 Model

In this section, we develop a model where construction firms compete with one another for projects in the product market and for workers in the labor market. Workers have heterogeneous preferences

⁷Ideally, we would compare the winners to the runner ups. While the point estimates do not materially change if we restrict the control groups to only include the runner ups, the standard errors increase significantly. Thus, we include both second and third place firms in the control group in this robustness check.

over non-wage job characteristics or amenities. This heterogeneity gives rise to imperfect competition in the labor market. There are two product markets in which the construction firms may choose to participate: private market projects and government projects, the latter of which are procured through auctions. Firms are allowed to have market power in both the product and the labor market.

At the outset, it is useful to make clear the purposes of the model. First, it offers an economic interpretation of the treatment effects of winning a procurement auction that we presented in Section 4. Second, the model makes explicit the assumptions needed to recover the parameters that govern the behavior of firms and workers in the construction industry. Third, the model lets us quantify the size and sharing of rents in the construction industry, with a particular focus on whether government spending on infrastructure projects creates rents for firms, for workers, or for both. Fourth, the model makes it possible to perform counterfactuals to explore how increases in the market power of firms, in either the product market or the labor market, affect the outcomes and behavior of workers and firms in the construction industry.

5.1 Preferences and Labor Supply

Worker i has the following preferences over being employed at a given firm j ,

$$u_i(j, W_j) = \log W_j + g_j + \eta_{ij} \quad (3)$$

where W_j represents earnings, g_j represents the average value of firm-specific amenities, and η_{ij} captures worker i 's idiosyncratic tastes for the amenities of firm j . Since we allow amenities to be unobserved to the analyst, they can include a wide range of characteristics, such as distance of the firm from the worker's home, flexibility in the work schedules, the type of tasks performed, the effort required to perform these tasks, the social environment in the workplace, and so on.

Our specification of preferences allows for the possibility that workers view firms as imperfect substitutes. The term g_j gives rise to *vertical* employer differentiation: some employers offer good amenities while other employers offer bad amenities. The term η_{ij} gives rise to *horizontal* employer differentiation: workers are heterogeneous in their preferences over the same firm. The importance of horizontal differentiation is governed by the variability across workers in the idiosyncratic taste for a given firm. We parameterize the distribution of η_{ij} as i.i.d. Type-1 Extreme Value (T1EV) with dispersion θ . When θ is larger, horizontal employer differentiation becomes relatively more important, as η_{ij} has greater variability.

We consider an environment where labor is hired in a spot market and assume that firms are endowed with a fixed set of amenities g_j (or, more precisely, we restrict amenities to be fixed over the estimation window). It is important to note that this restriction neither imposes nor precludes that employers *initially* choose amenities to maximize profits. Indeed, it is straightforward to show that permitting firms to initially choose amenities would not affect any of our estimates.

We consider two additional assumptions on the supply of labor. First, firms do not observe the idiosyncratic taste for amenities of any given worker η_{ij} . This information asymmetry implies that employers cannot price discriminate with respect to workers' reservation wages. Instead, if a firm wants to hire more labor, it needs to offer higher wages to both marginal and inframarginal workers.

Second, since we find no evidence of changes in worker quality in response to winning a procurement auction, we assume homogenous labor. It is straightforward to extend the model and the empirical analysis to allow for differences in worker quality, provided that the firm's output depends on the total efficiency units of labor (see Lamadon et al., 2019).

Given these assumptions, the number of workers who accept a job at firm j for a posted wage offer W_j can be expressed as $L_j = W_j^{1/\theta} \mu_j^{-1/\theta}$ where $\mu_j^{-1/\theta} \equiv g_j \bar{\theta}$ captures the vertical differentiation g_j and the aggregate labor supply parameter $\bar{\theta}$.⁸ Equivalently, we can write the inverse labor supply curve as,

$$W_j = L_j^\theta \mu_j \quad (4)$$

The labor supply elasticity facing the firm, $1/\theta$, and thereby the wages it needs to pay to hire more workers, is decreasing in θ , which is the variability of idiosyncratic tastes. Thus, labor supply becomes more inelastic when idiosyncratic tastes are more dispersed. In what follows, we assume firms are “strategically small” in the sense that $\frac{\partial \mu_j}{\partial W_j} \approx 0$.⁹

5.2 Technology, Product Market, and Firm Behavior

We model firm behavior as a two-stage problem which we solve backwards. In the first stage, firms submit a bid for a government project that is procured through a first-price sealed-bid auction.¹⁰ The project specifies the amount of output that must be produced within a given time frame. At the end of the first stage, the firm learns the auction outcome. If the firm wins the auction, it receives as revenue the winning bid amount and commences production. In the second stage, the firm chooses inputs to maximize profit from total production, taking as given the outcome of the procurement auction. Production in both private and procurement projects occur simultaneously at the end of the second stage.

We begin by specifying the technology and the structure of the product market, before describing the firm's problem through the two stages.

Technology

Following Ackerberg et al. (2015), the production function (in physical units) is,

$$Q_j = \min\{\phi_j L_j^{\beta_L} K_j^{\beta_K}, \beta_M M_j\} \times \exp(e_j) \quad (5)$$

where ϕ_j denotes total factor productivity (TFP), K_j denotes capital, M_j denotes intermediate inputs (in physical units), and e_j represents measurement error.

We assume that capital markets are perfect, so firms can rent capital at constant rate p_K . The

⁸Formally, $\bar{\theta} \equiv \bar{L}/\bar{W}$, where \bar{L} is the total number of workers in the construction industry and $\bar{W} \equiv \sum_{j'} W_{j'}^{1/\theta} g_{j'}$ is the price index of labor.

⁹See Berger et al. (2019), Chan et al. (2019), and Jarosch et al. (2019) for models of the labor market in which this assumption is relaxed.

¹⁰For simplicity, we assume exogenous participation. Indeed, it is straightforward to extend the model to allow for a common, fixed cost of entry. The entry cost becomes sunk upon entry, and thus irrelevant for the firm's subsequent choices. As a result, the size of this fixed cost would not affect any of our estimates.

first-order condition for capital implies a composite production function,

$$Q_j = \min\{\Omega_j L_j^\rho, \beta_M M_j\} \times \exp(e_j) \quad (6)$$

where $\Omega_j \equiv \phi_j [\frac{\beta_K}{\beta_L} \frac{(1+\theta)\mu_j}{p_K}]^{\beta_K}$ and $\rho \equiv (1+\theta)\beta_K + \beta_L$. We refer to Online Appendix D for the derivation of the composite production function in equation (6). Since the production function is Leontief in the intermediate input, it follows that the firm's choice of M_j is given by the function,

$$M_j = \Omega_j L_j^\rho / \beta_M \quad (7)$$

This expression will prove useful for our identification argument because it gives an invertible relationship between labor and intermediate inputs.

Product Market

We assume there are two product markets in which firms may choose to participate. First, they may participate in the market for private projects, which we denote H . Quantity produced by firm j in the private market is denoted by Q_j^H , which is endogenously chosen by the firm. Private projects are priced at $p(Q_j^H)^{-\epsilon}$ which implies revenues $R_j^H = p(Q_j^H)^{1-\epsilon}$. The parameter $1/\epsilon$ is the price elasticity of demand in the private market. When $\epsilon > 0$, the demand curve facing the firm is downward-sloping and firms have price-setting power in the private market. Our derivations in the text focus on $\epsilon > 0$. We refer to Online Appendix E for derivations with perfect competition, $\epsilon = 0$. As we discuss below, $\epsilon = 0$ is at odds with our empirical results.

Second, firms may participate in the market for government projects, denoted by G . Government projects are allocated through procurement auctions, and the government sets the size of a project, \bar{Q}^G . If firm j loses the auction ($D_j = 0$), it does not produce in the government market ($Q_j^G = 0$). If firm j wins the auction ($D_j = 1$), it must produce exactly \bar{Q}^G in the government market ($Q_j^G = \bar{Q}^G$). The quantity produced by firm j in the government market can then be expressed $Q_j^G = \bar{Q}^G D_j$. Revenues from winning a project of size \bar{Q}^G are determined by equilibrium auction bidding, which is discussed below.

At the end of the second stage, firm j produces total output $Q_j = Q_j^H + Q_j^G$ simultaneously across both markets using the production function in equation (6).

Second stage: Optimal firm choice in private market, given government project

We first solve for the optimal private market behavior of firm j if it wins an auction and if it loses an auction. Denote profits before auction revenues by $\pi_{1,j}^H$ if $D_j = 1$ and $\pi_{0,j}^H$ if $D_j = 0$. Denote the bid by b_j . Total profits are then $\pi_{1,j} = b_j + \pi_{1,j}^H$ for winners and $\pi_{0,j} = \pi_{0,j}^H$ for losers. Observed profits are $\pi_j = \pi_{1,j} D_j + \pi_{0,j} (1 - D_j)$. Given \bar{Q}^G and D_j , the firm's second stage problem is to choose inputs $L_{d,j}$ and $M_{d,j}$ to maximize private market profits,

$$\pi_{d,j}^H = p(Q_{d,j} - \bar{Q}^G d)^{1-\epsilon} - W_j L_{d,j} - p_M M_{d,j} \quad (8)$$

for $d = 0, 1$, subject to the labor supply curve (equation 4), the production function (equation 6), the choice of intermediate inputs (equation 7), the price of intermediate inputs, p_M , and that sufficient output is produced to complete the government project, $Q_{1,j} \geq \bar{Q}^G$.

We define the opportunity cost of winning the auction as the difference in private market profits between losing and winning, $\Delta(\Omega_j) = \pi_{0,j}^H - \pi_{1,j}^H$, which emphasizes that firm productivity Ω_j is the only source of heterogeneity in the opportunity cost. Due to the upward-sloping labor supply curve, the firm faces increasing marginal cost.¹¹ Since the winning firm must allocate sufficient resources to the government project to produce \bar{Q}^G , increasing marginal cost implies that the marginal cost of projects in the private market is greater for winners. As a result, the opportunity cost of winning a contract is strictly positive, $\Delta(\Omega_j) > 0$. Note that the profit function for auction winners depends on \bar{Q}^G , so the opportunity cost also depends on \bar{Q}^G . For notational convenience, we suppress this dependence.

In Online Appendix C, we characterize the profit-maximizing choices of winners and losers. Here we emphasize several properties of the optimal solution. First, both winners and losers always produce strictly positive output in the private market. This follows from the fact that firms have market power which implies that the marginal revenue in the private market is strictly greater than marginal cost as private market output approaches zero. For the same reason, total production is strictly greater if the firm wins the auction than if it loses.

Second, we note that the government project crowds-out private projects if $1 + \theta > \rho$, and conversely, crowds-in private projects if $1 + \theta < \rho$. To see why this is the case, note that winning a government project increases the total output level. This requires more employment to achieve a greater level of production. Due to the upward-sloping labor supply curve, greater employment leads to higher costs of labor, determined by $1 + \theta$. On the other hand, greater scale induces private production under economies of scale, $\rho > 1$. Thus, the magnitude of $1 + \theta$ relative to ρ determines how winning a procurement auction affects the firm's production in the private market.

First stage: Auction model and optimal bidding for government project

In the first stage, bidders observe common information about the size of the project, \bar{Q}^G , the number of bidders, I , and the distribution of TFP, which we now describe. Each bidder begins by receiving an i.i.d. random draw of TFP $\Omega_j \sim \tilde{F}(\cdot)$, where $\tilde{F}(\cdot)$ is the TFP distribution. The TFP distribution and second stage solution imply a distribution of the opportunity cost, i.e., $\Delta(\Omega_j) \sim F(\cdot)$, where the distribution function $F(\cdot)$ is known by all firms. The benefit of winning the auction is the winning bid amount, b_j . Thus, the difference between the benefit and the opportunity cost of winning the auction with bid b_j is $b_j - \Delta(\Omega_j)$.

Given the realized draw of Ω_j , firm j chooses the optimal bid b_j that solves the problem,

$$\max_{b_j} \underbrace{(b_j - \Delta(\Omega_j))}_{\text{payoff}} \times \underbrace{\Pr(D_j = 1 | b_j)}_{\text{probability of winning}}$$

¹¹Whether the marginal costs are increasing is an empirical question and depends on the slope of the labor supply curve compared to the returns to scale. One the one hand, we estimate an increasing return to scale over capital and labor. On the other hand, we find that firms have significant wage-setting power. Furthermore, part of the marginal cost is intermediate inputs, which has a constant return to scale.

The first term is the payoff to winning an auction, which is increasing in b_j , while the second term is the probability of winning an auction, which is decreasing in b_j . Thus, the firm faces the usual trade-off between profits if one wins and the chances of winning. The profit-maximizing bidding strategy is,

$$b_j = \Delta(\Omega_j) + \frac{\int_{\Delta(\Omega_j)}^{\bar{\Delta}} [1 - F(u)]^{I-1} du}{[1 - F(\Delta(\Omega_j))]^{I-1}} \quad (9)$$

where I is the number of bidders.

This bidding strategy defines the unique symmetric equilibrium. To understand why, note that the existence of the private market provides a “walkaway” value for the bidder, to produce only in the private market. This gives an implicit participation constraint: the firm’s optimal bid must yield an expected payoff at least as high as the profit when losing, $\pi_{0,j}^H$, net of the private market profits received when winning, $\pi_{1,j}^H$ (the total payoff upon winning must be at least as great as the total payoff upon losing). Therefore, the bid must satisfy $b_j > \pi_{0,j}^H - \pi_{1,j}^H$, which is the opportunity cost, $\Delta(\Omega_j)$. Since $b_j > \Delta(\Omega_j)$ and the bidding strategy is strictly increasing in $\Delta(\Omega_j)$, it defines the unique symmetric equilibrium (Milgrom and Weber, 1982; Maskin and Riley, 1984).

5.3 Worker and Firm Rents

Given the specification of the labor and product markets above, we can now define the surplus or rents that firms and their workers accrue. We focus both on the total rents from production in the private market (in the absence of procurement projects) and the additional rents generated from winning a procurement auction or, equivalently, the incidence of procurement auctions.

Rents for Workers

In our model, the employer may face an upward-sloping labor supply curve, implying that the wage a firm pays can be an increasing function of its size. Since employers do not observe the idiosyncratic taste for amenities of any given worker, they cannot price discriminate with respect to workers’ reservation values. Instead, if a firm becomes more productive and thus wants to increase its size, the employer must offer higher wages to all workers. As a result, the equilibrium allocation of workers to firms creates surpluses or rents for inframarginal workers, defined as the excess return over that required to change a decision, as in Rosen (1986).

To define the additional rents to worker i from an exogenous wage increase at firm j from W_j to \widetilde{W}_j , we consider an equivalent variation (EV) representation. Denote worker i ’s preferred firm excluding j as j^* . The EV of worker i for the wage increase at firm j , V_{ij} , is defined by the equation,

$$\underbrace{\max \left\{ \begin{array}{l} \log \widetilde{W}_j + g_j + \eta_{ij}, \\ \log W_{j^*} + g_{j^*} + \eta_{ij^*} \end{array} \right\}}_{utility \text{ with wage increase at firm } j} = \underbrace{\max \left\{ \begin{array}{l} \log (W_j + V_{ij}) + g_j + \eta_{ij}, \\ \log (W_{j^*} + V_{ij}) + g_{j^*} + \eta_{ij^*} \end{array} \right\}}_{equivalent \text{ utility at the initial choice of firm}}$$

The EV is the amount of compensation required at the initial choice of firm (right-hand side) to

provide the same utility that the worker receives after the wage increase at firm j (left-hand side). There are two cases. If j is the initial choice of firm, then $V_{ij} = \widetilde{W}_j - W_j$. This is because the worker is an incumbent at firm j , so the wage gain at j is the amount of compensation required to achieve the same utility. If j^* is the initial choice of firm, V_{ij} is more complicated, as it must account for the differences in both wages and amenities at firms j and j^* .

Letting $V_j \equiv \sum_i V_{ij}$ denote the total EV at firm j , Theorem 2 of Bhattacharya (2015) implies that,

$$V_j = \int_{W_j}^{\widetilde{W}_j} l_j(W) dW \quad (10)$$

where $l_j(\cdot)$ is firm j 's labor supply curve, which depends only on the wage at firm j under the assumption that each firm is strategically small. From our labor supply curve in equation (4), the solution to this integral is,

$$V_j = \frac{\widetilde{W}_j \widetilde{L}_j - W_j L_j}{1 + 1/\theta} = \frac{\widetilde{B}_j - B_j}{1 + 1/\theta} \quad (11)$$

where $L_j = l_j(W_j)$ is the initial labor, $\widetilde{L}_j = l_j(\widetilde{W}_j)$ is labor after the wage increase, $B_j = W_j L_j$ is the initial wage bill, and $\widetilde{B}_j = \widetilde{W}_j \widetilde{L}_j$ is the wage bill after the wage increase. See Online Appendix C.2 for derivations.

It is useful to observe that the definition of total EV sheds light on two notions of rents. The first is the additional rents captured by workers due to working at a firm that wins a procurement auction. We define these additional worker rents as $V_{\Delta,j} \equiv \frac{B_{1,j} - B_{0,j}}{1 + 1/\theta}$. This can be computed from equation (11) by setting $W_j = W_{0,j}$ (the wage at firm j if it loses the auction) and $\widetilde{W}_j = W_{1,j}$ (the wage at firm j if it wins the auction). The second is the total rents that workers earn from working at a firm j if it loses the procurement auction and, thus, only produces output in the private market. We define this quantity as $V_{0,j} \equiv \frac{B_{0,j}}{1 + 1/\theta}$. It can be computed from equation (11) by setting $W_j = 0$ (the wage at which firm j shuts down production) and $\widetilde{W}_j = W_{0,j}$ (the wage at firm j if it loses the auction). For completeness, we also define the total rents to workers if the firm wins the auction, which we denote $V_{1,j}$, so that worker rents can be decomposed as,

$$\underbrace{V_{1,j}}_{\text{Total rents}} = \underbrace{V_{0,j}}_{\text{Baseline rents}} + \underbrace{V_{\Delta,j}}_{\text{Incidence}} = \underbrace{\frac{B_{0,j}}{1 + 1/\theta}}_{\text{Baseline}} + \underbrace{\frac{B_{1,j} - B_{0,j}}{1 + 1/\theta}}_{\text{Incidence}} \quad (12)$$

These notions of rents coincide with the ones used in Lamadon et al. (2019). Intuitively, they can be interpreted as the willingness-to-pay to stay at the current firm, which is greater when horizontal employer differentiation is more important (i.e., when θ is greater).

When using equation $V_{\Delta,j}$ to analyze the incidence of procurements, it is useful to decompose it into the additional rents captured by incumbent workers and additional rents captured by new hires

drawn into firm j by the wage increase. Expanding equation (10), we can write,

$$V_{\Delta,j} = \underbrace{L_{0,j}(W_{1,j} - W_{0,j})}_{\text{gain for incumbents}} + \underbrace{W_{1,j} \left(\frac{1}{1+1/\theta} L_{1,j} - L_{0,j} \right) + \frac{1/\theta}{1+1/\theta} B_{0,j}}_{\text{gain for new hires}} \quad (13)$$

This expression allows us to directly evaluate the share of additional rents from procurements captured by incumbent workers relative to new hires.

Rents for Firms

As our measure of firm rents, we use profits. There are three relevant measures of profits. First, $\pi_{0,j}$ is the profits that the firm captures from production in the private market if it loses the auction. Second, $\pi_{1,j}$ is the profits that the firm captures from joint production in the government and private markets if it wins the auction. Third, $\pi_{\Delta,j} \equiv \pi_{1,j} - \pi_{0,j}$ is the additional rents earned by the firm due to winning a procurement contract. We will make use of the decomposition,

$$\underbrace{\pi_{1,j}}_{\text{Total firm rents}} = \underbrace{\pi_{0,j}}_{\text{Baseline firm rents}} + \underbrace{\pi_{\Delta,j}}_{\text{Incidence on firms}} \quad (14)$$

It is important to observe that profits do not necessarily represent ex-ante rents for the employer. Suppose, for example, that each employer initially chooses the amenities offered to the workers by deciding on the firm's location, the working conditions, or both. Next, the employers compete with one another for the workers who have heterogeneous preferences over the chosen amenities. These heterogeneous preferences give rise to wage-setting power which employers can use to extract additional profits or rents. Of course, the existence of such ex-post rents could simply be returns to costly ex-ante choices of amenities. On top of this, profits from the procurement auctions may, in part, reflect a fixed cost of entry to the auction. For example, in order to bid on procurement contracts, firms must hold licenses which are costly. While the presence of a fixed entry cost will affect the interpretation of profits, it will not affect identification of model parameters.

6 Identification of Model and Parameter Estimates

The purpose of this section is to identify, estimate and economically interpret the model parameters of interest $(\theta, \epsilon, \rho, \beta_L, \beta_K, \bar{\theta}, p, \beta_M/p_M, F(\cdot), \mathbb{E}[V_{0,j}], \mathbb{E}[\pi_{0,j}], \mathbb{E}[V_{\Delta,j}], \mathbb{E}[\pi_{\Delta,j}])$ given the data $(L_j, W_j, \pi_j, R_j, p_M M_j, D_j, b_j)$. We provide a formal identification argument in the text while summarizing, in Table 2, the moments used to identify each parameter of interest. The identification argument forges a direct link between our model in Section 5 and the procurement effects analysis in Section 4. For notational simplicity and without loss of generality, the formal argument keeps the conditioning on $X = 1$ and the fixed effects implicit, or, equivalently, D_j is treated as randomly assigned.

At the outset, we emphasize three assumptions that are key for our identification results:

Assumption 1: Workers' idiosyncratic taste over non-wage attributes is distributed T1EV.

This specification of preferences is standard in the empirical literature on imperfect competition in the labor market. It is useful for identification because it gives a parsimonious measure of wage-setting power through a constant elasticity of labor supply.

Assumption 2: The production function is Leontief in intermediate inputs.

This common specification of technology implies that intermediate inputs are proportional to output, which rationalizes a value added production function. It makes it possible to derive an invertible relationship between intermediate inputs and labor, which can be used to control for unobserved productivity differences across firms.

Assumption 3: Demand elasticity in the private product market is constant and finite.

A constant elasticity offers tractability, while a finite elasticity (i.e., $\epsilon > 0$) ensures that firms that win auctions also participate in the private market (as we observe in the data).

As our identification argument makes clear, many of the parameters of interest do not require all three assumptions. Thus, some of our findings may be considered more reliable than others.

6.1 Labor Supply Elasticity, Rents and Rent-Sharing

We begin by identifying and estimating the labor supply elasticity, $1/\theta$, and the rents of workers and firms defined in Subsection 5.3.

Identification and Estimate of the Labor Supply Elasticity

Under Assumption 1, the log wage bill B_j can be expressed $\log B_j = (1+\theta) \log L_j + \log \mu_j$. The term $\log \mu_j$ captures the firm-specific amenity, which is unobserved and affects the number of employees in the firm, L_j . To address this endogeneity problem, we make use of the (conditional) random assignment of winning a procurement auction. In particular, it is possible to recover θ from the expression,

$$1 + \theta = \frac{\mathbb{E}[\log B_j | D_j = 1] - \mathbb{E}[\log B_j | D_j = 0]}{\mathbb{E}[\log L_j | D_j = 1] - \mathbb{E}[\log L_j | D_j = 0]} \quad (15)$$

Intuitively, θ determines the cost of hiring additional workers, which can be identified from the change in labor expenses compared to the change in labor due to winning the procurement auction.

The main estimate of θ is displayed in Panel A of Table 2. The point estimate of the firm-specific labor supply elasticity is 4.1. This indicates that, if an American construction firm aims to increase the number of employees by 10 percent, it needs to increase wages by around 2.4 percent. Lamadon et al. (2019) estimate a local labor supply elasticity of 4.6, while Card et al. (2018) pick 4.0 as the preferred value in their calibration exercise. A related literature using experimentally manipulated piece-rate wages for small tasks typically finds labor supply elasticities ranging from 3.0 to 5.0 (Caldwell and Oehlsen, 2018; Dube et al., 2020; Sokolova and Sorensen, 2018).

Figure 2(a) provides the labor supply elasticity estimates, $1/\theta$, corresponding to each of the robustness exercises discussed in Section 4. The robustness checks include restricting to those firms that made bids close to the winning bid, in a cardinal sense (“Close Bidders Cardinal”) and in an ordinal sense (“Close Bidders Ordinal”), including all time periods in the estimation (“All Time

Periods”), restricting the control group to those that did not win subsequent auctions in the near future (“Non-winners”), separately estimating the effect within each auction and then averaging (“Within Auction”), and estimating the labor supply elasticity as the log change in employees divided by the log change in mean earnings of stayers (“Stayers”) rather than relying on the log change in wage bill. Across all the robustness checks, the labor supply elasticity estimates range from 3.5 to 5.1, which are close to the baseline estimate and align with the range of estimates in the literature.

As shown above, our identification of θ relies on the argument that winning an auction shifts the firm’s demand for labor along the labor supply curve. One potential reason this argument may fail is adjustment costs: If labor enters the firm slowly over time rather than immediately when the new wage is posted, the short-run relation between wages and quantity of labor may underestimate the longer-run elasticity of labor supply. The evidence in Section 3 is at odds with such adjustment costs. Both wages and labor appear to respond relatively quickly to winning the auction (see Online Appendix Figure A.1f,g). Indeed, the implied labor supply elasticity estimate varies relatively little over time.

Another possible threat to our identification of the labor supply curve is skill upgrading: If the wage bill increases for the winning firm both because more workers are hired and because the new workers are more efficient, then the estimator will include a bias term related to the change in worker composition. In Section 4, we provided evidence that the composition of new hires does not appear to change in response to winning an auction. When conditioning on the incumbent workers in the firm so that composition mechanically does not affect the wage change, we estimate approximately the same labor supply elasticity (see the “stayers” bar in Figure 2). Thus, we argue our empirical evidence is at odds with significant changes in the skill composition of workers.

Identification and Estimates of Worker and Firm Rents

We now show how to quantify the rents earned by workers and firms. Given that D_j is (conditionally) randomly assigned, it follows from equations (12) and (14) that we can obtain the total rents earned if the firm wins the auction. For workers, total rents are given by,

$$\mathbb{E}[V_{1,j}] = \frac{1}{1 + 1/\theta} \mathbb{E}[B_j | D_j = 1]$$

For firms, total rents are given by,

$$\mathbb{E}[\pi_{1,j}] = \mathbb{E}[\pi_j | D_j = 1]$$

Our estimates of these total rents are displayed by the inner pie of Figure 3. In the typical firm, we estimate that total worker rents are about \$9,200 per worker. This implies that workers are, on average, willing to pay about 20 percent of their wages to stay in their current firms. We estimate that total firm rents are about \$20,100 per worker. Comparing these worker rents to those earned by firms suggests that about two-thirds of the total rents go to the employers.

Panel A. Labor Supply and Rents		
	Moments used in Identification	
	Definition	Estimate
<i>Estimand for winning an auction:</i>		
Estimand log wage bill	$\tau_b \equiv \mathbb{E}[\log B_j D_j = 1] - \mathbb{E}[\log B_j D_j = 0]$	0.104
Estimand log employment	$\tau_l \equiv \mathbb{E}[\log L_j D_j = 1] - \mathbb{E}[\log L_j D_j = 0]$	0.083
Estimand log profits	$\tau_\pi \equiv \mathbb{E}[\log \pi_j D_j = 1] - \mathbb{E}[\log \pi_j D_j = 0]$	0.143
Labor Supply and Rent Parameters		
	Identifying Equation	Estimate
Labor supply elasticity	$1/\theta = \tau_l / (\tau_b - \tau_l)$	4.084
Total Rents to Workers (\$1,000/employee)	$\frac{V_1}{L_1} = \frac{B_1}{L_1} \frac{1}{1+1/\theta}$	9.266
Total Rents to Firms (\$1,000/employee)	$\frac{\pi_1}{L_1} = \frac{V_1}{L_1} \frac{V_1}{V_1 + \pi_1}$	20.103
Workers' Share of Total Rents	$\frac{V_1 + \pi_1}{V_1} = \frac{B_1}{L_1} \frac{\tau_b}{1+1/\theta}$	0.316
Incidence of Procurements on Workers (\$1,000/employee)	$\frac{V_\Delta}{L_1} = \frac{B_1}{L_1} \frac{\tau_b}{1+1/\theta}$	0.959
Incidence of Procurements on Firms (\$1,000/employee)	$\frac{\pi_\Delta}{L_1} = \frac{\pi_1}{L_1} \tau_\pi$	2.873
Workers' Share of Incidence of Procurements	$\frac{V_\Delta}{V_\Delta + \pi_\Delta}$	0.250
Panel B. Firm's Problem, Technology, and Private Market Structure		
	Moments used in Identification	
	Definition	Estimate
<i>Estimand for winning an auction:</i>		
Estimand log inputs relative to labor	$\tau_{m/l} \equiv \frac{\mathbb{E}[\log p_M M_j D_j = 1] - \mathbb{E}[\log p_M M_j D_j = 0]}{\mathbb{E}[\log L_j D_j = 1] - \mathbb{E}[\log L_j D_j = 0]}$	1.600
Estimand log private revenues	$\tau_{R-b} \equiv \mathbb{E}[\log(R_j - b_j) D_j = 1] - \mathbb{E}[\log R_j D_j = 0]$	0.069
<i>Auction loser log covariances:</i>		
Var. of log inputs	$\sigma_{m 0}^2 \equiv \text{Var}[\log(p_M M_j) D_j = 0]$	3.062
Cov. of log inputs and log revenues	$\sigma_{m,r 0} \equiv \text{Cov}[\log(p_M M_j), \log(R_j) D_j = 0]$	2.559
System of Equations		
	Identifying Equation	Evaluated Right-hand Side
Optimal intermediate inputs to employees (eq 18)	$\rho = \tau_{m/l}$	1.600
Optimal labor to value added ratio (eq 19)	$\beta_L = \mathbb{E}\left[\frac{(1+\theta)B_j}{(1-\epsilon)R_j - M_j} D_j = 0\right]$	0.587
Diminishing returns to private output (eq 20)	$1 - \epsilon = \sigma_{m,r 0} / \sigma_{m 0}^2$	0.836
First-order condition with crowd-in (eq 21)	$\rho = \frac{\tau_{R-b}}{\tau_l} + \frac{\mathbb{E}\left[\log\left(\frac{1+\theta}{\beta_L} B_j + p_M M_j\right) - \log((1-\epsilon)R_j)\right] D_j = 1}{\tau_l}$	1.401
GMM Results		
	Parameters	Estimate
Private demand elasticity	$1/\epsilon$	7.343
Returns to labor	β_L	0.597
Composite scale parameter	ρ	1.419
Panel C. Remaining Parameters for Price, Scale, and TFP		
	Moments used in Identification	
	Definition	Estimate
Mean log wage bill	$\mathbb{E}[\log(B_j)]$	13.682
Mean log employment	$\mathbb{E}[\log(L_j)]$	2.914
Mean log intermediate expenditure	$\mathbb{E}[\log(p_M M_j)]$	14.958
Mean log revenues	$\mathbb{E}[\log(R_j)]$	15.291
Remaining Parameters		
	Identifying Equation	Estimate
Scale of optimal log wage	$\mathbb{E}[\log(\mu_j)] = \mathbb{E}[\log(B_j)] - (1 + \theta)\mathbb{E}[\log(L_j)]$	10.055
Scale term for intermediates	$\log \frac{\beta_M}{p_M} = \rho \mathbb{E}[\log(L_j)] - \mathbb{E}[\log(p_M M_j)]$	-10.824
Scale of log output price	$\log p = \mathbb{E}[\log(R_j)] - (1 - \epsilon)(\log \frac{\beta_M}{p_M} + \mathbb{E}[\log(p_M M_j)])$	11.719
Interquartile range of log TFP	$\text{IQR}(\log \Omega_j) = \text{IQR}(\log p_M M_j - \rho \log L_j)$	0.973

Table 2: Model Identification and Parameter Estimates

Notes: This table summarizes results on identification and estimation of the model. In Panel A, it provides the parameters needed to estimate the incidence of procurements on firms and workers. Incidence is evaluated at the median firm in our sample. In Panels B and C, it provides the parameters needed to simulate counterfactual results from the model.

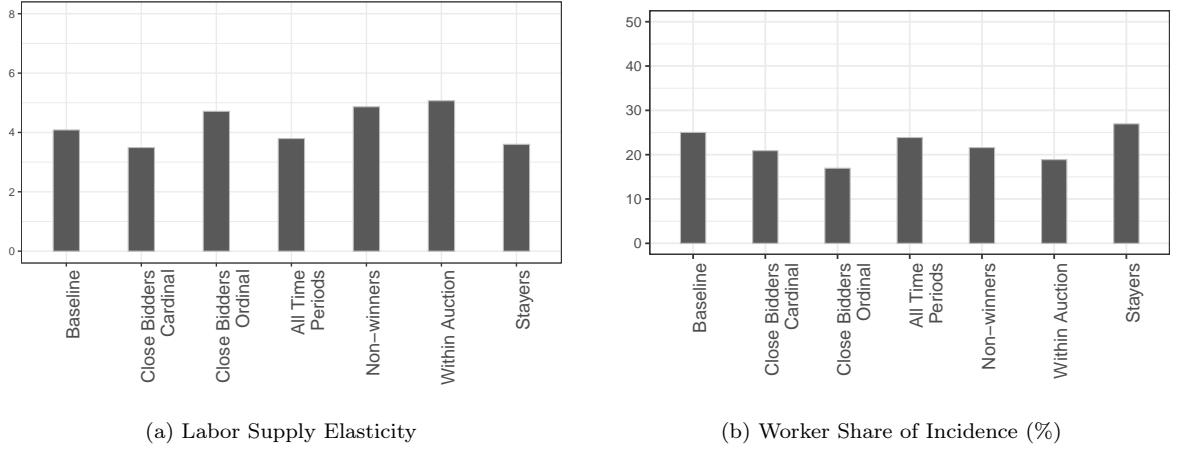


Figure 2: Labor Supply Elasticity and Incidence Share Estimates

Notes: This figure presents the baseline estimate and robustness checks for the labor supply elasticity, $1/\theta$, and the worker share of incidence for the typical auction winner. Specification details on the robustness checks and alternative sample definitions are provided in Section 4 and Online Appendix B.1.

In the outer pie of Figure 3, we decompose the total rents into the baseline rents that would be earned if the firm lost the auction and the additional rents due to winning the auction. Given that D_j is (conditionally) randomly assigned, the additional rents for workers are,

$$\mathbb{E}[V_{\Delta,j}] = \frac{\mathbb{E}[B_j|D_j = 1] - \mathbb{E}[B_j|D_j = 0]}{1 + 1/\theta} \quad (16)$$

By comparison, the additional rents for firms are,

$$\mathbb{E}[\pi_{\Delta,j}] = \mathbb{E}[\pi_j|D_j = 1] - \mathbb{E}[\pi_j|D_j = 0] \quad (17)$$

In the typical firm, we estimate that the additional rents for workers are almost \$1,000 per worker while the additional rents for firms are about \$2,900 per worker. Comparing these additional rents to the total rents, we conclude that only 13 percent of total rents come from government spending on procurement auctions and that about 25 percent of the additional rents go to the workers. By applying the decomposition in equation (13), we find that 92 percent of the additional workers rents is captured by incumbent workers and only 8 percent goes to the new hires.

Figure 2(b) provides the estimated worker share of additional rents corresponding to each of the robustness exercises discussed in Section 4. Across all the robustness checks, the range of estimates is 17 percent to 27 percent, which are relatively close to the baseline estimate. By comparison, Suárez Serrato and Zidar (2016) find that the incidence of corporate tax changes on workers in the U.S. is 28 percent.

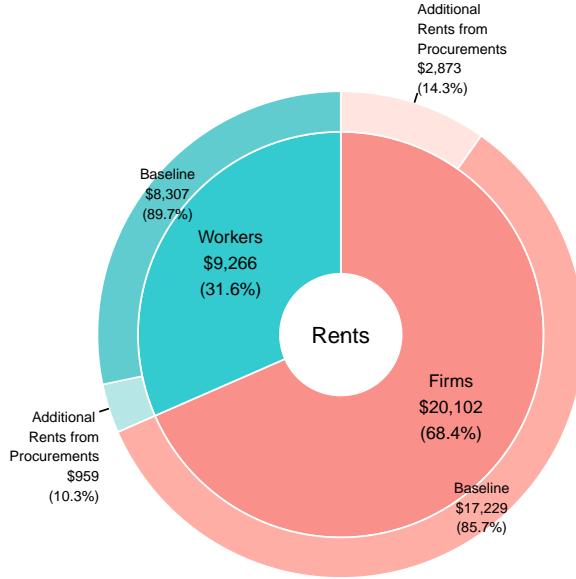


Figure 3: Aggregate Rents

Notes: This figure presents the total rents for the typical auction winner in the economy. It divides the rents into those captured by firms (red) and those captured by workers (blue). It further decomposes rents into those earned if the firm loses the auction (“Baseline”) and the additional rents due to winning the procurement auction (“Additional Rents from Procurements”).

6.2 Firm Technology and Product Market

The previous subsection demonstrated identification of the labor supply elasticity and the rents under Assumption 1. In this subsection, we provide identification results for the three main parameters that govern the product market and firm technology. These parameters are the product demand elasticity in the private market, $1/\epsilon$, the returns to labor in production, β_L , and the composite production parameter, ρ . Identification of these parameters requires Assumptions 1-3, as well as the estimate of $1/\theta$ from the previous subsection.

Identification of Parameters Governing Firm Technology and Product Market

Consider first how to recover ρ from the condition for the optimal choice of intermediate inputs. Under Assumption 2, equation (7) can be written as

$$\log M_j = \log \Omega_j + \rho \log L_j - \log \beta_M$$

where $\log \Omega_j$ captures firm-specific productivity, which is unobservable and affects the log number of employees in the firm, $\log L_j$. We make use of the (conditional) random assignment of winning a procurement auction to identify ρ in the presence of this endogeneity. In particular, since D_j is (conditionally) independent of $\log \Omega_j$, we can write ρ in terms of changes induced by winning a

procurement auction as,

$$\rho = \frac{\mathbb{E}[\log(p_M M_j) | D_j = 1] - \mathbb{E}[\log(p_M M_j) | D_j = 0]}{\mathbb{E}[\log L_j | D_j = 1] - \mathbb{E}[\log L_j | D_j = 0]} \quad (18)$$

Identification relies on the optimal proportionality between labor and intermediate inputs as the firm increases output. Intuitively, if ρ is high, this means that for a given change in labor, intermediate inputs must adjust by more to maintain proportionality.

Next, consider how to identify the returns to labor, β_L . Under Assumptions 1-3, the first-order condition with respect to labor for firms that only operate in the private market ($D_j = 0$) provides a relationship between the returns to labor, β_L , and the ratio between labor expenses and revenues. Using that $\rho \equiv (1 + \theta)\beta_K + \beta_L$ and taking the expectation across losing firms, the choice of labor if the firm loses the auction (maximizing profits from equation 8) implies,

$$\beta_L = \mathbb{E}\left[\frac{(1 + \theta)B_j}{(1 - \epsilon)R_j - p_M M_j} | D_j = 0\right] \quad (19)$$

We focus on auction losers since their labor choices do not depend on features of the auction. The firm equates the marginal cost of labor $W_j(1 + \theta)$ with the marginal benefit

$\frac{1}{L_j}((1 - \epsilon)R_j\beta_L - p_M M_j\beta_L)$. This expression for the marginal benefit of labor includes an adjustment for intermediate inputs. The reason is that Assumption 2 implies the firm needs to increase both labor and intermediate inputs if it wants to produce more. In the limiting case as $\theta \rightarrow 0$ and $\epsilon \rightarrow 0$, β_L is equal to the labor share (wage bill divided by value added). The terms related to θ and ϵ account for the fact that both the labor market and the product market are imperfectly competitive. If labor is very productive at the margin, the firm will optimally choose a higher wage bill. Conversely, the extent to which the wage bill is high relative to value added reveals that the marginal product of labor must also be high.

The next problem is to identify the private market demand elasticity, $1/\epsilon$, which is the percent change in revenues resulting from a one percent change in the output quantity. There are two challenges. First, we do not observe the output quantity, and must instead use inputs to infer output. Second, because productivity determines both labor and the elasticity of output with respect to labor, we face an endogeneity problem when inferring output from labor. Intuitively, variation in the relationship between labor and revenues is due both to the downward-sloping private market demand curve and variation across firms in TFP. Following Ackerberg et al. (2015), we use intermediate inputs instead of labor to infer output (see also the discussion by Gandhi et al. 2019). Under Assumption 2, TFP does not appear in the relationship between private market revenues and intermediate inputs, but is instead subsumed by intermediate inputs. Using Assumptions 2 and 3, private market revenues are log-additive in intermediate input costs and the measurement error e_j (see Online Appendix C.3). Since M_j is determined before the firm observes e_j (Ackerberg et al., 2015), it follows that $\text{Cov}[e_j, \log(p_M M_j)] = 0$, which implies,

$$1 - \epsilon = \frac{\text{Cov}[\log(R_j), \log(p_M M_j) | D_j = 0]}{\text{Var}[\log(p_M M_j) | D_j = 0]} \quad (20)$$

Lastly, it is useful to observe that ρ is over-identified. Maximizing profits from equation (8) and using Assumptions 1-3 (see Online Appendix C.3), we arrive at a moment condition involving ρ , β_L , and $1/\epsilon$,

$$\underbrace{\mathbb{E} \left[\log (R_j - b_j) \middle| D_j = 1 \right] - \mathbb{E} \left[\log R_j \middle| D_j = 0 \right]}_{\text{Crowd-in}} = \rho \underbrace{\mathbb{E} \left[\log L_j \middle| D_j = 1 \right] - \mathbb{E} \left[\log L_j \middle| D_j = 0 \right]}_{\text{Total labor response}} \quad (21)$$

$$- \underbrace{\mathbb{E} \left[\log \left(\frac{1+\theta}{\beta_L} B_j + p_M M_j \right) - \log ((1-\epsilon) R_{1,j}^H) \middle| D_j = 1 \right]}_{\text{Adjustment for labor used to complete procurement projects}}$$

This moment condition is useful for two reasons. Combining it with the moment conditions reported in equations 18-20 may improve the estimates of $(1/\epsilon, \rho, \beta_L)$. Additionally, equation 21 makes precise the empirical conditions under which winning a procurement auction crowds-in or crowds-out production in the private market.

It is important to note that identification of both ρ and $1/\epsilon$ above relies on the argument that intermediate inputs adjust simultaneously with labor (to identify ρ) as well as with output and revenues (to identify $1/\epsilon$). One potential reason this argument may fail is adjustment costs which lead revenues, labor, and intermediate inputs to adjust at different speeds (see the discussion by Gandhi et al. 2019). The evidence in Section 3 is at odds with large adjustment costs. Revenues, labor, and intermediate inputs appear to respond relatively quickly to winning an auction (see Online Appendix Figure A.1a,e,f).

Estimates of Parameters Governing Firm Technology and Product Market

We use the general method of moments (GMM) to jointly estimate $(1/\epsilon, \rho, \beta_L)$ based on equations 18-21. To simplify the search space in the numerical solver, we impose the natural constraints $\epsilon \geq 0$, $\rho \geq 0$, $\beta_L \in [0, 1]$, and $\rho(1 - \epsilon) < (1 + \theta)$, where the latter constraint ensures that firms do not optimally choose to be infinitely large. However, none of the constraints bind at the numerical solution.

The results are presented in Panel B of Table 2. We estimate $1/\epsilon$ to be 7.3. This implies that, in order for a firm to increase output by 7.3 percent, it must reduce its price by 1 percent. Though we do not find directly comparable estimates of the price elasticity of demand from the construction industry, some estimates from the literature suggest our estimate is within a reasonable range. Goldberg and Knetter (1999) estimate residual demand elasticities for German beer of 2.3-15.4. Goldberg and Verboven (2001) estimate average price elasticities of demand for foreign cars of 4.5-6.5.

We estimate β_L to be 0.60 and ρ to be 1.4. The value of β_L implies that a 100 percent increase in a firm's employment results in 60 percent more output, all else equal. This 60 percent share is broadly similar to the aggregate labor share of income in the U.S. over the same time period. The value of ρ implies that, if a firm has 100 percent more labor than another firm, we expect it to produce 140 percent more output, *not* holding all else equal. The larger firm will optimally have greater utilization of capital from the rental market and intermediate inputs from the intermediate

market. From the definition of ρ , we can back out the implied returns to scale (over labor and capital) as $\beta_L + \beta_K = \beta_L + \left(\frac{\rho - \beta_L}{1+\theta}\right)$, which equals about 1.2. Reassuringly, our returns to scale estimate is comparable to the range of estimates from 1.0 to 1.2 by Levinsohn and Petrin (2003). Note that imperfect competition in the product and labor markets attenuates incentives for firms to grow infinitely large even with increasing returns to scale.

Model Fit

Because of the tight link between the data and the parameters of interest, our model fits many moments perfectly. However, some moments could potentially fit poorly. For example, it is possible for the model to imply a private market crowd-in of procurements that does not match our estimate from the data. It is reassuring to find that the crowd-in rate implied by the estimated model is 0.07 (see Panel B of Table 2), which is nearly identical to our estimate in Section 4. Similarly, the returns to scale and diminishing returns to private output equations are closely fit by the estimated parameters.

6.3 Identification and Estimation of the Remaining Parameters

For the few remaining model parameters, the identifying equations and estimates are provided in Panel C of Table 2. These include the scale of the labor market, $\bar{\mu} \equiv \mathbb{E}[\mu_j]$, the relative price in the private market, p , the relative intermediate inputs returns versus cost, β_M/p_M , and the interquartile range of distribution of estimated TFP, to characterize $F(\cdot)$. Identification requires Assumptions 1-3 as well as the estimates of $1/\theta$, ρ , and $1/\epsilon$ from the previous subsections. Although the magnitudes of these parameters are perhaps not of interest on their own, they are needed to perform counterfactual simulations in the next section. Online Appendix C.3 provides derivations of the identifying equations.

6.4 Heterogeneity in Firm Outcomes and Behavior

So far, we have reported results for the median firm in the TFP distribution. However, the behavior of the firm depends on productivity, as evident from Figure 4. The x-axis displays the firm's percentile in the TFP distribution. In Subfigure 4(a), the y-axis presents the firm's labor, wage, wage bill, output, and profits, where each is normalized relative to the firm with median TFP. When a firm is more productive, it chooses to produce more output, which requires hiring more workers. Since the labor supply curve is upward-sloping, it must bid up wages to increase employment, which also increases the wage bill. Despite each firm facing a downward-sloping product demand curve (decreasing marginal revenues) and an upward-sloping labor supply curve (increasing marginal costs), higher TFP firms are able to produce more output and achieve substantially greater profits. Empirically, we find relative to the median firm that a firm at the 75th percentile of the TFP distribution employs 5 percent more labor, pays 1 percent higher wages and a 7 percent greater wage bill, produces 25 percent more output, and earns 27 percent more profits. By contrast, a firm at the 25th percentile of the TFP distribution employs 9 percent less labor, pays 2 percent lower

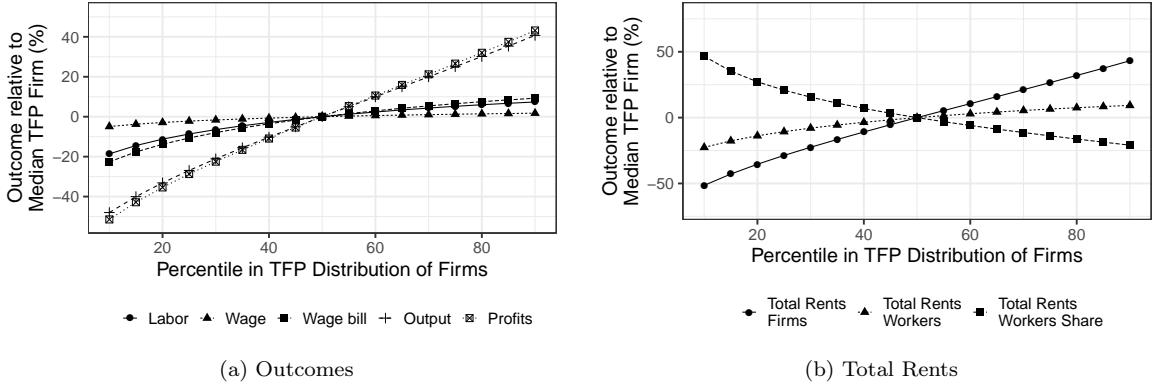


Figure 4: Firm Heterogeneity

Notes: This figure presents the counterfactual values of labor, wages, the wage bill, output, and profits (subfigure a) as well as total rents (subfigure b). It expresses these values as percentage differences from the typical firm, defined as the firm with median TFP.

wages and a 11 percent lesser wage bill, produces 27 percent less output, and earns 29 percent lower profits.

In 4(b), we compare the rents earned by firms and workers across the TFP distribution. Total rents earned by workers are proportional to the wage bill, and total rents earned by firms are equal to profits, so these estimates mirror the results for wage bill and profits in Subfigure 4(a). Since firm rents increase much more than worker rents as TFP increases, the share of rents captured by workers is decreasing in TFP.

7 Imperfect Competition and Incidence

In this section, we use the model to understand how imperfect competition in the labor and product markets affects the outcomes and behavior of workers and firms in the American construction industry.

Before presenting the results from this analysis, it is important to observe that simulating counterfactuals is computationally challenging. In particular, since $1/\theta$ and $1/\epsilon$ both appear in the firm's opportunity cost $\Delta(\Omega_j)$ (recall the definition associated with equation 8), it follows that changing these parameters also changes the optimal bid b_j^* (equation 9). In turn, the bid affects the additional rents captured by firms from winning a procurement contract. To perform the counterfactuals, we first solve the second stage problem for each Ω_j to find the counterfactual distribution of opportunity costs. Next, we solve the first stage problem to obtain the distribution of optimal bids given the counterfactual opportunity costs. Finally, we combine the optimal bid distribution from the first stage with the optimal private market profits from the second stage. From this, we recover the counterfactual outcomes, such as profits. To ease the computational burden in solving for these distributions in the two-stage problem, we implement the quantile representation method of Luo (2020). We focus on counterfactual results for the typical firm (as defined by the firm with the

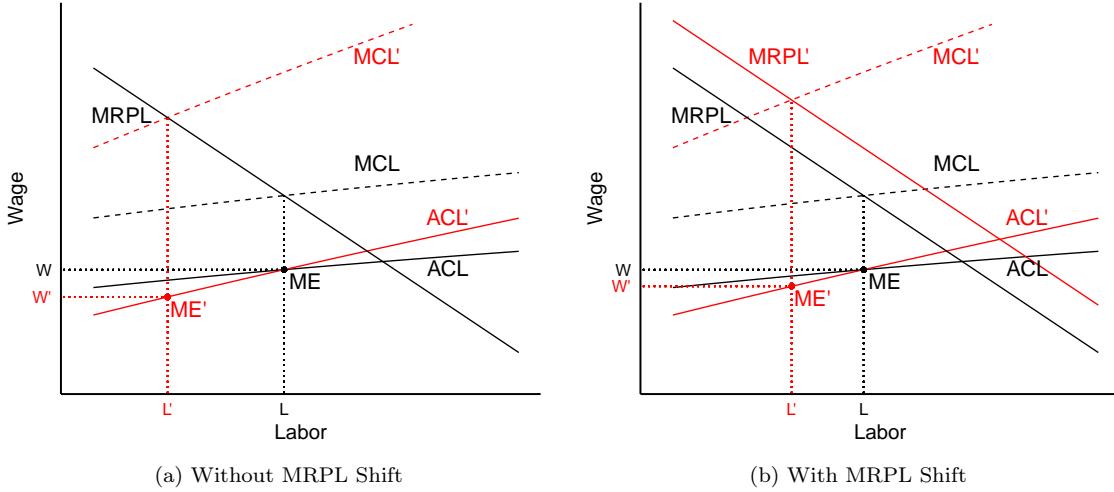


Figure 5: Illustration: Rotation of the Labor Supply Curve

Notes: This diagram visualizes the counterfactual exercise of making the labor market less competitive. ACL denotes the average cost of labor, MCL denotes the marginal cost of labor, ME denotes the monopsonistic equilibrium, and MRPL denotes the marginal revenue product of labor. Black colors denote the initial economy, and red colors denote the new economy after rotating the labor supply curve through a compensated decrease in the labor supply elasticity, $1/\theta$. In subfigure (a), MRPL is not allowed to adjust when $1/\theta$ decreases, while in subfigure (b), the MRPL is allowed to adjust when $1/\theta$ decreases.

median value of Ω_j), which further reduces the computational burden. Computational details are provided in Online Appendix F.

7.1 The Importance of Imperfect Competition in the Labor Market

Defining and Interpreting the Counterfactual

To study the importance of imperfect competition in the labor market, we consider a compensated rotation of the labor supply curve of a given firm, holding all other firms fixed, so that the labor supply elasticity, $1/\theta$, decreases while the initial equilibrium labor and wage choices remain feasible for the firm. In practice, this means that we first solve for the initial monopsonistic equilibrium (ME) in the labor market, (L_j, W_j) , shift $1/\theta$ to $1/\theta'$, then compensate firm j for this increase in the average cost of labor by shifting the firm-specific labor supply curve intercept μ_j to μ'_j so that (L_j, W_j) is still on the labor supply curve.

Figure 5 provides an illustration of rotating the labor supply curve. It considers a fictional firm j , with labor on the x-axis and the wage on the y-axis. The initial equilibrium is in black, while the equilibrium after rotating the labor supply curve is in red. The initial average cost of labor curve (ACL, solid line) and its associated marginal cost of labor curve (MCL, dashed line) are in black. The marginal revenue product of labor curve (MRPL) is also in black. To determine the equilibrium (ME), the monopsonistic firm chooses labor to equate MCL and MRPL, then marks down the wage by choosing the lowest feasible wage at this quantity of labor, which is on the ACL curve directly below the intersection of MCL and MRPL.

The red lines in Figure 5(a) demonstrate how the equilibrium adjusts when the labor supply curve is made “steeper” by lowering $1/\theta$ to $1/\theta'$. Lowering $1/\theta$ raises the average cost of labor, so we compensate the firm by decreasing the intercept of each firm’s labor supply curve until the initial ME is on the new labor supply curve (that is, we ensure ME is on ACL'). The new marginal cost of labor curve (MCL') is higher, so the point at which $MRPL$ intersects MC' is at a lower level of labor (that is, L' is less than L on the x-axis). Since ACL' is lower than ACL , it follows that ME' must also have a lower wage than ME (W' is less than W on the y-axis). Furthermore, since ME is a feasible choice of the firm, and the firm chooses a different point ME' to maximize profits, it must have higher profits with the counterfactual labor supply curve. Thus, the counterfactual exercise in Figure 5(a) always results in firm j employing fewer workers, paying a lower wage to each employee, producing less private market output, becoming more capital-intensive, and earning higher profits.

Figure 5(b) presents the same exercise, but allowing the $MRPL$ to also shift in response to the decrease in $1/\theta$. The reason decreasing $1/\theta$ results in higher $MRPL$ is because firms produce using capital, which is rented in a perfect capital market. When the marginal cost of labor is higher, firms will choose to use more capital per worker. Thus, a one worker increase in labor corresponds to a greater marginal increase in capital if $1/\theta$ is lower, which implies that $MRPL$ increases when $1/\theta$ decreases. As a result, the point at which MC' intersects $MRPL'$ is to the right of the point at which MC' intersects $MRPL$, which implies that L' is greater when $MRPL$ shifts than when $MRPL$ does not shift. Thus, the counterfactual exercise in Figure 5(b) results in a less extreme decrease in labor and wages than the exercise in Figure 5(a).

Characteristics of the Actual and Counterfactual Labor Markets

In Figure 6, we present the empirical results from the counterfactual analysis where we increase the degree of imperfect competition in the labor market by rotating the labor supply curve. We find that, as the firm gains more market power, it employs fewer workers and pays a lower wage to each employee. By taking advantage of its market power to increasingly markdown wages below marginal products, the firm earns higher profits. These results are consistent with the predictions from the diagram in Figure 5. Because of the monotonic relationships across values of the labor supply elasticity, we focus on comparing the actual value ($1/\theta = 4.08$) and half of this amount ($1/\theta' = 2.04$).

In the counterfactual economy where the labor supply elasticity of a given firm is reduced by half, the firm employs 15 percent fewer workers and decreases wages by 7 percent. Capital only falls by 4 percent, indicating a shift toward capital-intensive production as the marginal cost of labor rises. While total output is reduced by 12 percent, the profit of the firm is 3 percent higher because it takes advantage of its additional market power in the labor market to increasingly markdown wages. Taken together, these results highlight the scope for increased labor market power to affect the wages that firms pay and the profits they accrue.

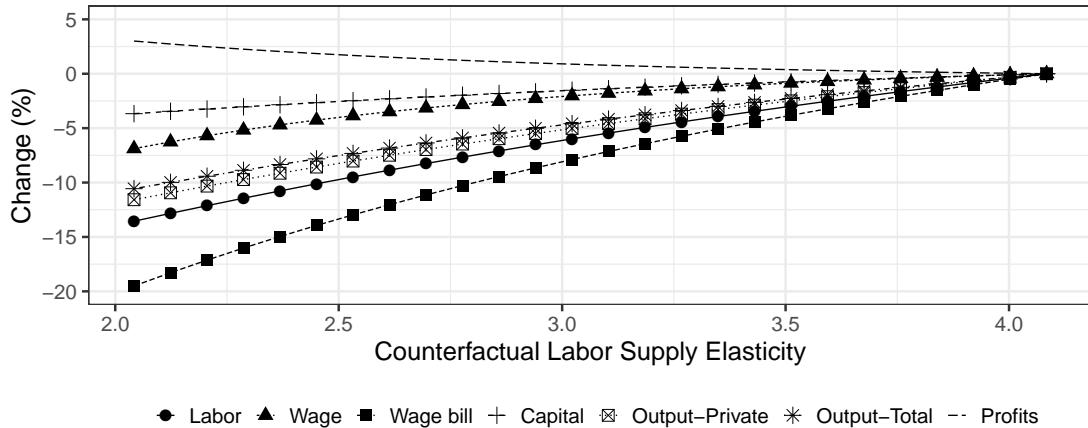


Figure 6: Counterfactual Rotation of the Labor Supply Curve

Notes: This figure presents the counterfactual median values of labor, wages, the wage bill, capital, private market output, total output, and profits when the labor market becomes less competitive. It expresses these values as percentage changes relative to the actual economy for the typical firm.

Winning the Procurement Auction in the Actual and Counterfactual Labor Markets

In Table 3, we quantify the impact of winning an auction by estimating the percentage change in various outcomes of interest if the firm wins the auction versus if it loses the auction. It compares these percentage changes induced by auctions in the actual economy ($1/\theta = 4.08$, first column) and the counterfactual economy in which firms have greater labor market power ($1/\theta' = 2.04$, second column).

In both economies, winning the auction induces the firm to increase total output, both to complete the procurement project and to produce additional private market output (due to crowd-in). The key difference in the economies is that the marginal cost of increasing output is greater when the labor supply curve is steeper. The firm chooses to increase employment by less and thus increase output less in the private market. When the labor supply curve is steeper, the firm must bid up wages more to achieve the increase in employment. Given that the firm hires less additional labor but at a greater wage, the wage bill may in theory be higher or lower when the labor supply curve is steeper. Empirically, we find that when the labor supply curve is steeper, total output increases by 14.6 percent (versus 14.8 percent in the actual economy), private market output increases by 1.7 percent (versus 3.5 percent in the actual economy), employment increases by 9.2 percent (versus 10.5 percent in the actual economy), the wage rate increases by 4.5 percent (versus 2.6 percent in the actual economy), and the wage bill increases by 13.8 percent (versus 13.0 percent in the actual economy).

We now examine the additional rents captured by workers if the firm it belongs to wins versus loses the procurement auction. Our expressions in Section 5.3 make clear that marginal rents for workers depend on the change in the wage bill relative to the labor supply elasticity. Since the wage bill increases and the elasticity decreases in the counterfactual economy, this serves to increase the marginal rents for workers which is reflected in the table. In particular, workers earn

Changes Induced by Winning an Auction		
Labor Supply Elasticity ($1/\theta$)	Actual (4.08)	Counterfactual (2.04)
Employment	10.5%	9.2%
Wage	2.6%	4.5%
Wage bill	13.0%	13.8%
Output - Private Market	3.5%	1.7%
Output - Total	14.8%	14.6%
Firm Rents (Profits)	7.6%	7.6%
Worker Rents	15.0%	16.0%

Table 3: Changes Induced by Winning an Auction: Actual and Counterfactual Labor Markets

Notes: This table presents the percentage change in each outcome for the typical firm if it wins the auction versus if it loses. It shows these percentage changes both in the actual economy (first column) and in the counterfactual economy in which the labor supply elasticity is half as great (second column).

16 percent additional rents in the counterfactual economy, which is slightly greater than the 15 percent additional rents in the actual economy. This is consistent with standard intuition from public economics that as the elasticity of workers decreases (holding constant the labor demand elasticity), this increases the incidence on workers.

We also examine the additional rents captured by the firm if it wins versus loses the procurement auction, which is equal to the gain in profits (equation 17). Our findings indicate that the change in profits is nearly identical in the actual and counterfactual economies, with the firm increasing profits by about 8 percent if it wins the auction versus if it loses the auction. If it wins, the firm wishes to increase output. To do so, it hires additional labor. The marginal cost of labor is greater when the labor supply curve is steeper, which tends to decrease marginal profits. However, the firm also has greater market power and suppresses the number of new hires in order to markdown wages, which tends to increase marginal profits. Accounting for these opposing forces in the model, we find that the change in profits is nearly identical in the actual and counterfactual economies, with the firm increasing profits by about 8 percent if it wins the auction versus if it loses the auction.

7.2 The Importance of Imperfect Competition in the Product Market

Defining and Interpreting the Counterfactual

To study market power in the private product market, we consider a compensated rotation of the private product market demand curve (hereafter, demand curve) so that the demand elasticity, $1/\epsilon$, decreases while the initial equilibrium output and price combination remains feasible. In practice, this means that we first solve for the initial monopolistic product market equilibrium (PE), (Q_j^H, R_j^H) , shift $1/\epsilon$ to $1/\epsilon'$, then compensate firm j for this decrease in the average revenue per unit of output by shifting the demand curve scale term p to p' so that (Q_j^H, R_j^H) is still on the demand

curve.

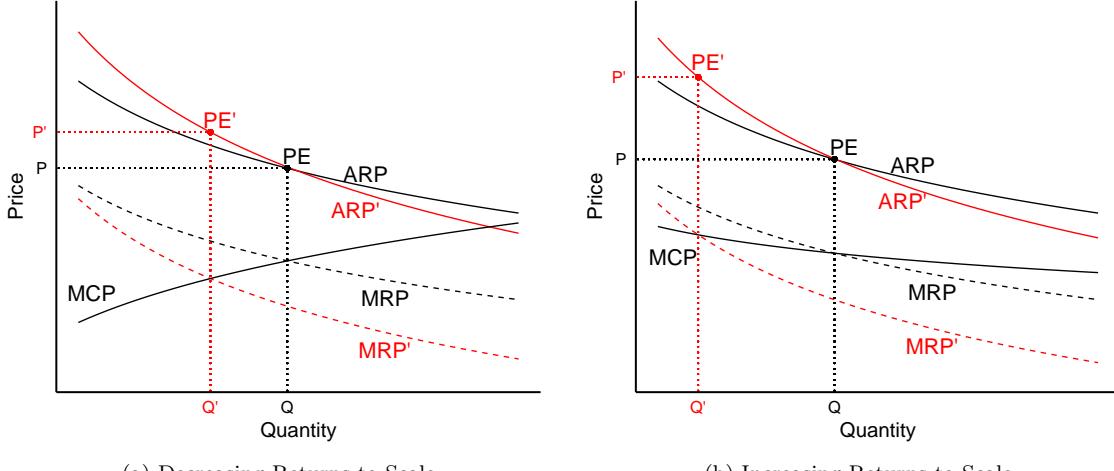


Figure 7: Illustration: Rotation of the Private Demand Curve

Notes: This diagram visualizes the counterfactual exercise of making the private product market less competitive. MCP denotes the marginal cost of production, MRP denotes marginal revenue product, ARP denotes average revenue product, and PE denotes the monopolistic product market equilibrium. Black colors denote the initial economy, and red colors denote the new economy after rotating the private demand curve through a compensated decrease in the demand elasticity, $1/\epsilon$. In subfigure (a), we represent decreasing returns to scale with an upward-sloping MCP, while in subfigure (b), we represent increasing returns to scale with a downward-sloping MCP.

Figure 7 provides an illustration of rotating the demand curve. It considers a fictional firm j , with private market output quantity on the x-axis and private market price on the y-axis. The initial equilibrium is in black, while the equilibrium after rotating the private demand curve is in red. The initial average revenue product (ARP, solid line) and its associated marginal revenue product (MRP, dashed line) are in black. The marginal cost of production curve (MCP) is also in black. To determine the equilibrium (PE), the monopolistic firm optimally chooses output to equate MCP and MRP, then marks up the price by choosing the highest feasible price at this quantity of output, which is on the ARP curve directly above the intersection of MCP and MRP.

The red lines in Figure 7(a) demonstrate how the equilibrium adjusts when the private demand curve is made “steeper” by lowering $1/\epsilon$ to $1/\epsilon'$. Lowering $1/\epsilon$ lowers the average revenue product, so we compensate the firm by increasing the multiplicative term p until the initial PE is on the new demand curve (that is, we ensure PE is on ARP'). The new marginal revenue product curve (MRP') is lower, so the point at which MCP intersects MRP' is at a lower level of output (that is, Q' is less than Q on the x-axis). Since ARP' is above ARP at Q' , it follows that PE' must also have a higher price than PE (P' is greater than P on the y-axis). Since the firm wishes to produce less, it needs to decrease inputs. To decrease labor, the firm lowers the wages it pays each employee, which also results in a lower wage bill. The relative price of labor to capital decreases, so the substitution effect results in capital decreasing more than labor. Furthermore, since PE is a feasible choice of the firm, and the firm chooses a different point PE' to maximize profits, it must have higher profits with

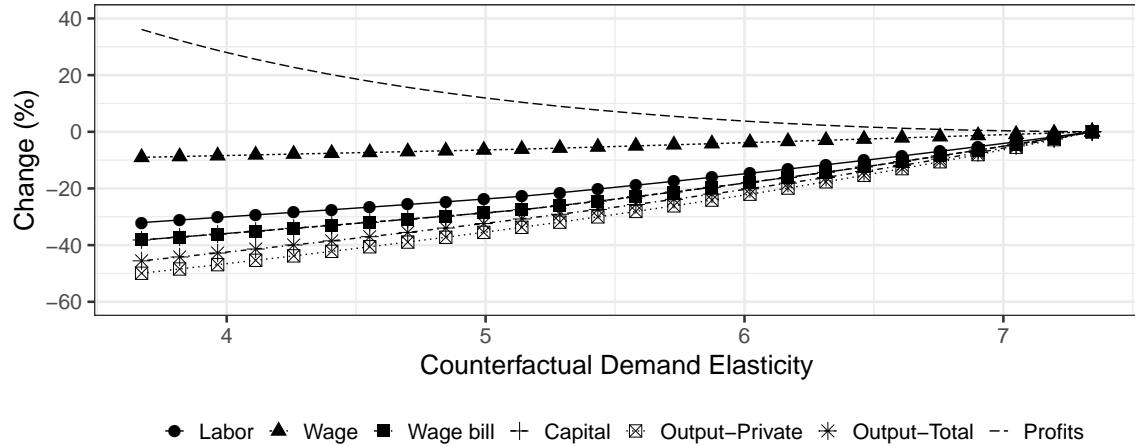


Figure 8: Counterfactual Rotation of the Private Demand Curve

Notes: This figure presents the counterfactual median values of labor, wages, the wage bill, capital, private market output, total output, and profits when the private product market becomes less competitive. It expresses these values as percentage changes relative to the actual economy for the typical firm.

the counterfactual demand curve. Thus, the counterfactual exercise in Figure 7(a) always results in firm j producing less private market output, employing fewer workers, paying a lower wage to each employee, using less capital, and earning higher profits. Note that increasing returns to scale may partially reverse some of these effects, and we account for these returns to scale in the empirical application.

Figure 7(b) presents the same exercise, but accounting for a downward-sloping MCP curve. The downward-sloping MCP is due to increasing returns to scale (over labor and capital), which effectively makes the marginal cost decreasing in the output quantity. When the MCP is downward-sloping, a rotation of the private demand curve results in MCP intersecting MRP' at a lower output quantity Q' . Thus, the counterfactual exercise in Figure 7(b) results in a more extreme decrease in output and and more extreme markup of prices than the exercise in Figure 7(a).

Characteristics of the Actual and Counterfactual Private Product Markets

In Figure 8, we present the counterfactual analysis where we increase the degree of imperfect competition by rotating the demand curve. We find that, as the firm gains more market power, it cuts production in the private market and marks up the price. This allows it to increase profits. To reduce output, it employs fewer workers and pays a lower wage to each employee. These results are consistent with the predictions from the diagram in Figure 7. Because of the monotonic relationships across values of the demand elasticity, we focus on comparing the actual value ($1/\epsilon = 7.34$) and half of this amount ($1/\epsilon' = 3.67$).

The empirical estimates from our counterfactuals show that, when the demand elasticity is reduced by half, the firm produces 50 percent less output in the private market and 45 percent less total output. To do so, it employs 30 percent fewer workers. Wages decrease by 10 percent and the

Changes Induced by Winning an Auction		
Private Demand Elasticity ($1/\epsilon$)	Actual (7.34)	Counterfactual (3.67)
Employment	10.5%	17.1%
Wage	2.6%	4.2%
Wage bill	13.0%	21.2%
Output - Private Market	3.5%	3.0%
Output - Total	14.8%	24.2%
Firm Rents (Profits)	7.6%	5.6%
Worker Rents	15.0%	27.0%

Table 4: Changes Induced by Winning an Auction: Actual and Counterfactual Private Product Demand

Notes: This table presents the percentage change in each outcome for the typical firm if it wins the auction versus if it loses. It shows these percentage changes both in the actual economy (first column) and in the counterfactual economy in which the private demand elasticity is half as great (second column).

wage bill decreases by nearly 40 percent. Capital also decreases by 40 percent. Despite the large reduction in output, profits increase by nearly 40 percent in the counterfactual, as firms increasingly markup prices. Taken together, these results highlight the scope for increased product market power to affect the wages that firms pay and the profits they accrue.

Winning the Procurement Auction in the Actual and Counterfactual Product Markets

In Table 4, we quantify the impact of auctions by estimating the percentage change in various outcomes of interest if the firm wins the auction versus if it loses the auction. It compares these percentage changes induced by auctions in the actual economy ($1/\epsilon = 7.34$, first column) and the counterfactual economy in which firms have greater private product market power ($1/\epsilon' = 3.67$, second column). When the private market demand curve is steeper, the firm chooses to produce less in total so that it can markup prices. Thus, a smaller share of output is produced in the private market when the demand curve is steeper. Due to increasing returns to scale, winning the auction makes the firm wish to increase private market activity, both in the actual and counterfactual economies. But when the firm has more market power, this increase is mitigated by the firm choosing to keep output low so that it can markup prices. Because government output accounts for a greater share of total output when the demand curve in the private market is steeper, winning the contract gives a greater percent change in total output but a smaller percent change in private market output.

We now examine the additional rents captured by workers and firms if the firm wins versus loses the procurement auction. Because the firm increases total output by a greater percent if it wins the auction in the counterfactual economy, it must also increase employment by a greater percent. To increase employment by a greater percent, it must bid up wages by a greater percent in the counterfactual economy. The greater percent increase in both wages and employment translates into a greater percent increase in rents captured by workers in the counterfactual economy. However,

in the counterfactual economy, marginal revenue in the private market is lower, making it less profitable to increase private market output, which decreases the additional rents captured by firms in the counterfactual economy. Empirically, we find that if the firm wins the auction, workers earn 27 percent additional rents and firms earn 6 percent additional rents in the counterfactual economy, which is substantially greater than the 15 percent additional rents in the actual economy for workers but less than the 8 percent gain in rents for firms in the actual economy.

8 Conclusion

The primary goal of our paper was to quantify the importance of imperfect competition in the U.S. construction industry by estimating the size of rents earned by American firms and workers. To obtain a comprehensive measure of the total rents and to understand its sources, we take into account that rents may arise both due to markdown of wages and markup of prices.

Our analyses combined the universe of U.S. business and worker tax records with newly collected records from U.S. procurement auctions. We first examined how firms respond to a plausibly exogenous shift in product demand through a difference-in-differences design that compares first-time procurement auction winners to the firms that lose, both before and after the auction. Motivated and guided by these estimates, we next developed, identified, and estimated a model where construction firms compete with one another for projects in the product market and for workers in the labor market. The firms may participate both in the private market and in government projects, the latter of which are procured through first-price sealed-bid auctions.

We found that American construction firms have significant wage- and price-setting power. This imperfect competition generates a considerable amount of rents, two-thirds of which is captured by the firms. We concluded our empirical analyses by using the estimated model to perform counterfactual analyses which reveal how increases in the market power of firms, in the product market or the labor market, would affect the outcomes and behavior of workers and firms in the construction industry.

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For Online Publication

A Additional Tables and Figures

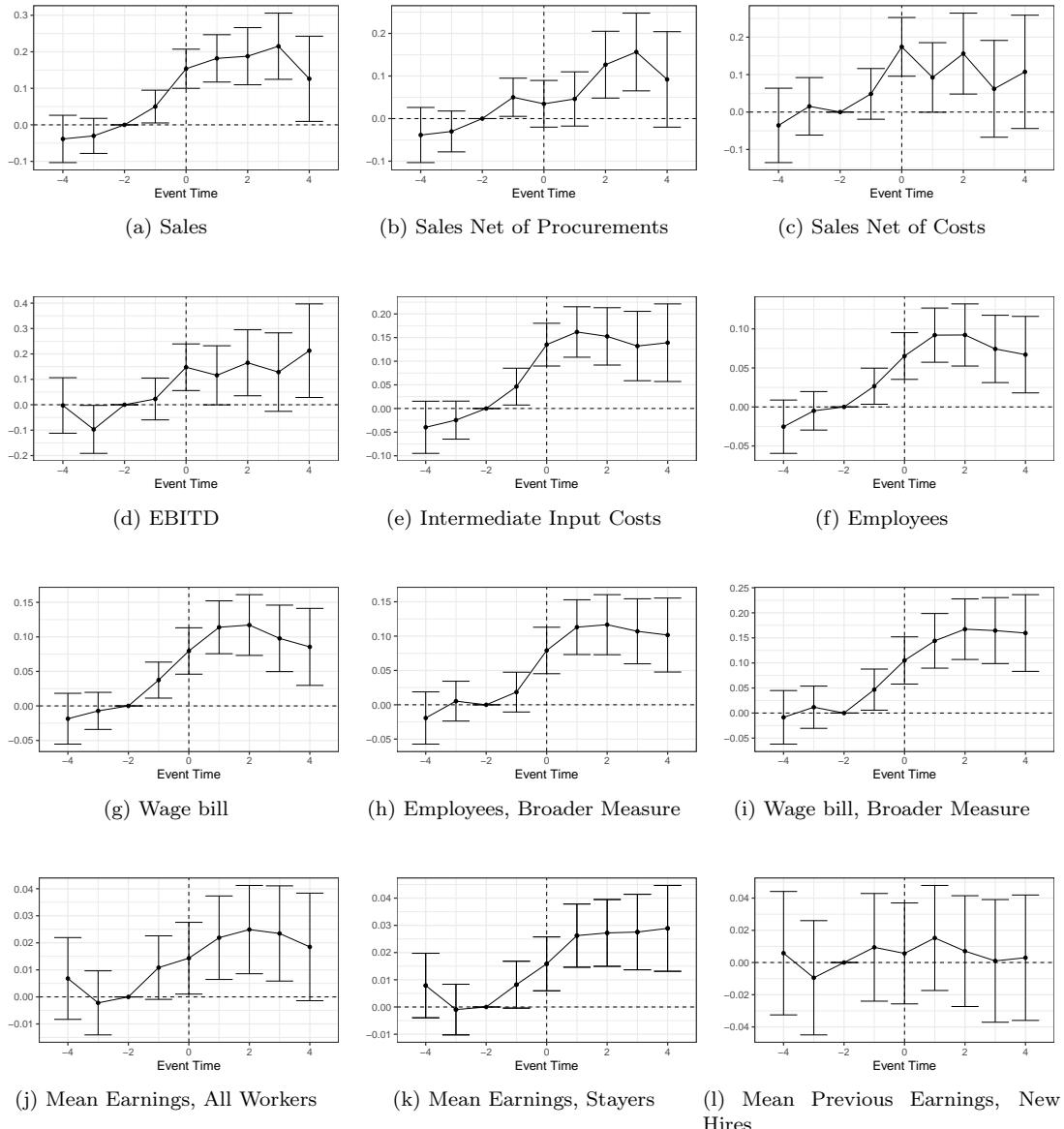


Figure A.1: Difference-in-differences Estimates at Annual Frequency

Notes: This figure presents average treatment effect on the treated estimates using the difference-in-differences specification defined in the text. All outcomes are in log units. All results include firm fixed effects. The control units are those firms that place a bid in a procurement auction in the same year that the reference treatment cohort wins. The omitted relative time is -2 . 90 percent confidence intervals are displayed, clustering on firm. See Online Appendix B.1 for additional details on sample definitions.

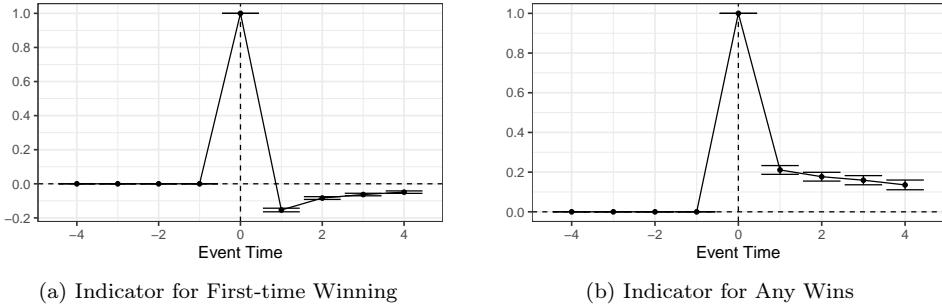
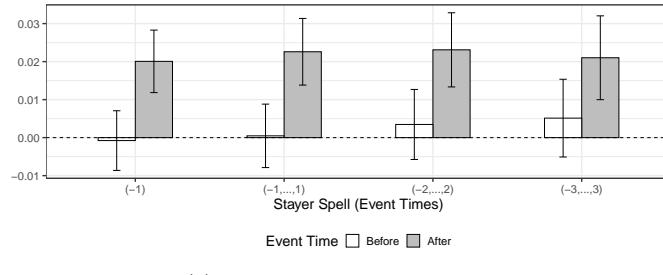
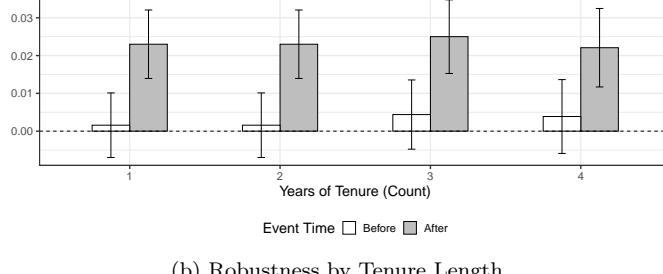


Figure A.2: Visualizing the Difference-in-differences Research Design

Notes: This figure presents average treatment effect on the treated estimates using the difference-in-differences specification defined in the text. All results include firm fixed effects. The control units are those firms that place a bid in a procurement auction in the same year that the reference treatment cohort wins. The omitted relative time is -2 . 90 percent confidence intervals are displayed, clustering on firm. See Online Appendix B.1 for additional details on sample definitions and outcomes.



(a) Robustness by Stayer Spell



ification defined in the text. All outcomes are in log units. All results include firm fixed effects. “Before” refers to relative times $\{-4, -3, -2\}$ and “After” refers to relative times $\{0, 1, 2\}$. The Baseline sample restricts the control units to those that place a bid in a procurement auction in the same year that the reference treatment cohort wins. The omitted relative time is -2 . 90 percent confidence intervals are displayed, clustering on firm. Subfigure (a) varies the window in which the worker must have been employed by the bidding firm, where “ $(-2, \dots, 2)$ ” is treated as the baseline definition of stayers. Subfigure (b) varies the window over which the worker must have been employed prior to the auction bid, e.g., tenure of 4 means that the worker was employed from relative time -4 until at least relative time 0 . See Online Appendix B.1 for additional details on sample definitions and outcomes.

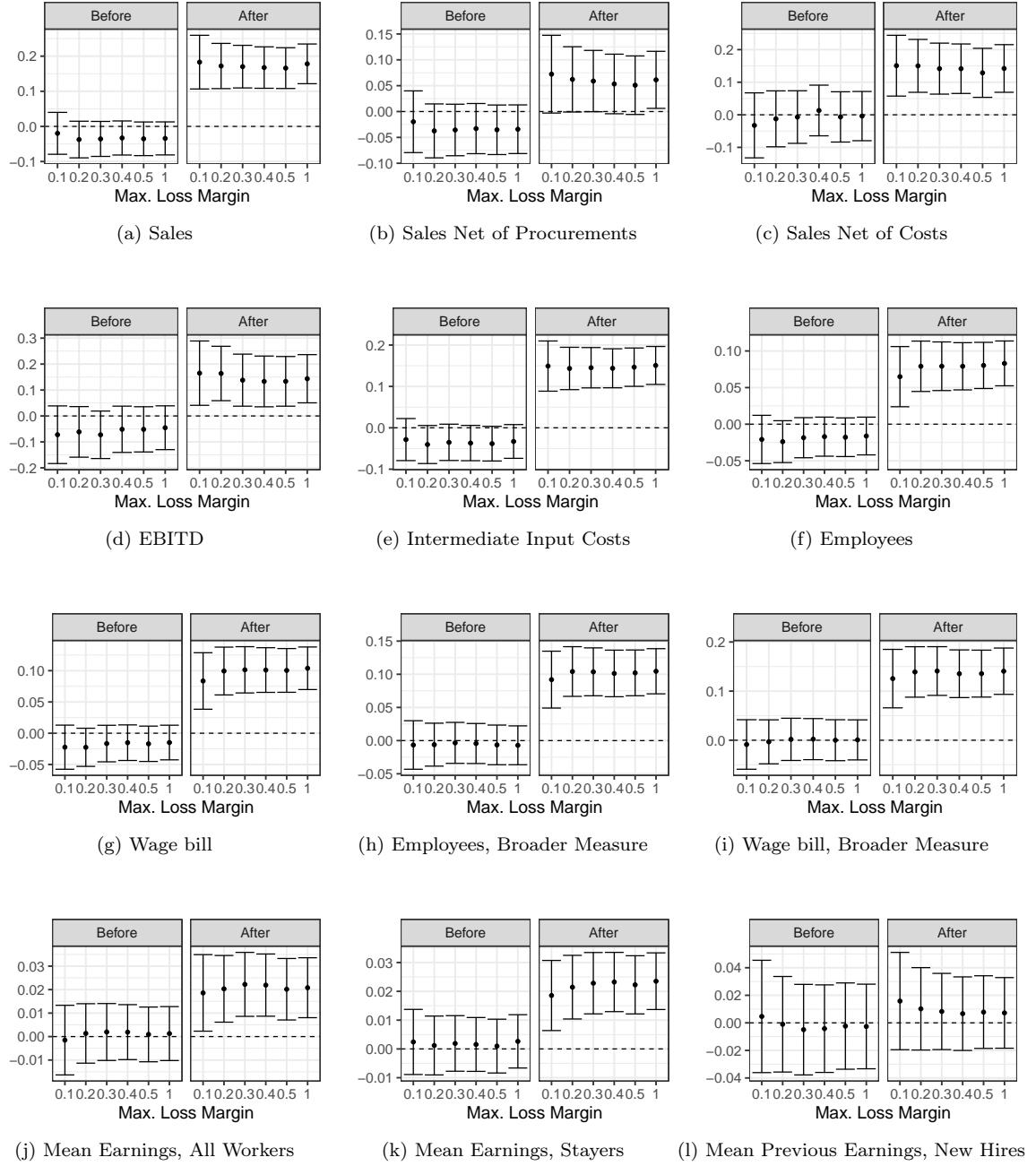


Figure A.4: Restricting the Control Group's Bid Loss Margin

Notes: This figure presents average treatment effect on the treated estimates using the difference-in-differences specification defined in the text. All outcomes are in log units. All results include firm fixed effects. “Before” refers to relative times $\{-4, -3, -2\}$ and “After” refers to relative times $\{0, 1, 2\}$. The Baseline sample restricts the control units to those that place a bid in a procurement auction in the same year that the reference treatment cohort wins. We then restrict the control group to firms whose bid loss margin was lower than the number displayed on the x-axis. See Online Appendix B.1 for additional details on sample definitions and outcomes.

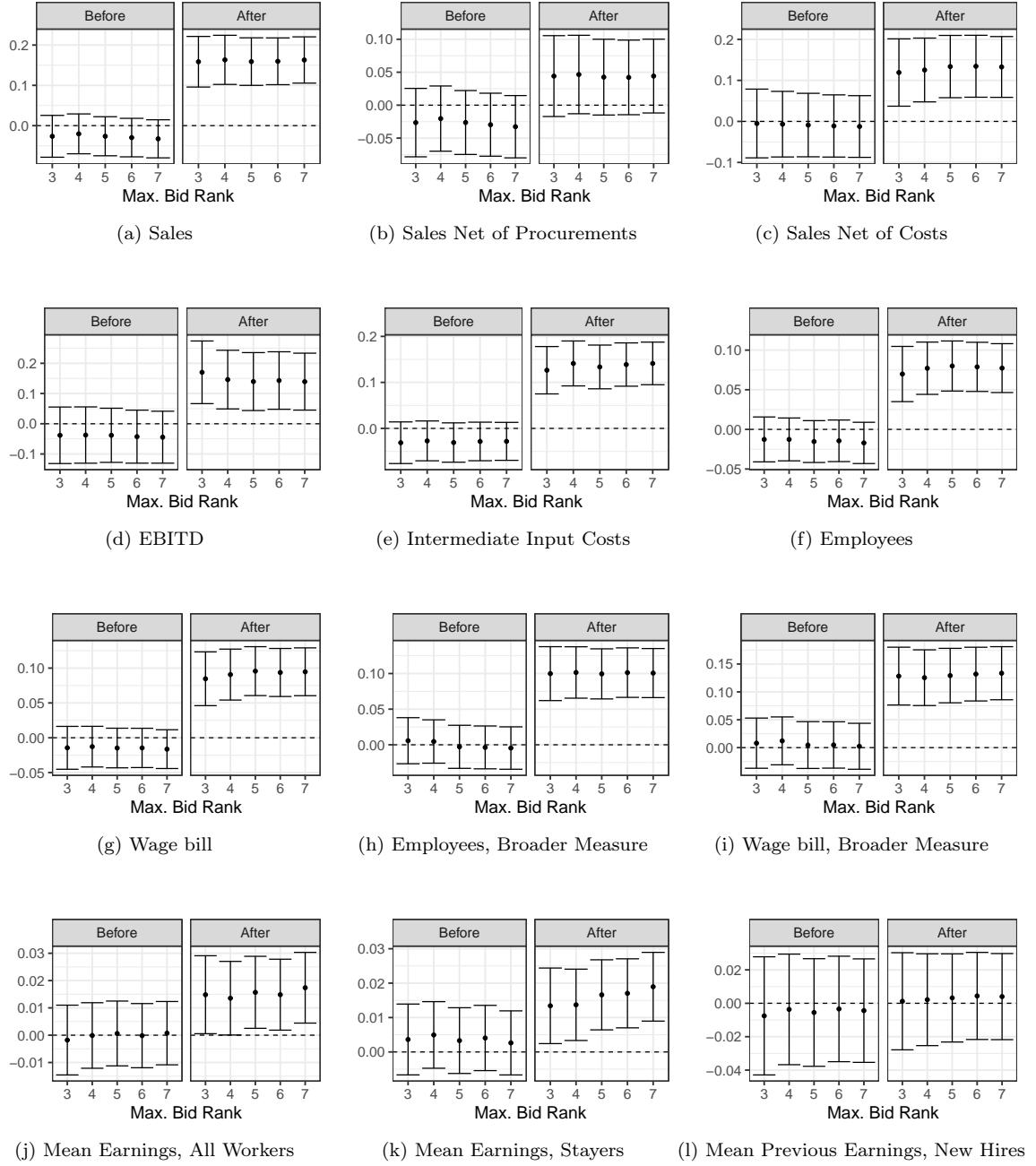


Figure A.5: Restricting the Control Group's Bid Ranks

Notes: This figure presents average treatment effect on the treated estimates using the difference-in-differences specification defined in the text. All outcomes are in log units. All results include firm fixed effects. “Before” refers to relative times $\{-4, -3, -2\}$ and “After” refers to relative times $\{0, 1, 2\}$. The Baseline sample restricts the control units to those that place a bid in a procurement auction in the same year that the reference treatment cohort wins. We then restrict the control group to firms whose bid rank was less than or equal to the number displayed on the x-axis. See Online Appendix B.1 for additional details on sample definitions and outcomes.

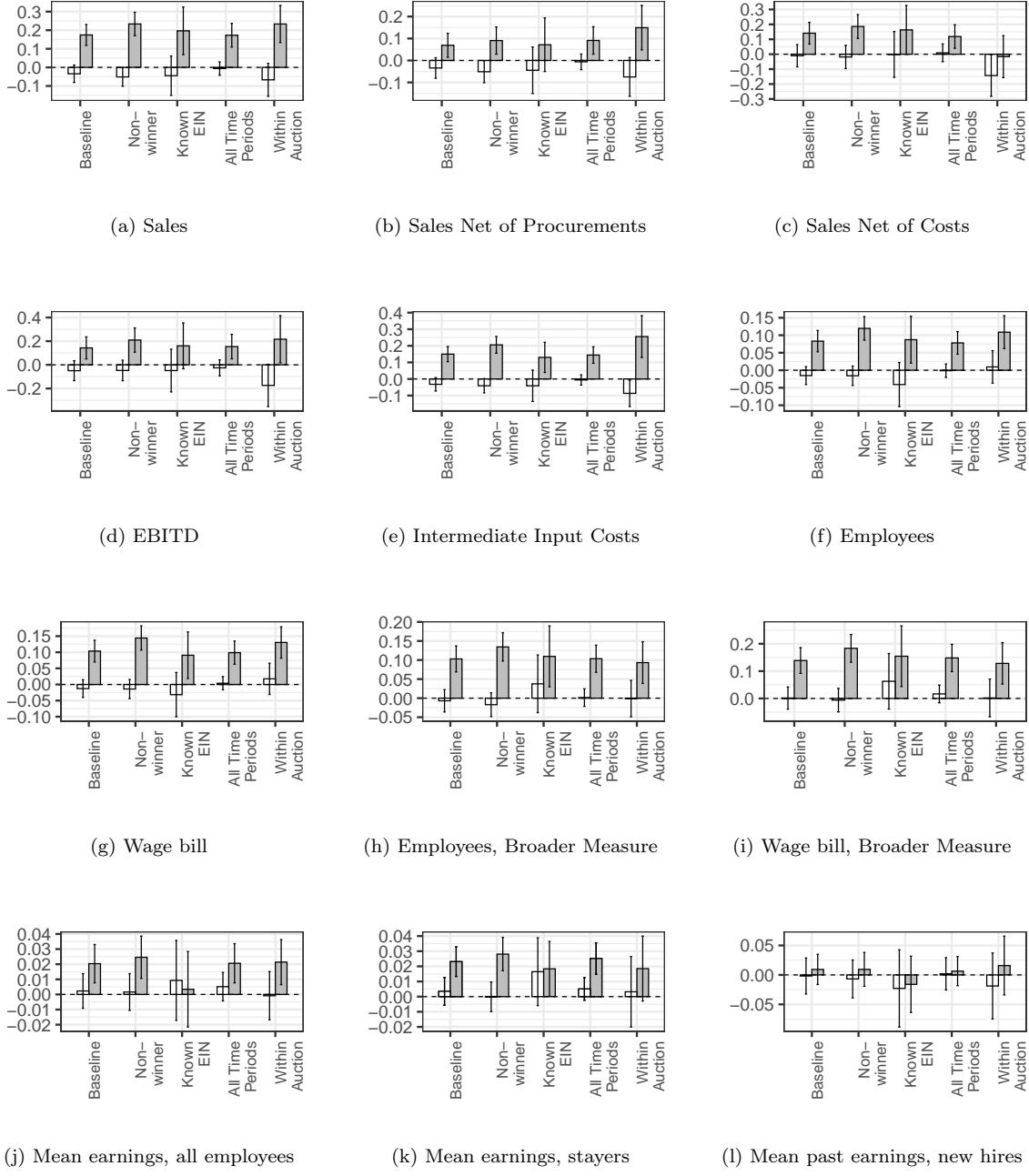


Figure A.6: Robustness and Specification Checks

Notes: This figure presents average treatment effect on the treated estimates using the difference-in-differences specification defined in the text. All outcomes are in log units. All results include firm fixed effects. “Before” refers to relative times $\{-4, -3, -2\}$ and “After” refers to relative times $\{0, 1, 2\}$. “Baseline” restricts the control firms to those that place a bid in a procurement auction in the same year that the reference treatment cohort wins. “Non-winner” further restricts the control firms to those that do not win an auction until at least relative time 4. In “All Time Periods”, “Before” refers to relative times $\{-4, -3, -2, -1\}$ and “After” refers to relative time $\{0, 1, 2, 3, 4\}$. “Within Auction” further restricts the control firms to those that place bids within the same auction as the winner, then estimates the difference-in-differences specification separately by auction and averages the estimates across auctions. The omitted relative time is -2 . 90 percent confidence intervals are displayed, clustering on firm. See Online Appendix B.1 for additional details on sample definitions and outcomes.

B Online Appendix: Data Sources

B.1 Tax Data

All firm-level variables are constructed from annual business tax returns over the years 2001-2015: C-Corporations (Form 1120), S-Corporations (Form 1120-S), and Partnerships (Form 1065). Worker-level variables are constructed from annual tax returns over the years 2001-2015: Direct employees (Form W-2) and independent contractors (Form 1099).

Tax Return Variable Definitions:

- **Earnings:** Reported on W-2 box 1 for each Taxpayer Identification Number (TIN). Each TIN is de-identified in our data.
- **Employer:** The Employer Identification Number (EIN) reported on W-2 for a given TIN. Each EIN is de-identified in our data.
- **Employees:** Number of workers matched to an EIN in year t from Form W-2 with annual earnings above the annualized full-time minimum wage and where the EIN is this worker's highest-paying employer.
- **Wage bill:** Total earnings among employees in year t .
- **Contracted worker:** Number of 1099-MISC individuals matched to an EIN in year t .
- **Employees, Broader Measure:** Total number of W-2 workers plus 1099 contracted workers matched to an EIN in year t .
- **Wage bill, Broader Measure:** Sum of earnings for the broader sample of employees matched to an EIN in year t .
- **NAICS Code:** The NAICS code is reported on line 21 on Schedule K of Form 1120 for C-corporations, line 2a Schedule B of Form 1120S for S-corporations, and Box A of form 1065 for partnerships. We consider the first three digits to be the industry. We code invalid industries as missing.
- **Sales:** Line 1 of Form 1120 for C-Corporations, Form 1120S for S-Corporations, and Form 1065 for partnerships. Also referred to as gross revenues.
- **Intermediate Input Costs:** Line 2 of Form 1120 for C-Corporations, Form 1120S for S-Corporations, and Form 1065 for partnerships. Also referred to as cost of goods sold.
- **EBITD:** We follow Kline et al. (2019) in defining Earnings Before Interest, Taxes, and Depreciation (EBITD) as the difference between total income and total deductions other than interest and depreciation. Total income is reported on Line 11 on Form 1120 for C-corporations, Line 1c on Form 1120S for S-corporations, and Line 1c on Form 1065 for Partnerships. Total deductions other than interest and depreciation are computed as Line 27 minus Lines 18 and 20 on Form 1120 for C-corporations, Line 20 minus Lines 13 and 14 on Firm 1120S for S-corporations, and Line 21 minus Lines 15 and 16c on Form 1065 for partnerships.

- **Sales Net of Costs:** This is sales minus intermediate input costs minus wage bill.

Procurement Auction Variable Definitions:

- **Bid:** The dollar value submitted by the firm as a price at which it would be willing to complete the procurement project.
- **Auction winner:** A firm is an auction winner if it placed the lowest bid in a procurement auction.
- **Amount of winnings:** Bid placed by the winner in each auction.
- **Year of first win:** First year in which the firm is an auction winner. To account for left-censoring, we do not define a win as a “first win” unless there were at least two observed years of data during which the firm could have won and did not win an auction. For example, if a state provided auction records for 2001-2015, and a firm is first observed winning in 2001 or 2002, we do not consider this firm a first-time winner, but if the firm is first observed winning in 2003 or later, we consider it a first time winner.

Firm sample definitions:

- **Baseline sample:** A firm that files tax form 1120, 1120-S, or 1065 is considered part of the baseline sample centered around auction cohort c if it is observed bidding in an auction in year c .
- **Sample of close bidders (cardinal):** A firm in the baseline sample at c is also in the sample of close bidders (cardinal) if, in at least one auction in year c , its bid was less than $\mathcal{T} \times 100$ percent greater than the bid of the winner, where \mathcal{T} is referred to as the loss margin. For example, if $\mathcal{T} = 0.10$, the firm must have placed a bid within 10 percent of the winner’s bid in at least one auction at c .
- **Sample of close bidders (ordinal):** A firm in the baseline sample at c is also in the sample of close bidders (ordinal) if, in at least one auction in year c , it had at least the R lowest bid in the auction, where R is referred to as the bid rank. For example, if $R = 3$, the firm must have been among the 3 lowest bidders (inclusive of the winner) in at least one auction at c .
- **Sample of non-winners:** A firm in the baseline sample at c that does not win an auction before or during c is called a non-winner if it continues to not win any auctions until at least relative time $t \geq 4$. For example, if $c = 2005$, then a non-winner must not win its first auction until at least 2009.
- **Known EIN sample:** Firms from the six states in which the auction records included the EIN, thus allowing us to link records exactly rather than using a fuzzy matching algorithm.

Worker sample definitions:

- **Main sample:** A worker is considered part of the main sample at c if the worker’s highest-paying firm at c on Form W-2 is in the baseline sample of firms and the W-2 wage payments from that firm are greater than \$15,000 in 2015 USD. We also restrict to workers aged 25-60.

- **Broader sample:** A worker is considered part of the broader sample at c if the worker receives a W-2 or 1099 form associated with a firm in the baseline sample of firms at c .
- **Stayers:** A worker is a stayer for $2k+1$ years at firm j in the baseline sample of firms at c if the worker's highest-paying W-2 firm is the same firm during each time period in $(c-k, \dots, c+k)$ and the W-2 wage payments from that firm in each year are greater than \$15,000 in 2015 USD.
- **Tenure:** A worker has k years of tenure at firm j in the baseline sample of firms at c if the worker's highest-paying W-2 firm is the same firm during each time period in $(c-k, \dots, c)$ and the W-2 wage payments from that firm in each year are greater than \$15,000 in 2015 USD.
- **New Hires:** A worker is a new hire at firm j in year t if the worker's highest-paying W-2 employer in year t was firm j and highest-paying W-2 employer in year $t-1$ was firm $j' \neq j$, where the worker received W-2 wage payments greater than \$15,000 in 2015 USD from j' in $t-1$ as well as from j in t .

B.2 Acquisition and Preparation of Auction Data

This appendix describes our data sources for auction bids and how we build the data set for our main application. Online Appendix Table A.4 provides a summary of the sources of DOT records by state.

Bid Express Auction Records

The Bid Express website collects information on bids and bidders for procurement auctions held by Departments of Transportation of many US states. It can be freely accessed at www.bidx.com, although the access to information on the bidders requires a paid account registration. We scraped 17 states' DOT auction records from Bid Express. We performed the scraping using the Python library *Selenium* to automate browser actions. We registered a BidX.com account, which is required to access bidder information.

We collect the auction information for a given state using the following procedure:

1. We go to the web page of that state on BidX.com and select the latest letting.

Browser actions: visit www.bidx.com, select the desired agency from “Select a U.S. Agency” drop down menu and click the button “go”. An illustration is provided in Online Appendix Figure A.7a. Then click the “Letting” tab on the top left corner of the new refreshed web page and click the first letting date hyperlink in “List of Letting” table. An illustration is provided in Online Appendix Figure A.7b.

2. There are two different sources of information - “Apparent Bids” and “Bid Summary” - on a letting page. More specifically, “Apparent Bids” and “Bid Summary” contain auction information but in different formats, and both of them have links to additional bidder information, which requires a paid account to access. Starting from the latest letting page, our scraper clicks the hyperlink “Apparent Bids” (Online Appendix Figure A.7c) then downloads a csv file for every

bidder by clicking on the bidder hyperlink (Online Appendix Figure A.7d) and “Export(csv)” on the refreshed page.

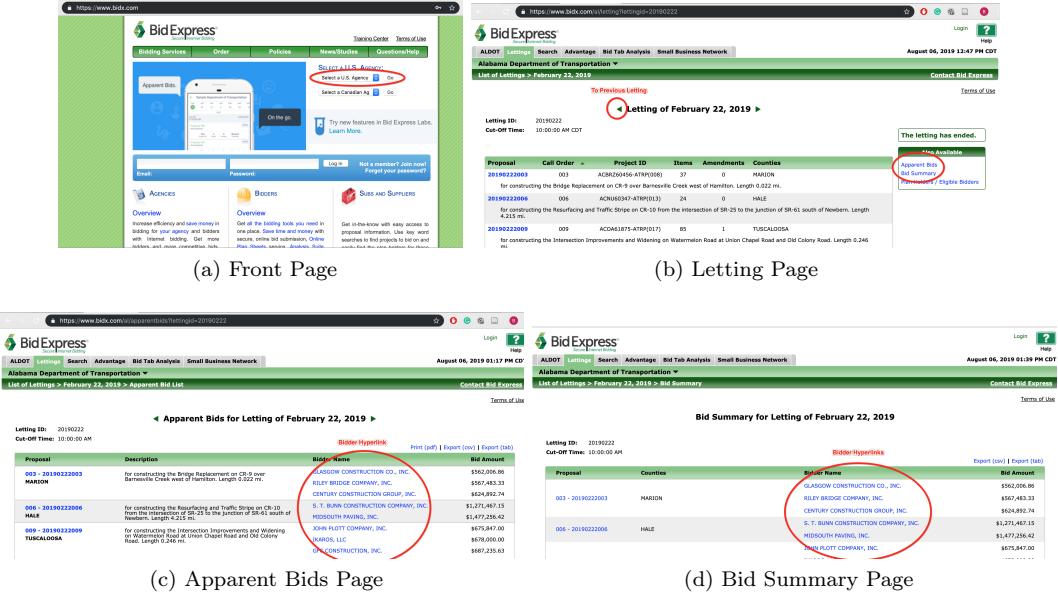


Figure A.7: Web Pages from BidX.com

If there is no information on the refreshed page, it moves to a new letting by clicking the arrow with html class “prev_arrow”. The procedure is iterated until the arrow is not clickable. We repeat the same procedure for the “Bid Summary” hyperlink.

Through this procedure, we obtain three tables for each letting:

- auction information from “Apparent Bids”, which contains: bidder names, bidder ID, bidder ranks, bid amounts, bidder call orders, project description, counties, letting ID and letting date. We do note that a few states record two extra variables: DBE Percentage and DBE Manual.
- auction information from “Bid Summary”, which contains: bidder names, bidder ID, bidder ranks, bid amounts, bidder call orders, counties, proposal ID and letting date.
- additional bidder information from bidder links, which contains: company name, company address, company phone number, company fax number.

We then merge the table c into a and b. Therefore, two files are created for every letting, one for “Apparent Bids” and one for “Bid Summary” with both auction and firm level information.

The information at the letting level is then further aggregated for each state as follow:

- For a state X , we merge its “Apparent Bids” files into one single file $X_apparentbid$ and “Bid Summary” files into one single file $X_bidsummary$. Then we add a new variable $State$, which is the two-letter abbreviation of states, in $X_apparentbid$ and $X_bidsummary$.

2. Then we find lettings that are in $X_{bidsummary}$ but not in $X_{apparentbid}$, and augment them so that they have the same variables as lettings in $X_{apparentbid}$.¹ The variables added are filled with “N/A”. Then we merged these lettings with $X_{apparentbid}$ into one file X_{all}
3. We merge all $*_{all}$ files into one final file.

As a result, we obtain a comprehensive file that has the following variables: Date of the auction, unique auction identifier, name of the bidding firm, address of the bidding firm, unique firm identifier, total bid amount, and state in which the auction occurred.

State-specific Auction Records

We obtained auction records on 12 other states from two types of sources: scraping state-specific bidding websites (7 states) and submitting Freedom of Information Act (FOIA) requests to state governments (5 states). Each data set included different variables and were organized in different formats. For example, the data from Texas included 121 variables while the data from West Virginia included only 11 variables. We harmonized these data sets focusing on the core set of variables: Date of the auction, unique auction identifier, name of the bidding firm, address of the bidding firm, unique firm identifier, total bid amount, and state in which the auction occurred. Note that one state, West Virginia, transitioned from its own website to Bid Express in 2011, so we use combined records from both sources. Once harmonized, we combined the various state-specific DOT auction records with the records obtained from Bid Express.

EIN Availability

We were able to obtain the EINs for firms that bid in DOT auctions in six states:

- Florida, Indiana, and West Virginia: These states’ DOT auction records were scraped from state-specific websites. The EINs were available from these websites.
- Colorado and Kansas: These states’ DOT auction records were obtained through FOIA requests. The requested data included EINs.
- Texas: This state’s DOT auction records were obtained through a FOIA request. Although this request did not include EINs, we were able to look up EINs by firm name and address through a Texas state government website: <https://mycpa.cpa.state.tx.us/coa/>.

B.3 Matching Auction Data to Tax Records

This appendix describes the procedure adopted to match the bidders in our auction sample to the tax data. For a subset of bidders the Employer Identification Number (EIN) is available in the auction data, providing a unique identifier for the matching. For those observations an exact matching can be performed. We refer to this subset of perfect matches as the *training data*. In any other case, we rely on the fuzzy matching algorithm described below.

¹Proposal in $X_{bidsummary}$ is treated as Letting ID.

The procedure takes advantage of some regularities in the denomination of firms and common abbreviations to improve the quality of matching. Furthermore, in order to properly distinguish different branches of the same company, additional information on value added or state will be used.

Overview of denominations

Generally, a business name consists of three parts: a distinctive part, a descriptive part, and a legal part.² The distinctive part is named by the business owner and is usually required by governments to be “*substantially different*” from any other existing name. The descriptive part describes what the business does, or its sector.³ Finally, the legal part refers to the business structure of a corporation. For example, for the name “Rogers Communications Inc.”, “Rogers” is the distinctive part, “Communication” is the descriptive part, and “Inc.” is the legal part. Most of the discrepancies of company names between different sources arise from the descriptive and the legal parts, since they are more subject to be abbreviations or common synonyms.

The legal part of corporation names takes a fairly small number of denominations, therefore can be identified using a properly constructed dictionary and treated separately. Conversely, disentangling the distinctive and the descriptive parts is not as straightforward. However, conventionally, the descriptive part follows the distinctive one within the string. This observation motivates a procedure that gives more weight to the first words within a company name, since they are more likely to be part of the distinctive part.

Legal-Parts Dictionary

In order to construct a uniform abbreviation in the legal part, we constructed a many-to-one dictionary using a subsample of our training data. We manually select abbreviations (including for misspelled words) by comparing mismatched names for the same firm in multiple databases. For example, “Incorporated” appears as “Inc.” “INC”, “Incorp” and so on in our data. Therefore, these abbreviations, when found, are mapped into “Incorporated” as described below. Our dictionary and matching algorithm are available upon request for replicability.

Matching Algorithm

We now describe the database matching algorithm (written in Python). A pseudocode representation of this procedure is provided in Online Appendix Algorithm 1. For each company name in the auction database, the algorithm searches the best match in the tax database. Although the algorithm is meant for the comparison of corporate names, it can be augmented with additional information if available. In our main application, the auction data contains information about the name and the state of origin of the bidding firms. The latter can be used to improve the quality of the matching by using a “blocking” procedure that prioritizes firms from the same origin state, as explained below. Let a be the firm, S^a be the firm’s string name and $State^a$ be the firm’s state of origin. The state

²Although there are no specific regulations on this naming structure, it is in alignment with naming convention and government guidelines. <https://www.ic.gc.ca/eic/site/cd-dgc.nsf/eng/cs01070.html>

³An example would be California Code of Regulations for business entities. <https://www.sos.ca.gov/administration/regulations/current-regulations/business-business-entity-names/#section-21000>

Algorithm 1 Matching Algorithm Pseudocode

```

Input:  $S^a$ ,  $State^a$ ,  $Dict$ ,  $IRS\_FirmList\_normalized$ 
Output:  $Match^a$ ,  $Score^a$ 

1 1. Name Normalization:
2  $S_{norm}^a$  = Remove non-alphanumeric characters and double spaces from  $S^a$  and set uppercase letters;
3  $W^a \equiv \{w_1^a, w_2^a, \dots, w_n^a\}$  = Split substrings at spaces ( $S_{norm}^a$ );
4 for  $i = 1, \dots, n$  do
5   if  $w_i \in Dict$  then  $W = W -' \{w_i\}$ ;
6  $S_{norm}^a$  = Merge words in  $W$ ;
7 2. Shortlisting:  $Shortlist = IRS\_FirmList\_normalized$ 
8 Candidate="Unmatched"
9 Out=0
10 i=0
11 repeat
12   i=i+1
13   C= {FirmName  $\in IRS\_FirmList\_normalized$  |  $w_i^a \in FirmName\}$ 
14   Shortlist= Shortlist  $\cap C$ 
15   if Shortlist is singleton then
16     Candidate= Shortlist
17     Out=1
18   if Shortlist is empty then
19     Out = 1
20   else
21     Candidate= Shortlist
22 until Out=1;
23 3. Scoring
24 for  $c \in Candidate$  do
25    $Score^c = \text{Levenshtein distance}(c, S_{norm}^a)$ 
26 Best=  $argmax\{Score^c\}$ 
27 if Levenshtein distance(Best,  $S_{norm}^a$ ) $< 0.6$  then
28   Matcha = "Unmatched"
29 else
30   Matcha=Best;
31   Scorea= Levenshtein distance(Best,  $S_{norm}^a$ )

```

of origin is only used if the *state* option is enabled in the code provided. The algorithm proceeds as follow.

1. NAME NORMALIZATION

All non-alphanumeric characters with the exception of spaces are removed from S^a and all letter characters are capitalized. Consecutive white spaces are replaced with one white space. Any sub-string separated by one space is considered a “word”. Every word in the legal-parts dictionary is removed. For example, “Amnio Brothers Inc.” is composed by the three words “Amnio” “Brothers” and “Inc.”. After the first step, it would be normalized to “AMNIO BROS”, since the word “Brothers” is recognized in our dictionary as a synonym for “BROS” and “Inc.” is recognized in our dictionary as a legal part and therefore removed. We refer to the normalized string as S_{norm}^a . The same normalization is applied to every company name in the tax database. If the normalized name is not unique in the tax database, we restrict to the ones that ever filed at least one of the three firm tax returns (1120,1120-S or 1065). If the same firm name filed multiple firm tax returns, we select the one with highest value added, as the firm with greater value added is participating in more economic activity and therefore more likely to be the firm that participated in the auction.

2. SHORTLISTING

Let S_{norm}^a be composed by $n \geq 2$ words. Starting from the first word, we search in the list of normalized tax data company names the subset of names that contains that word. If the subset is empty, no matching occurs and the matching for A ends. If the subset is a singleton, A is paired with the unique element of the set and the shortlisting step ends for A . If the

Steps	Output
String Normalization	Normalized Name: HANNAFORD BROS DISTRIBUTION
Shortlisting	The names(in bracket) and normalized names in the shortlist are shown below. The shared word is in bold. KELLY HANNAFORD BROS DISTRIBUTION (Kelly Hannaford Brothers Distribution Company) HANNAFORD BROS DISTRIBUTION (Hannaford Brothers Distri. C.) HASTING HANNAFORD BROS DISTRIBUTION (Hasting Hannaford Bros. Distribution Inc.)
Scoring	Normalized names in the shortlist are shown below. The scores are shown on the right of the names. KELLY HANNAFORD BROS DISTRIBUTION (LR = 0.9) HANNAFORD BROS DISTRIBUTION (LR =1) HASTING HANNAFORD BROS DISTRIBUTION (LR =0.87)
Unique match	HANNAFORD BROS DISTRIBUTION(Hannaford Brothers Distri. C.)

Table A.1: Example Search

subset has more than one element, we proceed with the second word in S_{norm}^a and consider only the candidate matches that also contain the second word. If the set still contains more than one element, we proceed with the third word and so on, until all the n words are used or we obtain either a singleton or an empty set. If this iteration leads to a singleton, A is paired with the unique element of the set. If it leads to an empty set, then A is paired with the smallest non-empty subset from the previous iterations. In short, this step selects a shortlist of candidate matches that share, after normalization, the highest number of initial words with A . If the *state* option is enabled, only firms that match exactly the $State^a$ are considered for shortlisting.

3. SCORING

This step employs the Levenshtein ratio (LR), a widespread measure of distance between strings, to select the best match from the shortlist. For each element of the set paired to A we compute its LR with respect to S^a . The company whose name has the highest score is selected as the match. If multiple companies tie for the top score, the one with the highest value added is selected. If the option *strict* is enabled, all the company names that do not reach a minimum threshold $T \in (0, 1)$ in their LR are dropped. If all candidate matches are dropped, then A is considered unmatched. Hence the higher the T , the more stringent is the matching process. In our application, we considered $T = 0.6$.

Online Appendix Table A.1 illustrates how the algorithm works with an example search, using “Hannaford Bros. Distribution Co.” as the search query. In our example, *strict* and *state* are disabled.

	Simple Search	Fuzzy Match			
	(1)	(2)	(3)	(4)	(5)
% Bidders Matched to Any Tax Record	80.2	99.9	97.6	99.9	95.8
% Bidders Matched to the True Tax Record	65.3	63.0	62.5	71.0	70.3
% Potential Matches Correctly Matched to Tax Records	78.6	75.8	75.1	85.4	84.5
Algorithm Parameters:					
Match must be perfect (string score = 1.0)	✓	✗	✗	✗	✗
Match must be high-quality (string score ≥ 0.6)	✗	✗	✓	✗	✓
Prefer matches in same state as auction	✓	✗	✗	✓	✓

Table A.2: In-Sample Algorithm Validation

Notes: This table provides summary statistics on the in-sample performance of the matching algorithm when applied to the six states that provided EINs. For these six states, we observe the true match between auction and tax records. Since some contractors are individuals rather than firms or are otherwise not required to file one of the three firm tax forms, not all contractors in auction data have a true match in firm tax records. First row provides share of contractors in the auction data that the algorithm matches to a firm tax record. Second row provides share of contractors in the auction data that the algorithm matches to a firm tax record and the match is true. Third row provides share of contractors in the auction data that the algorithm matches to a firm tax record and the match is true, among contractors in the auction data for which the true match exists in the firm tax data.

In-Sample Algorithm Validation

In order to validate the algorithm, we apply it to the subset of firms for which we were provided the EIN by the state DOT, thus allowing us to link records exactly rather than using the algorithm (the “Known EIN” sample). The results are displayed in Online Appendix Table A.2. In Column (1), we provide results from using a simple string matching algorithm, in which a firm in the auction database is only matched to a firm in the tax database if they have identical names. In Columns (2-5), we apply our approach presented in Online Appendix Algorithm 1. Overall, the algorithm outperforms string matching in both accuracy and number of matches achieved. In our preferred specification in column (5), the algorithm correctly matches 84.5 percent of the bidders whose EIN are known and could be found in tax database. The use of the *State* option proves effective in increasing the number of true matches, while the *Strict* option with $T = 0.6$ improves accuracy by reducing the false matches.

Out-of-Sample Algorithm Validation

In order to assess the external validity of the algorithm outside our specific application, we constructed two test data sets using data from the Employee Benefits Security Administration (ESBA). Our test data sets, *PensionData* and *PensionTest*, are constructed using Form 5500 data sets that are published by the Employee Benefits Security Administration (ESBA)⁴. Form 5500 data sets contain information, including company names and EINs, about the operations, funding and investments of approximately 800,000 business entities. We consider both retirement and Health and Welfare data sets, drop every variable except the Company Name and EIN, then remove duplicate observations. For every unique EIN, we find all names that are associated with it, then we discard any duplicate

⁴<https://www.dol.gov/agencies/ebsa/researchers/data>

names. Most of the EINs are associated with multiple company names, which reproduces a challenge in the tax database. For each EIN, if multiple names are associated with it, we select the first name and put it into the *PensionData* data set and all the others into the *PensionTest* data set. If there is only one name associated with the EIN, we still add that name into *PensionData*. This gives us 709,850 companies in *PensionTest* and 1,270,079 companies in *PensionData*. We then proceeded to test our program using *PensionData* as a main data set and *PensionTest* as a query set.

T	0	0.2	0.4	0.6	0.8	0.9	1
Matches	99.05%	99.04%	98.46%	91.68 %	74.52%	64.44%	49.01%
Correct Matches	70.36%	70.37%	70.57%	73.39 %	80.69%	84.12%	82.58%

Quantile	1%	10%	30%	50 %	70%	90%	99%
Length	1	1	1	1	2	37	2733

Table A.3: Out-of-Sample Algorithm Validation using Pension Data

We tested the program by searching in *PensionData* all the 709,850 *PensionTest* firms. Since we have the EIN for all the names in the two data sets, we can evaluate the matching performance. The program achieved an average speed of 152 queries per second and an average accuracy of 73.39 percent among matched queries for a $T = 0.6$ using the *strict* option. Online Appendix Table A.3a presents the percentage of correctly matched firms and false matches for different values of T . We note that the percentage of correct matches is not monotone in T when T is close to 1. In fact, requiring extreme level of string similarity leads to a loss of correct matches that outweighs the gains in precision. Therefore, we do not recommend setting T above 0.9. In Online Appendix Table A.3b, instead, we provide a closer look at the effectiveness of the shortlisting step. Looking at the distribution of the shortlists' length, we see that over 50% of the sample is matched at the shortlisting step and 70 percent of the candidate matches requires the scoring of at most 2 candidates. Furthermore, the 99th percentile of the longest shortlist amounts to 2,733 candidates. This is only 0.2 percent of the potential matches that a standard matching algorithm would have to consider for each query and, therefore, much more efficient.

State	DOT Auction Records		Final Sample: Matched Auction-Tax Data		
	Data Source	Includes EIN	Bidders in 2010 (Num. Firms)	Share of 2010 Construction Sector: Value Added	FTE Workers
AL	State Website	X	196	15.7%	17.4%
AR	State Website	X	149	7.9%	12.8%
AZ	No	X	*	*	*
CA	State Website	X	1,041	8.3%	11.2%
CO	FOIA Request	✓	241	12.6%	14.7%
CT	FOIA Request	X	126	9.4%	15.5%
FL	State Website	✓	344	30.7%	10.6%
GA	BidX Website	X	137	4.3%	7.0%
IA	BidX Website	X	256	15.4%	20.7%
ID	BidX Website	X	112	17.2%	13.6%
IL	No	X	*	*	*
IN	State Website	✓	213	10.6%	16.6%
KS	BidX Website	✓	130	13.7%	21.6%
KY	No	X	*	*	*
LA	BidX Website	X	167	11.5%	10.8%
MA	No	X	*	*	*
MD	No	X	*	*	*
ME	BidX Website	X	141	13.7%	16.9%
MI	BidX Website	X	391	9.5%	16.3%
MN	BidX Website	X	262	13.5%	19.8%
MO	BidX Website	X	179	14.9%	13.3%
MS	No	X	*	*	*
MT	FOIA Request	X	122	15.0%	23.6%
NC	BidX Website	X	135	5.2%	9.8%
ND	FOIA Request	X	*	*	*
NE	No	X	*	*	*
NH	No	X	*	*	*
NJ	No	X	*	*	*
NM	BidX Website	X	*	*	*
NV	No	X	*	*	*
NY	No	X	*	*	*
OH	BidX Website	X	320	43.7%	17.5%
OK	No	X	*	*	*
OR	No	X	*	*	*
PA	No	X	*	*	*
SC	No	X	*	*	*
SD	No	X	*	*	*
TN	BidX Website	X	140	5.3%	11.5%
TX	FOIA Request	✓	551	4.9%	9.6%
UT	No	X	*	*	*
VA	BidX Website	X	241	14.2%	12.0%
VT	BidX Website	X	*	*	*
WA	BidX Website	X	200	7.5%	14.0%
WI	BidX Website	X	194	12.1%	14.6%
WV	BidX and State Websites	✓	103	13.7%	19.0%
National			6,792	10.7%	9.9%

Table A.4: Summary of Auction Data by State

Notes: The first two columns provide information on in-state DOT data sources by state, where “state” refers to the state in which the auction occurred. The first column indicates the source from which we obtained data on that state’s DOT auctions, and the second column indicates whether or not EINs were included in the auction records. The final three columns provide information on the final sample of firms in the matched auction-tax data, where “state” refers to the state in which the firm filed taxes. Among firms in the construction sector in 2010, the last two columns consider the share of value added and FTE workers due to the firms that participated in auctions in our sample. We drop from these calculations firms that have missing values on the variables displayed, so the total sample size must be smaller than in Table 1 in the main text. An asterisk (*) denotes that number of bidders is non-zero but below the disclosure threshold.

C Online Appendix: Model Derivations

C.1 Second stage: optimal input choices

This subsection solves the second stage assuming a monopolistic competitive product market ($\epsilon > 0$) and increasing returns ($\rho > 1$), consistent with the empirical evidence.

If the firm loses the auction, its profit maximization problem is,

$$\max_{L_{0,j}} p (\Omega_j L_{0,j}^\rho)^{1-\epsilon} - \mu_j L_{0,j}^{1+\theta} - p_M \Omega_j L_{0,j}^\rho / \beta_M$$

where we substituted equations (4) and (6) into equation (8) for the case with $d = 0$. The first-order condition is,

$$\frac{\partial \pi_{0,j}}{\partial L_{0,j}} \equiv p \Omega_j^{1-\epsilon} (1-\epsilon) \rho L_{0,j}^{(1-\rho)\epsilon-(1-\rho)-\epsilon} - \mu_j (1+\theta) L_{0,j}^\theta - \frac{p_M}{\beta_M} \Omega_j \rho L_{0,j}^{-(1-\rho)} = 0$$

Multiplying both sides of $\frac{\partial \pi_{0,j}}{\partial L_{0,j}} = 0$ by $L_{0,j}^{1-\rho}$ and rearranging, we have,

$$p \Omega_j^{1-\epsilon} (1-\epsilon) \rho L_{0,j}^{-\rho\epsilon} - \mu_j (1+\theta) L_{0,j}^{\theta+1-\rho} = \frac{p_M}{\beta_M} \Omega_j \rho \quad (22)$$

The left-hand side converges to infinity when $L_{0,j}$ approaches zero, while the right-hand side is a constant. Thus, it is never optimal to choose $L_{0,j} = 0$, so $L_{0,j} > 0$.

Similarly, if the firm wins, its profit maximization problem is,

$$\max_{L_{1,j}: \Omega_j L_{1,j}^\rho \geq \bar{Q}^G} p (\Omega_j L_{1,j}^\rho - \bar{Q}^G)^{1-\epsilon} - \mu_j L_{1,j}^{1+\theta} - p_M \Omega_j L_{1,j}^\rho / \beta_M$$

The first-order condition is,

$$\frac{\partial \pi_{1,j}}{\partial L_{1,j}} \equiv p \Omega_j (1-\epsilon) \rho (\Omega_j L_{1,j}^\rho - \bar{Q}^G)^{-\epsilon} L_{1,j}^{-(1-\rho)} - \mu_j (1+\theta) L_{1,j}^\theta - \frac{p_M}{\beta_M} \Omega_j \rho L_{1,j}^{-(1-\rho)} = 0 \quad (23)$$

As $\Omega_j L_{1,j}^\rho$ approaches \bar{Q}^G , $(\Omega_j L_{1,j}^\rho - \bar{Q}^G)^{-\epsilon}$ approaches infinity while all other terms involving $L_{1,j}$ approach constants. Thus, $\Omega_j L_{1,j}^\rho > \bar{Q}^G$ is necessary to satisfy the equation. Since $Q_{1,j} = \Omega_j L_{1,j}^\rho$, it follows that $Q_{1,j}^H = Q_{1,j} - \bar{Q}^G > 0$, so the winning firm always produces in the private market. Furthermore, it is always true that $\frac{\partial \pi_{1,j}}{\partial L_{1,j}}|_{L_{1,j}=L_{0,j}} > 0$. Thus, total production will be larger if the firm wins the auction than if it loses.

Lastly, it is interesting to consider if winning a procurement project will lead a firm to produce more in the private market (crowd in) or less (crowd out). To determine this, we evaluate the marginal profits of the winner when the total output is $\hat{Q}_{1,j} \equiv \bar{Q}^G + Q_{0,j}^H$, that is, $\hat{Q}_{1,j}$ is the hypothetical output of the firm if it wins such that there is neither crowd in nor crowd out. The winner would prefer to produce more than $\hat{Q}_{1,j}$ if the marginal profit is positive, and less otherwise. Let the corresponding labor choice be $\hat{L}_{1,j}$ such that $\Omega_j \hat{L}_{1,j}^\rho - \bar{Q}^G = Q_{0,j}^H = \Omega_j L_{0,j}^\rho$. Note that, since $\rho > 1$ and $\hat{L}_{1,j}^\rho = L_{0,j}^\rho + \frac{\bar{Q}^G}{\Omega_j}$, then $\hat{L}_{1,j}^\rho > L_{0,j}$. Evaluating equation (23) at $\hat{L}_{1,j}$, marginal profits for

the firm if it wins and produces hypothetical output $\hat{Q}_{1,j}$ are,

$$\frac{\partial \pi_{1,j}}{\partial L_{1,j}}|_{L_{1,j}=\hat{L}_{1,j}} = p\Omega_j(1-\epsilon)\rho(Q_{0,j}^H)^{-\epsilon}\hat{L}_{1,j}^{\rho-1} - \mu_j(1+\theta)\hat{L}_{1,j}^\theta - \frac{p_M}{\beta_M}\Omega_j\rho\hat{L}_{1,j}^{\rho-1}$$

Multiplying by $L_{1,j}^{1-\rho}$ and substituting $Q_{0,j}^H = \Omega_j L_{0,j}^\rho$, we have,

$$L_{1,j}^{1-\rho}\frac{\partial \pi_{1,j}}{\partial L_{1,j}}|_{L_{1,j}=\hat{L}_{1,j}} = p\Omega_j^{1-\epsilon}(1-\epsilon)\rho L_{0,j}^{-\rho\epsilon} - \mu_j(1+\theta)\hat{L}_{1,j}^{\theta+1-\rho} - \frac{p_M}{\beta_M}\Omega_j\rho$$

Finally, substituting equation (22), this simplifies to,

$$L_{1,j}^{1-\rho}\frac{\partial \pi_{1,j}}{\partial L_{1,j}}|_{L_{1,j}=\hat{L}_{1,j}} = \mu_j(1+\theta)(L_{0,j}^{\theta+1-\rho} - \hat{L}_{1,j}^{\theta+1-\rho})$$

Since $\hat{L}_{1,j} > L_{0,j}$, we have that $\frac{\partial \pi_{1,j}}{\partial L_{1,j}}|_{L_{1,j}=\hat{L}_{1,j}} < 0$ if $\theta + 1 - \rho > 0$, and $\frac{\partial \pi_{1,j}}{\partial L_{1,j}}|_{L_{1,j}=\hat{L}_{1,j}} > 0$ otherwise. Therefore, winning a government project crowds out private projects when $1 + \theta > \rho$ and crowds in otherwise.

C.2 Proof of Worker Rents Expression

We prove that equation (10) implies the results in equations (11) and (13). Defining $u = l, dv = dW$, we calculate V_j for a wage change from $W_j = W_j^0$ using integration by parts:

$$V_j = \int_{W_j^0}^{W_j^1} l(W)dW = [l(W)W]_{W_j^0}^{W_j^1} - \int_{W_j^0}^{W_j^1} \frac{dl}{dW}WdW = \underbrace{l(W_j^0)\Delta W}_{\text{incumbents}} + \underbrace{\int_{W_j^0}^{W_j^1} (W_j^1 - W) \frac{dl}{dW}dW}_{\text{new hires}}$$

where $\Delta W \equiv W_j^1 - W_j^0$. Following Lamadon et al. (2019), define $\omega \equiv \frac{W}{W_j^1}$ so that $\frac{d\omega}{dW} = \frac{1}{W_j^1}$. Next, $l(\omega_j W_j^1) = \frac{(\omega_j W_j^1)^{1/\theta} g_j}{\sum_{j'} (\omega_{j'} W_{j'})^{1/\theta} g_{j'}} = \omega_j^{1/\theta} l(W_j^1)$. Thus, $\frac{dl}{dW}dW = \frac{dl}{d\omega}d\omega$. Moreover, $\frac{dl}{d\omega} = \frac{\partial \omega^{1/\theta}}{\partial \omega} l(W_j^1)$. Then,

$$\begin{aligned} V_j &= l(W_j^0)\Delta W + W_j^1 \int_{\frac{W_j^0}{W_j^1}}^1 (1-\omega) \frac{dl}{d\omega} d\omega \\ &= l(W_j^0)\Delta W + W_j^1 l(W_j^1) \int_{\frac{W_j^0}{W_j^1}}^1 (1-\omega) \frac{\partial \omega^{1/\theta}}{\partial \omega} d\omega \\ &= l(W_j^0)\Delta W + W_j^1 l(W_j^1) \left[\left[(1-\omega) \omega^{1/\theta} \right]_{\frac{W_j^0}{W_j^1}}^1 + \int_{\frac{W_j^0}{W_j^1}}^1 \omega^{1/\theta} d\omega \right] \\ &= \frac{W_j^1 l(W_j^1)}{1+1/\theta} - \frac{W_j^0 l(W_j^0)}{1+1/\theta} \end{aligned}$$

C.3 Additional Identification Derivations

If the firm loses the auction, its revenues are $R_{0,j} = p(Q_{0,j}^H)^{1-\epsilon}$. From equation 6, the relationship between private market revenues and intermediate inputs if the firm loses is $R_{0,j} = p(\beta_M M_{0,j} \exp e_j)^{1-\epsilon}$. Then, dividing and multiplying $M_{0,j}$ by p_M and taking logs, we have,

$$\log R_{0,j} = \log p + (1 - \epsilon) \log(\beta_M / p_M) + (1 - \epsilon) \log(p_M M_{0,j}) + (1 - \epsilon) e_j$$

from which equation (20) follows.

From equation (8) and Assumptions 1-3, we can write output in the private market as,

$$\log Q_{d,j}^H = [\log \Omega_j + \rho \log L_{d,j}] - d \left[\log \left(\frac{1+\theta}{\beta_L} B_{1,j} + p_M M_{1,j} \right) - \log ((1-\epsilon) R_{1,j}^H) \right]$$

for cases $d = 0, 1$, from which equation (21) follows.

We identify the size of the labor market $\bar{\theta}$ by taking the expectation of equation (4) in logs,

$$\log \bar{\mu} = \mathbb{E}[\log B_j - (1 + \theta) \log L_j]$$

Given ρ , we identify β_M / p_M from the Leontief first-order condition, $\Omega_j L_j^\rho = \beta_M M_j$, which implies,

$$\log(\beta_M / p_M) = \mathbb{E}[\rho \log L_j - \log(p_M M_j)]$$

where we have normalized $\log \Omega_j$ to have zero mean. Given $\log(\beta_M / p_M)$ and ρ , we can recover TFP for every firm in our data as,

$$\log \Omega_j = \log(\beta_M / p_M) + \log(p_M M_j) - \rho \log L_j$$

Moreover, since we obtained $\log p + (1 - \epsilon) \log(\beta_M / p_M)$ above, we identify $\log p$ as,

$$\log p = \mathbb{E}[\log R_j] - (1 - \epsilon)(\log \beta_M / p_M + \mathbb{E}[\log(p_M M_j)])$$

D Online Appendix: Accounting for Capital

We consider the problem of including capital in the production function of firms. We build on the approach of Lamadon et al. (2019) by allowing firms to rent capital in a competitive market with constant rental rate. We write revenues and costs as functions of Q_j so as to separate the joint maximization in two steps: first find the optimal combination (K_j, L_j) for each Q_j , then find the optimal Q_j .⁵

⁵By contrast, Lamadon et al. (2019) consider profit maximization that accounts for revenue and cost jointly, but do so sequentially: first, they find the optimal K_j for each L_j to maximize conditional profits; second, they find the optimal L_j . This paper considers optimal inputs for each Q_j because Q_j may be set externally by the auction. In practice, the difference is that Lamadon et al. (2019) subtract the capital costs from revenues (accounting for capital on the revenue-side), while this paper adds the capital costs to the labor costs (accounting for capital on the cost-side). This difference results in different definitions of the total return to labor, ρ .

Formally, suppose that firms can rent capital at price p_K and hire labor at price $W_j = \mu_j L_j^\theta$. Consider a Cobb–Douglas production function (in physical units)

$$Q_j = \phi_j K_j^{\beta_K} L_j^{\beta_L}$$

Given any production level Q_j , the firm can find the most cost efficient combination (K_j, L_j) by solving the cost-minimization problem,

$$\min_{(K_j, L_j): Q_j = \phi_j K_j^{\beta_K} L_j^{\beta_L}} p_K K_j + \mu_j L_j^{1+\theta}$$

where $p_K K_j + \mu_j L_j^{1+\theta}$ represents the total cost. This leads to the Lagrangian,

$$\mathcal{L}_j \equiv p_K K_j + \mu_j L_j^{1+\theta} + \lambda_j (Q_j - \phi_j K_j^{\beta_K} L_j^{\beta_L})$$

where λ_j is the Lagrange multiplier. The first-order condition for capital is,

$$p_K = \lambda_j \phi_j \beta_K K^{\beta_K-1} L^{\beta_L}$$

while the first-order condition for labor is,

$$(1+\theta) \mu_j L_j^\theta = \lambda_j \phi_j \beta_L K_j^{\beta_K} L_j^{\beta_L-1}$$

which leads to the optimal choice of capital as a function of labor

$$K_j = \frac{\beta_K}{\beta_L} \frac{(1+\theta)\mu_j}{p_K} L_j^{1+\theta}$$

or simply $K_j = \chi_j L_j^{1+\theta}$, where $\chi_j = \frac{\beta_K}{\beta_L} \frac{(1+\theta)}{p_K} \mu_j$.

Substituting $Q_j = \phi_j (\chi_j L_j^{1+\theta})^{\beta_K} L_j^{\beta_L}$, the optimal labor choice is

$$L_j = \left(\frac{Q_j}{\phi_j \chi_j^{\beta_K}} \right)^{\frac{1}{(1+\theta)\beta_K + \beta_L}}$$

Thus, the cost function can be written,

$$C_j(Q_j) = p_K \chi_j L_j^{1+\theta} + \mu_j L_j^{1+\theta} = (p_K \chi_j + \mu_j) \left(\frac{Q_j}{\phi_j \chi_j^{\beta_K}} \right)^{\frac{1+\theta}{(1+\theta)\beta_K + \beta_L}} = L_j^\rho (p_K \chi_j + \mu_j) = \tilde{\mu}_j L_j^{1+\theta}$$

where $\rho \equiv (1+\theta)\beta_K + \beta_L$ and $\tilde{\mu}_j \equiv \left(\frac{\beta_K}{\beta_L} (1+\theta) + 1 \right) \mu_j$, and output simplifies as,

$$Q_j = L_j^\rho \left(\phi \chi_j^{\beta_K} \right) = L_j^\rho \Omega_j$$

where $\Omega_j \equiv \phi_j \chi_j^{\beta_K} \equiv \phi_j \left(\frac{\beta_K}{\beta_L} \frac{(1+\theta)}{p_K} \mu_j \right)^{\beta_K}$. The new (gross) revenue is $\Omega_j L_j^\rho$ for any labor choice. The new cost inclusive of capital and labor expenses is $\tilde{\mu}_j L_j^{1+\theta}$ for any labor choice.

E Online Appendix: Product Market with Perfect Competition

This section solves the second stage assuming a perfectly competitive product market ($\epsilon = 0$). Denote the competitive price as p . We need to distinguish two types of solutions.

In the case of an interior solution, the winner with TFP Ω maximizes the following problem

$$\max_L p[\Omega L^\rho - \bar{Q}^G] - \theta_0 L^{1+\theta}$$

whose FOC gives the optimal labor choice $L_{interior}^*(\Omega) = [\frac{p\Omega\rho}{\theta_0(1+\theta)}]^{-\frac{1}{\theta+1-\rho}}$ and the optimal output level $Q_{interior}^*(\Omega) = \Omega[\frac{p\Omega\rho}{\theta_0(1+\theta)}]^{\frac{\rho}{\theta+1-\rho}}$. Note that both optimal choices are independent of \bar{Q}^G . Moreover, the optimal profit is

$$\Pi_{interior}^*(\Omega|\bar{Q}^G) = (p\Omega)^{\frac{1+\theta}{\theta+1-\rho}} \theta_0^{-\frac{\rho}{\theta+1-\rho}} \left[\left(\frac{\rho}{1+\theta} \right)^{\frac{\rho}{\theta+1-\rho}} - \left(\frac{\rho}{1+\theta} \right)^{\frac{1+\theta}{\theta+1-\rho}} \right] - p\bar{Q}^G$$

In the case of a corner solution, i.e. $Q_1 > Q_{interior}^*(\Omega)$, the firm produces only \bar{Q}^G so that $\Omega L^\rho = \bar{Q}^G$, which gives $L_{corner}^*(\Omega) = (\bar{Q}^G/\Omega)^{\frac{1}{\rho}}$. The profit is

$$\Pi_{corner}^*(\Omega|\bar{Q}^G) = -\theta_0 \left(\frac{\bar{Q}^G}{\Omega} \right)^{\frac{1+\theta}{\rho}}$$

The optimal profit achievable is defined by $\Pi^*(\Omega|\bar{Q}^G) = \max\{\Pi_{corner}^*(\Omega|\bar{Q}^G), \Pi_{interior}^*(\Omega|\bar{Q}^G)\}$. Note that for the loser, it is always optimal to adopt the interior solution. On the other hand, the winner adopts the interior solution when \bar{Q}^G is small and the corner solution otherwise. In summary,

- When \bar{Q}^G is small, i.e., $\bar{Q}^G < Q_{interior}^*(\Omega)$, regardless of its winning status, this firm hires the same amount of labor to equalize the marginal revenue and marginal labor cost. It produces the same amount of output in physical units in both cases. It makes a profit $\Pi_{interior}^*(\Omega|\bar{Q}^G)$ upon winning and $\Pi_{interior}^*(\Omega|\bar{Q}^G) + p\bar{Q}^G$ upon losing. Therefore, in the bidding stage, the firm knows the opportunity cost of winning the auction is $\Delta(\Omega|\bar{Q}^G < Q_{interior}^*(\Omega)) = p\bar{Q}^G$, where $p\bar{Q}^G$ is essentially the opportunity cost of selling the same amount Q_1 to the private market.
- When \bar{Q}^G is large, i.e., $\bar{Q}^G > Q_{interior}^*(\Omega)$, the government project pushes the firm to a high level of labor and a high marginal cost upon winning. In this case, the firm focuses on the government project and produces \bar{Q}^G upon winning the auction, which requires a labor amount s.t. $\Omega L^\rho = \bar{Q}^G$. That is, $L_1^* = (\frac{\bar{Q}^G}{\Omega})^{\frac{1}{\rho}}$. On the other hand, the firm still produces at the interior solution $Q_{interior}^* = \Omega[\frac{p\Omega\rho}{\theta_0(1+\theta)}]^{\frac{\rho}{\theta+1-\rho}}$ using $L_{interior}^* = [\frac{p\Omega\rho}{\theta_0(1+\theta)}]^{\frac{1}{\theta+1-\rho}}$ upon losing the auction. Note that winning leads to more production than losing and the difference is

$\bar{Q}^G - Q_{interior}^*$. Moreover, the firm hires more labor upon winning than losing. Overall, the firm knows the difference between winning and losing (opportunity cost) is $\Delta(\Omega|\bar{Q}^G > Q_{interior}^*(\Omega)) = \theta_0(\frac{\bar{Q}^G}{\Omega})^{\frac{1+\theta}{\rho}} + (p\Omega)^{\frac{1+\theta}{\theta+1-\rho}} \theta_0^{-\frac{\rho}{\theta+1-\rho}} \left[(\frac{\rho}{1+\theta})^{\frac{\rho}{\theta+1-\rho}} - (\frac{\rho}{1+\theta})^{\frac{1+\theta}{\theta+1-\rho}} \right]$.

The above two representations of the opportunity cost as a function of the TFP distribution gives an overall distribution of opportunity cost, i.e., $\Delta(\Omega) \sim F(\cdot)$. In the first stage, the firm chooses the optimal bid that solves the same problem as in the main text.

F Online Appendix: Simulating the Model Using the Quantile Representation

Overview

For any given TFP and the outcomes from the first-stage (winner status and size of procurement projects won), the second-stage of the model can be solved to give numerical values of the firm outcomes such as profits, wages, and employment, which is the information needed to perform counterfactual predictions. To solve the first-stage, we must account for equilibrium bidding behavior, which depends on the size of the procurement project, the number of bidders, and the TFP distribution. The symmetric equilibrium described in the main text involves numerical integration, which is costly since we need to solve this model many times in our counterfactual experiments. To speed up this calculation, we implement the quantile representation method of Luo (2020). Here, we provide an overview of the steps taken to solve the first-stage and second-stage problems.

Second stage: Denote the TFP quantile function as $\Omega(\alpha)$ where, for example, $\alpha = 0.10$ indicates the 10th quantile of the TFP distribution. We use a log Normal distribution to approximate the distribution of TFP, which allows for a simple mapping between Ω and α , choosing the standard deviation that matches the interquartile range of TFP (reported in Table 2). For each combination of winner status, TFP quantile, and auction size (d, α, \bar{Q}^G) , we solve the second-stage problem for firm and worker outcomes. This is done by numerical optimization of the profit function (equation 8) subject to the labor supply curve (equation 4), the production function (equation 6), and the optimal intermediate inputs condition (equation 7).

First stage: The challenge is to compute expectations of the second-stage across the distribution of outcomes from the first-stage. To solve the first-stage, note that the opportunity cost of winning an auction of size \bar{Q}^G is $\Delta(\alpha|\bar{Q}^G) = \pi_0^H(\alpha) - \pi_1^H(\alpha|\bar{Q}^G)$. Since π_1^H is the winning firm's revenue in the private market net of the total cost, it follows that $\pi_0^H > \pi_1^H$ and thus $\Delta > 0$. π_1^H is decreasing in \bar{Q}^G , and π_0^H does not depend on \bar{Q}^G . Moreover, Δ is decreasing in α . In other words, higher TFP firms have lower opportunity cost of producing in the government procurement market. Since α represents quantiles of TFP, it has the standard uniform distribution. The probability that the winning quantile is less than α is the probability that it is the lowest among all I bidders' draws from the standard uniform distribution, yielding the probability α^I and associated density function $f_1(\alpha, I) = I\alpha^{I-1}$. By similar reasoning, the density function of a losing firm's TFP quantile is $f_0(\alpha, I) = \frac{I}{I-1}(1 - \alpha^{I-1})$.

What do we mean by “solution”? Let $Y_d(\alpha|\bar{Q}^G)$ denote a second-stage outcome for a firm characterized by TFP quantile α bidding in an auction of size \bar{Q}^G . Using the distribution functions from the first stage, we compute the expected outcome as $\mathbb{E}[Y_d|\bar{Q}^G, I] = \int_0^1 Y_d(\alpha|\bar{Q}^G) f_d(\alpha, I) d\alpha$. For example, the probability that a bidder with TFP Ω_j wins the project is the probability that its TFP is the highest among all participating bidders, i.e., $H(\Omega_j)^I$, where H denotes the distribution of TFP. This implies that the density function of the winner’s TFP is $IH(\Omega_j)^{I-1}h(\Omega_j)$. The profit function depends on who wins the auction, in particular, the TFP of the winner. The expected profit of the winner is then,

$$\bar{\pi}_{1,j} = \int \pi_{1,j}(\Omega_j|\bar{Q}^G) \times [IH(\Omega_j)^{I-1}h(\Omega_j)] d\Omega_j = \int \pi_{1,j}(\Omega_j(\alpha)|\bar{Q}^G) \times I\alpha^{I-1} d\alpha$$

Note that this expectation depends on the combinations (\bar{Q}^G, I) . One possibility is to solve the model for each possible combination of (\bar{Q}^G, I) , and then average across them. In our setting, this is computationally infeasible. An alternative is to evaluate (\bar{Q}^G, I) at representative values. In practice, we choose the values of (\bar{Q}^G, I) that provide the best fit to the additional rents from procurements, (V_Δ, π_Δ) . The best fit yields a model-simulated incidence on workers of \$981, which is very close to the main estimate of \$959 in Table 2, and incidence on firms of \$3,098, which is very close to the main estimate of \$2,873 in Table 2. The implied incidence share on workers is about 24 percent, which is close to our main estimate of 25 percent. It is reassuring to find that the best fit is achieved at $I = 10$ bidders per auction, which is close to the mean observed value in the data of 8.7 bidders per auction.

Additional details

We now provide the derivation of the quantile representation of the optimal bidding strategy. Consider a procurement auction model. Following (Guerre et al., 2000), we can rewrite the first-order condition and obtain a representation of the cost as a function of observables:

$$c = b - \frac{1}{I-1} \frac{1-G(b)}{g(b)}$$

where $G(\cdot)$ and $g(\cdot)$ are the bid distribution and density, respectively. Since the bidding strategy is strictly increasing, we can further rewrite it in terms of quantiles:

$$c(\alpha) = b(\alpha) - \frac{1}{I-1} [1-\alpha] b'(\alpha)$$

where $c(\cdot)$ and $b(\cdot)$ are the cost quantile function and the bid quantile function, respectively. The boundary condition is that the least efficient firm bids the highest, i.e., $c(1) = b(1)$.

Following (Luo, 2020), we can solve this ODE and obtain the mapping from cost quantile function to bid quantile function

$$b(\alpha) = (I-1)(1-\alpha)^{1-I} \int_\alpha^1 c(x)(1-x)^{I-2} dx$$

This representation is convenient for numerically solving the first-price procurement auction model, as it allows us to write,

$$\begin{aligned} b'(\alpha) &= - (I-1)(1-I)(1-\alpha)^{-I} \int_{\alpha}^1 c(x)(1-x)^{I-2} dx \\ &\quad - (I-1)(1-\alpha)^{1-I} c(\alpha)(1-\alpha)^{I-2} \end{aligned}$$

Rearranging,

$$\begin{aligned} -\frac{1}{I-1}[1-\alpha]b'(\alpha) &= (1-I)(1-\alpha)^{1-I} \int_{\alpha}^1 c(x)(1-x)^{I-2} dx + c(\alpha) \\ &= c(\alpha) - b(\alpha). \end{aligned}$$

Moreover, when $\alpha \rightarrow 1$, using L'Hospital's rule,

$$b(1) = \lim_{\alpha \uparrow 1} (I-1) \frac{\int_{\alpha}^1 c(x)(1-x)^{I-2} dx}{(1-\alpha)^{I-1}} = c(1)$$