# Identifying Labor Market Power: A Quasi-Experimental Approach

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**Abstract**

We test whether firms react to changes in the wages and size of their competitors. We use a unique institutional feature of public procurement auctions in Brazil: the moment in which the auction ends is random. For close auctions, winner and runner-up are as good as randomly assigned. We first show that firm-specific demand shocks lead to increases in the size and wages of the firm receiving the shock. Then, we document that these firm-specific demand shocks lead to increased wages of other (competing) firms in the same local labor market. We do not find negative effects on competitors' firm size. The effect on competitors is driven by firms with high labor market share.

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# 1 Introduction

Do firms react strategically to wages and employment set by their competitors? The answer to this question is central to understanding wage and employment determination in the labor market, and in particular the transmission of changes in firm-specific demand or productivity to the rest of the market. Although this question is at the heart of labor economics, little progress has been made due to the difficulty of finding plausibly exogenous shifts in a firm's size or wage that are unrelated to the determinants of the size and wages of its competitors.

Strategic interaction is a natural implication of market power due to market concentration. Recent literature points to the relevance of labor market power, market concentration, and how the two interact (Kline et al., 2019; Kroft et al., 2020; Yeh et al., 2022; Azar et al., 2020, 2022; Berger et al., 2023). In the presence of labor market concentration firms react to the decisions of their competitors (Bhaskar et al., 2002; Berger et al., 2022). In particular, if one firm (exogenously) grows, all other firms in the labor market must react in terms of wage and employment size as a response. However, there is very little evidence on whether and how firms respond to their competitors. The empirical challenge is clear. It is very difficult to identify a firm-specific shock at the firm level, completely unrelated to other direct market effects on their competitors.

In this paper, we leverage quasi-experimental variation from procurement auctions where the winning firm sells goods to the government. A unique feature in these auctions generates randomness in the identity of the contract winner. We then test how wages and employment of firms within the same labor market react to a (size and wage increasing) demand shock on a competitor.

To do so, we obtained information on the universe of public procurement auctions conducted by the Brazilian federal government. We have scrapped the official government website containing millions of HTML records of these auctions and transformed them into usable data. In these auctions, firms repeatedly bid for a contract with the government, and all participants always observe the current winning (lowest) bid. The final (lowest) bid is the price the winning firm gets to sell to the government (descending first price auction).

Unlike other settings, these auctions have a unique feature: the moment in which the auction ends is random (chosen by a computer and unknown to participants). In particular, the duration of each auction comes from a uniform distribution, that is independent of any firm or auction characteristic, and bid behavior within the auction. Furthermore, they include products from all industries, from cleaning supplies to vehicle parts, medical equipment, and computers. We merged this data with employer-employee matched data for the universe of formal workers in Brazil, *Relação Anual de Informações Sociais* (RAIS). In this data, we observe both firm and worker characteristics, such as the start and end of employment, earnings, contractual wages, education, occupation, gender, and industry.

The random ending of the auction provides us with a natural experiment. For auctions in which two firms are constantly outbidding each other incrementally, the winner and runner-up are as good as randomly assigned (Ferraz et al., 2015; Carvalho et al., 2023). For the entirety of the paper, we focus on close auctions - which we define to be when the two lowest bids are within 0.5% difference in value and placed in the final 30 seconds of the auction. Intuitively, consider two firms, A and B, constantly outbidding each other by a few cents and placing their bids seconds apart. The random ending implies that the auction might end when either firm A or firm B is the lowest bidder. Then, both firms are in expectation similar in predetermined characteristics. As a result, we can use the runner-up as a natural counterfactual for the treated (winning) firm and credibly estimate the effect of firm-level demand shocks on the remaining firms in their same local labor market.

Carvalho et al. (2023) show that firms winning one of these close auctions increase their wages and number of employees for up to 4 years relative to the runner-up. A natural following question, therefore, is how other firms in the same labor market respond to this movement.

We use two theoretical frameworks to guide our empirical analysis and to think about the mechanisms underlying our empirical findings. The first setting we consider is one where granular firms compete (*a la* Cournot) against each other and internalize the fact that they each face an upward-sloping labor supply curve (Berger et al., 2022). The firm receiving the (size increasing) demand shock raises its wage, attracting a larger workforce, increasing its size. Using this theoretical framework, we formally characterize the response of the size and wage of a competitor firm.

Due to Cournot competition, employment levels are strategic substitutes across firms. Competitors are expected to decrease their size as a response. The magnitude of this negative response is expected to increase with the labor market share of the competitor in question, and decrease in labor market share of the firm receiving the (size increasing) demand shock. Generally, the wage response of competitor firms is ambiguous. However, for a low enough labor market share of the firm receiving the (size increasing) demand shock, competitors are expected to lower their wages. We test these predictions using our quasi-experimental variation.

The second setting is one of search and matching with bargaining under the presence of granular firms (Jarosch et al., 2019). In this context, granular firms commit to not re-hiring a worker if bargaining breaks down. This corresponds to firms taking out their own job posting from their workers outside option allowing the firm to pay workers lower wages. The larger the share of the firm in the local labor market the larger the mark down on wages due to this channel.

Under this setting, if a granular firm $j$ increases its wage, a competitor firm $i$ must increase its wages to keep its workers, leading to a higher bargained wage. This effect increases with the size of the granular firm $j$. In contrast, increases in wages by atomistic (approximately zero labor market share) firms have no impact on the wage paid by firm $i$.

This effect of wages of a granular firm $j$ in wages of firm $i$ is also increasing in the labor market share of firm $i$. Intuitively, because firms commit to not hiring the worker if bargaining breaks down, the larger a firm $i$ is, the longer the worker stays unemployed if negotiations with firm $i$ break down. This in turn makes the wage received by any granular competing firm $j$ all the more important for the worker's utility under a breakdown in negotiations (worker's outside option).

In our empirical analysis, we start by defining the local labor market as a municipality-industry-year cell. Then, for each close auction, we follow all firms in the same local labor market of the winner and runner-up. We find that winning a close auction leads to higher wages for other competing firms in the same local labor markets. We do not find negative effects on competitors' firm size. Consistent with the theoretical predictions, wages rise more for competitors with a high labor market share.

Our paper relates to the growing literature documenting empirically a negative relationship between market concentration and wages, consistent with market concentration leading to labor market power. The negative correlation between market concentration and wages is well documented (Azar et al. (2022) and Azar et al. (2020)), and it is robust to using within-occupation variation (Schubert et al., 2022) and to being instrumented by merger activity (Benmelech et al., 2022). There is also evidence that market concentration is negatively correlated to hiring (Marinescu et al., 2021) and has implications for worker composition and firm survival (Dodini et al., 2022).

Our paper also relates to a recent literature analyzing how a firm's share of the labor market impacts its wage and employment. Importantly, all else equal, firms with larger labor market share pay lower wages, irrespective of whether wages are set via wage bargaining (Jarosch et al., 2019) or wage posting (Berger et al., 2022; Azkarate-Askasua and Zerecero, 2023). Recent papers have studied this relationship empirically by using mass layoffs of competitors as shifts in a firm's labor market share (Azkarate-Askasua and Zerecero, 2023).

Finally, our paper also relates to a recent literature analyzing the effect of mergers on the wages paid to different types of workers in the firm (Lagaras, 2019; Thoresson, 2021; Prager and Schmitt, 2021; Guanziroli, 2022), and the effect of mergers on the wages paid in competing firms (Arnold, 2019; Guanziroli, 2022). While Arnold (2019) find that merger-induced market concentration is associated to lower wages in the local labor market, he also documents a positive correlation between concentration and market-level employment. Guanziroli (2022) find that a retail pharmacy merger led to lower wages and a statistically insignificant decrease in employment among merging firms while leading to lower wages and higher employment among competing firms.

While these three strands of literature have focused on how changes to market-level concentration or a firm's specific labor market share affects wages and employment in the firm or market-level, we focus, instead, on verifying how a (size increasing) demand shock to a firm affects its competitors. In doing so, we test not the effect of changes in market concentration, but rather, a natural implication of market power driven by market concentration, strategic wage and employment setting by firms.

# 2 Theoretical Frameworks

In this section we derive the expressions for the firm response to an increase in employment size and wages of a competitor. We consider two separate theoretical frameworks both of which have implications to how competitors react to a change in employment size or wage of a given firm in the local labor market.

## 2.1 Berger et al. (2022)

The first framework we consider is that of Berger et al. (2022) in which firms compete by choosing their optimal size given the size chosen by their competitors. The economy is composed of a continuum of local labor markets $j \in [0,1]$, each with an exogenous and finite number of firms. Since the equilibrium concept is Cournot, firms maximize profits taking the actions of competitors as given. Firm $i$ in market $j$ in period $t$ chooses capital, $k_{ijt}$, and employment size, $n_{ijt}$, to maximize

$$\max_{k_{ijt},n_{ijt}} z_{ijt}(k_{ijt}^{1-\gamma} n_{ijt}^{\gamma})^{\alpha} - R_t k_{ijt} - w(n_{ijt}, n^*_{-ijt}, N_t, W_t) n_{ijt} \tag{1}$$

where $R_t$ is the cost of renting capital. The maximization is done subject to the upward labor supply faced by the firm

$$w = \left(\frac{n_{ijt}}{n_{jt}(n_{ijt}, n_{-ijt})}\right)^{\frac{1}{\eta}} \left(\frac{n_{jt}(n_{ijt}, n^*_{-ijt})}{N_t}\right)^{\frac{1}{\theta}} W_t \tag{2}$$

where $n_{jt}$ is a market $j$ level index,

$$n_{jt}(n_{ijt}, n^*_{-ijt}) = [n_{ijt}^{\frac{\eta+1}{\eta}} + \sum_{k \neq i} n_{kjt}^{\frac{\eta+1}{\eta}}]^{\frac{\eta}{\eta+1}} \tag{3}$$

and $N_t$, $W_t$ are aggregate economy level indexes. $\eta$ captures the cost of moving labor across firms within market, while $\theta$ captures the cost of moving labor across markets. In order to have market power at the local labor market level, we need $\eta > \theta$. See Berger et al. (2022) for details in the derivation of the labor supply curve.

Let us first characterize the optimal choice of $n_{ijt}$ for firm $i$ at market $j$ given everything else. The first order condition for $n_{ijt}$ is given by

$$\alpha\gamma \frac{y_{ijt}}{n_{ijt}} = w_{ijt}[\frac{\partial w_{ijt}}{\partial n_{ijt}} \frac{n_{ijt}}{w_{ijt}} + 1]. \tag{4}$$

Now note that

$$\frac{\partial w_{ijt}}{\partial n_{ijt}} = \frac{w_{ijt}}{n_{ijt}}[\frac{1}{\eta} + (\frac{1}{\theta} - \frac{1}{\eta})\frac{\partial n_{jt}}{\partial n_{ijt}}] \quad \text{and} \quad \frac{\partial n_{jt}}{\partial n_{ijt}} = (\frac{n_{ijt}}{n_{jt}})^{\frac{1+\eta}{\eta}}, \tag{5}$$

and so,

$$\alpha\gamma \frac{y_{ijt}}{n_{ijt}} = w_{ijt}[\frac{1}{\eta} + (\frac{1}{\theta} - \frac{1}{\eta})(\frac{n_{ijt}}{n_t})^{\frac{1+\eta}{\eta}} + 1]. \tag{6}$$

The above equation completely characterizes the choice of optimal $n_{ijt}$. Note also that the expression for the elasticity of labor supply is

$$\frac{\partial w_{ijt}}{\partial n_{ijt}} \frac{n_{ijt}}{w_{ijt}} = \frac{1}{\eta} + (\frac{1}{\theta} - \frac{1}{\eta})(\frac{n_{ijt}}{n_t})^{\frac{1+\eta}{\eta}} = \frac{1}{\eta} + (\frac{\eta - \theta}{\theta\eta})(\frac{n_{ijt}}{n_t})^{\frac{1+\eta}{\eta}} > 0, \text{since } \eta > \theta. \tag{7}$$

From the expression above we see how the elasticity of labor supply faced by a firm depends on exogenous parameters $\theta$ and $\eta$ and an endogenous object, the labor share of the firm $\frac{n_{ijt}}{n_t}$.

Using this expression we can totally differentiate with respect to $n_{ijt}$ and $n_{kjt}$ to obtain Proposition 1 below.

**Proposition 1.**

$$\frac{dn_{ijt}}{dn_{kjt}} = \frac{-w_{ijt}(\frac{1}{\theta} - \frac{1}{\eta})(\frac{n_{ijt}}{n_t})^{\frac{1+\eta}{\eta}} \frac{1+\eta}{\eta}[\frac{1}{n_{ijt}} - \frac{1}{n_t}(\frac{n_{kjt}}{n_t})^{\frac{1+\eta}{\eta}}] - \frac{w_{ijt}}{n_{ijt}}(\frac{1}{\theta} - \frac{1}{\eta})^2(\frac{n_{ijt}}{n_t})^{\frac{2(1+\eta)}{\eta}}}{\alpha\gamma(1-\alpha\gamma)z_{ijt}k_{ijt}^{\alpha(1-\gamma)}n_{ijt}^{\alpha\gamma-2} + B(B+1) + w_{ijt}(\frac{1}{\theta} - \frac{1}{\eta})(\frac{1+\eta}{\eta})(\frac{n_{ijt}}{n_t})^{\frac{1}{\eta}}A} < 0 \tag{8}$$

*where*

$$B \equiv (\frac{1}{\eta} + (\frac{1}{\theta} - \frac{1}{\eta})(\frac{n_{ijt}}{n_t})^{\frac{1+\eta}{\eta}}) > 0. \tag{9}$$

*and*

$$A = (\frac{n_t^{1+\frac{1+\eta}{\eta}} - n_{ijt}^{1+\frac{1+\eta}{\eta}}}{n_t^2 n_t^{\frac{1+\eta}{\eta}}}) > 0. \tag{10}$$

*The sign of the derivative comes from the fact that*

$$\eta > \theta \Rightarrow \frac{1}{\theta} - \frac{1}{\eta} > 0 \tag{11}$$

*and by definition since* $n_t > n_{ijt}$*,* $n_t > n_{kjt}$ *for all* $j, k$*, then,*

$$\frac{1}{n_{ijt}} - \frac{1}{n_t}(\frac{n_{kjt}}{n_t})^{\frac{1+\eta}{\eta}} > 0. \tag{12}$$

It follows that employment of a firm $j$ unambiguously decreases with employment of a competing firm $k$. Some properties of this response

- For firms with very low labor market share $\frac{n_{ijt}}{n_t} \approx 0$ we get $\frac{dn_{ijt}}{dn_{kjt}} \approx 0$.
- When the firm $k$ receiving the shock has a higher labor market share, high $\frac{n_{kjt}}{n_t}$, the effect is smaller because the magnitude of $\frac{1}{n_{ijt}} - \frac{1}{n_t}(\frac{n_{kjt}}{n_t})^{\frac{1+\eta}{\eta}}$ decreases.

Next, we might wonder how does the wage of firm $j$ respond to an increase in the size of firm $k$. Proposition 2 characterizes the response.

**Proposition 2.**

$$\frac{dw_{ijt}}{dn_{kjt}} = \frac{1}{\eta}\frac{w_{ijt}}{n_{ijt}}\frac{dn_{ijt}}{dn_{kjt}} + (\frac{1}{\theta} - \frac{1}{\eta})\frac{w_{ijt}}{N_t}[\frac{dn_{ijt}}{dn_{kjt}}(\frac{n_{ijt}}{n_{jt}})^{\frac{1}{\eta}} + (\frac{n_{kjt}}{n_{jt}})^{\frac{1}{\eta}}], \tag{13}$$

*and*

$$\lim_{(\frac{n_{kjt}}{n_{jt}}) \to 0} \frac{dw_{ijt}}{dn_{kjt}} < 0. \tag{14}$$

From Proposition 2 see that

$$\frac{dn_{ijt}}{dn_{kjt}}(\frac{n_{ijt}}{n_{jt}})^{\frac{1}{\eta}} + (\frac{n_{kjt}}{n_{jt}})^{\frac{1}{\eta}} < 0 \Rightarrow -dn_{ijt}(\frac{n_{ijt}}{n_{jt}})^{\frac{1}{\eta}} > dn_{kjt}(\frac{n_{kjt}}{n_{jt}})^{\frac{1}{\eta}} \Rightarrow \frac{dw_{ijt}}{dn_{kjt}} < 0. \tag{15}$$

Intuitively, the sign of the derivative depends on the decrease in size of the competitor firm, $dn_{ijt}$, relative to the size increase in the firm receiving the demand shock, $dn_{ijt}$, weighted by their importance in the market, their labor market share. If the labor share weighted decrease in the size of the competitor $i$ is larger than that of the increase in size of firm $k$, then, firm $i$ decreases its wages. From the expression for $\frac{dw_{ijt}}{dn_{kjt}}$, we also see that when the firm receiving the shock has a very small labor share, $\frac{n_{kjt}}{n_{jt}} \approx 0$, then, the last term is close to zero and the derivative is negative.

In this framework, the only possibility for firms to not respond with their size is if their labor market share is sufficiently small, $\frac{n_{ijt}}{n_t} \approx 0$. In this case the expression for $\frac{dw_{ijt}}{dn_{kjt}}$ simplifies to

$$\frac{dw_{ijt}}{dn_{kjt}} = (\frac{1}{\theta} - \frac{1}{\eta})\frac{w_{ijt}}{N_t}(\frac{n_{kjt}}{njt})^{\frac{1}{\eta}} > 0. \tag{16}$$

In other words, firms with small labor market share respond to an increase in size by a competitor via wage increases without any change in firm size.

## 2.2 Jarosch et al. (2019)

The second framework we consider is a continuous time version of the search and matching framework with bargaining under granular firms proposed by Jarosch et al. (2019).[1] Different than bargaining under atomistic firms, granular firms commit to not hiring a worker if bargaining breaks down. In other words, firms take out their own job posting from their workers' outside option allowing them to pay lower wages. The larger the firm in the market the larger the markdown in wages due to this channel.

The economy is composed of a finite number of firms $i$ each with size $f_i$ in the labor market. Following the authors, we consider $f_i$ is also the probability an unemployed worker matches with firm $i$. Let $r$ denote the parameter controlling the discounting of the household. Let $\lambda$ be the rate at which an unemployed worker meets a firm and $b$ the income while unemployed. The value function of an unemployed worker, $U$ is given by

$$rU = b + \lambda \sum_i f_j(W_j - U) \tag{17}$$

where $W_i$ is the value function associated to working for firm $i$. Let $w_i$ denote wage paid by firm $i$ and $\delta$ the exogenous probability the match is destroyed, then,

$$rW_i = w_i + \delta(U - W_i). \tag{18}$$

Wages are determined by Nash Bargaining. When Bargaining with firm $i$, a worker takes into account that if negotiations break down, she will no longer be able to work for

[1] We consider a continuous time version to make the algebra cleaner. All derivations are unchanged if we consider discrete time.

firm $i$ until she finds another job first.[2] As a result, the outside option $U_i$ used by the worker when bargaining with firm $i$ is given by

$$rU_i = b + \lambda \sum_{j \neq i} f_j (W_j - U_i). \tag{19}$$

Let $J_i$ and $V_i$ be the usual value functions for a filled vacancy and unfilled vacancy, respectively (see Appendix for details). As a result, wages are determined by

$$\beta(J_i - V_i) = (1 - \beta)(W_i - U_i). \tag{20}$$

We consider as in Jarosch et al. (2019) that the free condition holds, $V_i = 0$. As a result, the bargaining equation above is simplified to

$$\beta(\frac{y_i - w_i}{r + \delta}) = (1 - \beta)(\frac{w_i + \delta U}{r + \delta} - U_i) \tag{21}$$

which implies wages are characterized by

$$w_i = \beta y_i + r(1 - \beta)U_i + (1 - \beta)\delta(U_i - U). \tag{22}$$

**Proposition 3.** *Holding fixed the size of firm $i$ in the market $f_i$ we obtain the following*

$$\frac{\partial w_i}{\partial w_j} = \frac{\lambda f_j}{(r + \delta)(r + \delta(1 - f_i))} + \frac{\delta \lambda^2 (1 - f_i) f_j}{r(r + \delta)(r + \delta + \lambda)(r + \lambda(1 - f_i))} > 0, \tag{23}$$

$$\frac{\partial w_i^2}{\partial w_j \partial f_j} > 0 \quad and \quad f_j = 0 \Rightarrow \frac{\partial w_i}{\partial w_j} = 0, \tag{24}$$

$$\frac{\partial w_i^2}{\partial w_j \partial f_i} = \frac{\delta \lambda f_j}{(r + \delta + \lambda)(r + \delta(1 - f_i))^2} > 0, \tag{25}$$

*and*

$$\frac{\partial w_i}{\partial f_j} = \frac{\lambda w_j}{(r + \delta)(r + \delta(1 - f_i))} + \frac{\delta \lambda^2 (1 - f_i) w_j}{r(r + \delta)(r + \delta + \lambda)(r + \lambda(1 - f_i))} > 0. \tag{26}$$

The proposition above tells us that the wage of a given firm $i$ is increasing in the wage of an arbitrary competitor $j$. Intuitively, the more a competitor firm $j$ pays the more firm $i$ needs to pay to keep the worker. This effect is no longer present if the competitor $j$ in question is atomistic ($f_j \approx 0$) since in this case the average wage the worker can get in firms other than $i$ is unchanged. Conversely, the increase in wage by $i$ is even larger if $j$ increases both their wage $w_j$ and their size $f_j$. A raise in $f_j$ directly

[2] Following the authors we consider that the punishment by a firm for a negotiation breakdown lasts until the worker finds a job with a competitor.

leads to higher $w_i$ and increases the response of $w_i$ to $w_j$. Finally, note that the response of $w_i$ to $w_j$ is stronger the larger is firm $i$. The larger the size of firm $i$, the longer the worker would stay unemployed if they decided to walk away from their job, making any wage received by a competing firm $j$ even more important in their threat to leave firm $i$.

Of course, the total response of wages of firm $i$ depends on the relative changes in $f_i$ and $f_j$ following the increase in $w_i$. In any case, the proposition above shows us that even if the size of firm $i$ does not change following the increase in $w_j$, their wage should.

Importantly, firm $i$ increases their wage $w_i$ even if they are atomistic ($f_i \approx 0$). Hence, even in the extreme case where the increase in size and wage by firm $j$, push firm $i$ to $f_i = 0$, the prediction that wages of firm $i$ increases still holds,

$$f_i = 0 \Rightarrow \frac{\partial w_i}{\partial w_j} = \frac{\lambda f_j}{(r+\delta)^2} + \frac{\delta \lambda^2 f_j}{r(r+\delta)(r+\delta+\lambda)(r+\lambda)} > 0. \quad (27)$$

## 2.3 Summary

We have gone over two theories of granular firms in imperfect labor markets. These theoretical frameworks suggest that firms can react to higher wages and size of their competitor by changing their wages and/or changing their size. Importantly, these responses depend on the labor market share of both the reacting firm and the firm that received the shock. In what follows, we test the presence of such strategic interaction in the data.

# 3 Data

We combine two large administrative data sets: matched employer-employee data from Relação Anual de Informações Sociais (RAIS) and online procurement auctions conducted by the government of Brazil in the ComprasNet platform. ComprasNet is the online environment where the government conducts its auctions, and where the auction records are stored.

## 3.1 Auctions Background and Data

In this section, we explain the features of the auctions in our data. The governmental branch interested in procuring goods publishes an announcement of the auction, specifying the product and quantity being procured, the date and time when the auction will be conducted, which documents should be provided by the winning firm, and the location and date where the goods should be delivered. In the data there are 3,264 purchasing governmental branches, which are relatively disaggregated governmental levels. These can be for example an Army battalion, a university or a hospital. After this announcement, interested firms submit a sealed bid before the time of the auction. When the auction begins, the sealed bids are revealed to all participants and firms may start placing new bids in a descending price auction. To do so, a bidder needs to type the bid value in the auction page.

At each moment, all firms observe the currently winning bid. The winner is the firm that has placed the lowest bid when the auction ends. The auction has two parts: there is a first phase when the auction cannot end, and a final, random phase that can end at any moment – and after which no more bids are accepted. After some time elapsed in the first phase, the auctioneer announces when the final, random phase of the auction will begin. The duration of the first phase is at the auctioneer's discretion. The final phase has a random duration between 0 and 30 minutes, drawn electronically by the platform from a uniform distribution.

No participant or auctioneer is able to interfere with the duration of the random phase, or to know it before the auction ends. When the random phase ends, no new bids are accepted and the firm that has placed the lowest bid at that moment has the chance of selling the procured good to the governmental branch. The auctioneer messages the lowest bidder and asks that it sends the required documentation, setting a deadline for this. This deadline is usually within a few hours after the random phase ends. If the lowest bidding firm doesn't send the documentation in time, the auctioneer eliminates this participant and asks the second-placed firm to send it. This continues until a firm successfully sends the required documents, or until all participants have been called. A firm that successfully sends the required documents wins the contract to sell the procured goods. If all firms are called and none is able to produce all needed documents the auction is canceled.

Each auction is automatically registered by the ComprasNet platform in an auction record, which contains detailed specifications and quantity of the products being procured, the government's reference price, the tax identification number (CNPJ) of each participating firm, all bids placed and their respective timestamps, the contract winner, and contract value. It also contains the timestamps of crucial moments in the auction, particularly the start and ending of the random phase. We have scraped each auction record from the government's website and complemented it with detailed product classification codes.[3] We process millions of auction reports into a data set with all 9.2 million ComprasNet online auctions conducted between 2011 and 2016. Auctions are not

[3] 6-digit product code based on the Federal Supply Classification (FSC), developed by the United States' Office of the Secretary of Defense. https://mn.gov/admin/assets/DISP_h2book[1]_tcm36-281917.pdf.

concentrated in any specific group of products (see Appendix Table A1 for a breakdown).[4]

### 3.2 Employer-Employee Data

Our labor market data comes from RAIS (Relação Anual de Informações Sociais), which contains the universe of formal jobs in Brazil. We take observations from 2009-2018 and merge it with the auctions data using the firm's tax identification number (Cadastro Nacional de Pessoa Jurídica, CNPJ). In RAIS, for each job we observe a unique worker identifier, contractual wage, hours, earnings, race, sex, age, schooling, occupation, hiring and separation dates. For each firm, we observe its CNPJ, the municipality where it is located and its industry. The level of observation in RAIS is a job, so to build an annual data set we take only jobs that existed at the end of each year.

For our identification strategy, which is explained in detail in Section 4, we focus only on close auctions where it is reasonable the lowest and second lowest bidders are as good as randomly assigned. After imposing this restriction and merging the two data sets, we are left with 256,697 close auctions with two firms in each, the lowest and second lowest bidder.

## 4 Empirical Design

In this section, we establish how we use a unique feature of Brazilian procurement auctions to obtain credible quasi-experimental variation in firm-specific demand shocks. Our main goal is to estimate the effect of demand shocks on firm wages. Clearly, simply comparing auction winners and losers raises several concerns. These firms are likely different in their production function, size, and worker composition, any of which could affect wages and be correlated with winning an auction.

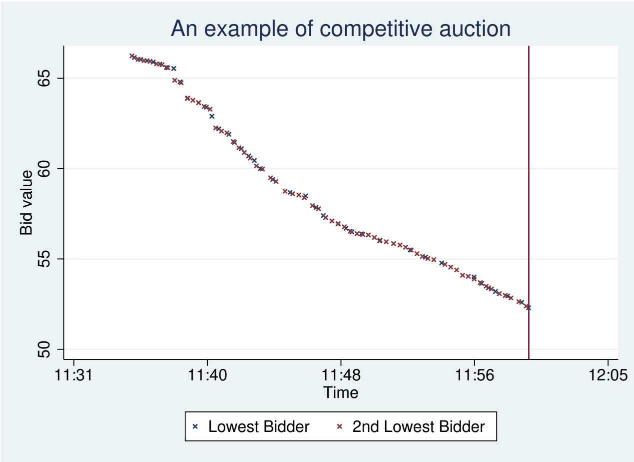
To overcome these endogeneity concerns, we use close auctions, relying on the practical frictions generated by the random ending and the manual time-consuming process for a firm to outbid a current winning bid. Figure 1 shows an example of a close auction. We plot the bid values of two competing firms: the first and the second placed bidder by the end of the auction. As time elapses each firm observes the lowest bid at the moment and decides whether to place a new bid. If it does, the firm must enter the bid manually on the auction page, which requires at least a few seconds. In the figure, we see how firms keep outbidding one another by incremental amounts until the end of the auction displayed by the vertical line. At this point, the lowest bidder wins the auction. Because the time the auction ends is not known, this creates randomness in the identity

[4] See Carvalho et al. (2023) for further detailed description of the data construction.

of the lowest bidder in close auctions. Had the auction ended a few seconds earlier or lasted a few seconds longer, the two lowest bidding firms would be switched. Since we observe each bid value and bid timestamp for each auction, we are able to verify that indeed the lowest bidder and runner-up identities switch if the auction had ended a few seconds earlier (see Appendix Table A2).

We use the time and value of each bid for all auctions and firms in our full data set to formulate our empirical definition of close auctions. We define these as auctions having at least two bids in the last 30 seconds and with a difference between bid values of at most 0.5%. After defining these auctions, we keep the firm that placed the lowest bid and the firm that placed the second lowest bid. By doing this, we ensure that we are on average looking at ex-ante identical firms.

Figure 1: Example of close auction




We interpret each close auction as an experiment in itself. So for each auction, we follow all firms from the same local labor market of the lowest bidder and runner-up, and compare their main outcomes. We use job-level information from RAIS to construct firm-level earnings and worker composition variables for periods before and after the auction date. Our analysis uses annual earnings and firm size as the main outcomes.

Our empirical design does not require any knowledge or assumption about the strategies of the firm. We are relying only on the practical frictions generated by the manual time-consuming insertion of the bid and the randomness of the auction end.[5] When the auction reaches the random phase, participants are not able to anticipate

[5] Szerman (2012) studies theoretically an auction model considering these features. The model generates two types of equilibria. In one, all bidders bid up to their true valuations before the random phase starts. In this equilibrium, firms do not bid during the random phase (and, therefore, would not be defined as a close auction in our design) and the winner is the one with highest valuation. The other equilibrium is where firms outbid each other by tiny amounts, trading off the probability of winning for a better selling price conditional on winning.

when it is about to end. Additionally, there is no automatic bidding in ComprasNet so it takes any participant a few seconds to react to a new bid placed by a competitor. See Figure 1 for example: it is clear that the second lowest bidder was about to place a new, incrementally lower new bid had it had a few more seconds. Additionally, had the auction ended a few seconds earlier the result would have been reversed. For that reason, as long as participants are outbidding one another frequently the identity of the lowest bidder is as good as randomly assigned (Appendix Table A3 shows exactly that: the average close auction's random phase lasts just under 15 minutes but it has more than 46 outbids).

## 4.1 Validating the Empirical Design

In this section, we provide preliminary evidence that validates our empirical design. First, Table 1 compares winners and runners-up in the close auctions we use in our analysis. All outcomes are measured at the year before the auction. Firms are identical in our main outcome: the difference in annual average wages is 7 *Reais* (around 1.4 dollars), and not statistically significant. Furthermore, there are no significant differences across winner and runner-up with respect to the number of employees or worker composition. The share of female employees, employees with college, high skilled, low skilled, and management occupations are similar. Finally, the difference in firm age between winner and runner-up is only of 4.08 months. These patterns reinforce the intuition that winner and runner-up are as good as randomly assigned in our design.

## 4.2 Empirical Estimation

Our first goal is to test whether a firm-specific demand shock affects wages and employment of competing firms in the same labor market. We test this by comparing lowest bidders and runners-up in close auctions, as defined above. For each competitive auction, we first keep only the lowest bidders and runners-up and discard all other firms in the auction. Then, we identify all firms in the local labor market of each lowest bidder. These firms are our treatment group. As our control group we consider all firms in local labor market of each runner-up. Finally, we compare treated and control firms for each auction. To do that, we estimate the following reduced-form specification:

$$Y_{iat} = \beta_0 + \beta_1 Lowest\ Bidder_{ia} + \theta_a + \delta' X_{ia} + u_{iat} \tag{28}$$

Our main outcome $Y_{iat}$ is the outcome of interest (wage or employment) of a firm $i$, that is in the same labor market of a participant in an auction $a$. We run this specification separately for $t = 0, 1, 2$ years after the auction. *Lowest Bidder* is a dummy

Table 1: Balancing: Winner *versus* Runner-up

| | Means | | Difference |
|---|---|---|---|
| Variables at Year$_{t-1}$ | Runner-up | Winner | Runner-up vs Winner |
| (Annual average) Wage (2018 R$) | 1186 | 1194 | 7 |
| | (692) | (746) | (8) |
| Contractual Wage (2018 R$) | 1139 | 1148 | 9 |
| | (618) | (618) | (7) |
| Employees | 14.2 | 13.3 | -0.9 |
| | (163.1) | (132.3) | (0.9) |
| Firm age (years) | 9.07 | 8.73 | -0.34*** |
| | (7.85) | (7.80) | (.11) |
| % College | 15.7 | 16.2 | 0.5 |
| | (26.4) | (26.9) | (0.4) |
| % High Skill | 5.0 | 5.0 | 0.0 |
| | (15.6) | (15.6) | (0.2) |
| % Intermediate Skill | 6.1 | 6.1 | -0.05 |
| | (16.4) | (16.3) | (0.2) |
| % Low Skill | 81.6 | 81.4 | -0.3 |
| | (27.3) | (27.6) | (0.4) |
| % Female | 41.3 | 41.3 | 0.1 |
| | (33.8) | (33.9) | (0.5) |
| Log(quality) | 6.73 | 6.74 | 0.01 |
| | (0.69) | (0.70) | (0.01) |
| Observations | 105,668 | 105,668 | 211,336 |

Notes: Table shows means and standard deviations of selected pre-determined variables for winners and runners-up of close auctions. Difference is obtained from a regression with auction-fixed effects and standard errors clustered at the firm level. Standard errors are shown in parenthesis. All firm outcomes are measured at the year before the auction. "Log quality" represents predicted log wage based on worker demographics. * represents 10% significance, ** represents 5% significance and *** represents 1% significance.

with value equal to 1 if the firm is in the local labor market of the lowest bidder at the (random) end of the auction (equal to 0, for those in the labor market of the runner-up). We add auction fixed-effects, $\theta_a$, since the quasi-randomization is at the auction-level. Finally, $X_{ia}$ are potential additional firm-specific controls. In general, we control for the firm size of the auction participant, and firm size and wage of the competing firm (all measured at year before the auction).

In our setting, after winning an auction the lowest bidder must submit additional documentation confirming that the firm satisfies all conditions to produce the goods demanded by the government. In exceptional cases, if the documentation is not provided in a satisfactory way, the firm does not win the contract and the next firm (in final bid ascending order) is invited to do so. Following this logic, we estimate the effect of being in the winner's labor market on wages and employment. Given the endogeneity generated by the submission of documents, we use being the same labor market as the lowest bidder (lowest bidder indicator) as an instrument for being in the winner's labor market. In fact, the lowest bidder becomes the contracted firm in around 75% of cases. Thus, the first and second-stage equations are:

$$Contract\ Winner_{ia} = \alpha_0 + \alpha_1 Lowest\ Bidder_{ia} + \lambda_a + \gamma' X_{ia} + u_{iat} \quad (29)$$

$$log(w)_{iat} = \beta_0 + \beta_1 Contract\ Winner_{ia} + \theta_a + \delta' X_{ia} + u_{iat} \quad (30)$$

Equation (29) is the first stage. Equation (30) is the second stage of our estimation. The parameter of interest is $\beta_1$. Therefore, we estimate the effect of being in the labor market of a procurement contract winner using only the variation coming from the quasi-random assignment generated by the auction design.

### 4.3 Local Labor Market Definitions

An important step for our analysis is the definition of a local labor market. The literature on labor market concentration has consider many different definitions, commuting zone-industry-occupation (Azkarate-Askasua and Zerecero, 2023), county-occupation-time (Guanziroli, 2022; Azar et al., 2020, 2022; Marinescu et al., 2021), microregion-occupation pairs (Felix, 2022), county-industry-year (Benmelech et al., 2022), and commuting zone-industry (3-digit) pairs (Berger et al., 2022). In this paper we define local labor markets as a municipality-industry-year combination.[6]

## 5 Results

### 5.1 Employment and Wage Effects on Auction Winners

The theoretical framework above has shown how changes in wage and employment of a firm can impact wages and employment of other firms in the market. For this reason, we must first verify whether winning an auction impacts the size and the wages paid by the winning firm. Once this is verified, we can proceed in analysing the potential effects on other firms of the same market.

Therefore, we start by considering a sample with firms that are either the lowest bidder or runner-up only. The results reported in this subsection come mostly from Carvalho et al. (2023). Panel A of Table 2 shows the (reduced-form) effect of being the lowest bidder on firm size.[7] We find that being the lowest bidder causes the firm to have

[6] Municipalities in our data are closest to counties in the US

[7] The number of observations varies across our estimations for two main reasons. First, it is due to the overlap between our auction data (2011-2016) and RAIS (2009-2017). We are not able to follow firms for long periods for more recent auctions. For instance, to estimate the wage effects 4 years later, we can only use auctions conducted in 2013 or before. Second, firms may not be observed in future years

1.9% more employees on average one year after the auction, an effect that is significant at the 1% level. Two years after the auction the effect is 1.2% (significant at the 10% level). Panel B and C of Table 2 report the IV and first-stage estimates. As expected, the lowest bidder is a strong instrument for the contract winner. Lowest bidders are 75% more likely to become the actual contract holder (Panel C). Given the imperfect compliance, the magnitude of the coefficients in the IV estimation are larger than the reduced-form. The results show that contract winners grow 2.5% more in the following year (significant at 1%), and 2% more in four years (significant at 10%), relative to (close) losers (Panel B).

Next, we estimate the effects on firm wages (Table 3). As shown in Panel A, wages in the lowest bidder firm are 1.4% higher compared to runners-up one year after the auction date. After two years, auction winners pay 1.6% higher wages. Results persist even three years later when wages are still 1.4% higher; and four years later when they are 1.6% higher for the lowest bidder. All of these estimates are significant at the 1% level.[8] The IV results (Panel B) point to an 1.8% increase in wages driven by this exogenous firm-specific shock one year later. The effect persists (2.0%) four years after the auction.

Winning a competitive auction is not necessarily a meaningful demand shock for every firm. The demand shock is likely more substantial for younger firms.[9] Motivated by this, we run our analysis splitting the sample between young (age less or equal to 8 years) and old (9 years or older firms). The effect is present for both young and old firms in the short-run, but persists (and increases) only for young firms (Table 4).

The effect of winning an auction on wages is stronger for young firms. The reduced-form estimates (Table 5, columns 1-4) show that being the lowest bidder causes a significant effect of 2% on wages one year after the auction. This effect is amplified as time goes by reaching 2.9% after four years. Again, the IV strategy produces larger coefficient estimates (Panel B). Winning the contract leads to 2.7% higher wages after one year and 3.8% higher wages after four years for young firms. All of these are significant at the 1% level. On the other hand, our point estimates for older firms are economically small and not statistically significant (Columns 5-8), while the first stage is strong.

in the data (firm survival or attrition). Together, these factors make our number of observations drop substantially across the years of analysis.

[8]The number of observations varies across our estimations for two main reasons. First, it is due to the overlap between our auction data (2011-2016) and RAIS (2009-2017). We are not able to follow firms for long periods for more recent auctions. For instance, to estimate the wage effects 4 years later, we can only use auctions conducted in 2013 or before. Second, firms may not be observed in future years in the data (firm survival or attrition). Together, these factors make our number of observations drop substantially across the years of analysis. This is also the reason why we are severely restricted to perform an event study analysis which would require to follow the same firms across years after and before the auction (when young firms - the most affected by the shocks - were not necessarily born).

[9]Ferraz et al. (2015) show that procurement demand shocks are mostly relevant for young firms.

Table 2: Effect on Number of Employees
Auction Participants

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Panel A. Reduced form estimates | | | |
| *Dep Var* | $\log(n)_{t+1}$ | $\log(n)_{t+2}$ | $\log(n)_{t+3}$ | $\log(n)_{t+4}$ |
| Lowest Bidder | 0.019*** | 0.012* | 0.009 | 0.015* |
| | (0.005) | (0.006) | (0.007) | (0.009) |
| | Panel B. IV estimates | | | |
| *Dep Var* | $\log(n)_{t+1}$ | $\log(n)_{t+2}$ | $\log(n)_{t+3}$ | $\log(n)_{t+4}$ |
| Contract Winner | 0.025*** | 0.015* | 0.012 | 0.020* |
| | (0.007) | (0.008) | (0.009) | (0.011) |
| | Panel C. First-stage estimates | | | |
| *Dep Var* | Contract Winner | | | |
| Lowest Bidder | 0.745*** | 0.752*** | 0.758*** | 0.768*** |
| | (0.005) | (0.005) | (0.006) | (0.006) |
| Auction FEs | ✓ | ✓ | ✓ | ✓ |
| Observations | 248972 | 191732 | 132324 | 81254 |

Notes: Reduced form and IV Regressions of log number of employees $j = \{1, 2, 3, 4\}$ years after the auction on contract winner. Unit of observation is an auction-firm. Regressions are run separately for each $j$. *Contract winner* is a dummy taking value 1 if the firm won the auction contract or 0 if the firm did not. Winning the contract is instrumented by a dummy taking value 1 if the firm was the lowest bidder and 0 if the firm was the runner-up. Regressions only include lowest bidder and runner-up firms of close auctions. All regressions include auction fixed effects. Standard errors are clustered at the firm level. * represents 10% significance, ** represents 5% significance and *** represents 1% significance.

Table 3: Effect on Wages
Auction Participants

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Panel A. Reduced form estimates | | | |
| *Dep Var* | $\log(w)_{t+1}$ | $\log(w)_{t+2}$ | $\log(w)_{t+3}$ | $\log(w)_{t+4}$ |
| Lowest Bidder | 0.014*** | 0.016*** | 0.014*** | 0.016*** |
| | (0.004) | (0.004) | (0.004) | (0.005) |
| | Panel B. IV estimates | | | |
| *Dep Var* | $\log(w)_{t+1}$ | $\log(w)_{t+2}$ | $\log(w)_{t+3}$ | $\log(w)_{t+4}$ |
| Contract Winner | 0.018*** | 0.021*** | 0.019*** | 0.020*** |
| | (0.005) | (0.005) | (0.005) | (0.006) |
| | Panel C. First-stage estimates | | | |
| *Dep Var* | Contract Winner | | | |
| Lowest Bidder | 0.745*** | 0.751*** | 0.758*** | 0.767*** |
| | (0.005) | (0.005) | (0.006) | (0.006) |
| Auction FEs | ✓ | ✓ | ✓ | ✓ |
| Observations | 247980 | 190570 | 131138 | 79376 |

Notes: Reduced form and IV Regressions of log of wages $j = \{1, 2, 3, 4\}$ years after the auction on contract winner. Unit of observation is an auction-firm. Regressions are run separately for each $j$. *Contract winner* is a dummy taking value 1 if the firm won the auction contract or 0 if the firm did not. Winning the contract is instrumented by a dummy taking value 1 if the firm was the lowest bidder and 0 if the firm was the runner-up. Regressions only include lowest bidder and runner-up firms of close auctions. All regressions include auction fixed effects. Standard errors are clustered at the firm level. * represents 10% significance, ** represents 5% significance and *** represents 1% significance.

Table 4: Effect on Number of Employees
Auction Participants: Young vs Old Firms

| | Young Firms | | | | Old Firms | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | Panel A. Reduced form estimates | | | | | | | |
| *Dep Var* | $\log(n)_{t+1}$ | $\log(n)_{t+2}$ | $\log(n)_{t+3}$ | $\log(n)_{t+4}$ | $\log(n)_{t+1}$ | $\log(n)_{t+2}$ | $\log(n)_{t+3}$ | $\log(n)_{t+4}$ |
| Lowest Bidder | 0.017** | 0.006 | 0.005 | 0.029** | 0.020** | 0.018* | 0.017 | 0.009 |
| | (0.008) | (0.009) | (0.009) | (0.014) | (0.008) | (0.010) | (0.012) | (0.015) |
| | Panel B. IV estimates | | | | | | | |
| *Dep Var* | $\log(n)_{t+1}$ | $\log(n)_{t+2}$ | $\log(n)_{t+3}$ | $\log(n)_{t+4}$ | $\log(n)_{t+1}$ | $\log(n)_{t+2}$ | $\log(n)_{t+3}$ | $\log(n)_{t+4}$ |
| Contract Winner | 0.023** | 0.008 | 0.007 | 0.038** | 0.026** | 0.023* | 0.022 | 0.012 |
| | (0.011) | (0.013) | (0.013) | (0.018) | (0.010) | (0.013) | (0.016) | (0.020) |
| | Panel C. First-stage estimates | | | | | | | |
| *Dep Var* | Contract Winner | | | | | | | |
| Lowest Bidder | 0.735*** | 0.743*** | 0.754*** | 0.766*** | 0.770*** | 0.771*** | 0.773*** | 0.771*** |
| | (0.007) | (0.007) | (0.008) | (0.009) | (0.008) | (0.009) | (0.010) | (0.011) |
| Auction FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 107988 | 83240 | 57516 | 34484 | 34278 | 25752 | 17846 | 11304 |

Notes: IV Regressions of log number of employees $j = \{1, 2, 3, 4\}$ years after the auction on contract winner by firm age. Columns (1) to (4) report results for young firms, defined as those with 8 years or less of existence. Columns (5) to (8) report results for firms with age of 9+ years. Unit of observation is an auction-firm. Regressions are run separately for each $j$. *Contract winner* is a dummy taking value 1 if the firm won the auction contract or 0 if the firm did not. Winning the contract is instrumented by a dummy taking value 1 if the firm was the lowest bidder and 0 if the firm was the runner-up. Regressions only include lowest bidder and runner-up firms of close auctions. All regressions include auction fixed effects. Standard errors are clustered at the firm level. * represents 10% significance, ** represents 5% significance and *** represents 1% significance.

These results are consistent with recent evidence that winning a procurement contract affects firm growth, specially among young firms. The impact on young firms is likely due to building reputation, learning-by-doing, and the overcoming of financial and demand constraints (Ferraz et al., 2021; Lee, 2021; Giovanni et al., 2024). Importantly, regardless of why the firm grows, our main object of interest is how competitors react as a result.

Table 5: Effect on Wages
Auction Participants: Young vs Old Firms

| | Young Firms | | | | Old Firms | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | Panel A. Reduced form estimates | | | | | | | |
| *Dep Var* | $\log(w)_{t+1}$ | $\log(w)_{t+2}$ | $\log(w)_{t+3}$ | $\log(w)_{t+4}$ | $\log(w)_{t+1}$ | $\log(w)_{t+2}$ | $\log(w)_{t+3}$ | $\log(w)_{t+4}$ |
| Lowest Bidder | 0.020*** | 0.024*** | 0.023*** | 0.029*** | -0.001 | 0.005 | 0.001 | -0.005 |
| | (0.005) | (0.005) | (0.006) | (0.007) | (0.008) | (0.008) | (0.008) | (0.010) |
| | Panel B. IV estimates | | | | | | | |
| *Dep Var* | $\log(w)_{t+1}$ | $\log(w)_{t+2}$ | $\log(w)_{t+3}$ | $\log(w)_{t+4}$ | $\log(w)_{t+1}$ | $\log(w)_{t+2}$ | $\log(w)_{t+3}$ | $\log(w)_{t+4}$ |
| Contract Winner | 0.027*** | 0.032*** | 0.031*** | 0.038*** | -0.002 | 0.006 | 0.001 | -0.007 |
| | (0.007) | (0.007) | (0.007) | (0.009) | (0.010) | (0.010) | (0.011) | (0.012) |
| | Panel C. First-stage estimates | | | | | | | |
| *Dep Var* | Contract Winner | | | | | | | |
| Lowest Bidder | 0.735*** | 0.743*** | 0.754*** | 0.765*** | 0.770*** | 0.771*** | 0.773*** | 0.770*** |
| | (0.007) | (0.007) | (0.008) | (0.009) | (0.008) | (0.009) | (0.010) | (0.012) |
| Auction FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 107674 | 82716 | 56990 | 33646 | 34186 | 25632 | 17638 | 11122 |

Notes: IV Regressions of log of wages $j = \{1, 2, 3, 4\}$ years after the auction on contract winner by firm age. Columns (1) to (4) report results for young firms, defined as those with 8 years or less of existence. Columns (5) to (8) report results for firms with age of 9+ years. Unit of observation is an auction-firm. Regressions are run separately for each $j$. *Contract winner* is a dummy taking value 1 if the firm won the auction contract or 0 if the firm did not. Winning the contract is instrumented by a dummy taking value 1 if the firm was the lowest bidder and 0 if the firm was the runner-up. Regressions only include lowest bidder and runner-up firms of close auctions. All regressions include auction fixed effects. Standard errors are clustered at the firm level. * represents 10% significance, ** represents 5% significance and *** represents 1% significance.

## 5.2 Employment and Wage Effects on Other (Competing) Firms

Having established that winning a close auction leads to higher wages and size, we now want to estimate our main object of interest: how do other firms in the same labor market (competitors) react as a result.

Table 6 shows the (reduced-form) effect of being in the same local labor market of the lowest bidder on firm size (Columns (1)-(3)) and firm-level wages (Columns (4)-(6)) relative to being in the same local labor market as the runner-up. We find that being in the same local labor market as the lowest bidder causes firms to have 0.2% more employees on average at the year of the auction, an effect that is significant at the 1% level. The effect is no longer significant one and two years after the auction, decreasing to a magnitude of 0.1%. Next, looking at the effect on firm wages, we find that being in the same local labor market as the lowest bidder leads to 0.15% higher wages in the year of the auction, an effect that is significant at the 1% level (Columns (4)-(6)). This grows to 0.18% and 0.023% one year and two years later respectively while remaining significant at the 1% level. These magnitudes imply that for every 1% increase in wages by the lowest bidder, wages increase by 0.128% for competitors one year later, and by 0.14% two years later.[10]

[10] These numbers were calculated by dividing the effect found for wages of the lowest bidder (Panel A of Table 3) by the effect found wages of competitors, $\frac{0.00179}{0.014}$ and $\frac{0.00225}{0.016}$

Table 6: Effects on Competitors

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| *Dep Var* | $\log(\text{n})_t$ | $\log(\text{n})_{t+1}$ | $\log(\text{n})_{t+2}$ | $\log(\text{w})_t$ | $\log(\text{w})_{t+1}$ | $\log(\text{w})_{t+2}$ |
| Lowest Bidder | 0.00206*** | -0.00092 | 0.00161 | 0.00147*** | 0.00179*** | 0.00225*** |
| | (0.00079) | (0.00131) | (0.00149) | (0.00034) | (0.00045) | (0.00058) |
| Auction FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 117,173,535 | 117,173,535 | 117,173,535 | 116,758,333 | 100,986,251 | 89,908,530 |

Notes: Reduced-form regressions of log of number of employees (columns 1-3) and log of wages (columns 4-6) of competing firms $j = \{0, 1, 2\}$ years after the auction on the lowest bidder of an auction participant in the same labor market. Unit of observation is a firm-auction-participant. The sample includes all firms in the same labor market of the auction lowest bidder and the runner-up. Regressions are run separately for each $j$. *Lowest bidder* is a dummy taking value 1 if the participant was the lowest bidder and 0 if the participant was the runner-up. All regressions include auction fixed effects. Standard errors are clustered at the participant level. * represents 10% significance, ** represents 5% significance and *** represents 1% significance.

Next, motivated by the fact that the long-run effect on the wages and size of lowest bidders were driven by young firms, we verify to what extent the effect on wages and size of competitors depends on auction participant's age. The effect on size of competitors is imprecisely estimated for both young and old auction participants, becoming significant in the long run only for young auction participants (Columns (1)-(3) of Table 7). The effect on wages of competitors is present for both young and old auction participants (Columns (4)-(6) of Table 7).

To summarize, being in the same local labor market as a winner of a close auction leads to an increase in wages by competitors with no discernible change in their firm size. A first explanation is that firms strategically compete for workers with each other on the margin of wages. A second possible explanation is that when the lowest bidder grows (after winning a close auction), aggregate labor demand increases in the local labor market putting upward pressure on wages via general equilibrium effects. Intuitively, we would expect the strategic interaction motive to be stronger for competing firms with a larger share of their local labor market. In contrast, general equilibrium effects should imply higher wages for competing firms regardless of their local labor market share. With this in mind, we now verify to what extent our results differ by the labor market share of the competing firm. We find no effect on firm size of being in the same local labor market as the lowest bidder for both below and above median labor market share competitors (Columns (1)-(3) of Table 8). Now focusing on wages, we find that the effect is driven by competing firms with above median local labor market shares (Columns (4)-(6) Table 8). Overall our findings are consistent with the interpretation that firms strategically compete with each other via wages, as opposed to size.

Table 7: Effects on Competitors: Young *versus* Old Auction Participants

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | | | Panel A. Young Auction Participants | | | |
| *Dep Var* | $\log(n)_t$ | $\log(n)_{t+1}$ | $\log(n)_{t+2}$ | $\log(w)_t$ | $\log(w)_{t+1}$ | $\log(w)_{t+2}$ |
| Lowest Bidder | 0.00201 | -0.00040 | 0.00563*** | 0.00120*** | 0.00111*** | 0.00157*** |
| | (0.00129) | (0.00237) | (0.00184) | (0.00037) | (0.00050) | (0.00061) |
| Auction FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 79,960,814 | 79,960,814 | 79,960,814 | 79,670,550 | 68,651,076 | 61,390,665 |
| | | | Panel B. Old Auction Participants | | | |
| *Dep Var* | $\log(n)_t$ | $\log(n)_{t+1}$ | $\log(n)_{t+2}$ | $\log(w)_t$ | $\log(w)_{t+1}$ | $\log(w)_{t+2}$ |
| Lowest Bidder | 0.00187 | 0.00281 | -0.00151 | 0.00229*** | 0.00320*** | 0.00382*** |
| | (0.00156) | (0.00198) | (0.00222) | (0.00082) | (0.00112) | (0.00151) |
| Auction FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 37,209,259 | 37,209,259 | 37,209,259 | 37,084,320 | 32,331,202 | 28,513,606 |

Notes: Reduced-form regressions of log of number of employees (columns 1-3) and log of wages (columns 4-6) of competing firms $j = \{0, 1, 2\}$ years after the auction on the lowest bidder of an auction participant in the same labor market. Unit of observation is a firm-auction-participant. The sample includes all firms in the same labor market of the auction lowest bidder and the runner-up. Regressions are run separately for each $j$. *Lowest bidder* is a dummy taking value 1 if the participant was the lowest bidder and 0 if the participant was the runner-up. All regressions include auction fixed effects. Standard errors are clustered at the participant level. Panel A reports results for young participants, defined as those with 8 years or less of existence. Panel B reports results for participants with age of 9+ years. * represents 10% significance, ** represents 5% significance and *** represents 1% significance.

Table 8: Effects on Competitors by Labor Market Share

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | | | Panel A. Labor Market Share *Below* the Median | | | |
| *Dep Var* | $\log(n)_t$ | $\log(n)_{t+1}$ | $\log(n)_{t+2}$ | $\log(w)_t$ | $\log(w)_{t+1}$ | $\log(w)_{t+2}$ |
| Lowest Bidder | 0.00257 | -0.00035 | 0.00160 | 0.00084 | 0.00087*** | 0.00104 |
| | (0.00146) | (0.00186) | (0.00212) | (0.00078) | (0.00110) | (0.00140) |
| Auction FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 47,071,955 | 47,071,955 | 47,071,955 | 46,852,024 | 39,286,045 | 34,278,869 |
| | | | Panel B. Labor Market Share *Above* the Median | | | |
| *Dep Var* | $\log(n)_t$ | $\log(n)_{t+1}$ | $\log(n)_{t+2}$ | $\log(w)_t$ | $\log(w)_{t+1}$ | $\log(w)_{t+2}$ |
| Lowest Bidder | 0.00164* | -0.00114 | 0.00220 | 0.00124*** | 0.00160*** | 0.00216*** |
| | (0.00084) | (0.00128) | (0.00163) | (0.00029) | (0.00038) | (0.00049) |
| Auction FEs | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 70,097,507 | 70,097,507 | 70,097,507 | 69,902,294 | 61,696,664 | 55,627,283 |

Notes: Notes: Reduced-form regressions of log of number of employees (columns 1-3) and log of wages (columns 4-6) of competing firms $j = \{0, 1, 2\}$ years after the auction on the lowest bidder of an auction participant in the same labor market. Unit of observation is a firm-auction-participant. The sample includes all firms in the same labor market of the auction lowest bidder and the runner-up. Regressions are run separately for each $j$. *Lowest bidder* is a dummy taking value 1 if the participant was the lowest bidder and 0 if the participant was the runner-up. All regressions include auction fixed effects. Standard errors are clustered at the participant level. Panel A reports results for firms with labor market share below the median. Panel B reports results for firms with high labor market share. * represents 10% significance, ** represents 5% significance and *** represents 1% significance.

# 6 Conclusion

In this paper we tackle the important question: how do firms react to wages and employment set by their competitors. We leverage quasi-experimental variation from procurement auctions where the winning firm sells goods to the government as our sources of firm-specific demand. A unique feature in these auctions generates randomness in the identity of the contract winner: the moment the auction ends is random (chosen by a computer and unknown to participants). Focusing on auctions in which winner and runner-up are constantly outbidding each other incrementally implies winner and runner-up are as good as randomly assigned.

We find that winning one of these close auctions leads to increases in wages and number of employees of the auction winner and higher wages of other (competing) firms in the local labor market. The effects are driven by competing firms with high labor market share. Overall, our results are consistent with firms strategically interacting with each other via prices in the labor market (wages). We see our results as directly causally linking a firm's share of labor market (market concentration) to their strategic behaviour (implied by market power).

# References


Arnold, D. (2019). Mergers and acquisitions, local labor market concentration, and worker outcomes. *Local Labor Market Concentration, and Worker Outcomes (October 27, 2019)*.

Azar, J., Marinescu, I., and Steinbaum, M. (2022). Labor market concentration. *Journal of Human Resources*, 57(S):S167–S199.

Azar, J., Marinescu, I., Steinbaum, M., and Taska, B. (2020). Concentration in us labor markets: Evidence from online vacancy data. *Labour Economics*, 66:101886.

Azkarate-Askasua, M. and Zerecero, M. (2023). Union and firm labor market power. Technical report, Working Paper.

Benmelech, E., Bergman, N. K., and Kim, H. (2022). Strong employers and weak employees: How does employer concentration affect wages? *Journal of Human Resources*, 57(S):S200–S250.

Berger, D., Herkenhoff, K., and Mongey, S. (2022). Labor market power. *American Economic Review*, 112(4):1147–93.

Berger, D. W., Herkenhoff, K. F., Kostøl, A. R., and Mongey, S. (2023). An anatomy of monopsony: Search frictions, amenities and bargaining in concentrated markets. Technical report, National Bureau of Economic Research.

Bhaskar, V., Manning, A., and To, T. (2002). Oligopsony and monopsonistic competition in labor markets. *Journal of Economic Perspectives*, 16(2):155–174.

Carvalho, M., da Fonseca, J. G., and Santarrosa, R. (2023). How are wages determined? a quasi-experimental test of wage determination theories. Technical report, Rimini Centre for Economic Analysis.

Dodini, S., Løken, K. V., and Willén, A. (2022). The effect of labor market competition on firms, workers, and communities. *NHH Dept. of Economics Discussion Paper*, (17).

Felix, M. (2022). Trade, labor market concentration, and wages.

Ferraz, C., Finan, F., and Szerman, D. (2015). Procuring firm growth: the effects of government purchases on firm dynamics. Technical report, National Bureau of Economic Research.

Ferraz, C., Finan, F., and Szerman, D. (2021). Procuring firm growth: the effects of government purchases on firm dynamics. Technical report.

Giovanni, J. D., García-Santana, M., Jeenas, P., Moral Benito, E., and Pijoan Mas, J. (2024). Buy big or buy small? procurement policies, firms' financing and the macroeconomy.

Guanziroli, T. (2022). Does labor market concentration decrease wages? evidence from a retail pharmacy merger.

Jarosch, G., Nimczik, J. S., and Sorkin, I. (2019). Granular search, market structure, and wages. Technical report, National Bureau of Economic Research.

Kline, P., Petkova, N., Williams, H., and Zidar, O. (2019). Who profits from patents? rent-sharing at innovative firms. *The Quarterly Journal of Economics*, 134(3):1343–1404.

Kroft, K., Luo, Y., Mogstad, M., and Setzler, B. (2020). Imperfect competition and rents in labor and product markets: The case of the construction industry. Technical report, National Bureau of Economic Research.

Lagaras, S. (2019). M&as, employee costs and labor reallocation. *Available at SSRN 3560620*.

Lee, M. (2021). Government purchases and firm growth. *Available at SSRN 3823255*.

Marinescu, I., Ouss, I., and Pape, L.-D. (2021). Wages, hires, and labor market concentration. *Journal of Economic Behavior & Organization*, 184:506–605.

Prager, E. and Schmitt, M. (2021). Employer consolidation and wages: Evidence from hospitals. *American Economic Review*, 111(2):397–427.

Schubert, G., Stansbury, A., and Taska, B. (2022). Employer concentration and outside options.

Szerman, D. (2012). *Public procurement auctions in Brazil.* PhD thesis, The London School of Economics and Political Science (LSE).

Thoresson, A. (2021). Employer concentration and wages for specialized workers. Technical report, IFAU-Institute for Evaluation of Labour Market and Education Policy.

Yeh, C., Macaluso, C., and Hershbein, B. (2022). Monopsony in the us labor market. *American Economic Review*, 112(7):2099–2138.

# Appendices

## Appendix A Proofs

*Proof of Proposition 1.* We are interested in how the $n_{ijt}$ changes with the size of a competing firm $n_{kjt}$. Let us take a total derivative with respect to $n_{kjt}$ and $n_{ijt}$:

$$\alpha\gamma\frac{\partial\frac{y_{ijt}}{n_{ijt}}}{\partial n_{ijt}}dn_{ijt} + \alpha\gamma\frac{\partial\frac{y_{ijt}}{n_{ijt}}}{\partial n_{kjt}}dn_{kjt} = \frac{\partial w_{ijt}}{\partial n_{ijt}}[\frac{1}{\eta} + (\frac{1}{\theta} - \frac{1}{\eta})(\frac{n_{ijt}}{n_t})^{\frac{1+\eta}{\eta}} + 1]dn_{ijt}$$
$$+\frac{\partial w_{ijt}}{\partial n_{kjt}}[\frac{1}{\eta}+(\frac{1}{\theta}-\frac{1}{\eta})(\frac{n_{ijt}}{n_t})^{\frac{1+\eta}{\eta}}+1]dn_{kjt}+w_{ijt}(\frac{1}{\theta}-\frac{1}{\eta})\frac{\partial(\frac{n_{ijt}}{n_t})^{\frac{1+\eta}{\eta}}}{\partial n_{ijt}}dn_{ijt}+w_{ijt}(\frac{1}{\theta}-\frac{1}{\eta})\frac{\partial(\frac{n_{ijt}}{n_t})^{\frac{1+\eta}{\eta}}}{\partial n_{kjt}}dn_{kjt} \tag{31}$$

Using the expression for $\frac{\partial w_{ijt}}{\partial n_{ijt}}$

$$\alpha\gamma\frac{\partial\frac{y_{ijt}}{n_{ijt}}}{\partial n_{ijt}}dn_{ijt} + \alpha\gamma\frac{\partial\frac{y_{ijt}}{n_{ijt}}}{\partial n_{kjt}}dn_{kjt} = (\frac{1}{\eta} + (\frac{1}{\theta} - \frac{1}{\eta})(\frac{n_{ijt}}{n_t})^{\frac{1+\eta}{\eta}})[\frac{1}{\eta} + (\frac{1}{\theta} - \frac{1}{\eta})(\frac{n_{ijt}}{n_t})^{\frac{1+\eta}{\eta}} + 1]dn_{ijt}$$
$$+\frac{\partial w_{ijt}}{\partial n_{kjt}}[\frac{1}{\eta}+(\frac{1}{\theta}-\frac{1}{\eta})(\frac{n_{ijt}}{n_t})^{\frac{1+\eta}{\eta}}+1]dn_{kjt}+w_{ijt}(\frac{1}{\theta}-\frac{1}{\eta})\frac{\partial(\frac{n_{ijt}}{n_t})^{\frac{1+\eta}{\eta}}}{\partial n_{ijt}}dn_{ijt}+w_{ijt}(\frac{1}{\theta}-\frac{1}{\eta})\frac{\partial(\frac{n_{ijt}}{n_t})^{\frac{1+\eta}{\eta}}}{\partial n_{kjt}}dn_{kjt} \tag{32}$$

$$\frac{\alpha\gamma}{n_{ijt}}\frac{\partial y_{ijt}}{\partial n_{kjt}}dn_{kjt}-\frac{\partial w_{ijt}}{\partial n_{kjt}}[\frac{1}{\eta}+(\frac{1}{\theta}-\frac{1}{\eta})(\frac{n_{ijt}}{n_t})^{\frac{1+\eta}{\eta}}+1]dn_{kjt}-w_{ijt}(\frac{1}{\theta}-\frac{1}{\eta})\frac{\partial(\frac{n_{ijt}}{n_t})^{\frac{1+\eta}{\eta}}}{\partial n_{kjt}}dn_{kjt} = -\alpha\gamma\frac{\partial\frac{y_{ijt}}{n_{ijt}}}{\partial n_{ijt}}dn_{ijt}$$
$$+ (\frac{1}{\eta} + (\frac{1}{\theta} - \frac{1}{\eta})(\frac{n_{ijt}}{n_t})^{\frac{1+\eta}{\eta}})[\frac{1}{\eta} + (\frac{1}{\theta} - \frac{1}{\eta})(\frac{n_{ijt}}{n_t})^{\frac{1+\eta}{\eta}} + 1]dn_{ijt}$$
$$+ w_{ijt}(\frac{1}{\theta} - \frac{1}{\eta})\frac{\partial(\frac{n_{ijt}}{n_t})^{\frac{1+\eta}{\eta}}}{\partial n_{ijt}}dn_{ijt} \tag{33}$$

Now use the fact that

$$\frac{\partial w_{ijt}}{\partial n_{kjt}} = \frac{w_{ijt}}{n_{ijt}}(\frac{1}{\theta} - \frac{1}{\eta})(\frac{n_{ijt}}{n_t})^{\frac{1+\eta}{\eta}} > 0 \tag{34}$$

$$\frac{\partial y_{ijt}}{\partial n_{kjt}} = \frac{\partial z_{ijt}(k_{ijt}^{1-\gamma} n_{ijt}^{\gamma})^{\alpha}}{\partial n_{kjt}} = 0, \tag{35}$$

$$\frac{\partial \frac{y_{ijt}}{n_{ijt}}}{\partial n_{ijt}} = \frac{\partial z_{ijt} k_{ijt}^{\alpha(1-\gamma)} n_{ijt}^{\alpha\gamma-1}}{\partial n_{ijt}} = -(1-\alpha\gamma) z_{ijt} k_{ijt}^{\alpha(1-\gamma)} n_{ijt}^{\alpha\gamma-2} < 0, \tag{36}$$

$$\frac{\partial (\frac{n_{ijt}}{n_t})^{\frac{1+\eta}{\eta}}}{\partial n_{ijt}} = (\frac{1+\eta}{\eta})(\frac{n_{ijt}}{n_t})^{\frac{1}{\eta}} (\frac{n_t^{1+\frac{1+\eta}{\eta}} - n_{ijt}^{1+\frac{1+\eta}{\eta}}}{n_t^2 n_t^{\frac{1+\eta}{\eta}}}) > 0, \tag{37}$$

and

$$\frac{\partial (\frac{n_{ijt}}{n_t})^{\frac{1+\eta}{\eta}}}{\partial n_{kjt}} = -(\frac{1+\eta}{\eta})(\frac{n_{ijt}}{n_t})^{\frac{1+\eta}{\eta}} (\frac{n_{kjt}}{n_t})^{\frac{1+\eta}{\eta}} \frac{1}{n_t} < 0 \tag{38}$$

to get

$$-\frac{w_{ijt}}{n_{ijt}}(\frac{1}{\theta}-\frac{1}{\eta})(\frac{n_{ijt}}{n_t})^{\frac{1+\eta}{\eta}}[\frac{1+\eta}{\eta}+(\frac{1}{\theta}-\frac{1}{\eta})(\frac{n_{ijt}}{n_t})^{\frac{1+\eta}{\eta}}]dn_{kjt}+\frac{w_{ijt}}{n_t}(\frac{1}{\theta}-\frac{1}{\eta})(\frac{1+\eta}{\eta})(\frac{n_{ijt}}{n_t})^{\frac{1+\eta}{\eta}}(\frac{n_{kjt}}{n_t})^{\frac{1+\eta}{\eta}}dn_{kjt}$$
$$= \alpha\gamma(1-\alpha\gamma) z_{ijt} k_{ijt}^{\alpha(1-\gamma)} n_{ijt}^{\alpha\gamma-2} dn_{ijt} + (\frac{1}{\eta}+(\frac{1}{\theta}-\frac{1}{\eta})(\frac{n_{ijt}}{n_t})^{\frac{1+\eta}{\eta}})[\frac{1}{\eta}+(\frac{1}{\theta}-\frac{1}{\eta})(\frac{n_{ijt}}{n_t})^{\frac{1+\eta}{\eta}}+1]dn_{ijt}$$
$$+ w_{ijt}(\frac{1}{\theta}-\frac{1}{\eta})(\frac{1+\eta}{\eta})(\frac{n_{ijt}}{n_t})^{\frac{1}{\eta}}(\frac{n_t^{1+\frac{1+\eta}{\eta}} - n_{ijt}^{1+\frac{1+\eta}{\eta}}}{n_t^2 n_t^{\frac{1+\eta}{\eta}}})dn_{ijt} \tag{39}$$

Combining terms gives

$$- w_{ijt}(\frac{1}{\theta}-\frac{1}{\eta})(\frac{n_{ijt}}{n_t})^{\frac{1+\eta}{\eta}} \frac{1+\eta}{\eta}[\frac{1}{n_{ijt}}-\frac{1}{n_t}(\frac{n_{kjt}}{n_t})^{\frac{1+\eta}{\eta}}]dn_{kjt} - \frac{w_{ijt}}{n_{ijt}}(\frac{1}{\theta}-\frac{1}{\eta})^2(\frac{n_{ijt}}{n_t})^{\frac{2(1+\eta)}{\eta}}dn_{kjt}$$
$$= \alpha\gamma(1-\alpha\gamma) z_{ijt} k_{ijt}^{\alpha(1-\gamma)} n_{ijt}^{\alpha\gamma-2} dn_{ijt} + (\frac{1}{\eta}+(\frac{1}{\theta}-\frac{1}{\eta})(\frac{n_{ijt}}{n_t})^{\frac{1+\eta}{\eta}})[\frac{1}{\eta}+(\frac{1}{\theta}-\frac{1}{\eta})(\frac{n_{ijt}}{n_t})^{\frac{1+\eta}{\eta}}+1]dn_{ijt}$$
$$+ w_{ijt}(\frac{1}{\theta}-\frac{1}{\eta})(\frac{1+\eta}{\eta})(\frac{n_{ijt}}{n_t})^{\frac{1}{\eta}}(\frac{n_t^{1+\frac{1+\eta}{\eta}} - n_{ijt}^{1+\frac{1+\eta}{\eta}}}{n_t^2 n_t^{\frac{1+\eta}{\eta}}})dn_{ijt} \tag{40}$$

Then it follows that

$$\frac{dn_{ijt}}{dn_{kjt}} = \frac{-w_{ijt}(\frac{1}{\theta}-\frac{1}{\eta})(\frac{n_{ijt}}{n_t})^{\frac{1+\eta}{\eta}} \frac{1+\eta}{\eta}[\frac{1}{n_{ijt}}-\frac{1}{n_t}(\frac{n_{kjt}}{n_t})^{\frac{1+\eta}{\eta}}] - \frac{w_{ijt}}{n_{ijt}}(\frac{1}{\theta}-\frac{1}{\eta})^2(\frac{n_{ijt}}{n_t})^{\frac{2(1+\eta)}{\eta}}}{\alpha\gamma(1-\alpha\gamma) z_{ijt} k_{ijt}^{\alpha(1-\gamma)} n_{ijt}^{\alpha\gamma-2} + B(B+1) + w_{ijt}(\frac{1}{\theta}-\frac{1}{\eta})(\frac{1+\eta}{\eta})(\frac{n_{ijt}}{n_t})^{\frac{1}{\eta}} A} < 0 \tag{41}$$

where

$$B \equiv (\frac{1}{\eta}+(\frac{1}{\theta}-\frac{1}{\eta})(\frac{n_{ijt}}{n_t})^{\frac{1+\eta}{\eta}}) > 0. \tag{42}$$

and

$$A = (\frac{n_t^{1+\frac{1+\eta}{\eta}} - n_{ijt}^{1+\frac{1+\eta}{\eta}}}{n_t^2 n_t^{\frac{1+\eta}{\eta}}}) > 0. \tag{43}$$

The sign of the derivative comes from the fact that

$$\eta > \theta \Rightarrow \frac{1}{\theta} - \frac{1}{\eta} > 0 \tag{44}$$

and by definition since $n_t > n_{ijt}$, $n_t > n_{kjt}$ for all $j, k$, then,

$$\frac{1}{n_{ijt}} - \frac{1}{n_t}(\frac{n_{kjt}}{n_t})^{\frac{1+\eta}{\eta}} > 0. \tag{45}$$

It follows that employment of a firm $j$ unambiguously decreases with employment of a competing firm $k$. Some properties of this response

1. For firms with very low labor market share $\frac{n_{ijt}}{n_t} \approx 0$ we get $\frac{dn_{ijt}}{dn_{kjt}} \approx 0$.
2. When the firm $k$ receiving the shock has a higher labor market share, high $\frac{n_{kjt}}{n_t}$, the effect is smaller because the magnitude of $\frac{1}{n_{ijt}} - \frac{1}{n_t}(\frac{n_{kjt}}{n_t})^{\frac{1+\eta}{\eta}}$ decreases.

□

*Proof of Proposition 2.* Taking the derivative of $w_{ijt}$ with respect to $n_{kjt}$:

$$\frac{dw_{ijt}}{dn_{kjt}} = \frac{\partial w_{ijt}}{\partial n_{ijt}} \frac{dn_{ijt}}{dn_{kjt}} + \frac{\partial w_{ijt}}{\partial n_{jt}} \frac{\partial n_{jt}}{\partial n_{ijt}} \frac{dn_{ijt}}{dn_{kjt}} + \frac{\partial w_{ijt}}{\partial n_{jt}} \frac{\partial n_{jt}}{\partial n_{kjt}} \tag{46}$$

Now note that

$$\frac{\partial w_{ijt}}{\partial n_{jt}} = (\frac{1}{\theta} - \frac{1}{\eta})\frac{w_{ijt}}{N_t} > 0, \tag{47}$$

$$\frac{\partial w_{ijt}}{\partial n_{ijt}} = \frac{1}{\eta}\frac{w_{ijt}}{n_{ijt}} > 0, \tag{48}$$

and

$$\frac{\partial n_{jt}}{\partial n_{kjt}} = (\frac{n_{jt}}{n_{jt}^{\frac{\eta+1}{\eta}}}) n_{kjt}^{\frac{1}{\eta}} = (\frac{n_{kjt}}{n_{jt}})^{\frac{1}{\eta}}, \forall k, \tag{49}$$

and so,

$$\frac{dw_{ijt}}{dn_{kjt}} = \frac{1}{\eta}\frac{w_{ijt}}{n_{ijt}}\frac{dn_{ijt}}{dn_{kjt}} + (\frac{1}{\theta} - \frac{1}{\eta})\frac{w_{ijt}}{N_t}[\frac{dn_{ijt}}{dn_{kjt}}(\frac{n_{ijt}}{n_{jt}})^{\frac{1}{\eta}} + (\frac{n_{kjt}}{n_{jt}})^{\frac{1}{\eta}}]. \tag{50}$$

Now taking the limit of $\frac{dw_{ijt}}{dn_{kjt}}$ for $(\frac{n_{kjt}}{n_{jt}}) \to 0$ we obtain

$$\lim_{(\frac{n_{kjt}}{n_{jt}}) \to 0} \frac{dw_{ijt}}{dn_{kjt}} < 0. \tag{51}$$

From the above expression we see that if

$$\frac{dn_{ijt}}{dn_{kjt}}(\frac{n_{ijt}}{n_{jt}})^{\frac{1}{\eta}} + (\frac{n_{kjt}}{n_{jt}})^{\frac{1}{\eta}} < 0 \Rightarrow -\frac{dn_{ijt}}{dn_{kjt}} > (\frac{n_{kjt}}{n_{ijt}})^{\frac{1}{\eta}}. \tag{52}$$

then $\frac{dw_{ijt}}{dn_{kjt}} < 0$. In other words, if the response in employment of a competitor $i$, $n_{ijt}$, to increases in $n_{kjt}$ of firm $k$ is larger than the relative employment of firm $k$ to $i$, wages of the competitor $i$ decrease. We also see when the firm receiving the shock has a very small labor share, $\frac{n_{kjt}}{n_{jt}} \approx 0$, then, the last term is close to zero and the derivative is negative. □

*Proof of Proposition 3.* To start let us explicitly state the value functions for a filled and unfilled vacancy. The value function for a filled vacancy is given by

$$rJ_i = y_i - w_i + \delta(V_i - J_i) \tag{53}$$

where $y_i$ is the amount produced by one worker in firm $i$. Let $c_i$ denote the cost of posting a vacancy for a firm $i$ and $q$ the probability of a firm finding a worker, then,

$$rV_i = -c_i + q(J_i - V_i). \tag{54}$$

Let us start by deriving the explicit expression for the wage paid by a firm $i$. The first step is to find an expression for $U_i - U$.

Note that

$$rU_i = b + \lambda \sum_j f_j W_j - U_i \lambda \sum_{j \neq i} f_j - \lambda f_i W_i \tag{55}$$

Next, subtracting $rU$ from this expression we get

$$r(U_i - U) = -\lambda(U_i \sum_{j \neq i} f_j - U) - \lambda f_i W_i = -\lambda(U_i(1 - f_i) - U) - \lambda f_i W_i \tag{56}$$

$$U_i - U = -\frac{\lambda f_i(W_i - U_i)}{r + \lambda} \tag{57}$$

Now using the bargaining condition we can rewrite this as

$$U_i - U = -\frac{\lambda\beta(J_i - V_i)}{(1 - \beta)(r + \lambda)} \tag{58}$$

Now using the free entry condition $V_i = 0$, we get

$$J_i - V_i = \frac{c_i}{q} \tag{59}$$

then,

$$U_i - U = -\frac{\lambda\beta c_i}{q(1 - \beta)(r + \lambda)} \tag{60}$$

Next, using the expression for $W_i$

$$W_i = \frac{w_i + \delta U}{r + \delta} \tag{61}$$

and replacing that in the expression for $U$ gives us

$$U = \frac{b(r+\lambda)}{r(r+\delta+\lambda)} + \frac{\lambda \sum_j f_j w_j}{r(r+\delta+\lambda)}. \tag{62}$$

Next, replacing the expression for $W_i$ inside $U_i$ gives us

$$\frac{U_i(r(r+\delta) + (r+\delta)\lambda \sum_{j\neq i} f_j)}{r+\delta} = b + \frac{\lambda \sum_{j\neq i} f_j w_j}{r+\delta} + \frac{\delta U \lambda \sum_{j\neq i} f_j}{r+\delta}. \tag{63}$$

$$U_i = \frac{b}{r + \lambda(1-f_i)} + \frac{\lambda \sum_{j\neq i} f_j w_j}{(r+\delta)(r+\lambda(1-f_i)} + \frac{\delta\lambda(1-f_i)U}{(r+\delta)(r+\lambda(1-f_i)}. \tag{64}$$

Combining the expression for $U_i$ and $U$

$$U_i = \frac{b}{r+\lambda(1-f_i)} + \frac{\lambda \sum_{j\neq i} f_j w_j}{(r+\delta)(r+\lambda(1-f_i))} + \frac{\delta\lambda(1-f_i)b}{r(r+\delta+\lambda)(r+\lambda(1-f_i))} + \frac{\delta\lambda^2(1-f_i)\sum_j f_j w_j}{r(r+\delta)(r+\delta+\lambda)(r+\lambda(1-f_i))}. \tag{65}$$

It follows that the expression for $w_i$ is given by

$$w_i = \beta y_i + r(1-\beta)\Big[\frac{b}{r+\lambda(1-f_i)} + \frac{\lambda \sum_{j\neq i} f_j w_j}{(r+\delta)(r+\lambda(1-f_i))} + \frac{\delta\lambda(1-f_i)b}{r(r+\delta+\lambda)(r+\lambda(1-f_i))} + \frac{\delta\lambda^2(1-f_i)\sum_j f_j w_j}{r(r+\delta)(r+\delta+\lambda)(r+\lambda(1-f_i))}\Big] + \frac{-\lambda\delta\beta c_i}{q(r+\lambda)} \tag{66}$$

Now taking the derivative with respect to $w_j$ we get

$$\frac{\partial w_i}{\partial w_j} = \frac{\lambda f_j}{(r+\delta)(r+\delta(1-f_i))} + \frac{\delta\lambda^2(1-f_i)f_j}{r(r+\delta)(r+\delta+\lambda)(r+\lambda(1-f_i))} > 0. \tag{67}$$

Taking the derivative of this expression with respect to $f_j$ and $f_i$ completes the proof.

□

# Appendix B Tables

Table A1: % Auctions and % Value per Group of Products

| Categories | % auctions | % value |
|---|---|---|
| Vehicles and parts | 4.61% | 14.78% |
| Industrial, commercial and agri equipment | 5.42% | 6.65% |
| Safety, cooling, hydraulic, etc. equipment | 6.87% | 7.27% |
| Building materials, tools, etc. | 11.02% | 9.79% |
| Electric and communication equipment | 7.66% | 6.09% |
| Medical and scientific equipment | 12.81% | 12.86% |
| Computers, parts, etc. | 4.23% | 2.13% |
| Furniture | 3.64% | 4.71% |
| Food preparation utensils and equipment | 6.16% | 4.28% |
| Office supplies and printed material | 7.06% | 3.72% |
| Recreation, sports and musical equipment | 2.94% | 1.19% |
| Cleaning supplies, packages | 6.86% | 4.49% |
| Personal hygiene and clothing | 4.70% | 4.70% |
| Live animals ans agricultural supplies | 1.84% | 1.56% |
| Food | 4.92% | 7.31% |
| Fuels and minerals | 3.18% | 4.03% |
| Misc. | 6.06% | 4.45% |

Notes: The table groups close auctions into product categories and reports the fraction of auctions and the fraction of total value in *Reais* that corresponds to each category.

Table A2: Placebo identity of lowest bidder when auction ended $x$ seconds earlier

| Placebo Lowest Bidder if auction ended... | | |
|---|---|---|
| | Lowest Bidder | Runner-up |
| 2 seconds earlier | 0.83 | 0.17 |
| 6 seconds earlier | 0.57 | 0.40 |
| 10 seconds earlier | 0.43 | 0.50 |
| 14 seconds earlier | 0.40 | 0.50 |
| 18 seconds earlier | 0.47 | 0.41 |
| 22 seconds earlier | 0.60 | 0.29 |
| 26 seconds earlier | 0.63 | 0.25 |

Notes: The Column "Lowest Bidder" shows the fraction of lowest bidder firms that would have won the contract if the action ended $x$ seconds earlier. The Column "Runner-up" shows the fraction of runner-up firms that would have won the contract if the auction ended $x$ seconds earlier.

Table A3: Close Auction Summary Statistics

| | Mean | Standard Deviation |
|---|---|---|
| Reference Value (BRL) | 52,992 | 694,242 |
| Winning Bid (BRL) | 28,287 | 433,888 |
| Auction Duration (min) | 51.8 | 51.3 |
| Random Phase Duration (min) | 14.7 | 8.4 |
| Number of firms who submit initial proposal | 9.0 | 6.3 |
| Number of firms during auction | 6.1 | 4.3 |
| Number of firms during random phase | 4.5 | 2.7 |
| Number of firms during last 30 Seconds | 2.3 | 0.7 |
| % Difference between 2 lowest bids | 0.12 | 0.13 |
| Rank of Lowest Bidder's Initial Proposal | 2.1 | 1.3 |
| Rank of Runner-up's Initial Proposal | 2.0 | 1.2 |
| Number of bids in auction | 72.6 | 52.1 |
| Number of bids in random phase | 55.0 | 45.1 |
| Number of outbids in random phase | 46.8 | 36.9 |
| Lowest Bidder's Outbids During Random Phase | 18.6 | 15.0 |
| Runner-up's Outbids During Random Phase | 17.0 | 14.6 |
| Lowest Bidder's Outbids During Last 30 Seconds | 1.3 | 0.4 |
| Runner-up's Outbids During Last 30 Seconds | 1.0 | 0.3 |
| Lowest Bidder's Seconds as Leader During Last 30 Seconds | 10.8 | 6.4 |
| Runner-up's Seconds as Leader During Last 30 Seconds | 9.0 | 5.8 |
| Observations | 225,093 | |

Notes: This table shows summary statistics for close auctions held by federal purchasing units between 2011 and 2016. We define close auctions as those auctions where (i) both the winner and runnerup placed bids in the last 30 seconds of the auction, and (ii) the runnerup bid does not exceed the winning bid by more than 0.5%.