

The Impact of Labor Market Conditions on Job Creation: Evidence from Firm Level Data

Ekaterina Roshchina*

Evans School of Public Policy & Governance

University of Washington

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Abstract

Labor market conditions, i.e. labor market tightness and prevailing wages, determine the cost of hiring new workers and thus can have a profound impact on employment growth. In this paper, I estimate firm level elasticity of labor demand with respect to changes in labor market conditions, allowing for heterogeneous response both across firms and across regions. I consider changes along two margins: labor market tightness and wages, and quantify the contribution of each margin to employment growth. Using the employer-employee matched dataset from Brazil, I show that a one percent increase in labor market tightness reduces employment growth by 1 percentage points, and a one percent increase in wages reduces employment growth by 1-2 percentage points. I find that low-paying firms have 20-30% larger labor demand elasticity than high-paying firms. However, the contribution of labor market conditions to regional employment growth is small, and most of the effect of labor market conditions is driven by changes in labor market tightness rather than wages.

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1 Introduction

Labor market conditions, i.e. labor market tightness and wages, affect cost of hiring for firms, and can have a profound impact on employment growth. If this impact is large, economic policies which alter labor market conditions, such as extending unemployment benefits or increasing minimum wage, will have unintended consequences for employment growth. Furthermore, labor market conditions vary substantially over the business cycle, making hiring faster and cheaper during recessions, when markets are slack, and harder and more expensive during expansions, when markets are tight. This mechanism acts as an automatic stabilizer, which can reduce employment fluctuations over the business cycle. If firms are sensitive to labor market conditions, imposing economic policies which make hiring more expensive can, for instance, slow down recovery. On the other hand, if firm response to labor market conditions is weak, policy makers can focus on redistributive aspect of such policies without worrying about hurting job creation.

Though the idea behind the effect of labor market conditions on job creation is very intuitive, its magnitude has never been estimated directly. In particular, the macro literature has extensively studied the volatility of vacancies and unemployment over the business cycle (Shimer, 2005; Hagedorn and Manovskii, 2008), but has essentially taken as given the following response of demand for labor to slacker labor markets. On the other hand, the micro literature has concentrated on migratory (Yagan, 2014) and wage (Davis and von Wachter, 2011) consequences of recessions and has abstracted from the labor demand adjustment. Finally, several recent studies have documented differential employment growth across firms at times of low and high unemployment (Moscarini and Postel-Vinay, 2012; Kahn and McEntarfer, 2014; Fort et al., 2013), but have not specifically analyzed the effect of labor market conditions on job creation.

In this paper, I use employer-employee matched dataset from Brazil to estimate firm level elasticity of labor demand with respect to changes in labor market conditions, allowing for heterogeneity in elasticity across firms. Unlike the previous studies, which have focused either on changes in unemployment (Moscarini and Postel-Vinay, 2012; Kahn and McEntarfer, 2014; Fort et al., 2013) or wages, I consider both margins of adjustment: changes in labor market tightness and changes in wage. Furthermore, I study both the direct impact of changes in labor market conditions on labor demand, and the net effect on employment growth when wage adjustment has been taken into account. Understanding the size of the first effect is Finally, I evaluate the contribution of changes in labor market conditions to employment growth and quantify the impact of each margin on employment growth.

I find that firms respond with similar magnitude to changes in labor market tightness and wages, and low-paying firms are more sensitive to changes in labor market conditions than high paying firms. However, the contribution of labor market conditions to regional employment growth is small, and most of the effect of labor market conditions is driven by changes in labor market tightness rather than wages.

The key mechanism which I study stems from the idea that an increase in demand for labor

in one industry has a general equilibrium effect on firms in other industries who hire workers on the same labor market. This mechanism propagates through two channels: change in labor market tightness and change in wages. If one industry is expanding, it tightens the labor market by reducing the total number of workers available for hire. Similarly, if one industry starts paying higher wages, other industries have to match this increase to be able to attract workers. This general equilibrium mechanism was first clearly formulated in Beaudry et al. (2012), who have shown that an expansion of a high paying industry in a city leads to an overall wage increase in that city. Beaudry, Green, and Sand have used this framework to estimate the long-term elasticity of labor demand in Beaudry et al. (2014). In this paper, I apply their idea to the employment fluctuations over the local business cycles. My paper innovates on Beaudry et al. (2012) and Beaudry et al. (2014) in three ways. First, I introduce heterogeneous firms into their theoretical framework and allow for heterogeneous sensitivity to labor market conditions across regions. Second, Beaudry et al. (2014) have studied the long-term (decennial) labor demand elasticities, and I focus on the effect of labor market conditions on employment growth over the business cycle. And finally, I estimate labor demand elasticity at the firm level, rather than at the regional level.

My analysis is based on employer-employee matched data from Brazil in 1998-2009. The richness of the data allows me to construct reliable series of wage changes, which are usually unavailable in the aggregate data. I control for worker characteristics (age, education and gender), job characteristics (occupation and tenure of the job), and firm characteristics (firm age and the status of a multi-establishment firm) and calculate real wage series for a fixed demographics group.

The fundamental challenge in estimating labor demand elasticity lies in separating the changes in labor market conditions from the changes in firm's productivity. This identification problem is analogous to distinguishing the movement along the demand curve from the shift of the demand curve itself in a standard demand estimation. Indeed, a more productive firm will be able to pay higher wages to its workers, but the resulting wage growth will not be caused by the changes in labor market conditions. Likewise, an increase in productivity of a large firm can lead to a substantial number of additional hires and affect the labor market tightness for the whole region.

In order to isolate the movements of labor market conditions, I rely on two types of instruments. First, I build on the idea of Beaudry et al. (2014) that the labor demand shocks to other firms in the same location can be used as a supply shock to the firm under consideration and utilize a Bartik shock, a common instrument for labor demand¹, as a source of exogenous variation in labor market tightness. A Bartik shock in employment measures how big employment growth in each region would have been if each industry expanded at the national rate of growth in that industry. Thus, a Bartik shock is a predictor of overall employment growth at the regional level.²

¹See, for example, Bartik (1991); Blanchard and Katz (1992); Bound and Holzer (2000); Notowidigdo (2013); Diamond (2012).

²Following the common practice, I exclude employment growth in each region from the national trend calculation and use the lagged industrial composition in each region to construct the predicted regional growth. This procedure ensures that a Bartik shock is not contaminated with the local trends or changes in firm's own productivity.

I instrument for the change in wages at the firm level in a similar manner by calculating predicted rate of wage growth in each region using the national trends in each industry. Since each firm in the region would have to match this wage increase to be able to attract workers, the wage increase at the firm level due to the overall wage increase would capture the effect of the change in labor market conditions rather than an increase in the revenue of that firm. Second, I explore the fact that Brazil has a federally mandated minimum wage, which is set discretionarily and changes approximately once a year.³ For each firm, I calculate the share of workers in the previous year which did not meet this year minimum wage threshold and use this measure as a wage shock to the firm.

However, this identification strategy is invalid if the demand shocks are correlated across industries. The minimum wage and Bartik instruments are orthogonal to local- and firm-specific demand shocks, but still both contain nationwide industry shocks. To resolve this concern, in my estimation equation I control for nationwide industry shocks explicitly, using the nationwide average wage growth in each industry as a proxy for a demand shock in that industry. In addition, I restrict the analysis to manufacturing firms, which allows me to assume that the demand for goods in the economy is exogenous to the local industrial composition and abstract from the effect of local multipliers.

I estimate the model using General Method of Moments (GMM), allowing the elasticities of the labor demand to depend on the wage a firm is paying. I show that a one percent increase in labor market tightness reduces employment growth by 1 percentage points, and a one percent increase in wages reduces employment growth by 1-2 percentage points. I find that low-paying firms have 20-30% larger labor demand elasticity than high-paying firms. However, the contribution of labor market conditions to regional employment growth is small, and most of the effect of labor market conditions is driven by changes in labor market tightness rather than wages.

I use these estimates to analyze the contribution of changes in labor market conditions to regional employment growth. I consider a scenario in which any change in the demand for labor is exactly offset by migration, so that the labor market tightness remains the same, and neither an increase in worker's outside options nor the growth of firm's revenue translate into higher wages, keeping the wage level in each firm constant. I show that the contribution of labor market conditions to employment growth is relatively small – if labor market conditions did not change, the variance of regional employment growth would have been 4-6% higher. Furthermore, I demonstrate that 90% of this effect is driven by changes in labor market tightness rather than wages.

My analysis faces two limitations. First, I focus on the intensive margin and do not take into account changes in the regional employment growth due to entry of the new firms. Next, because I use the data on manufacturing firms in the formal sector, my results should be interpreted as the impact of labor market conditions on fluctuations in the formal employment in the tradable sector. For instance, if the increase in the competition for workers pushes more firms to hire workers informally, my results would capture this effect but suggest that employment is growing slower.

³Each state can impose its own minimum wage, but it cannot be lower than the federal minimum.

Thus, I will not be able to distinguish between the slow down in the overall employment growth and the increase in the incidence of informality.

My paper connects several strands of literature. I revisit the widely studied question of regional response to shocks, first extensively covered in Blanchard and Katz (1992). However, unlike the many studies in this literature, who investigated the migratory response to shocks (see, for instance, Notowidigdo, 2013; Yagan, 2014), I analyze the labor market adjustment of the demand side of the market.

I also contribute to a large body of literature which uses a local labor market approach to study the effect of shocks (Autor et al., 2013; Dix-Carneiro and Kovak, 2015; Topalova, 2007; Beaudry et al., 2012). This approach allows me to exploit differential exposure to nationwide shocks across regions and provides a clear identification strategy of the effect of labor market conditions on employment growth.

Next, my paper provides new evidence on differential sensitivity to labor market conditions across firms. Though the findings in this literature suggest differential cyclicalities of employment growth across low- and high-paying firms in the US (Moscarini and Postel-Vinay, 2012; Kahn and McEntarfer, 2014; Fort et al., 2013), existing studies provide descriptive evidence rather than estimate the causal relationship. To my knowledge, this is the first paper to estimate firm level elasticity of labor demand with respect to changes in labor market conditions.

Finally, my paper is close in spirit to the studies which aim to match firm level dynamics to the stylized facts on aggregate fluctuations (Cooper et al., 2007; Elsby and Michaels, 2013). These papers focus on modeling decisions of firms to generate observed aggregate volatility of employment and wages in response to revenue shocks. I take this response as given instead and estimate the magnitude of general equilibrium adjustment to the resulting changes in labor market conditions.

The rest of the paper is structured as follows. First, I develop a model of local labor markets with heterogeneous firms and derive the firm-specific response to a change in local labor market conditions in section 2. Next, I explain the identification strategy in section 3 and discuss its strength and limitations in light of the model of the local labor markets. I take the model to the data and present results on the magnitude of labor demand elasticity in section 5. Then I discuss the impact of labor market conditions on employment growth at the regional level in section 6. Finally, I summarize the findings and suggest the steps for future research in section 7.

2 Effect of Labor Market Conditions on Employment Growth

In this section I describe a theoretical framework for studying the effect of the changes in labor market conditions on employment growth. I build a search and bargaining model of local labor markets with heterogeneous firms, which has two crucial features. First, because hiring is costly due to frictions, labor demand depends on the labor market tightness. Second, because wages are

determined through Nash bargaining and firms differ in marginal productivity per worker, wage paid by each firm depends on the distribution of wages in the whole labor market, as in Beaudry et al. (2012). As a result, both changes in firm's own productivity and changes in prevailing wages in the labor market affect its labor demand.

Next, I argue that in this model marginal productivity per worker affects not only the size of the firm, but its sensitivity to changes in labor market conditions as well, because more productive firms can sustain larger changes in wages than less productive ones.

Finally, I show that firm employment growth can be decomposed into three components: growth due to changes in labor market tightness, growth due to changes in wages and growth due to changes in firm's productivity or hiring costs. To be able to consistently estimate labor demand elasticity, one needs to find a source of exogenous variation in labor market conditions which is not correlated with changes in firm's productivity. I discuss in detail how I solve this identification challenge in section 3.

2.1 Model of local labor markets

I model firms' employment and wages using a continuous-time search and bargaining framework with heterogeneous firms. I let firms differ in two parameters: flow revenue per worker and fixed cost of hiring. The first parameter affects firms' surplus from opening a new vacancy and the second one changes how expensive it is to expand. Together, these two parameters determine the optimal size of the firm. However, only the flow revenue per worker affects wages and firm's sensitivity to changes in labor market conditions.

Firms are located in L isolated regions which produce J traded goods, sold at the national price p_j .⁴ Each industry j in a region l is populated by a continuum of firms, who take the prices of goods as given, but can choose how many vacancies to post. Firms can fill the posted vacancies from the pool of unemployed workers, but hiring takes time due to search frictions. Once a vacancy is matched with a worker, the firm and the worker split the surplus of the match according to Nash bargaining.

Workers in the model are looking for jobs in all industries, and they get some of the firm-specific surplus once they find a job. As a result, wages do not equalize across firms and wages paid by each firm depend on the distribution of productivity in the whole labor market, as in Beaudry et al. (2012). This wage setting can be regarded as a reduced form approximation of a second-price auction for a worker, as in Cahuc et al. (2006) and Flinn (2006).

Matching function. All firms hire workers on the same region-specific labor market. There are no economies of scale in hiring and workers don't observe firm characteristics before they are matched with a vacancy. As a result, an open vacancy at any firm is filled at a constant vacancy filling rate ϕ_l . The equilibrium vacancy filling rate ϕ_l is determined by the total number of vacan-

⁴Thus, in the model I do not allow markets to interact through migration or local multipliers. However, I show in section 3 that my identification strategy is robust to these interactions as well.

cies posted by each industry in the region l , since I treat the number of workers in each region as fixed. Following a standard DMP model, I assume that the matching function exhibits constant returns to scale with parameter σ . Furthermore, I assume that workers are perfectly mobile across industries.⁵ As a result, one additional unemployed worker increases the vacancy filling rate by the same rate in all firms and all the industries. Thus, firms from all industries respond to an increase in unemployment in the same way, and do not care about the composition of unemployment workers.

Denoting the number of unemployed workers by U_l , and the total number of vacancies by V_l , the total number of the new matches can be written as $V_l^\sigma U_l^{1-\sigma}$. Thus, the vacancy filling rate ϕ_l and the job arrival rate ψ_l are:

$$\phi_l = \left(\frac{V_l}{U_l} \right)^{-(1-\sigma)}, \quad (2.1)$$

$$\psi_l = \left(\frac{V_l}{U_l} \right)^\sigma. \quad (2.2)$$

Labor supply. Workers can be either employed or unemployed. Unemployed workers look for jobs in all industries independently of their previous employment.⁶ I assume that search is random, and an unemployed worker meets a vacancy from an industry j and firm i with a probability proportional to the number of unfilled vacancies it has on the market. Thus, a worker receives a job offer from an industry j at the rate $\psi_l \eta_{jl}$, where $\eta_{jl} = V_{jl}/V_l$ is the share of unfilled vacancies of industry j in the market and ψ_l is the job arrival rate. While unemployed, the worker receives per-period utility b , which can be thought of as the value of home-production or work at the informal sector. Denoting by J^u the value of unemployment and by J_j^e the expected value of employment at industry j , the value of unemployment can be written as:

$$\rho J_l^u = b + \psi_l \left(\sum_j \eta_{jl} J_{jl}^e - J_l^u \right). \quad (2.3)$$

When a worker receives a job offer, a firm and a worker agree on the wage rate w_{ijl} according to the Nash bargaining rule, and the worker becomes employed. Firms in the same industry pay different wages because workers have non-zero bargaining power and receive some of the surplus of the match, and on the other hand workers cannot direct their search towards the higher paying firms due to search frictions. An employed worker can separate from a firm in two cases. Either the firm closes or scales down (endogenous separation), or the match is dissipated (exogenous separation), which occurs at rate δ . In steady-state the firm's revenue is constant, and the only source of separations is the dissipation rate. Denoting by J_{ijl}^e the value of employment at a firm ijl , the Bellman equation for it writes:

$$\rho J_{ijl}^e = w_{ijl} + \delta (J_l^u - J_{ijl}^e). \quad (2.4)$$

⁵This assumption is made for simplicity and can be relaxed at the cost of introducing additional $(J-1)L$ parameters to the model. However, partial mobility across industries is required.

⁶This assumption can be relaxed if the detailed data on the composition of unemployed workers for each region is available, which is not the case of Brazil.

The value of employment at the industry j is the weighted average of employment at each firm i of industry j in the region l , where the probability to be employed at each firm is proportional to the share of its unfilled vacancies in the industry $\eta_{ijl} = \frac{V_{ijl}}{V_{jl}}$. Denoting by $w_{jl} = \sum_i \eta_{ijl} w_{ijl}$ the average wage the industry i pays, where the expectation is taken over the firm-specific parameters which will be described later, the expected value of employment at this industry is:

$$\rho J_{ijl}^e = \mathbb{E} [\eta_{ijl} J_{ijl}^e] = w_{jl} + \delta (J_l^u - J_{jl}^e). \quad (2.5)$$

Labor demand. Each firm i in industry j and region l receives flow revenue y_{ijl} from a filled vacancy. Firms take y_{ijl} as given and only decide how many vacancies to post. I model the flow revenue as a sum of three components: $y_{ijl} = p_j + \zeta_l + \varepsilon_i$, where p_j is the price of the good, ζ_l is a region-specific revenue-advantage, and ε_i is the firm's revenue advantage. I assume that all three components of the flow revenue are independent from each other. Each firm is characterized by two parameters: advantage in revenue per worker ε_i and the fixed cost of hiring ξ_i . The revenue per worker advantage allows a firm to get higher profit per \$1 of wages paid, and represent firm's savings on marginal costs not associated with labor, such as the price of materials etc. A lower fixed hiring cost helps a firm to expand at a lower cost, and can arise from a better hiring technology, a smaller bureaucratic burden associated with posting a vacancy etc. I do not impose any restrictions on the correlation between the revenue per worker and the fixed cost of hiring.

A vacancy brings profits only when it is filled, and firms pay a flow cost c to keep a vacancy open. Denoting by J_{ijl}^v the value of an open vacancy and by J_{ijl}^f the value of a filled vacancy, the value of an open vacancy can be written as:

$$\rho J_{ijl}^v = -c + \phi_l (J_{ijl}^f - J_{ijl}^v). \quad (2.6)$$

Once a vacancy is filled, the firm receives a stream of profits $y_{ijl} - w_{ijl}$, where w_{ijl} is the wage paid by firm ijl . The filled vacancy can be destroyed at the exogenous rate δ , and then it becomes open again. Thus, the value of a filled vacancy is:

$$\rho J_{ijl}^f = y_{ijl} - w_{ijl} + \delta (J_{ijl}^v - J_{ijl}^f). \quad (2.7)$$

To open a vacancy, firms have to pay a fixed cost, which increases with the size of the firm, denoted by E_{ijl} . This cost varies across firms: firm cost advantage ξ_i can make it lower. To post a vacancy a firm has to pay $(E_{ijl}/\xi_i)^\theta$. Since in the equilibrium the value of the marginal vacancy opened has to equal the fixed cost of its creation, this condition determines the size of each firm despite of the fact that there are no complementarities in production between jobs within the same firm.

Employment. In steady state, the size of each firm is defined by two conditions. First, the size of the firm has to be constant. That is, the number of workers who leave the firm is the same as the number of workers who join it:

$$\delta E_{ijl} = \phi_l V_{ijl}. \quad (2.8)$$

Second, the value of the last vacancy posted equals the cost to create it:

$$J_{ijl}^v = \left(\frac{E_{ijl}}{\xi_i} \right)^\theta. \quad (2.9)$$

After solving for the value of an open vacancy and using equations (2.8) and (2.9) to determine the size of the firm, I obtain the following expression for the steady-state size of the firm:

$$E_{ijl} = \xi_i \left(\frac{\phi_l / (\rho + \delta)}{\rho + \delta + \phi_l} \right)^{1/\theta} \left(y_{ijl} - w_{ijl} - \frac{\rho + \delta}{\phi_l} c \right)^{1/\theta}. \quad (2.10)$$

Thus, the size of the firm compared to its rivals in the same industry and region is determined by the revenue advantage ε_i and the hiring cost ξ_i . A firm can be larger either because it is more profitable and has higher ε_i , or because it is cheaper for it to hire new workers and it has higher ξ_i . At the same time, if the industry j is more profitable than others, or if region l has a comparative advantage, it will tend to have more large firms compared to other industries and/or regions.

Wages. Once a worker and a vacancy meet, they bargain to split the surplus. Though neither the worker nor the firm can direct their search to a particular type of firms (e.g. larger or more profitable firms) or workers (e.g. workers who have previously worked in the same industry), they observe each others' types when they are matched. That is, the worker knows the firm's flow revenue and its fixed hiring cost, and the firm knows the worker's previous employment history. The resulting wage is a solution to the following Nash bargaining rule:

$$J_{ijl}^f - J_{ijl}^v = \kappa (J_{ijl}^e - J_l^u). \quad (2.11)$$

After substituting in the expressions for workers's and firm's surpluses, and denoting by $\bar{w}_l = \sum_j \eta_{jl} w_{jl}$ the average potential wage paid in a region l , I can write the wage paid by the firm ijl with the cost advantage level ε_i as⁷:

$$w_{ijl} = \frac{\rho + \delta}{\Upsilon_{1,l}} (p_j + \zeta_l + \varepsilon_i + c) + \kappa \frac{\Upsilon_{2,l}}{\Upsilon_{1,l}} ((\rho + \delta)b + \psi_l \bar{w}_l), \quad (2.12)$$

where $\Upsilon_{1,l} = (\rho + \delta + \phi_l)\kappa + (\rho + \delta)$ and $\Upsilon_{2,l} = (\rho + \delta + \phi_l)/(\rho + \delta + \psi_l)$.⁸

Equation (2.12) demonstrates that a firm pays a higher wage if it's more profitable or if its workers have better outside options on the labor market or at home production. Since workers

⁷The worker's and the firm's surpluses are, respectively:

$$\begin{aligned} J_{ijl}^f - J_{ijl}^v &= \frac{1}{\rho + \delta + \phi_l} (p_j + \zeta_l + \varepsilon_i + c - w_{ijl}) \\ J_{ijl}^e - J_l^u &= \frac{1}{\rho + \delta + \psi_l} \left(w_{ijl} - b + \frac{\psi_l}{\rho + \delta} (w_{ijl} - \bar{w}_l) \right) \end{aligned}$$

⁸If there is a minimum wage, as is the case in Brazil, firm pays wages w_{ijl}^* , which is the maximum of the minimum wage, denoted by MW , and w_{ijl} described in the equation (2.12).

can look for a job in all the industries, equilibrium wages in any particular firm is driven upwards whenever an average firm in the same industry or any other industries can pay higher wages. However, the role of this effect is smaller if workers have low bargaining power or if the labor market is slack, i.e. there are plenty of unemployed workers but few jobs.

2.2 Employment growth decomposition

Employment growth in response to shocks. Having derived firm's employment and wages in subsection 2.1, I now turn to firm's response to change in labor market conditions. Labor market tightness and wages are equilibrium outcomes themselves, so to derive firm's response to shocks I linearize equation (2.10) around the steady state⁹ and take full differential. There are two sources of exogenous shocks in the model: shocks to firm's flow revenue per worker, denoted by dy_{ijl} , and shocks to costs of hiring, denoted by $d\xi_{ijk}$. In turn, the shock to flow revenue per worker has three components:

$$dy_{ijl} = dp_j + d\zeta_l + d\varepsilon_i, \quad (2.13)$$

where dp_j is a nationwide shock to the price of a good j , $d\zeta_l$ is a region specific shocks to the region comparative advantage, and $d\varepsilon_i$ is an idiosyncratic revenue shock. I assume that all four shocks dp_j , $d\zeta_l$, $d\varepsilon_i$, and $d\xi_{ijk}$ are orthogonal to each other. Furthermore, I assume that the firm's idiosyncratic shock is orthogonal to the firm's steady-state value of profit advantage ε_i (i.e. ε_i is random walk). However, I will not impose such a restriction on shocks to prices, which can have both autocorrelation and cross-correlation across industries.

Then firm's employment growth in response to shocks is given by:

$$\tilde{E}_{ijl} = \alpha_1 \tilde{\psi}_l + \beta_1 dw_{ijl} - \beta_1 (dp_j + d\zeta_l + d\varepsilon_i) + \tilde{\xi}_i, \quad (2.14)$$

where $\alpha_1 = -\frac{\sigma}{1-\sigma} \frac{1}{\theta} \left[\frac{\rho+\delta}{\rho+\delta+\phi_l} + \frac{\rho+\delta}{\phi_l} c (y_{ijl} - w_{ijl} - \frac{\rho+\delta}{\phi_l} c)^{-1} \right]$ and $\beta_1 = -\frac{1}{\theta} (y_{ijl} - w_{ijl} - \frac{\rho+\delta}{\phi_l} c)^{-1}$. In equation (2.14), $\tilde{x} = dx/x$ denotes the percentage deviation from the steady state of the variable x , α_1 is the elasticity of the labor demand with respect to change in the job arrival rate ψ_l , and β_1 is the firm-specific is a semi-elasticity of labor demand with respect to wage change.

Labor demand elasticity. Both labor demand elasticity with respect to job arrival rate and with respect to wage change vary across firms. The elasticity with respect to change in job arrival rate writes as¹⁰:

$$\begin{aligned} \alpha_1 &= -\frac{\sigma}{1-\sigma} \frac{1}{\theta} \left[\frac{\rho+\delta}{\rho+\delta+\phi_l} + \frac{\rho+\delta}{\phi_l} c \left(y_{ijl} - w_{ijl} - \frac{\rho+\delta}{\phi_l} c \right)^{-1} \right] \\ &= -\frac{\sigma}{1-\sigma} \frac{1}{\theta} \left[\frac{\rho+\delta}{\rho+\delta+\phi_l} + \frac{c}{\rho+\delta+\phi_l} \left(\frac{E_{ijl}}{\xi_{ijl}} \right)^{-\theta} \right], \end{aligned} \quad (2.15)$$

⁹Steady-state is considered with respect to the distribution of flow revenue per worker and costs of hiring across firms.

¹⁰The elasticity with respect to arrival rates is derived by first finding the elasticity with respect to vacancy filling rate $\tilde{\phi}_l$ and using the fact that $\tilde{\psi}_l = -\frac{\sigma}{1-\sigma} \tilde{\phi}_l$

and the elasticity with respect to wage changes is:

$$\begin{aligned}\beta_1 &= -\frac{1}{\theta} \left(y_{ijl} - w_{ijl} - \frac{\rho + \delta}{\phi_l} c \right)^{-1} \\ &= -\frac{1}{\theta} \frac{\phi_l / (\rho + \delta)}{\rho + \delta + \phi_l} c \left(\frac{E_{ijl}}{\xi_i} \right)^{-\theta}.\end{aligned}\quad (2.16)$$

The labor demand elasticity with respect to job arrival rate depends on two parameters: how tight the market is, i.e. how easy it is to find workers, and on the cost of keeping the vacancy open. Since the costs of keeping an open vacancy are the same across firms, but expected profits per worker depend on the wage and flow revenue, the labor demand elasticity with respect to job arrival rates varies with the profits per workers. The labor demand elasticity with respect to wages is directly linked to profits per worker, and thus diminishes with profits per worker as well.

Furthermore, using the expression for profits per worker¹¹, I can rewrite labor demand elasticities α_1 and β_1 solely as functions of firm's wage w_{ijl} :

$$\alpha_1 = \frac{1}{a_{1,l} + a_{2,l}w_{ijl}}, \quad (2.17)$$

$$\beta_1 = \frac{1}{b_{1,l} + b_{2,l}w_{ijl}}, \quad (2.18)$$

Note that in this parametrization both elasticities depend on only on firm-specific wage, which is observed in the data, and region-specific parameters $a_{1,l}$, $a_{2,l}$, $b_{1,l}$, $b_{2,l}$. Estimating these parameters is the first goal of this paper.

Employment growth decomposition. Equation (2.14) also shows that employment growth can be decomposed into three effects: growth due to change in labor market tightness $\alpha_1 \tilde{\psi}_l$, growth to change in wages $\beta_1 dw_{ijl}$ and growth due to exogenous shocks $-\beta_1(dp_j + d\zeta_l + d\varepsilon_i) + \tilde{\xi}_i$. However, some of the change in wages is caused by growth in firm's productivity rather than changes in labor market conditions. Wage change can be decomposed into three components as well:

$$dw_{ijl} = \gamma_{1,l} \tilde{\psi}_l + \gamma_{2,l} d\bar{w}_l + \gamma_{3,l} dy_{ijl}. \quad (2.19)$$

As a result, employment growth can be rewritten as follows:

$$\tilde{E}_{ijl} = \alpha_2 \tilde{\psi}_l + \beta_2 d\bar{w}_l - \beta_1 (\gamma_{3,l} - 1) dy_{ijl} + \tilde{\xi}_i, \quad (2.20)$$

where $\alpha_2 = (\alpha_1 + \beta_1 \gamma_{1,l})$, $\beta_2 = \beta_1 \gamma_{2,l}$. Equations (2.14) and (2.20) differ by the change in wage which they take into account. Equation (2.14) show firm response to firm specific wage change dw_{ijl} , while equation (2.20) shows firm response to change in average potential wage in the local labor market \bar{w}_l . Average potential wage represents outside option for workers when they look for jobs, and firms have to take into account this outside option for workers when bargaining over

¹¹Profits per worker are given by $y_{ijl} - w_{ijl} - \frac{\rho + \delta}{\phi_l} c = \kappa \frac{\rho + \delta + \phi_l}{\rho + \delta} w_{ijl} - \frac{\rho + \delta + \phi_l}{\phi_l} c - \kappa \frac{\rho + \delta + \phi_l}{\rho + \delta + \psi_l} \left(b + \frac{\psi_l}{\rho + \delta} \bar{w}_l \right)$.

wages. Thus, $\alpha_2\tilde{\psi}_l$ is employment growth due to change in labor market tightness, which has a direct impact on labor demand and indirect effect through changing firm wages, and $\beta_2d\bar{w}_l$ is employment growth due to change in prevailing wages. Estimating coefficients α_2 and β_2 and evaluating contribution of changes in labor market conditions to employment growth is the second goal of this paper.¹²

3 Identification Strategy

The goal of the paper is the estimation of labor demand elasticity at the firm level in equations (2.14) and (2.20). Equation (2.14) can be rewritten as:

$$\tilde{E}_{ijlt} = \alpha_1\tilde{\psi}_{lt} + \beta_1dw_{ijlt} + u_{ijlt}, \quad (3.1)$$

$$u_{ijlt} = -\beta_1(dp_{jt} + d\varepsilon_{it} + d\zeta_{lt}) + \tilde{\xi}_{it}, \quad (3.2)$$

and equation (2.20) can be rewritten as:

$$\tilde{E}_{ijlt} = \alpha_2\tilde{\psi}_{lt} + \beta_2d\bar{w}_{lt} + v_{ijlt}, \quad (3.3)$$

$$v_{ijlt} = -\beta_1(\gamma_{3,l} - 1)(dp_{jt} + d\varepsilon_{it} + d\zeta_{lt}) + \tilde{\xi}_{it}. \quad (3.4)$$

Equation (3.1) demonstrates direct effect of changes in labor market tightness and wages on employment growth, and equation (3.3) show the net effect of changes in labor market conditions on employment growth after taking into account the effect of changes in labor market conditions on firm wages. In both equations, I am interested in estimating the elasticity with respect to changes in labor market tightness, denoted by α_1 and α_2 , and with respect to changes in wages, denoted by β_1 and β_2 . There are two identification problems associated with estimating labor demand elasticity: omitted variable bias, because the realizations of the shocks are not observed by an econometrician, and selection into surviving firms.

Omitted variable bias is typical for demand estimation, because demand shifter are usually unobserved. Thus an increase (decrease) in firm's revenue leads both to a wage increase (decrease) and employment growth (decline). This mechanism creates a positive correlation between the error term u_{ijlt} and the wage changes. For the same reason, if a firm is large enough to affect the overall employment level at the local labor market, the error term can also be correlated with the change in the labor market tightness $\tilde{\psi}_{lt}$.

Selection arises because wage changes are not observed for the exiting firms, as they do not have any employees after they exit. This leads to a positive correlation between the error term and wages as well, since surviving firms have smaller negative (or larger positive) revenue shocks. However, selection is not an issue for equation (3.3), because the change in average wage is observed for all firms in the market, not just the surviving ones.

¹²Note that testing if $\beta_2 = 0$ also provides a test for the Nash Bargaining component of the model.

I overcome the simultaneity problem, I instrument the changes in labor market conditions with firm exposure to increase in the nationwide minimum wage in Brazil and with Bartik shocks, a widely used measure of local labor demand shocks (See, for example, Bartik, 1991; Blanchard and Katz, 1992; Bound and Holzer, 2000; Notowidigdo, 2013; Diamond, 2012). I deal with selection by using wage changes at a reference firm in the same microregion as a measure of wage change for exiting firms. In the next two subsections I describe the instrument strategy first and then explain how the reference firm is constructed.

3.1 Sources of exogenous variation in labor market conditions

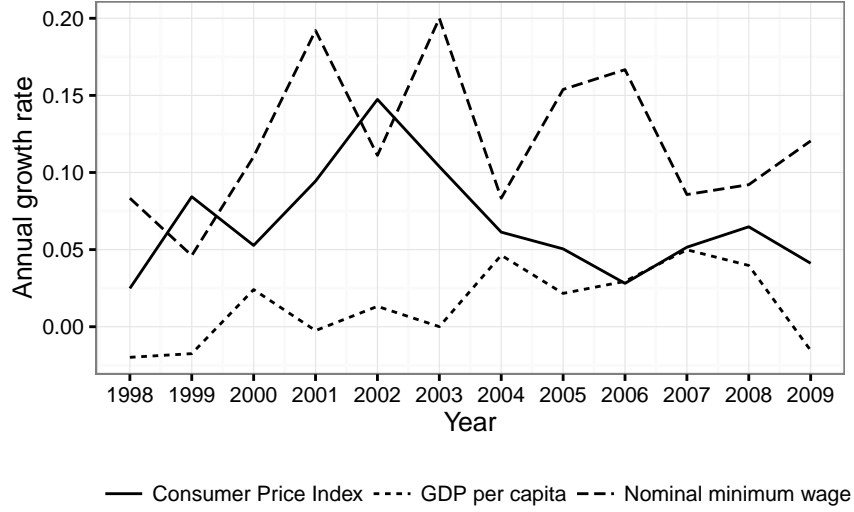
To estimate the labor demand elasticity, one needs to find shifters of the firm level wages and labor market tightness which are uncorrelated with the error term u_{ijlt} (equation (3.2)). I use two such shifters: Bartik shocks, and firm’s exposure to the raise in the nationwide minimum wage in Brazil. The error term u_{ijlt} has four unobserved components: the idiosyncratic shock to the firm’s revenue advantage $d\varepsilon_{it}$, the idiosyncratic shock to the firm’s hiring cost advantage $\tilde{\xi}_{it}$, the nationwide demand shock dp_{jt} and the location specific demand shock $d\zeta_{lt}$. I argue that both of the proposed shifters are independent of the location specific demand shock and the firm specific idiosyncratic shocks. However, the instruments can be potentially correlated with the nationwide demand shock in each industry. Therefore, I construct a control variable which allows me to account for the nationwide demand shock dp_{jt} explicitly.

Exposure to minimum wage change. Brazil has a federally mandated minimum wage, which imposes a limit on a monthly salary for workers in the formal sector and was adjusted on average once a year and loosely matches inflation plus growth rate of GDP per capita (see figure 1). For each firm, I calculate the share of workers in year $t - 1$ whose monthly nominal wages was below the minimum wage threshold in year t , i.e. next year minimum wage, and use it as an instrument for the firm’s wage change between $t - 1$ and t . This measure has been used by studies evaluating the impact of minimum wage hike on firms’ profits and labor demand (Draca et al., 2011), and it is highly correlated with the observed wage change, as I show in section 5. Similarly, I calculate the share of workers in region l in year $t - 1$ whose monthly wages are below the minimum wage in year t , and use it as an instrument for a change in average wage paid in region l to estimate the equation (3.3).

Since I use the share of workers in year $t - 1$ with wages below the minimum wage in t , both measures are not correlated with the idiosyncratic changes in revenue $d\varepsilon_{it}$ and hiring cost $\tilde{\xi}_{it}$ as long as these shocks are not correlated with the lagged wage level $w_{ijl,t-1}$. Similarly, because minimum wage are set at the national level, it is reasonable to assume that they are not correlated with the local demand shocks $d\zeta_{lt}$. Moreover, during the 2000s minimum wage in Brazil was rapidly growing – the rates of growth were higher than inflation and GDP per capita growth (figure 1).

Bartik instruments. Aside from using variation in exposure to minimum wage change, I ex-

Figure 1. Annual changes in nominal minimum wage, Consumer Price Index and GDP per capita



Source: IPEA

plore variation in competition for workers between firms located in the same labor market, and construct labor demand shifters which are driven by nationwide change in labor demand – Bartik shocks. Bartik shocks measure predicted growth rate in employment (or wages) at the local labor market if each industry in that location grew at the same rate as the nationwide average. Bartik shocks were first used to estimate the slope of the labor demand by Beaudry et al. (2014). Intuitively, an increase in demand for labor makes workers more expensive and harder to hire. As a result, the labor market tightens (i.e. vacancy filling rate decreases and the job arrival rate increases), and the wages each firm has to pay go up. The instrument is relevant as long as firms from different industries hire workers at the same labor market, i.e. workers are at least partially mobile across industries.

I use the following instrument for the change in the labor maker tightness:

$$\widehat{NEG}_{lt} = \sum_j s_{jl,t-1} NEG_{jt,-l}, \quad (3.5)$$

where $s_{jl,t-1} = \frac{E_{jl,t-1}}{E_{l,t-1}}$ is the share of industry j in total employment in the region l in year $t - 1$ and $NEG_{jt,-l}$ is the nationwide average net employment growth of employment in the industry j , excluding the region l , calculated as $NEG_{jt,-l} = \sum_{m \neq l} \frac{E_{jm,t-1}}{\sum_{m \neq l} E_{jm,t-1}} NEG_{jmt}$.

The equilibrium condition implies that the change in the job arrival rate is proportional to the change in demand for labor at the local labor market:

$$\tilde{\psi}_{lt} = \frac{\sigma}{2 - \sigma} \tilde{E}_{lt}, \quad (3.6)$$

where σ is the parameter of the matching function, and \tilde{E}_{lt} is the change in the employment in the

labor market. The Bartik shock \widehat{NEG}_{lt} is a predictor of \tilde{E}_{lt} and thus has a direct impact on the change in the job arrival rate $\tilde{\psi}_{lt}$.

I also construct Bartik shocks for change in regional wage. Average wage can change either due to the wage changes in each of the industries or because one of the industries grew substantially:

$$d\bar{w}_{lt} = \sum_j s_{jl,t-1} dw_{jlt} + \sum_j ds_{jlt} w_{jl,t-1}. \quad (3.7)$$

Following Beaudry et al. (2012), I construct the Bartik shocks for the change in wages which correspond to each of these channels:

$$\widehat{dw}_{1,lt} = \sum_j s_{jl,t-1} WG_{jt,-l} w_{jl,t-1}, \quad (3.8)$$

$$\widehat{dw}_{2,lt} = \sum_j s_{jl,t-1} NEG_{jt,-l} w_{jl,t-1}, \quad (3.9)$$

where $WG_{jt,-l}$ is the nationwide average wage growth rate in the industry j in year t , excluding region l . These instruments capture predicted changes in the average potential wages \bar{w}_{lt} , which a worker can get if he looks for a job. Since wages are set through the Nash bargaining, each firm has to match \bar{w}_{lt} to be able to make a hire. Thus, an increase in the average potential wage causes an increase in the firm level wage *regardless* of firm level revenue changes. As a result, these changes provide identifying variation in wages.

By construction all the Bartik instruments \widehat{NEG}_{lt} , $\widehat{dw}_{1,lt}$ and $\widehat{dw}_{2,lt}$ exclude the information from the own region l in year t , and use the lagged industrial composition in the location l . This makes the identification requirements relatively weak. First, there has to be no spatial correlation in wages or employment growth across cities. This ensures that the location demand shock $d\zeta_{lt}$ is orthogonal to the nationwide employment and wage trends. Note that this assumption does not rule out migration between the nearby regions in response to shocks (e.g. when one region is doing better than the other), but requires instead that these migration flows are small enough not to affect the nationwide trends.

Second, to be able to use lagged levels of firm wages as instruments, location demand shocks $d\zeta_{lt}$ have to be orthogonal to steady-state values of the firm revenue advantage ε_i and location revenue advantage ζ_l . The requirement implies that local markets with both small and large wage premia can receive large positive (or negative) shocks. However, this assumption allows for heteroskedasticity or autocorrelation in location demand shocks.

Together these two assumptions ensure that Bartik shocks are not correlated with the location demand shocks. Finally, an assumption that idiosyncratic shocks to firm's revenue and hiring advantage are orthogonal to industry and location demand shocks implies that Bartik shocks are uncorrelated with the firm-specific shocks as well.

However, since Bartik shocks capture trends in industrial growth, they are likely to be correlated with the own industry shock dp_{jt} . This correlation can arise either because of the income

effect or due to increase in demand for the intermediate goods. Labor demand growth in any industry leads to an increase of the overall income level in a region, which, in turn, results in higher demand for locally produced goods and services and newly created jobs in the non-tradable sector. This effect is well-documented and can be quite large (Moretti, 2010). Growth of labor demand in one industry can affect another industry if the latter industry produces inputs to the former industry. For instance, if ethanol producers are expanding because the prices on ethanol went up, they will also purchase more sugarcane from sugarcane producers, who, in turn, will hire more labor. To ensure that my estimates are not contaminated by the income effect, I focus on the traded goods industries only. To deal with the potential increase in demand for intermediate goods within the country, I develop a control variable strategy to account for the demand shock in own industry explicitly.

Control variable for nationwide demand shocks. I have argued that the minimum wage instrument and Bartik instruments are orthogonal to firms' idiosyncratic shocks and the local demand shocks under mild requirements. However, both of these instruments are correlated with the nationwide demand shocks in each industry dp_{jt} . Bartik shocks represent nationwide trends in employment in wages projected at the local industrial composition. The shocks to different industries dp_{jt} are likely to be correlated with each other, because the output of some industries is an input for other industries. Similarly, the minimum wage is adjusted more often if the economy is growing faster, and thus the minimum wage instrument is likely to be correlated with the nationwide demand shock dp_{jt} as well.

If the nationwide shocks dp_{jt} were observed, one could explicitly control for them in the estimation equation (3.1). Alternatively, one could estimate equation (3.1) with industry-year fixed effects if all firms within the industry were responding to the industry specific shocks in the same way¹³. In both cases, the error term would become $u'_{ijt} = \beta_1(d\varepsilon_{it} + d\zeta_{it}) + \tilde{\xi}_{it}$, which is orthogonal to both instruments. Based on this intuition, I propose a control variable approach to account for the nationwide demand shocks dp_{jt} .

The wage change in firm i in industry j writes as:

$$dw_{ijt} = -\frac{\kappa\phi_l}{\Upsilon_{1,l}}\tilde{\phi}_{lt}w_{ijt} + \frac{\rho + \delta}{\Upsilon_{1,l}}(dp_{jt} + d\zeta_{lt} + d\varepsilon_{it}) + \kappa\frac{\Upsilon_{2,l}}{\Upsilon_{1,l}}d\Psi_{lt}, \quad (3.10)$$

where $d\Psi_{lt} = ((\rho + \delta)b + \psi_{lt}\bar{w}_{lt})\tilde{\Upsilon}_{2,lt} + \psi_{lt}d\bar{w}_{lt} + \bar{w}_{lt}d\psi_{lt}$. Then, the deviation of the wage change in firm i from the average wage change in the market l , denoted by dw_{lt} is:

$$dw_{ijt} - dw_{lt} = -\frac{\kappa\phi_{lt}}{\Upsilon_{1,l}}\tilde{\phi}_{lt}(w_{ijt} - w_{lt}) + \frac{\rho + \delta}{\Upsilon_{1,l}}\left(dp_{jt} - \sum_j s_{j,l,t-1}dp_{jt}\right) + \frac{\rho + \delta}{\Upsilon_{1,l}}(d\varepsilon_{it} - d\varepsilon_{lt}), \quad (3.11)$$

¹³This is a strategy used in Beaudry et al. (2012) and Beaudry et al. (2014).

where $d\varepsilon_{lt} = \sum_i s_{il,t-1}d\varepsilon_{it}$. Estimates of the term $\frac{\rho+\delta}{\Upsilon_{1,l}} \left(dp_{jt} - \sum_j s_{jl,t-1}dp_{jt} \right)$ can be obtained as microregion-industry-year fixed effects in a regression of $dw_{ijlt} - dw_{lt}$ on $\tilde{\phi}_{lt}(w_{ijlt} - w_{lt})$. Then, these estimates can be used to construct the control variable \widehat{dp}_{jlt} :

$$\begin{aligned} \widehat{dp}_{jlt} &= \sum_{m \neq l} \frac{E_{m,t-1}}{E_{t-1}} \frac{\rho + \delta}{\Upsilon_{1,m}} \left(dp_{jt} - \sum_j s_{jm,t-1}dp_{jt} \right) \\ &= \left(\sum_{m \neq l} \frac{E_{m,t-1}}{E_{t-1}} \frac{\rho + \delta}{\Upsilon_{1,m}} \right) dp_{jt} - \left(\sum_{m \neq l} \frac{E_{m,t-1}}{E_{t-1}} \frac{\rho + \delta}{\Upsilon_{1,m}} \sum_j s_{jm,t-1}dp_{jt} \right). \end{aligned} \quad (3.12)$$

First, note that just as Bartik shocks, \widehat{dp}_{jlt} excludes the information from the region l in period t and thus varies across regions. Second, \widehat{dp}_{jlt} is a linear function of dp_{jt} and thus dp_{jt} can be expressed as:

$$dp_{jt} = \lambda_{0,lt} + \lambda_{1,l} \widehat{dp}_{jlt} + \nu_{jlt}. \quad (3.13)$$

Therefore, the main estimation equation (3.1) can be redefined as follows:

$$\tilde{E}_{ijlt} = \alpha_1 \tilde{\psi}_{lt} + \beta_1 dw_{ijlt} - \beta_1 (\lambda_{0,lt} + \lambda_{1,l} \widehat{dp}_{jlt}) + u'_{ijlt}, \quad (3.14)$$

$$u'_{ijlt} = -\beta_1 (d\varepsilon_{it} + d\zeta_{lt}) + \tilde{\xi}_{it} + \nu_{jlt}. \quad (3.15)$$

Since the error term u'_{ijlt} no longer contains the nationwide demand shock dp_{jt} , the minimum wage and the Bartik instruments can be used to consistently estimate the labor demand elasticity parameters β_1 and β_1 . For this assumption to hold, it is required that prices are set nationally, i.e. there is no input-output relationship between industries which affects the firm's revenue in a different way in locations l and k . However, since by construction \widehat{dp}_{jlt} excludes changes in wages in the own market l , \widehat{dp}_{jlt} is a valid instrument for the equation (3.14) as well. The downside of the control variable approach is the increase in the number of parameters to be estimated: the nuisance parameters $\lambda_{0,lt}$ and $\lambda_{1,l}$ need to be estimated as well.

Similarly, equation (3.3) can be rewritten as:

$$\tilde{E}_{ijlt} = \alpha_2 \tilde{\psi}_{lt} + \beta_2 d\bar{w}_{lt} - \beta_2 (\gamma_{3,l} - 1) (\lambda_{0,lt} + \lambda_{1,l} \widehat{dp}_{jlt}) + v'_{ijlt}, \quad (3.16)$$

$$v'_{ijlt} = -\beta_1 (\gamma_{3,l} - 1) (d\varepsilon_{it} + d\zeta_{lt}) + \tilde{\xi}_{it} + \nu_{jlt}. \quad (3.17)$$

3.2 Unobserved wage changes for exiting firms

Information on employment growth, firm wage and firm size is available for all firms with non-zero employment in year $t - 1$. However, wage changes are unobserved for exiting firms in year t . Using only the sample of surviving firms to estimate the equation (3.1) would lead to inconsistent estimates of the labor demand elasticities, since firms with large negative idiosyncratic shocks will not be taken into account.

The model implies that the difference in the wage change in year t between two firms in the same industry and region is proportional to the difference in wages in year $t - 1$. Denoting by

dw_{1jlt} the wage change in the reference firm (e.g. the firm with the median wage in the industry j and region l) this relationship writes as:

$$dw_{ijlt} - dw_{1jlt} = -\frac{\kappa\phi_l}{\Upsilon_{1,l}}\tilde{\phi}_{lt}(w_{ijl,t-1} - w_{1jl,t-1}) + \frac{\rho + \delta}{\Upsilon_{1,l}}(d\varepsilon_{it} - d\varepsilon_{1t}). \quad (3.18)$$

Plugging this expression back into the equation for the employment growth at the firm level (3.14), I obtain a modified equation for the exiting firms:

$$\begin{aligned} \tilde{E}_{ijlt} = & \alpha_l\tilde{\phi}_{lt} - \beta_1 \left(dw_{1jlt} + \gamma_{1,l}\tilde{\phi}_{lt}(w_{ijl,t-1} - w_{1jl,t-1}) + \gamma_{0,lt} \right) \\ & + \beta_1(\lambda_{0,lt} + \lambda_{1,l}\widehat{dp}_{jlt}) + u''_{ijlt}, \end{aligned} \quad (3.19)$$

where $u''_{ijlt} = u'_{ijlt} + \frac{\rho+\delta}{\Upsilon_{1l}} d\varepsilon_{it}$, $\gamma_{1,l} = -\frac{\kappa\phi_l}{\Upsilon_{1,l}}$, and $\gamma_{0,lt} = \frac{\rho+\delta}{\Upsilon_{1,l}}(d\varepsilon_{it} - d\varepsilon_{1t})$. The two equations (3.14) and (3.19) can be combined into a new estimation equation:

$$\begin{aligned} \tilde{E}_{ijlt} = & \alpha_l\tilde{\psi}_{lt} + \beta_1 dw_{ijlt} \text{Survival}_{ijlt} + \beta_1 dw_{1jlt} \text{Exit}_{ijlt} \\ & + \beta_1(\gamma_{0,lt} + \gamma_{1,l}\tilde{\psi}_{lt}(w_{ijl,t-1} - w_{1jl,t-1}))\text{Exit}_{ijlt} \\ & - \beta_1(\lambda_{0,lt} + \lambda_{1,l}\widehat{dp}_{jlt}) + u'''_{ijlt}, \end{aligned} \quad (3.20)$$

where the combined error term is $u'''_{ijlt} = \left(-\beta_1 + \frac{\rho+\delta}{\Upsilon_{1l}} \text{Exit}_{ijlt} \right) d\varepsilon_{it} - \beta_1 d\zeta_{it} + \tilde{\xi}_{it} + \nu_{jlt}$. Parameters $\gamma_{1,l}$ and $\gamma_{0,lt}$ are nuisance parameters associated with firms' exit and will be estimated along with parameters of interest.

Estimation of equation (3.20) requires an additional instrument because the exit status of the firm is endogenous to the error term as well. I estimate propensity score for exit at the firm level and include it into the set of instruments for equation (3.20). I model the propensity score for each firm using average national exit rate in its own industry excluding own location, and lagged characteristics of the firm, such as wages, size and age indicators. In section 5.2 I show that propensity score, constructed in this way, is a strong predictor of exit at the firm level. The intuition behind this instrument is similar to Bartik shocks, and the same identification requirements apply.

4 Data

4.1 Relação Anual de Informações Sociais (RAIS)

I study the impact of labor market conditions on job creation using *Relação Anual de Informações Sociais (RAIS)* — an administrative dataset from Brazil, collected annually by the Brazilian Ministry of Labor. It is an employer-employee matched dataset which covers all formal sector jobs in Brazil.¹⁴ RAIS contains detailed information on each job, such as the month of hire and separation, tenure on the job, monthly salary, contract hours, occupation as well as gender, education and age

¹⁴Formal sector employed around 44-50% during 1998-2009 of all workers, including self-employed.

of a worker. It also provides information on location of an establishment and its industry affiliation. However, just as other datasets which are based on payroll data, RAIS does not have any balance sheet information about establishments, such as sales, assets etc.

Definition of a local labor market. I study microregions – statistical units which combine several municipalities – as isolated local labor markets. Microregions cover the whole territory of Brazil and are a commonly used definition of a local labor market in the context of Brazil (See, for example, Kovak, 2013; Dix-Carneiro and Kovak, 2015). A microregion is defined by the Brazilian Institute of Geography and Statistics (*Instituto Brasileiro de Geografia e Estatística*, IBGE) as a “region which encompasses local production, distribution, exchange and consumption”. The geographical borders of microregions were revised several times during the period of observation, so I use the minimally geographically consistent definitions of microregions, which result in 486 microregions in total. However, because some microregions have very small presence of manufacturing, I restrict the analysis to the microregions which had at least 20 firms in manufacturing in each year of the sample, which leads to 339 microregions which are included in the sample.

Estimation sample. To estimate the model, I assemble a firm-level sample on manufacturing firms in Brazil in 1998-2009 based on the data from the employer-employee matched dataset. Beside the sample on firms, I build a sample of average net employment growth and average wage change at the industry–microregion level, which are used to construct the Bartik instruments and the control variable.

I restrict my analysis to the manufacturing sector only, which allows me to treat the goods which firms produce as tradable, which is essential for identification. I discuss this requirement at length in section 3. Furthermore, though Brazil has a large informal sector, which employed 67% of workers in a median microregion in 2000 according to the Demographic Census, the incidence of informality is less severe in manufacturing, where a median region had only 47% of workers employed informally. Finally, manufacturing sector in Brazil mostly employed full-time workers, which allows me to abstract from labor demand adjustment in hours of work rather than in the number of jobs.

I define a firm as a single-establishment productive unit (i.e. a plant), which operates in one location. Though the data allows me to distinguish between single-establishment and multi-establishment firms, I use a narrow definition of a firm so that the local market where the firm hires its workers is well-defined. However, to ensure that none of the results are driven by the multi-establishment nature of a firm, I include controls for a multi-establishment firm in all estimation equations.

The firm sample is constructed in five steps. First, I obtain information on the total employment in a firm in December of each year. Second, I estimate the average wage of a 35 year old male production worker with a high school degree and zero tenure at each firm. Using the standard Mincer regressions (see appendix A detail), I take away the wage premium associated with workers’ tenure, gender, age, education, and occupation and use the average residualized logarithm of the real wages per hour as a measure of firm’s wage level. This procedure allows me to abstract

from differences in workforce composition across firms. Next, I calculate firm’s age using the year when the firm was first observed as the year of entry. Since the data on firms spans back to 1986¹⁵, I truncate the age at 10 years and consider all firms older than 10 years old as one age group. I also construct longitudinally consistent industry affiliation and location data for each firm by using the mode of reported industry and location for each firm. Finally, though RAIS is an administrative dataset, it is not uncommon for a firm record to be missing for some years. On average 3% of observations have a gap in reporting between 1998 and 2010. Whenever possible, I impute missing firm size and wage by extrapolating size and wage using the last available observation before the gap in records and the first available observation after the gap in record (see appendix A for details).

I focus on firms 1 year and older only and study firms which had 10 or more workers in at least one year between 1997 and 2010. Though entry in manufacturing is common – on average, new entrants account for 6.9% firms – they provide a small share of jobs on the labor market. New entrants account only for 3.8% of jobs. Similarly, though small firms are much more common and account for 55% of establishments, they provide less than 5% of jobs.

Next, I use CNAE 1995 3 digit industry classification code, which contains 104 manufacturing industries.¹⁶ Under this classification, firms producing food and beverages are distinguished from apparel manufacturing, and, for example, sugar mills, and coffee roasting and grinding are considered different groups of activity.

I focus on two measures of growth at the firm level: net employment growth rate and the change in average log wages. I calculate the net employment growth rate using the mid-year firm size (see Davis and Haltiwanger, 1992), which allows me to keep exiting firms in the sample:

$$NEG_{ijlt} = \frac{E_{ijlt} - E_{ijl,t-1}}{0.5 (E_{ijl,t-1} + E_{ijl,t})}, \quad (4.1)$$

where E_{ijlt} is the size of the firm i in industry j and microregion l in year t .

Wage changes can only be calculated for firms who have some employees both in $t - 1$ and t , and thus is only available for surviving firms. On average, 2% firms exit every year, and the change in wages is observed for 1,903,464 firm-year observations (table 1). For surviving firms, I obtain the wage change as follows:

$$\Delta w_{ijlt} = w_{ijlt} - w_{ijl,t-1}, \quad (4.2)$$

where w_{ijlt} is the average log wage at the firm i after having taken away the effect of the workforce composition.

The estimation sample has 277,191 unique firms in 339 microregions. An average firm in the sample is 9.3 years old, has 45 employees and pays 4 reais in hourly wage (approximately 1.4 dollars in 2005 prices), or a little more than twice as much as the minimum wage in 2005.

¹⁵Though RAIS spans back to 1986, detailed industry classification is available starting in 1994.

¹⁶Complete list of industries can be found at www.cnae.ibge.gov.br (in Portuguese). I exclude from the analysis industry “Production of nuclear fuels” (CNAE code 233), which employs about 7,000 people annually, but is concentrated in a single location.

Table 1. Summary statistics on the estimation sample.

(a) Summary statistics on firms.

	Mean	Sd	25th percentile	Median	75th percentile
Lagged size	45	190	7	14	31
Lagged log wage	1.3	0.41	1.04	1.3	1.6
Lagged age	9.3	6.1	4	8	14
Share paid below next year minimum wage	0.13	0.27	0	0	0.1
Exit	0.019	0.14	0	0	0
Net employment growth	0.011	0.53	-0.1667	0	0.22
Change in log wage paid by a firm	-0.001	0.19	-0.08866	-0.0031	0.084
Change in log average wage paid by in a region	-0.0036	0.051	-0.03203	0.00059	0.028
Change in log employment to population ratio	0.019	0.082	-0.03106	0.021	0.062
Change in hazard rate to be hired by manufacturing	0.1	0.2	0.011	0.11	0.2

No firm-year obs.: 1,940,786

No of firm-year obs. with observed wage change: 1,903,464

No of unique firms: 277,191

Source: RAIS

(b) Summary statistics on regions.

	Mean	Sd	25th percentile	Median	75th percentile
Population in 2000, mln people	0.45	1	0.13	0.22	0.39
Share employed in manufacturing in 2000	0.15	0.082	0.088	0.12	0.18
Formal sector share in manufacturing in 2000	0.66	0.16	0.57	0.7	0.79
Log total employment to population ratio in 2000	-0.9375	0.13	-1.03	-0.9149	-0.8511
Average wage premium paid by the region	-1.395	0.25	-1.575	-1.398	-1.234
Share of workers paid below next year minimum wage	0.0073	0.0072	0.0021	0.0047	0.011
Number of manufacturing firms	477.09	1300	86.75	180.83	446.33

No microregions: 339.

Source: RAIS and Census.

4.2 Measuring local labor market conditions

Labor market conditions are characterized by two margins: labor market tightness and prevailing wages. Together, labor market conditions determine the cost of hiring. Labor market tightness, defined as a ratio of vacancies over unemployed, determines how easy it is for a firm to find a new worker, and prevailing wages shows how much a firm has to pay to make a hire.

Labor market tightness. Traditionally, labor market tightness is measured either by the ratio of vacancies to unemployed, or by the unemployment level. Since RAIS does not report vacancies, and the data on unemployment is not available at the microregion level at the annual frequency, I use two alternative measures of labor market tightness.

The first measure of labor market tightness is based on the idea that in tighter markets it is harder for a firm to fill a vacancy, but easier a worker to find a job. Thus, the frequency of transitions from non-employment to employment can be used to estimate labor market tightness. Formally, job offer arrival rate ψ is related to the vacancy filling rate ϕ in the following way:

$$\psi = \left(\frac{V}{U} \right)^{-\frac{\sigma}{1-\sigma}}. \quad (4.3)$$

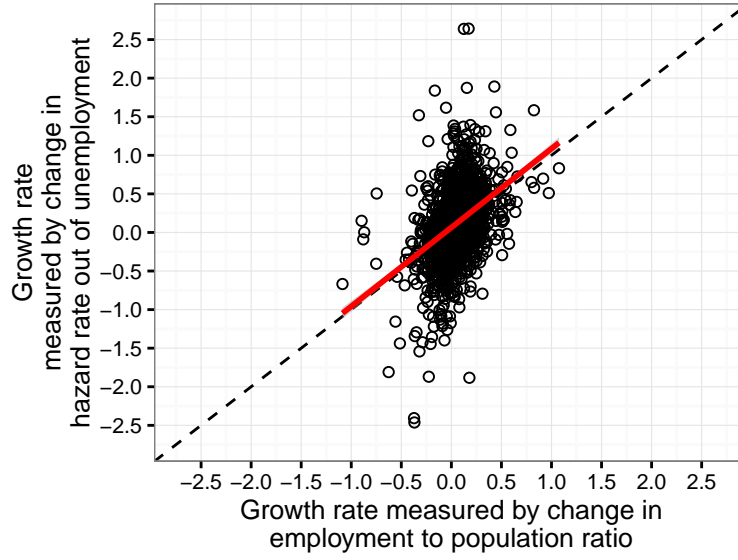
To measure the changes in job arrival rate in each microregion, I estimate a survival model of finding a job in manufacturing using data on workers who separated from a manufacturing in the previous two years. Because it involves estimating high-dimensional fixed effects on a large sample size, I use the fact that exponential model can be expressed as a Poisson model, and implement Guimares and Portugal (2010) method of estimating fixed effects to compute the coefficients (see appendix B for details). One of the concerns with this procedure is that I do not observe hires into the informal sector and thus would underestimate the job arrival rate in manufacturing, if the share of workers who switch from formal to informal sector is high. According to PNAD, 25% of newly hired workers by the informal sector within each year have had their previous job in the formal sector. To minimize this concern, I use only workers who have left a formal sector in the current or previous year, as the share of workers taking a job in the informal sector will be higher for longer spells outside of the formal sector.

The second alternative measure of labor market tightness is the change in employment to population ratio, which is closely linked to vacancies over unemployment ratio through the matching function (Beaudry et al., 2012). Since I focus on manufacturing, I use annual percentage changes in the ratio of formal employment in manufacturing to population to measure the changes in labor market tightness. The two measures of labor market tightness are highly correlated (figure 2), but the change in probability to be hired has higher variance.

Prevailing wages. RAIS contains detailed information on firms and workers, which allows me to construct wage series at the firm and microregion level, adjusted for differences in workforce composition across firms and regions.

To construct firm level wages, I first take away the differences in wages explained by workforce composition. After this, I obtain the firm specific wage level as the average wages paid to a 35 year

Figure 2. Comparison of two alternative measures of changes in labor market tightness.



old male production worker with a high school degree and zero tenure at the firm. Finally, I calculate the wage change for each firm as a simple difference of the firm level wage (see appendix [A](#) for details). This measure of wage change is available only for surviving firms, and I deal with selection into exit using the methods described in section 3.

To construct change in average wage paid in each microregion, I first estimate a microregion-year fixed effect in the following model¹⁷:

$$w_{ijlt} = \bar{w}_{lt} - \nu_{ijlt}, \quad (4.4)$$

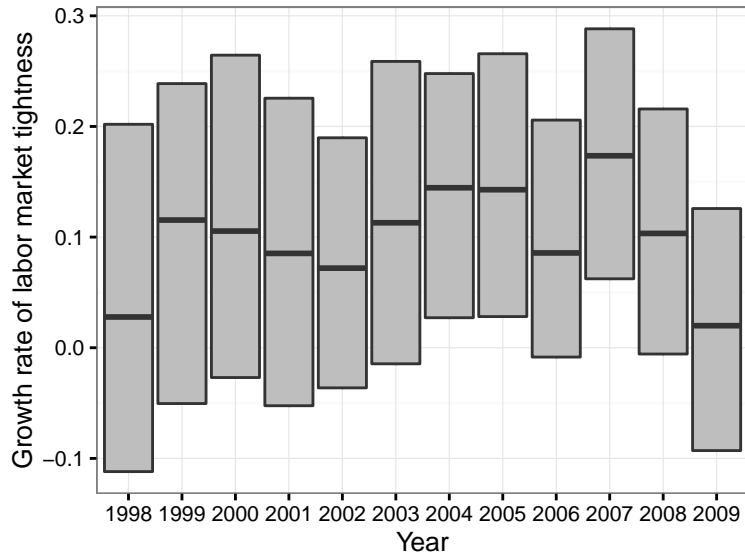
and then calculate changes in wages as $\Delta \bar{w}_{lt} = \bar{w}_{lt} - \bar{w}_{l,t-1}$. This estimate of the change in average wage captures both changes in wages paid by surviving firms, as well as changes in wage distribution due to entry and exit.

Figures [3a](#) and [3b](#) present the variation in labor market conditions over time. First, even though labor market conditions tend to move together across regions, there is still a substantial variation across region in any given year. Second, changes in labor market tightness have much larger variance than changes in wages – both across and within years.

¹⁷I use command `reghdfe` written by Correia (2014) to estimate high-dimensional fixed effects throughout this paper.

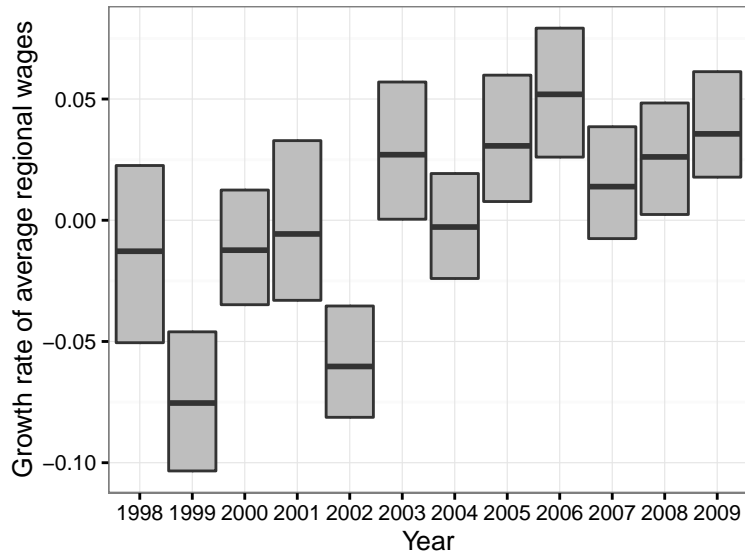
Figure 3. Box plots of annual growth rates in local labor market conditions across time.

(a) Annual growth rates in labor market tightness.



Source: RAIS. 1st quartile, median and 3rd quartile plotted.

(b) Annual growth rates in average regional wages.



Source: RAIS. 1st quartile, median and 3rd quartile plotted.

5 Elasticity of Labor Demand

In this section, I take the model to the data. I estimate the model with the General Method of Moments (GMM), using the sample of manufacturing firms in Brazil in 1998-2010, who are 1 year and older and have 10 and more employees at some moment during their lifetime. I first introduce the estimation equation and the necessary parametrization. After that, I show that the instruments outlined in section 3 have power. Finally, I describe the estimation results. I find that a one percent increase in labor market tightness reduces employment growth by 1 percentage points, and a one percent increase in wages reduces employment growth by 1-2 percentage points. Furthermore, I show that low-paying firms have 20-30% larger labor demand elasticity than high-paying firms. However, the differences across regions are just as large as the differences across firms: regions with a smaller share of formal sector in manufacturing have 40-50% larger elasticity of labor demand than the regions with higher share of formal sector.

5.1 Empirical specification

Following the discussion in section 3, I estimate two empirical specifications. First, I estimate labor demand elasticity with respect to change in labor market tightness and firm level wage change using the following equation:

$$\begin{aligned}
 NEG_{ijlt} = & x'_{ijlt}\delta + \alpha_1 \Delta \log \psi_{lt} \\
 & + \beta_1 \Delta w_{ijlt} \text{Survival}_{ijlt} + \beta_1 \Delta w_{1jlt} \text{Exit}_{ijlt} \\
 & + \beta_1 (\gamma_0 + \gamma_1 \Delta \log \psi_{lt} (w_{ijl,t-1} - w_{1jl,t-1})) \text{Exit}_{ijlt} \\
 & - \beta_1 (\lambda_{10} + \lambda_{11} \widehat{dp}_{jlt}) + u_{ijlt}
 \end{aligned} \tag{5.1}$$

The vector of controls x_{ijlt} includes indicators for lagged firm age, an indicator for multi-establishment firm, year dummies and the share of the formal sector in manufacturing in the region in 2000 interacted with the year dummies.

Next, I estimate labor demand elasticity with respect to change in labor market tightness and regional wage change using the following specification:

$$\begin{aligned}
 NEG_{ijlt} = & x'_{ijlt}\delta + \alpha_2 \tilde{\psi}_{lt} + \alpha_3 \tilde{\psi}_{lt} s_{ijlt} \Delta \log MW_t \\
 & + \beta_2 \Delta \bar{w}_{lt} + \beta_3 \Delta \bar{w}_{lt} s_{ijlt} \Delta \log MW_t \\
 & - \beta_2 (\lambda_{20} + \lambda_{21} \widehat{dp}_{jlt}) \\
 & - \beta_3 (\lambda_{30} + \lambda_{31} \widehat{dp}_{jlt}) s_{ijlt} \Delta \log MW_t + v_{ijlt},
 \end{aligned} \tag{5.2}$$

where $\Delta \log MW_t$ is the change in log real nationwide minimum wage, and s_{ijlt} is the share of firm's workers in year $t - 1$ who were paid below the minimum wage in year t . Together, $s_{ijlt} \Delta \log MW_t$ measure how much an increase in the nationwide minimum wage should have affected firm's wage change. I allow firms which were exposed to the minimum wage shock, to

have different elasticity compared to the non-exposed firms in order not to overestimate the effect of an increase in average wages on employment growth.

Estimating both of these specifications allows me to distinguish between direct impact of changes in labor market conditions on labor demand from the effect of labor market conditions on firm wages. Furthermore, estimating equation (5.2) will allow me to evaluate the contribution of labor market conditions to firm employment growth.

I estimate both equations (5.1) and (5.2) using GMM, and cluster standard errors within industry – year cells. I also weight equations by firm’s lagged size, because smaller firms tend to have more measurement error both in wage change and employment growth. To estimate equation (5.1) I include the share of workers in each firm in year $t - 1$ who were paid less than minimum wage in year t , Bartik shock in employment, two measures of Bartik shock in wages, and firm’s propensity score to exit, as well as all the variables included into controls, estimated demand shock in firm’s own industry in each year, and all the variables used to parametrize labor demand elasticity, as well as their interactions. To estimate equation (5.2), I use the share of workers in each region in year $t - 1$ who were paid below the minimum wage in year t , i.e. I instrument regional wage change with the regional exposure (instead of firm exposure) to the minimum wage change. In addition, I do not include the propensity score to exit as an instrument for equation (5.2), because the coefficients for surviving and exiting firms are same. All the other instruments are the same as for the equation (5.1).

Parametrization of labor demand elasticity. I let labor demand elasticities α and β vary both across firms and across regions. Based on the derivation from section 2.2, I model labor demand elasticity as follows:

$$\alpha_1 = \frac{1}{a_1 + a_2 w_{ijl,t-1}}, \quad (5.3)$$

$$\beta_1 = \frac{1}{b_1 + b_2 w_{ijl,t-1}}, \quad (5.4)$$

where $w_{ijl,t-1}$ is the lagged average wage paid at the firm. Furthermore, I let parameters a_1 , a_2 , b_1 and b_2 depend on regional characteristics. Guided by the model, I allow parameters a_1 and b_1 to depend on the log of total employment (including both formal and informal employment) to population ratio in the region in 2000, share of employment in formal sector in manufacturing in 2000, and the average wage premium paid by the region, as well as their interactions I let parameters a_2 and b_2 depend on the log of employment tot population ration in 2000, share of the formal sector in manufacturing in 2000 and their interactions. These variables capture how tight the regional labor market is and if it pays a larger wage premium. Both tighter market and larger wage premiums lead to more competition in the labor market, which, in turn, pushed less productive firms from the market. As a result, the model suggests that regions with tighter markets and larger wage premiums should have smaller labor demand elasticity. I parametrize elasticities α_2 , β_2 , β_2 , and β_2 in a similar way. Finally, I let coefficients γ_0 , γ_1 , λ_{10} , λ_{11} , λ_{20} , and λ_{21} depend on

the log employment to population ration in 2000 and the share of formal sector in manufacturing in 2000 as well.

5.2 First stage

Before estimating the model, I show that instruments proposed in the section 3 have power. Table 2a presents the results of the first stage regressions at the regional level, and table 2b presents results of the firm level regressions. All regressions have been weighted with the lagged region size and firm size respectively. In addition, I include for lagged firm age, multi-establishment indicator, year dummies and year dummies interacted with the share of the formal sector in manufacturing in 2000, as well as control variable for firm's own demand shock in all firm level regressions. I include year dummies and year dummies interacted with the share of the formal sector in manufacturing in 2000 in region level regressions as well. These are the set of controls used in the main specification.

The regression results demonstrate that exposure to the increase in minimum wage is a very strong predictor of the observed wage change both at the regional and at the firm level. F-statistics for the corresponding regressions are very high. On average, an additional one percentage point exposure to the minimum wage increase is associated with additional 0.13 percentage point wage growth at the firm level, and 1.6 percentage point increase in average regional wage. Bartik shocks have less predictive power than the minimum wage instruments. Though the coefficients at Bartik instruments are significant, F-statistics vary in the range of 4–11, i.e. they barely reach an acceptable level of significance. Finally, the coefficient at propensity score to exit is significant as well, and F-statistics is high as well. Propensity score is estimated using the logit model using firm lagged characteristics and exit rate in the same regions in other regions as predictors of firm exit.

5.3 Results and goodness of fit

Table 3 presents the estimated labor demand elasticities for models (5.1) and (5.2). Model (5.1) estimates direct response of employment growth to changes in labor market tightness and average firm wages, without taking into account that some of the wage growth might be caused by growth in firm's own productivity rather than by changes in prevailing wage. Model (5.2) accounts for this possibility, and estimates labor demand elasticity adjusting for the effect of labor market conditions on wages. Thus, elasticities in the model (5.1) should be interpreted as direct effect of labor market tightness and firm average wage on employment growth, and elasticities in the model (5.2) should be interpreted as net effect of labor makret tightness and prevailing wage on employment growth.

Estimates demonstrate that employment growth responds to a one percent increase in labor market tightness with a 1 percentage point decrease in employment growth, and to a one precent increase in wages with a 1-2 percentage point decrease in employment growth. Median firm in the sample usually does not change in size (i.e. growth is 0), and average annual growth among all firms is 1%, while average growth among surviving firms is 5%. Thus, the effect of labor market

Table 2. First Stage.

(a) Instruments for the change in labor market tightness and average wage change at the regional level.

Variable	(1) Δ Hazard to be hired	(2) $\Delta \log ER$	(3) $\Delta \bar{w}_{lt}$	(4) $\Delta \bar{w}_{lt}$	(5) $\Delta \bar{w}_{lt}$
\widehat{NEG}_{lt}	0.65** (0.26)	0.42** (0.15)			
$\widehat{dw}_{1,lt}$			0.14** (0.063)		0.1* (0.052)
$\widehat{dw}_{2,lt}$			-0.21 (0.14)		-0.13 (0.13)
Regional share below MW				1.6*** (0.31)	1.4*** (0.26)
Year FE	X	X	X	X	X
Year MMC controls	X	X	X	X	X
Obs	4,068	4,068	4,068	4,068	4,068
R ²	0.091	0.27	0.49	0.49	0.49
IV F-stat.	6.22	7.66	4.24	26.22	10.01
P-value	0.03	0.02	0.04	0	0

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. Robust s.e. in parenthesis. All regressions have been weighted with lagged region employment size. See text for variable definitions. Source: RAIS, 1998-2009. 339 microregions.

(b) Instruments for firm level wage change and firm exit.

Variable	(1) Δw_{ijlt}	(2) Δw_{ijlt}	(3) Δw_{ijlt}	(4) Exit
$\widehat{dw}_{1,lt}$	0.13*** (0.034)		0.061* (0.035)	
$\widehat{dw}_{2,lt}$	-0.18*** (0.063)		0.041 (0.064)	
Firm share below MW		0.13*** (0.0049)	0.13*** (0.0049)	
\widehat{dp}_{jlt}	0.084*** (0.029)	0.081*** (0.03)	0.08*** (0.029)	
P-score to exit				0.66*** (0.093)
Year FE	X	X	X	X
Year MMC controls	X	X	X	X
Age controls	X	X	X	X
Obs	1,903,464	1,903,464	1,903,464	1,941,745
R ²	0.045	0.063	0.063	0.0065
IV F-stat.	11.33	669	233	50.48
P-value	0	0	0	0

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. S.e. clustered within industry-year in parenthesis. All regressions have been weighted with lagged firm size. See text for variable definitions. Source: RAIS. Existing manufacturing firms with 10 or more employees, 339 microregions.

conditions on employment growth can be large, if the labor market conditions are changing drastically. However, on average labor market tightness varies over time much more than prevailing wages. During the period of observation, labor market tightness on average grew 10% annually (with a standard deviation of 20%), while average wage paid by a firm declined by 0.1%, and average prevailing firm declined by 0.3%. These numbers suggest that wage changes have a limited ability to affect employment growth, and are unlikely to stimulate firms to hire more during recessions. However, if wage changes are large, which can be the case during minimum wage hikes, wage changes can limit employment growth, especially in small and young firms, which tend to grow faster (Fort et al., 2013), but are more sensitive to changes in labor market conditions.

Next, table 4 presents the differences in labor demand elasticity between low-paying and high-paying firms. Low-paying firm is defined as a firm at the 25th percentile of firm average wage distribution within the region, and high-paying firm is defined as a firm at the 75th percentile. The estimates suggest that low-paying firms consistently have 20-30% larger labor demand elasticities than high-paying firms. This result is consistent with the evidence in Moscarini and Postel-Vinay (2012) and Kahn and McEntarfer (2014) that employment growth in small and low-paying firms is less cyclical than in large and high-paying firms. It also suggests that low-paying firms are more vulnerable to changes in economic policies, which tighten labor markets or increase prevailing wages.

Finally, I find that labor demand elasticity varies across regions just as much as it varies between firms within regions. In particular, high-elasticity regions have approximately 50% larger labor demand elasticity with respect to changes in labor market tightness and 40% larger labor demand elasticity with respect to changes in wages than low-elasticity regions. Figure 5 show that estimated elasticity of labor demand varies substantially with the share of the formal sector in manufacturing, but not with such regional characteristics as wage premium or employment to population ratio.

Figure 4 shows how well the model fits the data. Overall, the model over-predicts employment growth, but fits employment growth in high-paying firms much better. This is expected as I weight the estimation equations by firm size, and large firms tend to be high-paying as well.

Table 3. Estimated elasticity of labor demand with respect to one percent change in labor market conditions, percentage points (i.e. $100 \times$ elasticity).

	25th percentile	Median	75th percentile
Direct labor demand response (model (5.1))			
Labor market tightness (α_1)	-2.4	-1.9	-1.58
Firm wage (β_1)	-2.29	-1.86	-1.57
Labor demand response after accounting for wage response (model (5.2))			
Labor market tightness (α_2)	-1.67	-1.3	-1.07
Average wage (β_2)	-1.44	-1.13	-0.94

Table 4. Ratio of labor demand elasticity of low-paying firm to labor demand elasticity of high-paying firm in the same region.

	25th percentile	Median	75th percentile
Direct labor demand response (model (5.1))			
Labor market tightness (α_1)	1.24	1.26	1.3
Firm wage (β_1)	1.21	1.23	1.27
Labor demand response after accounting for wage response (model (5.2))			
Labor market tightness (α_2)	1.23	1.26	1.3
Average wage (β_2)	1.25	1.28	1.33

Low-paying firm is defined as a firm paying average wage at 25th percentile in its region, high-paying firm is defined as a firm paying average wage at 75th percentile in its region.

Figure 4. Goodness of fit, by percentile of lagged wage

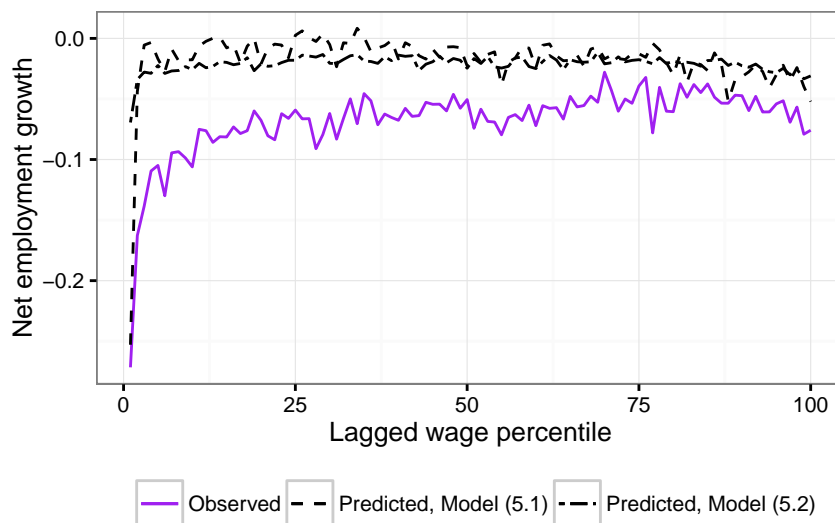
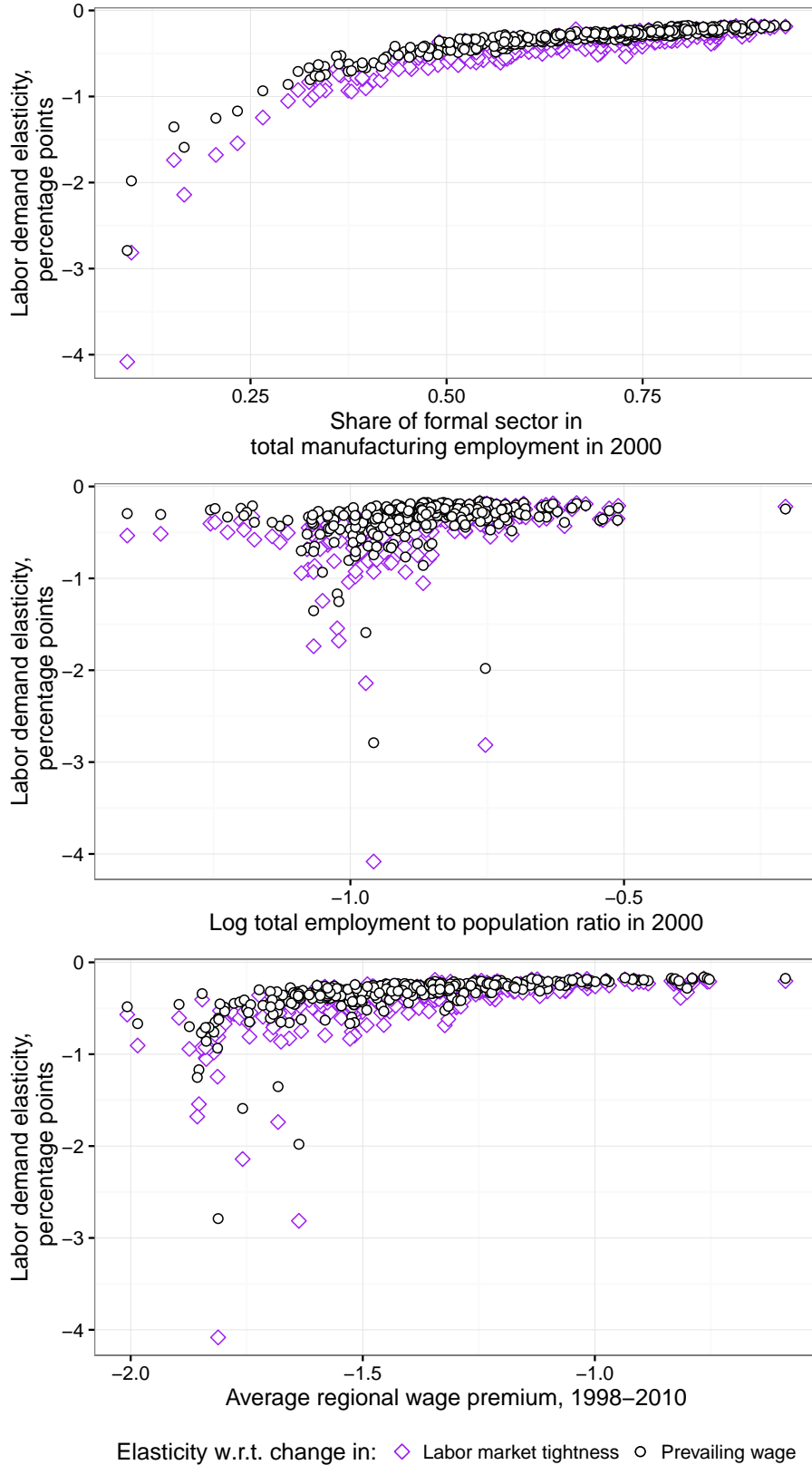


Figure 5. Estimated labor demand elasticity in a firm with median wage.
 Labor demand response after accounting for wage response (model (5.2))



6 Contribution of Changes in Labor Market Conditions to Employment Growth

In this section, I evaluate the role of labor market conditions in employment growth. Because net employment growth is bounded between -2 and 2, but predicted net employment growth is not bounded, I focus on employment growth among surviving firms only.

Table 5 presents the variance decomposition of employment growth across firms. It suggests that changes in labor market conditions explain only a small fraction of variation in employment growth across firms – less than 1%. Furthermore, table 5 demonstrates that most of this effect is driven by changes in labor market tightness rather than wages. However, labor market conditions have a larger impact on employment growth across regions (table 6). Variance decomposition demonstrates that variance of employment growth across regions would have been 4-6% higher if labor market conditions did not change. Similarly to the variance decomposition results across firms, 90% of this effect is driven by changes in labor market tightness. This finding is not surprising given that firms exhibit similar magnitude of labor demand elasticity with respect to changes in each margin, but labor market tightness tends to vary much more both across regions and over time than wages.

These results suggest that labor market conditions overall have a limited effect on regional employment growth, and have only mild effect on business cycles. Similarly, these findings are consistent with the small or zero effects of policies which change labor market conditions, like increases in minimum wage, on labor demand.

7 Conclusion

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Table 5. Variance decomposition of employment growth across firms, surviving firms.

	Direct impact		Impact after accounting for wage response	
	Absolute	%	Absolute	%
Variance of employment growth				
Var of Observed NEG	0.2009	100	0.2009	100
Var of NEG due to change in labor market conditions	1e-04	0.03	0	0.02
Var of NEG due to other reasons	0.2011	100.09	0.201	100.06
2Cov	-2e-04	-0.12	-2e-04	-0.08
Variance of employment growth due to labor market conditions				
Var of NEG due to change in labor market conditions	1e-04	100	0	100
Var of NEG due to change in labor market tightness	1e-04	88.14	0	87.88
Var of NEG due to change in wage	0	7.97	0	8.48
2Cov	0	3.39	0	3.64

Table 6. Variance decomposition of employment growth across regions, surviving firms.

	Direct impact		Impact after accounting for wage response	
	Absolute	%	Absolute	%
Variance of employment growth				
Var of Observed NEG	0.0114	100	0.0114	100
Var of NEG due to change in labor market conditions	2e-04	1.44	1e-04	0.84
Var of NEG due to other reasons	0.0121	106.23	0.0119	104.3
2Cov	-9e-04	-7.67	-6e-04	-5.14
Variance of employment growth due to labor market conditions				
Var of NEG due to change in labor market conditions	2e-04	100	1e-04	100
Var of NEG due to change in labor market tightness	2e-04	94.51	1e-04	94.79
Var of NEG due to change in wage	0	2.87	0	2.5
2Cov	0	1.22	0	2.5

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A Construction of the estimation sample

Missing records. It is not uncommon for a firm record to be missing for certain years in RAIS. This problem affects 3.6% of firm-year observations in the analysis sample. To keep these observations in the estimation sample, I impute the missing firm size and wage by interpolation the size and wage between the last observation before the missing record and the first observation after the missing record. Then, if before the missing record a firm had E_{t_0} workers, and after the missing record it had E_{t_1} workers, I calculate size in each missing year using the following rule:

$$E_t = E_{t_0} + \frac{t - t_0}{t_1 - t_0} (E_{t_1} - E_{t_0}). \quad (\text{A.1})$$

This procedure allows me to recover 74% of missing size observations and 60% of missing wage observations. In the estimation sample, 2.9% of employment growth observations and 4.5% of wage growth observations were imputed.

Average wage paid by a firm. To construct firms' wages, I first take away the differences in wages explained by workforce composition. I use a sample of all the workers employed in manufacturing in December of each year and regress the logarithm of their hourly wages (in constant 2005 prices) on workers' characteristics using the following specification:

$$\begin{aligned} \log \text{wage}_{mijlt} = & \beta_{0t} + \beta_{1t}(\text{age}_{mt} - 35) + \beta_{2t}(\text{age}_{mt} - 35)^2/100 \\ & + \beta_{3t} \text{female}_m + \beta_{4t} \text{tenure}_{mit} \\ & + \sum_k \beta_{5kt} \text{education}_{mkt} + \sum_p \beta_{6pt} \text{occupation}_{mt} + \mu_{jlt} + \nu_{mijlt}, \end{aligned} \quad (\text{A.2})$$

where k denotes an individual, i denotes firm, j denotes industry, l denotes microregion, t denotes year, and female_k is an indicator for female, tenure_{kt} is the tenure on the job in years, age_{kt} is the age in years, education_{kt} and occupation_{kt} are the full set of indicators for education and occupation categories, and μ_{jlt} is the industry–location–year fixed effect. I fit the specification (A.2) separately for each year, using the sample of all workers in Brazil employed in manufacturing in December of that year. The estimation results are presented in tables 7 and 8.

After this, I obtain the firm specific wage level as the average wages paid to a 35 year old male production worker with a high school degree and zero tenure at the firm i :

$$w_{ijlt} = \frac{1}{M_{ijlt}} \sum_m (\hat{\beta}_0 + \hat{\mu}_{jlt} + \hat{\nu}_{mijlt}) \quad (\text{A.3})$$

where M_{ijlt} is the number of employees in the firm in December of each year.

Finally, I estimate the wage change for each firm as a simple difference of the firm level wage:

$$\Delta w_{ijlt} = w_{ijlt} - w_{ijl,t-1}. \quad (\text{A.4})$$

Table 7. Coefficients of the regression of the logarithm of real hourly wages on workers characteristics (specification (A.2)), 1997-2003.

Variable	Dependent variable: Log hourly real wage						
	1997	1998	1999	2000	2001	2002	2003
Intercept	1.6	1.6	1.5	1.5	1.5	1.4	1.4
Age-35	0.012	0.012	0.012	0.012	0.012	0.011	0.011
(Age-35) ² /100	-0.064	-0.063	-0.06	-0.06	-0.055	-0.054	-0.05
Tenure	0.027	0.027	0.027	0.025	0.026	0.027	0.025
Female	-0.25	-0.23	-0.23	-0.22	-0.21	-0.2	-0.2
Illiterate	-0.39	-0.37	-0.38	-0.36	-0.34	-0.3	-0.4
4th gr incomplete	-0.42	-0.42	-0.41	-0.39	-0.36	-0.34	-0.33
4th gr complete	-0.38	-0.36	-0.36	-0.34	-0.32	-0.29	-0.28
8th gr complete	-0.32	-0.31	-0.31	-0.29	-0.27	-0.25	-0.25
8th gr incomplete	-0.25	-0.24	-0.24	-0.23	-0.21	-0.2	-0.2
HS incomplete	-0.18	-0.18	-0.18	-0.17	-0.16	-0.15	-0.15
Col incomplete	0.25	0.25	0.25	0.26	0.27	0.28	0.26
Col complete	0.53	0.54	0.57	0.58	0.61	0.63	0.63
Professionals	0.33	0.34	0.32	0.33	0.32	0.32	0.27
Senior managers	0.48	0.56	0.52	0.54	0.58	0.57	0.4
Administration	0.043	0.04	0.032	0.03	0.033	0.029	0.023
Sales	0.04	0.036	0.037	0.039	0.035	0.036	0.034
Services	-0.13	-0.14	-0.14	-0.13	-0.13	-0.13	-0.1
Agriculture	-0.32	-0.3	-0.28	-0.27	-0.25	-0.24	-0.23
Production							
Region Industry FE	X	X	X	X	X	X	X
Obs	21,592,484	21,944,120	22,646,764	23,313,822	24,816,872	26,141,204	27,046,444
R ²	0.65	0.65	0.65	0.65	0.65	0.65	0.64

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. Sample: all workers employed in manufacturing in December of each year (RAIS). All coefficients are significant at 1% level using robust s.e. Omitted education group: high school graduates. Omitted occupation group: production workers. “gr” stands for grade, “HS” stands for high school, “Col” stands for college.

Table 8. Coefficients of the regression of the logarithm of real hourly wages on workers characteristics (specification (A.2)), 2004-2009.

Variable	Dependent variable: Log hourly real wage					
	2004	2005	2006	2007	2008	2009
Intercept	1.4	1.4	1.5	1.5	1.5	1.5
Age-35	0.011	0.011	0.01	0.01	0.0097	0.0095
(Age-35) ² /100	-0.049	-0.046	-0.044	-0.042	-0.039	-0.038
Tenure	0.026	0.025	0.025	0.025	0.026	0.026
Female	-0.2	-0.2	-0.2	-0.2	-0.19	-0.19
Illiterate	-0.4	-0.38	-0.36	-0.34	-0.35	-0.33
4th gr incomplete	-0.32	-0.3	-0.29	-0.27	-0.27	-0.25
4th gr complete	-0.27	-0.26	-0.25	-0.23	-0.23	-0.22
8th gr complete	-0.24	-0.23	-0.21	-0.2	-0.2	-0.19
8th gr incomplete	-0.19	-0.18	-0.17	-0.15	-0.15	-0.15
HS incomplete	-0.15	-0.14	-0.13	-0.12	-0.12	-0.11
Col incomplete	0.25	0.25	0.24	0.23	0.24	0.22
Col complete	0.63	0.63	0.63	0.62	0.64	0.64
Professionals	0.29	0.31	0.3	0.3	0.28	0.28
Senior managers	0.38	0.37	0.4	0.41	0.4	0.41
Administration	0.02	0.021	0.022	0.023	-0.0052	-0.0061
Sales	0.04	0.036	0.043	0.05	0.027	0.034
Services	-0.094	-0.093	-0.088	-0.085	-0.11	-0.12
Agriculture	-0.22	-0.22	-0.2	-0.2	-0.2	-0.2
Production						
Region Industry FE	X	X	X	X	X	X
Obs	28,635,812	30,354,786	32,027,088	34,074,296	35,832,696	37,443,616
R ²	0.64	0.63	0.63	0.63	0.63	0.63

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. Sample: all workers employed in manufacturing in December of each year (RAIS). All coefficients are significant at 1% level using robust s.e. Omitted education group: high school graduates. Omitted occupation group: production workers. “gr” stands for grade, “HS” stands for high school, “Col” stands for college.

B Estimation of high-dimensional fixed effects in survival models

Though RAIS does not provide data on a worker when she does not have a formal sector job, I can estimate the duration model of non-employment spells to get some information on job offer arrival rate.

I track all workers who separate from manufacturing jobs every year in the data. Then, I use the data on workers who separated from a job in the current year and workers who separated from a job in the previous year but were unable to find a job until January of the current year, to estimate the duration model. By construction, duration of non-employment is censored at 2 years for workers who separated from a job in January of the previous year and did not find a job until December of the current year.

I model the duration of non-employment spells using exponential survival model and assume that the log hazard rate out of non-employment takes the following form:

$$\begin{aligned} \log h_{mlt} = & \beta_{1t}(age_{mt} - 35) + \beta_{2t}(age_{mt} - 35)^2/100 \\ & + \beta_{3t} female_m + \sum_k \beta_{4kt} education_{mkt} + \mu_{lt}, \end{aligned} \quad (\text{B.1})$$

where m denotes an individual, l denotes a microregion, t denotes year, and μ_{lt} is the microregion-year fixed effect. I estimate this model using each year of the data separately, and allow coefficients $\beta_{1t}-\beta_{4kt}$ to vary across years, but not across microregions.

Though conceptually estimating equation B.1 is straightforward, it is computationally costly because of the large number of fixed effects. To estimate the model, I use the fact that the likelihood function for the exponential duration model with censored data has the same first order conditions as a Poisson model for the number of individuals getting jobs at each duration on non-employment, where duration of the spell is used as offset (Rodríguez, 2007). In turn, Poisson model can be estimated by iterative procedure as described in Guimares and Portugal (2010). The estimation results are presented in tables 7 and 8.

Table 9. Coefficients of the survival model estimation (specification (B.1)), 1998-2003.

Variable	Dependent variable: Log hourly real wage					
	1998	1999	2000	2001	2002	2003
Female	-0.7	-0.68	-0.66	-0.64	-0.65	-0.67
Age-35	0.038	0.038	0.029	0.024	0.023	0.024
(Age-35) ² /100	-0.19	-0.19	-0.17	-0.15	-0.15	-0.15
Illiterate	-0.33	-0.48	-0.45	-0.54	-0.48	-0.54
4th gr incomplete	0.099	-0.0087	-0.084	-0.24	-0.16	-0.15
4th gr complete	0.24	0.12	0.039	-0.11	-0.12	-0.2
8th gr complete	0.44	0.32	0.26	0.14	0.11	0.033
8th gr incomplete	0.26	0.2	0.18	0.069	0.076	0.025
HS incomplete	-0.21	-0.25	-0.23	-0.33	-0.32	-0.35
Col incomplete	-0.89	-0.93	-0.95	-0.96	-1.1	-1.2
Col complete	-0.34	-0.36	-0.42	-0.5	-0.63	-0.63
Region Industry FE	X	X	X	X	X	X
Obs	1,335,941	1,324,035	1,316,250	1,368,651	1,414,769	1,443,334
Number of hires	816,065	823,032	876,090	919,994	990,661	1,037,582

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. Sample: workers who separated from a formal sector manufacturing job in the current or previous year and have not found a job by January of the current year (RAIS). All coefficients are significant at 1% level using robust s.e. Omitted education group: high school graduates. “gr” stands for grade, “HS” stands for high school, “Col” stands for college.

Table 10. Coefficients of the survival model estimation (specification (B.1)), 2004-2009.

Variable	Dependent variable: Log hourly real wage					
	2004	2005	2006	2007	2008	2009
Female	-0.64	-0.69	-0.7	-0.72	-0.7	-0.68
Age-35	0.021	0.021	0.025	0.021	0.022	0.027
(Age-35) ² /100	-0.14	-0.15	-0.16	-0.15	-0.15	-0.16
Illiterate	-0.52	-0.69	-0.84	-0.99	-1.1	-1.2
4th gr incomplete	-0.23	-0.31	-0.39	-0.51	-0.65	-0.75
4th gr complete	-0.31	-0.49	-0.61	-0.74	-0.86	-0.97
8th gr complete	-0.045	-0.21	-0.35	-0.45	-0.52	-0.63
8th gr incomplete	-0.031	-0.16	-0.26	-0.35	-0.43	-0.49
HS incomplete	-0.4	-0.51	-0.59	-0.64	-0.7	-0.78
Col incomplete	-1.2	-1.2	-1.4	-1.5	-1.6	-1.7
Col complete	-0.82	-0.82	-0.84	-1.00	-1.1	-1.2
Region Industry FE	X	X	X	X	X	X
Obs	1,476,703	1,532,970	1,604,897	1,636,394	1,715,774	1,780,478
Number of hires	1,178,435	1,231,559	1,322,983	1,507,344	1,615,158	1,596,710

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$. Sample: workers who separated from a formal sector manufacturing job in the current or previous year and have not found a job by January of the current year (RAIS). All coefficients are significant at 1% level using robust s.e. Omitted education group: high school graduates. “gr” stands for grade, “HS” stands for high school, “Col” stands for college.