The Effects of Tenure-Dependent Employment Protection Legislation*

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Abstract

This paper exploits tenure-dependence in employment protection legislation (EPL) to estimate its equilibrium effects. In Brazil, EPL applies after a 3 month probationary period, which we show causes a spike in job terminations just before 3 months. Using this variation, we estimate a model in which firms learn about match quality over time, and find that removing EPL reduces unemployment by between 9 and 40 percent, with larger effects when wages are rigid. This effect is driven by increased job creation. While EPL affects the timing of job terminations, it has virtually no impact on the overall level of terminations.

Keywords: Employment Protection, Job Separation Hazard, Unemployment

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I. Introduction

Employment Protection Legislation (EPL) is a pervasive feature of modern labor markets. While EPL mandates certain benefits to workers, its effect on equilibrium unemployment is typically ambiguous theoretically. Although EPL dampens firms' incentives to terminate jobs, lowering inflows to unemployment, it also reduces the payoff to creating new jobs, lowering outflows from unemployment.[1]

Despite a large body of research, the quantitative general equilibrium effects of EPL are still uncertain. Early studies utilizing cross-country policy variation likely suffer from important omitted variable bias. More recent work uses within-country, between-firm policy variation to identify the effects of EPL on firm-level employment. However, this approach only identifies *partial* effects of EPL (e.g., differences in employment levels between firms that face high vs. low firing costs), and cannot capture the aggregate effects often of interest to policy makers. Relatedly, the broad and often non-monetary nature of EPL makes it difficult to measure holistically, implying policy variation can generally only capture the effect of changes in the directly observable components of EPL.[2]

In this paper, we combine new empirical evidence with a structural search model to estimate the aggregate effects of EPL on unemployment. The distinguishing feature of our approach is to exploit the fact that in Brazil, EPL only applies to jobs with tenures greater than 3 months. This allows use to use the discrete jump in EPL costs to estimate the impact on firm's firing decisions. To map this reduced-form impact to a general equilibrium outcome, we build a structural search model of the labor market. We then use this model to make quantitative statements about the overall effect on unemployment, allowing us to resolve the theoretical ambiguity highlighted above.

We begin by estimating the impact of EPL on the hazard rates of job termination. As discussed above, EPL in Brazil only applies to a job with tenure greater than 3 months. Using administrative data from the *Relação Anual de Informações Sociais* (RAIS), we find a significant increase in the job termination hazard rate at exactly 3 months of tenure, precisely when EPL takes effect. We argue that this spike in job terminations arises because firms are uncertain about match productivity and prefer to end matches at 3 months if the expected productivity is too low, rather than risk incurring the costs of EPL. To bolster this argument, we rule out a number of alternative explanations for the observed spike in the

[1]While we focus on EPL in the search and matching framework, the ambiguity applies more generally (Ljungqvist, 2002). Furthermore, the ambiguity survives whether EPL is a tax or transfer when wages are less than fully flexible (Garibaldi and Violante, 2005).

[2]For example, EPL in Brazil consists of both monetary costs to firms in the form of firing penalties, and non-monetary costs in the form of legal recourse and termination notice periods.

hazard rate at 3 months. First, we find that the spike in job termination occurs consistently across industries and is uncorrelated with month-to-month employment changes, implying seasonal demand volatility cannot explain the spike in firings at 3 months. Second, we find that spikes occur consistently across occupations, including high-wage occupations, implying the bulk of the spike is likely not driven by firms rotating through low-skill workers to avoid paying EPL costs. Given these results, we interpret the spike in the job termination hazard as firms firing permanent workers with low expected productivity.

To map the effect of EPL on the job termination hazard into equilibrium outcomes such as unemployment, we next add EPL to a structural model of the labor market. Guided by the empirical results, we embed EPL in a general equilibrium model that combines a frictional labor market à la Diamond-Mortensen-Pissarides with endogenous job destruction through learning about match productivity (Moscarini, 2005). We calibrate a number of parameters to conventional values, and then use simulated method of moments to estimate 4 parameters that determine the shape of the job termination hazard rate schedule: the firm's initial belief about match quality, the speed at which firms learn about match quality over time, the size of the jump in EPL costs at 3 months' tenure, and the rate at which EPL increases with tenure beyond 3 months. We show that each parameter has a distinct effect on the hazard rate schedule, and so is plausibly identified. Importantly, the size of the spike in the hazard rate at 3 months is particularly informative about the size of the jump in EPL costs. This allows us to infer the effective cost of EPL without having to make assumptions about hard-to-measure components of EPL such as litigation costs and advanced notices of dismissal. This strategy of inferring hard-to-measure policy parameters from their identified effects in the data builds on Garicano et al. (2016), and ensures that the estimated model parameter captures the equivalent real cost that EPL imposes on firms. Our estimated model closely matches salient features of the empirical job termination hazard rate schedule, including the spike at 3 months' tenure.

We use our model to study the effects of removing EPL. The hazard rates fall at shorter tenures but rise at longer tenures as firms prolong matches in the absence of EPL, but eventually terminate those of low quality. Setting the unemployment rate at 15% with EPL, we find that removing the policy lowers the unemployment rate by 5.8 percentage points when wages are rigid, and by 1.3 points when wages are flexible and set using Nash bargaining.[3] As shown by Garibaldi and Violante (2005), when EPL is predominantly a transfer (as is the case in our setting), its effects can be partially undone by an appropriately designed flexible wage contract (see also Lazear, 1990). Consistent with this notion, we find that the degree

[3]Since our data does not contain sufficiently detailed information on wages to use in estimation, we present results for the range of possibilities.

of wage flexibility has large quantitative effects on the macroeconomic impact of EPL.

To understand the mechanism through which removing EPL lowers unemployment, we decompose the change in unemployment into changes in job creation and job destruction. This decomposition shows that decline in unemployment when EPL is removed is entirely driven by increased job creation by firms. Intuitively, removing EPL raises the payoff of a match to firms, who subsequently post more vacancies in equilibrium. In contrast, the overall level of job terminations is virtually unchanged by the removal of EPL, suggesting that its effect is purely compositional: EPL causes a shift in the timing of job terminations but does not affect the overall rate at which terminations occur.

We confirm the robustness of this result in a number of other simulation experiments. First, we show that delaying the onset of EPL lowers the cost to firms, and hence lowers unemployment through increased job creation. Second, we re-estimate our model using the hazard rates of job termination from labor submarkets segmented by job skill level, and find that EPL is particularly detrimental in the market for high-skill jobs, where initial beliefs about match quality are high but learning takes more time. In all cases, removing EPL lowers unemployment entirely through increased job creation. While EPL affects the timing of job terminations, it has only a negligible impact on the overall rate of terminations.

Related Literature Our paper relates to a number of distinct literatures. First, we contribute to an extensive literature on the effect of employment protection legislation on job terminations and unemployment. One strand of this literature considers cross-country variation in EPL to estimate its impact on unemployment (Bentolila and Bertola, 1990; Lazear, 1990; Gregg and Manning, 1997; Botero et al., 2004; Di Tella and MacCulloch, 2005). The strength of this approach is that it can be informative about general equilibrium effects of EPL. However, variation in employment protection legislation across countries may be confounded by important omitted variable bias. Therefore, a more recent literature has improved on identification by exploiting quasi-experimental changes or variation in EPL protection across regions, industries, firms, or jobs within a country (Autor et al., 2007; Kugler and Pica, 2008; Cappellari et al., 2012; Daruich et al., 2017), including studies in the Brazilian context (Gonzaga, 2003; Pinto, 2015). While these papers have made substantial progress on understanding the effects of EPL, these approaches generally identify changes in components of EPL, making it difficult to estimate its total impact inclusive of components not altered by legislation. In contrast, the variation we use is instead driven by a probationary period during which EPL costs are set to zero, and after which both monetary and non-monetary components apply to the job.

To map the empirical effect of EPL on the job termination hazard into unemployment, we estimate a structural model of the labor market. Therefore, our paper also contributes to to the literature that studies the effects of EPL on macroeconomic outcomes through the lens of a general equilibrium models (Cahuc and Postel-Vinay, 2002; Ljungqvist, 2002; Garibaldi and Violante, 2005; Pries and Rogerson, 2005; Boeri et al., 2017). Relative to these papers, we introduce empirically relevant tenure-dependent EPL and exploit this feature to estimate key latent parameters governing the learning process of firms and the cost of EPL, both of which crucially determine firms' optimal job termination decisions. We also pay special attention to the interaction of EPL with wage flexibility, and show that endogenizing the transition of jobs from unprotected to protected using the job termination decision prevents flexible wages from completely neutralizing the effects of EPL, in contrast to the conventional wisdom (Lazear, 1990; Garibaldi and Violante, 2005).

In contemporaneous work, Cahuc et al. (2019) use similar structural methods to study the effects of EPL on French labor market outcomes.[4] In addition to focusing on a markedly different labor market, our work and results differ in a number of meaningful, but complementary ways. First, we offer a micro-foundation for stochastic productivity by embedding EPL into the learning model of Moscarini (2005) and estimating the latent learning parameters. In contrast, Cahuc et al. (2019) follow Prat (2006) and assume that productivity follows a geometric brownian motion, and calibrate the drift of the process exogenously. We use the richness of the Brazilian matched employer-employee data to provide direct evidence that learning about productivity is a key driver of job separations, and to estimate our model across different labor submarkets segmented by skill. These estimations imply intuitive differences across the learning parameters of low and high skill job markets: in low skill jobs, initial expected quality is lower and it takes longer for firms to learn about true quality than in high skill jobs. Second, the empirical hazard in Brazil features a distinct spike at 3 months' tenure, in contrast to the French case, which instead features a kink at 2 years (the tenure at which EPL jumps in France). To generate this spike, we show it is necessary to depart from the continuous time termination strategies considered in Cahuc et al. (2019) in favor of discrete termination opportunities. Furthermore, the difference in timing EPL drives effect on the aggregate job separation rate. The shorter activation tenure in Brazil causes EPL to raise job termination rates before EPL activates, but lower them afterwards. Quantitatively, we find that these changes almost exactly offset. In contrast, when EPL jumps at 2 years' tenure, there is little change in termination rates at longer tenures since most matches are of sufficiently high productivity that endogenous termination is a rare occurrence. As a result, the main effect of EPL is to increase terminations before the jump point.

[4]The authors exploit the fact that severance payments feature a discrete jump in magnitude for jobs with tenure greater than 2 years.

The paper proceeds as follows: Section II introduces our data and institutional setting within the Brazilian labor market. In Section III, we document the hazard rate spike created by the EPL, and show that it is robust feature of a wide variety of labor submarkets. We develop our theoretical framework in Section IV, and describe the estimation and calibration procedure in Section V. We present our main quantitative exercise together with robustness checks in Section VI. Section VII concludes.

II. Institutional Setting and Data

A. EPL in Brazil

In Brazil, EPL is composed of many parts. For example, formal sector workers in Brazil are guaranteed severance pay if dismissed without cause, yearly bonuses equivalent to one month's salary, and 30 days' notice for any termination.Furthermore, in the event of a separation, the employer firm must pay a firing penalty, which is equal to roughly one month of the worker's salary for every year the worker has been employed at the firm.Overall, EPL is best conceptualized as a transfer from firms to workers, rather than simply a tax on firms. While there is a pure tax component, the bulk of the firing penalty (80 percent) is paid to the worker as severance. We are careful to account for this distinction in our structural analysis.

The key feature of EPL in Brazil that facilitates our analysis is its tenure-dependence: all dimensions of EPL only apply to firms and workers that have been in an employer-employee match for at least 3 months. This sharp discontinuity in the cost of EPL as a function of tenure is the basis of our empirical identification strategy, and is crucial for estimating our structural model. Intuitively, the jump in EPL costs at 3 months incentivizes firms to terminate matches just before this tenure is reached to avoid incurring the higher costs of termination should the match deteriorate soon after 3 months. Finally, it is useful to note that this structure of EPL with an initial trial period is common in many countries (OECD, 2008), making our empirical and theoretical approach widely applicable.

B. Data

Our analysis utilizes administrative data from the *Relação Anual de Informações Sociais* (RAIS), years 2002-2007. The RAIS data contains linked employer-employee records from a mandatory survey administered by the Brazilian Ministry of Labor and Employment (MTE). Fines are levied on firms which provide inaccurate or incomplete information on the survey.

Each entry in the RAIS dataset is an employee-employer match. Each individual, firm, and establishment are assigned unique administrative identifiers which do not change over time. Importantly, the data track each the tenure of each employer-employee match (job). For our analysis, we bin tenure into 15 day intervals due to "heaping" in the distribution of tenure (e.g. it is much more likely to observe a 30 days job spell than a 29 day job spell). In Appendix Figure A1 we plot tenure duration at the most disaggregated level possible in the data (reported in tenths of a month). As can be seen in the plot, there are large spikes at half-month intervals, and much lower frequency at other durations. This plot motivates our decision to bin tenure into 15 day intervals and will also guide how we treat the timing of firing decisions in our model.

The data include additional information about the job, such as occupation, hours, type of labor contract, whether the job has ended, and why the job has ended, and also contain demographic data on individuals, such as education, gender, and ethnicity. We exploit these features as part of our empirical strategy, and also examine heterogeneity across occupation through the lens of our structural model. In particular, when looking at terminations, we consider terminations of the contract as a job separation. This will not include jobs that end due to retirement or transfers, for example.

Finally, we note that while the data includes some information about wages, this data is only available at an annual frequency. As a result, it is not possible to observe how wages within a job evolve with tenure for a period less than a year in the RAIS dataset. We adapt our structural analysis to this limitation by computing outcomes under two opposing wage assumptions: rigid wages, and flexible wages set using Nash bargaining. For more information about the dataset and the definition of variables, see Appendix Section C.

C. Sample Selection

Our identification strategy hinges on the spike in job terminations at 3 months' tenure being solely driven by the timing of EPL. A natural confounder is therefore the presence of workers on temporary 3 month contracts. In Brazil, temporary contracts are subject to approval by the Ministry of Labor (MTE) and about 5 percent of workers at a given time are employed under such contracts. These contracts are approved to meet temporary increases in demand and many of these contracts last for three months. Therefore, a spike in the job termination hazard may naturally arise at 3 months due to the existence of such contracts.[5] Given the focus of our paper is on the effects of EPL on permanent employment contracts, we therefore use the contract information included in our dataset to eliminate temporary contracts from the majority of our empirical and theoretical analysis.

In addition to eliminating temporary contracts, we restrict attention to workers aged 18-

[5]While the presence of EPL may theoretically cause increased substitution towards temporary contracts (Daruich et al., 2017), the regulated usage of temporary contracts likely limits this substitution in Brazil.

65, and working in full-time jobs (at least 35 hours per week). We exclude individuals with invalid identifiers (less than one percent of the data). Column 1 of Table 1 presents summary statistics for the population of 18-65 year olds. Column 2 presents summary statistics for jobs which last less than or equal to 3 months, which comprises a non-negligible fraction of all jobs. In total, there are 92,023,307 jobs corresponding to 29,438,306 unique workers. 24,427,409 jobs last 3 months or less (i.e. 26.5 percent of all jobs).

III. The Impact of EPL on the Job Termination Hazard

In this section, we document a visible spike in the job termination hazard rate at a tenure of 3 months, and argue that it predominantly reflects the early termination of permanent employment contracts caused by the tenure dependence built into EPL in Brazil.

A. Estimating Bunching in Job Terminations

To summarize the quantitative magnitude of the spike in the job termination hazard rate at 3 months' tenure, we estimate a "bunching" statistic. This summary statistic is useful as it is comparable across different labor submarkets and can be used to explore potential driving mechanisms of the hazard rate spike.

We follow the public finance literature (see Kleven (2016) for a review) to estimate bunching. Specifically, we fit a flexible polynomial to the empirical job termination hazard, excluding data from around the spike point T_1, which is the tenure at which EPL takes affect. Formally, let $\mathcal{J} = \{15, 30, 45, ...\}$ define a set of bin edges (measured in days) and let H_j denote the hazard rate of job termination in the bin with upper edge $j \in \mathcal{J}$. For example, H_{90} denotes the probability that a job ends between 75 and 90 days, given the job has lasted for 75 days. To fit a polynomial to the empirical hazard rate schedule excluding the data around the spike, we estimate the following regression:

$$H_j = \sum_{i=0}^{q} \beta_i \cdot (j)^i + \sum_{k \in \mathcal{K}} \gamma_k \cdot \mathbf{1}[j = k] + \varepsilon_j \tag{1}$$

where q is the order of the polynomial and $\mathcal{K}$ denotes the set of excluded bins around the spike. In practice, we set $q = 10$ and $\mathcal{K} = \{75, 90, 105\}$, and therefore exclude any jobs that end between 60 and 105 days in the estimation of the counterfactual hazard rate. We use the results from (1) to estimate the counterfactual hazard as:[6]

$$\hat{H}_j = \sum_{i=0}^{q} \hat{\beta}_i (j)^i \tag{2}$$

The normalized excess mass, which we refer to as bunching, b, is defined as the difference in the true hazard rate and the counterfactual hazard rate divided by the counterfactual hazard rate at tenure duration T_1,

$$b = (H_{T_1} - \hat{H}_{T_1})/\hat{H}_{T_1} \tag{3}$$

To compute standard errors for the bunching statistic, we generate bootstrapped bunching statstics by resampling the residuals in Equation (1). The standard error is then equal to standard deviation of the distribution of the bunching estimates over 500 bootstrap samples.

Figure 1 displays the job termination hazard rate. There is a visible spike in the hazard rate at a tenure of 3 months, which results in significant bunching. We find that the excess mass is equal to 1.4, with a standard error of 0.234, indicating that the true hazard rate is more than double the predicted counterfactual hazard rate at 3 months' tenure. We also note that there is another much smaller spike in the hazard rate at around six months' tenure. Van Doornik et al. (2018) shows that this spike is due to "fake separations". If a worker is fired after six months of tenure, the worker can receive unemployment insurance from the government. This incentivizes firms to fire workers and then split the unemployment insurance. In order to focus on the effects driven by the timing of EPL, we drop the hazard rates at 5.5, 6, and 6.5 months' tenure when we estimate the model.

The sizable excess mass at 3 months' tenure indicates a non-trivial response by firms, who alter their job termination decisions in the presence of tenure-dependent EPL. An intuitive explanation, and indeed the mechanism we will focus on, is that the presence of EPL for jobs with tenures of at least 3 months incentivizes firms to terminate a significant number of jobs with low expected productivity at exactly three months. This learning mechanism is formalized by our structural model in Section IV, in which the size of EPL exactly pins down the size of the hazard rate spike at 3 months' tenure.

In order to justify this intuition empirically, we now argue that the observed bunching is indeed predominantly driven by the early termination of permanent employment contracts, as opposed to firms optimally choosing to hire workers on short-term or temporary contracts.

[6]In the empirical analysis, we use the term counterfactual hazard as the estimated hazard rate schedule when we exclude the spike, following the literature on bunching. In Section VI, we study structural counterfactual hazard rates using our estimated model.

B. Temporary Contracts

An advantage of our data is that we can drop all matches labeled as temporary contracts to ensure that our bunching analysis is not confounded by mechanical job terminations at 3 months' tenure.[7] However, hiring workers on temporary contracts is itself a regulated process in Brazil. To hire a worker under a temporary contract, firms must get permission from the Ministry of Labor and must also establish that the worker needs to be hired on a temporary contract in order to meet seasonal fluctuations in demand. Therefore, in order to sidestep these regulatory frictions, firms desiring short-term employment arrangements may simply hire workers on permanent contracts with the intention of firing them after 3 months, thus mimicking the temporary contract. This behavior of creating artificial temporary contracts is not directly observable in our data and would have important implications for the appropriate way to model firms' responses in our structural model. We now examine and rule out two key reasons that could cause firms to create artificial temporary contracts.

B.1 Demand Volatility

Firms that face volatile demand for their product will naturally have volatile labor demand that is best served via short term employment contracts. Such firms will therefore find it optimal to create artificial temporary contracts when official temporary contracts are unavailable.

One simple way to discern how much of the bunching is driven by this behavior is to compare bunching across different industries, where some industries are naturally more prone to short-term labor hiring than others. Specifically, we estimate bunching separately across industries at the 3-digit level, and then correlate bunching with the month-to-month variation in employment in the given 3-digit industry.[8] If labor demand volatility is a significant driver of bunching, we would expect industries with higher employment volatility to also display greater magnitudes of bunching.

To estimate demand volatility, we compute a normalized measure of monthly employment changes in industry j at time t as:

$$\Delta E_{j,t} = \frac{\text{hires}_{j,t} - \text{fires}_{j,t}}{\text{hires}_{j,t}} \tag{4}$$

We then compute volatility of industry j as $V_j = Var(\Delta E_{j,t} - \Delta E_{j,t-1})$. In words, we create a time series of month-to-month net employment changes scaled by the total number

[7] To understand the role of temporary contracts, Appendix Figure A2 plots the job termination hazard rate which includes temporary contracts. As can be seen in the figure, the amount if bunching is larger with temporary contracts include (1.9 vs. 1.4).

[8] Industries are reported under the *CNAE* (*Classificação Nacional de Atividade Econômica*).

of hires. We then take the variance of the first difference as our measure of employment volatility. We then correlate this measure with bunching by running the following regression:

$$\ln(V_j) = \alpha + \beta b_j + \varepsilon_j \tag{5}$$

where β captures the correlation between bunching and employment volatility. Figure 2 shows the results of this regression as well as a scatterplot of bunching across industries. The first thing to notice in the figure is that bunching is positive in every single 3-digit industry, indicating that positive bunching is an important feature across many industries. Additionally, it does not appear as if bunching is strongly correlated with demand volatility. Demand volatility is actually *negatively* correlated with bunching, although the correlation is not significant. This suggests that demand volatility does not play a quantitatively important role in determining the amount of bunching that we estimate once official temporary contracts have been removed from the analysis sample. In Appendix Figure A3, we plot the entire hazard for a few representative sectors. We find significant levels of bunching even in industries that experience relatively stable output, such as health and education.

B.2 Rotating through Low-Skill Workers

In addition to volatile labor demand, firms may want to create artificial temporary contracts if high worker turnover does not impact the production process. For example, if firms can simply replace production workers every 3 months, then it may be profit maximizing to continually rotate through workers. In this case, the bunching would not be driven by firms learning about worker quality, and would confound our structural story.

Intuitively, this channel seems most prevalent for low-skill occupations (constant replacement of engineers, for example, seems very unrealistic). Therefore, in order to examine how much it contributes towards the bunching we observe, we divide occupations into different skill levels, where skill level is defined by the International Standard Classification of Occupations (ISCO). Low-skill occupations are characterized by the performance of simple and routine physical tasks, and includes occupations such as cleaners and construction laborers. Medium-skill jobs involve performing more complex tasks, such as operating machinery, and includes occupations such as office clerks and skilled craftsman. High-skill jobs require workers to perform complex tasks and in many cases, some form of advanced education. High-skill occupations include technicians, managers and professionals.[9]

Given these definitions, we expect the channel to be stronger for low-skill workers, as the

[9]ISCO also breaks down high-skill occupations into medium-high skill and high-skill. For this paper, we have aggregated these two groups and defined them as high-skilled.

tasks they perform require little training. As can be seen in Figure A4, however, bunching occurs across all skill levels. For example, bunching in both the high-skill and low-skill categories is equal to 1.5. While it is true that job termination is in general higher in low-skill occupations, the excess firing at three months is similar across skill levels.

To show this result is consistent, we estimate bunching across all 3-digit occupations. To capture a crude measure of skill level, we use the average wage in the occupation. In Figure A4, we plot the estimated bunching against the average log monthly wage. As can be seen in the figure, there is a slight but insignificant negative correlation between average log monthly wage and bunching. This suggests that bunching is not driven by firms rotating through low-skill workers that are relatively easy to replace quickly, but is a feature even in high-skill, high-wage occupations, and hence must reflect the early termination of truly permanent employment contracts.

C. Summary

In this section we have documented a visible spike in the job termination hazard rate at a tenure of 3 months, and have argued that it predominantly reflects the early termination of permanent employment contracts caused by the tenure dependence built into EPL in Brazil.

While our empirical analysis exploits this tenure dependence allows us to cleanly identify the effect of EPL on the hazard rate of job termination via firms' decisions at the micro level, it cannot say how these decisions aggregate up and affect macroeconomic outcomes such as unemployment. In order to address these questions, we now develop a structural framework that formalizes the mapping between EPL, hazard rates, and general equilibrium macroeconomic outcomes.

IV. A Model of Endogenous Job Termination and EPL

We embed EPL in a general equilibrium model of endogenous job termination and unemployment (Moscarini, 2005). We study the steady state equilibrium of this economy and use $t \geq 0$ to denote job tenure. Given our focus on the interaction of tenure-dependent EPL and firms' termination decisions, we model the job heterogeneity driven by tenure-dependent perceptions about match quality, and do not explicitly address heterogeneity driven by permanent differences in worker or firm characteristics, which would not affect the endogenous termination decision as tenure increases. In this sense, our model complements the approach taken in Engbom and Moser (2018), who model the interaction between permanent heterogeneity and the minimum wage in Brazil.[10] Furthermore, if we adopt their assumption that labor markets are perfectly segmented by skill, then we can apply our model to each skill submarket separately. We pursue this extension in Section VI.

A. Production, Beliefs, and Flow Profits

A final good is produced in continuous time by pairwise firm-worker matches. The match-specific productivity of a match, μ, can take two values $\mu \in \{\mu^L, \mu^H\}$, where $\mu^L < \mu^H$. We refer to μ^L as a bad match, and μ^H as a good match. μ is ex-ante unknown by both the firm and worker. Let $p_0 = \Pr(\mu = \mu^H)$ be the firm's initial prior that the match is good.

The output generated by a match is subject to idiosyncratic shocks. In a small interval dt, the flow production of a match is given by

$$dX_t = \mu dt + \sigma dZ_t \tag{6}$$

where dZ_t is a standard Brownian motion and $\sigma > 0$ is a noise parameter. In other words, realized output is a noisy indicator of true match productivity.

Firms update their belief of match quality using the history of realized output, denoted by the filtration $\mathcal{F}_t^X$, to update their prior belief in a Bayesian manner,

$$p_t = \Pr\left(\mu = \mu^H | \mathcal{F}_t^X\right) \tag{7}$$

The solution to this inference problem is a stochastic differential equation for p_t,

$$dp_t = p_t\left(1 - p_t\right)\zeta d\bar{Z}_t \tag{8}$$

where $\zeta = (\mu^H - \mu^L)/\sigma$ is the signal-to-noise ratio and

$$d\bar{Z}_t = (dX_t - (p_t\mu^H + (1 - p_t)\mu^L)dt)/\sigma \tag{9}$$

is a standard Brownian motion with respect to $\mathcal{F}_t^X$.[11] Intuitively, beliefs move faster when there is less noise (σ is smaller) or when the current belief is closer to $p = 1/2$ so that observing realized output is more informative about match quality.

Let $\bar{\mu}\left(p\right) = p\mu^H + \left(1 - p\right)\mu^L$ denote the expected output of a match with current belief p, and let $w(p, t)$ denote the wage paid to a worker in a match with belief p and tenure t. Flow profits are then $\pi(p, t) = \bar{\mu}(p) - w(p, t)$. Since the main implications of different wage

[10] In line with this interpretation, we find that our estimated model generates productivity dispersion in line with the residual dispersion estimated by Engbom and Moser (2018), and not captured by their model.

[11] For a formal discussion of this result, see Moscarini (2005) and the references therein.

setting protocols are quantitative in nature, we delay the details of how we specify $w(p, t)$ and hence $\pi(p, t)$ to Section V.

B. EPL

When the expected sum of discounted profits from a match is low enough, firms will optimally choose to terminate the match. Upon termination, firms must pay a cost $\kappa(t)$ that may depend on the tenure of the match. Crucially, $\kappa(t) = 0$ for $t \in [0, T_1)$ while $\kappa(t) > 0$ for $t \geq T_1$, where T_1 is the tenure at which EPL jumps (e.g. 3 months in our data). Rather than set $\kappa(t)$ directly using its observable components, we follow Garicano et al. (2016), and parameterize and estimate the function to match the shape of the hazard rate of job termination. In this way, we can capture the effects of both the monetary, and non-monetary and hard-to-measure components of EPL on firms' termination decisions.

C. Firm Value Functions and Optimal Termination Choices

As shown in Appendix Figure A1, the empirical rate of job termination is not a smooth function of tenure at measurement frequencies below 15 days. From the perspective of our continuous time model, job termination occurs predominantly at discretely-spaced tenures. To capture this feature of the data, let $\mathcal{T} = \{t_0, t_1, t_2, ...\}$ denote a countable and ordered ($t_i < t_{i+1}$) set of tenures at which endogenous job termination can occur. We assume that $T_1 \in \mathcal{T}$, and that $t_0 = 0$. To allow for terminations outside of $\mathcal{T}$, we also assume that matches are exogenously terminated at rate $\delta > 0$. Exogenous terminations capture a range of idiosyncratic shocks to the match orthogonal to the learning process, such as technological obsolescence and firm restructurings.

We solve for firm value functions using backward induction in the tenure dimension. To initialize this procedure, we first obtain a stationary value function that does not depend on tenure. To this end, we impose that $\mathcal{T}$ is finite with final element $t_{I+1} = T_2$.[12] After tenure has reached T_2, we assume that EPL remains fixed at $\kappa(T_2)$, and that firms can fire workers continuously. Under these assumptions, the value function for matches with tenure greater than T_2 is stationary and depends only on the belief p. We use this value function to initialize the boundary conditions in the tenure dimension. See Appendix B for further details.

For tenures $t < T_2$, we now derive conditions that describe the value of a match to a firm and her optimal termination decision for an arbitrary interval of tenures $[t_i, t_{i+1}]$ where $t_i, t_{i+1} \in \mathcal{T}$. To better understand how the jump in EPL at T_1 affects firms' decisions, it is useful to divide the analysis into two cases: $t_{i+1} \neq T_1$ and $t_{i+1} = T_1$, where the second case

[12] In practice, we set $T_2 = 4$ years so that it does not affect the hazard rates of interest.

captures the case in which EPL jumps at the end of the tenure interval. We assume that firms are risk neutral and discount the future at rate $r > 0$. Define $\Sigma(p) = \frac{1}{2}\zeta^2 p^2 (1-p)^2$ as half the variance of dp, and let V denote the value of opening a vacancy.

C.1 $t_{i+1} \neq T_1$

For all tenures $t \in [t_i, t_{i+1})$, the value of the match J^i satisfies the continuous time Hamilton-Jacobi-Bellman (HJB) equation

$$rJ^i(p,t) = \pi(p,t) + J^i_t(p,t) + \Sigma(p)J^i_{pp}(p,t) + \delta\left(V - \kappa(t) - J^i(p,t)\right) \tag{10}$$

The flow value of the match to the firm consists of 3 components. First, the firm receives the flow profits of the match. Second, the firm value has a capital gain component due to changes in tenure and beliefs via Bayesian updating.[13] Finally, the possibility of exogenous separation creates another source of capital gain in which the firm loses the current value and the cost of EPL, but gains the value of vacancy posting.

At t_i, the firm has the option of terminating the match. Termination will occur if the match value is weakly less than the firm's alternative of paying EPL and creating a vacancy,

$$J^i(p,t_i) \leq V - \kappa(t_i) \tag{11}$$

Assuming that J^i is increasing in p, we can define a threshold belief $\underline{p}(t_i)$ such that any match with belief $p_{t_i} \leq \underline{p}(t_i)$ is terminated at tenure t_i, where $J^i(\underline{p}(t_i), t_i) = V - \kappa(t_i)$.[14]

Given optimal termination behavior at t_i, we can define the optimal value function just before t_i by $J^{i-1}(p,t_i) = \max\{J^i(p,t_i), V - \kappa(t_i)\}$. Applying this logic to the upper limit t_{i+1} then gives us the boundary condition in the tenure dimension required to solve the HJB equation backwards through tenures over the interval $[t_i, t_{i+1}]$,

$$J^i(p,t_{i+1}) = \max\{J^{i+1}(p,t_{i+1}), V - \kappa(t_{i+1})\} \tag{12}$$

Note that the boundary conditions in the belief dimension are pinned down by the stationary value function for tenures $t \geq T_2$, and are described in Appendix B.

[13] Throughout, subscripts denote partial derivatives.

[14] In the absence of EPL, it is simple to show analytically that J is increasing in p (Moscarini, 2005). In the presence of EPL, we verify this assumption numerically.

C.2 $t_{i+1} = T_1$

When the upper limit equals T_1, the boundary condition for (10) must account for the special nature of optimal termination behavior that occurs when EPL activates. At T_1, the firm realizes that she can terminate a match the instant before EPL activates to avoid incurring the cost. Since the value of the match will not change at the moment of activation, waiting for EPL to activate before choosing to terminate is never optimal.[15] Therefore, the boundary condition for the interval $[t_i, T_1]$ is

$$J^i(p, T_1) = \max\{J^{i+1}(p, T_1), V\} \tag{13}$$

The boundary condition (13) underlies why the model is able to generate a spike in job terminations just before EPL activates at T_1. To see this, we compare the three termination thresholds around T_1: the last pre-EPL threshold $\underline{p}(t_i)$, the first post-EPL threshold $\underline{p}(T_1)$, and the threshold applied just before EPL activates defined by (13), $\bar{p}(T_1)$, where $J^{i+1}(\bar{p}(T_1), T_1) = V$.

We first note that since J^{i+1} is increasing in p, we have $\bar{p}(T_1) > \underline{p}(T_1)$. This implies that the productivity belief of a match not terminated at T_1 is strictly greater than the first termination threshold post-EPL activation. This causes fewer jobs to be terminated immediately after T_1, so that there is a drop in job terminations after EPL activates, just as we documented empirically.

Working backwards, we also have $\bar{p}(T_1) > \underline{p}(t_i)$, so that the threshold applied just before EPL activates is higher than the threshold used at the previous termination tenure. While we have verify that $\bar{p}(T_1) > \underline{p}(t_i)$ numerically, an intuition is as follows: consider a match with belief $p_{t_i} = \bar{p}(T_1)$ at tenure t_i. The option to terminate the match at T_1 if the belief worsens implies that the firm only faces upside risk at t_i, so that $J^i(\bar{p}(T_1), t_i) > V$. Since J^i is increasing in p, we must have $\bar{p}(T_1) > \underline{p}(t_i)$ for $J^i(\underline{p}(t_i), t_i) = V$. This implies that there is a positive mass of matches which survive termination at t_i, but are subsequently terminated just before T_1, thus increasing the total job terminations in the window just before EPL activates. Combined with the drop in terminations immediately after T_1, this generates a spike in terminations around T_1, similar to the data.

Finally, we note that the existence of a spike is also closely linked to the discrete nature of job terminations in the data and model. Were firms able to terminate matches continuously before T_1, the termination thresholds increasing continuously with tenure up to $\bar{p}(T_1)$. As a result, the rate of job termination would also increase continuously up to T_1, before dropping once EPL activates, and so would not feature a spike.[16]

[15] Formally, EPL activation is a "jump" event, during which the continuous match value remains fixed.

[16] Cahuc et al. (2019) use a model with continuous terminations to successfully capture the hazard rate

D. Hazard Rates of Job Termination

To derive an expression for the hazard rate of job termination at some tenure $t \in \mathcal{T}$, we first show how to track the distribution of beliefs for a cohort of matches that began production at the same moment in calendar time. We again divide the analysis into two cases for any interval $[t_i, t_{i+1}]$ where $t_i, t_{i+1} \in \mathcal{T}$: $t_i \neq T_1$ and $t_i = T_1$.

D.1 $t_i \neq T_1$

Let f^i denote the density of beliefs for a cohort of matches that began production at the same moment in calendar time, and have reached tenure t_i. We can characterize the evolution of f^i using the Kolmogorov Forward Equation (KFE), which states that f^i satisfies

$$\frac{\partial}{\partial t} f^i(p,t) = \frac{\partial^2}{\partial p^2}\left[\Sigma(p) f^i(p,t)\right] - \delta f^i(p,t) \tag{14}$$

The KFE states that the change in density at a belief p over a small change in tenure is the sum of two components. First, beliefs move around in the distribution according to (8). The change in density caused by these movements is captured by the first term on the right-hand side. Second, at any belief, a fraction δ of matches end exogenously, causing a negative change to the density captured by the second term.

Given an initial condition $f^i(p, t_i)$, we solve the KFE forward to the termination tenure t_{i+1}. Given the the termination threshold for beliefs $\underline{p}(t_{i+1})$, we can define a new distribution starting from t_{i+1} by

$$f^{i+1}(p, t_{i+1}) = f^i(p, t_{i+1})\mathbf{1}\{p \in [\underline{p}(t_{i+1}), 1]\} \tag{15}$$

which sets the density of beliefs to zero for all beliefs weakly less than the termination threshold. Applying this logic to the termination tenure t_i yields the initial condition to solve the KFE forward,

$$f^i(p, t_i) = f^{i-1}(p, t_i)\mathbf{1}\{p \in [\underline{p}(t_i), 1]\} \tag{16}$$

Finally, if $t_i = t_0 = 0$, we initialize $f^0(p, 0)$ using the firm's prior so that $f^0(p, 0)$ places all its mass at p_0. In steady state, balanced worker flows into employment implies that the total mass of $f^0(p, 0)$ equals the mass of newly created matches $m > 0$.[17]

of terminations in French data, which does not feature a spike, in contrast to our setting.

[17] This condition implies that the $\{f^i\}$ are not strictly densities since they do not integrate to 1. Instead, we normalize the mass of the initial distribution f^0, and define the total mass summing over all the f^i functions as total employment.

D.2 $t_i = T_1$

If $t_i = T_1$, then the initial condition for $f^i(p, T_1)$ must account for the special termination behavior that occurs at T_1. Formally, we set

$$f^i(p, T_1) = f^{i-1}(p, T_1)\mathbf{1}\{p \in [\bar{p}(T_1), 1]\} \tag{17}$$

which uses the pre-EPL termination threshold $\bar{p}(T_1)$ rather than the post-EPL threshold $\underline{p}(T_1)$ to determine which beliefs have zero density at T_1.

D.3 Hazard Rates of Job Termination

Let $h(t, t+s)$ denote the hazard rate of job termination between tenures t and $t+s$, i.e. the probability of a match being terminated by tenure $t+s$ conditional on the match surviving to tenure t. Using $\{f^i\}$, we can construct the hazard rate function

$$h(t, t+s) = \left(\int_0^1 f^{i(t)}(p, t)dp - \int_0^1 f^{i(t+s)}(p, t+s)dp\right) / \left(\int_0^1 f^{i(t)}(p, t)dp\right) \tag{18}$$

where $i(t) = \max\{i : t_i \leq t, t_i \in \mathcal{T}\}$. Intuitively, we compute $h(t, t+s)$ by dividing the change in cohort mass between tenures t and $t+s$ by the cohort mass at tenure t.

E. General Equilibrium Closure

We close the model using standard ingredients from the search and matching literature: free entry into vacancy creation, and a constant returns to scale matching function.[18]

E.1 Vacancy Posting

A vacant firm that posts a vacancy has value V that satisfies

$$rV = -c + q(J(p_0, 0) - V) \tag{19}$$

where q is the probability of filling the vacancy, and c is the per-period cost of maintaining a vacancy. Free entry guarantees that $V = 0$ and $c = qJ^0(p_0, 0)$ in equilibrium.

[18] Although standard in the literature, the free entry assumption has quantitative implications that we discuss as part of our numerical results.

E.2 The Matching Function

New jobs m are generated by the matching function $m = zu^{\eta}v^{1-\eta}$ where v is the mass of vacancies, and u is the mass of unemployed workers. z is matching efficiency and $\eta \in (0,1)$ is the elasticity of matches to unemployment. We can then define the job finding rate $\lambda = z\theta^{1-\eta}$, and job filling rate $q = z\theta^{-\eta}$, where $\theta = v/u$ is labor market tightness.

E.3 Equilibrium Unemployment

Summing over the $\{f^i\}$ yields the stationary distribution of beliefs,

$$g\left(p\right) = \sum_{t_i \in \mathcal{T}} \int_{t_i}^{t_{i+1}} f^i(p,t)dt \tag{20}$$

Aggregate employment is $e = \int_0^1 g(p)dp$. Normalizing the total labor force to $l > 0$, equilibrium unemployment is the number u that satisfies $u = l - e$ and $m = \lambda u$.[19]

V. Model Calibration and Estimation

We describe the functional forms for EPL and wages, and discuss how we calibrate a subset of parameters. We then describe how we use the empirical hazard rate function to identify and estimate key latent parameters governing EPL and the endogenous learning process.

A. Functional Forms

A.1 EPL

To capture the salient tenure-dependence of EPL in our empirical setting, we adopt the following specification for the EPL function,

$$\kappa\left(t\right) = \begin{cases} 0 & \text{if} \quad t < T_1 \\ \kappa_1 + \kappa_2(t - T_1) & \text{if} \quad t \geq T_1 \end{cases} \tag{21}$$

where $\kappa_1, \kappa_2 \geq 0$ are constants, and T_1 is a tenure at which the termination cost becomes active. κ_1 captures the jump in EPL costs at tenure T_1, while κ_2 measures the rate at which EPL increases with tenure.

[19]In the model without EPL, Moscarini (2005) shows that equilibrium unemployment is unique. While we cannot prove this in the model with EPL, our numerical analyses suggest the equilibrium is indeed unique.

A.2 Wages

As emphasized by Garibaldi and Violante (2005), the flexibility of wages matters when EPL is predominantly a transfer paid to workers upon match termination, as is the case in our empirical setting. Following the intuition formalized by Lazear (1990), when wages are flexible, the firm and worker can write a mutually beneficial wage contract that neutralizes the allocative effects of the transfer: the firm subtracts the value of EPL from the worker's wages, while the worker receives the interest earned on the saved EPL principal during the match, and receives the principal back upon match termination.

To investigate the applicability of this neutrality result in our setting, and given the absence of high frequency wage information in our data, we therefore consider both rigid and flexible wage schedules. To model flexible wages, we follow Garibaldi and Violante (2005) and the wider search literature, and use the Nash bargaining protocol. Let $w^R(p,t) = w$ denote the rigid wage. The derivation of the flexible wage under Nash bargaining is standard (we describe the notation and steps Appendix B),

$$w^F(p,t) = \beta\bar{\mu}(p) + (1-\beta)b + \theta\beta c + r\kappa(t) - \kappa'(t) \tag{22}$$

where $\beta \in (0,1)$ is the worker's bargaining power, and b is the worker's outside option.

Examining (22) shows the extent to which the neutrality intuition applies. At tenures beyond T_1, the worker agrees to a wage that includes the interest earned on the EPL principal amount $\kappa(t)$, but prepays any increases in EPL as tenure lengthens, captured by the slope $\kappa'(t) \geq 0$. Therefore, once tenure has reached T_1, further increases in EPL above $\kappa(T_1)$ do not affect the flow payoff of a match to the firm, and hence do not directly affect endogenous terminations decisions.[20] In contrast, the flexible wage does not neutralize at all the jump in EPL at tenure T_1. Intuitively, workers will not agree to prepay the amount $\kappa(T_1)$ because they realize that firms could subtract the prepayment from the wage, but then choose to terminate the match anyway. In other words, under Nash bargaining, firms are unable to commit not to fire a worker endogenously before T_1 in exchange for a wage schedule that neutralizes the jump in EPL at T_1.[21] This non-neutrality contrasts with Garibaldi and Vi-

[20]Increases in EPL do affect termination decisions indirectly by increasing the cost to the firm of an exogenous termination event that occurs at rate δ: as EPL increases, the higher cost of exogenous separation may cause the firm to end the match endogenously to avoid incurring the higher cost in the future. However, this effect is quantitatively weak and is insufficient to identify the EPL slope from the data. We ultimately choose to normalize the slope to zero when estimating the flexible wage model.

[21]While this non-neutrality is technically a result of our assumed bargaining protocol, the fact that we observe time variation in the empirical job termination rate before T_1 suggests that it is a reasonable benchmark. Furthermore, we have experimented with wage schedules that include prepayments before T_1, but found that they did not generate realistic hazard rate patterns.

olante (2005), who show that flexible wages can completely neutralize EPL even if it only applies after the match has been active for some time. The difference is that the probability of becoming eligible for EPL is exogenous in their setting, whereas it is endogenous in ours, and hence can be manipulated by firms.

B. Calibrated Parameters

Table 2 summarizes the parameters that we calibrate. We set $T_1 = 3$ months to reflect the tenure at which EPL becomes active in Brazil, and set $t_{i+1} - t_i$ to 15 days for all $t_i, t_{i+1} \in \mathcal{T}$ to mimic our measurement of the empirical hazard rate. We set the annual discount rate to $r = 7.5\%$, which is in line with Brazilian interest rates. The weight on unemployment in the matching function, η, is set to 0.5, in line with Petrongolo and Pissarides (2001). The exogenous match termination rate δ determines the level to which the hazard rate converges as tenure increases and the learning process becomes less prevalent. Therefore, we set $\delta = 0.0117$ to match the empirical hazard rate at 24 months' tenure.[22] Following Shimer (2005), we normalize steady state market tightness to $\theta = 1$. Given this, the per-period job finding rate is equal to the matching efficiency parameter, $\lambda = z$, which we set to 0.079 target a steady state unemployment rate of 15%, consistent with recent Brazilian data.[23] The flow cost of posting a vacancy, $c = 1.493$, is pinned down endogenously by the free entry condition for vacancy posting (19).

In the model with rigid wages, we normalize $\mu^H = 1$ and $\mu^L = 0$ to set the location and scale of production (Moscarini, 2005). To make the model with flexible wages as comparable as possible, we exploit the fact that we can renormalize μ^H and μ^L so that the implied flow profit function is identical to the rigid wage case, except for the neutrality term $r\kappa(t) - \kappa'(t)$, thus isolating the key effect of flexible wage setting.[24] Finally, we need to set the rigid wage w, which determines the flow profits of the match. As a baseline, we set $w = 0.4$, which implies that workers receive about 50% of the expected output of the match when it forms (we estimate an initial belief that the match is high quality of about 0.8). We show below that the interaction of the free entry condition (19) with the size of match profits is important for determining the quantitative impact of EPL on unemployment. As such we also present sensitivity results for $w \in \{0.3, 0.5\}$. Given that the impact of EPL turns out to increase

[22] In Appendix Tables A1 - A3 and Figure A5, we show that our results do not change if we calibrate $\delta = 0.008$, which allows for the very slow decline in hazard rates from 24 to 48 months.

[23] In Appendix Tables A4 and A5 we show our results are robust to targeting a much higher unemployment rate of 40%, which would include employment in the informal sector.

[24] Formally, in our calibrated rigid wage model, $\pi^R(p,t) = p - w$. Under Nash bargaining, $\pi^F(p,t) = \bar{\mu}(p) - (\beta\bar{\mu}(p) + (1-\beta)b + \theta\beta c + r\kappa(t) - \kappa'(t))$. To obtain $\pi^F(p,t) = \pi^R(p,t) - (r\kappa(t) - \kappa'(t))$, choose some values for β and b, and set θ and c to their calibrated values in the rigid wage model. Then, normalize μ^H and μ^L in the flexible wage model to $\mu^L = b - (w - \beta c) / (1-\beta)$ and $\mu^H = \mu^L + 1/(1-\beta)$.

with w, we view our results as conservative.

C. Estimated Parameters

To estimate the vector of remaining parameters $\Xi = (p_0, \sigma, \kappa_1, \kappa_2)'$, we exploit their close connection to the model-implied hazard rates and use the simulated method of moments. Formally, let H be a vector of empirical hazard rates, and let $\mathcal{H}(\Xi)$ denote the vector of corresponding model-implied hazard rates. The estimated parameter vector satisfies

$$\hat{\Xi} = \arg\min_{\Xi}(\mathcal{H}(\Xi) - H)'(\mathcal{H}(\Xi) - H) \tag{23}$$

The vector of target hazards H contains the empirical hazard rates for all tenures from 0 to 24 months, except those at 5.5, 6, and 6.5 months, which are likely contaminated by measurement error due to "fake separations" (Van Doornik et al., 2018). To generate the model-implied hazard rates, we solve the continuous time model using finite-difference methods, and use a pattern search algorithm to minimize the objective (23). See Appendix B for further details.

C.1 Identification

Although we estimate the parameters in Ξ jointly, we argue that each parameter has a distinct effect on the hazard rate schedule, and is therefore identified by a different source of empirical variation. To see this graphically, Figure 4 plots the model-implied hazard rate schedules when we vary one parameter at a time in the rigid wage model. The underlying parameter variations and fixed values are chosen purely to illustrate the identification argument.

Consider first the initial prior p_0. As the top left panel of Figure 4 shows, changing p_0 mostly affects the hazard rates at early tenures. Intuitively, given the optimal termination thresholds chosen by firms at early tenures, the initial belief p_0 determines how far new matches are from the initial thresholds. All else equal, a higher value of p_0 will create a greater distance to the early tenure thresholds, and hence a smaller probability that a given match will reach them. Note that this results in slightly elevated hazard rates after EPL activates as more matches survive initially, but eventually hit the termination threshold. Therefore, we can use the initial empirical hazard rates to identify and estimate p_0.

Next, consider the effects of changing the EPL parameters κ_1 and κ_2, shown in the bottom two panels of Figure 4. In the bottom left panel, we set $\kappa_2 = 0$, and consider the effect of increasing the jump parameter κ_1. The plot shows that increasing κ_1 predominantly affects the size of the hazard rate spike at 3 months' tenure. Intuitively, a larger jump in EPL at 3 months creates a stronger incentive for firms to terminate matches just before EPL activates, and also reduces the rate of termination just after EPL activates as only higher belief matches survive termination at 3 months. As κ_1 rises, these effects are amplified and the spike is more pronounced. To understand the effects of varying the slope parameter κ_2, the bottom right panel plots the hazard rate schedules when we then fix κ_1 at its estimated value, and increase κ_2. There are two effects. First, similar to κ_1, increasing the slope parameter drives up the relative size of the hazard rate spike at 3 months. Intuitively, a higher slope increases the EPL cost faced by firms, who then terminate more workers at 3 months in anticipation. Second, and distinct from the jump effect, a steeper EPL profile lowers the relative level of hazard rates after 3 months compared to the spike. For example, the ratio of the hazard rate spike to the peak hazard after 3 months increases from 1.5 to 2.2 as κ_2 increases in Figure 4. Intuitively, when EPL increases more quickly with tenure after 3 months, firms lower their termination thresholds and terminate fewer matches, resulting in relatively lower hazard rates after 3 months' tenure. Therefore, we can use the hazard rate spike and the relative level of hazard rates after 3 months to identify the EPL parameters. We note that due to the neutrality result, we can only identify κ_1 in the flexible wage model. In that case, we set $\kappa_2 = 0$.

Finally, consider the top right panel of Figure 4, which plots the hazard rates for low and high values of the noise parameter σ, which determines the signal-to-noise ratio in (8), and hence governs the speed at which firms learn about true match productivity. The plot shows that increasing σ lowers the hazard rate schedule, particularly at early tenures before convergence to the exogenous separation rate δ occurs. Intuitively, a higher value of σ lowers the signal-to-noise ratio and hence the speed of learning (under our calibration, the signal-to-noise ratio is $1/\sigma$). Hence, firms need more time to learn about match quality before deciding whether to terminate the job, which results in lower hazard rates at all tenures. Therefore, we can identify σ from the overall level of the hazard rate schedule.

C.2 Parameter Estimates and Model Fit

The top panel of Table 3 reports the parameter estimates for both the rigid and flexible wage models, while Figure 5 plots the model-implied and empirical hazard rate functions.[25] Our parsimonious parameterization is able to successfully capture key quantitative features of the empirical hazard rate schedule, including the spike at 3 months' tenure. In the rigid wage model, the estimated initial belief $\hat{p}_0 = 0.816$ implies that a sufficiently long-lasting match will experience productivity growth of 25% as p increases to unity. The estimated jump value of EPL, $\hat{\kappa}_1 = 2.455$ implies that the real cost to the firm of firing a worker at 3 months is equivalent to a lump sum payment of approximately 3 months' wages. In addition,

[25]We omit bootstrapped standard errors, which are very small due to the size of our dataset.

the estimated slope parameter $\hat{\kappa}_2 = 0.365$ indicates that the cost of EPL increases by slightly less than the rigid wage in each period.[26] The estimated noise parameter $\hat{\sigma} = 1.314$ implies that steady state variance of match productivity is 0.105, which is in line with measures of residual productivity (wage) dispersion across jobs in Brazil (e.g. Engbom and Moser, 2018). Finally, we note that these parameter estimates are based on a full sample estimation, and so potentially mask heterogeneity across labor submarkets. We explore this in more detail in Section VI.

The estimated parameters are similar in the flexible wage model. The initial belief is essentially unchanged, while the noise parameter is slightly lower, indicating that firms learn about true productivity more quickly than in the rigid wage case. Intuitively, flexible wages allow firms to reduce wages when expected productivity falls so that expected flow profits and match value are less sensitive to changes in beliefs. As a result, the speed of learning must be higher in order for the model to reproduce the hazard rates in the data. Finally, the EPL jump parameter is about 1.5 times higher than the rigid wage model. Intuitively, since we set $\kappa_2 = 0$ due to the lack of identification under flexible wages, a larger jump component is required to generate the same size hazard rate spike.

The lower two panels of Table 3 report the estimated parameters when we calibrate the rigid wage w to 0.3 and 0.5, so that about 40% or 60% of the initial match surplus flows to the worker. As w increases, the flow profits from a match decrease at all beliefs, which changes the dynamics of firm value, and hence slightly alters the parameter estimates. For example, the estimated jump component of EPL declines while the slope component increases in the rigid wage model. Intuitively, when flow profits are smaller, there is a higher chance that the firm terminates the match when expected productivity declines. Hence only a small jump in EPL costs is required to generate a spike in terminations at 3 months, while a large slope component is necessary to prevent firms from firing more workers after EPL has activated.

VI. The Equilibrium Effects of EPL

We use our structural model to study how EPL affects the hazard rates of job termination, and equilibrium unemployment. We also discuss the role of tenure-dependence, and the sensitivity of our results to our calibrated parameters and auxiliary modeling assumptions. Finally, we study how the effects of EPL vary across jobs of different skill.

[26] Our identification strategy implies that κ_2 captures any channels that affect the job termination hazard after 3 months' tenure. Therefore, it is plausible that our estimate of κ_2 captures both increases in EPL and also higher costs of termination due to negative spillover effects in the production process when a worker with high tenure is terminated. In this case, our estimate of EPL overstates its slope component.

A. The Macroeconomic Effects of EPL

To study how EPL affects the economy, we set $\kappa_1 = \kappa_2 = 0$ and re-solve our structural model holding all other parameters fixed at their estimated or calibrated values. We then compare the hazard and unemployment rates in this counterfactual scenario to the estimated baseline model. Since comparing steady states ignores the transitional period during which the economy adjusts to the removal of EPL, we interpret our results as long run effects rather than immediate economic implications of removing EPL.

We begin with the hazard rate schedule. As shown in Figures 6a and 6b, the biggest effect of removing EPL on the pattern of endogenous job separations is the disappearance of the hazard rate spike at 3 months' tenure. Without the jump in EPL, firms face no incentive to terminate many matches just before tenure reaches the 3 month mark. In fact, the absence of EPL lowers the job termination hazard rate at early tenures as firms are more willing to wait and see how match quality evolves. Hence, an important effect of EPL is to increase the turnover of low tenure jobs, especially just before EPL activates at 3 months. This finding is consistent with international empirical evidence (e.g. Hijzen et al., 2017). In contrast, removing EPL actually increases the termination rate for jobs with longer tenures beyond 3 months.[27] Intuitively, when firms terminate fewer matches early on, the average quality of matches at higher tenures declines. As a result, firms eventually terminate more matches than they would have in the presence of EPL, especially since terminating longer tenure matches is now cheaper. Therefore, the counterfactual hazard rates show that a key effect of EPL is to cause a forward shift in the timing of job terminations.

Next, we turn to the response of the unemployment rate. As shown in the top panel of Table 4, we find that removing EPL from the economy causes the unemployment rate to fall from 15% to 9.2% in the rigid wage economy, but only to 13.7% in the flexible wage economy. The larger effect under rigid wages naturally follows from the additional impact of the EPL slope parameter, which raises the cost of EPL to firms, and hence amplifies the transmission mechanism to unemployment. Although the estimated jump component is somewhat larger in the flexible wage economy, the lack of further increases in EPL at longer tenures weakens its overall economic impact considerably.

To further understand the transmission mechanism from EPL to unemployment, we also report changes in the job finding rate λ, and the separation rate, which we define as the number s such that the steady state balanced flow equation $u = s/(s + \lambda)$ holds. Given the fixed exogenous termination rate δ, changes in s summarize the aggregate effects of endoge-

[27] Without EPL, the hazard rate function follows the standard hump shape (Farber, 1994). The faster speed of learning estimated under flexible wages implies that the peak of the counterfactual hazard rate occurs earlier than when wages are rigid.

nous changes in the hazard rate schedule. In both the rigid and flexible wage economies, the decline in unemployment is entirely driven by an increase in the job finding rate. There is virtually no change in the rate of job separations, in contrast to the standard comparative static of EPL on job separations (e.g. Garibaldi and Violante, 2005). Therefore, while EPL causes a compositional shift in the timing of job terminations, the increase in early terminations almost exactly offsets the decline in later terminations. As a result, imposing EPL has a negligible effect on the overall level of job terminations.

Finally, it is useful to note that comparing δ to the average level of s across the estimated and counterfactual economies implies that endogenous terminations account for about 15% of total terminations. This small share reflects the fact that because EPL activates so early in our setting, its effects dissipate at shorter tenures too as firms learn about the true quality of a given match. As a result, most terminations in steady state are the result of exogenous shocks rather than endogenous learning. To verify that this is not spuriously driving our results, we have checked that our results also hold when we calibrate $\delta = 0.008$, which captures the very slow decline in hazard rates between 24 and 48 months' tenure, and allows for endogenous terminations to last longer into the tenure profile (see Appendix Tables A1 - A3 and Figure A5). Hence, our results are not driven by how early we let exogenous terminations dominate the hazard rate. Instead, our estimated model yields a learning process that generates a realistic hazard rate schedule, and implies that endogenous job terminations play only a small role in the overall steady state rate of job separation.

A.1 Sensitivity to Match Surplus

The decline in unemployment caused by the removal of EPL is driven by a higher job finding rate that is the result of increased vacancy creation by firms. Intuitively, the absence of EPL increases the value of a match to firms, who then post more vacancies in equilibrium, as dictated by the free entry condition (19), $c = qJ^0(p_0, 0)$. As is now well understood, the size of this response depends crucially on the fundamental match surplus (Ljungqvist and Sargent, 2017), which is roughly captured by $p_0 - w$ in our setting. When the fundamental surplus is smaller, the removal of EPL has a larger effect on the overall profits of a match, and hence causes a larger increase in vacancy creation and a larger decline in equilibrium unemployment.

This mechanism is borne out in the lower two panels of Table 4, which report results from the EPL removal experiment when w is lower (0.3) or higher (0.5) than its baseline value. When w is lower, the fundamental surplus is larger so that EPL plays a less important role in determining a firm's match value. As a result, the resulting change in match value is smaller when we remove EPL, which dampens the vacancy creation response, leading to a smaller increase in the job finding rate and a correspondingly smaller decline in unemployment, which falls to 12.1% in the rigid wage economy, and 14.0% in the flexible wage economy. In contrast, when $w = 0.5$ and the fundamental surplus is smaller, the removal of EPL has an outsized positive impact on the value of a match to vacant firms, who increase their vacancy creation in response. As a result, the job finding rate more than doubles in the rigid wage economy, which sees unemployment decline to 7.1%. Under flexible wages, the response is considerably more muted, though unemployment falls to 13.5%. In all cases, the separation rate is essentially unchanged, again indicating that the general equilibrium effects of removing EPL transmit predominantly through the vacancy creation channel.

A.2 The Role of Tenure Dependence

In addition to analyzing the macroeconomic impact of removing EPL, we can also examine the effects of changing its activation tenure by varying T_1. Table 5 reports the macroeconomic impact when we remove tenure dependence completely ($T_1 = 0$), and when we quadruple the probationary period to 24 months ($T_1 = 24$), fixing the other EPL parameters at their estimated values. Across all model specifications, extending the probationary period lowers unemployment by increasing the job finding rate. Intuitively, delaying the onset of EPL lowers the potential cost to firms of hiring workers, and so encourages vacancy creation. Similar to the removal of EPL, this mechanism is stronger when wages are rigid, and when the fundamental surplus is smaller (w is higher). In all cases, the response of the aggregate separation rate to changes in T_1 is extremely weak, again highlighting the offsetting effects that changes in EPL has on the job termination hazard rate function.

B. Heterogeneity by Job Skill

We now apply our structural model to labor submarkets, segmented by skill. Using the same definitions as Section III, we consider low-skill, medium-skill, and high-skill job markets. For each skill level, we adopt the same calibration as before, estimate Ξ using the empirical hazard rate schedules, and then compute the counterfactual scenarios in which we remove EPL or change its tenure-dependence.[28]

Table 6 reports the estimated parameters for each skill level, where we again estimate both rigid and flexible wage specifications. While the estimates are certainly skill-dependent, the differences are intuitive. For example, the estimated initial prior is increasing in skill and naturally captures the idea that hiring into higher skill jobs likely uses better screening processes to ensure that matches are of higher average quality initially. Relatedly, the noise

[28]We adjust the calibration of δ to match the long run hazard rate within each skill level group. While we cannot target different unemployment rates by skill due to data limitations, doing so would likely not affect our results, as shown in Appendix Tables A4 and A5 for the aggregate economy.

parameter estimates are lowest in medium skill jobs, which reflects the notion that firms may learn about match quality more quickly in higher skill situations, but that match quality may also be harder to infer in the highest skill setting where work may be done in teams or production may be prone to more risk (e.g. investment banking). Finally, the cost of EPL is noticeably higher for high skill jobs, which reflects the fact that even though these jobs have high initial priors, there is a still a substantial spike in the hazard rate at 3 months' tenure (see Appendix Figure A4). The large costs of EPL required to generate this spike could reflect the non-monetary or unobservable components of EPL such as legal recourse upon firing, that seem particularly relevant in high skill jobs.[29]

Turning to the counterfactuals, Table 7 reports the changes in the unemployment, job finding, and job separation rates when we remove EPL from each labor market. Focusing on the rigid wage model, removing EPL has the largest effect in the high skill labor market which sees a 10.4 percentage point drop in the unemployment rate. This follows from the combination of large EPL costs and high initial prior, together which imply that the value of a job is significantly higher in the absence of EPL. Thus, removing EPL causes a large increase in vacancy creation and the job finding rate. Results in the flexible wage models are dampened for similar reasons to the aggregate case. Finally, the effects of tenure-dependence are reported in Table 8, and follow similar patterns, with the largest effects in the high skill labor market. Notably, across all skill levels and wages, removing EPL or changing its tenure dependence has virtually no effect on the job separation rate. Similar to the aggregate case, while EPL affects the timing of endogenous job terminations, it has no impact on the overall level.

VII. Conclusion

We make two contributions to the literature that studies the macroeconomic effects of EPL. First, we exploit tenure-dependence in the design of Brazilian EPL to obtain clean identification of its effect on firms' decisions to terminate jobs. Second, we estimate a structural model of a frictional labor market augmented to include tenure-dependent EPL in order to compute the counterfactual economic implications of removing EPL. We find that removing EPL lowers unemployment mainly through increased job creation, and has virtually no effect on the overall level of job terminations, even though it affects the timing. Tenure-dependence is a common feature of EPL across many countries. It would be interesting to apply our methods we have developed here to other settings, in order to further improve our

[29]It is also plausible that our estimates of EPL capture direct costs to firms of terminating high skill workers. For example, terminating an important managerial employee could have negative spillover effects on other workers in the production process. In this case, the effect of removing EPL is an upper bound on the true effect.

understanding of the macroeconomic impacts of EPL.

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Table 1: Descriptive Statistics for Estimation Sample, 2002-2007

	All Jobs	Short Duration Jobs
Panel A: Demographics	(1)	(2)
Age	31.535	30.405
High School Graduate	0.336	0.305
College Graduate	0.072	0.038
Male	0.658	0.693
Panel B: Job Characteristics		
Monthly Wage	819.212	670.909
Tenure	13.332	1.681
Hours	43.108	43.444
Panel C: Firm Characteristics		
Manufacturing	0.199	0.185
Agriculture	0.093	0.140
Public Administration	0.074	0.022
Health and Education	0.039	0.023
All Other Sectors	0.595	0.631
Unique Workers	29,438,306	13,312,346
Number of Jobs	92,023,307	24,427,409

Note: Column 1 reports descriptive statistics for jobs held by workers between age 18-65 from the years 2002-2007, excluding workers on temporary contracts. Column 2 reports descriptive statistics for jobs which last less than three months. Tenure is measured in months. Wages are denominated in Brazilian Real. The data is drawn from the *Relação Anual de Informações Sociais* (RAIS)

Table 2: Parameter Calibration

Parameter		Value	Source
T_1	EPL Activation Tenure	3 months	EPL Activation
$t_{i+1} - t_i$	Job Termination Frequency	15 days	Empirical Measurement
r	Discount Rate	7.5%	Annual Interest Rate
η	Matching Elasticity	0.5	Petrongolo and Pissarides (2001)
δ	Exogenous Termination Rate	0.0117	Long Run Hazard Rate
z	Matching Efficiency	0.079	Unemployment Rate = 15%
c	Vacancy Posting Cost	1.493	Free Entry Condition (19)
μ^L	Bad Match Productivity	0	Normalization
μ^H	Good Match Productivity	1	Normalization
w	Rigid Wage	0.4	Baseline Calibration

Calibrated parameters for the rigid wage model. The flexible wage model uses the same calibration because we can implicitly renormalize μ^H and μ^L so that their interaction with Nash bargaining parameters produces the same flow profit function. See footnote 24 for further details.

Table 3: Parameter Estimates

	Initial Belief p_0	Noise Parameter σ	EPL Jump κ_1	EPL Slope κ_2
Baseline Calibration: $w = 0.4$				
Rigid Wages	0.816	1.314	2.455	0.365
Flexible Wages	0.799	1.132	3.634	0.000
Low Calibration: $w = 0.3$				
Rigid Wages	0.800	1.172	3.298	0.182
Flexible Wages	0.803	1.050	3.401	0.000
High Calibration: $w = 0.5$				
Rigid Wages	0.840	1.379	1.741	0.431
Flexible Wages	0.798	1.204	3.401	0.000

Estimated parameters for rigid and flexible wage models across different calibrated values of the wage parameter w. Parameters are estimated jointly using the simulated methods of moments. We use the empirical hazard rates at 0 - 24 months as targets, except those at 5.5, 6, and 6.5 months, which we drop due to measurement error caused by "fake separations" (Van Doornik et al., 2018).

Table 4: No EPL Counterfactual

	Rigid Wages		Flexible Wages	
	EPL	No EPL	EPL	No EPL
Baseline Calibration: $w = 0.4$				
Unemployment Rate	0.150	0.092	0.150	0.137
Finding Rate	0.079	0.135	0.080	0.088
Separation Rate	0.014	0.014	0.014	0.014
Low Calibration: $w = 0.3$				
Unemployment Rate	0.150	0.121	0.150	0.140
Finding Rate	0.080	0.102	0.080	0.086
Separation Rate	0.014	0.014	0.014	0.014
High Calibration: $w = 0.5$				
Unemployment Rate	0.150	0.071	0.150	0.135
Finding Rate	0.079	0.176	0.080	0.090
Separation Rate	0.014	0.013	0.014	0.014

Equilibrium effects of removing EPL for rigid and flexible wage models across different calibrated values of w. The unemployment rate is the steady state unemployment rate, while the finding rate and separation rate are computed at a 15 day frequency. The separation rate is computed as $s = \lambda u/(1-u)$.

Table 5: Tenure Dependence Counterfactuals

	Rigid Wages			Flexible Wages		
	$T_1 = 0$	$T_1 = 3$	$T_1 = 24$	$T_1 = 0$	$T_1 = 3$	$T_1 = 24$
Baseline Calibration: $w = 0.4$						
Unemployment Rate	0.164	0.150	0.124	0.152	0.150	0.145
Finding Rate	0.071	0.079	0.098	0.079	0.080	0.083
Separation Rate	0.014	0.014	0.014	0.014	0.014	0.014
Low Calibration: $w = 0.3$						
Unemployment Rate	0.155	0.150	0.138	0.151	0.150	0.146
Finding Rate	0.076	0.080	0.087	0.078	0.080	0.082
Separation Rate	0.014	0.014	0.014	0.014	0.014	0.014
High Calibration: $w = 0.5$						
Unemployment Rate	0.177	0.150	0.110	0.152	0.150	0.144
Finding Rate	0.064	0.079	0.111	0.079	0.080	0.084
Separation Rate	0.014	0.014	0.014	0.014	0.014	0.014

Equilibrium effects of changing the tenure dependence of EPL for rigid and flexible wage models across different calibrated values of w. The unemployment rate is the steady state unemployment rate, while the finding rate and separation rate are computed at a 15 day frequency. The separation rate is computed as $s = \lambda u/(1-u)$.

Table 6: Parameter Estimates by Skill Level

	Initial Belief p_0	Noise Parameter σ	EPL Jump κ_1	EPL Slope κ_2
Low Skill				
Rigid Wages	0.719	1.518	2.104	0.332
Flexible Wages	0.686	1.317	3.245	0.000
Medium Skill				
Rigid Wages	0.768	1.381	1.910	0.282
Flexible Wages	0.758	1.193	2.924	0.000
High Skill				
Rigid Wages	0.919	1.683	3.229	0.761
Flexible Wages	0.855	1.398	9.564	0.000

Estimated parameters for rigid and flexible wage models across different job skill levels with $w = 0.4$. Parameters are estimated jointly using the simulated methods of moments. We use the empirical hazard rates at 0 - 24 months as targets, except those at 5.5, 6, and 6.5 months, which we drop due to measurement error caused by "fake separations" (Van Doornik et al., 2018).

Table 7: No EPL Counterfactual by Skill Level

	Rigid Wages		Flexible Wages	
	EPL	No EPL	EPL	No EPL
Low Skill				
Unemployment Rate	0.150	0.090	0.150	0.135
Finding Rate	0.095	0.163	0.096	0.108
Separation Rate	0.017	0.016	0.017	0.017
Medium Skill				
Unemployment Rate	0.150	0.103	0.150	0.139
Finding Rate	0.085	0.128	0.085	0.093
Separation Rate	0.015	0.015	0.015	0.015
High Skill				
Unemployment Rate	0.150	0.046	0.150	0.121
Finding Rate	0.062	0.221	0.064	0.082
Separation Rate	0.011	0.011	0.011	0.011

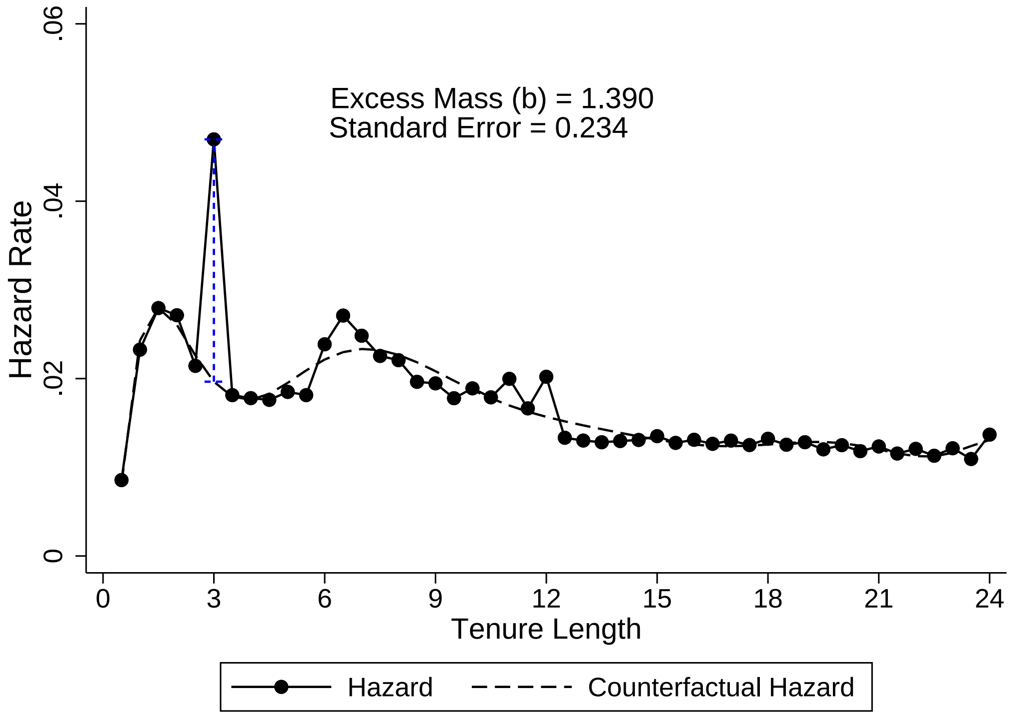
Equilibrium effects of removing EPL for rigid and flexible wage models across different job skill levels. The unemployment rate is the steady state unemployment rate, while the finding rate and separation rate are computed at a 15 day frequency. The separation rate is computed as $s = \lambda u/(1-u)$.

Table 8: Tenure Dependence Counterfactuals by Skill Level

	Rigid Wages			Flexible Wages		
	$T_1 = 0$	$T_1 = 3$	$T_1 = 12$	$T_1 = 0$	$T_1 = 3$	$T_1 = 12$
Low Skill						
Unemployment Rate	0.167	0.150	0.120	0.152	0.150	0.143
Finding Rate	0.083	0.095	0.119	0.094	0.096	0.101
Separation Rate	0.017	0.017	0.016	0.017	0.017	0.017
Medium Skill						
Unemployment Rate	0.160	0.150	0.129	0.151	0.150	0.145
Finding Rate	0.078	0.085	0.100	0.084	0.085	0.088
Separation Rate	0.015	0.015	0.015	0.015	0.015	0.015
High Skill						
Unemployment Rate	0.204	0.150	0.089	0.153	0.150	0.140
Finding Rate	0.042	0.062	0.110	0.062	0.064	0.070
Separation Rate	0.011	0.011	0.011	0.011	0.011	0.011

Equilibrium effects of changing the tenure dependence of EPL for rigid and flexible wage models across job skill levels. The unemployment rate is the steady state unemployment rate, while the finding rate and separation rate are computed at a 15 day frequency. The separation rate is computed as $s = \lambda u/(1-u)$.

Figure 1: Empirical Hazard Rates

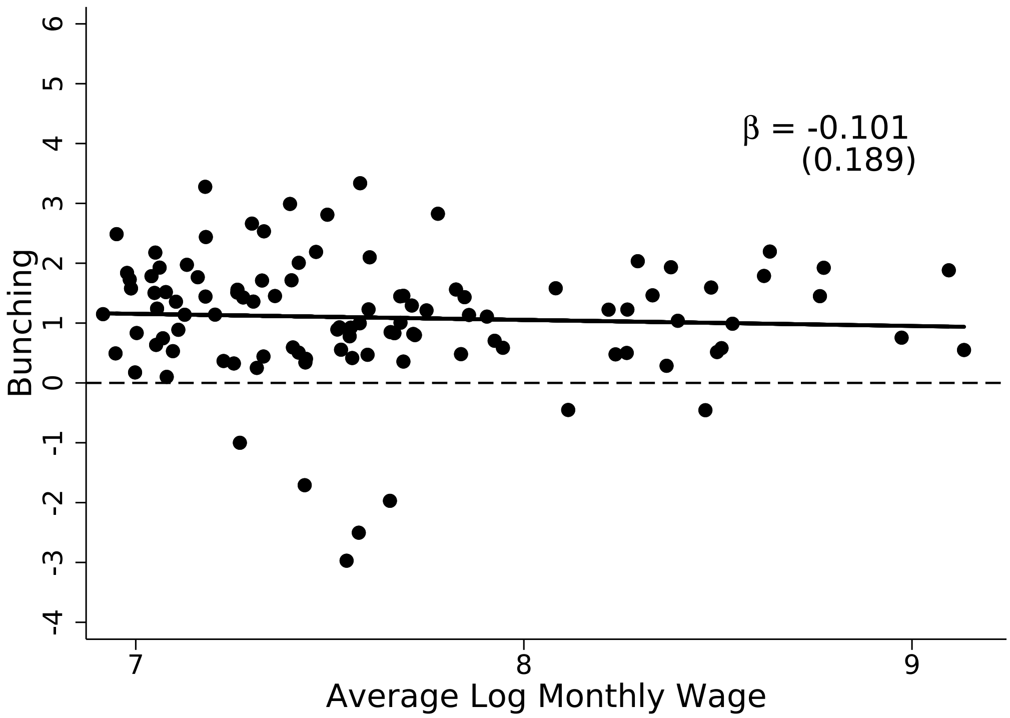


This figure plots the job termination hazard rate. Tenure duration is binned into 15 day intervals. The dashed curve is a tenth-degree polynomial fitted to the empirical hazard rate, excluding points 15 days away from the spike, as in Equation (1). The bunching statistic b and standard error are reported in the figure. The standard error is computed using a residual bootstrap procedure.

Figure 2: Bunching and Demand Volatility

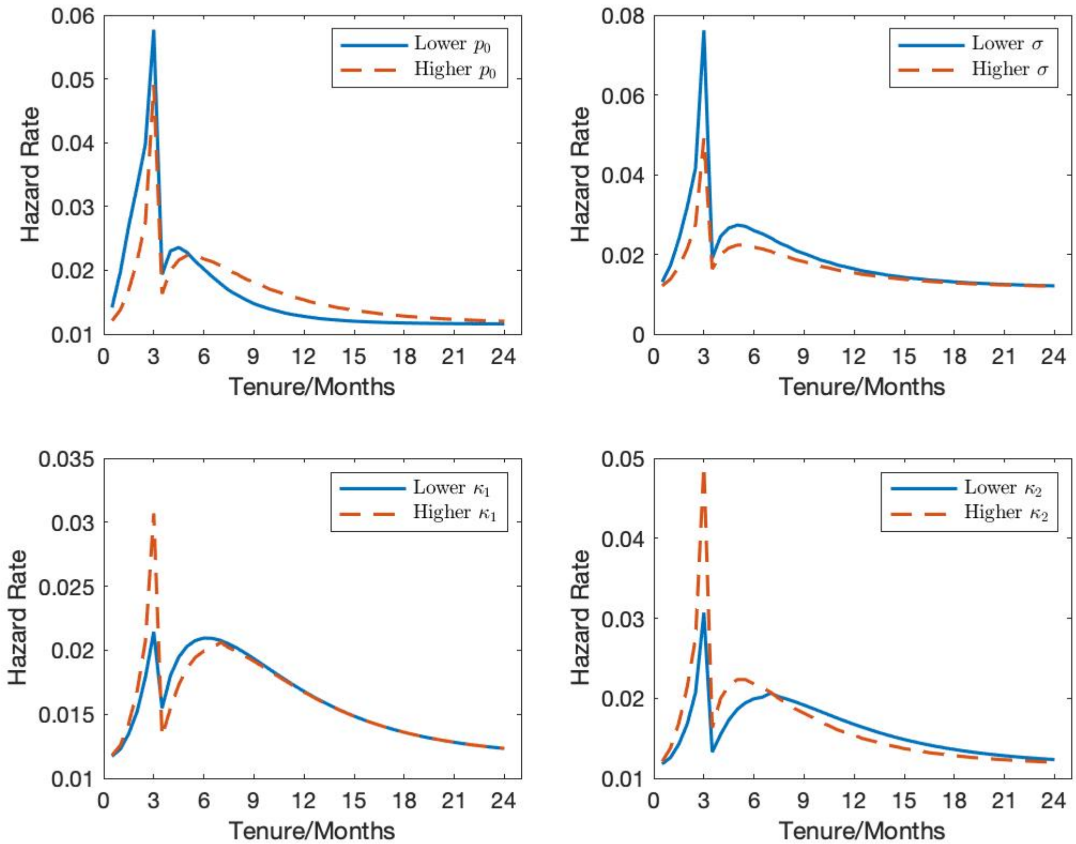
This figure plots the bunching estimate $\hat{b}$ by sector (defined by three-digit CNAE classification) and correlates the bunching to volatility in employment using the regression specified in Equation (5). The volatility is calculated as the standard deviation of month-to-month employment changes over the course of a year. The regression coefficient and its standard error are reported in the figure.

Figure 3: Bunching is Consistent Across Occupations and Uncorrelated with Wages



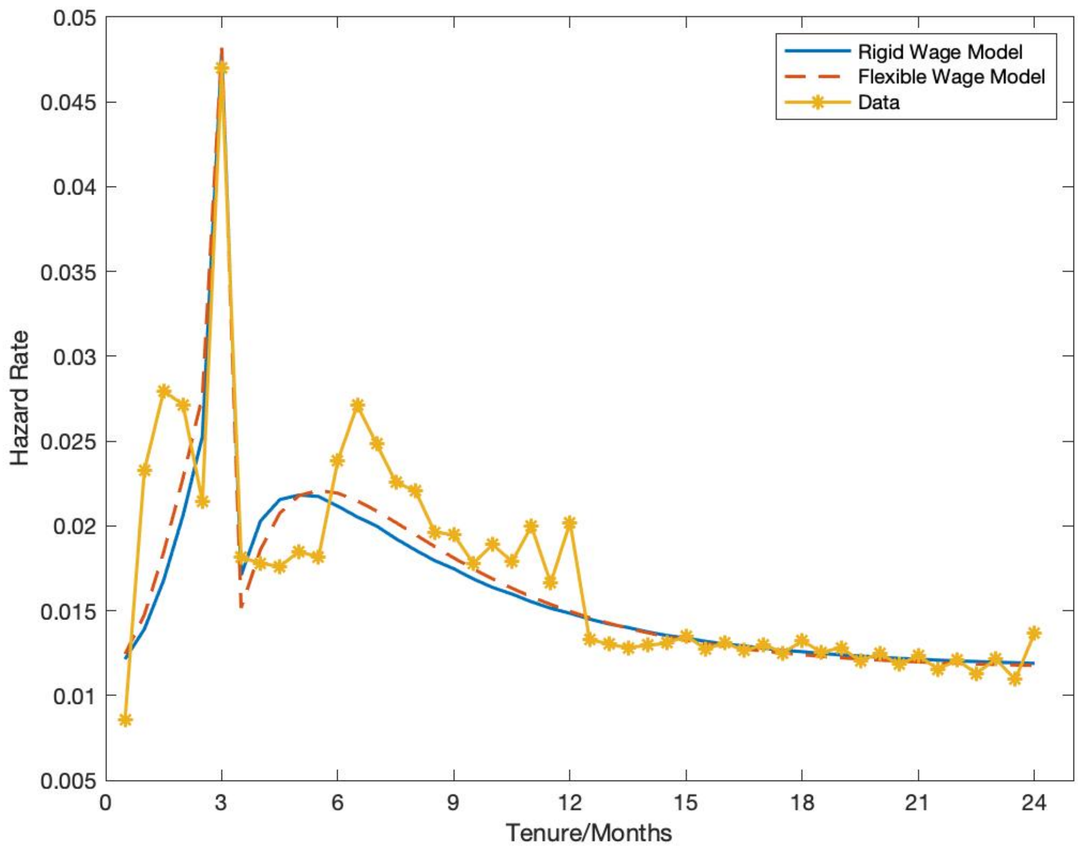
This figure plots the bunching estimate $\hat{b}$ by occupation (defined by three-digit ISCO identifier) and correlates the bunching to average log wages in each occupation using a simple linear regression. The regression coefficient and its standard error are reported in the figure.

Figure 4: Structural Model Identification



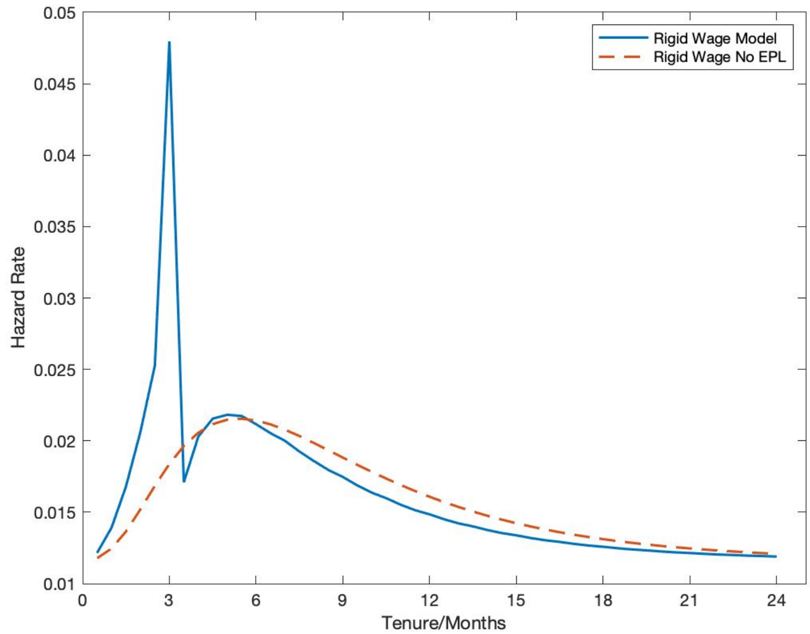
To demonstrate how each estimated parameter affects the hazard rate schedule, each panel plots the model-implied hazard rate schedule as we change one parameter, holding all others fixed. The parameter variations and fixed values are chosen purely to illustrate the identification argument.

Figure 5: Estimated and Empirical Hazard Rates

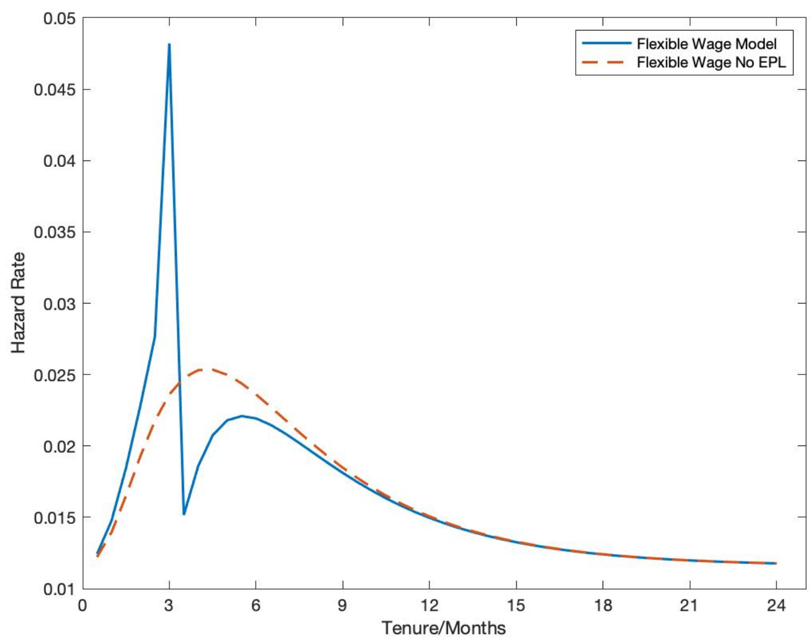


This figure plots the empirical hazard rate (asterisks) as well as the hazard rates from the estimated models with rigid (solid) and flexible (dashed) wages. Hazard rates are computed over 15 day bins in both the data and model. In the estimation, we use the empirical hazard rates at 0 - 24 months as targets, except those at 5.5, 6, and 6.5 months, which we drop due to measurement error caused by "fake separations" (Van Doornik et al., 2018).

Figure 6: Estimated and Counterfactual Hazard Rates



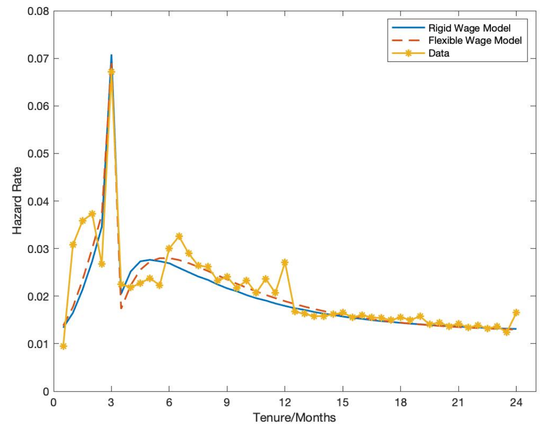
(a) Rigid Wage Model



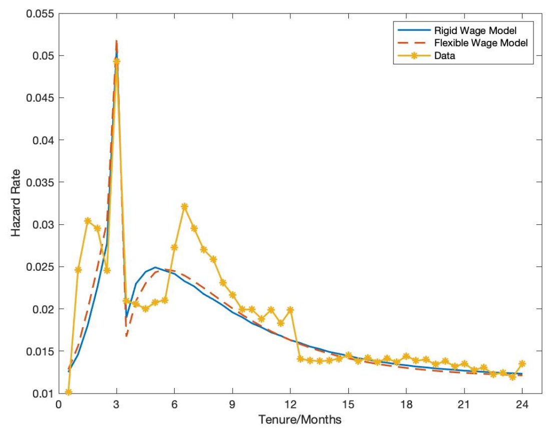
(b) Flexible Wage Model

This figure plots the hazard rates in the estimated flexible wage model (solid) and the counterfactual hazard rate (dashed) when we remove EPL by setting $\kappa_1 = \kappa_2 = 0$.

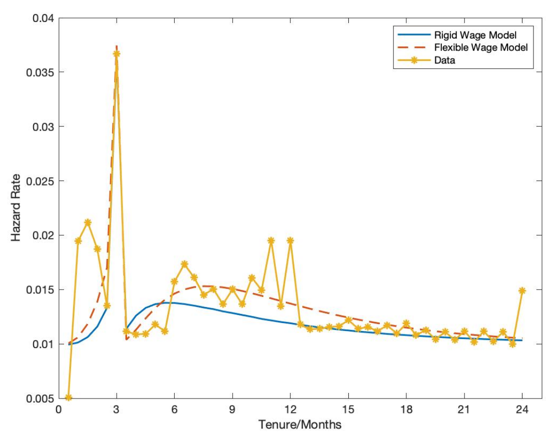
Figure 7: Estimated Hazard Rates by Skill



(a) Low Skill Jobs



(b) Medium Skill Jobs



(c) High Skill Jobs

This figure plots the hazard rates in the estimated rigid and flexible wage models across different skill levels.

Appendix: For Online Publication Only

Appendix A: Figures and Tables

Appendix Table A1: Parameter Estimates with $\delta = 0.008$

	Initial Belief p_0	Noise Parameter σ	EPL Jump κ_1	EPL Slope κ_2
Baseline Calibration: $w = 0.4$				
Rigid Wages	0.722	2.065	1.438	0.532
Flexible Wages	0.675	1.476	3.437	0.000
Low Calibration: $w = 0.3$				
Rigid Wages	0.686	1.953	1.660	0.532
Flexible Wages	0.670	1.410	3.480	0.000
High Calibration: $w = 0.5$				
Rigid Wages	0.714	2.152	1.416	0.376
Flexible Wages	0.672	1.607	3.125	0.000

Estimated parameters for rigid and flexible wage models when $\delta = 0.008$. Parameters are estimated jointly using the simulated methods of moments. We use the empirical hazard rates at 0 - 48 months as targets, except those at 5.5, 6, and 6.5 months, which we drop due to measurement error caused by "fake separations" (Van Doornik et al., 2018).

Appendix Table A2: No EPL Counterfactual with $\delta = 0.008$

	Rigid Wages		Flexible Wages	
	EPL	No EPL	EPL	No EPL
Baseline Calibration: $w = 0.4$				
Unemployment Rate	0.150	0.075	0.150	0.139
Finding Rate	0.063	0.127	0.064	0.070
Separation Rate	0.011	0.010	0.011	0.011
Low Calibration: $w = 0.3$				
Unemployment Rate	0.150	0.085	0.150	0.140
Finding Rate	0.064	0.115	0.064	0.069
Separation Rate	0.011	0.011	0.011	0.011
High Calibration: $w = 0.5$				
Unemployment Rate	0.150	0.082	0.150	0.137
Finding Rate	0.064	0.119	0.065	0.071
Separation Rate	0.011	0.011	0.011	0.011

Equilibrium effects of removing EPL for rigid and flexible wage models $\delta = 0.008$. The unemployment rate is the steady state unemployment rate, while the finding rate and separation rate are computed at a 15 day frequency. The separation rate is computed as $s = \lambda u/(1-u)$.

Appendix Table A3: Tenure Dependence Counterfactuals with $\delta = 0.008$

	Rigid Wages			Flexible Wages		
	$T_1 = 0$	$T_1 = 3$	$T_1 = 12$	$T_1 = 0$	$T_1 = 3$	$T_1 = 12$
Baseline Calibration: $w = 0.4$						
Unemployment Rate	0.170	0.150	0.114	0.151	0.150	0.145
Finding Rate	0.054	0.063	0.084	0.063	0.064	0.066
Separation Rate	0.011	0.011	0.011	0.011	0.011	0.011
Low Calibration: $w = 0.3$						
Unemployment Rate	0.166	0.150	0.120	0.151	0.150	0.146
Finding Rate	0.057	0.064	0.081	0.063	0.064	0.066
Separation Rate	0.011	0.011	0.011	0.011	0.011	0.011
High Calibration: $w = 0.5$						
Unemployment Rate	0.167	0.150	0.118	0.151	0.150	0.145
Finding Rate	0.056	0.064	0.082	0.064	0.065	0.067
Separation Rate	0.011	0.011	0.011	0.011	0.011	0.011

Equilibrium effects of changing the tenure dependence of EPL for rigid and flexible wage models $\delta = 0.008$. The unemployment rate is the steady state unemployment rate, while the finding rate and separation rate are computed at a 15 day frequency. The separation rate is computed as $s = \lambda u/(1-u)$.

Appendix Table A4: Parameter Estimates with $u = 0.4$

	Initial Belief p_0	Noise Parameter σ	EPL Jump κ_1	EPL Slope κ_2
Baseline Calibration: $w = 0.4$				
Rigid Wages	0.816	1.314	2.455	0.365
Flexible Wages	0.799	1.132	3.634	0.000
Low Calibration: $w = 0.3$				
Rigid Wages	0.800	1.172	3.298	0.182
Flexible Wages	0.803	1.050	3.401	0.000
High Calibration: $w = 0.5$				
Rigid Wages	0.840	1.379	1.741	0.431
Flexible Wages	0.798	1.204	3.401	0.000

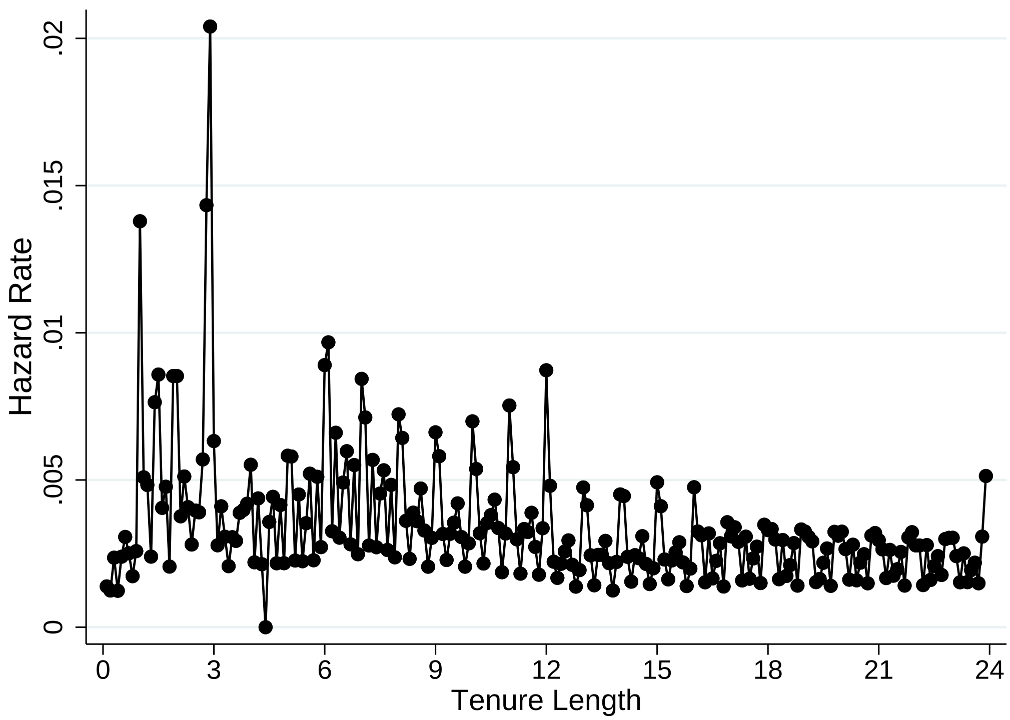
Estimated parameters for rigid and flexible wage models when $u = 0.4$. Parameters are estimated jointly using the simulated methods of moments. We use the empirical hazard rates at 0 - 48 months as targets, except those at 5.5, 6, and 6.5 months, which we drop due to measurement error caused by “fake separations” (Van Doornik et al., 2018).

Appendix Table A5: No EPL Counterfactual with $u = 0.4$

	Rigid Wages		Flexible Wages	
	EPL	No EPL	EPL	No EPL
Baseline Calibration: $w = 0.4$				
Unemployment Rate	0.400	0.277	0.400	0.375
Finding Rate	0.021	0.036	0.021	0.023
Separation Rate	0.014	0.014	0.014	0.014
Low Calibration: $w = 0.3$				
Unemployment Rate	0.400	0.341	0.400	0.380
Finding Rate	0.021	0.027	0.021	0.023
Separation Rate	0.014	0.014	0.014	0.014
High Calibration: $w = 0.5$				
Unemployment Rate	0.400	0.224	0.400	0.371
Finding Rate	0.021	0.047	0.021	0.024
Separation Rate	0.014	0.013	0.014	0.014

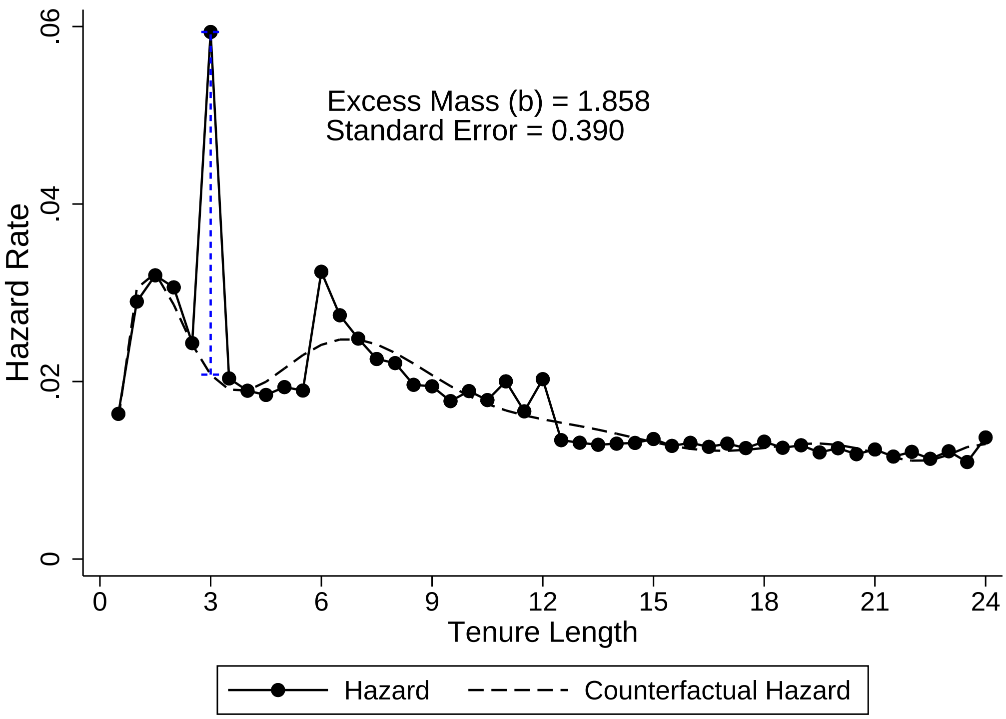
Equilibrium effects of removing EPL for rigid and flexible wage models $u = 0.4$. The unemployment rate is the steady state unemployment rate, while the finding rate and separation rate are computed at a 15 day frequency. The separation rate is computed as $s = \lambda u/(1-u)$.

Appendix Figure A1: Empirical Hazard Rates With Tenure reported as a Tenth of a Month



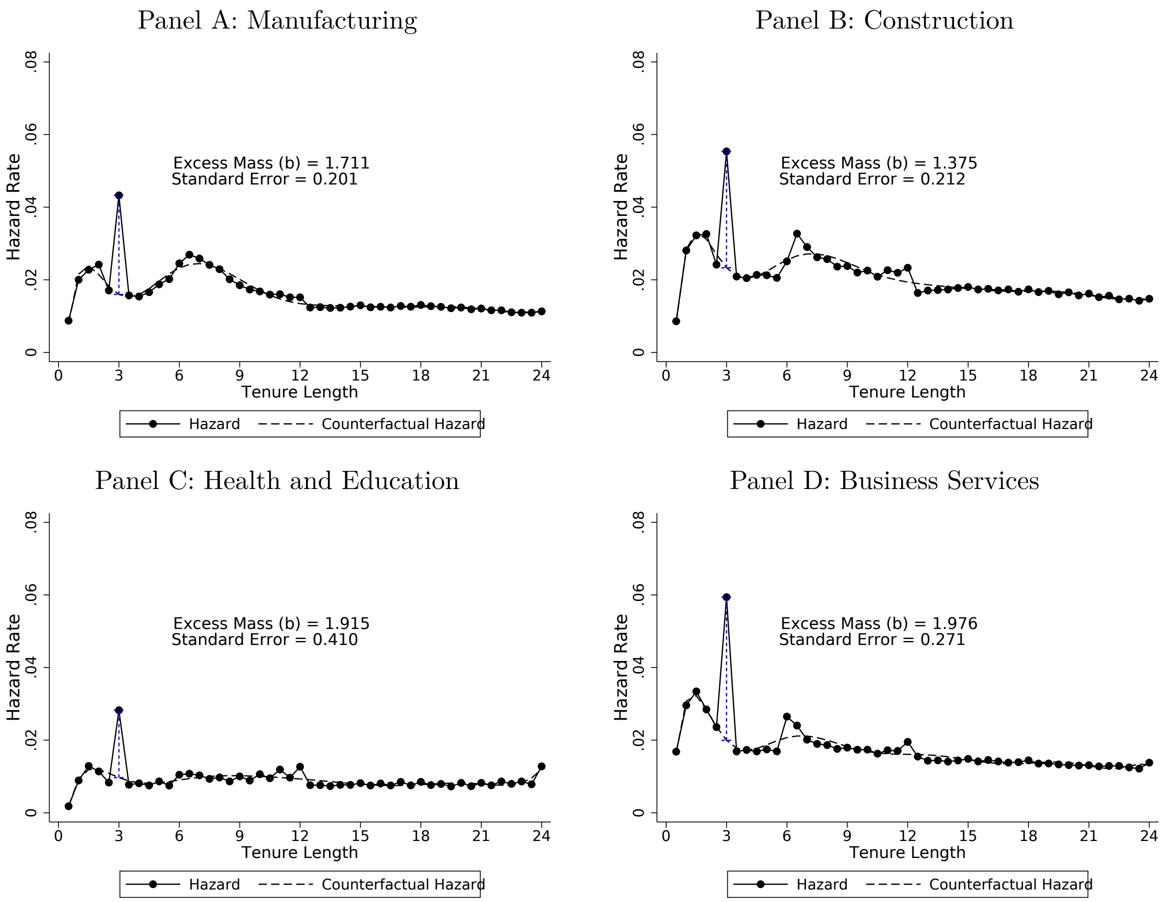
This figure plots the job termination hazard rate. Tenure duration is reported as tenths of a month (i.e., 1.1 months, 1.2 months, and so on). The dashed curve is a tenth-degree polynomial fitted to the empirical hazard rate, excluding points 15 days away from the spike, as in Equation (1). The vertical dotted line displays the excess mass B, while the normalized excess mass b and standard error are reported in the figure. The standard error is computed using a residual bootstrap procedure.

Appendix Figure A2: Bunching Including Temporary Contracts



Note: This figure plots the job termination hazard rate which includes temporary contracts. For details of the estimation see the notes to Figure 1.

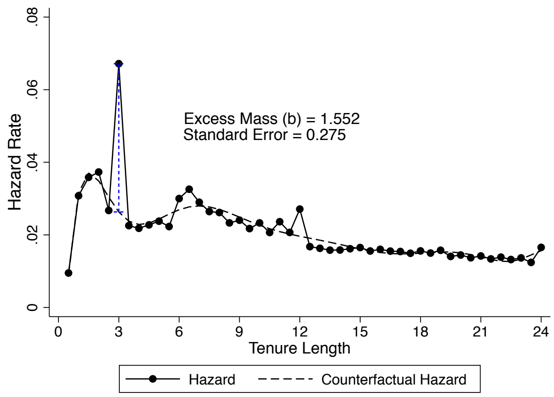
Appendix Figure A3: Heterogeneity in Bunching by Industry



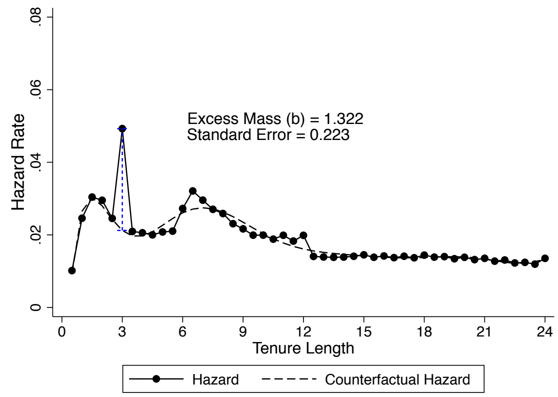
Note: This figure plots the layoff hazard rate by different industries. Tenure duration is binned into 15 day intervals. The dashed line is a tenth-degree polynomial fitted to the empirical hazard rate, excluding points 15 days away from the notch, as in Equation (1). The bunching statistic b and standard error are reported in the figure. The standard error is computed using a residual bootstrap procedure.

Appendix Figure A4: Heterogeneity in Bunching by Occupation and Skill

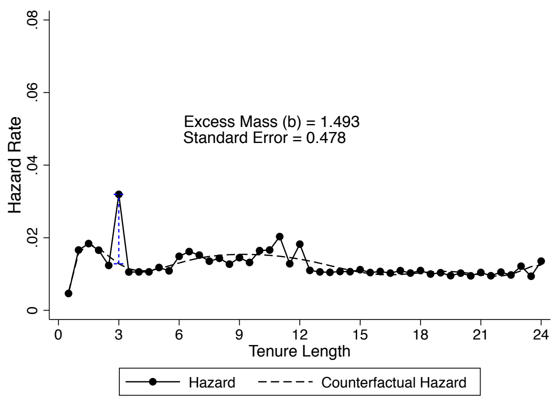
Panel A: Low-Skill



Panel B: Medium-Skill

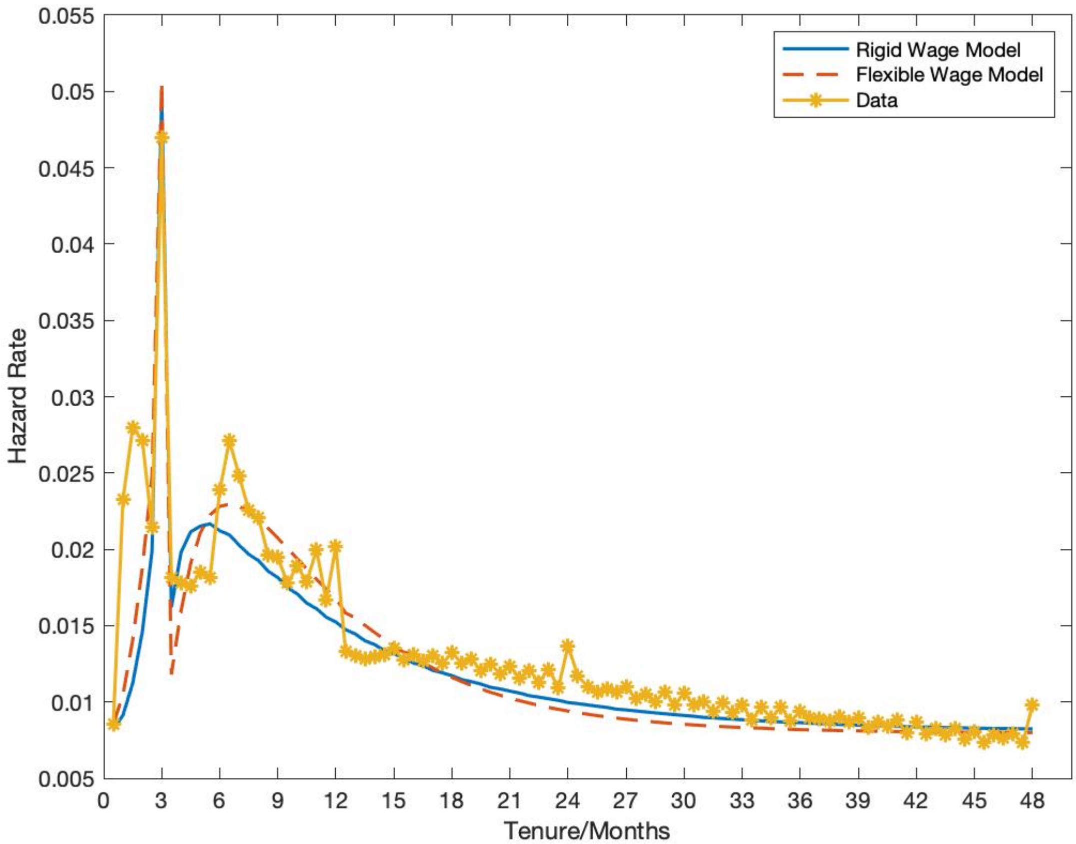


Panel C: High-Skill



Note: This figure plots the layoff hazard rate by different occupation skill levels. Skill level is defined by the International Standard Classification of Occupations (ISCO). Low skill occupations are characterized by the performance of simple and routine physical tasks, and includes occupations such as cleaners and construction laborers. Medium-skill jobs involve performing more complex tasks, such as operating machinery, and includes occupations such as office clerks and skilled craftsman. High-skill jobs require workers to perform complex tasks and requires significant practical knowledge, and is composed of technicians, managers and scientific professionals. Tenure duration is binned into 15 day intervals. The dashed line is a tenth-degree polynomial fitted to the empirical hazard rate, excluding points 15 days away from the notch, as in Equation (1). The bunching statistic b and standard error are reported in the figure. The standard error is computed using a residual bootstrap procedure.

Appendix Figure A5: Estimated and Empirical Hazard Rates with $\delta = 0.008$



This figure plots the empirical hazard rate (asterisks) as well as the hazard rates from the estimated models with rigid (solid) and flexible (dashed) wages when $\delta = 0.008$. Hazard rates are computed over 15 day bins in both the data and model. In the estimation, we use the empirical hazard rates at 0 - 48 months as targets, except those at 5.5, 6, and 6.5 months, which we drop due to measurement error caused by "fake separations" (Van Doornik et al., 2018).

Appendix B: Further Model Details

We explain how to solve and estimate the model numerically, and derive the expression for flexible wages under Nash bargaining.

A. Numerical Implementation

Solving the model can be broken into two steps: first solve for the equilibrium firm value functions and belief thresholds, and then solve for the equilibrium unemployment rate.

A.1 Solving for J^i and $\underline{p}(t_i)$

We solve the firm value function by backward induction. In order to initialize this method, we first need a stationary value function that can be solved for without a terminal boundary condition. To this end, we impose that $\mathcal{T}$ is finite with final element $t_{I+1} = T_2$. In practice, we set $T_2 = 4$ years so that it does not affect the hazard rates of interest. At tenure T_2, EPL stops increasing and remains fixed at $\kappa(T_2)$ for all $t \geq T_2$. Furthermore, we assume that firms can continuously fire workers at tenures $t \geq T_2$. Under these assumptions, the value function for matches at any tenure greater than T_2 is stationary and satisfies the differential equation and boundary conditions

$$(r + \delta)J(p) = \pi(p) + \Sigma(p)J_{pp}(p) - \delta\kappa(T_2) \tag{24}$$

$$J(\underline{p}) = -\kappa(T_2) \tag{25}$$

$$J_p(\underline{p}) = 0 \tag{26}$$

Here, $\underline{p}$ is the constant termination threshold that applies to matches of tenure $t \geq T_2$. In addition to the standard boundary condition (25), the threshold also satisfies the "smooth pasting" condition (26), which states that, when firms can continuously terminate matches, there must be no incentive to "wait-and-see" if the value improves when the belief reaches the threshold. Hence the slope of J must be zero at the threshold. Given the value function J, we can use it to construct the final boundary condition $J^I(p, t_{I+1}) = \max\{J(p), -\kappa(T_2)\}$.

To numerically solve for the firm value functions, fix an interval of termination tenures $[t_i, t_{i+1}]$. Imposing free entry into vacancy creation so that $V = 0$, the firm's value function J^i satisfies

$$(r + \delta)J^i(p, t) = \pi(p, t) + J^i_t(p, t) + \Sigma(p)J^i_{pp}(p, t) - \delta\kappa(t) \tag{27}$$

To solve this equation numerically, let $\mathcal{P} = \{0, p_1, ..., p_j, ..., p_{J-1}, 1\}$ denote an evenly spaced discretized domain of beliefs with step size $\Delta_p = p_j - p_{j-1}$, and let $J^i_{j,t} = J^i(p_j, t)$ and $\pi_{j,t} = \pi(p_j, t)$ denote the value function and flow profits evaluated at $p_j \in \mathcal{P}$ at tenure t. Using numerical derivatives to replace J^i_t and J^i_{pp}, (27) becomes

$$(r+\delta)J^i_{j,t} = \pi_{j,t} + (J^i_{j,t+\Delta_t} - J^i_{j,t})/\Delta_t + \Sigma(p_j)(J^i_{j+1,t} - 2J^i_{j,t} + J^i_{j-1,t})/\Delta_p^2 - \delta\kappa(t) \tag{28}$$

where Δ_t is the tenure step. Stacking over j yields a linear vector equation

$$BJ^i_t = \pi_t + J^i_{t+\Delta_t} - \delta\kappa(t) \tag{29}$$

where B is a $J \times J$ tridiagonal sparse matrix. Given the vector of values at the tenure one step ahead, $J^i_{t+\Delta_t}$, (29) can be solved by inverting the matrix B. In practice, we set $\Delta_t = t_{i+1} - t_i$, so that given $J^i_{t_{i+1}}$, $J^i_{t_i} = B^{-1}(\pi_t + J^i_{t_{i+1}} - \delta\kappa(t_i))$. The termination threshold $\underline{p}(t_i) = p_{j^*}$ where j^* satisfies $j^* = \min\{j : J^i_{j,t_i} \geq -\kappa(t_i)\}$.

Finally, we solve for the stationary value function J using the same finite-difference approximation, and by exploiting the fact that the optimal stopping problem characterizing the threshold can be solved as a linear complementarity problem (Huang and Pang, 2003).

A.2 Solving for f^i and u

Given the optimal belief thresholds, we use similar finite-difference approximations to solve the KFE forward in time, using the appropriate boundary conditions. Using these distributions to compute an implied unemployment rate then yields a simple iterative scheme to find the equilibrium unemployment rate.

B. Derivation of Wages under Nash Bargaining

To derive wages under Nash bargaining we introduce some additional notation. Let $W(p, t)$ and U denote the values of employment and unemployment to a worker,

$$rW(p,t) = w(p,t) + W_t(p,t) + \Sigma(p)W_{pp}(p,t) + \delta(U + \kappa(t) - W(p,t)) \tag{30}$$

$$rU = b + \lambda(W(p_0, 0) - U) \tag{31}$$

The interpretation of W is similar to the firm's value J, where we note that upon separation, the worker receives the value of EPL $\kappa(t)$. The value of unemployment depends on the worker's outside option b and the finding rate λ.

Given the worker's bargaining power $\beta \in (0,1)$, the wage under Nash bargaining solves

$$\max(J(p,t)+\kappa(t))^{1-\beta}(W(p,t)-U-\kappa(t))^{\beta} \tag{32}$$

The FOC is

$$\beta(J(p,t)+\kappa(t)) = (1-\beta)(W(p,t)-U-\kappa(t)) \tag{33}$$

Since (33) must hold for all (p,t), we can differentiate it to obtain

$$\beta J_t(p,t) = (1-\beta)(W_t(p,t)-\kappa'(t)) - \beta\kappa'(t) \tag{34}$$

$$\beta J_{pp}(p,t) = (1-\beta)W_{pp}(p,t) \tag{35}$$

Furthermore, evaluating (33) at $(p_0,0)$ and using the free entry condition yields

$$\beta c/q = (1-\beta)(W(p_0,0)-U) \tag{36}$$

Substituting these expressions and the equations for $J(p,t)$ and $W(p,t)$ into (33) yields

$$w^F(p,t) = \beta\bar{\mu}(p) + (1-\beta)b + \theta\beta c + r\kappa(t) - \kappa'(t) \tag{37}$$

Appendix C: Data Appendix

A. Overview

The *Relação Anual de Informações Sociais* (RAIS) is an employer-employee matched dataset which includes information on all workers and firms in the formal sector of Brazil. The main use of the RAIS is to compute federal wage-supplements (*Abono Salarial*). While not reporting can in theory result in fines, these fines are rarely issued in practice. However, workers and firms are incentivized to provide accurate wage information given the federal public wage-supplement is based on the wage reported in the RAIS.

B. Sample Selection

In the RAIS, workers are identified by an individual-specific PIS (Programa de Integração Social), a unique time-invariant worker identifier similar to a social security number. We follow Menezes-Filho and Muendler (2011) and drop workers with PIS identifiers less than 11 digits, as these are not valid identifiers. Errors in worker identifiers may be caused by (1) bad compliance and bookkeeping errors or (2) to allow workers to withdraw from their severance account through fake layoffs and rehires. We eliminate jobs for workers which begin on the same day for the same employer. A single employer may report multiple accounts for one worker so that the workers may access their employer-funded severance payment account, which by law should only be accessed in the case of a firing or for health-related reasons. However, individuals must work at an employer for more than six months in order to access the FGTS account. Therefore, the spike in the job termination hazard cannot be due to employers reporting multiple jobs for the same worker.

C. Variable Definitions

PIS: A PIS is a worker identifier that is unique to a given worker over time.

Occupation: Occupations are defined by the Classificação Brasileira de Ocupações (CBO) into 2355 distinct groups. We map these occupations to International Standard Classification of Occupations (ISCO) for comparability. Additionally, ISCO classifies occupations by skill level, where occupations that require more training or credentials, and require more specialized work have higher skill levels.

Industry: Industries are reported under the *CNAE* four-digit classification (*Classificação Nacional de Atividade Econômica*) for 654 industries.

Wage: Wage refers to total payments, including regular salary payments, holiday bonuses, performance-based and commission bonuses, tips, and profit sharing agreements, divided by total months worked during the year for that employer. Payments that are not considered part of the wage include severance payments for layoffs and indemnity pay for maternal leave.

Tenure: The duration the worker has been employed at the establishment. We recode the tenure duration so that it increases in increments of two weeks.

D. Additional Institutional Details

In Brazil, every firm must deposit 8 percent (increased to 8.5 peprcent in 2001) of a worker's monthly earnings in a *Fundo de Garantia por Tempo de Serviço* (FGTS account). The worker may only access this account in the event they are fired without cause and therefore cannot access these accounts if they quit a job voluntarily.

The FGTS account is important in determining the firing costs in Brazil, as the firing costs are a direct function of the amount that has accrued in the FGTS account during the worker's employment. Before September 2001, the firm was required to pay 40 percent of the total amount accrued in the FGTS account during the employment spell to the worker. Therefore, prior to 2001, the pure monetary firing cost FC is given by:

$$FC = \bar{w} \cdot T \cdot 0.08 \cdot 0.40 \tag{38}$$

Where $\bar{w}$ is the average monthly wage at the job, T is the total number of months at the job, 0.08 is the fraction of the wage that goes into the FGTS account and 0.40 is the fraction of the total accumulated FGTS account that gets transferred to the worker in the form of severance. After September 2001, there is an additional component that is a pure tax. The FC after 2001 is given by:

$$FC = \underbrace{\bar{w} \cdot T \cdot 0.08 \cdot 0.40}_{\text{Transfer Component}} + \underbrace{\bar{w} \cdot T \cdot 0.08 \cdot 0.10}_{\text{Tax Component}} \tag{39}$$