Employment Protection Legislation and the Macroeconomy: Evidence from Brazil*

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Abstract

This paper exploits tenure-dependence in the design of employment protection legislation (EPL) to identify its equilibrium impacts. In our setting, Brazil, EPL applies after a three-month probationary period, incentivizing firms to terminate jobs at exactly 3 months. We develop a structural model in which firms learn about match quality to map this effect on job termination to equilibrium macroeconomic outcomes. We find that EPL without a probationary period leads to a 2.4 percent increase in unemployment and 3.3 percent decrease in output. However, introducing a probationary period completely negates these effects by effectively increasing the value of an initial match.

Keywords: Employment Protection, Efficiency, Job Separation Hazard
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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, increased hiring costs could lead to higher unemployment and lower aggregate output. Throughout the late 1990s, a number of European countries relaxed EPL laws, believing increased flexibility would improve labor-market outcomes (OECD, 2000). However, EPL also raises the cost to fire workers, and could therefore lead to increases in aggregate employment.

Despite a large body of research, the 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 employment. However, this approach can only identify *partial* effects of EPL, for example, differences in employment levels between firms that face high vs. low firing costs. This analysis therefore cannot in general capture the aggregate effect of interest. Additionally, 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 certain components of EPL. In our setting, Brazil, EPL 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.

In this paper, we combine quasi-experimental evidence with a structural search model of the labor market to identify the aggregate effect of EPL on unemployment and output. We depart from the prior literature that uses structural search models to study employment protection legislation in two important ways. First, our model includes a probationary period, a feature common to most employment protection designs. For example, in our setting, Brazil, EPL only applies after a job lasts 3 months. Second, we exploit this tenure-dependence of EPL to cleanly identify its effect on the hazard rate of job termination, which we then use to estimate the structural model. 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.

In the first paper of the paper we argue that this spike in job termination arises because firms are uncertain about worker productivity and prefer to end matches at 3 months if the expected productivity is too low. To bolster this argument, we rule out a number of alternative explanations for the observed spike in the 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 bunching occurs consistently across occupations, including high-wage occupations, implying the bulk of this spike is likely not driven by firms rotating through low-skill workers to avoid paying firing costs. Given these results, we interpret the spike in the job termination hazard as firms firing permanent workers with low expected productivity.

In the second part of the paper, we develop a structural model of the labor market to map the effect of EPL on the job termination hazard to the general equilibrium outcomes of interest. Guided by the empirical results, we add EPL to the model of Moscarini (2005), which combines endogenous job destruction through learning about match productivity with a frictional labor market à la Diamond-Mortensen-Pissarides. We model EPL as a fixed cost that firms must pay if they terminate a worker with at least 3 months' tenure. Including a probationary period directly into the model is important for two reasons. First, it allows us to identify the equivalent real cost to firms of the wide variety of EPL regulation that firms face in reality through the effect on the job termination hazard. Second, our goal is to understand the efficiency effects of EPL, which we find depends crucially on the existence of a probationary period.

In the third part of the paper, we estimate the model by simulated methods of moments and consider the efficiency of different EPL designs. Intuitively, the spike in the empirical job termination hazard is used to infer the size of the fixed cost parameter that firms must pay due to EPL. This allows us to infer the 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, Lelarge and Van Reenen (2016), and ensures that the estimated model parameter captures the equivalent real cost that EPL imposes on firms. In addition, variation in the empirical hazard rate at early tenures allows us to identify and estimate model parameters governing the initial productivity of matches and the variance of the idiosyncratic shocks to a worker's production.

Turning to counterfactuals, we first situate ourselves in the broader literature and compare an economy without any EPL to an economy with fixed EPL that applies to all jobs, therefore ignoring the probationary period that exists in most contexts, but is often abstracted away from in models of EPL. In this case, we find that the reduction in hiring dominates any reductions in firings due to the policy, leading to increased unemployment, which we interpret as either true unemployment or reallocation to the informal sector. This reallocation of workers leads to a 3.3% drop in aggregate output.

While the effect of EPL on unemployment is ambiguous in theory (Ljungqvist, 2002), we find that quantitatively EPL increases unemployment when applied uniformly over time. This result stems from the fact that firms and workers learn about match quality over time in our model, which we view as capturing an important feature of long term labor market relationships. Given this learning, the majority of employed workers are in high quality matches that are unlikely to be terminated endogenously. As a result, the imposition of EPL only affects a small fraction of matches, resulting in a small increase in the job separation rate, whose effect on unemployment is dominated by the decline in vacancy creation.

Next, we reintroduce the probationary period and find that the negative effects of EPL are entirely negated. Relative to an economy with no EPL, tenure-dependent EPL actually raises aggregate output by 0.06 percent. Intuitively, allowing firms to learn about match quality before committing to a long-term employment contract for which EPL applies increases the value of a new job to the firm. This increase in value leads to more vacancies and therefore lower unemployment in equilibrium. Therefore, incorporating probationary periods into the model not only makes it more reflective of reality, but also has important efficiency and policy implications.

In order to further highlight the role that tenure-dependence plays in the effects of EPL, we study how the revenue generated by EPL depends on the length of probationary period. An increase in the probationary period length has two effects on the revenue generated by endogenous match terminations. First, a longer probationary period mechanically lowers revenue since fewer employment matches are required to pay EPL upon termination. Second, a longer probationary period actually raises aggregate employment, as shown in our quantitative analysis. All else equal, this increases the number of endogenous separations and hence the revenue generated by EPL. Quantitatively, we find that the revenue peaks when EPL applies to employment matches with tenure greater than 2 weeks. Through the lens of the model, this result implies that the gains from higher employment are dominated by the reduction in eligible matches that must pay the EPL fee upon termination when the probationary period extends beyond half a month.[1]

We confirm that our results do not depend on exactly how we calibrate unidentified model parameters. First, we show that the quantitative magnitudes are robust to changing the elasticity of matches to unemployment (holding the bargaining weight at its estimated value), and thus changing the quantitative violation of the Hosios (1990) condition. Hence our quantitative statement about efficiency losses is not simply a function of "correctly" calibrated parameters. Second, we show that the results are robust even when EPL is rebated back to newly terminated workers as a transfer. Intuitively, our results hinge on how the size and timing of EPL affect firm termination decisions. These decisions do not take into account where the costs of EPL go once the firm has paid them. Therefore, our

[1] Of course, in reality the policy may achieve other goals such as insurance and redistribution that we are silent on here. We leave the analysis of this interesting policy feature to future research.

results are robust to the fraction of EPL costs that are a transfer to newly unemployed workers. Finally, we show that introducing a minimum wage does not affect the equilibrium impact of EPL. In our estimated model, 3% of employed workers earn the minimum wage during the sample period. This fraction is line with our data as well as the evidence presented by Engbom and Moser (2018). In our setting, we find that the interaction between EPL and minimum wage policy is quantitatively insignificant.

Related Literature Our paper relates to two distinct literatures. First, our clean identification of the impact of EPL on firms' job termination decisions contributes to an extensive literature that explores the impact of EPL on macroeconomic outcomes (Lazear, 1990; Botero et al., 2004; Di Tella and MacCulloch, 2005; Garibaldi and Violante, 2005; Autor et al., 2007; Kugler and Pica, 2008; Daruich et al., 2017). These papers generally rely on two identification strategies. The first uses cross-country variation in EPL to estimate its impact, which may be confounded by omitted variables. The second uses within-country variation between-firm variation, for example, by exploiting EPL reforms or size-contingent laws to estimate similar causal effects.

Relative to these methods, we exploit tenure-dependence in the design of EPL in Brazil to identify its effect on job termination decisions. The identification strategy is similar to the public finance literature which utilizes discrete kinks or notches in budget constraints to estimate structural parameters (Saez, 2010; Chetty, 2012; Kleven, 2016). Furthermore, by estimating the behavioral response of firms at the microeconomic level, our estimation strategy relies on weaker assumptions than papers estimating the aggregate effect of EPL on macroeconomic outcomes. Instead, we build and estimate a structural model that makes this mapping explicit.

Our structural estimation exercise relates to the literature that studies the effects of EPL on macroeconomic outcomes through the lens of a search model (Ljungqvist, 2002; Garibaldi and Violante, 2005; Pries and Rogerson, 2005; Pinto, 2015). In these papers, EPL is modeled as a fixed cost that applies to jobs of all tenures, thus missing the tenure-dependence that is a key feature of many labor markets, including Brazil's (Cahuc et al., 2016). Our contribution, therefore, is to capture the tenure-dependence of EPL within a structural model, and to use our rich data to estimate key model parameters rather than relying solely on calibration.

In contemporaneous work, Cahuc et al. (2019) use similar structural methods to study the effects of EPL on French labor market outcomes.[2] In addition to focusing on a markedly different labor market, our work and results differ in a number of meaningful, but comple-

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

mentary ways. First, we offer a micro-foundation for stochastic productivity by embedding EPL into the learning model of Moscarini (2005). In contrast, Cahuc et al. (2019) assume that productivity follows an exogenous geometric brownian motion, and calibrate the drift of the process exogenously. We use the richness of the Brazilian matched employer-employee to provide evidence that learning about productivity is a key driver of job separations in our setting. Second, our model naturally features a stationary equilibrium, linking hazard rates to macroeconomic outcomes such as unemployment and GDP. We exploit this fact to study how the presence of EPL and its tenure-dependence affect the macroeconomy as a whole. This focus complements Cahuc et al. (2019), who focus instead on how EPL affects workers differently depending on their status as protected or non-protected.

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 VIII concludes.

II. Institutional Setting and Data

A. EPL in Brazil

In Brazil, EPL is composed of many components. 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 separation.[3] 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.

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 identification strategy in Section III. 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. A trial period for workers is common in many countries, though restrictions and durations vary across countries (OECD, 2008).

[3] In the event that a worker is given advance notice of a termination, the worker must be allotted time to search for a new job.

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 a 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 (i.e. it is much more likely to observe a 30 days job spell than a 29 day job spell). The data include additional information about the job, such as occupation, wage, 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, ethnicity, and occupation. 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.[4] Given the focus of our paper is on the effects of EPL on permanent employment contracts, we therefore eliminate temporary contracts from the majority of our empirical and theoretical analysis.[5]

In addition to eliminating temporary contracts, we restrict attention to workers aged 18-65, 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. Short-duration workers are slightly younger (30.4 vs. 31.5), less likely to be a college graduate (3.8 percent vs. 7.2 percent), are paid lower monthly wages (670.90 Real vs 819.21 Real), and are less likely to be in public administration

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

[5]Importantly for our study, the RAIS dataset includes information on the type of contract.

jobs (7.4 percent vs. 2.2 percent) and more likely to be in agricultural jobs (14.0 percent vs. 9.3 percent). 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 notch point T, which is the tenure length in which EPL takes affect. Formally, let $B_j = \{15, 30, ...\}$ define the bins and H_j indicate the hazard rate in bin j (i.e. H_{90} denotes the probability a job ends between 75 and 90 days, given the job has lasted for 75 days). To estimate the counterfactual hazard, we estimate the following regression:

$$H_j = \sum_{i=0}^{q} \beta_i \cdot (B_j)^i + \sum_{i=-R}^{R} \gamma_i \cdot \mathbb{1}[B_j = i] + \varepsilon_j^0 \tag{1}$$

where q is the order of the polynomial and R denotes the width of the excluded region around the notch in firing costs. In practice, we set $q = 10$ and $R = 15$, and therefore exclude any tenure durations that end between 75 and 105 days in the estimation of the counterfactual hazard rate. We use the results from Equation (1) to estimate the counterfactual hazard as:

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

The excess mass is defined as the difference in the true hazard rate and the counterfactual hazard rate at $T = 90$:

$$B = H_T - \hat{H}_T \tag{3}$$

The normalized excess mass, which we will refer to as bunching, b, is defined as the excess mass divided by the counterfactual hazard rate at tenure duration T.

$$b = \frac{B}{\hat{H}_T} \tag{4}$$

To compute standard errors for the excess mass and bunching, we generate hazards and excess mass by resampling the residuals in Equation (1). The standard error is then equal to standard deviation of the distribution of excess mass 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.[6] 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.

The sizable excess mass 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 are most interested in, 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.

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.[8] Therefore, in order to sidestep these regulatory frictions, firms desiring

[6]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, and to keep the structural model as parsimonious as possible, we abstract from the effects of EPL beyond the bunching that occurs at 3 months' tenure.

[7]To understand the role of temporary contracts, Appendix Figure A1 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]To hire a worker under a temporary contracts, firms must get permission from the Ministry of Labor. They must also establish that the worker needs to be hired on a temporary contract in order to meet seasonal fluctuations in demand.

short-term employment arrangements may simply hire workers on permanent contracts with the intention of simply 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 two key reasons that could cause firms to create artificial temporary contracts.

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.[9] 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:

$$\Delta E_{j,t} = \frac{hires_{jt} - fires_{jt}}{hires_{jt}} \tag{5}$$

We then compute volatility of sector 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 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:

$$ln(\hat{V}_j) = \beta_0 + \beta_1 \hat{b}_j + \varepsilon_j \tag{6}$$

where β_1 capture the correlation between bunching and employment volatility. Appendix 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

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

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.

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 estimates.

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.[10].

Given these definitions, we expect the channel to be stronger for low-skill workers, as the tasks they perform require little training. As can be seen in Figure A3, 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 A3, 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.

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[10]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

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 and aggregate output. 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. Model

In order to study the consequences of EPL for macroeconomic outcomes such as unemployment and aggregate output, we introduce EPL into the general equilibrium model of Moscarini (2005), which merges the theories of job turnover and unemployment in a computationally tractable manner.[11]

We study the steady state equilibrium of this economy. As such, aggregate variables do not have a time subscript, and we use $t \geq 0$ to unambiguously denote tenure for individual level variables.

A. Production and Belief Dynamics

A final good is produced in continuous time by pairwise firm-worker matches. The match-specific productivity of a match, μ, is ex-ante unknown by both the firm and worker. Upon forming the match, both firm and worker share a common prior on μ that is independent of their histories. The prior puts mass on two productivity levels, μ^L and μ^H, where $\mu^L < \mu^H$. We refer to μ^L as a bad match, and μ^H as a good match. Let $p_0 = \Pr\left(\mu = \mu^H\right)$ be the initial prior that the match is good.

Final good production is linear in match productivity, but is subject to idiosyncratic shocks. In a small interval dt, production of the good X is given by

$$dX_t = \mu dt + \sigma dZ_t$$

[11] Given the non-negligible role that the informal sector plays in the Brazilian economy, we will interpret unemployment as both true unemployment as employment in the informal sector. This interpretation will inform our estimation and calibration below.

where dZ_t is a standard Brownian motion. In other words, output is a noisy indicator of true match productivity, with the noise being scaled by $\sigma > 0$.

The presence of noise creates an inference problem that firms and workers solve by using the information provided by the history of output, denoted by the filtration $\mathcal{F}_t^X$, to update their prior belief in a Bayesian manner,

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

The solution to the continuous time inference problem for p_t has a well known solution in the form of the stochastic differential equation

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

where $s = \frac{\mu^H - \mu^L}{\sigma}$ is the signal-to-noise ratio and

$$d\bar{Z}_t = \frac{1}{\sigma}\left(dX_t - \left(p_t \mu^H + \left(1 - p_t\right)\mu^L\right) dt\right)$$

is a standard Brownian motion with respect to the filtration generated by X_t, $\mathcal{F}_t^X$.[12] Intuitively, beliefs move faster the more uncertain is the current belief ($p\left(1-p\right)$ has a maximum at $p = \frac{1}{2}$). In addition, it is useful to define

$$\Sigma\left(p\right) = \frac{1}{2} s^2 p^2 \left(1 - p\right)^2$$

which is interpreted as half the variance of the change in beliefs over a small change in tenure.

B. EPL and Job Termination

When the belief, and hence expected match productivity, is low enough, firms and workers will optimally choose to terminate the match endogenously. However, upon termination, firms must pay a cost $\kappa\left(t\right)$ that depends on the tenure t of the match in the following way:

$$\kappa\left(t\right) = \begin{cases} 0 & \text{if} \quad t < T_1 \\ \kappa & \text{if} \quad t \geq T_1 \end{cases}$$

where $\kappa > 0$ is a constant, and T_1 is a tenure after which the termination cost becomes active. This cost represents the effect of EPL on firms in the model economy. Ultimately, we will estimate κ to match the spike in the hazard rate of job termination so that we can

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

interpret it as the effective real cost of the EPL regulation imposed on firms.

In addition to endogenous terminations, matches are also subject to exogenous termination at rate $\delta > 0$. We assume that exogenous terminations also result in firms incurring the costs of EPL.

C. Value Functions

Given the presence of EPL costs, it is useful to divide the analysis into two stages of tenure: $t \in [0, T_1)$, and $t \geq T_1$. Throughout, let superscripts on functions and variables $i \in \{1, 2\}$ refer to each respective tenure stage, and let subscripts denote derivatives. E.g. J^i_{xx} is the second derivative of the function J^i with respect to the argument x.

Also, define $\bar{\mu}(p) = p\mu^H + (1-p)\mu^L$ as the expected productivity of a match when the belief is p, and let V be the value to a vacant firm of opening a vacancy. In equilibrium, free entry into the vacancy posting market ensures that $V = 0$. Finally, we assume that all agents discount the future at rate $r > 0$.

C.1 $t \geq T_1$

We proceed by backward induction, and start in stage two of a job's tenure. Since the cost of EPL is fixed, firm and worker value functions only depend the current belief, which is therefore the natural state variable.

Firms The value to a firm of a match with current belief p, $J^2(p)$ must satisfy the Hamilton-Jacobi-Bellman (HJB) equation

$$rJ^2(p) = \bar{\mu}(p) - w^2(p) + \Sigma(p) J^2_{pp}(p) - \delta\left(J^2(p) + \kappa\right)$$

where $w^2(p)$ is the wage paid to the worker in a match with belief p.

The flow value of the match to the firm consists of 3 components. First, the firm receives the flow profits of production minus the wage she pays the worker. Second, the firm value has a capital gain component due to the change in belief that occurs when the firm updates her belief. 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 (and gains the value of vacancy posting which is equal to zero).

When the belief of the match reaches some threshold $\underline{p}^{2,J}$, the firm will optimally choose to terminate the match. Optimality requires that the firm's choice of threshold and HJB equation jointly satisfy the two boundary conditions

$$J^2\left(\underline{p}^{2,J}\right) = -\kappa$$

$$J_p^2\left(\underline{p}^{2,J}\right) = 0$$

The first condition states that, at the termination threshold $\underline{p}^{2,J}$, the value of the match to the firm equals the value of termination, which is equal to the value of entering the vacancy posting stage (zero in equilibrium) minus the EPL cost that the firm must pay to terminate the match in the second stage of tenure.[13]

The second condition states that, at the termination threshold, the slope of the value function must be zero. Intuitively, this condition ensures that the firm is indifferent between terminating the match as soon as the belief hits the threshold, and waiting for a small amount of time to see what happens.[14]

Workers The value to an employed worker of a match with current belief p satisfies the HJB equation

$$rW^2(p) = w^2(p) + \Sigma(p)\, W_{pp}^2(p) - \delta\left(W^2(p) - U - \alpha\kappa\right)$$

The value of the match to the worker equals the flow benefit (the wage) plus capital gains stemming from the change in beliefs and the possibility of exogenous separation, where U is the value to the worker of entering unemployment, and is defined shortly. The parameter $\alpha \in [0,1]$ governs the share of EPL that flows to the worker as a transfer payment upon separation.

Similarly to the firm, when the belief of the match reaches some threshold $\underline{p}^{2,W}$, the worker will optimally choose to terminate the match (a quit). Optimality requires that the worker's threshold choice and HJB equation jointly satisfy the two boundary conditions

$$W^2\left(\underline{p}^{2,W}\right) = U$$

$$W_p^2\left(\underline{p}^{2,W}\right) = 0$$

The first condition states that value of the match at the threshold is equal to the value to the worker from quitting, which is equal to the value of unemployment (EPL does not apply when the worker chooses to quit the match). The second condition states that, at

[13]This condition is often referred to as the "value matching" condition in the optimal stopping literature.

[14]This condition is referred to as the "smooth pasting" condition.

the termination threshold, the slope of the value function must be zero so that the worker is indifferent between terminating the match as soon as the belief hits the threshold, and waiting for a small amount of time to see what happens.

C.2 $t \in [0, T_1)$

For matches of tenure $t \in [0, T_1)$, the value functions depends on both the belief p and tenure t since the time until EPL costs become non-zero changes with tenure.

Firms The value to a firm of a match with current belief p and tenure t must satisfy the HJB equation

$$rJ^1(p,t) = \bar{\mu}(p) - w^1(p,t) + J_t^1(p,t) + \Sigma(p) J_{pp}^1(p,t) - \delta J^1(p,t)$$

where w^1 is the wage of a match with belief p and tenure t. This has the same interpretation as the stage two HJB equation, except that the capital gains now includes the change in value due to the increase in tenure and hence the reduction in time until the firing cost becomes active.

As in stage two, when the belief reaches a tenure threshold, the firm will choose to terminate the match. The key difference is that the thresholds now depend on tenure, and so satisfy the boundary conditions

$$J^1\left(\underline{p}^{1,J}(t), t\right) = 0$$

$$J_p^1\left(\underline{p}^{1,J}(t), t\right) = 0$$

The first condition ensures that at the threshold $\underline{p}^{1,J}$ at tenure t, the value to the firm of the match equals the value of entering the vacancy posting stage, which is now zero since there is no firing cost to pay. The second condition ensures that the threshold is optimal by a similar logic to the stage two case.

In addition to these conditions, there is another boundary condition in the tenure dimension that pins down the function $J^1(p, T_1)$,

$$J^1(p, T_1) = J^2(p) + \kappa$$

Intuitively, as tenure crosses T_1, the firm understands that she must now subtract κ from her match profit in order to pay the costs of EPL in the future. Therefore, the value of a given match drops by κ as tenure crosses T_1.

Workers The value to an employed worker of a match with current belief p and tenure t must satisfy the HJB equation

$$rW^1(p,t) = w^1(p,t) + W_t^1(p,t) + \Sigma(p) W_{pp}^1(p,t) - \delta\left(W^1(p,t) - U\right)$$

As in the firm case, in stage one, worker belief thresholds now depend on tenure, and satisfy the boundary conditions

$$W^1\left(\underline{p}^{1,W}(t), t\right) = U$$

$$W_p^1\left(\underline{p}^{1,W}(t), t\right) = 0$$

As in the firm case, $W^1(p, T_1)$ is pinned down by the additional boundary condition

$$W^1(p, T_1) = W^2(p)$$

Since workers do not have to pay EPL, the value of a match does not change as tenure crosses T_1.

Finally, the value of unemployment, U, satisfies the HJB equation

$$rU = b + \lambda\left(W^1(p_0, 0) - U\right)$$

The value of being unemployed equals the flow value from unemployment, b, plus the gain from becoming employed times the probability of entering a match, given by the job finding rate λ.[15]

D. Wage Determination via Nash Bargaining

Once a firm and worker have formed a match, they must decide how to split the surplus generated by the production process. We assume that the surplus is split according to a Nash Bargaining protocol that is subject to a minimum wage constraint.[16] To this end, let $\beta \in (0,1)$ denote the bargaining weight of workers.

It is again useful to proceed by backward induction.

[15]In line with our interpretation of unemployment including employment in the informal sector, we interpret b as a home production parameter rather than the flow value of unemployment insurance benefits.

[16]In Brazil, 2-3% of employed workers earn wages at the minimum wage. We target a similar level when estimating the model with this constraint.

D.1 $t \geq T_1$

Given the firm and worker value functions, we can define the surplus of a match with current belief p and tenure $t \geq T_1$ as the sum of the values of the match to the firm and worker minus their respective outside options,

$$S^2(p) = J^2(p) + \kappa + W^2(p) - U$$

The Nash Bargaining protocol selects a wage according to

$$w^2_{NB}(p) = \arg\max_w \left(W^2(p) - U\right)^{\beta} \left(J^2(p) + \kappa\right)^{1-\beta}$$

which has the FOC

$$\beta\left(J^2(p) + \kappa\right) = (1-\beta)\left(W^2(p) - U\right)$$

Note that this condition together with the first boundary conditions of the firm and worker HJB equations imply that

$$\underline{p}^{2,J} = \underline{p}^{2,W} = \underline{p}^2$$

so that optimal firm and worker belief thresholds coincide at all tenures in stage two.

Using the expressions for the value functions to solve for the Nash Bargaining wage function yields

$$w^2_{NB}(p) = \beta\left(\bar{\mu}(p) + r\kappa\right) + (1-\beta)\left(rU - \delta\alpha\kappa\right)$$

which shows how the Nash Bargaining wage is a bargaining share weighted average of the flow value of the match (production plus the interest earned on the resources set aside for EPL by the firm) and the worker's outside option (the flow value of unemployment minus the share of EPL the worker receives should her match be terminated exogenously).[17] Combining this wage with the minimum wage level w_{min} yields the equilibrium wage function

$$w^2(p) = \max\left\{w^2_{NB}(p), w_{min}\right\}$$

[17]This expression also shows how EPL affects the splitting of the match surplus between the firm and worker. In particular, when $\beta > \frac{\delta\alpha}{r+\delta\alpha}$, the worker receives a larger share of the match surplus in equilibrium than she would in the absence of EPL.

D.2 $t \in [0, T_1)$

Similarly to stage two, we can define the surplus of a match with current belief p and tenure t as the value of the match to the firm and worker minus their respective outside options,

$$S^1(p,t) = J^1(p,t) + W^1(p,t) - U$$

where the cost of EPL is now zero. The Nash Bargaining solution is hence given by

$$w^1_{NB}(p,t) = \arg\max_w \left(W^1(p,t) - U\right)^\beta \left(J^1(p,t)\right)^{1-\beta}$$

which has the FOC

$$\beta\left(J^1(p,t)\right) = (1-\beta)\left(W^1(p,t) - U\right)$$

Note that this condition together with the first boundary conditions of the firm and worker HJB equations imply that

$$\underline{p}^{1,J}(t) = \underline{p}^{1,W}(t) = \underline{p}^1(t)$$

so that optimal firm and worker belief thresholds coincide at all tenures. Using the expressions for the value functions to solve for the Nash Bargaining wage function yields

$$w^1_{NB}(p,t) = \beta\bar{\mu}(p) + (1-\beta)\, rU$$

which is the standard expression for wages determined by Nash Bargaining.

Combining this wage with the minimum wage level w_{min} yields the equilibrium wage function

$$w^1(p,t) = \max\left\{w^1_{NB}(p,t), w_{min}\right\}$$

E. Hazard Rate Spike at Tenure $t = T_1$

The key feature of our model is that firms must pay EPL costs in order to terminate a match that has tenure of at least T_1. The following logic formalizes how this firing cost creates a spike in the hazard rate of match termination at T_1, thus providing an explicit micro-foundation for the link between EPL and the hazard rate spike that we documented in the data.

Define the firm-specific thresholds $\underline{p}^{1,J}(T_1)$ and $\bar{p}^{1,J}(T_1)$, that satisfy the conditions

$$J^1\left(\underline{p}^{1,J}(T_1), T_1\right) = 0$$

$$J^2\left(\bar{p}^{1,J}(T_1)\right) = J^1\left(\bar{p}^{1,J}(T_1), T_1\right) - \kappa = 0$$

where $\bar{p}^{1,J}(T_1) > \underline{p}^{1,J}(T_1)$ since firm value functions are increasing in the current belief. Given these threshold definitions, any match with belief $p_{T_1} \in \left[\underline{p}^{1,J}(T_1), \bar{p}^{1,J}(T_1)\right]$ at tenure $t = T_1$ will be immediately terminated since the value of such a match will instantaneously drop to $J^2(p, T_1) < 0$. This extra termination creates a spike in the hazard rate at T_1.

Intuitively, when tenure reaches T_1, there is an interval of beliefs such that a match with a belief in that interval would not be terminated were it not for the presence of a firing cost. While such matches are reasonably productive, they are not productive enough to warrant the firm continuing the match and paying the firing cost if productivity deteriorates later. All matches with beliefs in this interval are therefore terminated at tenure T_1, thus creating a spike in the hazard rate at tenure T_1.

F. Ergodic Distribution of Beliefs

We again divide to derivation into 2 stages, according to match tenure, and define 2 belief distribution functions f^1, and f^2, where the function $f^i(p,t)$ is the distribution over the unit interval of beliefs for a cohort of matches that began production at the same moment in calendar time, and have reached tenure t.[18]

F.1 $t \leq T_1$

We can characterize the evolution of the distribution of beliefs using the Kolmogorov Forward Equation (KFE), which states that f^1 evolves according to the equation

$$\frac{\partial}{\partial t} f^1(p,t) = \frac{\partial^2}{\partial p^2}\left[\Sigma(p) f^1(p,t)\right] - \delta f^1(p,t)$$

The KFE states that the change in density at a belief p for a small change in tenure is the sum of two components. First, beliefs move around in the distribution according the evolution equation. 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.

The initial distribution satisfies the conditions

$$\int_{\underline{p}^1(0)}^{1} f^1(p,0)\, dp = \lambda u$$

[18] The f functions are not strictly distributions since we do not require them to sum to 1. Instead, their total mass will be total employment, and hence 1 minus total unemployment since we have normalized the mass of workers to unity.

$$f^1(p,0) = \Delta(p - p_0)$$

where we recall that λ is the finding rate and u is the mass of unemployed workers, and we define Δ as the Dirac delta function that places all mass at the initial prior p_0.

In addition, at each tenure $t < T_1$, f^1 satisfies the boundary condition

$$f^1\left(\underline{p}^1(t), t\right) = 0$$

which ensures that there is always zero mass at the termination threshold at tenure t, since when a match belief reaches the threshold, it is immediately terminated.

F.2 $t \geq T_1$

The KFE again states that f^2 evolves according to

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

At tenure $t = T_1$, we initialize f^2 with the condition

$$f^2(p,T_1) = f^1(p,T_1)\,\mathbf{1}\left\{p \in \left[\bar{p}^{1,J}(T_1), 1\right]\right\}$$

where $\mathbf{1}$ is the indicator function. This condition ensures that only matches with belief above the threshold $\bar{p}^{1,J}$ survive the termination process at tenure T_1.

Similarly to stage one, at each tenure $t \geq T_1$, f^2 satisfies the boundary condition

$$f^2\left(\underline{p}^2, t\right) = 0$$

which has the same interpretation as in stage one.

F.3 Ergodic Distribution of Beliefs

Combining f^1 and f^2 yields the ergodic distribution of beliefs,

$$g(p) = \int_0^{T_1} f^1(p,t)\,\mathbf{1}\left\{p \geq \underline{p}^1(t)\right\} dt + \int_{T_1}^{\infty} f^2(p,t)\,\mathbf{1}\left\{p \geq \underline{p}^2\right\} dt$$

Normalizing the mass of workers to 1, the mass of unemployed workers is given by

$$u = 1 - \int_0^1 g(p)\,dp$$

G. Vacancy Posting

A vacant firm has a value function V that satisfies

$$(r+q)\,V = qJ^1\left(p_0, 0\right) - c$$

where q is the job filling rate, and c is the per-period cost of maintaining a vacancy expressed in units of the final good. We assume that there is a large mass of firms in the economy, so that free entry into the market for vacancies guarantees that $V = 0$ in equilibrium.

H. The Matching Function

Let v be the mass of open vacancies. Together with the mass of unemployed workers u, v vacancies generate m new job matches according to the matching function

$$m = zu^{\eta}v^{1-\eta}$$

where z is matching efficiency and $\eta \in (0,1)$ is the elasticity of matches to unemployment. This implies the job finding rate $\lambda = z\theta^{1-\eta}$, and job filling rate $q = z\theta^{-\eta}$, where $\theta = \frac{v}{u}$ is labor market tightness.

I. Equilibrium

Definition 1. A steady state equilibrium is a set of scalars

$$\left\{\lambda, q, \theta, u, v, \underline{p}^2\right\}$$

and functions

$$\left\{J^1, J^2, W^1, W^2, U, \underline{p}^1, w^1, w^2, f^1, f^2\right\}$$

such that:

1. $\left\{J^1, J^2, W^1, W^2, U, \underline{p}^1, \underline{p}^2\right\}$ satisfy their HJB equations and boundary conditions.
2. $\{w^1, w^2\}$ satisfy the Nash Bargaining condition.
3. $\{f^1, f^2\}$ satisfy their KFEs, and boundary and initial conditions.
4. $\{\lambda, q, \theta\}$ satisfy their definitions.
5. v ensures free entry in the vacancy posting market.
6. u is consistent with total unemployment implied by $\{f^1, f^2\}$.

J. Aggregate Output and Welfare

Since production is linear in productivity beliefs, we can define formal sector output as

$$Y = \mu^H \int_0^1 pg\left(p\right) dp + \mu^L \int_0^1 \left(1-p\right) g\left(p\right) dp - cv$$

which has the simple interpretation of the number of good matches times the productivity of a good match plus the number of bad matches times the productivity of a bad match minus the flow costs of vacancy creation.

Exploiting the linearity of preferences, and recalling that $u = 1 - \int_0^1 g\left(p\right) dp$, we can define steady state welfare (equal to aggregate output across both the formal and informal sectors) as

$$\mathcal{W} = b\left(1 - \int_0^1 g\left(p\right) dp\right) + \mu^H \int_0^1 pg\left(p\right) dp + \mu^L \int_0^1 \left(1-p\right) g\left(p\right) dp - cv$$

which is the flow value of unemployment times the mass of unemployed workers plus formal sector production.

Importantly, these expressions also show that EPL affects production and welfare through 3 channels: the level of unemployment as captured by total mass of the function g, the level of labor productivity as captured by the shape of the function g, and the total costs of posting vacancies.

K. Efficiency

In our economy, there are two decision margins: match termination by firms and workers, and vacancy creation by firms. In the absence of EPL (when $\kappa = 0$), match termination decisions are efficient due to the Nash Bargaining protocol, which ensures that a match is terminated when its surplus is zero.[19] Formally, Nash Bargaining ensures that firm and worker values are linear functions of the match surplus, so that the boundary conditions for match termination occur when the match surplus is zero.

Vacancy creation by firms is efficient when the Hosios (1990) condition, $\beta = \eta$, is satisfied. As is well known, vacancy creation by firms imposes 2 externalities on the economy. First, an additional vacancy lowers the job filling rate of all other vacant firms, thus creating a negative externality. Second, an additional vacancy increases the job finding rate for all unemployed workers, thus creating a positive externality. When $\beta = \eta$, the externalities exactly cancel each other out, resulting in an efficient equilibrium.

The imposition of EPL affects both decision margins in the economy. First, EPL distorts the match termination decision of firms, and creates a spike in the hazard rate of match termination at 3 months' tenure, as we have shown both empirically and theoretically. Second, EPL alters the incentive for firms to create vacancies, since it affects their valuation of new matches, $J^1(p_0, 0)$.

If the Hosios condition holds, then the imposition of EPL must be inefficient. However, if the Hosios condition does not hold, then the overall effect of EPL on efficiency and welfare is ambiguous. For example, EPL may increase overall labor productivity, but could also increase unemployment while decreasing vacancy creation. In order to quantify these competing channels, and to measure whether the Hosios condition holds in the data we now turn to our quantitative exercise.

V. Model Estimation Strategy

The model contains 15 parameters: $T_1, \mu^L, \mu^H, r, \eta, \alpha, \delta, c, z, b, \beta, w_{min}, \sigma, p_0, \kappa$. Since our key data variation is the hazard rate schedule, we use these data in conjunction with other

[19] In order to focus on the efficiency implications of EPL, we assume that the minimum wage is not binding. We show that our results are robust to including the minimum wage in section VII.

aggregate moments to identify and estimate z, b, σ, p_0, β, and κ. We normalize or calibrate the remaining parameters.

A. 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. Since μ^L and μ^H simply set the location and scale of production in the economy, we normalize them to $\mu^L = 0$ and $\mu^H = 1$ respectively. 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 0.25, in line with the estimates in Hoek (2007) who estimates a Cobb-Douglas matching function for Brazil. As a baseline, we set $\alpha = 0$, and assume that the minimum wage does not bind by setting $w_{min} = 0$. We confirm that our results are robust to other values for η, α, and w_{min} in section VII.[20]

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 $\delta = 0.013$ to match the long run level of the empirical hazard rate (beyond 24 months' tenure).

Finally, the flow cost of posting a vacancy, c, is pinned down endogenously by the free entry condition for vacancy posting, $c = z\theta^{-\eta} J^1 (p_0, 0)$.

B. Estimation Procedure

We estimate the remaining vector of parameters ($\Xi = (z, b, \beta, \sigma, p_0, \kappa)'$) by the method of simulated moments. Formally, let M be a vector of six empirical moments which we will define below and let $M(\Xi)$ be the vector of corresponding moments generated by the model. We choose Ξ^* to solve

$$\Xi^* = \arg\min_{\Xi} \left(M(\Xi) - M\right) W^{-1} \left(M(\Xi) - M\right)'$$

where W is a weighting matrix. We set W to a diagonal matrix with diagonal equal to the square of each empirical moment.

[20] While the minimum wage is certainly binding in Brazil, as shown in Engbom and Moser (2018), we show in the appendix that the bindingness of the minimum wage does not change our qualitative results concerning the impact of EPL on macroeconomic outcomes.

C. Identification

Following Shimer (2005), we normalize market tightness $\theta = 1$. Given this, the per-period job finding rate is equal to the matching efficiency parameter, $\lambda = z$, which we estimate to target a steady state unemployment rate of approximately 30%. This figure is consistent with recent Brazilian data (Engbom and Moser, 2018), where we interpret unemployment as including both true unemployment, and employment in the informal sector.

In order to estimate the flow value of unemployment b, we target an income share of the informal sector equal to 20% of total income (de Holanda Barbosa Filho, 2012). Intuitively, b pins down the productivity of the informal sector, and hence its share of aggregate income.

We choose β so that the expected cost of vacancy creation, c/q is equal to 4 months' average wages, similar to the value of vacancy costs in Hornstein et al. (2005). Intuitively, a higher value for β increases the wages of employed workers, and hence lowers the expected profits from a new job, $J^1(p_0, 0)$. Since $J^1(p_0, 0) = c/q$ in equilibrium, β directly affects the expected cost of posting a new vacancy.

In order to estimate σ, p_0 and κ, we aim to match the empirical job termination hazard rate. p_0 and σ determine the initial level and slope of the hazard rate pattern. The larger is the initial prior p_0, the less likely it is that the belief falls low enough to warrant endogenous match termination, and hence the lower are the initial hazard rates of match termination. Similarly, the larger is σ, the slower firms and workers learn about match productivity, and the lower is the initial slope in the hazard rate of match termination. Therefore, we use the hazard rates at tenures of 0.5 and 1 month to estimate p_0 and σ.[21]

Finally, the identification of κ follows similar arguments to the empirical identification as described in Section E. The fact that EPL only becomes active at 3 months of tenure creates a strong incentive for firms to terminate matches just before this tenure is reached. This behavior creates a spike in the hazard rate schedule at 3 months' tenure. Hence, we use the spike in the empirical hazard, captured by the hazard rates at tenures of 2.5, 3, and 3.5 months to infer the value of κ.

To illustrate the identification of the model's parameters, we first show that the estimated parameters, denoted Ξ^*, are indeed a global minimum. To do so we proceed parameter by parameter, following Bilal et al. (2019). To proceed, we move each parameter, Ξ_i around the estimated value Ξ_i^*, keeping fixed the other estimated values at Ξ_{-i}^*. If the estimated parameter vector is indeed a global minimum of the estimation objection, then the objective

[21] The particular moments of the hazard rate to choose for estimation is a bit ambiguous in general. We have chosen two parameters so that the model is just identified, but utilizing more moments of the job termination hazard rate leads to very similar estimates. In particular, we have estimated alternative over-identified specifications in which we use the entire job termination hazard rate to estimate the parameters of the model.

function should increase as we move away from the estimated parameter value. Figure 4 plots the the minimized value of the estimation objective as we vary each parameter. As can be seen in the figure, the U-shaped curves offer evidence that the objective is globally minimized at our estimated parameter vector.

D. Estimated Parameters and Model Fit

Table 3 presents the parameter estimates along with the targeted moments. While each parameter is associated with a given moment, in practice, all moments are used simultaneously to estimate the vector of parameters.

To understand how these parameters map to the data, it is useful to plot the model-implied job termination hazard rate. Recall from the model that the hazard rate is driven by three separate parameters: the initial productivity belief, the speed of learning, and the cost of EPL. As can be seen in Figure 5, this sparse parameterization does a good job of capturing key features of the empirical job termination hazard rate. Intuitively, the firing cost κ successfully replicates the spike in the hazard at three months. Its estimated value $\kappa = 1.23$ implies that the real cost of terminating a match is equivalent to about 1.5 times the mean wage in the economy, or 6.2 times the flow cost of maintaining a vacancy. The relatively high initial belief of productivity, $p_0 = 0.87$, indicates that the hazard rate of job termination starts at a relatively low level. Lastly, the speed of learning, $\sigma = 1.95$ dictates the overall shape of the curve. The higher the speed of learning, the quicker the hazard rate will flatten out, indicating that at long tenures job destruction is driven by exogenous reasons (δ in the model) and not by endogenous learning about match quality.[22]

VI. Results

Counterfactual Hazard Rates Figure 6 plots the hazard rate in the data, in the estimated model, and in the counterfactual model with the EPL removed ($\kappa = 0$). In the absence of firing costs, the hazard rate function resembles the standard hump shape (Farber, 1994). In particular, the hazard rate without firing costs does not spike at three months, and is uniformly higher than the hazard with firing costs at tenures greater than three months, but lower than the hazard with firing costs at tenures less than three months. In other words, the presence of firing costs causes firms to terminate matches earlier than they otherwise would, just as the theory predicted and as we found in the data.

[22]Table 3 also presents estimates for the bargaining power of workers ($\beta = 0.56$) and the flow value of unemployment ($b = 0.39$). Although often applied in a different settings, these numbers are quite similar to numbers often used in the search literature (See Shimer (2005) for example).

A. The Equilibrium Effects of EPL

In order to compute the macroeconomic effects of EPL, we proceed in stages. First, we compute the change in outcomes when we impose constant EPL that applies to jobs of all tenures. Then we compute the change in outcomes when we impose tenure-dependent EPL, that only applies to jobs with tenure greater than 3 months, as is currently the case in Brazil.

A.1 Constant EPL

Column 1 of Table 4 summarizes the macroeconomic implications of constant EPL in our estimated model. Intuitively, the presence of EPL lowers the profit from hiring a worker, which causes firms to post fewer vacancies. As a result, the unemployment rate increases by 2.4 percentage points, and workers are reallocated from the formal sector to the relatively less productive informal sector, which includes true unemployment. This reallocation in turn causes a decrease in formal sector output of 3.3%, and a decline in aggregate output of 1.3%. Therefore, the imposition of constant EPL has a meaningful negative effect on the macroeconomy, and causes a relatively large shift from formal sector employment to informal sector employment or unemployment.

In theory, the imposition of EPL has two opposing effects on unemployment. First, the drop in vacancy creating lowers the job-finding rate which causes higher unemployment. Second, the costs of termination lower the job-separation rate which causes lower unemployment. In our setting, the first channel strongly dominates the second. Intuitively, the majority of employed workers in our economy are in matches with sufficient tenure so that the probability of being high quality (p_t) is close to one. For these matches, the imposition of EPL has a negligible effect on the probability of the match being terminated. As a result, EPL barely affects the aggregate job-separation rate. Therefore, while the theoretical literature emphasizes the ambiguous nature of EPL on unemployment (Ljungqvist, 2002), we find that quantitatively EPL leads to an increase in unemployment, which is driven by reduced vacancies.

Decomposing the Fall in Output We can shed further light on the driving force behind the decline in formal sector output by examining a simple decomposition that breaks the total output decline into components that reflect each of the decision margins in the economy. Letting asterisks * denote outcomes in the counterfactual economy without EPL, we can write the change in aggregate output as

$$Y - Y^* = \int_0^1 p\left(g\left(p\right) - g^*\left(p\right)\right) dp - c\left(v - v^*\right)$$

which can be decomposed into 3 parts,

$$Y - Y^* = \underbrace{\int_0^1 p\left(g(p) - \frac{1-u^*}{1-u} g(p)\right) dp}_{\text{unemployment}} + \underbrace{\int_0^1 p\left(\frac{1-u^*}{1-u} g(p) - g^*(p)\right) dp}_{\text{productivity}} - \underbrace{c(v - v^*)}_{\text{vacancies}}$$

The unemployment channel measures how much of the change in output is driven by the change in unemployment, holding the distribution over productivities fixed at g. Naturally, if EPL causes higher unemployment due to increased match termination at 3 months' tenure, then $u > u^*$ and aggregate output is lower, ceteris paribus.

The productivity channel measures how much of the change in output is driven by the change in the distribution over beliefs, and hence productivities. Intuitively, we expect that EPL causes firms to terminate matches with lower expected productivity at 3 months' tenure, leading to an increase in average productivity for matches with tenure greater than 3 months. This increase in productivity is a force for EPL to increase output.

Finally, the vacancies channel measures how much of the change in output is due to a change in the total costs of posting vacancies in the economy. Firms' incentives to create vacancies hinges on the job-filling rate, q, which is decreasing in the overall level of labor market tightness, $\theta = \frac{v}{u}$. Therefore, if EPL causes higher unemployment, the larger mass of unemployed workers increases the probability that a vacant firm finds a match. This increase in the job-filling rate incentivizes firms to post more vacancies, so that EPL causes an increase in total vacancy posting costs, which is a force for lower aggregate output.

Applying this decomposition to our estimated model, we find that the overall fall in formal sector output caused by constant EPL is driven by the increase in unemployment, which accounts for a 4.1% drop. The decrease in vacancy posting costs provides an offsetting force that causes a 1.0% increase in formal sector output all else equal. [23]

A.2 Tenure-Dependent EPL

Column 2 of Table 4 summarizes the macroeconomic implications of tenure-dependent EPL. Delaying the onset of EPL to jobs with tenure greater than 3 months erases all of the macroeconomic costs associated with the constant EPL policy. In equilibrium, formal sector output actually increases by 0.06% relative to the economy without EPL. Unemployment falls by 0.07 percentage points, and aggregate output increases by 0.01%.

Intuitively, the creation of a probationary period allows firms and workers to learn about match quality without the risk of facing a costly termination fee. This raises the value of

[23] This result is robust to deriving the unemployment and productivity channels using the counterfactual distribution g^* instead of g.

a new match to a firm, and incentivizes them to create more vacancies in equilibrium. As a result, unemployment falls, and output increases. This result can also be understood by looking directly at the counterfactual hazard rate of job termination when we remove EPL from the economy. As can be seen in Figure 6, while the job termination hazard is much higher at three months with EPL, it subsequently falls. By 9 months, the hazard rates of job termination between an economy with tenure-dependent EPL and no EPL are essentially the same. Therefore, tenure-dependent EPL does incentivize job matches to be terminated earlier, but does not change the overall number of vacancies in the economy, and therefore does not have a large aggregate effect on unemployment.

Therefore, our results offer evidence for the benefits of tenure-dependent EPL policies. By allowing firms to learn about match quality before committing to a full-time employment contract, tenure-dependent EPL increases the value of an initial match and limits the effect of EPL on aggregate employment.

B. A Laffer Curve for EPL

Like other tax policies, the imposition of EPL on employment matches generates revenue for the policy maker. For a given real cost of EPL κ, the total per-period revenue generated by the policy can be computed as

$$R = \kappa \int_{T_1}^{\infty} s(t)e(t)dt$$

where $e(t)$ is total employment at tenure t, and $s(t)$ is the corresponding separation rate (stemming from endogenous and exogenous terminations).

Consider how an increase in T_1 affects EPL revenue R. There are two channels. First, holding total employment fixed, higher T_1 mechanically lowers R since fewer matches are eligible for EPL payments upon termination. Second, as shown above, an increase in T_1 raises aggregate employment. All else equal, this increases the number of matches that must pay EPL upon termination. Which of these channels dominates depends on T_1.[24]

Figure 9 plots R as a function of T_1, holding all other parameters fixed at their estimated or calibrated values.[25] We see that revenue increases when EPL only applies to matches with tenure of at least half a month instead of applying to all matches regardless of tenure. However, further increases in T_1 lead to revenue declines. Intuitively, although aggregate employment increases, the number of matches terminated for endogenous reasons actually

[24]As mentioned previously, κ captures both the monetary and non-monetary costs of EPL. However, we expect that T_1 would effect the monetary component in a similar manner to that described here.

[25]For ease of comparison, we normalize the scale so that the revenue equals unity when $T_1 = 0$.

decreases as by tenure $T_1 \geq 1$ month, firms and workers have learned enough about the true quality of the match to make the probability of endogenous separation very small.

This analysis shows that while some tenure-dependence is beneficial, too much may be detrimental from a revenue perspective. Of course, in reality the policy may achieve other goals such as insurance and redistribution that we are silent on here. We leave the analysis of this interesting policy feature to future research.

C. The Role of Learning

In our model, learning about match quality plays an important role in determining the effect of EPL on job termination decisions. Termination decisions occur when the expected productivity of a match falls below a cutoff. EPL creates a discontinuous jump in this cutoff threshold and therefore the effect of EPL depends on the fraction of jobs that fall between the two cutoffs.[26]

While we have estimated the set of learning parameters that rationalizes the data, these parameters could change over time. For example, if the economy experiences a shock to productivity, this could decrease the fraction of jobs that are productive, which is captured by the parameter p_0 in our model. Additionally, the speed of learning about match quality, captured by σ, could change due to innovations in technology or through government programs, such as active labor market programs that seek to improve the match between workers and firms. In this section, we consider how changes to the learning parameters change the results regarding the impact of EPL on macroeconomic outcomes.

First, we consider how changes to the percent of matches that are high-quality (p_0) impacts the effect of EPL on macroeconomic outcomes. In Figure 7, we plot the percentage point change in unemployment (Panel A) and the percent change in output (Panel B) that results from moving from an economy without EPL to an economy with tenure-dependent EPL. As can be seen in the figure, EPL tends to have better results in an economy in which a high fraction of the initial matches are productive. For example, starting at the estimated value in the data (0.87), we find that tenure-dependent EPL results in a roughly zero percent change in aggregate output. As we decrease the fraction of high-quality matches, EPL tends to reduce output. This occurs because when the initial belief is lower, there is a higher fraction of matches near the threshold for termination. This results in larger spikes in job separation at three months as more jobs are destroyed early directly due to the imposition of EPL.

Next we consider the speed in the learning process in Figure 8. As can be seen in Panel

[26] Specifically using the model notation, the fraction of jobs that fall between $p_{T_1} \in \left[\underline{p}^{1,J}(T_1), \bar{p}^{1,J}(T_1)\right]$ are terminated at 3 months.

A, an economy with tenure-dependent EPL tends to decrease unemployment relative to an economy without EPL, though the effects are quite small across a large range of learning speeds. However, the minimum decrease in unemployment occurs roughly at the actual speed of learning estimated in the model. Turning to output, we see that this implies that the change in output due to EPL is minimized at the speed of learning we found in the estimated model. At all other speeds, tenure-dependent EPL tends to *increase* output relative to an economy without EPL.

This result stems from the fact that the job termination hazard is close to maximized at the estimated (σ). Given job firings are maximized at the estimated σ, there are a relatively large fraction of jobs near the threshold of termination, implying EPL has larger impacts on job separations. By changing σ, we essentially change the job tenure at which firing is maximized, and thus change the fraction of workers impacted by EPL. In this setting, we find that the discontinuity for the probationary period is set at the worst possible length, given it expires precisely when there is a large fraction of workers close to the termination threshold.

VII. Robustness

In this section we show that our results are robust to changes in the value of calibrated parameters: the elasticity of matches to unemployment η, the share of EPL that workers receive upon involuntary termination α, and the minimum wage w_{min}.

Relative to the baseline economy, we consider $\eta = 0.75$, $\alpha = 1$, and $w_{min} = 0.7$. This minimum wage ensures that 3% of employed workers earn the minimum wage in equilibrium. This fraction is consistent with our data, and with the results in Engbom and Moser (2018). For each parameter variation, we re-estimate the model and then compute the results of our counterfactual exercises with constant and tenure-dependent EPL.

The results are contained in Table 5. Consider first the effect of increasing the elasticity of matches with respect to unemployment η. Compared the baseline in wich $\eta = 0.25$, setting $\eta = 0.75$ causes a reversal of the effect of tenure-dependence: constant EPL increases formal sector output while adding tenure-dependence lowers it. However, these effects are quantitatively insignificant, with output changing by less than 0.3% in both cases.

When $\alpha = 1$, newly unemployed workers receive the full cost of EPL as a lump sum payment. In this case, the costs of constant EPL are somewhat muted relative to the baseline: formal sector output falls by 1.8%. Furthermore, the benefits of tenure-dependence are amplified, with formal sector output increasing by 1.3% relative to the no EPL case. Intuitively, higher α actually lowers the Nash bargaining wage paid by firms since workers receive the full EPL payment upon termination. As a result, matches are more profitable and firms create more vacancies in equilibrium, thus reducing the costs of EPL.

Finally, the presence of a minimum wage amplifies both the costs of constant EPL, and the benefits of tenure-dependent EPL. Intuitively, the minimum wage disincentivizes firms to post vacancies since matches are less profitable. This amplifies the costs of constant EPL. Tenure-dependence is then more powerful because the probationary period closely coincides with the period in which the minimum wage constraint is most likely to bind, thus reducing the costs of EPL when they are most potent. As a result, formal sector output increases by 1.3% when EPL is tenure-dependent.

VIII. Conclusion

We make two contributions to the literature that studies the effects of EPL on macroeconomic outcomes. 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 implications of removing EPL on unemployment and aggregate output.

Our results imply that the design of EPL can have substantial negative effects on macroeconomic outcomes. These negative effects stem from the fact that constant EPL causes a significant shift of workers from the formal sector to the informal sector or unemployment, leading to aggregated declines in output and welfare. However, we find that introducing tenure-dependence can alleviate these costs since a probationary period offers firms and workers the opportunity to learn about match quality without facing a costly termination fee.

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 understanding of the macroeconomic impacts of EPL.[27]

[27] In contemporaneous work, Cahuc et al. (2019) use similar methods to explore the consequences of French labor market regulations on job finding and separation rates.

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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	Target
T_1	Timing of EPL	3 months	Timing of EPL
μ^L	Low Match Productivity	0	Normalization
μ^H	High Match Productivity	1	Normalization
r	Discount rate	7.5%	Annual real interest rate
δ	Exogenous Separation Rate	0.013	Long run hazard rate
η	Elasticity of Matches to unemployment	0.25	Hoek (2007)
c	Vacancy Posting Cost	0.19	Free-entry condition
α	EPL Transfer Component	0	Baseline Calibration

Note: This table reports the calibrated parameters model parameters along with the moments used to calibrate the parameters. $T_1 = 3$ reflects that in Brazil there is a three-month probationary period at which EPL costs are set to zero. r is set to match interest rates in Brazil, δ is equal to the long-term hazard rate in the data, η is the elasticity of matches to unemployment and c is the flow cost of a vacancy which is determined endogenously by the free entry condition for vacancy posting. For the baseline calibration, we set the amount of EPL costs that get transferred to workers as zero, but show robustness to this decision in Appendix Table 5.

Table 3: Estimated Parameters and Targeted Moments

Parameter		Value	Moment	Model	Data
z	Matching Efficiency	0.03	Unemployment Rate	0.34	0.30
b	Flow Value of unemployment	0.39	Income share of Informal Sector	0.19	0.20
β	Bargaining Share	0.56	Cost of a Vacancy / Mean monthly wage	3.8	4
p_0	Initial Belief	0.87	0.5 month Hazard Rate	0.01	0.009
σ	Std. Dev. of Output Shocks	1.95	1 month Hazard Rate	0.02	0.02
κ	EPL Cost	1.23	3 month Hazard Rate Spike	0.05	0.04

Note: This table reports the estimated model parameters. Parameters are estimated jointly using simulated methods of moments. The parameter, κ, is estimated using the hazard rates at 2.5, 3, and 3.5 months, which together are informative of the hazard rate spike at 3 months' tenure.

Table 4: The Effect of Different EPL Designs on Macroeconomic Outcomes Relative to No EPL

	Constant EPL	Tenure-Dep. EPL
	(1)	(2)
Panel A: Macroeconomic Outcomes		
$\Delta \mathcal{W}$ (%)	-1.3	0.01
Δu (p.p.)	2.4	-0.07
ΔY (%)	-3.3	0.06
Panel B: Formal Sector Output Decomposition		
Productivity (%)	-0.2	0.06
Vacancies (%)	1.0	0.11
Unemployment (%)	-4.1	-0.11

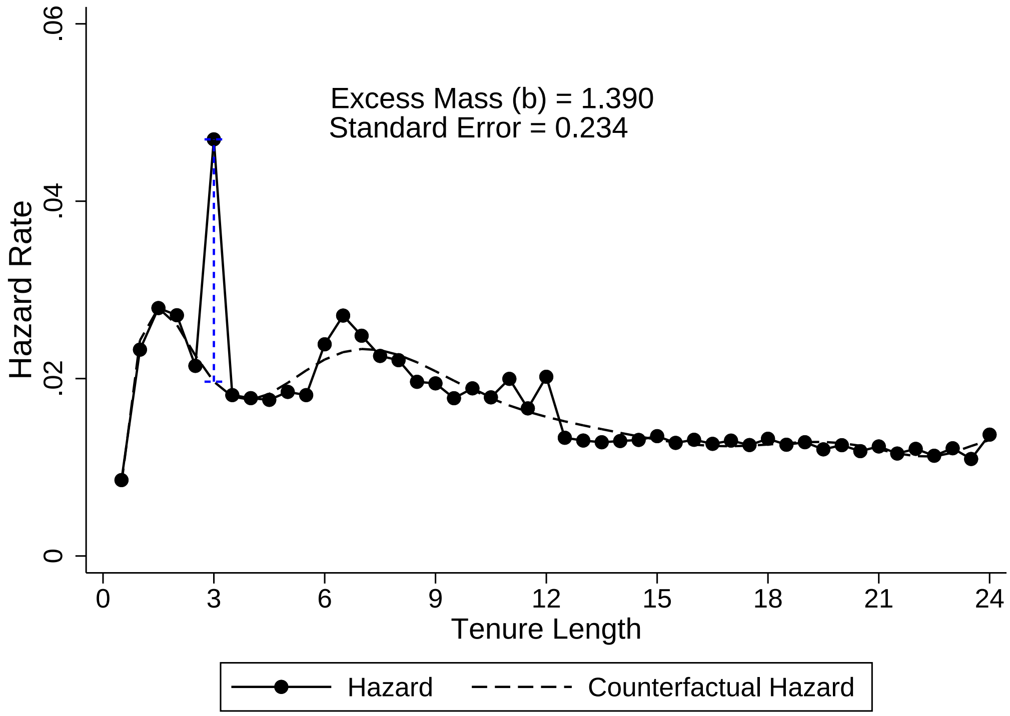
Note: This table reports the change in macroeconomic outcomes for different changes to employment protection legislation (EPL). The baseline is an economy without any EPL (i.e. $\kappa = 0$). The first column reports changes when we impose tenure-*in*dependent EPL (i.e. setting κ to its estimated value for all tenures, implying $T_1 = 0$). In the second column we show the changes when we impose tenure-dependent EPL (i.e. setting κ to its estimated value for all tenures greater than 3 months). This is the design of EPL currently imposed in Brazil.

Table 5: Robustness Exercises

	Baseline		$\eta = 0.75$		$\alpha = 1$		Min. Wage	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta\mathcal{W}$ (%)	-1.3	0.01	0.45	0.12	-0.67	0.49	-1.4	0.51
Δu (p.p.)	2.4	8.5	0.40	0.07	1.4	-1.0	2.9	-0.96
ΔY (%)	-3.3	0.06	0.29	-0.20	-1.8	1.3	-3.7	1.29

Note: This table reports the effect of EPL on macroeconomic outcomes under different parameter specifications. For each specification, the first column reports the macroeconomic effects of imposing tenure-*in*dependent EPL, while the second column reports the effects of imposing tenure-dependent EPL. Columns (1) and (2) contain the baseline results. In columns (3) and(4), we set the elasticity of matches with respect to unemployment, η, equal to 0.75, much higher than the baseline estimate that uses $\eta = 0.25$. In columns (5) and (6), we set $\alpha = 1$, so that upon separation, the cost of EPL is directly transferred to the newly unemployed worker. In columns (7) and (8), we allow for a minimum wage, which we estimate so that 3% of the employed workforce earn the minimum wage in equilibrium, in line with our data, and Engbom and Moser (2018).

Figure 1: Hazard Rates around Firing Cost Notch

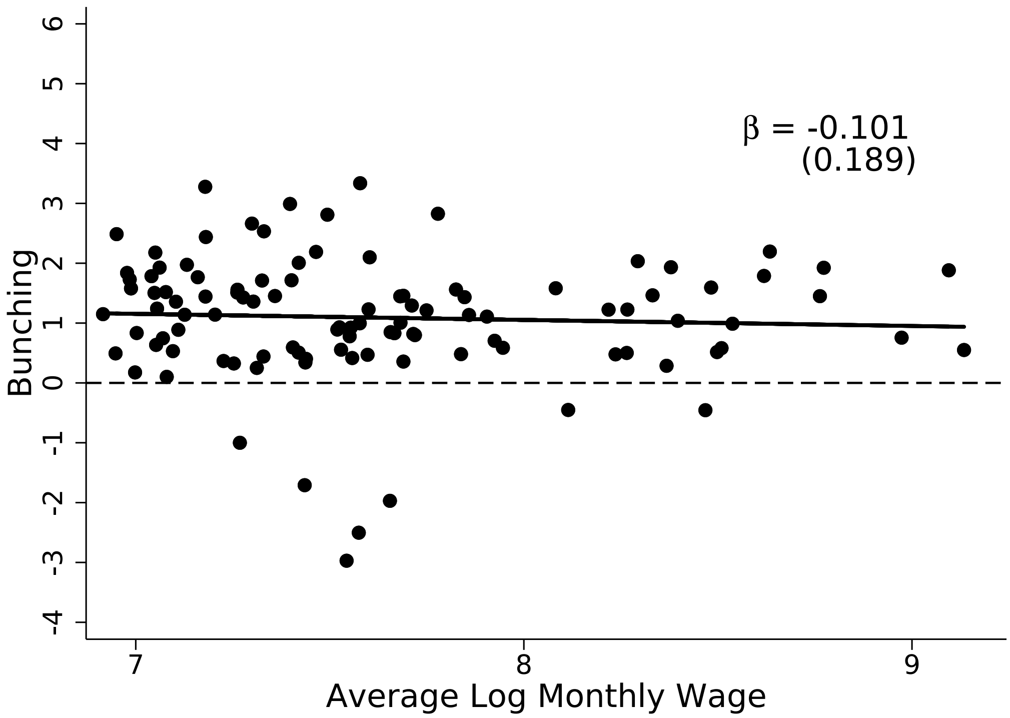


Note: This figure plots the layoff hazard rate. Tenure duration is binned into 15 day intervals. The dashed line is a tenth-degree polynomial fitted to the empirical hazard rate, excluding points 15 days away from the notch, as in Equation (1). The vertical dotted line displays the excess mass B, while the normalized excess mass b and standard error is reported in the figure. The standard error is computed using a residual bootstrap procedure.

Figure 2: Bunching and Demand Volatility

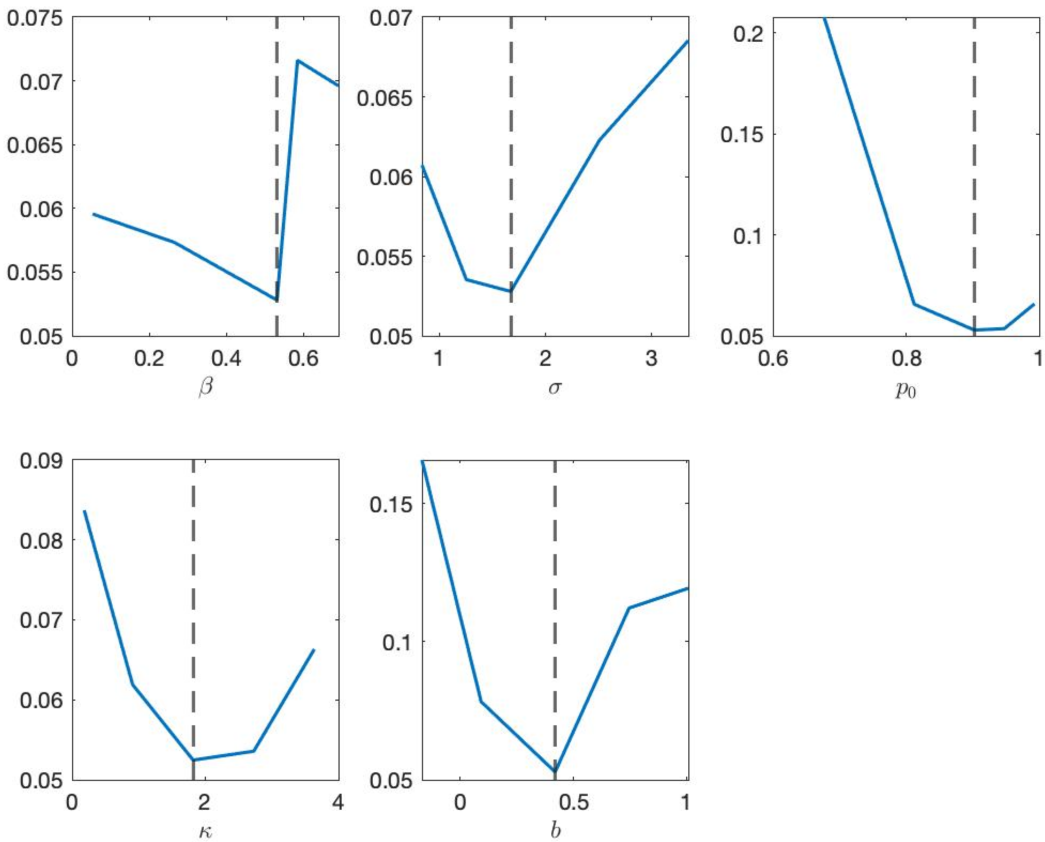
Note: This figure plots the bunching estimate by sector (defined by three-digit CNAE classification) and correlates the bunching to volatility in employment. The volatility is calculated as the standard deviation of month-to-month employment changes over the course of a year.

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



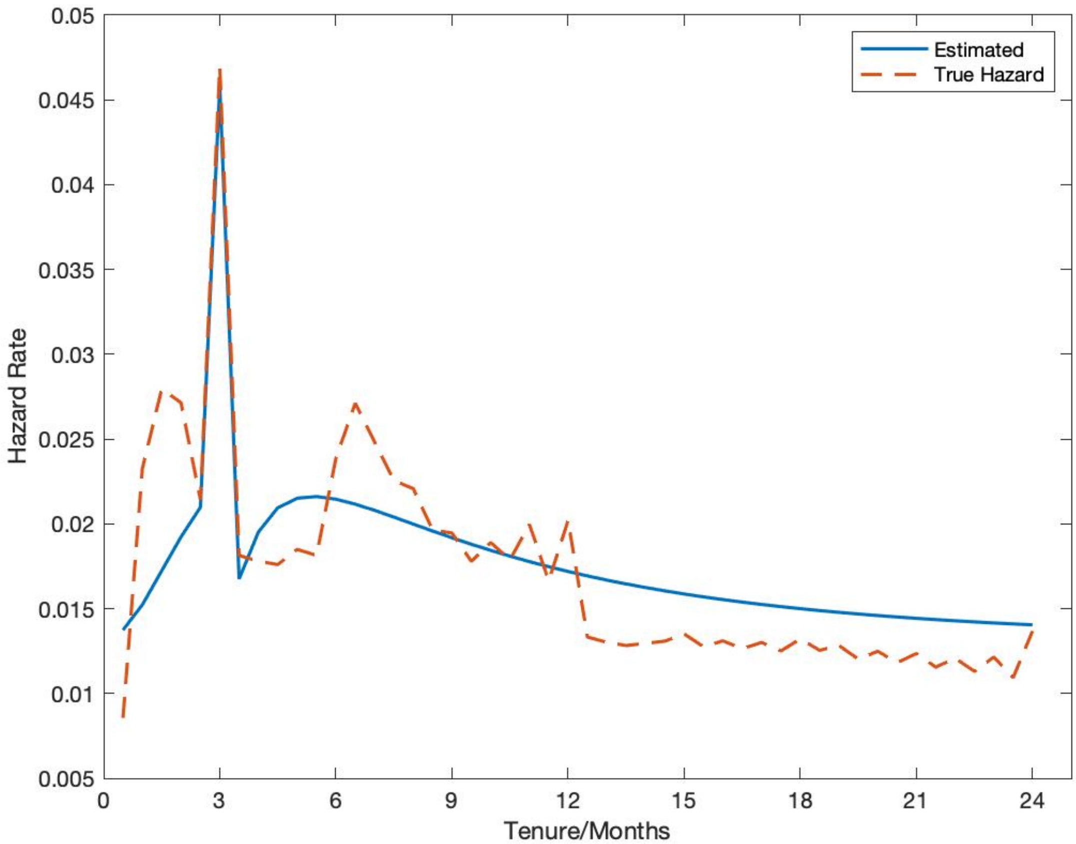
Note: This figure plots the bunching estimate by occupation (defined by three-digit ISCO identifier) and correlates the bunching to average wages. The coefficient displayed is the estimate of the coefficient of a regression of the bunching estimate on the variable on the x-axis.

Figure 4: Structural Model Identification



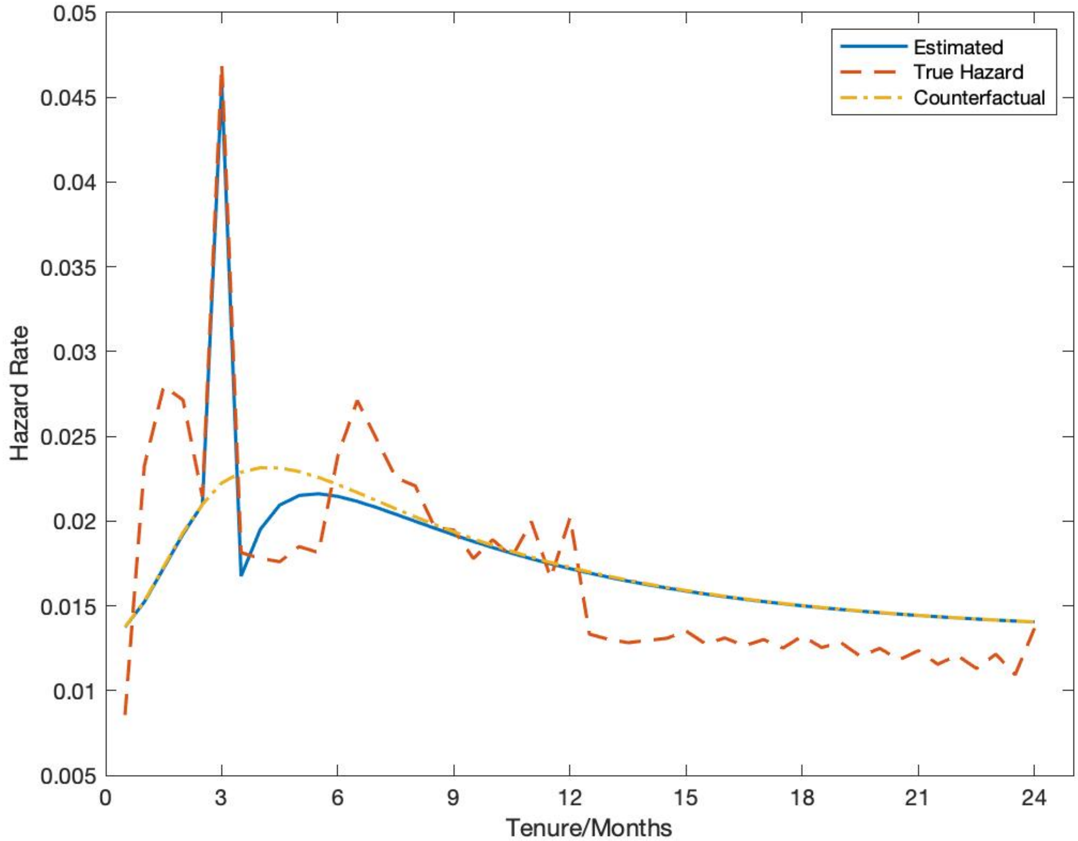
Note: This figure plots the minimized value of the estimation objective as we vary each parameter, holding all other parameters fixed at the estimated values. The black dashed line indicates the estimated parameter value.

Figure 5: Estimated and Empirical Hazard Rates



Note: This figure plots the empirical layoff hazard rate (dashed) as well as the hazard rate from the estimated model (solid). Tenure duration is binned into 15 day intervals to estimate the empirical layoff hazard.

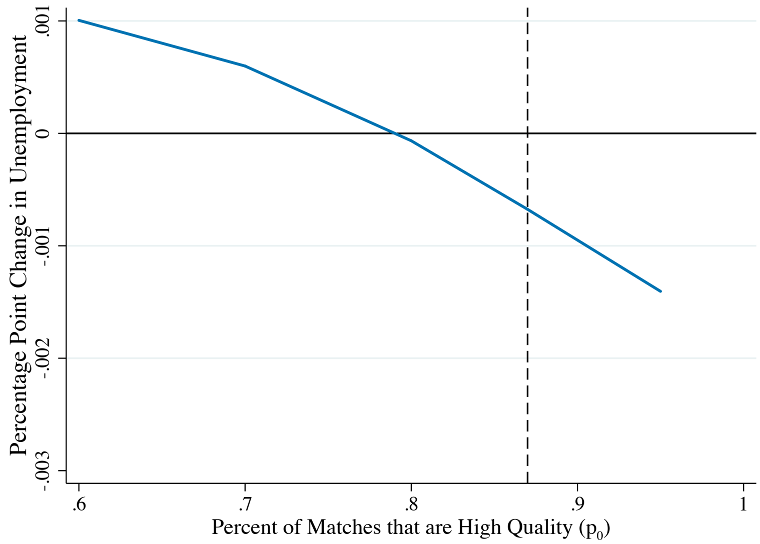
Figure 6: Estimated, Empirical, and Counterfactual Hazard Rates



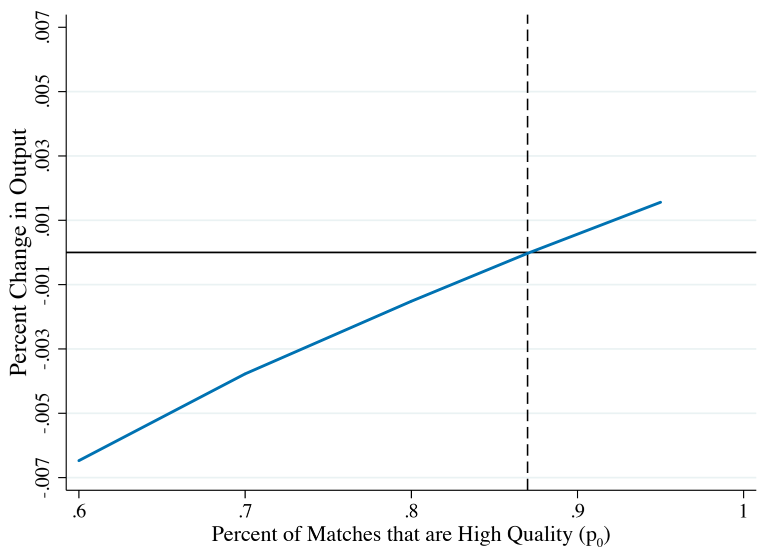
Note: This figure plots the empirical layoff hazard rate (dashed), the estimated hazard rate generated by the model (solid), and a counterfactual hazard rate (dotted) when $\kappa = 0$. Tenure duration is binned into 15 day intervals to estimate the empirical layoff hazard.

Figure 7: Changes in Macroeconomics Outcomes due to EPL for Different Values of Percent of High-Quality Matches (p_0)

Panel A: Percentage Point Change in Unemployment



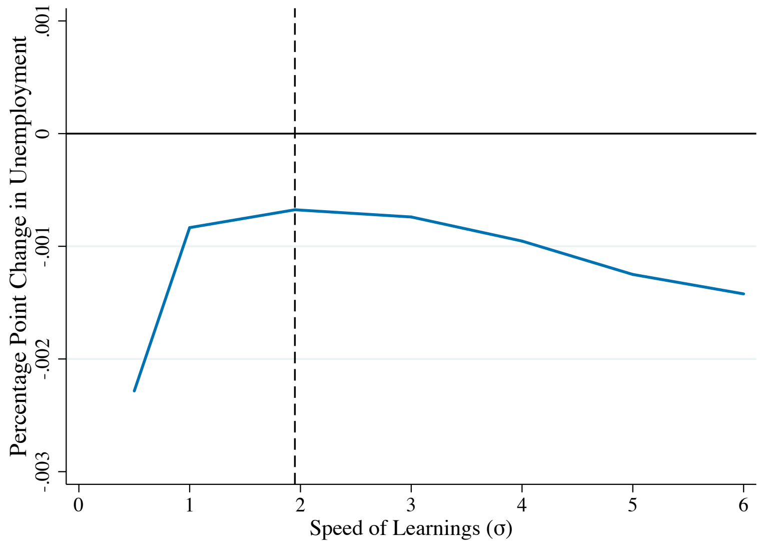
Panel B: Percent Change in Output



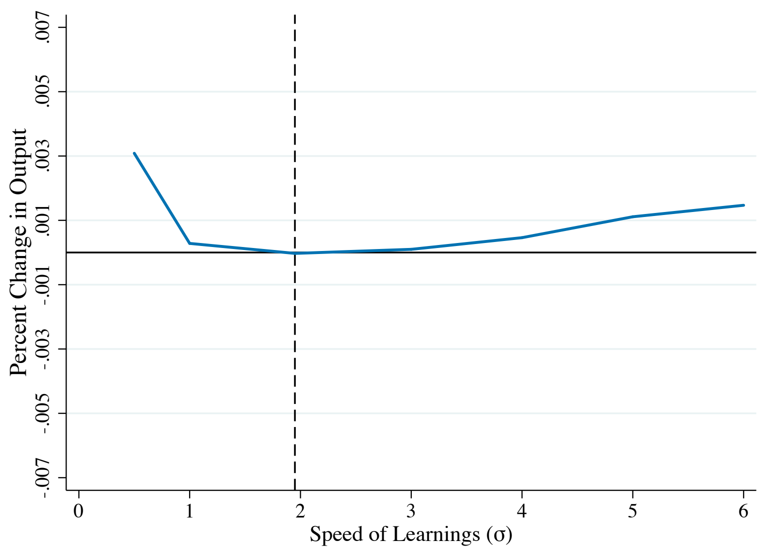
Note: This figure plots the percent point change in unemployment (Panel A) and the percent change in output (Panel B) that occurs from moving from an economy with no EPL to an economy with EPL that applies to all jobs that last at least three months over a range of values of p_0, which is the fraction of matches in the economy that are high-quality. The dashed line is the value of p_0 that we estimate from the structural model. All other parameters are set to the calibrated or estimated values that appear in Tables 2 and 3.

Figure 8: Changes in Macroeconomics Outcomes due to EPL for Different Values of Learning Speed (σ)

Panel A: Percentage Point Change in Unemployment

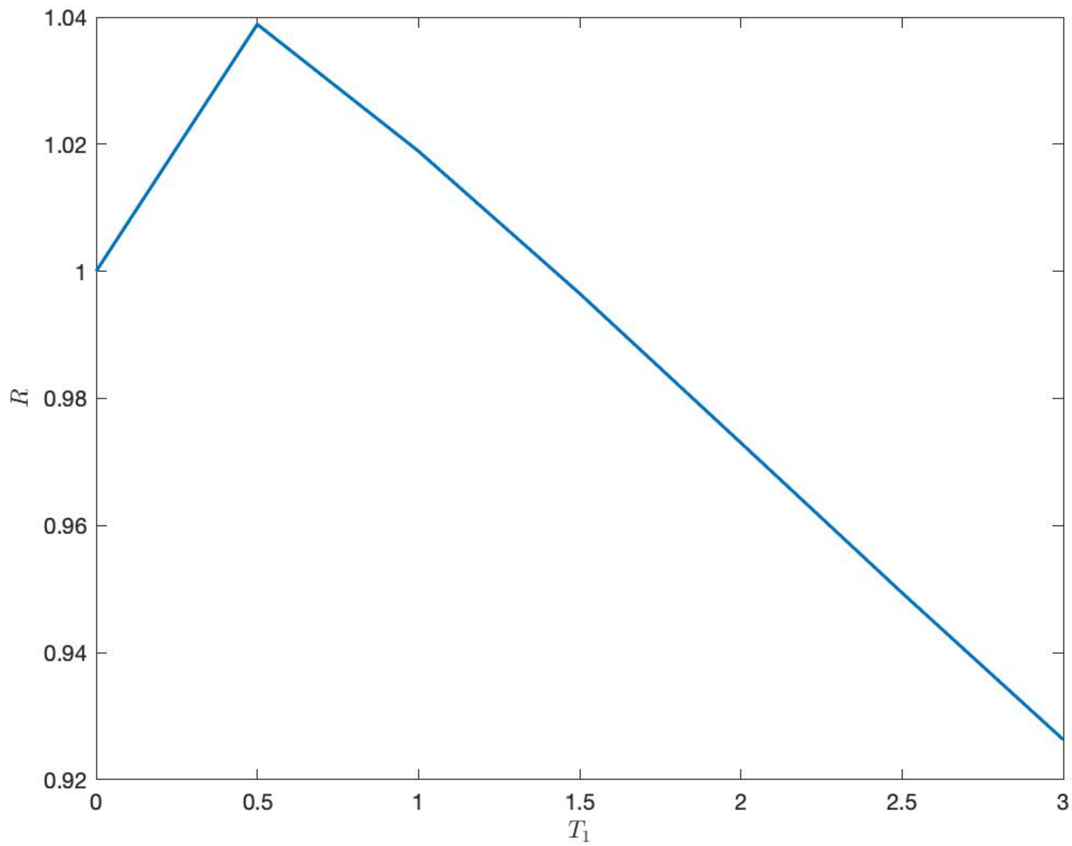


Panel B: Percent Change in Output



Note: This figure plots the percent point change in unemployment (Panel A) and the percent change in output (Panel B) that occurs from moving from an economy with no EPL to an economy with EPL that applies to all jobs that last at least three months over a range of values of σ, which governs the speed at which firms and workers learn about match quality. The dashed line is the value of σ that we estimate from the structural model. All other parameters are set to the calibrated or estimated values that appear in Tables 2 and 3.

Figure 9: Revenue from EPL as a function of the Length of the Probationary Period T_1

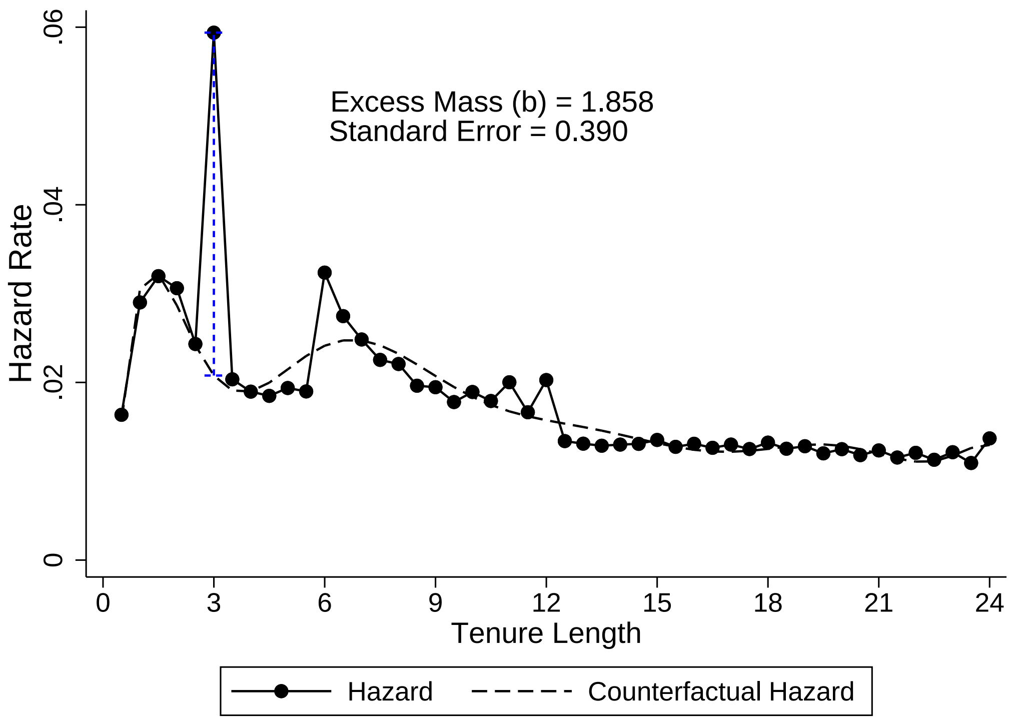


Note: This figure plots the revenue from EPL R as a function of the length of the probationary period, which is captured by T_1. The revenue at $T_1 = 0$ (i.e. no probationary period) is rescaled to unity.

Appendix: For Online Publication Only

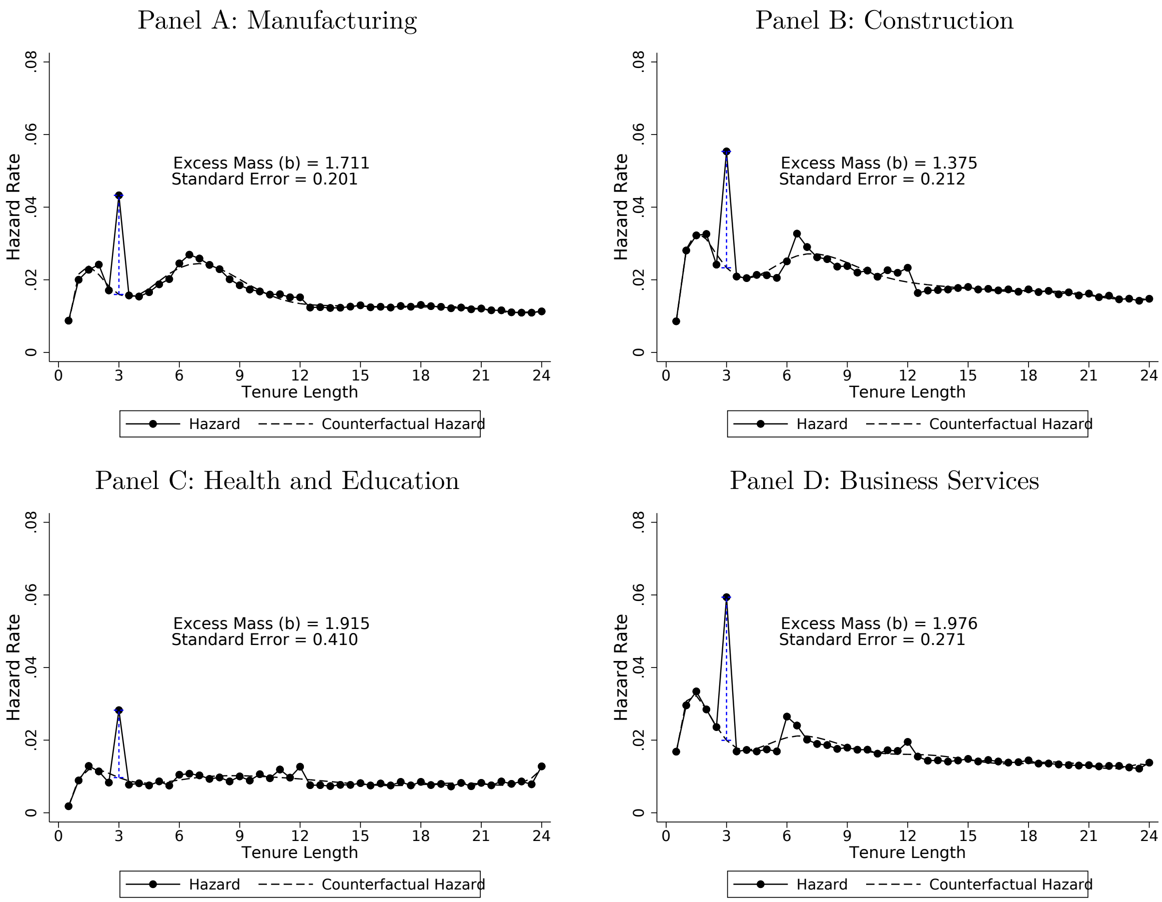
Appendix A: Figures and Tables

Appendix Figure A1: Bunching Including Temporary Contracts



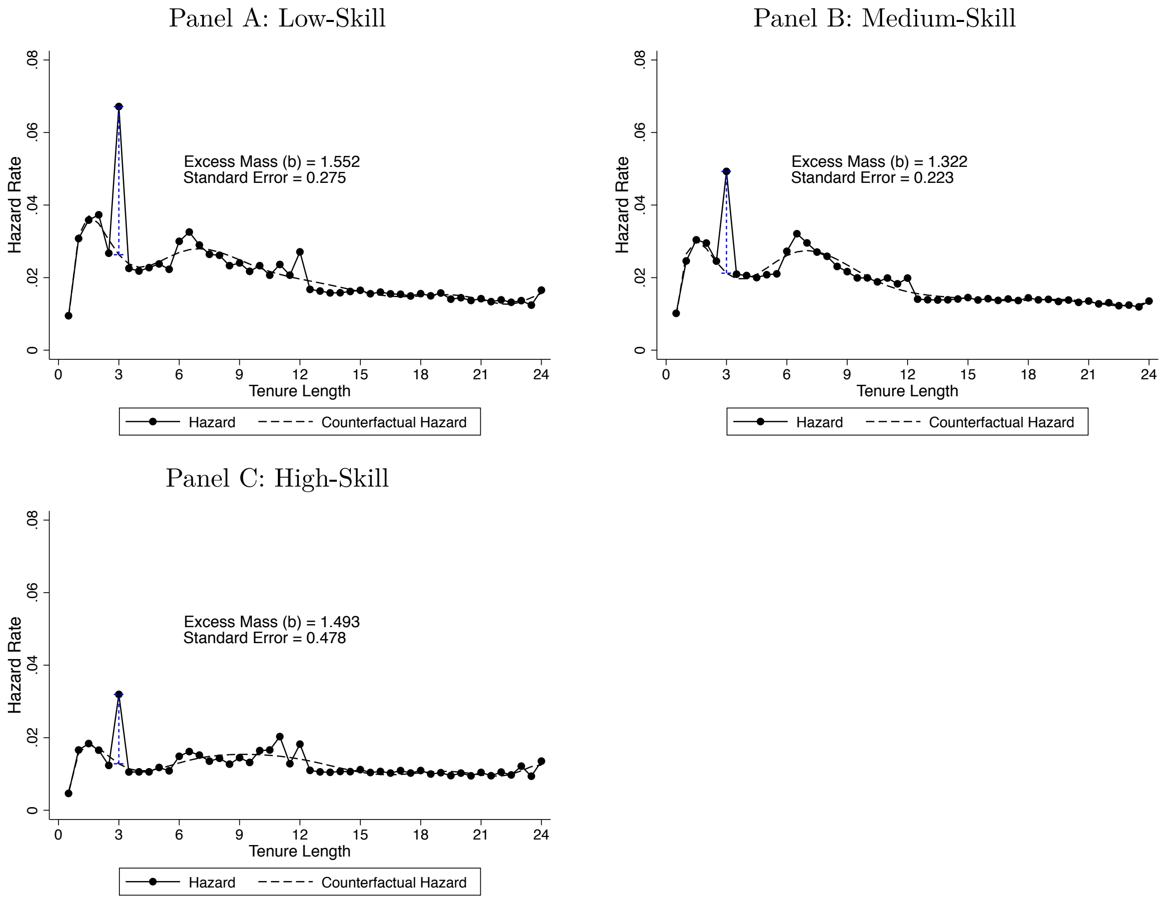
Note: This figure plots the job termination hazard rate which includes temporary contracts.

Appendix Figure A2: Heterogeneity in Bunching by Industry



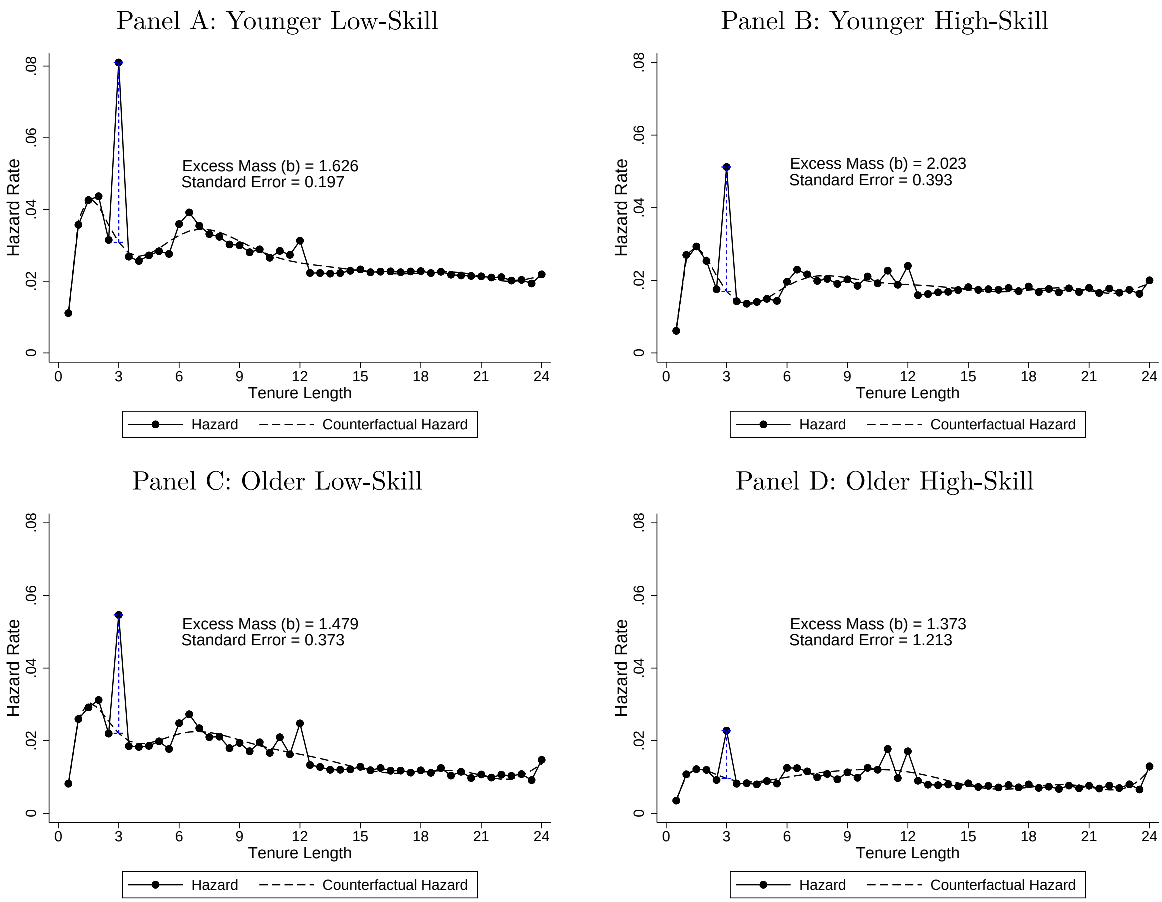
Note: This figure plots the layoff hazard rate by different industries. Tenure duration is binned into 15 day intervals. The dashed line is a tenth-degree polynomial fitted to the empirical hazard rate, excluding points 15 days away from the notch, as in Equation (1). The vertical dotted line displays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

Appendix Figure A3: Heterogeneity in Bunching by Occupation and 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 vertical dotted line displays the excess mass B, while the normalized excess mass b and standard error is reported in the figure. The standard error is computed using a residual bootstrap procedure.

Appendix Figure A4: Relationship between Bunching and Age



Note: This figure plots the layoff hazard rate by different occupation skill levels and age. Skill level is defined by the International Standard Classification of Occupations (ISCO). Younger workers are individuals who are between 20 and 25 years of age at the beginning of the employment spell. Older workers are individuals who are between 40 and 45 years of age at the beginning of the employment spell. 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 vertical dotted line displays the excess mass B, while the normalized excess mass b and standard error is reported in the figure. The standard error is computed using a residual bootstrap procedure.

Appendix B: Numerical Implementation

A. Algorithm to solve the model

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 $\underline{p}^i$

After substituting the wage into the firm value functions, we essentially have to solve for 2 HJB equations together with the optimal belief threshold functions. To do this, we use a finite-difference approximation to the HJB equation, and exploit the fact that the optimal stopping problem characterizing the thresholds can be solved as a linear complementarity problem (Huang and Pang (2003)). Specifically, we start by solving for J^2 and $\underline{p}^2$ for $t \geq T_1$ since these objects are stationary. Given these objects, we can then work backwards to solve for J^1 and $\underline{p}^1$.

A.2 Solving for f^i

Given the thresholds and a guess of the unemployment rate, we can use a similar finite-difference approximation to solve the KFE forward in time, using the appropriate initial and boundary conditions, to get f^1, and f^2. Using these distributions to compute an implied unemployment rate then yields a simple iterative scheme to find the equilibrium unemployment rate.

Given these objects, all other equilibrium objects can be computed using the relationships stated in the theoretical exposition.

B. Estimation Algorithm

In order to estimate the model, we use a pattern search algorithm in MATLAB to minimize the objective function, using the algorithm stated above to find the model equilibrium and compute model moments for each candidate parameter vector Ξ. In order to check out estimated parameter vector attains the global minimum, we fix a given parameter in Ξ, and use pattern search to minimize the estimation objective over the remaining parameters. Repeating this over a grid of values for the parameter in question, we then plot the objective as a function of the parameter to confirm that it is minimized globally at the parameter estimate.

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.