The effects of firing costs on labor market dynamics

Armando Näf*, Yannic Stucki** and Jacqueline Thomet***

*University of Bern **Swiss National Bank ***Swiss National Bank

July 14, 2020

Abstract

We examine the role of employment protection legislation (EPL) on labor market dynamics in a search and matching model with costly firing. To guide our modeling approach, we establish three empirical regularities. First, average job destruction flows are much larger than average net reductions in employment. Second, stronger EPL is associated with a larger relative variability of job creation vs job destruction flows. Third, stronger EPL is associated with a weaker Beveridge curve relation measured as the negative correlation between vacancies and unemployment. We then use our model to examine the role of job destruction flows for the assessment of the firing costs' impact on labor market dynamics. We find that considering only net reductions in employment instead of job destruction flows biases the quantitative evaluation. The impact of firing costs on the labor market is an order of magnitude smaller when only net reductions in employment are costly. In addition, the distortionary impact of firing costs on labor market dynamics is underestimated. Firms opt to adjust labor input more strongly along the job creation and the intensive margin (hours worked per worker) when firing costs apply to job destruction flows.

JEL class: E32, F44, J22

Keywords: Search and matching, firing costs, employment protection legislation, job destruction, labor supply margins.

DISCLAIMER

The views, opinions, findings, and conclusions or recommendations expressed in this paper are strictly those of the authors. They do not necessarily reflect the views of the Swiss National Bank (SNB). The SNB takes no responsibility for any errors or omissions in, or for the correctness of, the information contained in this paper.

INTRODUCTION

There is a large literature on the role of employment protection legislation (EPL) for labor market outcomes, including the seminal contributions of Garibaldi (1998), Hamermesh (1996), Hopenhayn and Rogerson (1993), Nickell (1986), Oi (1962), Pries and Rogerson (2005), and Veracierto (2008). Most of this literature has studied the role of EPL in the long-run. In this paper, we seek to shed more light on the influence of EPL on labor market dynamics over the business cycle.

A few papers have studied the role of EPL for labour market dynamics over the business cycle frequencies (see e.g. Veracierto (2008), Llosa, Ohanian, Raffo, and Rogerson (2014), Wesselbaum (2016)). A shortcoming of these contributions is that they remain vastly silent about the interplay between EPL and job creation and destruction flows. For instance Llosa et al. (2014) even abstract from such flows and consider only net changes in employment for their analysis of EPL. In contrast to these papers, we are particularly interested in the role of job creation and destruction flows for the assessment of EPL.

There are reasons to believe that taking these flows into account matters for the assessment of EPL. For instance, whether firing cost apply to net changes in employment (as in Llosa et al. (2014)) or to the total amount of fired workers can be quantitatively very important. Net employment changes and firing flows may be very different in size. Also, firms may opt to adjust employment more strongly along the hiring margin when firing workers becomes more costly. Hence, to adequately capture the distortionary effects of firing costs, job creation and destruction flows should be considered.

In our empirical part, we provide evidence that these considerations are quantitatively important. First, we document that firing flows are between 5 to 40 times larger than the average net reduction in employment. This finding is based on the recently-constructed 6th vintage of the CompNet data set and the business dynamics database of the US census bureau. Second, based on the same data set, we find that countries with higher EPL – measured by the OECD indicator for protection against dismissals – tend to have higher relative variability of the hiring versus the firing margin. Additionally, we document further empirical regularities between EPL and labor market dynamics to guide our modeling approach. More specifically, using the data set of Amaral and Tasci (2016), we find that EPL is associated with a weaker negative correlation between vacancies and unemployment. In other words, EPL is associated with a weaker Beveridge curve relation. A further empirical regularity that guides our modeling approach is the positive association between EPL and the relative variability of the intensive vs. extensive margin of labor (hours worked per worker vs. employment). This empirical regularity has been established by Llosa et al. (2014).

Our quantitative analysis is based on a search and matching model in the spirit of Mortensen and Pissarides (1994). To incorporate EPL in the model, we assume firing workers is subject to firing costs. The firing costs take the form of a wasteful tax – wasteful in the sense that the tax is paid by the employer to a third party, like procedural costs. Following Yashiv (2000a, 2000b, 2006) and Merz and Yashiv (2007), the model exhibits a convex hiring cost function. Further, to accommodate the criticism of Llosa et al. (2014), it exhibits explicitly an intensive and extensive margin of labor supply. We show that the model is able to replicate the most salient features of US labor market data. Further, the model is able to explain the documented stylized facts about the relation between EPL and labor market dynamics. That is, an increase in firing cost can explain the bulk of (i) the observed positive association between EPL and the higher relative variability of hiring versus firing flows and (ii) the observed negative association between EPL and the strength of the Beveridge curve relation. Further, the model is also able to explain the positive relation between EPL and the relative variability of the intensive versus extensive margin of labor supply – a stylized fact reported in Llosa et al. (2014).

To analyze the role of a distinct job creation and destruction margin, we compare our model to an alternative version in which firing costs are similar as in Llosa et al. (2014). More specifically, we assume that firing costs apply only to net reductions in employment. Hence, in the alternative version, the size of job destruction flows does not (directly) matter for firing costs. Also, firing costs do not (directly) incentivize using the hiring margin more strongly. Thus, in this sense, the comparison between both models reveals the (direct) role of job creation and destruction flows for the assessment of EPL.

We find that considering explicitly job creation and destruction flows for the quantitative assessment of EPL matters. In particular, the impact of the same size of firing costs is an order of magnitude larger when firing costs apply to job destruction flows instead of net reductions in employment. The reason is that in our model, like in the US data, average net reductions in employment are about 30 times smaller in size than average job destruction flows. Hence, everything else equal, the same increase in firing costs imposes much smaller effective costs in the alternative version of the model. Besides this "size effect", also the impact of firing costs on the labor market dynamics is different. Even when we control for the size effect, two major differences between the two modeling approaches of EPL arise. First, in face of firing costs, firms opt to adjust employment even more heavily along the job creation margin in our baseline model compared to the alternative version. Second, firms opt to adjust labor input even more heavily along the intensive margin of labor in our baseline model when faced with firing costs. Thus, the distortionary effects of firing costs on labor market dynamics are underestimated if job destruction flows are disregarded in the analysis of EPL.

The remainder of this paper is organized as follows. Section I documents stylized facts regarding the relationship between the OECD indicator for protection against dismissal and labor market dynamics. Section II provides our model. Section III presents the calibration of our model and its fit with US labor market data and the stylized facts documented in Section I. Section IV explains the models mechanism that underlies this fit and and analyzes the role of explicitly considering job creation and destruction flows for the assessment of EPL. Section V shows how robust the results are for different model specifications and Section VI concludes.

I EMPIRICAL LABOUR MARKET OUTCOMES AND EPL

This chapter sets out the empirical foundation for our analysis of the impact of EPL. It documents cross-country differences in labor market outcomes and establishes empirical regularities between EPL and labor market dynamics on the basis of novel data sets. These empirical findings guide our modeling approach for the subsequent assessment of EPL. As measure of EPL, we use the OECD indicator for Protection Against Dismissal. The OECD indicator gives us a synthetic cardinal measure of various costs involved in firing workers across countries. It measures the protection of permanent workers against individual and collective dismissal.

I.I *Job creation, job destruction flows and net reductions in employment*

Our first empirical finding is that average job destruction flows are in general much larger than average net reductions in employment. Table 1 shows the average net reduction in employment as proportion of average job destruction flows for a set of 19 countries. The average net reduction in employment is computed as follows. First, we compute the average absolute size of employment changes over all periods in which employment is reduced. Then we weight this number by the relative frequency of reductions in employment. In our data set, average job destruction flows are between 5 (Italy) to 40 (Lithuania) times larger than the average net reduction in employment. In the US, job destruction flows are about 30 times the average size of net reductions in employment. This suggests that, when modeling EPL as firing costs, it matters quantitatively whether job destruction flows or net changes in employment are considered.

Table 1: *Average net reduction in employment as proportion of average job destruction flows*

Belgium	7.3%	Hungary	8.4%	Slovakia	13.8%
Croatia	12.8%	Italy	2.4%	Slovenia	17.9%
Czech Republic	13.5%	Lithuania	21.1%	Spain	17.4%
Denmark	16.9%	Netherlands	8.4%	Sweden	4.7%
Finland	10.8%	Poland	10.1%	US	3.3%
France	5.7%	Portugal	10.6%		
Germany	19.0%	Romania	15.4%		

Our second empirical finding is that stricter EPL is associated with a larger variability of job creation vs. job destruction flows. This finding is shown in Figure 1. The figure shows data on employment flows and EPL from 15 European Union (EU) countries and the US. The vertical axis represents the variance of the job creation rate (jcr) relative to the variance in the job destruction rate (jdr). The horizontal axis denotes the OECD indicator for Protection Against Dismissal. The black line represents the fitted line of an OLS regression performed in logarithms. The intuition behind this result is as follows. When firing becomes more costly, firms opt to adjust employment more strongly along the job creation instead along the job destruction margin.

[Insert Figure 1 here]

The data on employment flows of the EU countries stems from release 6 of the ECB CompNet database. The database consists of a set of harmonized indicators drawn from firm-level data of 18 EU countries. For the analysis shown in Figure 1 we drop Croatia, Lithuania and Romania from the sample because for these countries, the OECD does not publish an indicator for Protection Against Dismissal. The maximum time period covered ranges from 1999-2016, but varies across countries. We use always the full available time period for each country in our analysis. The main advantage of using the CompNet database for analysing employment flows is the comparability across countries. The data is harmonized along key concepts such as the definition of the job creation and destruction rate, the industry coverage, the target firms and the method of aggregating firm-level data. Also, while many data sets on employment flows cover only one or few sectors, the CompNet database covers firms in all sectors of the business economy with the exception of mining and agriculture, utilities and the financial sector.[1] Although our focus lies on fluctuations in the short- to medium-run, we do not use HP-filtered data in our analysis. The reason is that in a short sample, the HP filter is rather unreliable. Nevertheless, to avoid that an underlying long-term trend drives the results, we focus on job creation and destruction *rates* and the employment growth *rate*.

The US data is based on the Business Dynamics Statistics of the US Census Bureau. This statistic is compiled from establishment-level data of the private non-agricultural sector of the economy. The data coverage starts in 1977. However, for better comparability, we only consider the 1999 to 2016 sample. Further information about the data can be found on the US Census Bureau's website. The measurement method of the US employment flows is not fully consistent with the CompNet data. Nevertheless we include US data into our analysis because the US economy is often taken as a benchmark. The qualitative results of our empirical analysis remain unchanged when we exclude the US.

I.II *The Beveridge curve: Correlation between vacancies and unemployment*

A further empirical finding we establish is that the stricter EPL is, the weaker is the negative correlation between vacancies and unemployment. Figure 2 shows this finding. In the figure, the correlation between vacancies and unemployment of 16 OECD countries is plotted against the OECD indicator for Protection Against Dismissal. The black line shows the OLS fitted line based on an OLS regression in levels. The specification in levels provides a better fit than the specification in logarithms. It shows the positive association of EPL with the correlation between vacancies and unemployment. The intuition behind this result is as follows. Consider an economy that has no legal firing restrictions and faces an increase in, say, aggregate demand. In response to this increase, firms seek to raise employment by posting more vacancies and by firing less workers. This behavior leads to lower unemployment and, hence, gives rise to the negative correlation between vacancies and unemployment. In general, the reduction in dismissals affects unemployment measures more directly than an increase in open vacancies because it takes time until an open vacancy is filled. As our first empirical regularity suggest, firms opt to adjust employment more strongly along the hiring margin when firing becomes more costly. Hence, higher firing costs reduces the *contemporaneous* correlation between vacancies and unemployment as unemployment responds more sluggishly to changes in hiring.

[Insert Figure 2 here]

The data set we use stems from Amaral and Tasci (2016). They gather data on vacancies and unemployment for a sample of 16 OECD countries. The data set covers, for most countries, at least the periods between 1980 and 2011. In our analysis, we use the full sample available for each country. However, our results also hold in the balanced data set that ranges from 1999Q4 to 2005Q1. The main advantage of using their data set is that they adjust the time series carefully to take into account structural breaks and missing data. Also, they use data on unemployment that is comparable across countries because it is based on the ILO definition. However, a limitation that also the data set of Amaral and Tasci (2016) is subject to is the comparability of the vacancy data across countries. Unlike for unemployment, there are no harmonized reporting schemes for vacancy data. Hence, also in their data set the definition, scope and reference period of the vacancy data may differ across countries. What mitigates the comparability issue is that we use the HP-filter to detrend the data in our analysis. As Amaral and Tasci (2016) emphasize, using the HP-filter gets rid of all the data collecting differences that manifest themselves at low frequencies.

I.III *Intensive and extensive margin of labor*

An additional empirical regularity, with which we guide our modeling approach, is the following. Stricter EPL is associated with larger relative fluctuations of the intensive vs. the extensive margin of labor (hours worked per worker vs. employment). This regularity has already been documented by Llosa et al. (2014). It is shown in Figure 3. The vertical axis denotes the relative standard deviation of the intensive margin vs. the extensive margin of labor. The horizontal axis shows the OECD indicator for Protection Against Dismissal. The black line shows the OLS fitted line based on an OLS regression in logarithms. It shows the positive association of EPL with the relative variability of the intensive vs. extensive margin of labor. This finding is quite intuitive. When firing becomes more costly, firms opt to adjust labor more strongly along the intensive margin of the labor input.

[Insert Figure 3 here]

Figure 6 is based on the data set of Ohanian and Raffo (2012), as in Llosa et al. (2014). Ohanian and Raffo (2012) construct a quarterly data set for hours worked per worker and total hours worked for 14 OECD countries. Their sample covers for most countries at least 50 years of data. In our analysis, we use the full sample available for each country and we detrend the variables using the HP-filter.

II FRAMEWORK

In this section, we introduce our baseline model, which allows us to quantitatively assess the impact of EPL. We consider a variant of the standard neoclassical growth model with labor market frictions in the spirit of Mortensen and Pissarides (1994), endogenous separation between workers and firms, and distinct intensive and extensive labor margin decisions. The search and matching framework of Mortensen and Pissarides (1994) allows us to quantify the importance of job creation and destruction flows in the analysis of EPL – a main objective of our paper. We consider an endogenous separation choice in order to implement EPL in a sensible way. The inclusion of distinct intensive and extensive margin decision allows us to address the critique of Llosa et al. (2014).

The economy is inhabited by a continuum of infinitely lived identical households and a continuum of firms. Households choose the time path of consumption to maximize lifetime utility. Firms choose the workforce sequence to maximize profits, subject to employment adjustment costs. Endogenous separation between employed household members (workers) and firms arises because of job-specific productivity shocks.

Households. Following Merz (1995) and Andolfatto (1996), each household consists of a continuum of family members of measure one. Income and risk is shared equally across the household. The household's lifetime utility $\mathcal{U}$ is:

$$\mathcal{U} = \mathbb{E}_0 \left\{ \sum_{t=0}^{\infty} \exp(d_t) \beta^t \left(\frac{c_t^{1-\sigma}}{1-\sigma} - \xi_h n_t \int_{\tilde{a}_t}^{\infty} \frac{h_t(a)^{1+\nu}}{1+\nu} \frac{g(a)}{1-G(\tilde{a}_t)} da - \xi_n n_t \right) \right\}, \qquad \text{(II.1)}$$

where c_t denotes average consumption per household member, n_t denotes the fraction of members that are employed, and $h_t(a)$ denotes the intensive margin, namely the number of hours worked for a worker with job-specific productivity level a. a is drawn from a time-invariant distribution with CDF $G(a)$ and density $g(a)$. Further, $\beta \in (0,1)$ denotes the deterministic discount factor, d_t denotes the stochastic discount factor, σ denotes the inverse elasticity of intertemporal substitution, ξ_h and ξ_n are preference shift factors, and ν determines the elasticity of labor supply at the intensive margin, respectively. We use $\tilde{a}_t$ to denote the threshold level of productivity below which firms and workers separate, which we will derive and discuss in more detail later in this section. With this definition of $\tilde{a}_t$, $1 - G(\tilde{a}_t)$ denotes the fraction of job-worker pairs that engage in production (*i.e.* the matches that remain productive), while $G(\tilde{a}_t)$ denotes the separation rate. We assume that each worker incurs convex disutility of hours worked of the form $\xi_h \frac{h(a)^{1+\nu}}{1+\nu}$. Unemployed household members work zero hours. Based on this assumption, it follows that the average disutility of hours worked *per household member* is $\xi_h n_t \int_{\tilde{a}_t}^{\infty} \frac{h_t(a)^{1+\nu}}{1+\nu} \frac{g(a)}{1-G(\tilde{a}_t)} da$. The last term in the per period utility function reflects fixed employment costs.

Households choose consumption c_t and bond holdings b_t to maximize their lifetime utility $\mathcal{U}$ subject to the period-by-period budget constraint:

$$c_t + b_t \leq R_{t-1} b_{t-1} + n_t \int_{\tilde{a}_t}^{\infty} w_t(a) h_t(a) \frac{g(a)}{1 - G(\tilde{a}_t)} da + t_t \tag{II.2}$$

where R_t is a riskless gross interest rate, the integral denotes the average labor income per worker, and $w_t(a)$ denotes the hourly wage of a worker with skill a. The last term t_t are transfers of firms profits. Optimal consumption and savings behavior of households yields the consumption Euler equation:

$$c_t^{-\sigma} = \beta R_t \mathbb{E}_t \left[\frac{\exp(d_{t+1})}{\exp(d_t)} c_{t+1}^{-\sigma} \right]. \tag{II.3}$$

All labor market decisions are part of the bargaining decision with firms, which are discussed later on.

Firms and the labour market. Firms use labor services as the only input to produce a homogeneous good. Within each firm, there is a continuum of jobs. To accommodate endogenous separation, we follow Mortensen and Pissarides (1994) and allow for heterogeneity in the productivity across jobs. In particular, every period, each job is hit by a job-specific productivity shock a. In addition, all firms are hit by a stationary aggregate productivity shock Z_t. Aggregate production then writes:

$$y_t = n_t \int_{\tilde{a}_t}^{\infty} Z_t h_t(a) a \frac{g(a)}{1 - G(\tilde{a}_t)} da. \tag{II.4}$$

The integral denotes the average product per worker that engages in production. Each worker with job-specific productivity $a > \tilde{a}_t$ contributes $Z_t h_t(a) a$ to overall production. Workers with $a < \tilde{a}_t$ are separated before production takes place, even if the match is new.

Job creation is subject to matching frictions and depends on aggregate labor market conditions and the hiring effort of firms. The aggregate flow of new matches in period $t-1$ is given by the matching function $m(u_{t-1}, v_{t-1}) = B u_{t-1}^{\mu} v_{t-1}^{1-\mu}$, where B is the matching efficiency, $u_{t-1} = (1 - n_{t-1})$ is the number of unemployed household members, and v_{t-1} is the number of vacancies. New matches in period $t-1$ enter the workforce of a firm in the beginning of period t, *before* production takes place and *before* the job-specific productivity shock a realizes. The probability that a vacancy is filled is given by $q(\theta_t) = \frac{m(u_t, v_t)}{v_t} = B\theta_t^{-\mu}$, where $\theta_t \equiv \frac{v_t}{u_t}$ denotes the labor market tightness. The aggregate law of motion of employment is given by:

$$n_t = (1 - jdr_t)(n_{t-1} + m_{t-1}), \tag{II.5}$$

where we use $jdr_t = G(\tilde{a}_t)$ to denote the endogenous job destruction rate (as all job-worker pairs with a draw $a < \tilde{a}_t$ are separated, irrespective of whether they are existing matches n_{t-1} or new matches m_{t-1}). The job creation rate jcr_t is defined as the fraction of new workers in the workforce in the beginning of period t: $jcr_t = m_{t-1}/(n_{t-1} + m_{t-1})$.

Firms can influence the workforce through two margins, either via vacancy posting or firing. The firm's optimization problem is to choose vacancies v_t, employment n_t and the threshold productivity level $\tilde{a}_t$ to maximize the current market value of profits $\mathcal{P}$ subject to the law of motion of employment (II.5) and taking wages and the probability of filling a vacancy as given. Profits are composed of production net of wage payments $n_t \int_{\tilde{a}_t}^{\infty} w_t(a) h_t(a) \frac{g(a)}{1-jdr_t}$, hiring costs $\psi\Gamma_t$, and the payment of a fixed cost F per firing:

$$\mathcal{P} = \mathbb{E}_0 \left\{ \sum_{t=0}^{\infty} \exp(d_t)\beta^t \lambda_t \left[y_t - n_t \int_{\tilde{a}_t}^{\infty} w_t(a)h_t(a)\frac{g(a)}{1-jdr_t}da - \psi\Gamma_t - \frac{jdr_t n_t}{1-jdr_t}F \right] \right\}. \tag{II.6}$$

The hiring cost function is in the spirit of Yashiv (2000a) and takes the following form

$$\psi\Gamma_t = \psi \frac{(\phi v_t + (1-\phi)m_t)^2}{2}\bar{y}_t. \tag{II.7}$$

Total hiring costs $\psi\Gamma_t$ are a quadratic function of a weighted average of the number of vacancies and new matches, where ϕ is the relative weight given to vacancies. The costs are measured in terms of aggregate output $\bar{y}_t$, which the firm takes as given. In the work by Yashiv (2000a, 2000b, 2006) and Merz and Yashiv (2007) they suggest that a convex hiring cost function like the one in (II.7) offers a better fit in capturing costs such as the advertising of vacancies, the screening of candidates, or the training of new workers. For the expression of profits $\mathcal{P}$, we use (II.5) to rewrite the amount of firings $f_t = jdr_t(n_{t-1} + m_{t-1})$ to $\frac{jdr_t n_t}{1-jdr_t}$. We assume firing costs F are wasteful, in the sense that they are not redistributed. The firing costs also apply to separations from new matches. In section V.II we solve an alternative model, where new matches can be dismissed at no cost.

The first-order conditions of the firm problem are:

$$\delta n_t: \ \tau_t = \frac{y_t}{n_t} - \int_{\tilde{a}_t}^{\infty} w_t(a)h_t(a)\frac{g(a)}{1-jdr_t}da - \frac{jdr_t}{1-jdr_t}F + \beta\,\mathbb{E}\left\{ \tau_{t+1}\frac{\exp(-d_{t+1})}{\exp(-d_t)}\frac{\lambda_{t+1}}{\lambda_t}(1-jdr_{t+1}) \right\} \tag{II.8}$$

$$\delta v_t: \ \frac{\psi\Gamma'_{t,v}}{q(\theta_t)} = \beta\,\mathbb{E}\left\{ \frac{\exp(-d_{t+1})}{\exp(-d_t)}\frac{\lambda_{t+1}}{\lambda_t}(1-jdr_{t+1})\tau_{t+1} \right\} \tag{II.9}$$

$$\delta \tilde{a}_t: \ \tau_t = \frac{y_t}{n_t} - Z_t h_t(\tilde{a}_t)\tilde{a}_t - \int_{\tilde{a}_t}^{\infty} w_t(a)h_t(a)\frac{g(a)}{1-jdr_t}da + w_t(\tilde{a}_t)h_t(\tilde{a}_t) - \frac{1}{1-jdr_t}F \tag{II.10}$$

where τ_t denotes the marginal value of employment (it is the Lagrange multiplier on the law of motion of employment) and $\Gamma'_{t,v}$ is a short notation for $\frac{\partial\Gamma_t}{\partial v_t}$. Combining equations (II.8) and (II.9) yields the job creation condition:

$$\frac{\psi\Gamma'_{t,v}}{q(\theta_t)} = \beta\,\mathbb{E}\left\{\frac{\exp(-d_{t+1})}{\exp(-d_t)}\frac{\lambda_{t+1}}{\lambda_t}\left[(1-jdr_{t+1})\left(\frac{y_{t+1}}{n_{t+1}} - \int_{\tilde{a}_{t+1}}^{\infty} w_{t+1}(a)h_{t+1}(a)\frac{g(a)}{1-jdr_{t+1}}da + \frac{\psi\Gamma'_{t+1,v}}{q(\theta_{t+1})}\right) - jdr_{t+1}F\right]\right\} \tag{II.11}$$

Condition (II.11) states that in equilibrium, the cost of filling a vacancy (left-hand-side) must equal the expected return on a vacancy (right-hand-side). With probability $1 - jdr_{t+1}$, the firm does not separate from the worker – then the return is the additional production plus the continuation value of the filled vacancy, net of wage payments. With probability jdr_{t+1} firm and worker separate, and the firm pays the firing cost F. The higher firing costs, the lower are the incentives to post a vacancy, as firms take into account that firing will later be costly.

Combining conditions (II.8)–(II.10) implicitly defines the optimal productivity threshold $\tilde{a}_t$:

$$w_t(\tilde{a}_t)h_t(\tilde{a}_t) = Z_t h_t(\tilde{a}_t)\tilde{a}_t + \frac{\psi\Gamma'_{t,v}}{q(\theta_t)} + F. \tag{II.12}$$

Equation (II.12) states that in equilibrium, the benefits of firing the marginal worker (*i.e.* the worker with job-specific productivity $\tilde{a}_t$) must equal its costs. The benefits correspond to saved wage payments $w_t(\tilde{a}_t)h_t(\tilde{a}_t)$. The costs are composed of lost production, the value of posting a new vacancy (which equals the missed out expected return of a filled vacancy, see (II.11)), and the payment of the firing cost F.

Wage and hours bargaining. Each firm-worker match generates a rent $\mathcal{S}_t(a)$, which is split in individual Nash bargaining. In every period firms and workers bargain over the hourly wage payment $w_t(a)$ and hours worked $h_t(a)$ by solving:

$$[w_t(a), h_t(a)] = \text{argmax}\left(\mathcal{S}_t^W(a)\right)^{\zeta}\left(\mathcal{S}_t^F(a) + F\right)^{1-\zeta}, \tag{II.13}$$

where $\mathcal{S}_t^W$ denotes the worker's surplus, $\mathcal{S}_t^F$ is the firm's surplus, and $\zeta \in (0,1)$ denotes the worker's relative bargaining power. Importantly, the firing cost F has to be included in the bargaining problem. The firing cost weakens the position of the firm and hence reduces the firm's threat point. The total surplus of a match is defined as $\mathcal{S}_t(a) \equiv \mathcal{S}_t(a)^W + \mathcal{S}_t(a)^F + F$.

The worker's surplus $\mathcal{S}_t^W(a)$ corresponds to the difference between the household's asset value of being employed and unemployed, $\mathcal{S}_t^W(a) = \mathcal{E}_t(a) - \mathcal{U}_t$. The relevant objects write:

$$\begin{aligned}\mathcal{E}_t(a) =& w_t(a)h_t(a) - \frac{1}{\lambda_t}\left(\xi_h \frac{h_t(a)^{1+\nu}}{1+\nu} + \xi_n\right) + \beta\,\mathbb{E}_t\left\{\frac{\exp(-d_{t+1})}{\exp(-d_t)}\frac{\lambda_{t+1}}{\lambda_t}\dots\right.\\ &\left.\left((1-jdr_{t+1})\int_{\tilde{a}_{t+1}}^{\infty}\mathcal{E}_{t+1}(a)\frac{g(a)}{1-jdr_{t+1}}da + jdr_{t+1}\mathcal{U}_{t+1}\right)\right\},\end{aligned} \tag{II.14}$$

$$\begin{aligned}\mathcal{U}_t =& \beta\,\mathbb{E}_t\left\{\frac{\exp(-d_{t+1})}{\exp(-d_t)}\frac{\lambda_{t+1}}{\lambda t}\left[\theta_t q(\theta_t)\dots\right.\right.\\ &\left.\left.\left((1-jdr_{t+1})\int_{\tilde{a}_{t+1}}^{\infty}\mathcal{E}_{t+1}(a)\frac{g(a)}{1-jdr_{t+1}}da + jdr_{t+1}\mathcal{U}_{t+1}\right) + (1-\theta_t q(\theta_t))\mathcal{U}_{t+1}\right]\right\}.\end{aligned} \tag{II.15}$$

The value of being employed (II.14) depends on job-specific productivity and is composed of the wage payment, the disutility of work, and the probability-weighted continuation value of staying employed or becoming unemployed. The asset value of being unemployed in (II.15) is identical for all unemployed household members. It is given by the probability-weighted continuation value of remaining unemployed or finding a job. In particular, $1-\theta_t q(\theta_t)$ denotes the probability of remaining unemployed, and $\theta_t q(\theta_t)$ denotes the probability of being matched with a firm. In the latter case, we further need to distinguish two cases: With probability jdr_{t+1} the match is separated before production takes place, while with probability $1-jdr_{t+1}$ the match remains intact.

The firm surplus $\mathcal{S}_t^F(a)$ corresponds to the difference between the asset value of a filled job and a vacancy, $\mathcal{S}_t^F(a) \equiv \mathcal{J}_t(a) - \mathcal{V}_t$. The relevant objects write:

$$\begin{aligned}\mathcal{J}_t(a) =& Z_t h_t(a)a - w_t(a)h_t(a) + \beta\,\mathbb{E}_t\left\{\frac{\exp(-d_{t+1})}{\exp(-d_t)}\frac{\lambda_{t+1}}{\lambda_t}\dots\right.\\ &\left.\left((1-jdr_{t+1})\int_{\tilde{a}_{t+1}}^{\infty}\mathcal{J}_{t+1}(a)\frac{g(a)}{1-jdr_{t+1}}da + jdr_{t+1}(\mathcal{V}_{t+1}-F)\right)\right\},\end{aligned} \tag{II.16}$$

$$\begin{aligned}\mathcal{V}_t =& -\psi\Gamma'_{t,v} + \beta\,\mathbb{E}_t\left\{\frac{\exp(-d_{t+1})}{\exp(-d_t)}\frac{\lambda_{t+1}}{\lambda t}\left[q(\theta_t)\left((1-jdr_{t+1})\dots\right.\right.\right.\\ &\left.\left.\left.\int_{\tilde{a}_{t+1}}^{\infty}\mathcal{J}_{t+1}(a)\frac{g(a)}{1-jdr_{t+1}}da + jdr_{t+1}(\mathcal{V}_{t+1}-F)\right) + (1-q(\theta_t))\mathcal{V}_{t+1}\right]\right\}.\end{aligned} \tag{II.17}$$

The value of a job $\mathcal{J}_t(a)$ defined in (II.16) consists of the revenue, the wage payments, and the probability-weighted continuation value of either keeping a job or having a vacancy. With probability $1-jdr_{t+1}$, the job remains active, and with probability jdr_{t+1} it becomes a vacancy and firing costs have to be payed. The asset value of a vacancy $\mathcal{V}_t$ defined in (II.17) is depends on the cost of posting a vacancy and the probability-weighted continuation value of the filled or open vacancy. The vacancy remains unfilled with probability $1 - q(\theta_t)$ and becomes filled with probability $q(\theta_t)$. In the latter case, the match may immediately separate (probability jdr_{t+1}) at the cost F or remain active (probability $1 - jdr_{t+1}$). Importantly, since we assume perfect competition and free entry, the value of a vacancy $\mathcal{V}_t$ is zero in equilibrium.

To obtain optimal hours worked and wage, we can solve the Nash bargaining using equations (II.14)–(II.17). We obtain:

$$h_t(a) = \left(\frac{Z_t \lambda_t a}{\xi_h}\right)^{\frac{1}{\nu}}, \tag{II.18}$$

$$\begin{aligned} w_t(a)h_t(a) =& \frac{1-\zeta}{\lambda_t}\left(\xi_h \frac{h_t(a)^{1+\nu}}{1+\nu} + \xi_n\right) + \zeta\Bigg(\theta_t \psi \Gamma'_{t,v} + Z_t h_t(a) a \\ &+ \left(1 - (1 - \theta_t q(\theta_t))\beta\, \mathbb{E}_t \left\{\frac{\exp(-d_{t+1})}{\exp(-d_t)} \frac{\lambda_{t+1}}{\lambda_t}\right\}\right) F\Bigg). \end{aligned} \tag{II.19}$$

According to (II.18), the optimal hours decision increases with aggregate and job-specific productivity and the marginal value of a unit of wealth (captured by λ). Condition (II.19) states that the individual wage payment increases with higher hours worked, higher job-specific and aggregate productivity, tighter labor markets, and higher marginal hiring costs of posting an additional vacancy. Individual wage payments also increase with higher firing costs given $(1 - \theta_t q(\theta_t))\beta \mathbb{E}_t \left[\frac{\exp(-d_{t+1})}{\exp(-d_t)} \frac{\lambda_{t+1}}{\lambda_t}\right] < 1$, which is the case as long as consumption is relatively smooth.

Equations (II.18) and (II.19) are expressed in terms of job-specific productivity a. Weighting with the distribution of idiosyncratic productivity, we obtain the following expressions of average hours worked per worker $H_t(\tilde{a}_t)$ and average labor income per worker:

$$H_t(\tilde{a}_t) = \left(\frac{Z_t \lambda_t}{\xi_h}\right)^{\frac{1}{\nu}} \int_{\tilde{a}_t}^{\infty} a^{\frac{1}{\nu}} \frac{g(a)}{1 - jdr_t} da, \tag{II.20}$$

$$\begin{aligned} \int_{\tilde{a}_t}^{\infty} w_t(a)h_t(a) \frac{g(a)}{1 - jdr_t} da =& (1-\zeta)\frac{1}{\lambda_t}\left(\xi_h \int_{\tilde{a}_t}^{\infty} \frac{h_t(a)^{1+\nu}}{1+\nu} \frac{g(a)}{1 - jdr_t} da + \xi_n\right) \\ &+ \zeta\Bigg(\frac{y_t}{n_t} + \theta_t \psi \Gamma'_{t,v} \\ &+ \left(1 - (1 - \theta_t q(\theta_t))\beta \mathbb{E}_t \left[\frac{\exp(-d_{t+1})}{\exp(-d_t)} \frac{\lambda_{t+1}}{\lambda_t}\right]\right) F\Bigg). \end{aligned} \tag{II.21}$$

Combining equations (II.12), (II.18), and (II.19) delivers an explicit expression for the job destruction threshold:

$$\tilde{a}_t = \left(\frac{\frac{\xi_n}{\lambda_t} + \frac{\zeta}{1-\zeta}\theta_t \psi \Gamma'_{t,v} - \frac{1}{1-\zeta}\frac{\psi \Gamma'_{t,v}}{q(\theta_t)} - \left(1 + \frac{\zeta}{1-\zeta}(1-\theta_t q(\theta_t))\beta\, \mathbb{E}_t \left[\frac{\exp(-d_{t+1})}{\exp(-d_t)}\frac{\lambda_{t+1}}{\lambda_t}\right]\right) F}{Z_t^{\frac{1+\nu}{\nu}} \left(\frac{\lambda_t}{\xi_h}\right)^{\frac{1}{\nu}}} \right)^{\frac{\nu}{1+\nu}} \tag{II.22}$$

Condition (II.22) shows that firing costs reduce the productivity threshold $\tilde{a}_t$. The intuition for this result is clear: As firing becomes costly, firms become more reluctant to separate, and less productive jobs remain intact.

Equilibrium and model solution. In equilibrium, all markets clear. The aggregate resource constraint is given by:

$$y_t = c_t + \psi \Gamma_t + \frac{n_t jdr_t}{1 - jdr_t} F. \tag{II.23}$$

To close the model, we assume that a follows a log-normal distribution with standard deviation σ_a and mean $\mu_a = -\frac{\sigma^2}{2}$ ($\mathbb{E}[a] = 1$). The aggregate productivity shock Z_t and the stochastic discount factor shock d_t both follow an AR(1) process of the form $\ln(Z_t) = \rho_z \ln(Z_{t-1}) + \varepsilon_z,\ \varepsilon_z \sim N(0, \sigma_z^2)$ and $d_t = \rho_d d_{t-1} + \varepsilon_d,\ \varepsilon_d \sim N(0, \sigma_d^2)$. While the aggregate productivity shock process is standard in the literature, shocks on the discount factor are not considered as often. We consider discount factor shocks because of the recent contribution by Hall (2017). Hall (2017) argues that business cycle variation in financial discounts plays an important role for unemployment fluctuations. In particular, he observes that in the data, discount rates implicit in stock markets are strongly positively correlated with unemployment. This finding is in line with the standard Mortensen and Pissarides (1994) model: From the employer's perspective, an increase in the discount rate reduces the net present value of the benefit of hiring a new worker. In turn, the lower incentives to create jobs lead to an increase in unemployment.

Appendix Section A contains an overview of all conditions that characterize the equilibrium of this economy. To solve the model, we first log-linearize the general equilibrium equations around the non-stochastic steady state. We then apply standard techniques for solving linear rational expectation models.

III CALIBRATION AND FIT

We now turn to the model calibration and examine its empirical performance. In our calibration exercise, we use the US as a benchmark country and calibrate our model to capture the most salient features of the US business cycle. Then, we simulate our model for a range of firing costs that is meant to capture the different EPL frameworks across countries. With this simulations we compute the model implied relationship between EPL and labour market dynamics. We choose the range of firings costs such that our model is best able to replicate the empirical EPL relationships we documented in Section I.

III.I *Calibration and parametrization*

Table 2 summarizes the calibration and parametrization values for the theoretical model. The discount rate β matches an annual real rate of 4%. We set the constant relative risk aversion parameter to 0.5, which represents an intermediate value between (1) the risk neutrality assumption used for instance in Shimer (2005), Hall (2005), Hagedorn and Manovskii (2008), or Pissarides (2009), and (2) the logarithmic utility case considered in Merz (1995) or Andolfatto (1996). We set the hours disutility curvature parameter ν equal to 1. Because ν has potentially a strong impact on the labor market dynamics, we consider different parameterizations of ν in our robustness section V. Regarding the matching function, we set the matching elasticity μ to 0.4, in line with empirical estimates by Blanchard and Diamond (1989). The matching efficiency B implies a quarterly probability of filling a vacancy of 0.9, in line with Merz (1995) and Andolfatto (1996). The bargaining power of workers ζ is set to ensure the Hosios (1990) condition, *i.e.* $\zeta = \mu$. Following Sedlácek (2014), the variance of the job-specific productivity shock σ_a is 0.155. The hiring cost scale parameter ψ and preference shift parameters ξ_h and ξ_n are chosen to imply (1) a steady state separation rate of 0.1 in line with the evidence presented in Shimer (2005), (2) a steady state intensive margin of 0.33 in line with average hours worked from Ohanian and Raffo (2012), and (3) a steady state unemployment rate of 0.1. As in Krause and Lubik (2007), we choose an unemployment rate which is higher than in the data to allow for participants in the matching market that are not registered as unemployed. The persistence of the technology shock process ρ_z is estimated using linearly detrended data on utilization-adjusted total factor productivity (TFP), constructed as in Fernald (2014). We obtain $\rho_z = 0.95$. In line with Albertini and Poirier (2014), we assume $\rho_d = 0.75$.

We then calibrate σ_d relative to σ_z by minimizing the equally weighted distance between standard business cycle moments implied by the model and the data (namely, standard deviations of vacancies, unemployment, hours worked, employment and output, and the correlation between unemployment and vacancies)The weighting parameter for the hiring cost function ϕ is calibrated together with the standard deviations of the shock processes to minimize the difference between the aforementioned moments. Finally, in our benchmark calibration, we set the firing cost parameter $F = 0$ to replicate the low EPL in the US. In table 3 we show the results of the calibration and compare it to the US-data.

Table 2: *Model parameters*

Parameter	**Role**	**Value**
Preferences		
β	Discount rate	0.99
σ	CRRA	0.5
ν	Hours disutility curvature	1
ξ_h	Preference shift parameter	5.6012
ξ_n	Preference shift parameter	0.2543
Matching, bargaining, separation, hiring and firing costs		
B	Matching efficiency	0.94
μ	Match elasticity	0.40
ζ	Bargaining power	0.40
σ_a	Standard deviation a	0.155
ψ	Hiring cost scale parameter	1.0587
ϕ	Hiring cost weighting parameter	0.4158
F	Firing costs	[0; 0.0406]
Shock processes: technology shock (Z) and discount factor shock (d)		
$\bar{Z}$	Steady state	1
ρ_z	Persistence	0.95
σ_z	Standard deviation	0.0066
$\bar{d}$	Steady state	1
ρ_d	Persistence	0.75
σ_d	Standard deviation	0.5527

III.II *Model-fit with US Data*

We now examine to what extent our calibrated model can fit key US business cycle moments.

Table 3: *Data moments vs. model moments (HP-filtered)*

	Data	**Model**
$\sigma(v)/\sigma(n)$	11.90	10.75
$\sigma(u)/\sigma(n)$	10.96	9.00
$\sigma(h)/\sigma(n)$	0.38	0.33
$\sigma(n)/\sigma(y)$	0.80	0.88
$\text{corr}(v, u)$	-0.92	-0.90
$\sigma(jcr)/\sigma(jdr)$	0.68	0.48

Table 3 summarizes standard US business cycle moments (first column) and the model-implied moments (second column). The data moments are taken from Krause and Lubik (2014), Ohanian and Raffo (2012) and the CompNet database. The data is in logs and HP-filtered with the exception of the job creation and job destruction rate. For these two variables the time-series is too short to apply the HP filter and obtain reliable results. The table shows that the model does a very good job, matching these moments. It is able to solve the Shimer puzzle (Shimer, 2005), that is it is able to generate a high volatility in unemployment and vacancies and generates a strong negative correlation between unemployment and vacancies. Further it replicates the fluctuations in the job creation vs. job destruction rate, which is not part of the calibration but of particular interest in our analysis.

III.III *Model-fit with Empirical EPL Relations*

We now turn our focus on the empirical regularities presented in Section I. Figures 4, 5 and 6 show that our model is able to replicate the empirical relationships with EPL presented in Section I well. Figure 4 shows the relationship between the relative variability of the job creation vs. job destruction rate, 5 the relationship between the Beveridge curve, and 6 the relationship between the relative variability of the intensive vs. extensive margin of labor with EPL or firing costs. The black lines correspond to the fitted OLS lines of the empirical relationships presented in Section I. The red lines show the models implied relationship between the variables at interest and the firing cost parameter F. We obtain the red line by solving the model for different values of the firing cost parameter, while keeping the other parameters constant. More precisely, we consider a range $F = [0, F_{max}]$, which we then linearly map to the OECD indicator. We calibrate F_{max} such that our model is best able to replicate the empirical relationships with EPL. That is, we choose F_{max} to minimize the sum of the squared deviations between the red and black lines. This procedure yields an F_{max} of 0.0406, roughly 11% of steady state wage payments.

[Insert Figure 4 here]

[Insert Figure 5 here]

[Insert Figure 6 here]

IV THE UNDERLYING MECHANISM

In this section, we discuss the firing cost mechanism of our model in detail. The purpose is to better understand our models ability to replicate the empirical relationships with EPL and the role distinct job creation and destruction choices play for the mechanism. First, we analyze the response of first and second moments to an increase in EPL. Second, we compare the benchmark model to an economy in which firing costs apply to net reductions in employment instead of job destruction flows.

IV.I *The effect of firing costs*

To illustrate the firing cost mechanism, we analyze the effect of an increase in the firing cost parameter F from 0 to F_{max} (11% of steady state average wage payments) on the model's first and second moments.

Steady State. Table 4 shows the effect of an increase in firing costs on the steady state of output, employment, average hours worked per employee, the number of vacancies posted, unemployment and both the job creation and job destruction rate.

The table shows that firing costs have a strong influence on the job destruction rate $j\bar{d}r$, dropping by almost 80%. This reduction is fairly intuitive, as the increased firing costs make it less attractive for firms to dismiss less productive workers. Firing costs reduce the job creation rate $j\bar{c}r$ by the same amount. The drop in the job creation rate goes hand in hand with the lower amount of vacancies posted $\bar{v}$. The lower amount of vacancies posted is the result of several mechanisms, as described in equation (II.11). On the one hand, raising firing costs

Table 4: *Steady State to Firing Cost Relation*

	F = 0%	**F ≈ 11%**	**Δ in %**
$\bar{y}$	0.31	0.32	2.07%
$\bar{n}$	0.90	0.96	6.92%
$\bar{h}$	0.33	0.32	-3.04%
$\bar{v}$	0.11	0.02	-82.83%
$\bar{u}$	0.10	0.04	-62.29%
$\bar{jcr}$	0.11	0.02	-78.00%
$\bar{jdr}$	0.11	0.02	-78.00%

Note: The last column shows the percentage change after an increase from $F = 0$ to $F = F_{\max}$

has a direct negative impact on the expected return on a vacancy because every filled vacancy leads to a future firing. At the same time, firing costs weaken the firms bargaining position and lower the revenue a firm gets net of wage payments. Furthermore, the reduction in the separation rate reduces the average productivity of a worker because less productive workers remain at the firm. In contrast, the lower separation rate implies longer lasting employment relationships, which raises incentives to post vacancies. In steady state, the former effects outweigh the latter. Firing costs reduce steady state average hours worked $\bar{h}$ and raise the steady state employment rate $\bar{n}$. The reduction in average hours worked can be explained by the effect of firing costs on the job destruction rate: As firing costs lead firms to lower the separation rate, workers with lower productivity remain at the firm. The lower the productivity of a worker, the lower is the optimal amount of hours worked (see equation (II.18)). In turn, the decrease in average hours worked reduces the average disutility of being employed. The lower average disutility leads to lower average wage payments per worker, which raises firms' demand for workers and hence steady state employment. The higher steady state employment is equivalent to lower steady state unemployment $\bar{u}$. Overall, the higher employment level outweighs the reduction in average hours worked and the economic output $\bar{y}$ increases slightly.

Business cycle fluctuations.

Table 5 shows the effect of firing costs on various second moments, measured based on HP-filtered simulations. Similar to the previous table the firing costs are increased from 0% to approximately 11% of steady state average wage payments per worker.

Table 5: *Second Moments to Firing Cost Relation*

	$\mathbf{F = 0\%}$	$\mathbf{F \approx 11\%}$	$\mathbf{\Delta}$ **in %**
$\sigma(y)$	1.63	1.21	-25.68%
$\sigma(n)$	1.43	0.30	-78.68%
$\sigma(h)$	0.47	0.29	-38.33%
$\sigma(v)$	15.36	15.32	-0.27%
$\sigma(u)$	12.86	7.78	-39.54%
$\sigma(jcr)$	0.40	0.17	-57.64%
$\sigma(jdr)$	0.83	0.15	-81.47%
$\mathrm{corr}(v,u)$	-0.90	-0.69	-22.69%
$\frac{\sigma(n)}{\sigma(jdr)}$	1.73	1.99	15.06%
$\frac{\sigma(jcr)}{\sigma(jdr)}$	0.48	1.10	128.55%
$\frac{\sigma(h)}{\sigma(n)}$	0.33	0.96	189.19%

Note: The standard deviations ($\sigma(.)$) are based on HP-filtered simulations. The last column shows the percentage change after an increase from $F = 0$ to $F = F_{\max}$

Several observations stand out. First, firing costs reduce fluctuations in the job destruction as well as the job creation rate. For the job destruction rate, the reason is immediate - firing costs discourage firings and firms focus on dismissing the most unproductive workers only. The reduction in the job creation rate is driven by two effects. First, creating new positions, will in later periods, lead to costly firing. Second, the decreased variation in the job destruction rate leads to a more stable average productivity of workers. From (II.11) we see that this stabilizes the creation of jobs. Quantitatively, firing costs stabilize more strongly the job destruction than the job creation rate. Hence, our model implies a positive relation between firing costs and the relative standard deviation of the job creation vs. job destruction rate ($\sigma(jcr)/\sigma(jdr)$), as shown in Figure 4 in the previous section. This result is intuitive. If firing taxes increase the costs of dismissal, firms opt to adjust the number of employees more strongly along the hiring than the firing margin. Second, as already shown in Figure 5 in the previous section, firing costs weaken the negative correlation between vacancies and unemployment. The reason for this relationship is easiest understood when we consider the impulse response shown in Figure 7 and 8. Firing taxes lead to a more hump-shaped reaction of unemployment to discount factor and technology shocks. The intuition for this more delayed reaction of unemployment is as follows. Firms can adjust employment either using the hiring or the firing margin. While firing workers affects immediately the workforce, the workforce only reacts with a delay to changes in the number of posted vacancies. An increase in firing costs leads firms to adjust employment more strongly along the hiring margin, leading to a more delayed response of unemployment in response to shocks. Hence, firing costs weaken the *contemporaneous* correlation between unemployment and vacancies.

[Insert Figure 7 here]

[Insert Figure 8 here]

The third observation is that firing costs reduce fluctuations in average hours worked and employment. The stabilization of average hours worked follows directly from the more stable job destruction rate. As can be seen in (II.20), the more stable job destruction rate also reduces fluctuation in the average productivity of workers, which, in turn, leads to less variation in average hours worked. The stabilizing impact of firing costs on employment follows directly from the stabilizing effect of firing costs on the job destruction and creation rate. Quantitatively, firing costs reduce the variability in employment more strongly than the variability in average hours worked (higher $\sigma(h)/\sigma(n)$). This relationships, which we have already shown in Figure 6 in the previous section, is also quite intuitive. When dismissing workers becomes more costly, firms opt to adjust their labor input more strongly along the intensive rather than the extensive margin.

IV.II *The role of the job creation and destruction margin*

To evaluate the role of the job creation and destruction margin, we compare our model to a version in which firing costs apply only to net reductions in employment instead of job destruction flows. Details can be found in Section B in the Appendix. Under this alternative modeling approach of EPL, the job creation and destruction flows do not (directly) matter for the impact of firing costs. In this sense, the comparison between both models reveals the (direct) role of job creation and destruction flows for the assessment of EPL.

Table 6 compares the impact of firing costs for both versions of our model. We focus on the impact of firing costs on labour market dynamics. Further information on the impact on the steady state can be found in section B.III of the appendix. The table shows that in contrast to our baseline model, imposing firing costs of size $F = F_{\max}$ has almost no impact in the alternative version of our model (second column from right in Table 6). The reason is that in our baseline model, like in the US data, average net reductions in employment are much smaller in size than average job destruction flows. Hence, everything else equal, the same increase in F imposes much smaller effective firing costs in the alternative model.

Table 6: *Standard Deviation to Firing Cost Relation*

	Baseline Model	Alternative Model	
	$\Delta F = F_{\max}$	$\Delta F = F_{\max}$	$\Delta F = 30 * F_{\max}$
$\sigma(y)$	-25.68%	-1.24%	-25.01%
$\sigma(n)$	-78.68%	-2.82%	-70.02%
$\sigma(h)$	-38.33%	-1.15%	-36.63%
$\sigma(v)$	-0.27%	-0.08%	-4.72%
$\sigma(u)$	-39.54%	-1.24%	-52.31%
$\sigma(jcr)$	-57.64%	0.09%	28.97%
$\sigma(jdr)$	-81.47%	-1.94%	-36.90%
$\text{corr}(v,u)$	-22.69%	0.02%	-11.28%
$\frac{\sigma(n)}{\sigma(jdr)}$	15.06%	-0.90%	-52.49%
$\frac{\sigma(jcr)}{\sigma(jdr)}$	128.55%	2.07%	104.38%
$\frac{\sigma(h)}{\sigma(n)}$	189.19%	1.72%	111.37%

Note: The standard deviations (std.) are based on HP-filtered simulations. ΔF refers to an increase from $F = 0$ to the indicated value.

Not only the effective size of firing costs differs among the different modeling approaches. Also the impact of firing costs on labor market dynamics is different. To show this assertion, we perform the following exercise. We compare the impact of firing costs for an increase from $F = 0$ to $F = F_{\max}$ in the baseline model (first column in the table) with the impact from an increase from $F = 0$ to $F = 30 \cdot F_{\max}$ in the alternative model (last column in the table). We choose the factor 30 because at $F = 0$ in our model, average net reductions in employment are about 30 times smaller in size than average job destruction flows (like in the US data). Hence, with this exercise we make sure that, everything else equal, the effectively imposed size of firing costs for firms is the same in both models. In other words, we control for the different size effect of firing costs. When doing this exercise, three differences stand out. First, the relative variability of employment vs job destruction flows ($\sigma(n)/\sigma(jdr)$) is dampened rather than amplified in the alternative model. This finding is quite intuitive because firing costs apply to net reductions in employment, not job destruction flows. Second, the relative volatility of job creation vs destruction flows ($\sigma(jcr)/\sigma(jdr)$) is raised less in the alternative model. The intuition is that firing costs do not incentivize firms directly to use the hiring margin to adjust employment. Third, firing costs lead to a stronger rise in the relative variability of hours worked vs. employment ($\sigma(h)/\sigma(n)$) in the baseline model. The reason is that for an immediate adjustment in labor input, firms need to adjust either the amount of hours worked per person or the amount of destroyed jobs. Firing costs discourage directly the use of the latter margin in the baseline model whereas they only affect indirectly the job destruction margin in the alternative model. Hence, in face of firing costs of a comparable size, firms opt to adjust labor input even more heavily along the intensive margin in the baseline model. To sum up, the distortionary effects of firing costs on labor market dynamics are underestimated when job destruction flows are disregarded in the assessment of EPL.

V ROBUSTNESS

We finish the main body of this paper by assessing the robustness of our results with regard to alternative parameterization of the hours disutility curvature parameter ν and a different modeling of EPL.

V.I *Different parameterizations of hours disutility curvature parameter ν*

The hours disutility curvature parameter ν determines how strongly households are willing to adapt hours worked per worker. Hence, the parameter choice is potentially crucial for the labor market dynamics in our model. We consider two alternative values for the hours disutility curvature parameter: $\nu = 2$, which corresponds to a low willingness to adapt hours worked per worker, and $\nu = 0.5$, which corresponds to high willingness to adapt hours worked per worker. To compute the results, we use the same calibration approach as in our benchmark model, except that we use the same range of firing costs as in the benchmark case. Table 7 and 8 shows the effect of firing costs on various second moments. The effect of firing costs on the steady state can be found in Section C in the appendix.

Overall, for $\nu = 2$, the impact of firing costs on the economy is remarkably similar to the benchmark model. The main difference is that the relative variability of hours worked vs. employment is raised much less compared to benchmark. This is intuitive and follows directly from the increased disutility, which workers face from additional working hours. Workers demand a higher wage increase for additional working hours. Hence, firms opt to adjust total labor input more strongly along the extensive labor margin. The weaker response of

Table 7: *Second Moments to Firing Cost Relation: Robustness check for* $\nu = 2$

	$\mathbf{F = 0\%}$	$\mathbf{F \approx 11\%}$	$\mathbf{\Delta}$ **in %**
$\sigma(y)$	1.64	1.05	-35.87%
$\sigma(n)$	1.57	0.48	-69.16%
$\sigma(h)$	0.31	0.16	-49.42%
$\sigma(v)$	14.86	15.59	4.94%
$\sigma(u)$	14.13	9.54	-32.52%
$\sigma(jcr)$	0.37	0.20	-44.30%
$\sigma(jdr)$	0.88	0.21	-75.54%
$\text{corr}(v, u)$	-0.89	-0.71	-20.65%
$\frac{\sigma(n)}{\sigma(jdr)}$	1.79	2.26	26.07%
$\frac{\sigma(jcr)}{\sigma(jdr)}$	0.42	0.96	127.73%
$\frac{\sigma(h)}{\sigma(n)}$	0.20	0.32	64.02%

Note: The standard deviations (std.) are based on HP-filtered simulations. The last column shows the percentage change after an increase from $F = 0$ to $F = F_{\max}$

Table 8: *Second Moments to Firing Cost Relation: Robustness check for* $\nu = 0.5$

	$\mathbf{F = 0\%}$	$\mathbf{F \approx 11\%}$	$\mathbf{\Delta}$ **in %**
$\sigma(y)$	1.50	1.25	-16.49%
$\sigma(n)$	1.18	0.10	-91.36%
$\sigma(h)$	0.60	0.47	-22.19%
$\sigma(v)$	16.21	15.04	-7.26%
$\sigma(u)$	10.64	5.19	-51.19%
$\sigma(jcr)$	0.48	0.11	-76.45%
$\sigma(jdr)$	0.78	0.10	-87.50%
$\text{corr}(v, u)$	-0.91	-0.12	-86.30%
$\frac{\sigma(n)}{\sigma(jdr)}$	1.52	1.05	-30.93%
$\frac{\sigma(jcr)}{\sigma(jdr)}$	0.61	1.16	88.35%
$\frac{\sigma(h)}{\sigma(n)}$	0.51	4.56	801.12%

Note: The standard deviations (std.) are based on HP-filtered simulations. The last column shows the percentage change after an increase from $F = 0$ to $F = F_{\max}$

the intensive margin of labor has also consequences for other labor market aggregates. But quantitatively, this influence is rather minor. For the case with $\nu = 0.5$, the effects of firing costs are qualitatively also the same as in the benchmark model. However, quantitatively, we observe stronger differences. In particular firing costs raise the relative variability of the intensive vs extensive margin of labor much stronger than in the benchmark model. The smaller disutility that workers face with additional working hours allows the firms to reduce the fluctuations in employment level more strongly and use the intensive margin more heavily to adjust total labor input. Further we find that the correlation between unemployment and vacancies is decreasing much stronger in absolute terms. The main reason is that firing costs lead to a stronger reduction in the use of the job destruction margin than in the benchmark model. The weaker the use of the job destruction margin, the more persistent is the development of unemployment and, hence, the lower the *contemporaneous* correlation between vacancies and unemployment.

Figures 9 and 10 show the fit with the empirical EPL relations presented in Section III.III. Overall, the fit remains relatively well for both alternative parameterizations of the willingness to adapt hours per worker. Only the fit with the empirical relationship between EPL and the relative variability of the intensive vs. extensive margin is more sensitive to the chosen ν. For $\nu = 2$, firing costs raise the relative variability of the intensive vs. extensive margin too little, while for $\nu = 0.5$, firing costs raise the relative variability too much. The fit with the empirical relationsships between EPL and relative variability of the job creations vs destruction margin, and between EPL and the correlation of vacancies and unemployment remains well irrespective of the chosen parameterization of ν.

[Insert Figure 9 here]

[Insert Figure 10 here]

To summarise, we find that the qualitative results of our benchmark model remain unchanged for different parameterizations of the households willingness to adapt hours worked per workers. In all chosen parameterizations, firing costs (i) raise the relative variability of the job creation vs job destruction rate, (ii) weaken the Beveridge curve relation measured as the negative correlation between vacancies and unemployment, and (iii) increase the relative fluctuations in the intensive vs extensive margin of labor supply. Quantitatively, especially the relative fluctuations of the intensive vs extensive margin are more sensitive to the chosen value of ν, with the benchmark parameterization leading the best fit with the observed empirical relationship documented in Section I.III.

V.II *Different Dismissal Procedure*

Our main interest in this paper is the effect of EPL on labour market dynamics. In this regard, a natural question is to what extent our modeling approach of EPL affects the results. In this section, we examine a different formulation of the firing cost mechanism. In contrast to our baseline model, we allow for firms to dismiss workers at no dismissal cost if the worker has just matched with the firm in the previous period and has not yet participated in the firm's production process. The details of the model and more results can be found in the appendix Section D. To calibrate the model, we use the same calibration approach as for our benchmark model, except that we use the same range of firing costs considered in our benchmark.

Table 9 shows the effect of an increase in firing costs on various second moments. The impact of firing costs is remarkably similar to our benchmark model. The only major difference concerns the increase in the variability of vacancies. In the benchmark model, the variability of vacancies remains roughly unchanged when firing costs are introduced. The intuition is that hiring is less risky when firms can dismiss new employees at no dismissal cost. Hence, a rise in firing costs leads firms to adjust employment more strongly along the job creation margin.

Table 9: *Second Moments to Firing Cost Relation: Robustness Check for Different Dismissal Procedure*

	F = 0%	**F ≈ 11%**	**Δ in %**
$\sigma(y)$	1.48	1.19	-19.17%
$\sigma(n)$	1.35	0.27	-80.36%
$\sigma(h)$	0.49	0.22	-55.01%
$\sigma(v)$	4.26	6.22	45.94%
$\sigma(u)$	12.18	6.53	-46.42%
$\sigma(jcr)$	0.49	0.15	-68.91%
$\sigma(jdr)$	0.88	0.16	-81.94%
$\mathrm{corr}(v,u)$	-0.76	-0.60	-21.59%
$\frac{\sigma(n)}{\sigma(jdr)}$	1.54	1.68	8.71%
$\frac{\sigma(jcr)}{\sigma(jdr)}$	0.56	0.96	72.11%
$\frac{\sigma(h)}{\sigma(n)}$	0.36	0.84	129.12%

Note: The standard deviations (std.) are based on HP-filtered simulations. The last column shows the percentage change after an increase from $F = 0$ to $F = F_{\max}$

Also the fit with the empirical EPL relations documented in Section III.III remains well. This can be seen in Figure 11. The main difference is that the effect of an increase in firing costs on the considered measures is a bit weaker at lower levels of the firing cost. Intuitively, as the firing cost only applies for workers that have been with the firm for at least one full period, the effect is smaller in size and, hence, has a smaller impact on the firms decision making. Therefore, the effect of firing cost is weaker and only becomes visible once the EPL have reached a certain level.

[Insert Figure 11 here]

To summarize, the results are robust to the different model specification. The qualitative outcomes that firing costs (i) raise the relative variability of the job creation vs job destruction rate, (ii) weaken the negative correlation between vacancies and unemployment, and (iii) increase the relative fluctuations in the intensive vs. extensive margin of labor supply remain intact. Further, the model with the alternative firing cost mechanism is still able to fit the empirical relationships documented in Section III.III.

VI CONCLUDING REMARKS

We explore the role of employment protection legislation (EPL) on labor market dynamics in a search and matching framework with costly firing. While the literature has mostly focused on the role of EPL in the long-run, we are mainly interested in labor market dynamics at business cycle frequencies. Our focus lies on the role of job destruction flows for the assessment of EPL – a dimension along which the literature has remained vastly silent or has even abstracted from.

Our contribution is threefold. First, we establish novel empirical regularities regarding labor market dynamics and their relationship with EPL. Based on the recently-constructed 6th vintage of the ECB's CompNet data set and the business dynamics database of the US census bureau, we document that job destruction flows are between 5 to 40 times larger than average net reductions in employment. The same data set also suggests a positive association between EPL – measured by the OECD indicator for protection against dismissals – and the relative variability of job creation vs. destruction flows. Further, based on the data set of Amaral and Tasci (2016), we find that the higher EPL is, the weaker is the Beveridge curve as measured by the negative correlation between vacancies and unemployment.

Second, we provide a search and matching model for the quantitative assessment of EPL that captures salient features of the data. It is able to replicate standard US business cycle facts and the empirical regularities between EPL and labor market aggregates documented in our empirical section. Further, our model reproduces the positive association between EPL and the relative variability of the intensive vs. extensive margin of labor supply (hours worked per workers vs. employment) reported by Llosa et al. (2014).

Third, we examine the role of job destruction flows for the quantitative assessment of firing costs in our search and matching model. To do so, we compare two versions of our model. In our baseline version, firing costs apply to job destruction flows whereas in the alternative version, firing costs apply only to net reductions in employment. Hence, in the alternative version, job destruction flows do not (directly) matter for the amount of firing costs a firm faces. The main findings are as follows. (i) The impact of the same size of firing costs is an order of magnitude larger when firing costs apply to job destruction flows instead of net reductions in employment. (ii) Even when controlling for this "size effect", firms opt to adjust labor input more heavily along the job creation margin and the intensive margin of labor when EPL applies to job destruction flows. Hence, the distortionary effects of firing costs on labor market dynamics are underestimated if job destruction flows are disregarded in the analysis of EPL.

Overall, our findings indicate that role of job destruction flows should be considered in any model that studies labor market policies.

ACKNOWLEDGEMENTS

We wish to thank Fabrice Collard, Harris Dellas, Christian Myohl and participants of the Macro Workshop at the University of Bern for helpful discussions and valuable comments. We also wish to thank Kyle Herkenhoff and Ellen McGrattan for helpful discussions at an early stage of this project. Jacqueline Thomet gratefully acknowledges financial support for this project from the "IMG Stiftung".

NOTES

1. A more detailed description of the database can be found in the User Guide, the Cross-Country Report and the Cross-Country Comparability Report on their website. The reader must be aware that data collection rules and procedures across countries are different, and out of CompNet's control. Hence, despite all efforts made to improve sample comparability across countries (including the use of population weights), some country samples might still suffer from biases. For a more detailed account of raw data characteristics and sample biases, please refer to the Cross-Country Comparability Report.

REFERENCES

Albertini, J., & Poirier, A. (2014). Discount factor shocks and labor market dynamics. SFB 649 Discussion Paper.

Amaral, P. S., & Tasci, M. (2016). The cyclical behavior of equilibrium unemployment and vacancies across oecd countries. *European Economic Review*, *84*, 184–201.

Andolfatto, D. (1996). Business cycles and labor-market search. *The American Economic Review*, 112–132.

Blanchard, O. J., & Diamond, P. (1989). The Beveridge curve. *Brookings Papers on Economic Activity*, *1*, 1–76.

Fernald, J. G. (2014). A quarterly, utilization-adjusted series on total factor productivity. Federal Reserve Bank of San Francisco Working Paper.

Garibaldi, P. (1998). Job flow dynamics and firing restrictions. *European Economic Review*, *42*(2), 245–275.

Guerrieri, L., & Iacoviello, M. (2015). Occbin: A toolkit for solving dynamic models with occasionally binding constraints easily. *Journal of Monetary Economics*, *70*, 22–38.

Hagedorn, M., & Manovskii, I. (2008). The cyclical behavior of equilibrium unemployment and vacancies revisited. *The American Economic Review*, *98*(4), 1692–1706.

Hall, R. E. (2005). Employment fluctuations with equilibrium wage stickiness. *The American Economic Review*, *95*(1), 50–65.

Hall, R. E. (2017). High discounts and high unemployment. *The American Economic Review*, *107*(2), 305–330.

Hamermesh, D. S. (1996). *Labor demand*. Princeton University Press.

Hopenhayn, H., & Rogerson, R. (1993). Job turnover and policy evaluation: A general equilibrium analysis. *Journal of Political Economy*, *101*(5), 915–938.

Hosios, A. J. (1990). On the efficiency of matching and related models of search and unemployment. *The Review of Economic Studies*, *57*(2), 279–298.

Krause, M. U., & Lubik, T. A. (2007). The (ir) relevance of real wage rigidity in the New Keynesian model with search frictions. *Journal of Monetary Economics*, *54*(3), 706–727.

Krause, M. U., & Lubik, T. A. (2014). Modeling labor markets in macroeconomics: Search and matching. The Federal Reserve Bank of Richmond Working Paper.

Llosa, G., Ohanian, L., Raffo, A., & Rogerson, R. (2014). Firing costs and labor market fluctuations: A cross-country analysis. 2014 Meeting Papers 533, Society for Economic Dynamics.

Merz, M. (1995). Search in the labor market and the real business cycle. *Journal of Monetary Economics*, *36*(2), 269–300.

Merz, M., & Yashiv, E. (2007). Labor and the market value of the firm. *The American Economic Review*, *97*(4), 1419–1431.

Mortensen, D. T., & Pissarides, C. A. (1994). Job creation and job destruction in the theory of unemployment. *The Review of Economic Studies*, *61*(3), 397–415.

Nickell, S. J. (1986). Dynamic models of labour demand. *Handbook of Labor Economics*, *1*, 473–522.

Ohanian, L. E., & Raffo, A. (2012). Aggregate hours worked in OECD countries: new measurement and implications for business cycles. *Journal of Monetary Economics*, *59*(1), 40–56.

Oi, W. Y. (1962). Labor as a quasi-fixed factor. *Journal of Political Economy*, *70*(6), 538–555.

Pissarides, C. A. (2009). The unemployment volatility puzzle: Is wage stickiness the answer? *Econometrica*, *77*(5), 1339–1369.

Pries, M., & Rogerson, R. (2005). Hiring policies, labor market institutions, and labor market flows. *Journal of Political Economy*, *113*(4), 811–839.

Sedlácek, P. (2014). Match efficiency and firms' hiring standards. *Journal of Monetary Economics*, *62*(100), 123–133.

Shimer, R. (2005). The cyclical behavior of equilibrium unemployment and vacancies. *The American Economic Review*, *95*(1), 25–49.

Veracierto, M. (2008). Firing costs and business cycle fluctuations. *International Economic Review*, *49*(1), 1–39.

Wesselbaum, D. (2016). The intensive margin puzzle and labor market adjustment costs. *Macroeconomic Dynamics*, *20*(6), 1458–1476.

Yashiv, E. (2000a). Hiring as investment behavior. *Review of Economic Dynamics*, *3*(3), 486–522.

Yashiv, E. (2000b). The determinants of equilibrium unemployment. *The American Economic Review*, *90*(5), 1297–1322.

Yashiv, E. (2006). Evaluating the performance of the search and matching model. *European Economic Review*, *50*(4), 909–936.

APPENDIX

A GENERAL EQUILIBRIUM OF THE BENCHMARK MODEL

$$\rho_t = G(\tilde{a}_t) \tag{A.1}$$

$$c_t^{-\sigma} = \beta R_t \mathbb{E}_t \left[\frac{\exp(d_{t+1})}{\exp(d_t)} c_{t+1}^{-\sigma} \right] \tag{A.2}$$

$$y_t = Z_t n_t \int_{\tilde{a}_t}^{\infty} h_t(a) a \frac{g(a)}{1-G(\tilde{a}_t)} da = n_t Z_t^{\frac{1+\nu}{\nu}} \left(\frac{\lambda_t}{\xi_h} \right)^{\frac{1}{\nu}} \int_{\tilde{a}_t}^{\infty} a^{\frac{1+\nu}{\nu}} \frac{g(a)}{1-G(\tilde{a}_t)} da \tag{A.3}$$

$$n_t = (1-\rho_t)(n_{t-1} + m_{t-1}) \tag{A.4}$$

$$m(u_t, v_t) = B u_t^{\mu} v_t^{1-\mu} = B \theta_t^{1-\mu} \underbrace{(1-n_t)}_{\equiv u_t} \tag{A.5}$$

$$q(\theta_t) = \frac{m(u_t, v_t)}{v_t} = B \theta_t^{-\mu} \tag{A.6}$$

$$\lambda_t = c_t^{-\sigma} \tag{A.7}$$

$$\begin{aligned} \frac{\psi \Gamma'_{t,v}}{q(\theta_t)} = \; & \beta \, \mathbb{E} \left\{ \frac{\exp(-d_{t+1})}{\exp(-d_t)} \frac{\lambda_{t+1}}{\lambda_t} \left[(1-\rho_{t+1}) \left(\frac{y_{t+1}}{n_{t+1}} \ldots \right.\right.\right. \\ & \left.\left.\left. - \int_{\tilde{a}_{t+1}}^{\infty} w_{t+1}(a) h_{t+1}(a) \frac{g(a)}{1-\rho_{t+1}} da + \frac{\psi \Gamma'_{t+1,v}}{q(\theta_{t+1})} \right) - \rho_{t+1} F \right] \right\} \end{aligned} \tag{A.8}$$

$$y_t = c_t + \psi \Gamma_t + \frac{n_t \rho_t}{1-\rho_t} F \tag{A.9}$$

$$h_t(a) = \left(\frac{Z_t \lambda_t a}{\xi_h} \right)^{\frac{1}{\nu}} \tag{A.10}$$

$$H_t(\tilde{a}_t) = \left(\frac{Z_t \lambda_t}{\xi_h} \right)^{\frac{1}{\nu}} \int_{\tilde{a}_t}^{\infty} a^{\frac{1}{\nu}} \frac{g(a)}{1-G(\tilde{a}_t)} da \tag{A.11}$$

$$\begin{aligned} w_t(a) h_t(a) = & \frac{1-\zeta}{\lambda_t} \left(\xi_h \frac{h_t(a)^{1+\nu}}{1+\nu} + \xi_n \right) + \zeta \Bigg(\theta_t \psi \Gamma'_{t,v} + Z_t h_t(a) a \ldots \\ & + \left(1 - (1-\theta_t q(\theta_t)) \beta \, \mathbb{E}_t \left\{ \frac{\exp(-d_{t+1})}{\exp(-d_t)} \frac{\lambda_{t+1}}{\lambda_t} \right\} \right) F \Bigg) \end{aligned} \tag{A.12}$$

$$\begin{aligned} \int_{\tilde{a}_t}^{\infty} w_t(a) h_t(a) \frac{g(a)}{1-G(\tilde{a}_t)} da = & (1-\zeta) \frac{1}{\lambda_t} \left(\xi_h \int_{\tilde{a}_t}^{\infty} \frac{h_t(a)^{1+\nu}}{1+\nu} \frac{g(a)}{1-G(\tilde{a}_t)} da + \xi_n \right) \ldots \\ & + \zeta \left(\frac{y_t}{n_t} + \theta_t \psi \Gamma'_{t,v} + \left(1 - (1-\theta_t q(\theta_t)) \beta \mathbb{E}_t \left[\frac{\exp(-d_{t+1})}{\exp(-d_t)} \frac{\lambda_{t+1}}{\lambda_t} \right] \right) F \right) \end{aligned} \tag{A.13}$$

$$\tilde{a}_t = \left(\frac{ \frac{\xi_n}{\lambda_t} + \frac{\zeta}{1-\zeta} \theta_t \psi \Gamma'_{t,v} - \frac{1}{1-\zeta} \frac{\psi \Gamma'_{t,v}}{q(\theta_t)} - \left(1 + \frac{\zeta}{1-\zeta} (1-\theta_t q(\theta_t)) \beta \, \mathbb{E}_t \left[\frac{\exp(-d_{t+1})}{\exp(-d_t)} \frac{\lambda_{t+1}}{\lambda_t} \right] \right) F }{ Z_t^{\frac{1+\nu}{\nu}} \left(\frac{\lambda_t}{\xi_h} \right)^{\frac{1}{\nu}} } \right)^{\frac{\nu}{1+\nu}} \tag{A.14}$$

$$\ln(Z_t) = \rho_z \ln(Z_{t-1}) + \varepsilon_z, \; \varepsilon_z \sim N(0, \sigma_z^2) \tag{A.15}$$

$$\ln(d_t) = \rho_d \ln(d_{t-1}) + \varepsilon_d,\ \varepsilon_d \sim N(0, \sigma_d^2) \tag{A.16}$$

B MODEL WITH FIRING COSTS ON NET EMPLOYMENT REDUCTION

In this section, we present an alternative version of our benchmark model in which firing costs apply only to *net reductions* in employment instead of job destruction flows. Because only net reductions but not net increases in employment are costly, firing costs introduce a strong non-linearity in the model. We use the piecewise linear solution method proposed in Guerrieri and Iacoviello (2015) to solve the model.

B.I *Model*

Compared to the benchmark model presented in Section II, only the firm problem changes (equation II.6):

$$\mathcal{P} = \mathbb{E}_0 \left\{ \sum_{t=0}^{\infty} \exp(d_t)\beta^t \lambda_t \left[y_t - n_t \int_{\tilde{a}_t}^{\infty} w_t(a) h_t(a) \frac{g(a)}{1 - G(\tilde{a}_t)} da - \psi \Gamma_t - F \mathbb{I}^{n_t < n_{t-1}} (n_{t-1} - n_t) \right] \right\},$$

where $\mathbb{I}^{n_t < n_{t-1}}$ denotes an indicator that equals one if employment in period t is reduced. When bargaining, firms and household take into account the asymmetric firing cost scheme. The general equilibrium equations are as follows (only equations A.8, A.9, A.12, A.13 and A.14 change):

$$\rho_t = G(\tilde{a}_t) \tag{B.1}$$

$$c_t^{-\sigma} = \beta R_t \mathbb{E}_t \left[\frac{\exp(d_{t+1})}{\exp(d_t)} c_{t+1}^{-\sigma} \right] \tag{B.2}$$

$$y_t = Z_t n_t \int_{\tilde{a}_t}^{\infty} h_t(a) a \frac{g(a)}{1 - G(\tilde{a}_t)} da = n_t Z_t^{\frac{1+\nu}{\nu}} \left(\frac{\lambda_t}{\xi_h} \right)^{\frac{1}{\nu}} \int_{\tilde{a}_t}^{\infty} a^{\frac{1+\nu}{\nu}} \frac{g(a)}{1 - G(\tilde{a}_t)} da \tag{B.3}$$

$$n_t = (1 - \rho_t)(n_{t-1} + m_{t-1}) \tag{B.4}$$

$$m(u_t, v_t) = B u_t^{\mu} v_t^{1-\mu} = B \theta_t^{1-\mu} \underbrace{(1 - n_t)}_{\equiv u_t} \tag{B.5}$$

$$q(\theta_t) = \frac{m(u_t, v_t)}{v_t} = B \theta_t^{-\mu} \tag{B.6}$$

$$\lambda_t = c_t^{-\sigma} \tag{B.7}$$

$$
\begin{aligned}
\frac{\psi\Gamma'_{t,v}}{q(\theta_t)} = \; & \beta\,\mathbb{E}\left\{\frac{\exp(-d_{t+1})}{\exp(-d_t)}\frac{\lambda_{t+1}}{\lambda_t}\left[(1-\rho_{t+1})\left(\frac{y_{t+1}}{n_{t+1}}\dots\right.\right.\right. \\
& \left.\left.\left. -\int_{\tilde{a}_{t+1}}^{\infty} w_{t+1}(a)h_{t+1}(a)\frac{g(a)}{1-\rho_{t+1}}da + \mathbb{I}^{n_{t+1}<n_t}F + \frac{\psi\Gamma'_{t+1,v}}{q(\theta_{t+1})}\right)\right]\right\}\dots \\
& -\beta^2\,\mathbb{E}\left[\frac{\exp(-d_{t+2})}{\exp(-d_t)}\frac{\lambda_{t+2}}{\lambda_t}(1-\rho_{t+1})\mathbb{I}^{n_{t+2}<n_{t+1}}F\right]
\end{aligned}
\tag{B.8}
$$

$$
y_t = c_t + \psi\Gamma_t + \mathbb{I}^{n_t<n_{t-1}}(n_t - n_{t-1})F \tag{B.9}
$$

$$
h_t(a) = \left(\frac{Z_t\lambda_t a}{\xi_h}\right)^{\frac{1}{\nu}} \tag{B.10}
$$

$$
H_t(\tilde{a}_t) = \left(\frac{Z_t\lambda_t}{\xi_h}\right)^{\frac{1}{\nu}}\int_{\tilde{a}_t}^{\infty} a^{\frac{1}{\nu}}\frac{g(a)}{1-G(\tilde{a}_t)}da \tag{B.11}
$$

$$
\begin{aligned}
w_t(a)h_t(a) = \; & \frac{1-\zeta}{\lambda_t}\left(\xi_h\frac{h_t(a)^{1+\nu}}{1+\nu}+\xi_n\right)+\zeta\left(\theta_t\psi\Gamma'_{t,v}+Z_t h_t(a)a\dots\right. \\
& \left. +\left(\mathbb{I}^{n_t<n_{t-1}}-\beta\,\mathbb{E}_t\left\{\frac{\exp(-d_{t+1})}{\exp(-d_t)}\frac{\lambda_{t+1}}{\lambda_t}\mathbb{I}^{n_{t+1}<n_t}\right\}\right)F\right)
\end{aligned}
\tag{B.12}
$$

$$
\begin{aligned}
\int_{\tilde{a}_t}^{\infty} w_t(a)h_t(a)\frac{g(a)}{1-G(\tilde{a}_t)}da = \; & (1-\zeta)\frac{1}{\lambda_t}\left(\xi_h\int_{\tilde{a}_t}^{\infty}\frac{h_t(a)^{1+\nu}}{1+\nu}\frac{g(a)}{1-G(\tilde{a}_t)}da+\xi_n\right)\dots \\
& +\zeta\left(\frac{y_t}{n_t}+\theta_t\psi\Gamma'_{t,v}+\left(\mathbb{I}^{n_t<n_{t-1}}-\beta\,\mathbb{E}_t\left\{\frac{\exp(-d_{t+1})}{\exp(-d_t)}\frac{\lambda_{t+1}}{\lambda_t}\mathbb{I}^{n_{t+1}<n_t}\right\}\right)F\right)
\end{aligned}
\tag{B.13}
$$

$$
\tilde{a}_t = \left(\frac{\frac{\xi_n}{\lambda_t}+\frac{\zeta}{1-\zeta}\theta_t\psi\Gamma'_{t,v}-\frac{1}{1-\zeta}\frac{\psi\Gamma'_{t,v}}{q(\theta_t)}-\left(\mathbb{I}^{n_t<n_{t-1}}-\beta\,\mathbb{E}_t\left\{\frac{\exp(-d_{t+1})}{\exp(-d_t)}\frac{\lambda_{t+1}}{\lambda_t}\mathbb{I}^{n_{t+1}<n_t}\right\}\right)F}{Z_t^{\frac{1+\nu}{\nu}}\left(\frac{\lambda_t}{\xi_h}\right)^{\frac{1}{\nu}}}\right)^{\frac{\nu}{1+\nu}} \tag{B.14}
$$

$$
\ln(Z_t) = \rho_z\ln(Z_{t-1})+\varepsilon_z,\; \varepsilon_z\sim N(0,\sigma_z^2) \tag{B.15}
$$

$$
\ln(d_t) = \rho_d\ln(d_{t-1})+\varepsilon_d,\; \varepsilon_d\sim N(0,\sigma_d^2) \tag{B.16}
$$

B.II *Solution method*

Because of the asymmetric firing costs, the linear solution method we use for our benchmark model is not useful. To obtain a solution of our model and simulate moments, we use the piecewise linear solution method of Guerrieri and Iacoviello (2015). Guerrieri and Iacoviello (2015) developed this method to solve dynamic models with occasionally binding constraints. We choose this solution method because of two reasons. First, the method is well suited to solve problems involving asymmetric adjustment costs. Second, since the method also takes a linear approximation around the steady state, the results are better comparable with the results of our baseline model, which are also computed based on a linear approximation.

The basic idea of the piecewise linear solution is that occasionally binding constraints can be treated as different regimes of the same model. Under one regime the constraint is slack.

Under the other regime, the constraint is binding. The solution method of Guerrieri and Iacoviello (2015) involves a linear approximation around the same point under each regime. Because the method takes into account how long agents expect to be in the regimes, the solution can be highly non-linear.

In our case, the two regimes are as follows. Under the unconstrained regime, there are no firing costs. The unconstrained regime is characterized by the general equilibrium equations presented in Section B.I with the indicator function $\mathbb{I} = 0$ at all times (or equivalently $F = 0$). The regime applies in period t when $n_t \geq n_{t-1}$. Vice versa, when $n_t < n_{t-1}$ the constrained regime applies. This regime is characterized by the general equilibrium equations with the indiactor function $\mathbb{I} = 1$ at all times.

The piecewise linear solution method involves the linearization of both regimes around a specific point. The steady state is a natural choice. However, in our case the steady state is at $n_t = n_{t-1} = n^{steady\ state}\ \forall t \in \mathbb{N}$ – the point at which the regimes switch. To avoid convergence issues, we follow Guerrieri and Iacoviello (2015) (see the model with asymmetric capital adjustment costs in their online appendix) and assume that the constrained regime applies when $n_t < n_{t-1} + \epsilon$, with ε being a small number. Hence, at the point $n_t = n_{t-1}$, the constrained regime holds and we linearize the model around the steady state of the constrained regime.

B.III *Impact of firing costs on steady state*

Table 10 shows the impact of firing costs on the steady state of the alternative model.

Table 10: *First Moments to Firing Cost Relation for EPL on Net Employment Reduction*

	$\mathbf{F = 0}$	$\mathbf{F = F_{max}}$	$\mathbf{F = 30 * F_{max}}$	$\mathbf{\Delta F = 30 * F_{max}}$
$\bar{y}$	0.31	0.31	0.32	2.06%
$\bar{n}$	0.90	0.90	0.93	3.86%
$\bar{h}$	0.33	0.33	0.33	-1.42%
$\bar{v}$	0.11	0.11	0.11	2.85%
$\bar{u}$	0.10	0.10	0.07	-34.71%
$\bar{jcr}$	0.10	0.10	0.08	-15.97%
$\bar{jdr}$	0.10	0.10	0.08	-15.97%

Note: The last column shows the percentage change after an increase from $F = 0$ to $F = 30 * F_{\max}$

C DIFFERENT PARAMETERIZATIONS OF HOURS DISUTILITY CURVATURE PARAMETER ν

Table 4 and 12 show the impact of firing costs on the steady state for the parameterization with $\nu = 2$ and $\nu = 0.5$:

Table 11: *Steady State to Firing Cost Relation: Robustness Check for* $\nu = 2$

	$\mathbf{F = 0\%}$	$\mathbf{F \approx 11\%}$	$\mathbf{\Delta}$ **in %**
$\bar{y}$	0.31	0.32	2.45%
$\bar{n}$	0.90	0.95	5.74%
$\bar{h}$	0.33	0.32	-1.56%
$\bar{v}$	0.11	0.02	-78.62%
$\bar{u}$	0.10	0.05	-51.68%
$j\bar{c}r$	0.11	0.03	-71.99%
$j\bar{d}r$	0.11	0.03	-71.99%

Note: The last column shows the percentage change after an increase from $F = 0$ to $F = F_{\max}$

Table 12: *Steady State to Firing Cost Relation: Robustness Check for* $\nu = 0.5$

	$\mathbf{F = 0\%}$	$\mathbf{F \approx 11\%}$	$\mathbf{\Delta}$ **in %**
$\bar{y}$	0.32	0.32	1.37%
$\bar{n}$	0.90	0.98	8.96%
$\bar{h}$	0.33	0.31	-5.64%
$\bar{v}$	0.11	0.01	-90.57%
$\bar{u}$	0.10	0.02	-80.73%
$j\bar{c}r$	0.11	0.01	-88.48%
$j\bar{d}r$	0.11	0.01	-88.48%

Note: The last column shows the percentage change after an increase from $F = 0$ to $F = F_{\max}$

D MODEL WITH DIFFERENT DISMISSAL PROCEDURE

In this section, we present a version of our benchmark with a different modeling approach for EPL. In contrast to our baseline model, firms can dismiss workers at no dismissal cost if the employee has just matched with the firm in the previous period and has not yet participated in the firm's production process. In the following, we describe briefly the model, the general equilibrium equations and some further results.

D.I *Model and general equilibrium equations*

With the alternative firing cost mechanism, we need to distinguish between new and already existing matches. Because firing costs only apply to worker-firm pairs that already existed in the previous period, the amount of hours worked, the wage payments and also the separation rate differs for new and existing matches differs. We denote ρ_t^i the job destruction rate, $\tilde{a}_t^i$ the threshold proctivity level, $h_t^i(a)$ hours worked and $w_t^i(a)$ the hourly wages of an already existing worker-firm pair ($i = E$) or of a new worker-firm match ($i = N$). The household problem (equation II.1) rewrites as follows:

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t \left[\frac{c_t^{1-\sigma}}{1-\sigma} - \left(\xi_h (1-\rho_t^E) n_{t-1} \int_{\tilde{a}_t^E}^{\infty} \frac{h_t^E(a)^{1+\nu}}{1+\nu} \frac{g(a)}{1-G(\tilde{a}_t)} da ... \right.\right.$$

$$\left.\left. ... + \xi_h (1-\rho_t^N) m_{t-1} \int_{\tilde{a}_t^N}^{\infty} \frac{h_t^N(a)^{1+\nu}}{1+\nu} \frac{g(a)}{1-G(\tilde{a}_t)} da + \xi_N \frac{n_t^{1+\eta}}{1+\eta} \right) \right]$$

$$\text{s.t. } c_t + b_t \leq R_{t-1} b_{t-1} + w h_t^E (1-\rho_t^E) n_{t-1} + w h_t^N (1-\rho_t^N) m_{t-1} + t_t$$

With $wh_t^i = \int_{\tilde{a}_t^i}^{\infty} w_t^i(a) h_t^i(a) \frac{g(a)}{1-G(\tilde{a}_t)} da$, with $i = E, N$

The production function (equation II.4) has to be adjusted to take into account the difference between new and existing matches:

$$y_t = Z_t^{\frac{1+\nu}{\nu}} \lambda_t^{\frac{1}{\nu}} \xi_h^{\frac{-1}{\nu}} \left(n_{t-1} \int_{\tilde{a}_t^E}^{\infty} a^{\frac{1+\nu}{\nu}} g(a) da + m_{t-1} \int_{\tilde{a}_t^N}^{\infty} a^{\frac{1+\nu}{\nu}} g(a) da \right)$$

The firm problem (equation II.6) has to be rewritten as:

$$\mathcal{P} = \mathbb{E}_0 \left\{ \sum_{t=0}^{\infty} \exp(d_t) \beta^t \lambda_t \left[y_t - n_t \int_{\tilde{a}_t}^{\infty} w_t(a) h_t(a) \frac{g(a)}{1-G(\tilde{a}_t)} da - \psi \Gamma_t - \rho_t^N n_{t-1} F \right] \right\}.$$

To solve the model, the wage and hours bargaining problem has to be solved for new and existing matches separately. Below is the list of general equilibrium equations. In case of no firing costs, the equilibrium is the same as in the benchmark model.

$$\rho_t^E = G(\tilde{a}_t^E) \tag{D.1}$$

$$\rho_t^N = G(\tilde{a}_t^N) \tag{D.2}$$

$$c_t^{-\sigma} = \beta R_t \mathbb{E}_t \left[\frac{\exp(d_{t+1})}{\exp(d_t)} c_{t+1}^{-\sigma} \right]. \tag{D.3}$$

$$y_t = Z_t^{\frac{1+\nu}{\nu}} \lambda_t^{\frac{1}{\nu}} \xi_h^{\frac{-1}{\nu}} \left(n_{t-1} \int_{\tilde{a}_t^E}^{\infty} a^{\frac{1+\nu}{\nu}} g(a) da + m_{t-1} \int_{\tilde{a}_t^N}^{\infty} a^{\frac{1+\nu}{\nu}} g(a) da \right) \tag{D.4}$$

$$n_t = (1 - \rho_t^E) n_{t-1} + (1 - \rho_t^N) m_{t-1} \tag{D.5}$$

$$\theta = v_t / u_t \tag{D.6}$$

$$m(u_t, v_t) = B u_t^{\mu} v_t^{1-\mu} = B \theta_t^{1-\mu} u_t \tag{D.7}$$

$$u_t = (1 - n_t) \tag{D.8}$$

$$q(\theta_t) = \frac{m(u_t, v_t)}{v_t} = B \theta_t^{-\mu} \tag{D.9}$$

$$\lambda_t = c_t^{-\sigma} \tag{D.10}$$

$$y_t = c_t + \psi \Gamma'_{t,v} + \rho_t^E n_{t-1} F \tag{D.11}$$

$$\begin{aligned} \frac{\chi \Gamma'_{t,v}}{q_t} &= \beta \mathbb{E}_t \left[\frac{\exp(-d_{t+1})}{\exp(-d_t)} \frac{\lambda_{t+1}}{\lambda_t} (1 - \zeta) Z_{t+1}^{\frac{1+\nu}{\nu}} \lambda_{t+1}^{\frac{1}{\nu}} \xi_h^{-\frac{1}{\nu}} \frac{\nu}{1+\nu} (1 - \rho_{t+1}^N) \dots \right. \\ & \left. \left(\int_{\tilde{a}_{t+1}^N}^{\infty} a^{\frac{1+\nu}{\nu}} \frac{g(a)}{1 - G(\tilde{a}_{t+1}^N)} da - \left(\tilde{a}_t^N \right)^{\frac{1+\nu}{\nu}} \right) \right] \end{aligned} \tag{D.12}$$

$$\begin{aligned} 0 &= (1 - \zeta) \frac{\nu}{1+\nu} Z_t^{\frac{1+\nu}{\nu}} \lambda_t^{\frac{1}{\nu}} \xi_h^{\frac{-1}{\nu}} \left(\tilde{a}_t^E \right)^{\frac{1+\nu}{\nu}} - (1 - \zeta) \frac{\xi_N n_t^{\eta}}{\lambda_t} - \zeta \theta_t \psi \Gamma'_{t,v} \dots \\ &+ \beta \mathbb{E}_t \left\{ \frac{\exp(-d_{t+1})}{\exp(-d_t)} \frac{\lambda_{t+1}}{\lambda_t} (1 - \zeta) \frac{\nu}{1+\nu} Z_{t+1}^{\frac{1+\nu}{\nu}} \lambda_{t+1}^{\frac{1}{\nu}} \xi_h^{\frac{-1}{\nu}} (1 - \rho_{t+1}^E) \dots \right. \\ & \left. \left(\int_{\tilde{a}_{t+1}^E}^{\infty} a^{\frac{1+\nu}{\nu}} \frac{g(a)}{1 - G(\tilde{a}_{t+1}^E)} da - \left(\tilde{a}_{t+1}^E \right)^{\frac{1+\nu}{\nu}} \right) \right\} \dots \\ &+ \left(1 - \beta \mathbb{E}_t \left[\frac{\exp(-d_{t+1})}{\exp(-d_t)} \frac{\lambda_{t+1}}{\lambda_t} \right] \right) (1 - \zeta) F \end{aligned} \tag{D.13}$$

$$\begin{aligned} 0 &= (1 - \zeta) \frac{\nu}{1+\nu} Z_t^{\frac{1+\nu}{\nu}} \lambda_t^{\frac{1}{\nu}} \xi_h^{\frac{-1}{\nu}} \left(\tilde{a}_t^N \right)^{\frac{1+\nu}{\nu}} - (1 - \zeta) \frac{\xi_N n_t^{\eta}}{\lambda_t} - \zeta \theta_t \psi \Gamma'_{t,v} \dots \\ &+ \beta \mathbb{E}_t \left\{ \frac{\exp(-d_{t+1})}{\exp(-d_t)} \frac{\lambda_{t+1}}{\lambda_t} (1 - \zeta) \frac{\nu}{1+\nu} Z_{t+1}^{\frac{1+\nu}{\nu}} \lambda_{t+1}^{\frac{1}{\nu}} \xi_h^{\frac{-1}{\nu}} (1 - \rho_{t+1}^E) \dots \right. \\ & \left. \left(\int_{\tilde{a}_{t+1}^E}^{\infty} a^{\frac{1+\nu}{\nu}} \frac{g(a)}{1 - G(\tilde{a}_{t+1}^E)} da - \left(\tilde{a}_{t+1}^E \right)^{\frac{1+\nu}{\nu}} \right) \right\} - (1 - \zeta) \beta \mathbb{E}_t \left[\frac{\exp(-d_{t+1})}{\exp(-d_t)} \frac{\lambda_{t+1}}{\lambda_t} \right] F \end{aligned} \tag{D.14}$$

$$H_t(\tilde{a}_t) = \left(\frac{Z_t \lambda_t}{\xi_h} \right)^{\frac{1}{\nu}} \left(\frac{(1 - \rho_t^E) n_{t-1}}{n_t} \int_{\tilde{a}_t^E}^{\infty} a^{\frac{1}{\nu}} \frac{G(a)}{1 - G(\tilde{a}_t^E)} da + \frac{(1 - \rho_t^N) m_{t-1}}{n_t} \int_{\tilde{a}_t^N}^{\infty} a^{\frac{1}{\nu}} \frac{g(a)}{1 - G(\tilde{a}_t^N)} da \right) \tag{D.15}$$

$$\begin{aligned} \int_{\tilde{a}_t}^{\infty} w_t(a) h_t(a) \frac{g(a)}{1 - G(\tilde{a}_t)} da &= \left(\zeta + \frac{1 - \zeta}{1+\nu} \right) \frac{y_t}{n_t} + (1 - \zeta) \frac{\xi_N n_t^{\eta}}{\lambda_t} + \zeta \theta_t \psi \Gamma'_{t,v} \dots \\ &+ \zeta \left(1 - \beta \mathbb{E}_t \left[\frac{\exp(-d_{t+1})}{\exp(-d_t)} \frac{\lambda_{t+1}}{\lambda_t} \right] \right) F - (1 - \rho_t^N) \frac{m_{t-1}}{n_t} \zeta F \end{aligned} \tag{D.16}$$

$$\ln(Z_t) = \rho_z \ln(Z_{t-1}) + \varepsilon_z, \ \varepsilon_z \sim N(0, \sigma_z^2) \tag{D.17}$$

$$\ln(d_t) = \rho_d \ln(d_{t-1}) + \varepsilon_d,\ \varepsilon_d \sim N(0, \sigma_d^2) \tag{D.18}$$

D.II *Further results*

Table 13 shows the effect of an increase in firing costs based on the alternative firing cost mechanism. As can be seen in the table, the impact of firing costs is qualitatively similar to the benchmark model. The main difference is concerns the size of the effect. In particular, firing costs reduce the steady state job creation and destruction rate by less if firing costs only occur with long lasting employment relationships.

Table 13: *Steady State to Firing Cost Relation: Robustness Check for Different Dismissal Procedure*

	$\mathbf{F = 0\%}$	$\mathbf{F \approx 11\%}$	$\mathbf{\Delta}$ **in %**
$\bar{y}$	0.31	0.32	2.75%
$\bar{n}$	0.90	0.96	6.77%
$\bar{h}$	0.33	0.32	-2.68%
$\bar{v}$	0.11	0.06	-44.36%
$\bar{u}$	0.10	0.04	-60.87%
$\bar{jcr}$	0.10	0.05	-52.11%
$\bar{jdr}$	0.10	0.05	-51.79%

Note: The last column shows the percentage change after an increase from $F = 0$ to $F = F_{\max}$

FIGURES

Figure 1: *Protection Against Dismissal and fluctuations in the job creation rate relative to the variance in the job destruction rate*

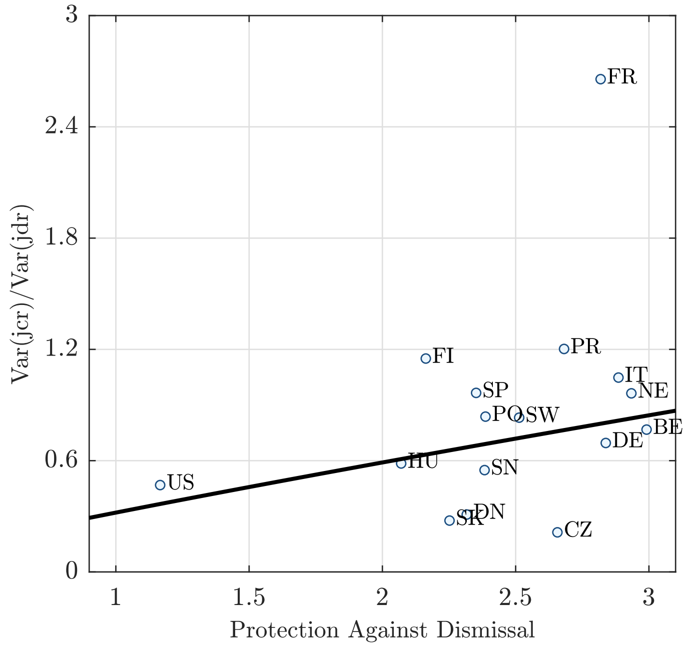


Figure 2: *Protection Against Dismissal and correlation between unemployment and vacancies*

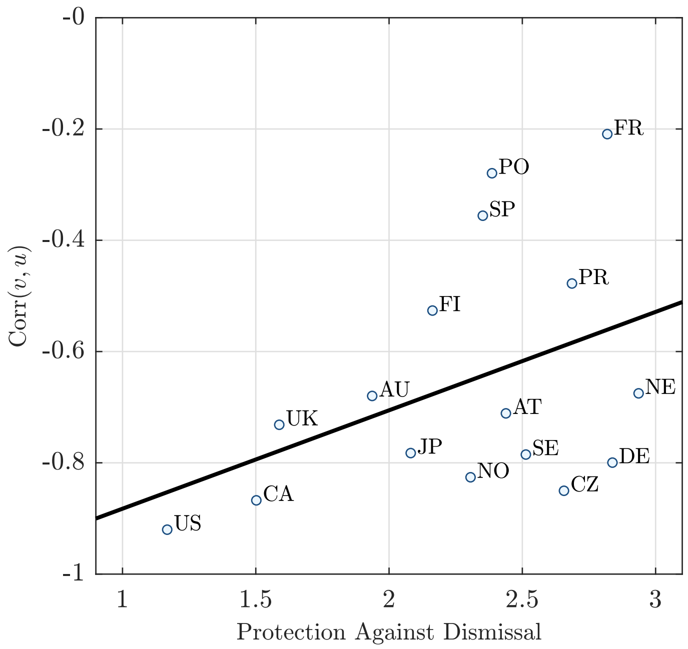


Figure 3: *Protection Against Dismissal and fluctuations in hours worked relative to fluctuations in employment*

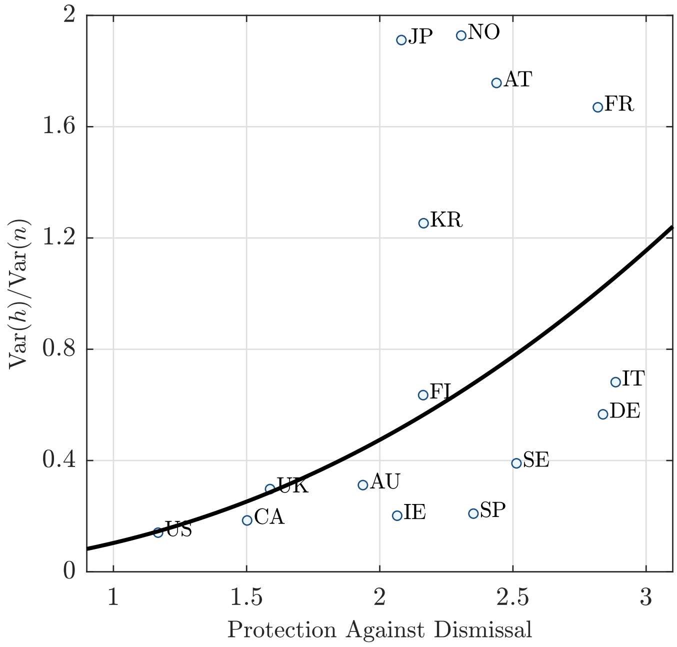


Figure 4: *Protection Against Dismissal and fluctuations in the job creation rate relative to the variance in the job destruction rate*

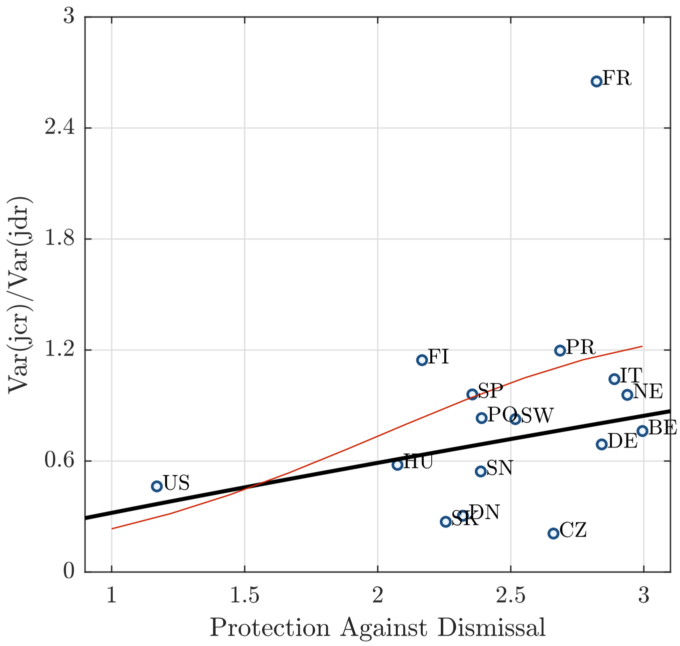


Figure 5: *Protection Against Dismissal and correlation between unemployment and vacancies*

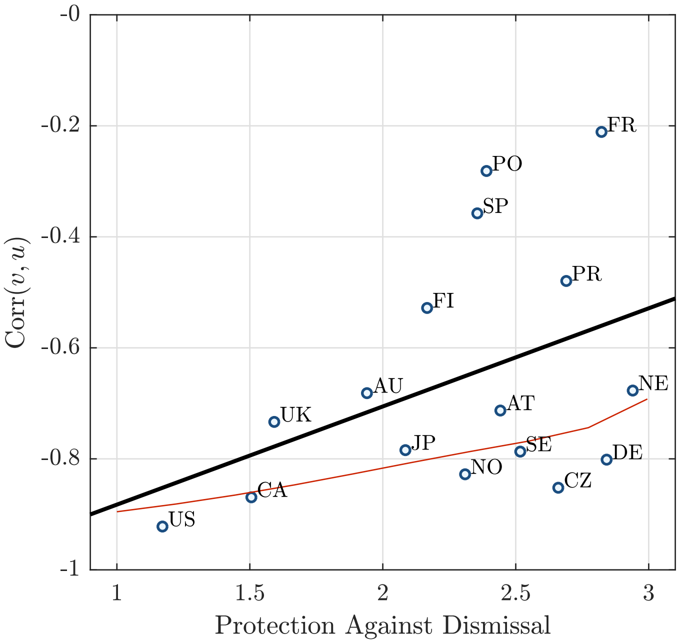


Figure 6: *Protection Against Dismissal and fluctuations in hours worked relative to fluctuations in employment*

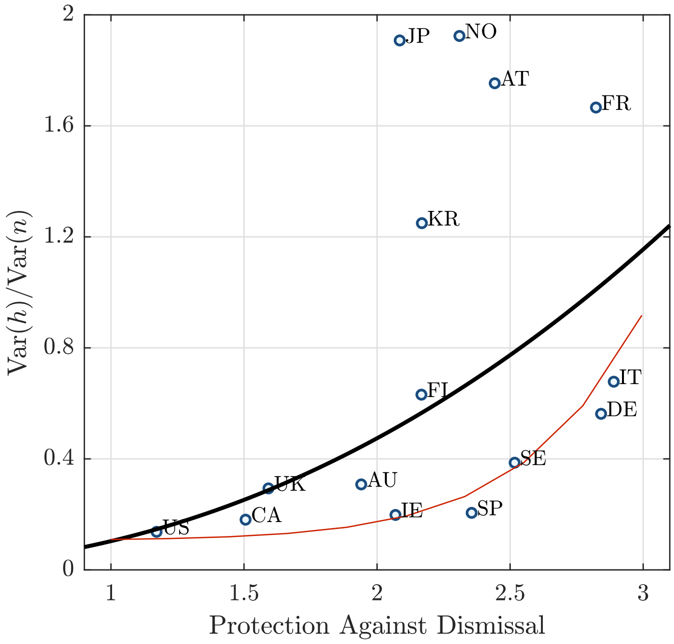
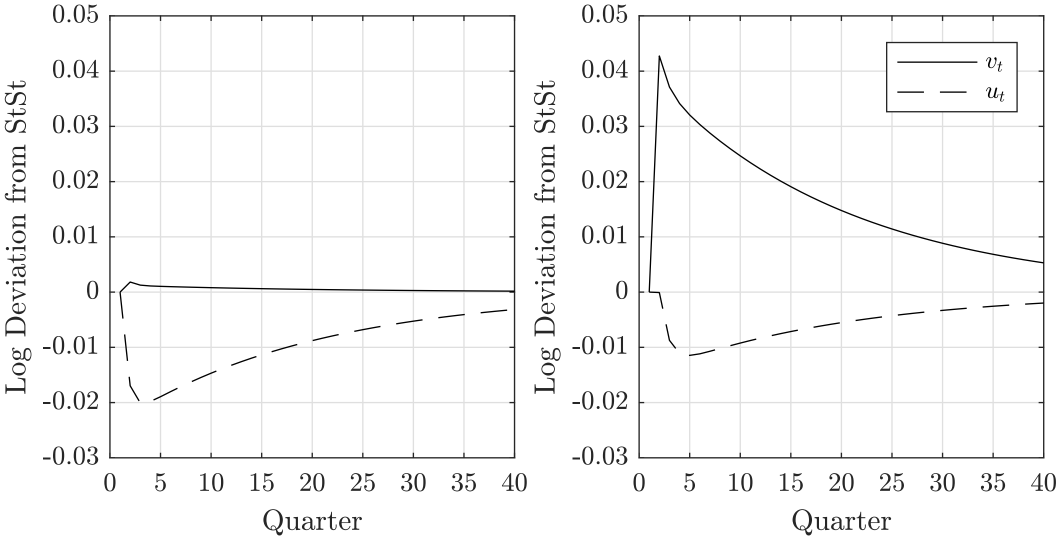
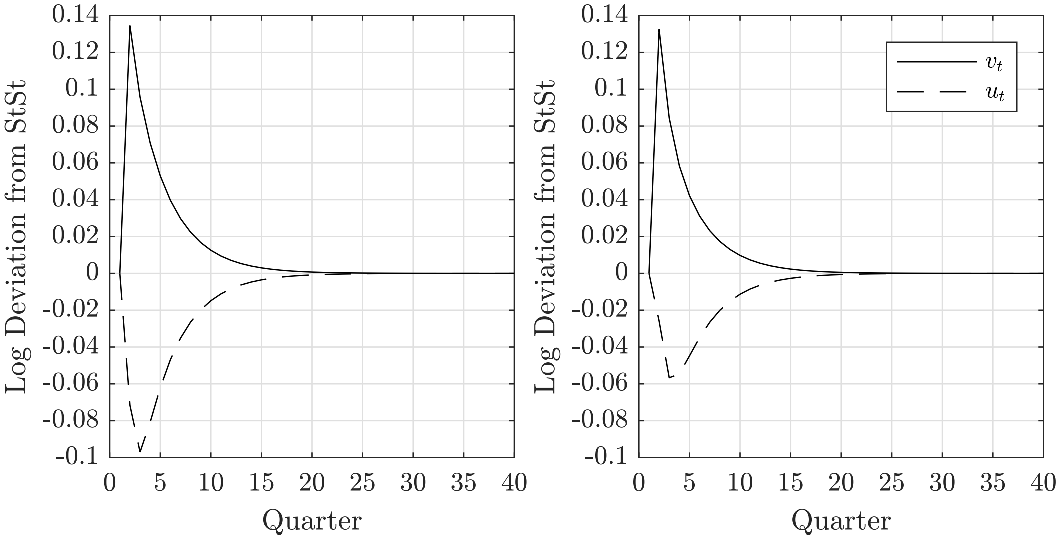


Figure 7: *Impulse response to a positive technology shock of size σ_z*



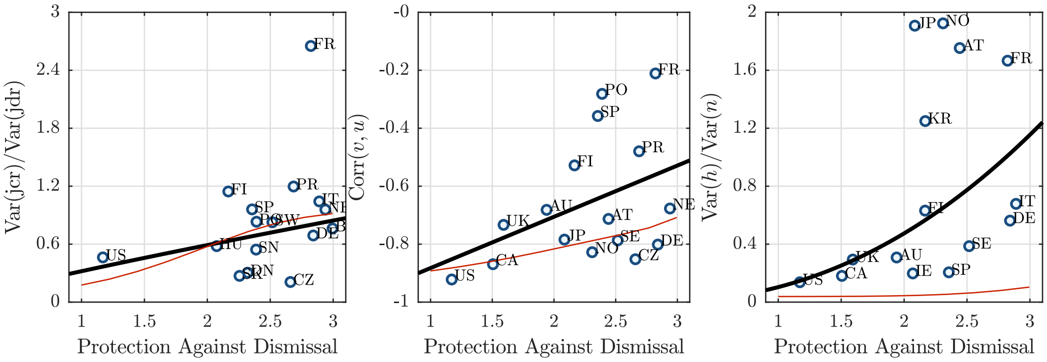
(a) $F = 0$ **(b)** $F = F_{max}$

Figure 8: *Impulse response to a positive discount factor shock of size σ_d*



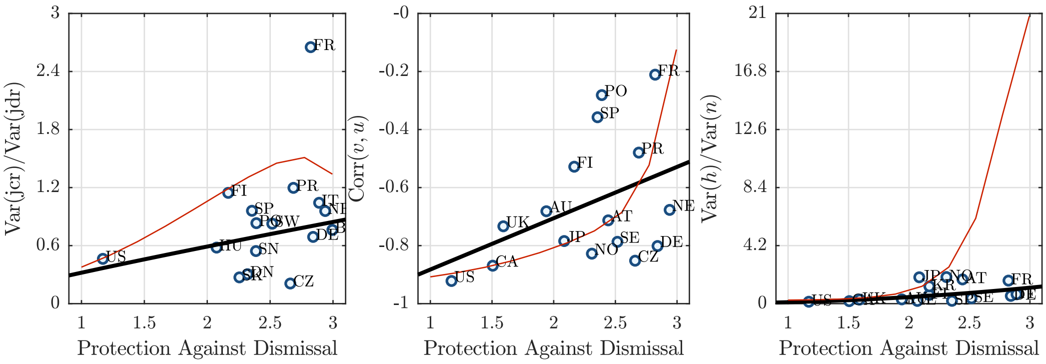
(a) $F = 0$ **(b)** $F = F_{max}$

Figure 9: *Empiricial Regularities: Model fit for $\nu = 2$*



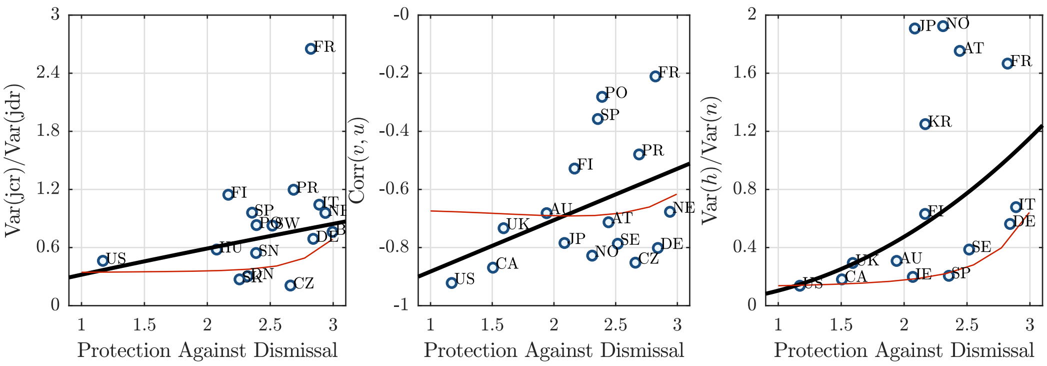
(a) *Var(JCR)/Var(JDR)* (b) *corr(v, u)* (c) *Var(h)/Var(n)*

Figure 10: *Empiricial Regularities: Model fit for $\nu = 0.5$*



(a) *Var(JCR)/Var(JDR)* (b) *corr(v, u)* (c) *Var(h)/Var(n)*

Figure 11: *Empiricial Regularities: Model fit for Different Firing Procedure*



(a) *Var(JCR)/Var(JDR)* (b) *corr(v, u)* (c) *Var(h)/Var(n)*