EMPLOYMENT PROTECTION LEGISLATION AND ECONOMIC RESILIENCE: PROTECT AND SURVIVE?

Nadav Ben Zeev and Tomer Ifergane

Discussion Paper No. 19-10

September 2019

Monaster Center for
Economic Research
Ben-Gurion University of the Negev
P.O. Box 653
Beer Sheva, Israel

Fax: 972-8-6472941
Tel: 972-8-6472286

Employment Protection Legislation and Economic Resilience: Protect and Survive?*

Nadav Ben Zeev†

Ben-Gurion University of the Negev

Tomer Ifergane‡

Ben-Gurion University of the Negev

September 26, 2019

Abstract

Employment protection legislation (EPL) policies are in use throughout the developed world but their role in the transmission of macroeconomic shocks into the real economy is mostly unstudied. We illustrate the potential role of these policies as amplifiers of macroeconomic shocks in a simple search and matching model which indicates that strict EPL can lead to factor-misallocation-induced output losses in the presence of adverse shocks. We then perform a quasi-natural experiment which utilizes global credit supply shocks, especially the large ones observed in the recent financial crisis, to study this role within a non-linear, state-dependent panel fixed-effects local projections framework using a panel of 21 OECD economies. We show that strict EPL is associated with a weaker initial response of the labor market, which is followed by a stronger and more persistent decline in real output as well as a slower return of unemployment and hours worked to their pre-shock levels. The stronger output decline can be mostly explained by a stronger fall in aggregate total factor productivity (TFP), suggesting that EPL strictness may hinder reallocation and thus act as a shock amplifier which prevents the recovery of output via persistent factor-misallocation-induced TFP losses.

JEL classifications: E02, E24, E32, E60, J08

Keywords: Employment protection, Factor Misallocation, Total Factor Productivity, Credit Supply Shocks, Economic resilience, Business cycles, Local projections

*We are grateful to Tatiana Baron, Tomer Blumkin,, Michael Burda, Mattias Doepke, Ezra Einy, Daniel Hamermesh, Zvi Hercowitz, Costas Meghir, Christian Merkl, Gerard Pfann, Eran Yashiv, and participants at IZA's 20th world labor conference, The Israeli Economic Association's annual conference 2018, and the BGU doctoral colloquium for helpful comments and suggestions.

†Department of Economics, Ben-Gurion University of the Negev, Israel. *E-mail:* nadavbz@bgu.ac.il.

‡Department of Economics, Ben-Gurion University of the Negev, Israel. *E-mail:* iftomer@gmail.com.

1 Introduction

How does employment protection legislation (EPL) affect the transmission of macroeconomic shocks? EPL is a widely used policy device in developed economies and it is an important institutional factor in the modern labor market. Most of the policy debate regarding EPL is centered around two main issues: its effects on long-term macroeconomic performance on the one hand, and its significance for microeconomic outcomes in the labor market on the other hand.[1] However, the use of such a policy device in times of economic adversity may alter the impact of macroeconomic shocks, influence their transmission mechanisms, and affect recovery.

What This Paper Does. Our aim in this paper is to explore the potential link between EPL and economic resilience. (We use the latter term in reference to an economy's ability to withstand macroeconomic shocks.) To accomplish this goal, this paper unfolds in two parts. First, we demonstrate the capacity of EPL to affect business cycle dynamics using a simple search and matching model which incorporates termination costs and advance notice. The model serves to show that strict EPL slows overall job flows in the economy and thus dampens the decrease in employment resulting from an adverse shock. Nevertheless, it does so at the cost of a decline in total factor productivity (TFP) stemming from factor misallocation. As such, the model highlights two channels of influence by which strict EPL affects the economy's resilience: a slower job flow based channel and a factor-misallocation-induced TFP channel. Following an adverse shock, these two channels affect output in conflicting directions, with the former moderating the decline in output and the latter amplifying it. While for the baseline calibration the former chan-

[1] The literature on EPL is vast and encompasses various fields, ranging from labor and political economics to macroeconomics; our focus in this paper is on the macroeconomic aspect of EPL and therefore we do not discuss much of the literature concerning EPL from other perspectives. For a comprehensive overview of this literature see Skedinger (2010) or chapter 10 in Boeri and van Ours (2013).

nel dominates the latter, the key takeaway from our model is the formal theory-rooted motivation for empirically studying these two conflicting mechanisms in the data.

Second, we utilize global shifts in credit conditions to conduct a quasi-natural experiment capable of uncovering the effects and propagation of such shifts into output and labor markets of economies exhibiting different levels of EPL. The central motivation for our empirical approach rests on the fact that the recent global financial crisis had a considerable effect on developed economies and that most of these economies vary substantially with respect to their labor market policies. We carry out this analysis by estimating state-dependent impulse response functions to the shock for measures of real activity and labor market activity. Our identification approach adapts the local projections method developed in Jorda (2005) to a panel setting, as in Auerbach and Gorodnichenko (2012), where inference is based on Driscoll and Kraay (1998) standard errors which control for temporal and cross-sectional correlation in the error term.

The main results from our empirical analysis can be summarized as follows. A strict EPL regime reduces the initial effect of the shock on the labor market, leading to a smaller and slower rise in unemployment, a smaller drop in employment, and to more stability in terms of labor-force participation. However, from roughly the 1.5-year mark onwards, economies under a strict EPL regime experience a stronger and more persistent decline in real output. The drop in output is in the opposite direction to the effect on employment and too fast and sizable to be accounted for by a differential decline in capital stock, which leads us to suspect a drop in TFP is taking place under the strict EPL regime. Such a drop is indeed evident in the data and is statistically significant. We further demonstrate that this sequence of differential responses in the labor market, real output, and TFP is statistically significant and robust to various choices of specifications, and samples. These results indicate that the transmission channels suggested by theory regarding the significance of EPL for business cycle dynamics are present in the data and that the amplification channel via a TFP decline is quantitatively dominant. Interpreted through the lens of the model from Section 2, this amplification mechanism has its roots in EPL's contribution to increased misallocation of labor.

Literature Review. This paper is most closely related to the literature on labor market institutions and their interaction with macroeconomic shocks. The work of Blanchard and Wolfers (2000) describes how changes in European unemployment data can be explained by the interactions the institutional factors in the labor market with various shocks. In addition to the long-term changes in unemployment, institutional factors had been linked to macroeconomic volatilities (e.g., Gnocchi et al. (2015) and Rumler and Scharler (2011)). The interaction between EPL and the business cycle has also been studied in Nunziata (2003) which demonstrates empirically and theoretically that strictness of EPL lowers the output elasticity of employment. Along this line, Duval and Vogel (2008) illustrate how strict EPL leads to more persistence in business cycle dynamics using output gap to identify cycles. The mechanism suggested by theory to explain this link between cyclical adjustment and EPL is that strict EPL should slow turnover dynamics and make the adjustment process to a shock longer as in Bentolila and Bertola (1990) and in Garibaldi (1998). The work of Messina and Vallanti (2007) provides support to this claim using firm-level data which indicates that strictness of EPL dampens the response of job destruction to the cycle, thus leading to less counter-cyclicality in job destruction.

This paper contributes to the empirical literature by conducting a comprehensive investigation of the link between EPL and the transmission of credit supply shocks to several outcome measures, such as real output, privet consumption, investment, capacity utilization, TFP, unemployment, employment to population ratio, and labor-force participation. Our identification strategy in this paper differs from the aforementioned works due to the use of an identified shock and higher data frequencies to estimate non-linear, state-dependent impulse response functions which allow observing EPL's effect on the shock's transmission channel rather than exploring EPL's effects on moments or long-term trends.

Outline. The rest of the paper proceeds as follows. We begin in Section 2 by presenting a motivating model for our empirical analysis which illustrates the potential significance of EPL for business cycle dynamics. We proceed by describing the data used with an emphasis on the measures for EPL in Section 3. In Section 4 we present our econometric method. In Section 5 we present and discuss our results. In Section 6 we analyze the robustness of our main results to different methodological choices and alternative institutional explanations. The final section concludes.

2 Theoretical Motivation

In this section, we demonstrate using a simulation of a simple, one-sector model how EPL can affect the transmission of an aggregate shock. EPL in our model will consist of a termination cost and a notice period. During the notice period, the worker awaits termination and thus has no incentive to exert effort in production. The firm is bound by legal constraints continue employing said worker under the same wage. Total separation costs for an employee are thus the sum of the cost of termination and wage paid during the notice period. In terms of aggregate production, this separation cost is an adjustment cost to the aggregate labor input. The more costly the adjustment is, the less likely it is to occur, which means that the firm will be less inclined to separate from less productive workers. This incentive lowers aggregate productivity which is the average productivity of all active matches.

This link between separation costs and productivity is presented in Lagos (2006) which shows that firing cost reduce aggregate steady-state productivity. His analysis builds on the framework of the textbook endogenous separation search and matching model found in Pissarides (2000) and links the reservation productivity level, the lowest productivity realization of a match that does not result in termination, and aggregate productivity. The lower the reservation level, the lower is aggregate TFP. Our model follows the two previous models closely but with two alterations. First, we add to the model advance notice instead of just a termination cost in a fashion similar to the treatment of notice in Garibaldi (1998) and Bentolila et al. (2012). Upon the choice of a matched pair to separate, the worker produces the minimum possible amount and is paid the average wage rate in the economy until a firing permission arrives and induces payment of the termination cost by the firm and final separation of the pair. Second, since we are interested in business cycle dynamics, we add aggregate risk into the model.

The canonical work on the business cycle implications of labor market frictions is Shimer (2005), which conducts two main stochastic exercises: a shock to the common productivity factor and a shock to the separation rate. We adopt the latter approach as it facilitates an endogenous TFP response, while the former assumes an exogenous shift in TFP which is exogenous and not EPL related. The simplest way to do so in an endogenous separation model is by the introduction of a Markov process for λ, the arrival rate of idiosyncratic shocks to match quality. Such a shock results in a given match having a higher risk of changing its quality. This is, of course, a reduced form way to consider a business-cycle-type shock as the model abstracts from the existence of capital, financial markets, and risk aversion. However, the shock is closely related to the mechanism of discount-induced changes in labor market dynamics presented in Hall (2017) as it affects the effective discount rate of an individual match.

Our theoretical device abstracts from many potential channels of influence for EPL. We abstract from EPL's potential impact on research and development expenditure as in Saint-Paul (2002), from the potential for distributional effects as in Kahn (2007), from nominal rigidities as in Zanetti (2011), and from EPL's effect on long-term human capital accumulation as in Gaetani and Doepke (2016). The reason for this simplification is twofold. The first is analytical tractability and the second is that most of these elements have a bearing on long-term growth and market structure while our key interest is cyclical dynamics for shorter horizons. Hence, the merits of using a stylized search and matching model as a theoretical motivation outweigh, in our eyes at least, its inherent limitations.

2.1 The Model

EPL can be seen as a multidimensional institutional factor in that it includes not only severance pay or layoff taxes but also the duration of advance notice and possibilities for legal recourse following termination notice. As such, we incorporate both termination cost and advance notice in the model. Suppose that there is a continuum of measure one of potential workers which can be employed, unemployed, or employed with advance notice to termination. A firm is an employer-employee pair which produces a single homogeneous good using a common productivity factor p and an idiosyncratic component x which can be considered as the quality of the match. At the time of the match formation, the pair's match quality is at its maximum level which is normalized to one. Match quality may experience an idiosyncratic shock that arrives at rate λ which re-draws x from the CDF $G(x)$ which is assumed to be uniform and bounded between zero to one. The arrival of such a shock may trigger a separation choice. We assume that the match cannot separate immediately due to EPL but that the separation decision results in the pair entering into a period of advance notice. The worker under advance notice receives a wage w^n which is the average wage in the economy at steady state. This worker has the minimum level possible of match quality, and its eventual termination arrives with the rate ϕ which corresponds to notice duration.

Value Functions. The value function of the vacant firm (V) is:

$$rV_i = -pc + \mathrm{q}(\theta_i)\ J_i^{\,0} + \tau E_i[V - V_i], \tag{1}$$

where r is the discount rate, c is the flow cost of a vacancy, $\mathrm{q}(\theta)$ is the vacancy-filling rate. Subscript i denotes the state of nature which corresponds to the value of λ. τ is the arrival rate of a shock that redraws λ from the state-space Λ and E_i denotes conditional expectations in state i. J^0 is the value from a newly occupied job which is given by:

$$rJ_i^{\,0} = p - w_i^{\,0} + \lambda_i \int_0^1 \max\{\mathrm{J}_i(s)\ , J_i^{\,n}\}\,\mathrm{dG}(s)\ - \lambda_i J_i^{\,0} + \tau E_i\Big[\mathrm{J}(1)\ - J_i^{\,0}\Big], \tag{2}$$

where $w_i^{\,0}$ is the wage of a newly hired worker in state i. The value of an existing job with match quality x is given by:

$$\begin{aligned} r\,\mathrm{J}_i(x)\ &= px - \mathrm{w}_i(x) + \lambda_i \textstyle\int_0^1 \max\{\mathrm{J}_i(s)\ , J_i^{\,n}\}\,\mathrm{dG}(s)\ - \lambda_i \mathrm{J}_i(x) \\ &+\tau E_i[\mathrm{J}(x)\ - \mathrm{J}_i(x)]\,, \end{aligned} \tag{3}$$

where $\mathrm{w_i}(x)$ is the wage rate at match quality x in state i. After notice had been served, the value of the firm from the job under advance notice J_n is

$$rJ_i^{\,n} = -w^n + \phi(V_i - J_i^{\,n} - f) + \tau E_i[J^n - J_i^{\,n}], \tag{4}$$

where f is a termination cost. For the sake of simplicity we abstract from government and its budget, so f can be considered as a non-pecuniary cost rather than a separation tax, such as a procedural cost. Note that the wage in this state is exogenously set since the pair had already chosen separation and only the existence of EPL keeps them together. The wage under notice w^n is calibrated to the steady-state average wage in the economy.

The unemployed person's value U is given by

$$rU_i = z + \theta_i \, \mathrm{q}\left(\theta_i\right) \left(W_i{}^0 - U_i\right) + \tau E_i[U - U_i], \tag{5}$$

where z is the flow value of unemployment, and $\theta_i \, \mathrm{q}\left(\theta_i\right)$ is the job finding rate at state i. W^0 is the value of a newly hired worker from employment which is given by:

$$rW_i{}^0 = w_i{}^0 + \lambda_i \int_0^1 \max\left\{ \mathrm{W}_i\left(s\right), W_i{}^n \right\} \mathrm{dG}\left(s\right) - \lambda_i W_i{}^0 + \tau E_i\left[\mathrm{W}\left(1\right) - W_i{}^0 \right]. \tag{6}$$

The employed worker in a job with match quality x is given by:

$$\begin{array}{l} r\,\mathrm{W}_i\left(x\right) \;=\; \mathrm{w}_i\left(x\right) + \lambda \int_0^1 \max\left\{ \mathrm{W}\left(s\right), W_i{}^n \right\} \mathrm{dG}\left(s\right) - \lambda\, \mathrm{W}_i\left(x\right) \\ +\tau E_i\left[\mathrm{W}\left(x\right) - \mathrm{W}_i\left(x\right) \right] \end{array}. \tag{7}$$

Finally, the value of a worker form a job after receiving advance notice is:

$$rW_i{}^n = w^n + \phi(U_i - W_i{}^n) + \tau E_i[W^n - W_i{}^n]. \tag{8}$$

Wage Setting. Wages are set by Nash bargaining with two bargaining problems. The first, for the newly hired worker, or outsider, and the second for the existing worker or insider. Thus, wage rates for outsiders w^0 and insiders $w(x)$ are given by:

$$w_i{}^0 = \arg\ \max \left(W_i^0 - U_i\right)^{\beta} \left(J_i^0 - V_i\right)^{1-\beta}, \tag{9}$$

$$\mathrm{w}_i(x) = \arg\max (\mathrm{W}_i(x) - W_i^{n})^{\beta}(\mathrm{J}_i(x) - J^{n})^{1-\beta}, \tag{10}$$

where β is the workers bargaining power.

As is conventional in the literature we assume free entry, i.e., $V_i = 0$ which together with Equation (1) which means that $J_i^{0} = \frac{pc}{\mathrm{q}(\theta_i)}$.

The insider's wage splits the following surplus:

$$\mathrm{S}_i(x) = \mathrm{J}_i(x) + \mathrm{W}_i(x) - W_i^{n} - J_i^{n}. \tag{11}$$

In a deterministic set-up it is easy to show that the surplus is strictly increasing in x so the reservation productivity level R is uniquely defined. In our stochastic set-up this generalizes into a unique reservation level R_i for each state.[2] This level is the realization of x that would result in $\mathrm{J_i}(R_i) = J_i^n$.

Solving the bargaining problem of the insider using the definition of R_i and substituting the value functions into the first order condition $\beta(\mathrm{J}_i(x) - J_i^{n}) = (1-\beta)(\mathrm{W}_i(x) - W_i^{n})$ results in the following wage solution:[3]

$$\begin{aligned} \mathrm{w}_i(x) =& \beta p x + \tau E_i[[\beta J^n - (1-\beta)W^n] - [\beta J_i^{n} - (1-\beta)W_i^{n}]] \\ & - \beta r J_i^{n} + (1-\beta) r W_i^{n}. \end{aligned} \tag{12}$$

The wage setting problem of the outsider, gives rise to the following surplus and first

[2]This uniqueness requires that the system of m surplus equations yield m strictly positive derivatives. Using the functional forms we obtain that the following linear system $(r + \lambda_i + \tau)\frac{\partial \mathrm{S}_i(x)}{\partial x} = p + \tau \sum_{j=1}^{m} \pi_{ij} \frac{\partial \mathrm{S}_j(x)}{\partial x}$, must yield a strictly positive $\frac{\partial \mathrm{S}_i(x)}{\partial x}$ for all $\lambda_i \in \Lambda$, where π_{ij} denotes the transition probability from state i to state j. In our quantitative exercise these conditions hold.

[3]See explicit solution in Appendix A.

order condition

$$S_i{}^0 = W_i{}^0 + J_i{}^0 - U_i,\;\; \beta J_i{}^0 = (1-\beta)\Big(W_i{}^0 - U_i\Big).$$

Note that since the wage does not affect the surpluses, one can write $S_i{}^0 = \mathrm{S}_i\,(1) + W_i{}^n + J_i{}^n - U_i$. The outsider's surplus can be expressed using the insider's surplus $S_i(1)$, and the value of J_i^0 can be substituted from the free-entry condition. Thus, this link can be expressed also as

$$\frac{pc}{\mathrm{q}\,(\theta_i)}\frac{1}{1-\beta} = \frac{1}{1-\beta}(\mathrm{J}_i\,(1)\; - J_i{}^n) + W_i{}^n + J_i{}^n - U_i. \tag{13}$$

Equation (13), along with Equation (3) with the wage solution, and Equations (4), (5), and (8) solve the model.[4]

Matching. We assume the standard Cobb-Douglas matching function $\mathrm{m}\,(u, v) = \sigma u^{\eta} v^{1-\eta}$ with $\theta = \frac{v}{u}$ denoting labor market tightness and the vacancy filling rate being $\mathrm{q}\,(\theta) = \frac{m}{v}$.

Population Composition and TFP. The population is normalized to unity and is composed of three groups: unemployed persons u, employed persons n, and those employed with advance notice n_a. Since we are interested in the effects on TFP, it is convenient to define the CDF of match quality in of active matches not under notice as $H(x)$. The law of motion for $H(x)$ is as follows. Although the model is in continuous time, time subscripts are added here for the sake of clarity and state subscripts and conditional expectations operators are omitted from the same reason:

[4]Numerically, Equation (3) needs to be discretized and thus it represents a system of equations, one for each level of x.

$$\frac{\mathrm{d}\,\mathrm{H}_t\,(x)}{\mathrm{d}\,t} = -\,\mathrm{H}_{t-1}\,(R_t)\;\frac{n_{t-1}}{n_t} + \lambda\frac{n_{t-1}}{n_t}(1-\,\mathrm{H}_{t-1}\,(x)\,)(\,\mathrm{G}\,(x)\;-\;\mathrm{G}\,(R_t)\,) \tag{14}$$
$$-\,\lambda\frac{n_{t-1}}{n_t}[\,\mathrm{H}_{t-1}\,(x)\;-\;\mathrm{H}_{t-1}\,(R_t)\,]\,\mathrm{G}\,(R_t)\;-\lambda\frac{n_{t-1}}{n_t}[\,\mathrm{H}_{t-1}\,(x)\;-\;\mathrm{H}_{t-1}\,(R_t)\,](1-\,\mathrm{G}\,(x)\,).$$

This expression holds everywhere except at $x = 1$ where there are also changes due to job-creation. The first term reflects advance notices given to workers due to a change in the reservation level, the last three refer to workers exposed to an idiosyncratic shock which leads to a decrease in match quality to a level above R, to a level below R , or an increase in match quality correspondingly. Since this is the time path of a distribution all these changes are adjusted to the change in measure. In steady state, the reservation level is fixed at its long-term expectation $\bar{R}$ so $H(\bar{R}) = 0$ and the law of motion results in $\mathrm{H}\,(x) \;=\; \mathrm{G}\,(x) \;-\; \mathrm{G}\,(\bar{R})$ for all but the point $x = 1$ at which by definition $H(1) = 1$.

The laws of motion for the population masses are:

$$\frac{\mathrm{d}\,u}{\mathrm{d}\,t} = -\theta_t\,\mathrm{q}\,(\theta_t)\;u_{t-1} + \phi {n_{t-1}}^{a}, \tag{15}$$

$$\frac{\mathrm{d}\,n}{\mathrm{d}\,t} = \theta_t\,\mathrm{q}\,(\theta_t)\;u_{t-1} - \lambda\,\mathrm{G}\,(R)\;n_{t-1}(1-\,\mathrm{H}_{t-1}\,(R_t)\,) - n_{t-1}\,\mathrm{H}_{t-1}\,(R_t)\,, \tag{16}$$

$$\frac{\mathrm{d}\,n_a}{\mathrm{d}\,t} = -\phi {n_{t-1}}^{a} + \lambda\,\mathrm{G}\,(R)\;n_{t-1}(1-\,\mathrm{H}_{t-1}\,(R_t)\,) + n_{t-1}\,\mathrm{H}_{t-1}\,(R_t)\,. \tag{17}$$

These yield, in steady state, the following Beveridge curve:

$$u = \frac{\phi\lambda\,\mathrm{G}\,(R)}{\theta\,\mathrm{q}\,(\theta)\;(\phi + \lambda\,\mathrm{G}\,(R)\,) + \phi\lambda\,\mathrm{G}\,(R)}. \tag{18}$$

Finally, TFP in the model is simply:

$$TFP = p\frac{n}{n+n_a}\int_R^1 xd\,\mathrm{H}\left(x\right). \quad (19)$$

Note that this equation simply means that TFP is the average of x in all matches, under notice or otherwise. In addition to the actively producing pairs whose proportion from the total labor force is $\frac{n}{n+n_a}$, there is a mass of $\frac{n_a}{n+n_a}$ matches under notice that is multiplied by its product which is zero under our assumptions.

2.2 The Effects of EPL on Business Cycle Dynamics

In this section, we perform a quantitative exercise aimed at illustrating the potential effects of EPL policies on business cycle dynamics. We calibrate the model to match France's job flows and institutional parameters. Our reason for choosing France is mainly one of data availability. Notably, this calibration and simulation exercise should not be viewed as an attempt to capture the complexity of France's labor market and its institutions but rather to outline a single mechanism that arises from a general class of policy devices. Using the calibrated model and an alternative, EPL-free institutional framework (henceforth, the no-EPL calibration) we demonstrate the propagation of an exogenous shock in the simulated economy.

Calibration. The model is calibrated to match France's job-finding rate of 23.1% and separation hazard of 2.1% based on Elsby et al. (2013) transformed into quarterly frequency. As in Shimer (2005), the steady state value of θ is normalized to unity and σ is calibrated to match the finding-rate. Institutional calibration is taken from Bentolila et al. (2012): the replacement rate is $z = 0.55$, $f = 0.33$, and $\phi = 0.75$, with the latter two being the EPL related parameters and reflecting values for permanent workers in France. As in Bentolila et al. (2012), the discount factor is set to $r = 0.01$, the bargaining power is

$\beta = 0.5$, $\eta = 0.5$, and the wage under notice w^n is the steady-state average wage in the economy. We normalize the common productivity factor and set $p = 1$.

Using these parameter values and flows we use the separation rate and the deterministic steady state's job creation and destruction equations[5] to calibrate for the average level of λ (denoted as $\bar{\lambda}$), the flow cost of a vacancy c, and steady-state R. A summary of these parameters and model steady-state values can be found in column 1 of Table 1.

As the no-EPL calibration, we set $f = 0$ and one day of advance notice which can be considered as the same institutional structure as in the U.S. The implied steady states and parameters can be found in column 2 of Table 1. Note that this calibration features a higher θ and a higher reservation level than the baseline calibration, both of which translate into unconditionally faster job-flows in the no-EPL economy.

The Shock Process. We introduce a simple two state Markov chain with two levels of λ, one 10% below and one 10% above the average calibrated level. The Markov matrix is presented in the lower third panel of Table 1.

The Role of EPL. The impulse responses to a temporary increase in λ for the two parameterizations are presented in Figure 1, with our baseline calibration in blue and the no-EPL calibration in red. An increased arrival of idiosyncratic shocks is a reduced form way to consider a business cycle in this economy as it generates increased risk to the value of each job. The impulse responses suggest that the shock results in a drop in output and employment and a rise in unemployment as we would expect in a business cycle.

How should EPL affect output's response during a recession in the model? On the one hand, EPL induces higher separation costs for the firm, thus implying that as the cost goes down, more separations will occur when market conditions change. This is, in essence,

[5] See Appendix A for details.

the transmission channel we referred to earlier as the job flow channel: when job flows are slower, output is less responsive to aggregate fluctuations.[6] On the other hand, there is the factor-misallocation-induced TFP channel: EPL contributes to the magnitude and persistence of factor misallocation in our model economy and thus lowers TFP.

In order to understand the importance of factor misallocation for the transmission of an adverse shock, we first need to understand its model representation. In the sense of Restuccia and Rogerson (2008) and Hsieh and Klenow (2009), misallocation is manifested as growing variance in the marginal products of factors of production across firms and establishments. In our model, the marginal product of labor is the product of a single match px, and higher variation in x across firms is factor misallocation. Hence, to tie our model more closely to this notion of misallocation as increased variance in the marginal products of labor across jobs, we also calculate the standard deviation of x in the labor-force. Notably, as the variance of match quality increases (i.e., misallocation increases), TFP decreases and vice-a-versa. Two variables are capable of altering this variance: first, the reservation level, which negatively affects the variance of the producing realizations of x, in accordance with Lagos (2006); and the mass of workers under notice which positively affects this variance as matches under notice have the lowest possible match quality.

What can ameliorate factor misallocation in our model? Faster reallocation that will produce a cleansing effect which is exactly what is prevented by strict EPL policies. Via the slower job flows, strict EPL lowers the capacity of the labor market to reallocate labor and thus hinders the return the return of the economy to its steady state. Hence, the persistence of the TFP decline owes much to the presence of slower turnover with the costs of separation and the slower turnover preventing less productive matches from separating. In the no-EPL calibration, where turnover is faster, TFP actually increases during the recession, generating a 'cleansing effect' of the business cycle. However, when EPL is strict,

[6] This is also present in the works of Garibaldi (1998), and Nunziata (2003).

TFP declines persistently during the recession which causes a 'sullying effect'.[7]

After explaining the model representation of factor misallocation and its connection to TFP, we turn our attention back to Figure 1. The increased likelihood of an idiosyncratic shock increases the probability of each particular match to experience an adverse realization that would lead to separation. As a result, the firm is willing to take such a risk only under a sufficiently high production value, which causes the reservation level to increase following the shock. This increase in the reservation level leads all the matches with match quality below the new reservation level to enter immediately into an advance notice period which translates into a decline in TFP on impact. If the notice period is short, TFP does not suffer long from this decline and aggregate productivity rises along with the reservation level, which is the case in the no-EPL calibration. In our baseline calibration, where notice period is considerably longer, the effect of workers under notice overshadows that of the increased reservation level, which is smaller than the rise in reservation in the no-EPL calibration, causing TFP to decline throughout the cycle.

To conclude, our quantitative exercise illustrates the potential of EPL to act as an amplifier or as a dampener to macroeconomic shocks. The presence of a strict EPL regime in the baseline calibration leads to a stronger TFP response and slower turnover. As a result, unemployment responds less during the cycle, but TFP declines more severely and persistently. In our exercise, slower job flows and slower turnover are quantitatively stronger than the misallocation channel, which causes output to decline in our baseline calibration by less than in the no-EPL calibration. Keeping the two transmission channels in mind, one must consider an interesting connection. Lax EPL entails more reallocation of labor and therefore an improved productivity. Following an adverse shock, these forces affect output in opposite directions and thus the total effect on output depends on the relative importance of each channel. If the slower turnover channel trumps the TFP

[7] See Barlevy (2002) for a review of these effects in the literature.

channel this would mean that strict EPL is conducive to economic resilience; however, if the TFP channel is stronger, then strict EPL is detrimental to economic resilience. With these implications in mind, we now turn our attention to the empirical analysis of EPL. Our empirical analysis will examine the effect of EPL on the transmission of global credit supply shocks, and asses the relative importance of each of these transmission channels.

3 Data

3.1 EPL Definition and Measurement

EPL is measured as a 'hierarchy of hierarchies', meaning it is the aggregate of several scales which rank the strictness of legislation (e.g., from 0 to 6 as in the OECD's indices), where these scales are aggregated according to predetermined weights.[8]

EPL is a broad institution and the OECD's database of EPL includes several indices measuring it which differ in terms of their coverage and of their implications:[9] regular employment protection, protection from collective dismissals, and protection of temporary workers. These indices, though grouped under the label of employment protection, relate to different segments of the labor-force, i.e., regular workers and temporary workers and apply to different circumstances. Thus, these legislative measures affect the dynamics of labor turn-over through different channels.

The first noteworthy difference is that between the protection of regular and temporary workers. Protection of regular employees includes the definition of wrongful termination, the procedure of terminating an individual employee, severance pay and notice due, and the legal recourse available to a wrongfully terminated worker. However, pro-

[8] A critique of this measurement method and its limitations can be found in Myant and Brandhuber (2016).

[9] A more comprehensive discussion of EPL measurements, coverage, and definitions can be found in Boeri and van Ours (2013).

tection for temporary workers includes just cause of hiring under a temporary contract, the verities of jobs a person thus contracted may preform, when can temporary work agencies be used, and the number of successive temporary contracts per worker. In other words, protection of regular workers is a tax and limitation on the separation process, while protection of temporary ones hampers hiring. Although the two are quite different, limitation on each form of employment makes the other form relatively more attractive for employers, so the interaction between the two forms of protection had received substantial focus in the literature and policy debate in recent years. [10]

The second is protection from collective or individual dismissals. The protection of regular employees relates to the case of individual termination. In the case of collective termination of workers due to rescaling, reorganization, or other changes in the firm level there are other protection measures that govern such a procedure.[11]

Our main interest in this paper is the protection of regular employees.[12] With this focus in mind, we chose as our EPL[13] measure the index 'Strictness of employment protection - individual dismissals (regular contracts)' (EPR V1).[14,15] The data for this EPL index runs annually from 1985 to 2013. Although our focus is on the protection of regular employees from individual dismissals, other forms of employment protection and other

[10] See Boeri and Garibaldi (2007), Cahuc et al. (2016) for through discussion on the substitutability of the two employment forms, and Bentolila et al. (2012) for a case study of these two protection forms in Spain and France and an overview of the policy debate on the subject.

[11] Examples of such legislative measures can be found in *EUR-Lex Directive 98/59.* (2016).

[12] For works dealing with the cyclical effects of protection of temporary measures see, e.g., Bentolila and Saint-Paul (1992), Nunziata and Staffolani (2007), and Cahuc et al. (2016)).

[13] For the sake of brevity, EPL in this paper refers to this form of protection only. When we refer to other protection policies those policies are explicitly named.

[14] See Table 2 for the break-down of the index to its components and the data that composes each.

[15] Data for this EPL index is also available annually for 1960-2004 in a database created by Nickell (2006). However, the index displayed there for the years 1960 to 1985 is a backward extension of the OECD's index created by assuming that its rate of change over time is the same as the change in another index which uses data taken from Blanchard and Wolfers (2000) and from Lazear (1990). From 1985 onward the index given by Nickell (2006) is the same as the OECD's index. Since the OECD's index is available for twenty eight consecutive years for most of our sample, we chose, for the sake of consistency, to rely on the OECD's index instead of utilizing a mixed measurement methodology.

labor market institutions are present alongside our main institution of interest. Taking this into consideration, we use data on other forms of employment protection and labor market institutions in our robustness analysis in Section 6 to assure that our results are not confounded by other institutional factor.

EPL indices are composed of several scores which are ordered variables. The final index can take non-integer values, as can the individual components, but that does not change the fact that the components themselves are a ranking system of ordinal variables. This point stresses the importance of using an identification strategy that allows for variation in an ordered variable and not a in a continuous one. We choose to use dummy variables to identify policy regimes rather than take the index's levels. This order-preserving identification approach avoids manipulations to the ranking scale that can result from using continuous interactions with the index. Specifically, one could possibly conceive of an order-preserving non-linear transformation of the EPL components which would reflect the same order of ranking but would change the results of a continuous-interaction-based regression analysis. Nevertheless, the conventional treatment of the EPL index has largely been as if it were a continuous variable. Noteworthy examples of this can be found in Blanchard and Wolfers (2000), Messina and Vallanti (2007), Nunziata (2003), and Duval and Vogel (2008). The only methodological exceptions to this, to the best of our knowledge, are studies which consider only the cardinal elements of EPL such as months of notice and months of payment offered as severance pay and ignore the regulatory environment as in Lazear (1990), or studies that focus on correlations and utilize Spearman correlation coefficient as in Gnocchi et al. (2015).

3.2 Outcome Measures

In order to examine the implications of EPL for macroeconomic resilience, we have created a panel containing the following variables:[16] Key labor market variables: unemployment, employment to population ratio, and labor force participation rates; National accounts data (all in real terms): output,[17] consumption, investment, government expenditure, imports, and exports; TFP; capacity utilization; total hours worked; hours worked per worker; our shock variable, EBP, which will be discussed shortly; and our state variable, the EPL index. We use data from 21 OECD economies for the period between 1985 to 2013.[18] Our choice of sample, both along the country dimension and the time dimension, arises from the availability of the EPL index.[19]

Our dependent variables are taken from the OECD's database.[20] All dependent variables are taken as log cumulative changes on the LHS of the regressions and as log-first-differences when controlled for in lags on the RHS of the regressions. We use the dependent variables in log cumulative changes in order to properly compare movements in a variable between different countries with different steady state levels.

[16]For further details and information on the data used in this paper see Appendix B.

[17]We use output and not output per-capita for two reasons: First, to be consistent with the other national accounts data that are available only without such normalizations; and second, due to data availability, for output we have 2,068 quarterly observations while for output per-capita only 1,774 such observations are available for the same countries and time-frame. In Section 6.1 we show that our results are robust to using this choice of measure.

[18]We use monthly data for unemployment and quarterly data for the rest of our variables of interest; all data are seasonally adjusted except EPL which is available only in annual frequency and assumed identical within each year.

[19]In the UK the OECD's EPL index is available for 2014 and therefore we use data from this year as well for the UK.

[20]All OECD data were retrieved from `http://stats.oecd.org/`; for exact details see Appendix B.

3.3 Shock Variable

As the shock variable in the analysis that follows we will use the Excess Bond Premium (EBP) measure from Gilchrist and Zakrajek (2012), who use micro-level data to construct a credit spread index which they decomposed into a component that captures firm-specific information on expected defaults and a residual component that they termed as the excess bond premium. To the best of our knowledge, there is no financial shock variable which was calculated specifically for every one of the economies we use in our analysis. That said, the increasingly global nature of the world economy means that EBP can be interpreted as a global shock variable whose effects on the economies in our sample can potentially vary as a function of the EPL regime in place.

4 Methodology

We follow the class of specifications that use the local projection method from Jorda (2005) to estimate impulse response functions and adapt it to a state-dependent setting as the one employed in Auerbach and Gorodnichenko (2012), Owyang et al. (2013), Ramey and Zubairy (2017), and Tenreyro and Thwaites (2016). The major advantage of this identification method is that it allows for state-dependent non-linear effects in a straightforward manner while involving estimation by simple regression techniques. Moreover, it is more robust to misspecification than a non-linear VAR. Additionally, it can be used to analyze data of differing measurement frequencies as one is not required to estimate the system in a joint fashion.

Definition of EPL States. In defining the state of EPL we wish to group observations together in a way that allows for sufficient differentiation to be made between the groups and in a manner that can describe broadly the policy regime in place; too many groups will limit sample sizes severely, while too few will not enable differentiation. In order to allow for sufficient differentiation, we use the following groups: first, the lower quartile of EPL distribution as a measure of a lax EPL state; second, the upper quartile of EPL distribution as a measure of a strict EPL state; and third, the rest of the observations (i.e., the interquartile range of the EPL distribution) as the measure of intermediate EPL. This kind of grouping allows us to identify differential effects across strict, intermediate, and lax EPL, where our interest lies mainly in looking at the difference between strict and lax EPL given that this gap reasonably captures a sufficiently large differentiation between EPL regimes for picking up any true effects in the data. While these policy regime dummies are time varying, it is important to notice that the EPL index exhibits very small temporal variation, as opposed to relatively large cross-sectional variance, resulting in relative stability of policy regimes over long horizons.

Econometric Specification. As in Auerbach and Gorodnichenko (2012), we make use of the Jorda (2005) local projections method within a fixed-effects panel model, where inference is based on Driscoll and Kraay (1998) standard errors that allow arbitrary correlations of the error term across countries and time. In particular, we estimate impulse responses to the credit supply shock by projecting a variable of interest on its own lags and contemporaneous and lagged values of the EBP variable from Gilchrist and Zakrajek (2012), while allowing the estimates to vary according to the EPL state in a particular country and time.

The following equation demonstrates the class of state-dependent models that we estimate using y as an example of a dependent variable:[21]

$$\begin{aligned}\ln y_{i,t+h} - \ln y_{i,t-1} = A_{i,t-4}[\alpha^h_{A,i} + \beta^h_A EBP_t + \Theta^h_A(L) EBP_{t-1} + \Gamma^h_A(L)\Delta \ln y_{i,t-1}] \\ +B_{i,t-4}[\alpha^h_{B,i} + \beta^h_B EBP_t + \Theta^h_B(L) EBP_{t-1} + \Gamma^h_B(L)\Delta \ln y_{i,t-1}] \\ +C_{i,t-4}[\alpha^h_{C,i} + \beta^h_C EBP_t + \Theta^h_C(L) EBP_{t-1} + \Gamma^h_C(L)\Delta \ln y_{i,t-1}] + \epsilon^h_{i,t+h},\end{aligned} \tag{20}$$

where i and t index countries and time; α_i is the country fixed effect; $\Theta(L)$ and $\Gamma(L)$ are lag polynomials; β^h gives the response of the outcome variable at horizon h to a credit supply shock at time t; $\epsilon^h_{i,t+h}$ is the residual; and, importantly, all the coefficients vary according to the state of EPL which is represented by the state dummies $A_{i,t-4}$, $B_{i,t-4}$, and $C_{i,t-4}$ that take the value of one when the EPL regime is lax, intermediate, or strict as we defined above. The estimated impulse responses to the credit supply shock for the three states at horizon h are simply β^h_A, β^h_B, and β^h_C, respectively.

Lags of y and EBP are included in the regression to remove any predictable movements in EBP; this facilitates the identification of an unanticipated shock to EBP, which is what is sought after. We assign the value of the order of lag polynomials $\Theta(L)$ and $\Gamma(L)$ to 8, i.e., we allow for 8 lags of the log-first-difference of the outcome variable and EBP in the regression. We assume a relatively large number of lags because of the construction of the EPL variable. Since the latter was converted from annual to quarterly frequency by assuming identical values within the year, it is necessary to include it in the regression with four lags so as to avoid correlation of the error term with it; this in turn requires that more than 4 lags of output and EBP be included in the regression so as to purge the state dummies of any potentially endogenous sources.[22]

[21] In order to correctly adopt a state-dependent model for panel data, we must refer to a form of normalized changes in variables for these changes to be commensurable between countries. To accomplish such normalization, we simply use a dependent variable of the form $\ln y_{i,t+h} - \ln y_{i,t-1}$ which represents the log-cumulative-difference in our variable of interest from the pre-shock horizon until horizon h.

[22] When using other data frequencies, we use two years of lagged values, following the same argument.

The EBP credit supply shock is normalized so that it has a zero mean and unit variance. Note that a separate regression is estimated for each horizon. We estimate a total of 21 regressions for our quarterly frequency specification and collect the impulse responses from each estimated regression, allowing for an examination of the state-dependent effects of credit supply shocks for 5 years following the shock.

Our form of state-dependence is slightly different from the conventional one (see, e.g., Ramey and Zubairy (2017)) which usually uses a binary state variable. Our identification utilizes an ordered ranking system by breaking down the raw EPL measure into 3 different ordered EPL regimes. If EPL's strictness indeed causes a change in the response of a certain variable then we would expect to see that its responses to the shock across EPL regimes will maintain an ordered pattern, i.e., $\beta_A^h > \beta_B^h > \beta_C^h$ or $\beta_A h < \beta_B^h < \beta_C^h$. Note that our identification does not assume anything that would guarantee such an ordering unless it is present in the data, unlike the results that would have been obtained from a continuous interaction exercise. In Section 6.1 we conduct an analysis of the results' robustness to the choice of cutoff values for the policy regime dummies to ensure that our results are not driven by our baseline cutoff value choices.

5 Empirical Analysis

In this section, we perform an empirical analysis of EPL's implications for economic resilience, utilizing the aforementioned identification method. Section 5.1 presents our results, with the subsequent Section 5.1 presenting a more in-depth examination of the causes behind the effect on real activity.

5.1 EPL's Implications for Business Cycle Dynamics

We estimate the state-dependent specification described in Equation (20) for output, consumption, investment, government expenditure, imports, exports, the real wage, the stock of vacancies, employment to population ratio, labor-force participation, and unemployment. The estimation results are presented in Figures 2 and 3, where the responses of economies under a strict EPL regime are shown in blue, those of economies under a lax regime in red, and the intermediate regime responses are presented in black.

Regardless of the EPL state, the credit supply shock causes the expected dynamics, i.e., an increase in unemployment and a decrease in real activity measures (most importantly, a decrease in real output, consumption and investment). Our interest lies in the differences of responses across the policy regimes, whose statistical significance is indicated by the shaded areas in Figures 2 and 3.

Labor Market Outcomes. The first form of differential response to arise between regimes is in the labor market and it is presented in Figure 2. Being in a lax EPL state produces an immediate increase in unemployment and a decrease in employment while being in a strict EPL state generates no significant change in unemployment until a year after the shock and no statistically significant decrease in employment at all horizons. This is in line with the slower turnover suggested by the model from Section 2. This pattern also agrees with the notion that job-destruction is less counter-cyclical under a strict EPL regime, thus making overall employment less responsive.[23] Notably, the labor market in the lax EPL state manages to recover back to steady state significantly faster than in the strict EPL state. Specifically, during the later phase of the cycle, the response of the unemployment rate is significantly higher and that of vacancies is significantly lower in the strict EPL state relative to the lax one.

[23] See Bentolila and Bertola (1990), Garibaldi (1998), and Nunziata (2003).

A difference observed across EPL states from which we abstract in our theoretical analysis is that labor-force participation is adversely affected by the shock in the lax EPL state while being in the strict EPL state produces no such effect. The effect on participation could be interpreted from a structural standpoint as being driven by the relatively higher value of the job-seeker from a future match with an employer, anticipating a longer employment duration which lowers discouragement from costly search activities.

Real Activity. The second form of differential response is the response of real activity measures presented in Figure 3. One year after the shock, we begin to see that real output starts to decline more in the strict EPL state than in the lax EPL state. This gap in output is steadily widening, starting to be significantly different from zero from the 7th quarter onwards and translating to a relative cumulative output loss of 0.75% after 2 years, 1.31% after three years, 2.18% after four years, and a peak 2.40% after five years.[24] Later, in Section 6.1, we will show that this response pattern is robust to cutoff values' selection, lag order selection, and alternative sample and output measure choices.

Other measures of real activity do not exhibit any statistically significant differential response pattern until at least two years after the shock. Consumption starts to decline in a significantly differential fashion from the 9th quarter onwards. For investment, a significant differential decline occurs from the 11th quarter onwards. Imports fall differentially from the 10th quarter onwards quarters whereas exports begin to decline differentially after 5 quarters, but only until the 7th quarter and then again after 12 quarters up to the 15th quarter (and at somewhat lower confidence levels relative to the other variables, with p-values always exceeding 5%). These differential responses all occur in the same direction as that of output's response, i.e., being in a strict EPL state generates a stronger decline

[24]We present all our results for a five-year horizon. However, to test that this effect does not grow further in magnitude, we estimated the corresponding difference after six years to be 1.55% using the same methods explained above.

in all these real activity measures relative to being in the lax EPL state. It is noteworthy that these differential responses all occur in the absence of any persistent significant changes in the real wage in all EPL regimes with similarly weak responses of government expenditures.

Linking the results from Figure 3 to those from Figure 2, it is important to observe that the initially stronger decline in employment from the latter figure occurs under the lax policy regime while the following stronger drop in output occurs under the strict one, with no differential response in employment taking place after the first two years. Moreover, the differential response of investment would not be able to account for any significant diminution in the capital stock available for production until at least three years after the shock (i.e., the decline in output precedes the drop in capital stock and not vice versa), and even then the differences are not strong enough to explain the differential output response by themselves.[25] In other words, the difference in output response across the policy regimes is too strong to be explained solely by changes in factor inputs at any point in time, giving rise to what at first pass seems like a contradiction.

However, viewing the results from Figures 3 and 2 through the lens of the model from Section 2 highlights a theoretically sound explanation for their joint occurrence. Specifically, this explanation posits that a larger output decline alongside a smaller employment response in the strict EPL state relative to the lax one are symptoms of the TFP-based amplification channel of EPL that has its roots in labor misallocation. According to this channel, misallocation-induced increases in the dispersion of match qualities in the economy drive TFP down and result in a stronger decline in aggregate output despite a lower response of overall employment. This would mean that unlike in our model, the data

[25] To illustrate, if we were to assume a 10% annual depreciation rate of the capital stock, and use the exact cumulative changes in investment from Figure 3, assuming that both EPL groups begin from the same level of steady-state capital stock, the differences between the capital stock in the strict and lax policy regimes will be less than 0.1% for the first three years of the cycle, 0.54% for the fourth year and 1.07% for the fifth one.

suggests that the slower turnover and job flows channel is not as strong as the TFP channel. If this is indeed the case, one would expect that hours worked and TFP data would present evidence of such a pattern. More precisely, to uncover the validity of such a misallocation-based channel, we need to inspect the data from a supply side perspective (i.e., production-function-based perspective), which is what we turn our attention to next.

A Closer Examination of the Supply Side. Since the form and magnitude of the differential output responses we observe cannot stem from the differences in investment response or from the response differences in employment to population ratio, we turn to further examine the behavior of inputs in production as well as to establish the behavior of TFP. The analysis that follows is driven by the following considerations: First, are we accurately accounting for the labor input actually used in production? And second, is TFP indeed responding in a fashion that could explain the differential responses in output across EPL states?

To account for better measurement of labor input, we use data on actual hours worked. Notwithstanding the lower, annual frequency of this series, using it has the potential of better measuring true variation in input quantity than using the number of employed persons. Next, if we consider a generalized production function then the real output will be determined by raw inputs' quantities, the degree to which they are utilized, and the level of TFP. With these two considerations in mind, we estimate the impulse responses of total hours worked and TFP, at an annual frequency, as well as those of capacity utilization at a quarterly frequency, again conditioning on the initial regime of EPL in place using the same identification as before.[26] Capacity utilization has the potential to confound our conclusions regarding TFP since our measure of TFP in not utilization-adjusted. It is therefore important to also look at the behavior of utilization as jointly examining un-

[26]Detailed description of the data series used can be found in Appendix B.

adjusted TFP and utilization can paint a much clearer picture regarding the behavior of utilization-adjusted, pure TFP.

The results of this exercise are shown in Figure 4. There is a significantly smaller initial decline in hours worked in the lax EPL state which reverses in a significant way in the fourth and fifth years after the shock, with hours worked returning significantly faster to steady state during these years in the lax EPL state. This response pattern is in line with our previous measure of labor input and support the theory-consistent conclusion that employment as an input in production responds less when EPL is strict.

TFP declines in the strict EPL state while under a lax regime TFP is not affected by the shock in a statistically significant way. This difference in TFP responses is sizable, peaking at 0.77% after three years, and statistically significant from the first through third year. The forms of the impulse responses are quite similar to those obtained from our simulation exercise in Section 2. So why does output take longer than TFP to respond differentially? Due to the conflicting effects of the slower change in employment and the stronger response of TFP on aggregate output, it is only when the difference in employment subsides that the TFP difference has a chance to manifest into a differential output drop. In terms of timing, this only holds after the first year of the cycle. What about the recovery period?

Capacity utilization, which can be thought of as a proxy for factor utilization, behaves in a significantly differential manner that can at least in part also account for the differential output response during the later phase of the cycle. Overall, across all 3 EPL states, we see that the beginning of the cycle is associated with a decrease in capacity utilization. However, the persistence of the decline in utilization is varying according to the initial state of EPL. For the first three years, during which the above-mentioned TFP channel is present, there are no differences in responses of utilization after the second quarter following the credit supply shock. After 10 quarters we begin to see a diverging pattern of recovery that is significant from about 3.5 years onwards, with utilization recovering much faster in the lax EPL state and the associated response difference peaking at 1.71% after 17 quarters. These results, which are also in accordance with the differential recovery of hours worked during the same time frame, indicate that the differential behavior of utilization in the later stage of the cycle constitutes an important contribution to the correspondingly stronger output drop in the strict EPL state relative to the lax one.

EPL and Misallocation: An Empirical Perspective. The differential response pattern of utilization does not occur during the same time as that of TFP, suggesting that the observed effect on TFP in the two policy regimes does not stem from differences in utilization. Hence, the results from Figure 4 indicate that the stronger drop in TFP is likely driven by non-utilization-related forces which in turn strengthen the effect of the original shock on aggregate output. This amplification mechanism further enhances the cycle's strength, contributes to its persistence, and leads to a slower recovery of the economy as a whole. Importantly, since our TFP measure is unadjusted for factor utilization changes and the differential drop in utilization takes place only after that in TFP occurs, we infer from the empirical evidence that a potentially important channel underlying TFP's differential decline lies in increased factor misallocation taking place in the strict EPL state.[27] Specifically, our results indicate that the stronger output decline in the first 3 years after the shock can be explained by a factor-misallocation-induced TFP decline, whereas the subsequent two-year differential output fall seems to be mostly driven by a corresponding differential drop in factor utilization and hours worked.

At the core of this interpretation of the results is the assertion that the joint prevalence

[27] Underlying this factor misallocation based interpretation is the assumption that technology is unaffected by credit supply shocks, which is what the literature on the TFP channel of credit supply shocks normally assumes (see, e.g., Buera et al. (2011), Pratap and Urrutia (2012), Petrosky-Nadeau (2013), Khan and Thomas (2013), Buera and Moll (2015), Buera et al. (2015), Gopinath et al. (2017), Buera and Shin (2017), and Manaresi and Pierri (2017)).

of the adverse shock and strict EPL is associated with more misallocation. The persistence of this factor misallocation stems from a slower reallocation of labor. Importantly, this assertion receives both theoretical and empirical support in the literature on EPL. A theoretical example of this connection can be found in the work of Garibaldi (1998) which concludes from a stochastic search model that firing restrictions reduce labor reallocation and slow turnover. More recent empirical evidence linking EPL and factor misallocation in general lend support this claim. Caballero et al. (2013) find that stricter EPL, especially with respect to dismissal regulations, is linked to a lower speed of adjustment to shocks which in turn lowers productivity growth, a process which they connect to Schumpeter's idea of 'creative destruction'. Using a difference in differences estimation and industry-level data, Bassanini et al. (2009) show that EPL strictness is associated with a lower productivity growth rate and that this effect is due to the binding limitation on termination which may lead to a lower change in aggregate productivity unless the market is extremely centered around industries for which terminations are not the primary source of turnover. Petrin and Sivadasan (2013) find from plant-level evidence in Chile's manufacturing industry that there is a reason to believe that changes in severance pay are responsible for an increase in the gap between the value of the employees' marginal product and their wage. This gap measures, in fact, the allocation inefficiency, which means that the introduction of stricter termination regulations in Chile may have induced an increase in factor misallocation. The work of Lashitew (2016) provides further support to this claim by using plant-level data to show that there is a link between EPL strictness and factor-misallocation-induced productivity losses.

Evidence From Job Flows. As stressed above, factor misallocation is at the heart of the TFP amplification channel and the feature that would foster such misallocation is a slower reallocation of labor following an adverse shock. We now turn to attempt to provide direct evidence on the validity of this feature in the data. Since job flow data is not as readily available as employment and unemployment data we use decomposed flow hazards from the work of Elsby et al. (2013) to examine if this indeed the case. The authors combine OECD data and additional surveys to compile data-series of job-finding rates and separation rates at an annual frequency for 14 countries in our sample for varying time frames until 2009.[28] We use this data to provide evidence consistent with the above misallocation-based structural interpretation along four dimensions.

First, we can see that the data from Elsby et al. (2013) agrees with the literature which states that strictness of EPL is associated with slower flows. Using a simple regression of the job-finding rate and the separation rate as dependent variables and the three policy dummies as independent variables we see that job flows in and out of employment are significantly slower as the policy becomes stricter. These results are presented in Table 3. The order of magnitude is such that hazard rates in the lax group are nearly three times as large as those in the strict one and almost twice as large as those in the intermediate group.

Second, without regard for the policy regime in question, the response of the logged hazard rates to the shock is in line with our previous results. The job-finding rate decreases in response to the shock and the separation rate increases albeit the increase is not statistically significant. These impulse responses are presented in the upper row of Figure 5 and are obtained from a non-state-dependent (linear) version of Equation (20) that effectively assumes coefficient equality across all EPL states. This statistically significant decrease in the finding rate is the reason for the general rise in unemployment at the beginning of the cycle from Figure 2.

Third, the results from estimating Equation (20) for logged job finding and separation hazard rates (presented in the second row of Figure 5) indicate that job flows respond to

[28] For additional detail see Appendix B.

the cycle differently across the policy states. Specifically, the strict EPL state exhibits a significantly larger increase in separation rates from the third year onwards than the lax EPL state and we also see higher separations in the lax state after the shock but less so. Job finding rates do not seem to exhibit differential responses.

Fourth, turning our focus to the role of EPL in amplifying the TFP response differences from Figure 4, we highlight that the implied changes in the *levels* of the job finding and separation rates are rather small. Taken together with their long-run averages the flows remain drastically higher in the lax EPL group than in the strict one. To illustrate this point, if we multiply the average rates in each group from Table 3 by the changes implied by the impulse response functions from the second row of Figure 5, we obtain that throughout the 5 years following the shock job flows remain considerably faster in the lax EPL state. The results of this illustrative exercise are presented in the third row of Figure 5 and stress that the differential speed of labor reallocation remains effectively unchanged between the considered EPL states.

Taken together, the results from Table 3 and Figure 5 are in line with the behavior of unemployment from Figure 2 and support our conclusion regarding the role of strict EPL as an amplifier of macroeconomic shocks through its capacity to delay labor reallocation after an adverse shock and consequentially hinder recovery through the lowering of TFP.

To recap, the strictness of EPL slows job flows and contributes to misallocation in the presence of the averse shock. In other words, combined with the adverse shock, strict EPL enhances the sullying effect of the business cycle and lowers TFP via misallocation. Slower job flows and labor market adjustment caused by strict EPL policies make this TFP decline more persistent and delay the cleansing effect that would ensue during the recovery period in the absence of these strict policies. This transmission channel makes the economy less resilient overall to shocks as it amplifies aggregate output response and leads to a slower recovery.

6 Robustness

This section examines the robustness of our main result, the differential response of output, from two perspectives. First, we analyze the robustness of the output response across EPL states to various alterations of our baseline specification: cutoff value selection for defining the EPL states, lag order selection, and alternative choices of output measure and samples. Second, we examine the causal interpretation of our central result by testing if determining the policy regimes according to other labor market institutions results in similar pattern of response.

6.1 Alternative specifications and Samples

Cutoff Values. Our identification strategy hinges upon the initial state of an ordered variable. Any strategy of this kind would be potentially sensitive by design to the choice of cutoff values. In order to assure that our results do not arise from a specific choice of cutoff values, but indeed from a change in the intensity of the policy variable, we preform the same estimation routine described by Equation (20) with the only difference being that we now use different percentile values for the state dummies. Specifically, we assign the state of strict EPL to the top 15, 25, 35, and 45 percentile values of the EPL index distribution, and the corresponding bottom percentile values to the state of lax EPL, where the remaining residual percentile range continues to cover the intermediate EPL state. Note that as the cutoff value increases, the number of observations assigned to the intermediate EPL state decreases while the number of observation assigned to the two extreme states of the distribution increases.

The results from this exercise for unemployment, employment to population ratio, output, and TFP are shown in Figure 6. For comparison purposes, notice that our baseline estimation results are those obtained for the 25th percentile and the 75th percentile as cutoffs for the lax and strict EPL regimes. The results from Figure 6 indicate that the differential response pattern of all the main variables in our analysis is robust to cutoff value selection as all cutoff values examined exhibit a significantly stronger output fall taking place under the strict EPL regime with the same employment and unemployment dynamics, accompanied by a similar differential TFP drop. Moreover, for every cutoff value of choice except the 45th percentile value, the response magnitude is ordered according to the initial state of EPL strictness with the responses of output and TFP growing in magnitude along with the increase in EPL state with similar ordering in the opposite direction for the labor market responses. The 45th percentile value offers the smallest intermediate group and it is therefore expected that responses in the intermediate EPL state would behave in a more erratic fashion and exhibit lower statistical significance using this cutoff value than the other ones.

Lag Order Selection. In order to prevent endogeneity problems, we must use a lagged value of the state dummies. Due to our assumption that EPL does not change within the same year, we must therefore include at least more than one year of lagged values in each estimation. Since the results may by influenced by the specific lag specification choice, we test their robustness by choosing a smaller lag order than our baseline of $L = 8$ for quarterly data frequencies and $L = 24$ for monthly ones resulting in a more parsimonious model specification. In Figures 7 and 8 we present the impulse responses of output, employment to population ratio, and unemployment to an adverse credit supply shock for different lag orders alongside our baseline results. This exercise results in no meaningful change to the differential response patterns' magnitude, duration, or statistical significance.

Alternative Measure of Output. As mentioned earlier, we use output instead of output per-capita in order to be consistent with the components of output in our baseline estimation and due to the sizable difference in sample sizes between the two series. Figure 9 also presents the results from using output per-capita instead of real output and shows that the differential response pattern is robust to using this choice of output measure and that the ordered response magnitude and the statistical significance of the results are similar across the different lag specifications.

Excluding the Global Financial Crisis Period and the U.S. Our choice of EBP as a shock variable is naturally based on its large realizations in the 2008-2009 financial crisis period as these facilitate identification. However, one could ask if our identification strategy does not capture merely the implications of this particular crisis, with its unique characteristics and implications for the European markets (most of which have rather strict levels of EPL), thus limiting the ability to draw reliable policy implications from it.

In order to test if our results are indeed sensitive to the exclusion of the global financial crisis we repeat our estimation while excluding all observations from 2008:Q1 onwards from the sample. It is noteworthy that this exclusion is likely to lower the significance of any result because we exclude more than 20% of our original sample which also consists of the large adverse credit supply shock realizations associated with the global financial crisis of 2008-2009.

Additionally, the global crisis has started in the U.S. which may have caused the U.S. economy to respond differently from the rest of the world, not as a result of its labor market policy but because it had experienced the crisis in a different fashion. Thus, we wish to test if the inclusion of the U.S. in the original sample affects our results by estimating the specification from Equation (20) using a sample that excludes the U.S.

The results of the above two tests are presented in Figure 10. We find that the differential response patterns are rather similar and statistically significant for these two specification tests as well, supporting our conclusions regarding the structural implications of EPL. The possible exceptions of that are the response of TFP without the U.S. that is slightly less statistically significant and the response of employment to population ratio without the periods of the financial crisis which display a somewhat erratic pattern for the strict policy groups. However, it is important to emphasize that the lower the data frequency, the more likely it is that these omissions will affect the statistical power of the results.

6.2 Other Forms of EPL and Other Institutional Factors

Our interest in EPL in the form of termination regulation stems from its potential cyclical implications. However, institutional factors are not assigned randomly to different countries and other institutions may affect business cycle dynamics and confound our identification. Examples of such institutional factors may be found in the work of Blanchard and Tirole (2008), which discuss the connection between EPL and unemployment insurance, and in the discussion on forms of employment protection in Subsection 3.1.

Other institutional factors act as state variables potentially affecting the shock's transmission. Our identification for the quarterly frequency data using one state variable requires fixed-effects for each regime-country pair, as well as 8 lagged values of the outcome variable and the shock and the contemporaneous shock which amounts to 51 coefficients and up to 63 fixed effects.[29] Adding another state variable to this analysis as a control in the same fashion will require the estimation of several hundred coefficients which will severely lower the statistical power and limit interpretation. Instead of controlling for

[29]This number is the upper limit of the fixed effects - 21 countries across 3 possible regimes. In actuality the number is closer to half of this, depending on specification, as institutional factors do not exhibit much temporal variation so transitions within the same country are rare.

these variables directly, we will carry out a similar estimation of impulse responses as described in detail in Section 4 but using each institutional factor as a single state variable. This estimation will allow us to look for other institutional factors which produce similar differential response patterns to those observed for EPL, whose existence would in turn suggest a similar amplification channel for the shock and warrant the concern that we may be partly picking up in our results an amplification role of an institution other than EPL. Conversely, not finding such similar response patterns would materially alleviate this concern.

With this aim in mind, we add to our panel institutional data regarding temporary employment protection, employment protection from collective dismissals, union density, collective bargaining coverage, and net replacement rates for the relevant countries and time periods[30] and estimate the state-dependent specification given by Equation (20) for different cutoff values. This is a replication of the results presented in Figure 6 using an alternative state variable. Results for this estimation are shown in Figures 11 through 15 for the state-dependent responses of unemployment, employment to population ratio, real output, and TFP.

Other Forms of Protection. Protection of temporary employment (EPT) measures seem to hinder unemployment response at the beginning of the cycle (Figure 11). This is probably due to the fact that the more restrictive is the hiring of such temporary workers in the first place, the more difficult it is to adjust employment during a cycle. This conjecture is in line with the results for employment to population ratio at the lower cutoff values. However, this pattern is absent for the 35th percentile and 45th percentile cutoffs as there is no statistically significant differential response pattern in employment. In terms of output, we observe a differential response pattern which is inconsistent along the different

[30]See Appendix B for detailed descriptions of the data series used.

cutoffs and of smaller size than that we observe for EPL. The response of output occurs without any differential response in TFP. Taken together, these responses suggest that the effect of EPT on business cycle dynamics is different from that of EPL, leading us to conclude that differences in EPT do not confound our results regarding EPL.

Using Protection from collective dismissals (EPC) as a state variable in our analysis results in little to no differential response pattern between the policy regimes in terms of labor market implication of the shock on impact (Figure 12). There is only a small statistically significant difference between the lax and strict policy regimes without the ordered pattern in responses which suggest that EPC may not be the driving force behind the observed response difference across the policy regimes. There is a differential output response pattern which also is not ordered by policy strictness and is smaller in magnitude than that of EPL and without the differential drop in TFP. Hence, all in all, the results from Figure 12 lead to the conclusion that our EPL based results are unlikely to be driven by the EPC-induced amplification mechanisms.

Other Labor Market Institutions. First, using union density as a state variable (Figure 13) results in a differential response pattern in unemployment, the statistical significance of which is decreasing in the cutoff value, without a differential response in employment to population ratio. Output and TFP respond differentially to the shock. However, the responses of real output are not ordered by union density and their duration is shorter than those obtained for EPL. Moreover, for TFP, the differential responses are similar to those obtained for EPL and even slightly stronger, but the differential strength is not in line with the response of output.

Second, if we look at collective bargaining coverage in a similar fashion (Figure 14), we may observe an interesting pattern. There is a differential impact TFP drop that grows in strength the more prevailing collective bargaining agreements are. The persistence of those responses and their statistical significance declines with the increase in cutoff values. There is, however, a differential response in recovery that is unlike that of our baseline results, i.e., a differentially faster recovery of real output, employment, and unemployment without a differential response on impact. This suggest that the less prevailing are collective bargaining arrangements are, the faster the economy can adjust to the shock's impact. The strength of the differential recovery in output is smaller than that in our baseline using EPL and the contributing factors seem different altogether pointing towards an interesting find but not to a threat to our conclusions.

Last, although there are complementarities between unemployment benefits generosity and EPL, the former do not seem to generate the same cyclical implication as the latter. Using net replacement rates as a state (Figure 15) results in no statistically significant differential response patterns that survive alternative choice of cutoff values and suggest a coherent contribution to the dynamic responses and little ordering in responses.

To conclude this subsection, although the exercises carried out in this subsection point towards interesting effects of other labor market institutions for cyclical dynamics, the results do not point towards a single institutional factor which may confound our results regarding EPL's amplifying effect on the shock's transmission via a slower reallocation of the labor input which results in lower aggregate TFP and slower recovery in real output.

7 Conclusion

This paper demonstrates the potential of EPL to amplify macroeconomic shocks in two steps. First, using a simple search and matching model, we illustrate the contribution of termination costs and advance notice practices to the propagation of shocks via slower job flows and a misallocation-induced TFP decline, with the former acting as shock-absorbers and the latter as shock-amplifiers. Second, we perform an empirical analysis of a panel of

21 countries aimed at examining the relationship between EPL and economic resilience using a state-dependent local projections based identification strategy.

Our empirical findings indicate that EPL strictness has the capacity to act as an amplifier of macroeconomic shocks. While diminishing the decrease in employment following an adverse credit supply shock, it severely hinders the recovery of real output to pre-shock levels. This sizable and robust relative decline in real activity seems to originate from a TFP decline that is present in the strict EPL state and is absent in the lax EPL one. This paper argues that the mechanism underlying this relative decline in TFP is derived from the misallocation present in our model simulation exercise. Evidence regarding job flows support this conclusion by showing that countries with stricter EPL have a reduced capacity to reallocate labor.

From a policymaking standpoint, our results indicate that relaxing EPL measures for the termination of regular employees may allow a faster recovery of real output in times of recessions. This sheds light on an often-overlooked potential of labor market policies to affect business cycle dynamics. From a theoretical standpoint, the empirical results of this paper may prove of value for model builders in the construction of models that can accommodate the type of link between EPL, TFP, and varying factors' utilization observed in the data conditional on a shock-induced business cycle.

References

Auerbach, A. J. and Gorodnichenko, Y.: 2012, *Fiscal Multipliers in Recession and Expansion*, University of Chicago Press, pp. 63–98.

Barlevy, G.: 2002, The Sullying Effect of Recessions, *The Review of Economic Studies* **69**(1), 65–96.

Bassanini, A., Nunziata, L. and Venn, D.: 2009, Job protection legislation and productivity growth in oecd countries, *Economic Policy* **24**, 349–402.

Bentolila, S. and Bertola, G.: 1990, Firing costs and labour demand: How bad is eurosclerosis?, *The Review of Economic Studies* **57**(3), 381–402.

Bentolila, S., Cahuc, P., Dolado, J. J. and Le Barbanchon, T.: 2012, Two-tier labour markets in the great recession: France versus spain*, *The Economic Journal* **122**(562), F155–F187.

Bentolila, S. and Saint-Paul, G.: 1992, The macroeconomic impact of flexible labor contracts, with an application to spain, *European Economic Review* **36**(5), 1013–1047.

Blanchard, O. J. and Tirole, J.: 2008, The joint design of unemployment insurance and employment protection: A first pass, *Journal of the European Economic Association* **6**(1), 45–77.

Blanchard, O. and Wolfers, J.: 2000, The role of shocks and institutions in the rise of european unemployment: the aggregate evidence, *The Economic Journal* **110**(462), 1–33.

Boeri, T. and Garibaldi, P.: 2007, Two tier reforms of employment protection: a honeymoon effect?, *Economic Journal* **117**(521), 357–385.

Boeri, T. and van Ours, J.: 2013, *The Economics of Imperfect Labor Markets: Second Edition*, stu - student edition edn, Princeton University Press.

Buera, F. J., Jaef, R. N. F. and Shin, Y.: 2015, Anatomy of a credit crunch: From capital to labor markets, *Review of Economic Dynamics* **18**(1), 101 – 117.

Buera, F. J., Kaboski, J. P. and Shin, Y.: 2011, Finance and development: A tale of two sectors, *American Economic Review* **101**(5), 1964–2002.

Buera, F. J. and Moll, B.: 2015, Aggregate implications of a credit crunch: The importance of heterogeneity, *American Economic Journal: Macroeconomics* **7**(3), 1–42.

Buera, F. J. and Shin, Y.: 2017, Productivity growth and capital flows: The dynamics of reforms, *American Economic Journal: Macroeconomics* **9**(3), 147–85.

Caballero, R. J., Cowan, K. N., Engel, E. M. and Micco, A.: 2013, Effective labor regulation and microeconomic flexibility, *Journal of Development Economics* **101**(C), 92–104.

Cahuc, P., Charlot, O. and Malherbet, F.: 2016, Explaining the spread of temporary jobs and its impact on labor turnover, *International Economic Review* **57**(2), 533–572.

Driscoll, J. C. and Kraay, A. C.: 1998, Consistent covariance matrix estimation with spatially dependent panel data, *Review of economics and statistics* **80**(4), 549–560.

Duval, R. and Vogel, L.: 2008, Economic resilience to shocks, **2008**.

Elsby, M. W. L., Hobijn, B. and ahin, A.: 2013, Unemployment Dynamics in the OECD, *The Review of Economics and Statistics* **95**(2), 530–548.

EUR-Lex Directive 98/59.: 2016, *Technical report*. Available at: [Accessed 13 Apr. 2016].

Gaetani, R. and Doepke, M.: 2016, Employment Protection, Investment in Job-Specific Skills, and Inequality Trends in the United States and Europe, *Technical report*.

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

Gilchrist, S. and Zakrajek, E.: 2012, Credit spreads and business cycle fluctuations, *American Economic Review* **102**(4), 1692–1720.

Gnocchi, S., Lagerborg, A. and Pappa, E.: 2015, Do labor market institutions matter for business cycles?, *Journal of Economic Dynamics and Control* **51**(C), 299–317.

Gopinath, G., Kalemli-Özcan, Ş., Karabarbounis, L. and Villegas-Sanchez, C.: 2017, Capital allocation and productivity in south europe, *The Quarterly Journal of Economics* **132**(4), 1915–1967.

Hall, R. E.: 2017, High discounts and high unemployment, *American Economic Review* **107**(2), 305–30.

Hsieh, C.-T. and Klenow, P.: 2009, Misallocation and manufacturing tfp in china and india, *The Quarterly Journal of Economics* **124**(4), 1403–1448.

Jorda, O.: 2005, Estimation and inference of impulse responses by local projections, *American Economic Review* **95**(1), 161–182.

Kahn, L. M.: 2007, The impact of employment protection mandates on demographic temporary employment patterns: International microeconomic evidence, *The Economic Journal* **117**(521), F333–F356.

Khan, A. and Thomas, J. K.: 2013, Credit shocks and aggregate fluctuations in an economy with production heterogeneity, *Journal of Political Economy* **121**(6), 1055–1107.

Lagos, R.: 2006, A model of tfp, *The Review of Economic Studies* **73**(4), 983–1007.

Lashitew, A. A.: 2016, Employment protection and misallocation of resources across plants: International evidence, *CESifo Economic Studies* **62**(3), 453–490.

Lazear, E. P.: 1990, Job security provisions and employment, *The Quarterly Journal of Economics* **105**(3), 699–726.

Manaresi, F. and Pierri, N.: 2017, Credit supply and productivity growth, *Working paper*, Stanford University.

Messina, J. and Vallanti, G.: 2007, Job flow dynamics and firing restrictions: Evidence from europe, *The Economic Journal* **117**(521), F279–F301.

Myant, M. and Brandhuber, L.: 2016, Uses and abuses of the oecd's employment protection legislation index in research and eu policy making, *Working paper*, ETUI.

Nickell, W.: 2006, The cep-oecd institutions data set (1960-2004), *Lse research online documents on economics*, London School of Economics and Political Science, LSE Library.

Nunziata, L.: 2003, Labour market institutions and the cyclical dynamics of employment, *Labour Economics* **10**(1), 31 – 53.

Nunziata, L. and Staffolani, S.: 2007, Shortterm contracts regulations and dynamic labour demand: Theory and evidence, *Scottish Journal of Political Economy* **54**(1), 72–104.

Owyang, M. T., Ramey, V. A. and Zubairy, S.: 2013, Are government spending multipliers greater during periods of slack? evidence from 20th century historical data, *American Economic Review, Papers and Proceedings* **103**(3), 129–134.

Petrin, A. and Sivadasan, J.: 2013, Estimating lost output from allocative inefficiency, with an application to chile and firing costs, *The Review of Economics and Statistics* **95**(1), 286–301.

Petrosky-Nadeau, N.: 2013, TFP during a credit crunch, *Journal of Economic Theory* **148**(3), 1150 – 1178.

Pissarides, C. A.: 2000, *Equilibrium Unemployment Theory, 2nd Edition*, Vol. 1 of *MIT Press Books*, The MIT Press.

Pratap, S. and Urrutia, C.: 2012, Financial frictions and total factor productivity: Accounting for the real effects of financial crises, *Review of Economic Dynamics* **15**(3), 336 – 358.

Ramey, V. A. and Zubairy, S.: 2017, Government spending multipliers in good times and in bad: Evidence from u.s. historical data, *Journal of Political Economy (forthcoming)* .

Restuccia, D. and Rogerson, R.: 2008, Policy Distortions and Aggregate Productivity with Heterogeneous Plants, *Review of Economic Dynamics* **11**(4), 707–720.

Rumler, F. and Scharler, J.: 2011, Labor market institutions and macroeconomic volatility in a panel of oecd countries, *Scottish Journal of Political Economy* **58**(3), 396–413.

Saint-Paul, G.: 2002, Employment protection, international specialization, and innovation, *European Economic Review* **46**(2), 375 – 395.

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

Skedinger, P.: 2010, *Employment Protection Legislation*, Edward Elgar Publishing.

Tenreyro, S. and Thwaites, G.: 2016, Pushing on a string: Us monetary policy is less powerful in recessions, *American Economic Journal: Macroeconomics* **8**(4), 43–74.

Zanetti, F.: 2011, Labor market institutions and aggregate fluctuations in a search and matching model, *European Economic Review* **55**(5), 644–658.

Appendix A Model Solution

A.1 The Wage Solution

In order to solve for the wage, we look at the first order condition for the insider's wage which is:

$$\beta(\,\mathrm{J}_i\,(x)\;-J^n\,)-(1-\beta)(\,\mathrm{W}_i\,(x)\;-W_i{}^n\,)=0. \tag{A.1}$$

After defining the reservation-level one can make the following changes in notation:

$$\begin{aligned} r\,\mathrm{J}_i\,(x)\; &= px-\;\mathrm{w}_i\,(x)\;+\lambda_i\int_{R_i}^{1}\mathrm{J}_i\,(s)\;\;\mathrm{dG}\,(s)\;\;+\lambda_i\,\mathrm{G}\,(R_i)\;J_i{}^n \\ &-\lambda_i\,\mathrm{J}_i\,(x)\;+\tau E_i[\,\mathrm{J}\,(x)\;-\;\mathrm{J}_i\,(x)\,], \end{aligned} \tag{A.2}$$

$$\begin{aligned} r\,\mathrm{W}_i\,(x)\; &=\;\mathrm{w}_i\,(x)\;+\lambda_i\int_{R_i}^{1}\mathrm{W}_i\,(s)\;\;\mathrm{dG}\,(s)\;\;+\lambda_i\,\mathrm{G}\,(R_i)\;W_i{}^n \\ &-\lambda_i\,\mathrm{W}_i\,(x)\;+\tau E_i[\,\mathrm{W}\,(x)\;-\;\mathrm{W}_i\,(x)\,]. \end{aligned} \tag{A.3}$$

These three equations can be combined into:

$$\begin{aligned} &\beta\Big(px-\;\mathrm{w}_i\,(x)\;+\lambda_i\int_{R_i}^{1}\mathrm{J}_i\,(s)\;\;\mathrm{dG}\,(s)\;\;+\lambda_i\,\mathrm{G}\,(R_i)\;J_i{}^n-\lambda_i\,\mathrm{J}_i\,(x)\;+\tau E_i[\,\mathrm{J}\,(x)\;-\;\mathrm{J}_i\,(x)\,]-rJ^n\Big)- \\ &-(1-\beta)\Big(\,\mathrm{w}_i\,(x)\;+\lambda_i\int_{R_i}^{1}\mathrm{W}_i\,(s)\;\;\mathrm{dG}\,(s)\;\;+\lambda_i\,\mathrm{G}\,(R_i)\;W_i{}^n-\lambda_i\,\mathrm{W}_i\,(x)\;+\tau E_i[\,\mathrm{W}\,(x)\;-\;\mathrm{W}_i\,(x)\,]-rW_i{}^n\Big) \end{aligned}$$

Notice that the first order condition can be rearranged into $\beta(\,\mathrm{J}_i\,(x)\,)-(1-\beta)(\,\mathrm{W}_i\,(x)\,)=\beta J_i{}^n-(1-\beta)W_i{}^n$. Substituting this into the previous equation results in:

$$\begin{aligned} &\beta(px-\;\mathrm{w}_i\,(x)\;+\lambda_i\,\mathrm{G}\,(R_i)\;J_i{}^n+\tau E_i[\,\mathrm{J}\,(x)\;-\;\mathrm{J}_i\,(x)\,]-rJ_i{}^n) \\ &-(1-\beta)(\,\mathrm{w}_i\,(x)\;+\lambda_i\,\mathrm{G}\,(R_i)\;W_i{}^n+\tau E_i[\,\mathrm{W}\,(x)\;-\;\mathrm{W}_i\,(x)\,]-rW_i{}^n) \\ &+(1-\;\mathrm{G}\,(R_i)\,)\lambda_i[\beta J_i{}^n-(1-\beta)W_i{}^n]-\lambda_i[\beta J_i{}^n-(1-\beta)W_i{}^n]=0. \end{aligned} \tag{A.4}$$

Simplifying and rearranging terms yields the wage solution:

$$\begin{aligned} \mathrm{w}_i\left(x\right) &= \beta p x + \tau E_i[[\beta J^n - (1-\beta)W^n] - [\beta {J_i}^n - (1-\beta){W_i}^n]] \\ &-\beta r {J_i}^n + (1-\beta) r {W_i}^n \end{aligned} . \tag{A.5}$$

A.2 Job-Creation and Job-Destruction Equations for the Deterministic Model

Recall that the reservation level is the level of x for which $J(R) = J^n$. Thus, from Equation (A.2) we can obtain:

$$r\,\mathrm{J}\left(R\right) = pR - \mathrm{w}\left(R\right) + \lambda \int_R^1 \mathrm{J}\left(s\right)\, d\,\mathrm{G}\left(s\right) \; - \lambda\,\mathrm{J}\left(R\right) + \lambda\,\mathrm{G}\left(R\right)\, J^n. \tag{A.6}$$

Subtracting this from Equation (A.2) results in

$$r(\,\mathrm{J}\left(x\right) - \mathrm{J}\left(R\right)\,) = p(x-R) - (\,\mathrm{w}\left(x\right) - \mathrm{w}\left(R\right)\,) - \lambda\,\mathrm{J}\left(x\right) + \lambda\,\mathrm{J}\left(R\right), \tag{A.7}$$

which after plugging in the wage solution gives us the value function

$$\mathrm{J}\left(x\right) = \frac{1-\beta}{r+\lambda} p(x-R) + J^n. \tag{A.8}$$

Combining Equations (A.6) and (A.8), and using the fact that $J(R) = J^n$ one obtains:

$$\begin{aligned} & rJ^n = (1-\beta)pR + \beta r J^n - (1-\beta) r W^n + \\ & \lambda \textstyle\int_R^1 \left[\frac{1-\beta}{r+\lambda} p(x-R) + J^n\right] d\,\mathrm{G}\left(s\right) \; - \lambda J^n + \lambda\,\mathrm{G}\left(R\right)\, J^n, \end{aligned}$$

which simplified can be reduced into the job-destruction condition of the model:

$$pR - r(J^n + W^n) + \frac{\lambda}{r+\lambda} p \int_R^1 (x - R) d\,\mathrm{G}(s) \;\; = 0. \tag{A.9}$$

Deriving the job-creation equation comes from the outsider's problem. The first order condition after imposing free-entry is:

$$\beta\Big(J^0\Big) - (1-\beta)\Big(W^0 - U\Big) = 0. \tag{A.10}$$

As we did earlier, the value functions can be restated as:

$$rJ^0 = p - w^0 + \lambda \int_R^1 \mathrm{J}(s)\; d\,\mathrm{G}(s) \;\; + \lambda\,\mathrm{G}(R)\; J^n - \lambda J^0, \tag{A.11}$$

and

$$rW^0 = w^0 + \lambda \int_R^1 \mathrm{W}(s)\; d\,\mathrm{G}(s) \;\; + \lambda\,\mathrm{G}(R)\; W^n - \lambda W^0. \tag{A.12}$$

These three equations can be combined into

$$\begin{aligned} &w^0 = \beta\Big(p + \lambda \textstyle\int_R^1 \mathrm{J}(s)\; d\,\mathrm{G}(s) \;\; + \lambda\,\mathrm{G}(R)\; J^n\Big) - \\ &(1-\beta)\Big(\lambda \textstyle\int_R^1 \mathrm{W}(s)\; d\,\mathrm{G}(s) \;\; + \lambda\,\mathrm{G}(R)\; W^n - rU\Big) - \lambda\beta J^0 + (1-\beta)\lambda W^0. \end{aligned} \tag{A.13}$$

Using the first order conditions for both bargaining problems combined with the above equation one can solve for the outsider's wage

$$w^0 = \beta p + \lambda(\beta J^n - (1-\beta)W^n) + (1-\beta)(\lambda + r)U. \tag{A.14}$$

From free entry we have that $J^0 = \frac{pc}{\mathrm{q}(\theta)}$, combining this fact with the value functions in

Equations A.11 and A.8 and the wage solution we obtain the job-creation condition:

$$\frac{r+\lambda}{1-\beta}\frac{pc}{\mathrm{q}(\theta)} = p\left[1 + \frac{\lambda}{r+\lambda}\int_R^1 (s-R)d\,\mathrm{G}(s)\ \right] + \lambda(W^n + J^n) - (\lambda + r)U, \qquad \text{(A.15)}$$

where $U = z + \theta pc\frac{\beta}{1-\beta}$, and $J^n + W^n = \phi\frac{U-f}{r+\phi}$.

Appendix B Data

B.1 Indicators of EPL

Variables Definitions. EPL is defined as the OECD's index Strictness of employment protection - individual dismissals (regular contracts) (EPR V1) which is defined according to a method of hierarchies of hierarchies on a 0 to 6 scale. The index aggregates several different scores spread over three equally weighted categories: procedural inconvenience (notification procedures and timing), notice and severance pay for no-fault individual dismissal, and difficulty of dismissal. The method of calculation is shown in Table 2. The series is used as annual data series and assumed identical over the course of each calendar year. Additionally, we use the series EPT V1 for the protection on temporary employment. This series is measured in a similar fashion, but this time as an aggregate of measures that limit the use of fixed-term and agency workers, and govern their utilization. Finally, we add the OECD series of employment protection from collective dismissals which is an aggregate of scores on the definition, procedures and costs involved with collective dismissals according to the OECD's predetermined weights.

Sample. Our panel for these variables includes the EPR V1, and EPT V1 indicators' values for the years of 1985-2014 for 21 countries during the following time periods (for collective dismissals the series is available for all the following countries for the years 1998-2013, and 1998-2014 for the United Kingdom): Australia 1985-2013; Austria 1985-2013; Belgium 1985-2013; Canada 1985-2013; Denmark 1985-2013; Finland 1985-2013; France 1985-2013; Germany 1985-2013; Greece 1985-2013; Ireland 1985-2013; Italy 1985-2013; Japan 1985-2013; Netherlands 1985-2013; New Zealand 1990-2013; Norway 1985-2013; Portugal 1985-2013; Spain 1985-2013; Sweden 1985-2013; Switzerland 1985-2013; United Kingdom 1985-2014; United States 1985-2013.

B.2 Credit Supply Shock

Variables Definition. To measure global credit supply shocks, we make use of the Gilchrist and Zakrajek (2012) credit supply shock series. Gilchrist and Zakrajek (2012) use micro-level data to construct a credit spread index which they decomposed into a component that captures firm-specific information on expected defaults and a residual component that they termed as the excess bond premium. The most updated series of the excess bond premium variable, available from Simon Gilchrist's website [31] is our measure of credit supply shocks in this paper. It is taken in monthly values from 1985:m1-2014:m12. Quarterly and annual values are averages of the corresponding raw monthly values for 1985:Q1-2014:Q4.

B.3 National accounts data

Variables Definitions. Output, consumption, investment, imports, exports and government expenditure are defined as the GDP measured by the expenditure approach, private final consumption expenditure, gross fixed capital formation, imports and exports of goods and services, and general government final consumption expenditure respectively. All six series are taken as volume indexes using OECD reference year and are seasonally adjusted. We use the data as log-first-differences. Output per-capita is defined as the quarterly GDP per capita in U.S. dollars, using constant prices, fixed PPP, and seasonally adjusted. The series are obtained from the OECD's database at http://stats.oecd.org/ and taken as log-first-differences.

Sample. Our panel includes observations for the years of 1985-2014 for 21 countries during the following time periods: Australia 1985:Q1-2013:Q4; Austria 1988Q1-2013:Q4 (out-

[31] The permanent link for this updated excess bond premium series is https://www.federalreserve.gov/econresdata/notes/feds-notes/2016/files/ebp_csv.csv.

put per capita 1995:Q1-2013:Q4); Belgium 1995:Q1-2013:Q4; Canada 1985:Q1-2013:Q4; Denmark 1995:Q1-2013:Q4; Finland 1990:Q1-2013:Q4; France 1985:Q1-2013:Q4; Germany 1991:Q1-2013:Q4; Greece 1995:Q1-2013:Q4; Ireland 1997:Q1-2013:Q4 (output per capita 1998:Q1-2013:Q4); Italy 1985:Q1-2013:Q4 (output per capita 1995:Q1-2013:Q4); Japan 1994:Q3-2013:Q4 (output per capita 2007:Q3-2013:Q4); Netherlands 1988:Q1-2013:Q4 (output per capita 1995:Q1-2013:Q4); New Zealand 1990:Q1-2013:Q4 (output per capita 1991:Q1-2013:Q4); Norway 1985:Q1-2013:Q4 (output per capita 1995:Q1-2013:Q4); Portugal 1995:Q1-2013:Q4; Spain 1995:Q1-2013:Q4; Sweden 1985:Q1-2013:Q4 (output per capita 1993:Q1-2013:Q4); Switzerland 1985:Q1-2013:Q4 (output per capita 1991:Q1-2013:Q4); United Kingdom 1985:Q1-2013:Q4 (output per capita 1995:Q1-2013:Q4); United States 1985:Q1-2013:Q4.

B.4 Unemployment

Variables Definitions. Our panel utilizes the OECD's harmonized unemployment (all persons) series in a monthly frequency. The series is taken as log-first-differences had been retrieved from the OECD's database at http://stats.oecd.org/.

Monthly sample. Our monthly panel for unemployment includes observations for the years of 1985-2014 for 19 countries (data for New Zealand and Switzerland is unavailable) during the following time periods: Australia 1985:M1-2013:M12; Austria 1993:M1-2013:M12; Belgium 1985:M1-2013:M12; Canada 1985:M1-2013:M12; Denmark 1985:M1-2013:M12; Finland 1988:M1-2013:M12; France 1985:M1-2013:M12; Germany 1991:M1-2013:M12; Greece 1998:M4-2013:M12; Ireland 1985:M1-2013:M12; Italy 1985:M1-2013:M12; Japan 1985:M1-2013:M12; Netherlands 1985:M1-2013:M12; Norway 1989:M1-2013:M12; Portugal 1985:M1-2013:M12; Spain 1986:M4-2013:M12; Sweden 1985:M1-2013:M12; United Kingdom 1985:M1-2014:M12; United States 1985:M1-2013:M12.

B.5 Population and Labor-Force Participation

Variables Definitions. We define labor-force participation as the ratio between the active population (persons actively engaged in search or currently in employment) and the working age population. Both measures include all persons aged 15 and over, other than for Spain, the United Kingdom, and the United States for which the lower bound is 16. We also make use of the ratio between the employed population to the working age population (employment to population ratio), again for the same ages as mentioned above. The raw data includes three data series (employed, active, and working age population) expressed in thousands of persons. The resulting ratios are taken as log-first-differences. All raw series used for the creation of these ratio series are from the OECD's database at http://stats.oecd.org/.

Sample. Our quarterly panel for these ratios includes observations for the years of 1985-2014 for 21 countries during the following time periods: Australia 1985:Q1-2013:Q4; Austria 1999:Q1-2013:Q4; Belgium 1999:Q1-2013:Q4; Canada 1995:Q1-2013:Q4; Denmark 1999:Q1-2013:Q4; Finland 2000:Q1-2013:Q4; France 2003:Q1-2013:Q4; Germany 2005:Q1-2013:Q4; Greece 1998:Q1-2013:Q4; Ireland 1999:Q2-2013:Q4; Italy 1998:Q1-2013:Q4; Japan 1985:Q1-2013:Q4; Netherlands 2000:Q1-2013:Q4; New Zealand 1990:Q1-2013:Q4; Norway 2000:Q1-2013:Q4; Portugal 1998:Q1-2013:Q4; Spain 1999:Q1-2013:Q4; Sweden 2001:Q1-2013:Q4; Switzerland 2010:Q1-2013:Q4 (available only for Q2 for 1999-2009); United Kingdom 1999:Q2-2014:Q4; United States 1985:Q1-2013:Q4.

B.6 Vacancies

Variables Definitions. We define vacancies as the ratio between the stock of vacancies normalized by the working age population from the previous subsection, which includes all persons aged 15 and over, other than for Spain, the United Kingdom, and the United States for which the lower bound is 16. The raw data includes two data series (total vacancy stock, and working age population) expressing numbers of persons and seasonally adjusted. The resulting normalized series is taken as log-first-differences. All raw series are from the OECD's database at http://stats.oecd.org/.

Sample. Our quarterly panel for vacancies includes observations for the years of 1985-2014 for 12 countries (Canada, Denmark, France, Greece, Ireland, Italy, Japan, Netherlands, and New Zealand are missing) during the following time periods: Australia 1985:Q1-2008:Q2 and 2009:Q4-2013:Q4; Austria 1999:Q1-2013:Q4; Belgium 1999:Q1-2004:Q1; Finland 2000:Q1-2013:Q4; Germany 2005:Q1-2013:Q4; Norway 2000:Q1-2013:Q4; Portugal 1998:Q1-2013:Q4; Spain 1999:Q1-2005:Q1; Sweden 2001:Q1-2013:Q4; Switzerland 2010:Q1-2013:Q4 (available only for Q2 for 1999-2009); United Kingdom 1999:Q2-2014:Q4; United States 2001:Q1-2013:Q4.

B.7 Real wage

Variables Definitions. We define the real wage as the ratio of total compensations in local currency and in current prices deflated using the country's own consumer price index using 1985 as a base year and dividing by the number of employed persons. The raw data includes three data series (the consumer price index, total compensations, and employed population) which are seasonally adjusted. The resulting ratio, the average real wage per employed person, is taken as log-first-differences. All raw series used for the creation of this series are from the OECD's database at http://stats.oecd.org/.

Sample. Our quarterly panel for these ratios includes observations for the years of 1985-2014 for 17 countries (Canada, Japan, New Zealand, and the United States are missing) during the following time periods: Australia 1985:Q1-2013:Q4; Austria 1995:Q1-2013:Q4; Belgium 1995:Q1-1997:Q4, 1999:Q1-2013:Q4; Denmark 1995:Q1-2013:Q4; Finland 1998:Q1-2013:Q4; France 2003:Q1-2013:Q4; Germany 1991:Q1-2013:Q4; Greece 1995:Q1-2013:Q4; Ireland 1998:Q1-2013:Q4; Italy 1998:Q1-2013:Q4; Netherlands 1998:Q1-2013:Q4; Norway 2000:Q1-2013:Q4; Portugal 1998:Q1-2013:Q4; Spain 1999:Q1-2013:Q4; Sweden 2001:Q1-2013:Q4; Switzerland 2010:Q1-2013:Q4 (available only for Q2 for 1999-2009); United Kingdom 1999:Q2-2014:Q4; United States 1985:Q1-2013:Q4.

B.8 Capacity utilization

Variables Definitions. We define capacity utilization as the rate of capacity utilization from the OECD's business tendency surveys for manufacturing industries. The raw data is in percentage points, seasonally adjusted, and used as log-first-differences. The series is from the OECD's database at http://stats.oecd.org/.

Sample. Our quarterly panel for this series includes observations for the years of 1985-2014 for 18 countries [32] during the following time periods: Austria 1996:Q1-2013:Q4; Belgium 1985:Q1-2013:Q4; Denmark 1987:Q1-2013:Q4; Finland 1991:Q1-2013:Q4; France 1985:Q1-2013:Q4; Germany 1985:Q1-2013:Q4; Greece 1985:Q1-2013:Q4; Ireland 1985:Q1-2008:Q3; Italy 1985:Q1-2013:Q4; Netherlands 1985:Q1-2013:Q4; New Zealand 1990:Q1-2013:Q4; Norway 1987:Q1-2013:Q4; Portugal 1985:Q1-2013:Q4; Spain 1985:Q1-2013:Q4; Sweden 1995:Q1-2013:Q4; Switzerland 1985:Q1-2013:Q4; United Kingdom 1985:Q2-2014:Q4; United States 1985:Q1-2013:Q4.

[32] Data for Canada is missing. Data for Australia and Japan is available however the range of values for these two countries is not comparable to the ones in the other countries. To illustrate according to the raw series the range of values for Australia is from -44 to 13, for Japan -36 to 13 and for all other countries in our sample from 47.4 to 93.4

B.9 Total Factor Productivity

Variables Definitions. TFP is defined as the OECD's MFP (multifactor productivity) series. The raw data is an index using 2010 as a base year, seasonally adjusted, and used as log-first-differences. The series is from the OECD's database at http://stats.oecd.org/.[33]

Sample. Our panel for this variable includes values for the years of 1985-2014 for 19 countries (Greece and Norway are missing) during the following time periods: Australia 1985-2013; Austria 1996-2013; Belgium 1985-2013; Canada 1985-2013; Denmark 1985-2013; Finland 1985-2013; France 1985-2013; Germany 1985-2013; Ireland 1985-2013; Italy 1985-2013; Japan 1985-2013; Netherlands 1985-2013; New Zealand 1990-2013; Portugal 1985-2013; Spain 1985-2013; Sweden 1985-2013; Switzerland 1992-2013; United Kingdom 1985-2014; United States 1985-2013.

B.10 Hours Worked

Variables Definitions. Hours worked per-employed person are defined as the OECD's series average annual hours worked which is the total number of hours actually worked per year divided by the average number of people in employment per year. The series on total hours worked is the product of this series with the annual average of the number of employed persons series described above. The raw data is in numbers of hours and used as log-first-differences. The series is from the OECD's database at http://stats.oecd.org/.

[33] for more information on the series see http://www.oecd.org/sdd/productivity-stats/2352458.pdf.

Sample. Our panel for these variables includes values for the years of 1985-2014 for 21 countries the following time periods: Australia 1985-2013; Austria 1995-2013; Belgium 1985-2013 (Total hours missing for 1998); Canada 1985-2013; Denmark 1985-2013 (total hours missing for 1985-1989); Finland 1985-2013 (total hours missing for 1985-1997); France 1985-2013 (total hours missing for 1985-2002); Germany 1991-2013; Greece 1985-2013 (total hours missing for 1985-1988); Ireland 1998-2013; Italy 1995-2013 (total hours missing for 1995-1997); Japan 1985-2013; Netherlands 1985-2013 (total hours missing for 1985-1997); New Zealand 1990-2013; Norway 1985-2013 (total hours missing for 1985-2000); Portugal 1985-2013 (total hours missing for 1985-1998); Spain 1985-2013 (total hours missing for 1985-1998); Sweden 1985-2013 (total hours missing for 1985-2000); Switzerland 1991-2013 (total hours missing for 1991-1997); United Kingdom 1985-2014 (total hours missing for 1985-1998); United States 1985-2013.

B.11 Union Density

Variables Definitions. Union density is defined as the OECD's series on trade union density rates which is the ratio of union members divided by the total number of employees based on administrative data if such data is unavailable, survey data had been imputed instead. The series is available at an annual frequency, assumed identical within each calendar year, in a similar fashion to the EPL series, and taken from the OECD's database at http://stats.oecd.org/.

Sample. Our panel for this variable includes values for the years of 1985-2014 for 21 countries during the following time periods: Australia 1985-2013; Austria 1985-2013; Belgium 1985-2013; Canada 1985-2013; Denmark 1985-2013; Finland 1985-2013; France 1985-2013; Germany 1985-2013; Greece 1985, 1990, 1992, 1995, 1998, 2001-2002, 2004-2006, 2008, 2011,2013; Ireland 1985-2013; Italy 1985-2013; Japan 1985-2013; Netherlands 1985-2013;

New Zealand 1990-2013; Norway 1985-2013; Portugal 1985-1990, 1995, 1997, 2002-2004, 2006, 2008, 2010-2011; Spain 1985-2013; Sweden 1985-2013; Switzerland 1985-2013; United Kingdom 1985-2014; United States 1985-2013.

B.12 Collective Bargaining Coverage

Variables Definitions. Collective bargaining coverage is the OECD's series of the same name which is the ratio of employees covered by collective agreements, divided by all wage earners with a right to bargaining. The series is available at an annual frequency, assumed identical within each calendar year, in a similar fashion to the EPL series, and taken from the OECD's database at http://stats.oecd.org/.

Sample. Our panel for this variable includes values for the years of 1985-2014 for 21 countries during the following time periods: Australia 1985, 1990, 1998, 2000, 2002, 2004, 2006, 2008, 2010, 2012; Austria 1985, 1990, 1995, 2000, 2005, 2008, 2010, 2013; Belgium 1985, 1990, 1995, 2000, 2002, 2008, 2013; Canada 1985-2013; Denmark 1985, 1990, 1993, 1997, 2000, 2004, 2006-2007, 2009-2010, 2013; Finland 1985, 1989, 1995, 2000, 2002-2006, 2008-2013; France 1985, 1990, 1997, 2004, 2008-2009, 2012; Germany 1985, 1990, 1995-2013; Greece 1985, 1990, 1995, 2000-2013; Ireland 2000, 2005, 2009; Italy 1985, 1990, 1995, 2000-2013; Japan 1985, 1988, 1990, 1995, 2000, 2005-2013; Netherlands 1985-1990, 1992-1993, 1996, 2000-2013; New Zealand 1990. 1992-2003, 2007, 2010-2011; Norway 1985, 1990, 1994, 1998, 2002, 2006, 2009, 2013; Portugal 1985, 1990, 1995, 1999-2013; Spain 1985, 1990, 1993-2013; Sweden 1985, 1990, 1994-1995, 1998, 2000, 2002, 2005, 2007, 2011, 2013; Switzerland 1985, 1990-1992, 1994, 1996, 1999, 2001, 2003, 2005, 2007, 2009-2010, 2012-2013; United Kingdom 1985, 1990, 1994-2014; United States 1985-2013.

B.13 Net Replacement Rate

Variables Definitions. Net replacement rate is the OECD's series on the generosity of unemployment benefits, taken as replacement rates at 6 months unemployment for an adult with an average wage partner and two children including housing benefits. Series available at http://stats.oecd.org/.

Sample. Our panel for this variable includes annual values for the years of 2001-2014 for 21 countries during the following time periods: Australia 2001-2013; Austria 2001-2013; Belgium 2001-2013; Canada 2002-2013; Denmark 2001-2013; Finland 2001-2013; France 2001-2013; Germany 2001-2013; Greece 2001-2013; Ireland 2001-2013; Italy 2001-2013; Japan 2001-2013; Netherlands 2001-2013; New Zealand 2001-2013; Norway 2001-2013; Portugal 2001-2013; Spain 2001-2013; Sweden 2001-2013; Switzerland 2001-2013; United Kingdom 2001-2014; United States 2001-2013.

B.14 Separation Rate and Job-Finding Rate

Variables Definitions. Both series are taken from the decomposition of OECD data on employment into flows carried out in Elsby et al. (2013) using the finale data series after both series had been tested and adjusted for duration dependence in case it exists. These series are available from the author's website at https://sites.google.com/site/mikeelsby/data.

Sample. Our panel for these variables include annual values for monthly flow hazards for the years of 1985-2009 for 17 countries during the following time periods: Australia 1985-2009; Canada 1985-2009; France 1985-2009; Germany 1985-2009; Ireland 1985-1997, 1999, 2001-2009; Italy 1985-2009; Japan 1985-2009; New Zealand 1987-2009; Norway 1985, 1988-2009; Portugal 1986-2009; Spain 1985-2009; Sweden 1985-2004, 2007-2009; United Kingdom 1985-2009; United States 1985-2009.

Table 1: Model Parameterization.

		Baseline (1)	No EPL (2)
		Parameters	Parameters
p		1.0000	1.0000
c		0.2990	0.2990
λ		0.0340	0.0340
β		0.5000	0.5000
ϕ		0.7500	62.7500
f		0.3300	0.0000
z		0.5500	0.5500
r		0.0100	0.0100
w^n		0.9007	0.9384
$q(\theta) = \sigma\theta^{-\eta}$		$q(\theta) = 0.231\theta^{-0.5}$	$q(\theta) = 0.231\theta^{-0.5}$
		Model Steady States	Model Steady States
u		0.1046	0.1098
n_a		0.0322	0.0004
n		0.8631	0.8898
TFP		0.9489	0.9933
R		0.8230	0.8881
θ		1.0011	1.1257
Output		0.8496	0.8842
Markov matrix			
		Transition Probabilities	
state	λ	1	2
1	1.1λ	0.9000	0.1000
2	0.9λ	0.1000	0.9000

Notes: This table consists of the parameters' values used for the model from Section 2.

Table 2: EPL: Components and Weights.

EPL index	Weights	OECD main series	Weights	OECD basic series
EPR v1 - regular contracts	33.3%	Procedural inconvenience	50.0%	Notification procedures
			50.0%	Delay involved before notice can start
	33.3%	Notice and severance pay for no-fault individual dismissal	14.3%	Length of the notice period at 9 months tenure
			14.3%	Length of the notice period at 4 years tenure
			14.3%	Length of the notice period at 20 years tenure
			19.0%	Severance pay at 9 months tenure
			19.0%	Severance pay at 4 years tenure
			19.0%	Severance pay at 20 years tenure
	33.3%	Difficulty of dismissal	25.0%	Definition of justified or unfair dismissal
			25.0%	Length of trial period
			25.0%	Compensation following unfair dismissal
			25.0%	Possibility of reinstatement following unfair dismissal

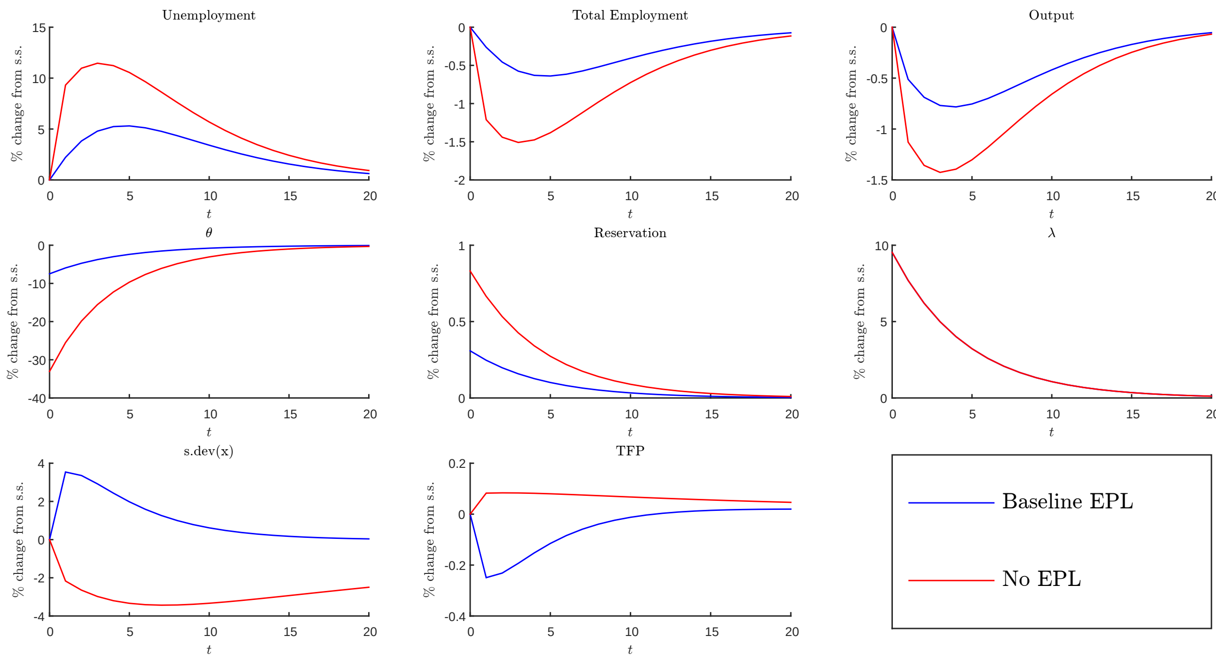
Notes: The weights and the basic series are those used by the OECD and retrieved from http://www.oecd.org/els/emp/oecdindicatorsofemploymentprotection.htm.

Table 3: Job Flows and EPL.

	Average flow hazards by policy regimes			
	Job finding rate		Separation rate	
	(1) Coef.	(2) P-value	(3) Coef.	(4) P-value
Lax	0.2512	0.0000	0.0178	0.0000
Intermediate	0.1819	0.0000	0.0101	0.0000
Strict	0.0861	0.0000	0.0063	0.0000
	Differences between groups			
	Coef.	P-value	Coef.	P-value
Lax-Intermediate	0.0693	0.0000	0.0077	0.0000
Intermediate-Strict	0.0958	0.0000	0.0038	0.0004
Lax-Strict	0.1651	0.0000	0.0115	0.0000

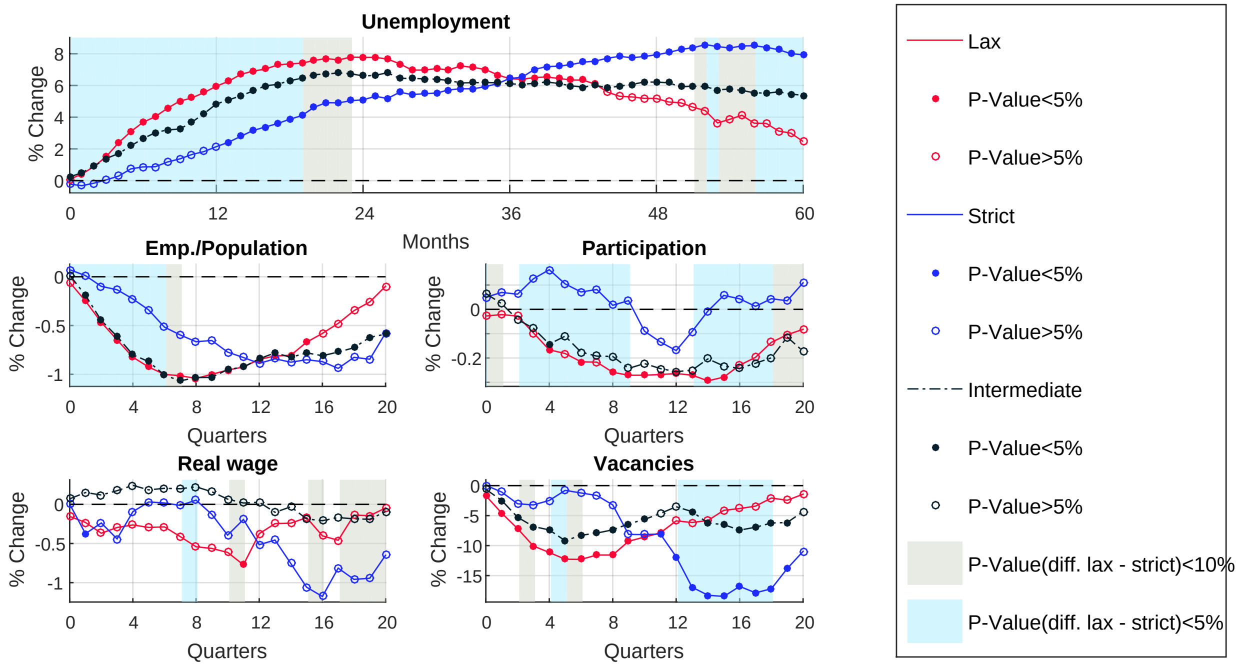
Notes: The first three rows are obtained from simply regressing the job-finding rate and separation rate data from Elsby et al. (2013) on the three policy dummies without a constant term so as to obtain the group averages. The last three rows indicate the differences between every pair of groups and their statistical significance. Inference is based on Driscoll and Kraay (1998) standard errors.

Figure 1: Theoretical Impulse Responses Conditional on EPL Regime.



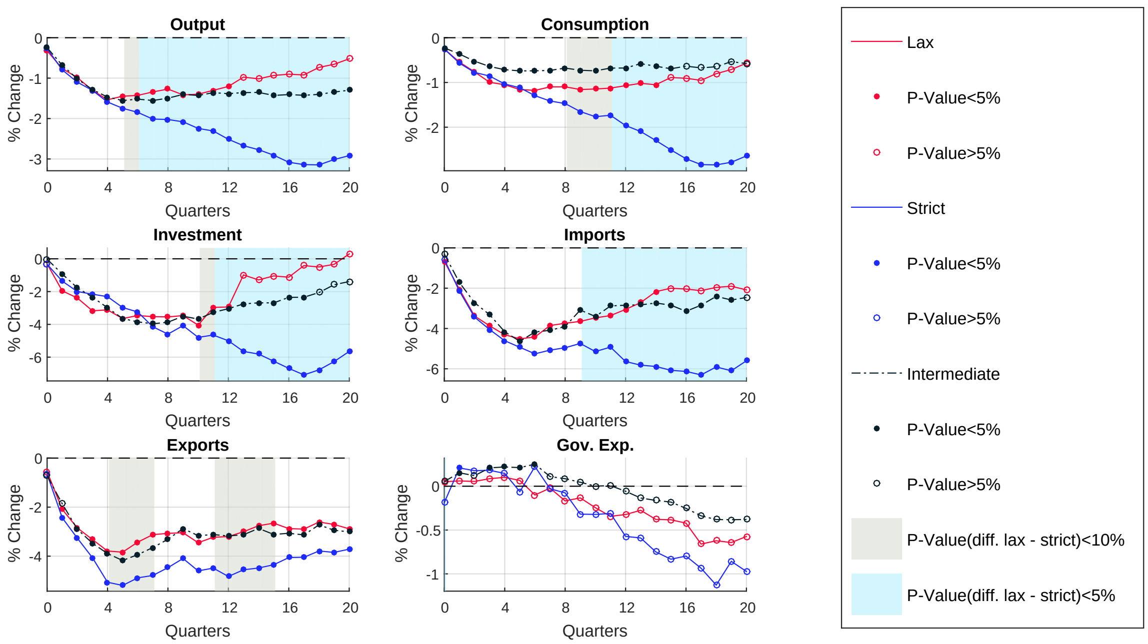
Notes: Theoretical impulse response functions for each variable to a 10% increase in the arrival rate of idiosyncratic shocks to match quality, λ. Impulse responses for our baseline EPL regime model, whose calibration appears in column 1 in Table 1, is presented in blue; impulse responses for the no-EPL regime, whose calibration appears in column 2 in Table 1, is shown in red. Horizon is in quarters and the vertical axis' units are the percentage changes from steady-state level of each variable in response to the shock.

Figure 2: Impulse Responses to a One Standard Deviation Credit Supply Shock Under Different EPL Regimes: Labor Market Variables.



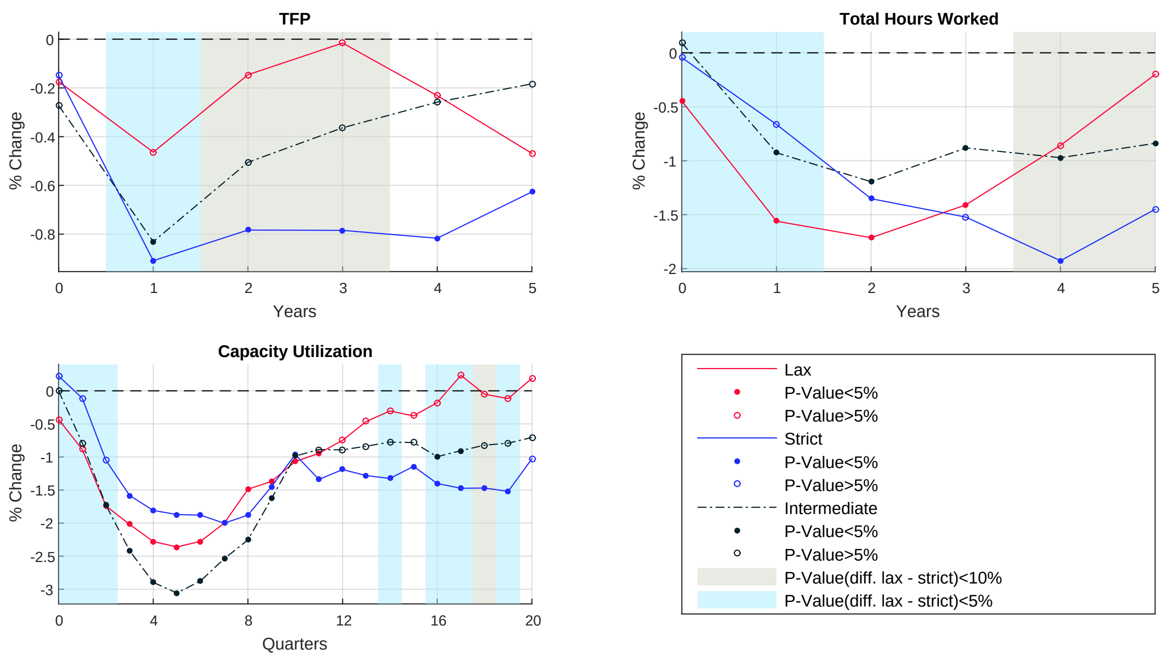
Notes: Impulse response functions for each outcome measure estimated using the state-dependent model described in Equation (20). The IRF for strict EPL regime is presented in blue, the IRF for the lax EPL regime in red and the intermediate regime in black. Full data points represent horizons at which the point estimate for the IRF is statistically significantly different than zero (p-value ≤ 0.05). Shaded areas indicate that the difference in response between the strict and lax groups is significantly different from zero (p-value ≤ 0.05 in light-blue shading and p-value ≤ 0.1 in gray). Inference is based on Driscoll and Kraay (1998) standard errors.

Figure 3: Impulse Responses to a One Standard Deviation Credit Supply Shock Under Different EPL Regimes: National Accounts.



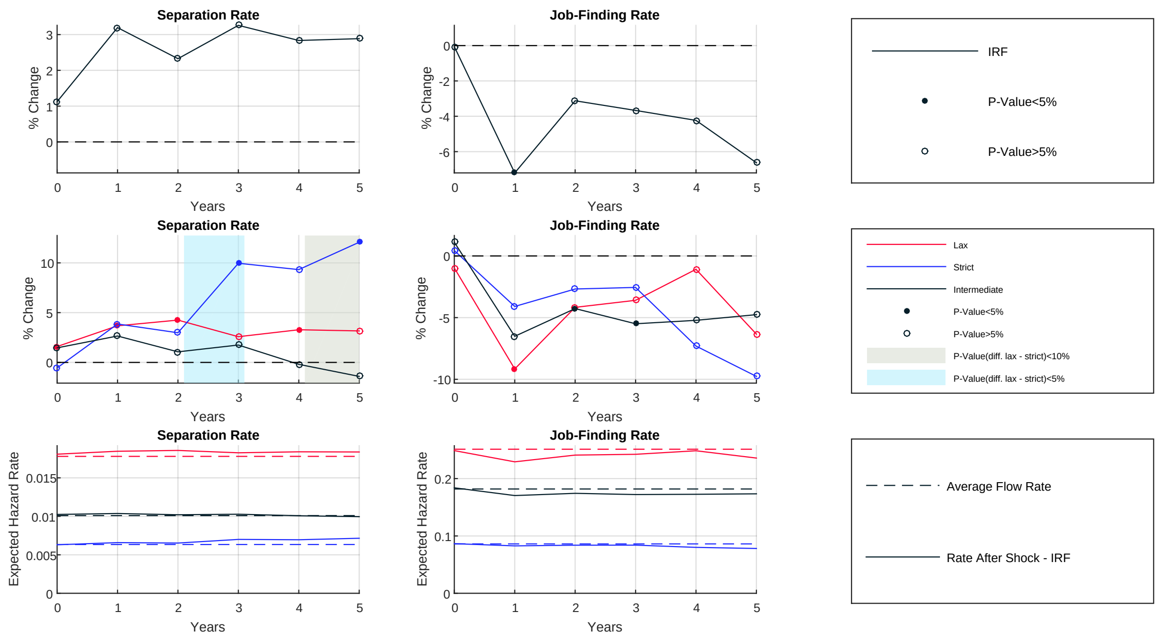
Notes: Impulse response functions for each outcome measure estimated using the state-dependent model described in Equation (20). The IRF for strict EPL regime is presented in blue, the IRF for the lax EPL regime in red and the intermediate regime in black. Full data points represent horizons at which the point estimate for the IRF is statistically significantly different than zero (p-value ≤ 0.05). Shaded areas indicate that the difference in response between the strict and lax groups is significantly different from zero (p-value ≤ 0.05 in light-blue shading and p-value ≤ 0.1 in gray). Inference is based on Driscoll and Kraay (1998) standard errors.

Figure 4: Impulse Responses to a One Standard Deviation Credit Supply Shock Under Different EPL regimes: TFP, Hours Worked, and Utilization.



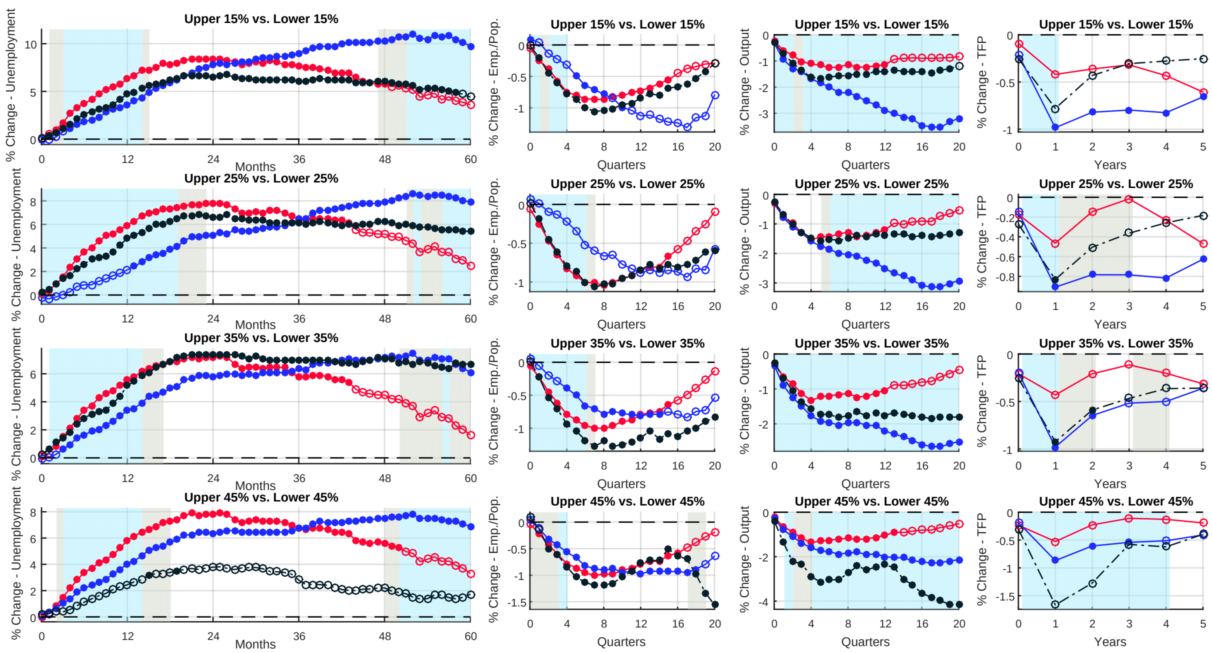
Notes: Impulse response functions for each outcome measure estimated using the state-dependent model described in Equation (20). The IRF for strict EPL regime is presented in blue, the IRF for the lax EPL regime in red and the intermediate regime in black. Full data points represent horizons at which the point estimate for the IRF is statistically significantly different than zero (p-value ≤ 0.05). Shaded areas indicate that the difference in response between the strict and lax groups is significantly different from zero (p-value ≤ 0.05 in light-blue shading and p-value ≤ 0.1 in gray). Inference is based on Driscoll and Kraay (1998) standard errors.

Figure 5: Impulse Responses to a One Standard Deviation Credit Supply Shock Under Different EPL regimes: Separation Rate and Job-Finding Rate.



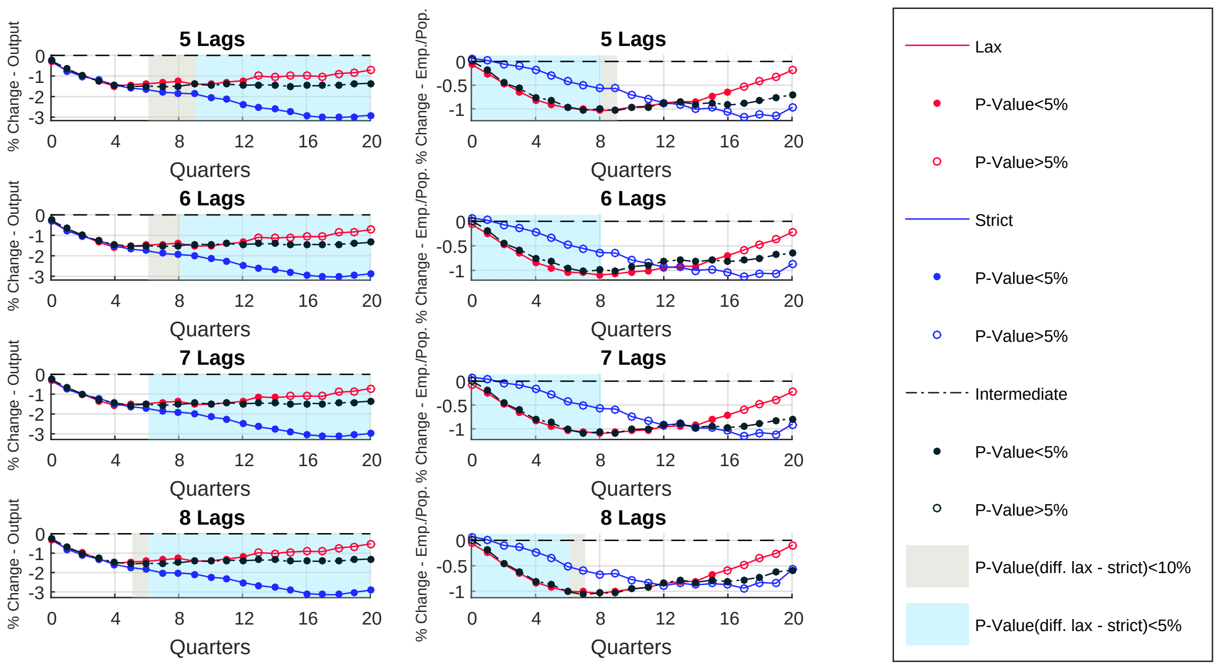
Notes: Impulse response functions for each rate estimated using the local projections without state-dependence are in the first row. Impulse response functions for each rate estimated using the state-dependent model described in Equation (20) are presented in the second. The IRF for strict EPL regime is presented in blue, the IRF for the lax EPL regime in red and the intermediate regime in black. Full data points represent horizons at which the point estimate for the IRF is statistically significantly different than zero (p-value $\leq$ 0.05). Shaded areas indicate that the difference in response between the strict and lax groups is significantly different from zero (p-value $\leq$ 0.05 in light-blue shading and p-value $\leq$ 0.1 in gray). The third row illustrates the implied rates obtained from the multiplying average level at each policy group with the impulse response in that particular horizon. Inference is based on Driscoll and Kraay (1998) standard errors.

Figure 6: Robustness to Different Cutoff Values.



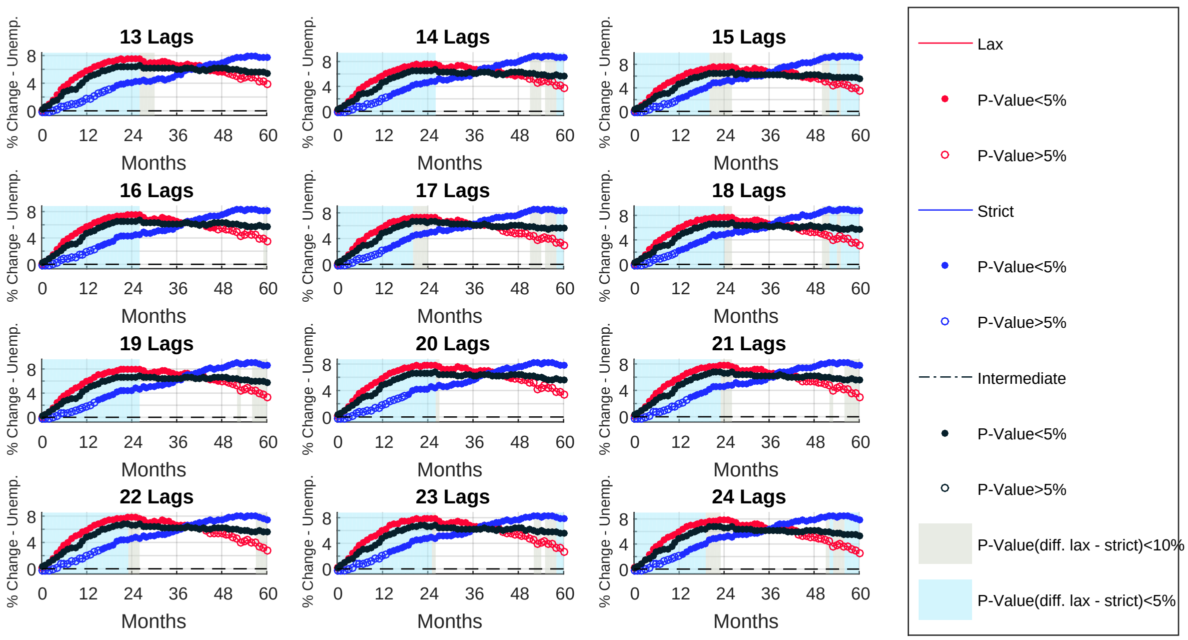
Notes: Impulse response functions for each outcome measure estimated using the state-dependent model described in Equation (20) with different cutoff values for EPL regimes. The IRF for strict EPL regime is presented in blue, the IRF for the lax EPL regime in red and the intermediate regime in black. Full data points represent horizons at which the point estimate for the IRF is statistically significantly different than zero (p-value ≤ 0.05). Shaded areas indicate that the difference in response between the strict and lax groups is significantly different from zero (p-value ≤ 0.05 in light-blue shading and p-value ≤ 0.1 in gray). Inference is based on Driscoll and Kraay (1998) standard errors.

Figure 7: Robustness to Different Lag Orders: Quarterly Variables.



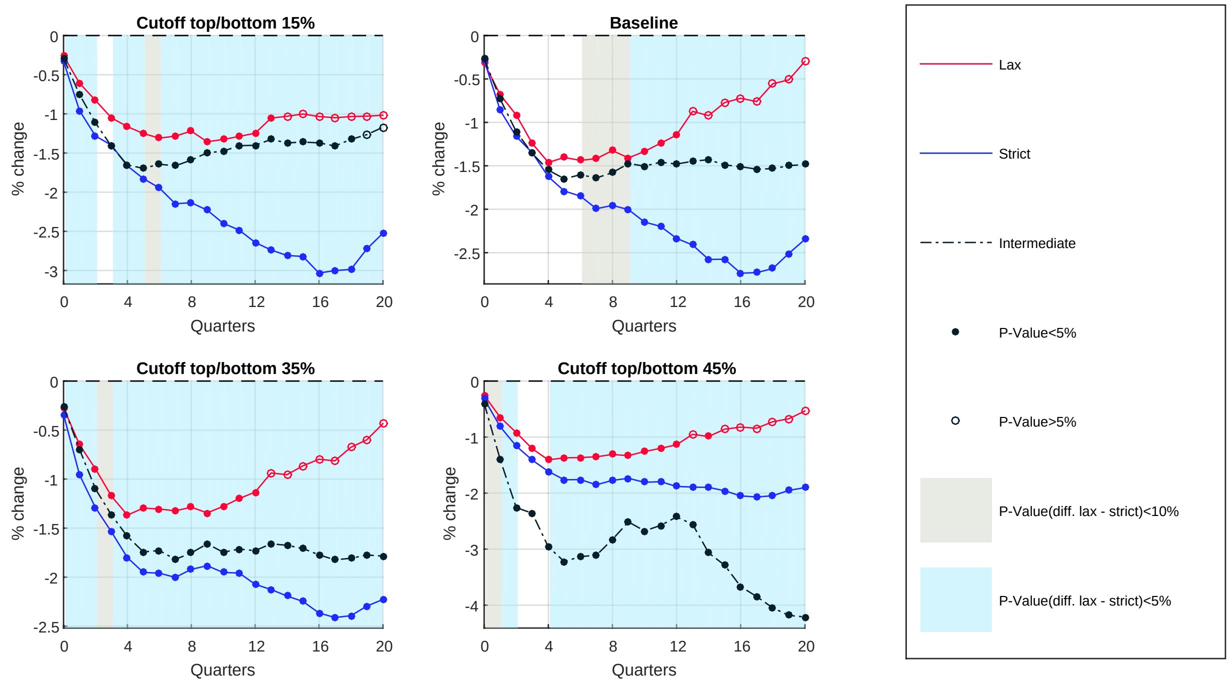
Notes: Impulse response functions for each outcome measure estimated using the state-dependent model described in Equation (20) with different lag specification. The IRF for strict EPL regime is presented in blue, the IRF for the lax EPL regime in red and the intermediate regime in black. Full data points represent horizons at which the point estimate for the IRF is statistically significantly different than zero (p-value $\leq$ 0.05). Shaded areas indicate that the difference in response between the strict and lax groups is significantly different from zero (p-value $\leq$ 0.05 in light-blue shading and p-value $\leq$ 0.1 in gray). Inference is based on Driscoll and Kraay (1998) standard errors.

Figure 8: Robustness to Different Lag Orders: Monthly Unemployment.



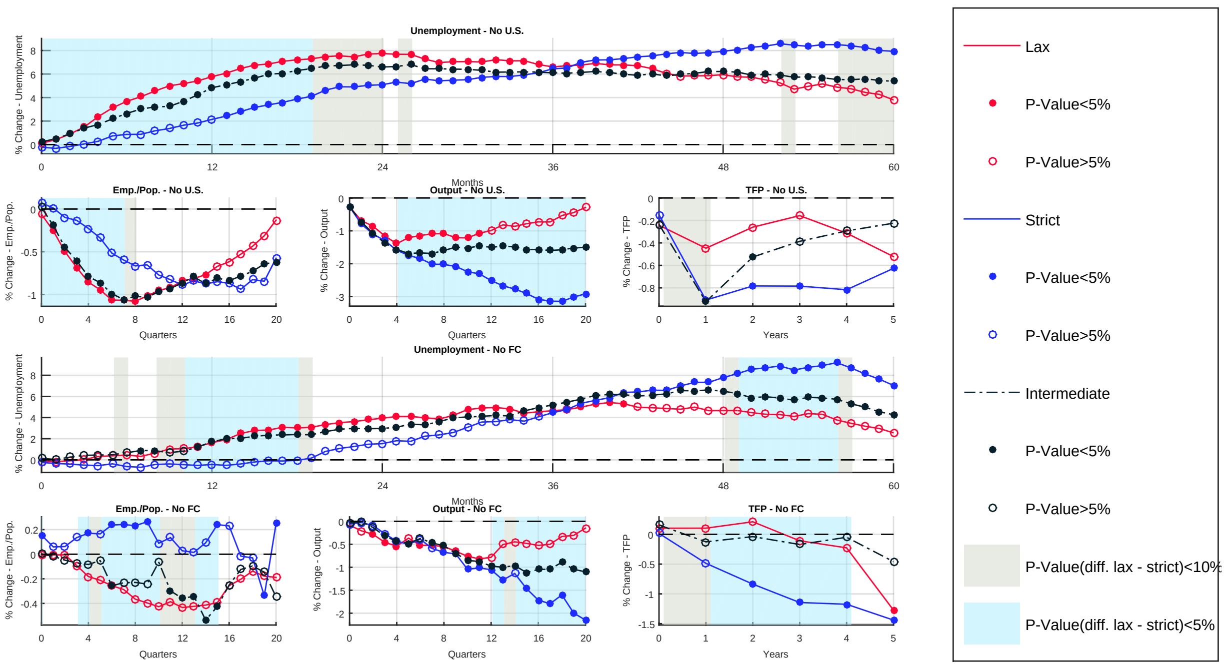
Notes: Impulse response functions for unemployment rates estimated using the state-dependent model described in Equation (20) with different lag specifications. The IRF for strict EPL regime is presented in blue, the IRF for the lax EPL regime in red and the intermediate regime in black. Full data points represent horizons at which the point estimate for the IRF is statistically significantly different than zero (p-value ≤ 0.05). Shaded areas indicate that the difference in response between the strict and lax groups is significantly different from zero (p-value ≤ 0.05 in light-blue shading and p-value ≤ 0.1 in gray). Inference is based on Driscoll and Kraay (1998) standard errors.

Figure 9: Robustness to Alternative Output Measure.



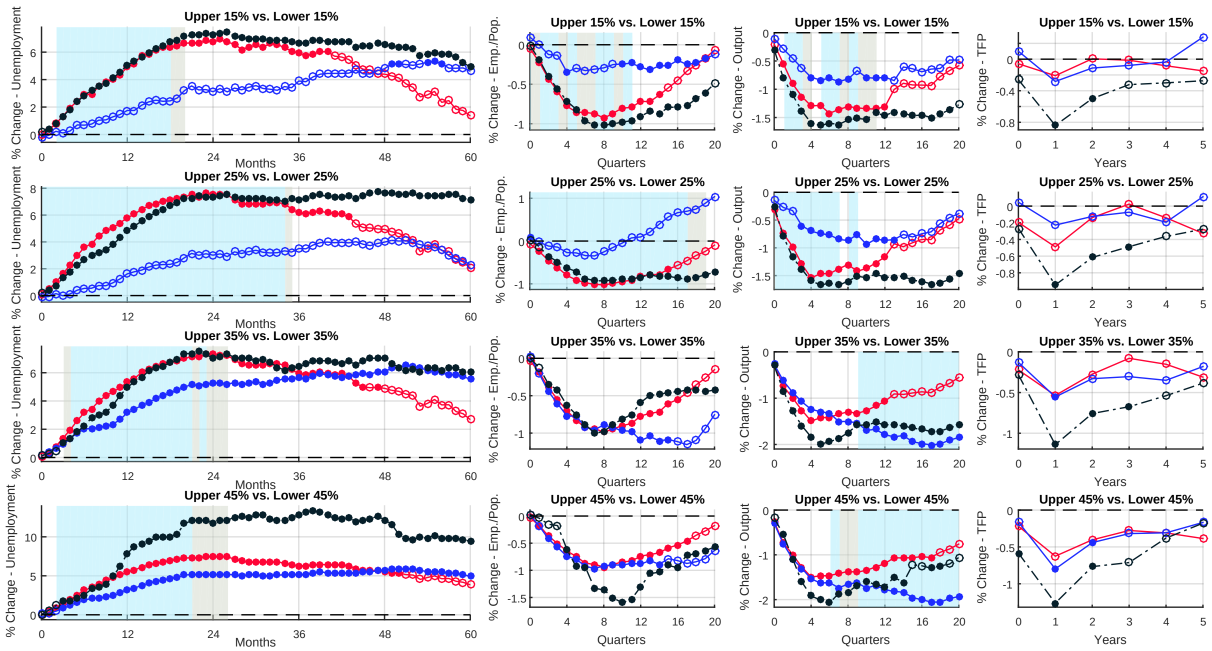
Notes: Impulse response functions output per-capita estimated using the state-dependent model described in Equation (20) while also considering different cutoff values for EPL regimes. The IRF for strict EPL regime is presented in blue, the IRF for the lax EPL regime in red and the intermediate regime in black. Full data points represent horizons at which the point estimate for the IRF is statistically significantly different than zero (p-value $\leq$ 0.05). Shaded areas indicate that the difference in response between the strict and lax groups is significantly different from zero (p-value $\leq$ 0.05 in light-blue shading and p-value $\leq$ 0.1 in gray). Inference is based on Driscoll and Kraay (1998) standard errors.

Figure 10: Robustness to Choice of Sample.



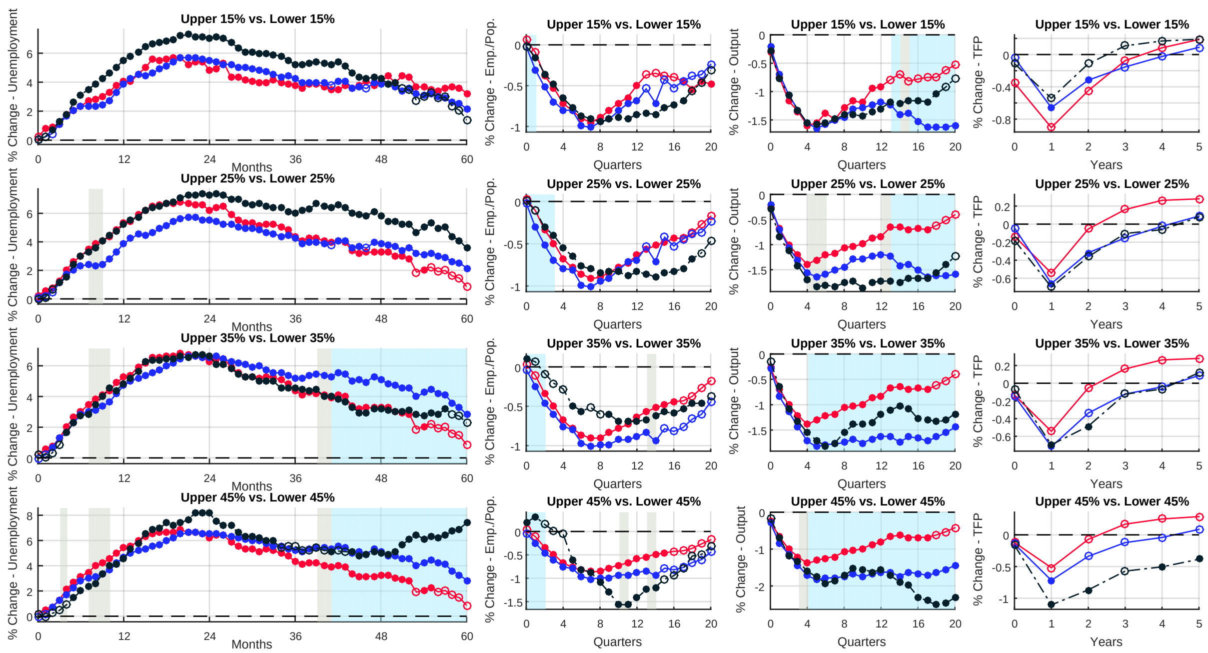
Notes: Impulse response functions for each outcome measure estimated using the state-dependent model described in Equation (20) for different sample choices. Abbreviations: No U.S.: sample without the united states; No FC: sample without the 2008 financial crisis. The IRF for strict EPL regime is presented in blue, the IRF for the lax EPL regime in red and the intermediate regime in black. Full data points represent horizons at which the point estimate for the IRF is statistically significantly different than zero (p-value ≤ 0.05). Shaded areas indicate that the difference in response between the strict and lax groups is significantly different from zero (p-value ≤ 0.05 in light-blue shading and p-value ≤ 0.1 in gray). Inference is based on Driscoll and Kraay (1998) standard errors.

Figure 11: Other Institutional Factors: Protection of Temporary Employees.



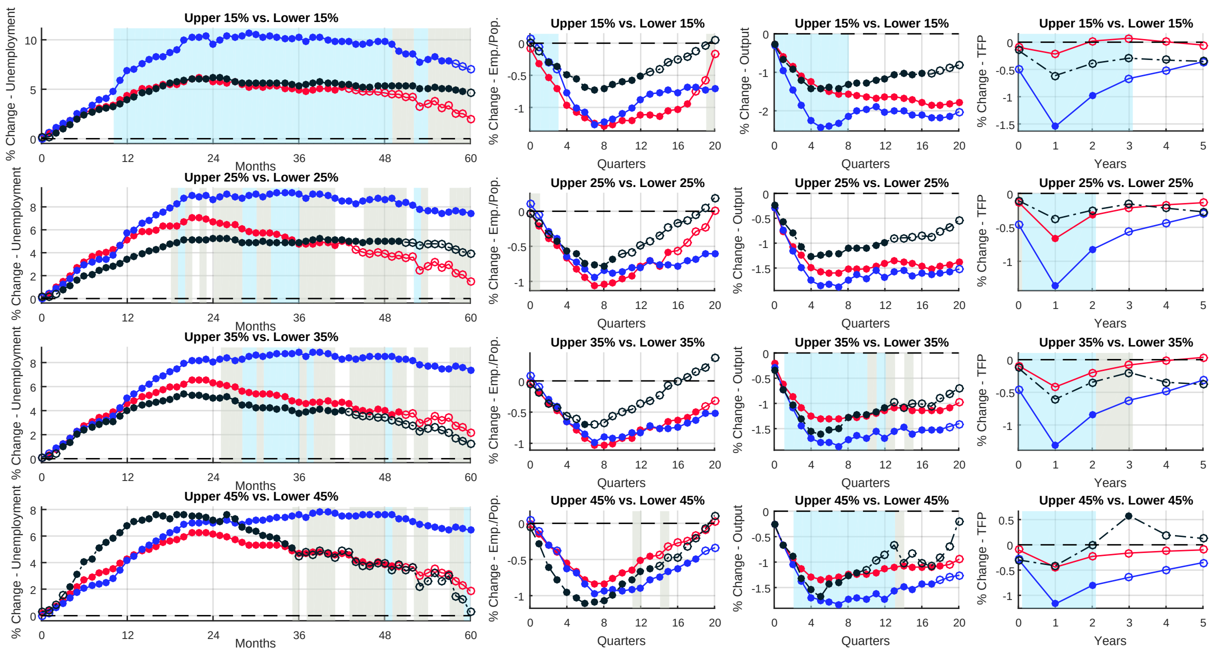
Notes: Impulse response functions for each outcome measure estimated using the state-dependent model described in Equation (20) with different cutoff values for EPT regimes. The IRF for strict EPT regime is presented in blue, the IRF for the lax EPT regime in red and the intermediate regime in black. Full data points represent horizons at which the point estimate for the IRF is statistically significantly different than zero (p-value ≤ 0.05). Shaded areas indicate that the difference in response between the strict and lax groups is significantly different from zero (p-value ≤ 0.05 in light-blue shading and p-value ≤ 0.1 in gray). All inference is based on Driscoll and Kraay (1998) standard errors.

Figure 12: Other Institutional Factors: Protection Collective Dismissals.



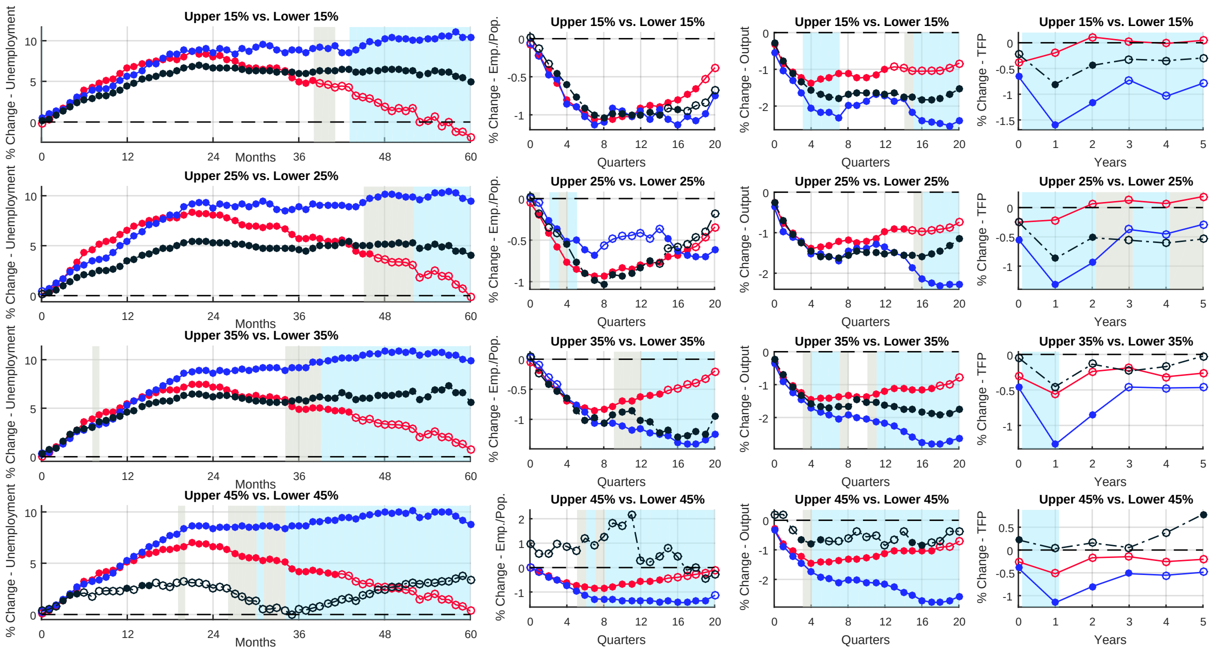
Notes: Impulse response functions for each outcome measure estimated using the state-dependent model described in Equation (20) with different cutoff values for EPC regimes. The IRF for strict EPC regime is presented in blue, the IRF for the lax EPC regime in red and the intermediate regime in black. Full data points represent horizons at which the point estimate for the IRF is statistically significantly different than zero (p-value ≤ 0.05). Shaded areas indicate that the difference in response between the strict and lax groups is significantly different from zero (p-value ≤ 0.05 in light-blue shading and p-value ≤ 0.1 in gray). All inference is based on Driscoll and Kraay (1998) standard errors.

Figure 13: Other Institutional Factors: Union Density.



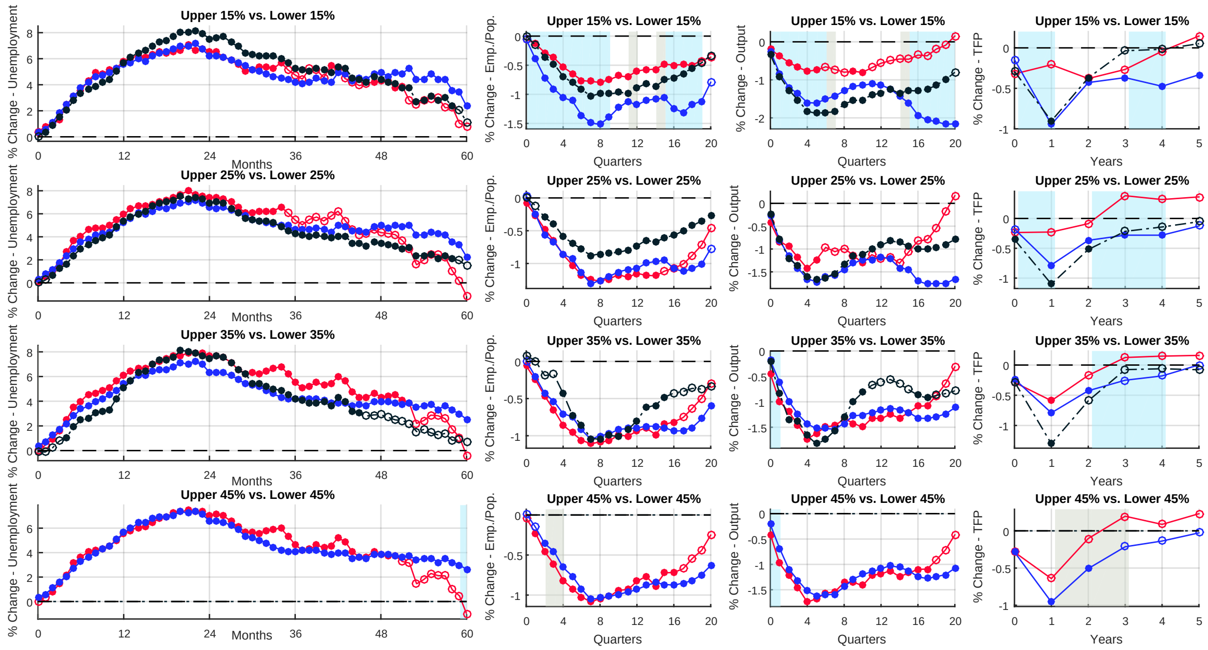
Notes: Impulse response functions for each outcome measure estimated using the state-dependent model described in Equation (20) with different cutoff values for levels of union density. The IRF for high union density is presented in blue, the IRF for the low union density in red and the intermediate regime in black. Full data points represent horizons at which the point estimate for the IRF is statistically significantly different than zero (p-value ≤ 0.05). Shaded areas indicate that the difference in response between the high and low groups is significantly different from zero (p-value ≤ 0.05 in light-blue shading and p-value ≤ 0.1 in gray). All inference is based on Driscoll and Kraay (1998) standard errors.

Figure 14: Other Institutional Factors: Collective Bargaining Coverage.



Notes: Impulse response functions for each outcome measure estimated using the state-dependent model described in Equation (20) with different cutoff values for collective bargaining coverage levels. The IRF for high collective bargaining coverage levels is presented in blue, the IRF for the low collective bargaining coverage levels in red and the intermediate regime in black. Full data points represent horizons at which the point estimate for the IRF is statistically significantly different than zero (p-value ≤ 0.05). Shaded areas indicate that the difference in response between the high and low groups is significantly different from zero (p-value ≤ 0.05 in light-blue shading and p-value ≤ 0.1 in gray). All inference is based on Driscoll and Kraay (1998) standard errors.

Figure 15: Other Institutional Factors: Net Replacement Rates.



Notes: Impulse response functions for each outcome measure estimated using the state-dependent model described in Equation (20) with different cutoff values for replacement rates generosity levels. The IRF for high replacement rate regime is presented in blue, the IRF for the low replacement rate regime in red and the intermediate regime in black. Full data points represent horizons at which the point estimate for the IRF is statistically significantly different than zero (p-value ≤ 0.05). Shaded areas indicate that the difference in response between the high and low groups is significantly different from zero (p-value ≤ 0.05 in light-blue shading and p-value ≤ 0.1 in gray). All inference is based on Driscoll and Kraay (1998) standard errors.