Labor market reforms and unemployment dynamics☆

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1. Introduction

A large number of studies have sought the source of persistent differences in European and American labor market outcomes in different labor market institutions. Following Bruno and Sachs (1985), research looked for the most effective labor market policies by running pooled cross-country time-series regressions of unemployment rates on various macroeconomic indicators (like GDP growth) and a battery of labor market institutional indices (see British Nickell and Layard, 1999, for a survey). Blanchard and Wolfers (2000) and Bertola et al. (2007) thus showed that different policy mixes induce different responses of unemployment to world-wide shocks (like an oil shock) and country-specific productivity shocks; and Bassanini and Duval (2009) emphasized the existence of complementarities between labor market policies. In parallel, in order to understand the mechanisms of these interactions, research spawned a collection of small dynamic stochastic equilibrium models focusing on one particular labor market policy at a time. For example, the influential work of Ljungqvist and Sargent (1998) emphasized the link between long-term unemployment and welfare policies, while Prescott (2004) and Rogerson (2008) emphasized the role of labor taxes.

In this paper we will try to incorporate the rich reduced forms of the former approach into a small equilibrium model of the latter kind. The idea is to identify a small set of parameters of the dynamic equilibrium model governing the responses to aggregate shocks of unemployment and turnover, and channeling a wide range of labor market policies at the same time. The number of policies simultaneously examined is potentially large, yet the number of parameters through which they impact the economy should be kept small for the model to be identified. Identification is indeed likely to fail if the number of intervention channels is greater than the number of independent series used in the analysis. Specifically, if we use series of unemployment stocks and flows, and vacancies, as labor market variables, it will be difficult to identify more than three separate channels for policy intervention.1

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1 The change in unemployment is the difference between the inflow and the outflow. So stocks and flows are not independent series.

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We develop a dynamic stochastic search-matching model with heterogeneous workers, where aggregate shocks to productivity fuel up the cycle, and unanticipated policy interventions displace the stationary stochastic equilibrium by shifting structural turnover parameters. This model is estimated for nine different countries (Australia, France, Germany, Japan, Portugal, Spain, Sweden, the United Kingdom and the United States), over the period 1985–2007, in two ways. First, a version without policy interventions is estimated on detrended series by the Simulated Method of Moments. Second, policy effects are introduced into the model, and estimated by minimizing the sum of squared residuals for the series of actual unemployment rates (i.e. trend plus cycle), unemployment flows and job vacancies.

The model builds on Mortensen and Pissarides (1994, henceforth MP). Yet, it is immune to Shimer’s (2005) critique. Shimer showed that in the MP model Nash bargaining converts most of the cyclical volatility of aggregate productivity into wage volatility, leaving little room for change to the key variable driving unemployment, market tightness. In the same AER issue, Hall (2005) presented a calibration showing that the unemployment volatility puzzle could indeed be solved by wage rigidity. However, his argument was recently contested by Pissarides (2009), who presented empirical evidence that the volatility of wages in new jobs, ever, his argument was recently contested by Pissarides (2009), who presented empirical evidence that the volatility of wages in new jobs.

For an extension of the model with heterogeneous workers and identical firms unemploy ment volatility puzzle could indeed be solved by wage rigidity. How-

A model extending the model of Robin (2011) by endogenizing labor demand through a matching function and vacancy creation. It also assumes that wage contracts are long term contracts that endogenize the surplus of a match with a worker of a given type in a given state of the economy, and it thus makes the dynamic stochastic equilibrium very easy to solve.

We use our model to assess the impact of labor market reforms on the actual (i.e. not American detrended) rate of unemployment by way of counterfactual simulations. We find that placement services, unemployment benefits and product market regulation are the main policy tools significantly influencing unemployment over the 1985–2007 period. These by all means classical policies are accountable for close to one, or more than one percentage point change in unemployment. The other policies yielded, on average, only between 20% and a third of a percentage point. Specifically, Australia and France reduced (or prevented a rise of) unemployment by increasing expenditure on placement services and deregulating product markets, Germany deregulated, Spain massively reduced unemployment benefits, deregulated and reduced employment protection. The UK reduced unemployment benefit, improved placement services and deregulated. The only countries implementing unemployment-augmenting policies are countries with low unemployment rates and hit by a deep and long-lasting recession at the end of the eighties or the beginning of the nineties. Thus, Japan and Sweden massively reduced ALMP expenditure. Lastly, Portugal and the US made no noticeable classical policy intervention. We do not find evidence of policy complementarity, as the sum of individual effects is similar in value to the Difference-in-Difference effect of the policy mix. Finally, we measure the relative contribution of LMPs and business cycle shocks to the long term variance of unemployment. In general, both contribute to about half of the total variance, with some exceptions: in Japan, business cycle shocks do not explain much unemployment.

The paper is organized as follows. In Section 2, a dynamic sequential-auction model with heterogeneous workers and identical firms is developed. Section 3 describes the data and Section 4 the estimation procedure. In Section 5, the business cycle version of the model is estimated on nine OECD countries. In Section 6, labor market policy effects are estimated. The last section concludes.

2. The model

Time is discrete and indexed by $t \in \mathbb{N}$. The global state of the economy is an ergodic Markov chain $y_t \in \{y_1, \ldots, y_N\}$ with transition matrix $H=(h_{ij})$. We use $y_t$ to denote the random variable and $y_t$ or $y_j$ to denote one of the $N$ possible realizations. There are $M$ types of workers and $f_m$ workers of each type, with $f_1 + \ldots + f_M = 1$. Workers of type $m$ have ability $x_m$ and $x_m < \bar{x}_m + 1$. All firms are identical. Workers and firm are paired into productive units. The per-period output of a worker of ability $x_m$ when aggregate productivity is $y_t$ is denoted as $y_t(m)$.
Fig. 1. Unemployment rate and turnover - trends and cycles.
Fig. 2. Labor market institutions - 1985–2007.
Define the exit rate from unemployment (or job finding rate) as the product of the meeting rate and the share of employable unemployed workers,

\[ f_t = \lambda_t \sum_{m} \frac{u_t(m)f_t[m][S_t(m) \geq 0]}{u_t} \]  

(1)

Define also the job destruction rate as the sum of the exogenous and the endogenous layoff rates,

\[ s_t = \sigma + (1-\sigma) \sum_{m} \frac{1-u_t(m)f_t[m][S_t(m) \leq 0]}{1-u_t} \]  

(2)

Aggregate unemployment then satisfies the usual recursion:

\[ u_{t+1} = u_t + s_{t}(1-u_t) - f_t u_t \]

2.1. Turnover and unemployment

Matches form and break at the beginning of each period. Let \( u_t(m) \) denote the proportion of unemployed in the population of workers of ability \( x_m \) at the end of period \( t \), or at the beginning of period \( t \), just before revelation of the aggregate shock for period \( t \), and let \( u_t = u_t(1) + ... + u_t(M) \) define the aggregate unemployment rate. Let \( S_t(m) \) denote the surplus of a match with a worker of type \( x_m \) at time \( t \), that is, the present value of the match minus the value of unemployment and minus the value of a vacancy (assumed to be nil). Only matches with positive surplus \( S_t(m) \geq 0 \) are viable.

At the beginning of period \( t \), \( y_t \) is realized and a new value \( S_t(m) \) is observed for the match surplus. An endogenous fraction \( \{1[S_t(m) \leq 0]\} \) of employed workers is immediately laid off if the match surplus becomes negative, and another fraction \( \delta_1[S_t(m) \geq 0]\) of employed unemployed workers is otherwise destroyed. In addition, a fraction \( \lambda_t[S_t(m) \geq 0]\) of unemployed employed workers meet with a vacancy. Finally, we also allow employees to meet with alternative employers, and move or negotiate wage increases (more on this later).

Aggregate shocks thus determine unemployment by conditioning job destruction and the duration of unemployment. The law of motion for individual-specific unemployment rates is \( u_{t+1}(m) = u_t(m) + \delta_1[1 - u_t(m)] - \lambda_t u_t(m) \), if \( S_t(m) \geq 0 \). The dynamics of unemployment by worker type depends on the dynamics of the whole match surplus, not on how the surplus is split between the employer and the worker.

2.1. Turnover and unemployment

Table 2: Labor market institutions - correlated change in 1985–2007.

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1) Initial replacement rate</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(2) ALMP: Placement</td>
<td>-0.042</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(3) ALMP: Training</td>
<td>0.568</td>
<td>0.488</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(4) ALMP: Incentives</td>
<td>0.557</td>
<td>0.572</td>
<td>0.944</td>
<td>1.000</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(5) Product market regulation</td>
<td>0.224</td>
<td>0.046</td>
<td>0.409</td>
<td>0.303</td>
<td>1.000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(6) Employment protection</td>
<td>0.196</td>
<td>0.067</td>
<td>-0.077</td>
<td>-0.049</td>
<td>0.170</td>
<td>1.000</td>
<td>1.000</td>
</tr>
<tr>
<td>(7) Tax wedge</td>
<td>0.047</td>
<td>-0.451</td>
<td>-0.356</td>
<td>-0.391</td>
<td>-0.393</td>
<td>0.037</td>
<td>1.000</td>
</tr>
</tbody>
</table>

Table 3: Estimates of Business Cycle Parameters.

<table>
<thead>
<tr>
<th></th>
<th>AUS</th>
<th>FRA</th>
<th>DEU</th>
<th>JAP</th>
<th>PRT</th>
<th>ESP</th>
<th>SWE</th>
<th>GBR</th>
<th>USA</th>
</tr>
</thead>
<tbody>
<tr>
<td>Productivity (y)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \rho )</td>
<td>0.970</td>
<td>0.938</td>
<td>0.933</td>
<td>0.942</td>
<td>0.842</td>
<td>0.972</td>
<td>0.961</td>
<td>0.970</td>
<td>0.959</td>
</tr>
<tr>
<td>( \sigma )</td>
<td>0.017</td>
<td>0.020</td>
<td>0.024</td>
<td>0.025</td>
<td>0.026</td>
<td>0.026</td>
<td>0.026</td>
<td>0.029</td>
<td>0.023</td>
</tr>
<tr>
<td>Worker heterogeneity ( (x) )</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Minimum ( (C) )</td>
<td>0.701</td>
<td>0.679</td>
<td>0.527</td>
<td>0.514</td>
<td>0.826</td>
<td>0.705</td>
<td>0.700</td>
<td>0.695</td>
<td>0.663</td>
</tr>
<tr>
<td>( \mu )</td>
<td>3.658</td>
<td>4.624</td>
<td>3.288</td>
<td>2.126</td>
<td>5.691</td>
<td>4.625</td>
<td>4.039</td>
<td>4.417</td>
<td>3.859</td>
</tr>
<tr>
<td>( \nu )</td>
<td>1.511</td>
<td>2.090</td>
<td>2.727</td>
<td>1.870</td>
<td>1.187</td>
<td>1.723</td>
<td>1.606</td>
<td>1.821</td>
<td>1.889</td>
</tr>
<tr>
<td>Mean ( (x \pm \frac{\nu}{\rho}) )</td>
<td>0.993</td>
<td>0.990</td>
<td>0.980</td>
<td>0.982</td>
<td>0.999</td>
<td>0.976</td>
<td>0.984</td>
<td>0.987</td>
<td>0.993</td>
</tr>
<tr>
<td>Mode ( (x \pm \frac{\nu}{\rho}) )</td>
<td>0.824</td>
<td>0.870</td>
<td>0.871</td>
<td>0.804</td>
<td>0.858</td>
<td>0.840</td>
<td>0.830</td>
<td>0.852</td>
<td>0.852</td>
</tr>
<tr>
<td>Std ( (x \pm \frac{\nu}{\rho}) )</td>
<td>0.416</td>
<td>0.432</td>
<td>0.461</td>
<td>0.446</td>
<td>0.353</td>
<td>0.413</td>
<td>0.416</td>
<td>0.422</td>
<td>0.434</td>
</tr>
<tr>
<td>Unemployment benefit ( z )</td>
<td>0.716</td>
<td>0.716</td>
<td>0.683</td>
<td>0.565</td>
<td>0.834</td>
<td>0.745</td>
<td>0.728</td>
<td>0.721</td>
<td>0.693</td>
</tr>
<tr>
<td>Vacancy cost ( \epsilon )</td>
<td>20.14</td>
<td>21.99</td>
<td>12.11</td>
<td>17.95</td>
<td>38.13</td>
<td>36.94</td>
<td>16.13</td>
<td>16.72</td>
<td>5.07</td>
</tr>
<tr>
<td>Matching function ( (\phi^0) )</td>
<td>2.195</td>
<td>1.268</td>
<td>1.244</td>
<td>1.868</td>
<td>1.963</td>
<td>1.801</td>
<td>2.611</td>
<td>1.871</td>
<td>1.698</td>
</tr>
<tr>
<td>Elasticity ( (\eta) )</td>
<td>0.500</td>
<td>0.500</td>
<td>0.500</td>
<td>0.500</td>
<td>0.500</td>
<td>0.500</td>
<td>0.500</td>
<td>0.500</td>
<td>0.500</td>
</tr>
<tr>
<td>Job destruction rate ( \delta^0 )</td>
<td>0.038</td>
<td>0.023</td>
<td>0.017</td>
<td>0.014</td>
<td>0.013</td>
<td>0.006</td>
<td>0.002</td>
<td>0.029</td>
<td>0.043</td>
</tr>
</tbody>
</table>

Note: Correlations of deviations of LMPs from country-specific means.
2.2. Rent sharing

We assume that employers have full monopsony power with respect to unemployed workers. They keep the whole surplus in this case and unemployed workers leave unemployment with a wage that is only marginally greater than their reservation wage. The assumption that unemployed workers have zero bargaining power relative to employers is mainly technical: it makes the dynamics of unemployment independent of wages. As the focus of this paper is on unemployment dynamics and worker flows, we believe that this decoupling is justified. Note however that we could easily allow for Nash bargaining between unemployed workers and firms, but this would complicate the model a lot for a marginal gain. We use 

Employed workers search on the job. When the search for an alternative employer is successful, we assume that Bertrand competition between the incumbent and the poacher transfers the entire surplus to the worker. The worker is indifferent between staying and moving. We assume that job-to-job mobility is then decided by coin tossing. Employer heterogeneity would eliminate this indeterminacy, at the cost of great additional complexity (see Lise and Robin, 2013, for an extension of this model with two-sided heterogeneity).

2.3. Vacancy creation and market tightness

Firms post vacancies \( V_t \) until ex ante profits are exhausted. The total vacancy cost is \( CV_t \). Vacancies can either randomly meet with an unemployed worker or with an employed worker. However, only the meetings with unemployed workers generate a profit to the firm. Free entry then ensures that

\[
CV_t = N_t \sum_{m=1}^{M} V_t(m)/S_t(m)^{x^+},
\]

where we denote \( x^+ = \max(x,0) \).

Define market tightness as the ratio of vacancies and workers’ aggregate search intensity,

\[
\theta_t = \frac{V_t}{u_t + k(1-u_t)},
\]

where \( k \) is the relative search intensity of employees with respect to unemployed. The meeting rate \( \lambda_t \) is related to market tightness via the meeting function, \( \lambda_t = f(\theta_t) \), where \( f \) is an increasing function, likely concave.

2.4. The value of unemployment and the match surplus

Let \( U_i(m) \) denote the present value of remaining unemployed for the rest of period \( r \) for a worker of type \( m \) if the economy is in state \( i \). It solves the following linear Bellman equation:

\[
U_i(m) = z_t(m) + \frac{1}{1+\rho} \sum_{j=1}^{J} \pi_{ij} U_j(m).
\]

This equation can be understood as follows. An unemployed worker receives a flow-payment \( z_t(m) \) for the period. At the beginning of the next period, the state of the economy changes to \( j \) with probability \( \pi_{ij} \) and the worker receives a job offer with some probability. We have assumed that employers offer unemployed workers their reservation

\[ \text{5 We state the model with on-the-job search. However, in this paper, contrary to Robin (2011), we shall not use wages in the empirical part. What really matters to solve the volatility puzzle is worker heterogenous productivities, which acts an amplification mechanism for aggregate shocks. We could as well use a standard Mortensen-Pissarides setup and rule out on-the-job search without changing much of the results.} \]

\[ \text{6 We use } k = 0.12 \text{ as in Robin (2011) but imposing a zero search intensity for employees has little influence on the estimation outcome.} \]

<table>
<thead>
<tr>
<th>Table 4</th>
<th>Fit of the business cycle moments.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean GDP</td>
<td>1.00</td>
</tr>
<tr>
<td>Std log GDP</td>
<td>0.017</td>
</tr>
<tr>
<td>Mean unemployment rate</td>
<td>1.00</td>
</tr>
<tr>
<td>Std log unemployment rate</td>
<td>0.017</td>
</tr>
<tr>
<td>Mean JFR</td>
<td>5.42</td>
</tr>
<tr>
<td>Std log JFR</td>
<td>0.066</td>
</tr>
<tr>
<td>Mean JDR</td>
<td>17.56</td>
</tr>
<tr>
<td>Std log JDR</td>
<td>0.066</td>
</tr>
<tr>
<td>Mean GDP elasticity of UNR</td>
<td>0.53</td>
</tr>
<tr>
<td>Std log GDP elasticity of UNR</td>
<td>0.017</td>
</tr>
<tr>
<td>Mean tightness</td>
<td>0.14</td>
</tr>
<tr>
<td>Std log tightness</td>
<td>0.37</td>
</tr>
</tbody>
</table>
wage on a take-it-or-leave basis, thus effectively reaping the whole surplus. As a consequence, the present value of a new job to the worker is only marginally better than the value of unemployment. Hence, the continuation value is the value of unemployment in the new state \( j \) whether the workers remains unemployed or not.

Let us now turn to the match surplus. After a productivity shock from \( t \) to \( j \) all matches yielding negative surplus are destroyed. Then, either on-the-job search is unsuccessful, and the match surplus only changes because the macroeconomic environment changes; or the worker is poached and Bertrand competition gives the whole match surplus to the new worker, without the old worker moving or not. As everything that the worker expects to earn in the future contributes to the definition of the current surplus, the surplus of a match with a worker of type \( m \) when the economy is in state \( i \) thus solves the following (almost linear) Bellman equation:

\[
S_i (m) = y_i(m) - z_i(m) + \frac{1 - \delta}{\delta} \sum_j \pi_{ij} S_j (m),
\]

This almost-linear system of equations can be solved numerically by value function iteration. As for the unemployment value, the match surplus only depends on the state of the economy.

2.5. Parameterization and functional forms

2.5.1. Unemployment exit rate and the matching function

The meeting rate, and hence the unemployment exit rate, are related to market tightness \( \theta_t \) via a Cobb-Douglas matching technology:

\[
\lambda_t = f(\theta_t) = \phi \theta_t^\delta. \tag{7}
\]

A standard cross-country OLS regression of job finding rates on tightness (in logs) simply defined as \( \psi/\mu \) delivers estimates of matching efficiency \( \psi = 0.712 \) and matching elasticity \( \delta = 0.32 \), in tune with the empirical literature (Murtin and de Serres, 2014).

2.5.2. Aggregate shocks

We assume that aggregate productivity follows a Gaussian AR(1) process:

\[
\ln y_t = \rho \ln y_{t-1} + \sigma \epsilon_t,
\]

where innovations are iid-normal \( N(0, \sigma) \). Note that the aggregate productivity shock \( y_t \) is a latent process that does not a priori coincide with observed output or output per worker. Indeed, observed output is the aggregation of match output \( y_i(m) \) across all active matches, say

\[
Y_t = \sum_m \frac{1 - u_i(m)}{u_i(m)} \epsilon_m y_i(m),
\]

and is thus endogenous. Therefore, the structural parameters \( (\rho, \sigma) \) cannot be directly inferred from the observed series of aggregate output.

We discretize the aggregate productivity process \( y_t \) as follows. Let \( F \) denote the estimated equilibrium distribution of \( y_t \). The joint distribution of two consecutive ranks \( F(y_t) \) and \( F(y_{t+1}) \) is a copula \( C \) (i.e. the CDF of the distribution of two random variables with uniform margins). To discretize the aggregate productivity processes we first specify a grid \( a_1 < ... < a_M \) on \([0,1] \subset \{0,1\} \) of \( N \) linearly spaced points including end points \( \epsilon = 0 \) and \( 1 = \epsilon \). Then we set \( y_t = F^{-1}(a_t) \) and \( \eta_{ij} = c(a_t; a_j) \), where \( c \) denotes the copula density and we impose the normalization \( \sum_j \eta_{ij} \). In practice, we use \( N = 150, \epsilon = 0.002 \); \( F \) is a log-normal CDF and \( c \) is a Gaussian copula density, as implied by the Gaussian AR(1) specification.

2.5.3. Worker heterogeneity

Match productivity is specified as \( y_{X,m} = y_x \phi_m \), where \( \{x_m, m = \ldots, M\} \) is a grid of \( M \) linearly spaced points on the interval \([C, C + 1]\). The choice of the support does not matter much provided that it is large enough and contains one. A beta distribution is assumed for the ability \( \phi_m \).

2.5.4. Leisure and vacancy costs

The opportunity cost of employment \( z_i(m) \) (aggregating the utility of leisure, unemployment insurance and welfare) is specified as a constant \( z \), with the normalization \( \sum_m \phi_m = 1 \). The beta distribution allows for a variety of shapes for the density (increasing, decreasing, non-monotone, concave or convex). We use a very dense grid of \( M = 500 \) points to guarantee a good resolution in the left tail.

2.5.5. Labor market institutions

Because of the feed-back effects implied by the model, it is important for identification that we restrict the channels of policy interventions. For example, any policy that directly impacts matching efficiency (\( \phi \)) immediately changes the meeting rate (\( \lambda_t \)) and, subsequently, the number of created vacancies (\( \nu_t \)) via the free entry condition. Both effects contribute to changing the job finding rate (\( f_j \)). If one makes the cost of posting a vacancy (\( c \)) a concurrent intervention channel for this policy, then the policy affects vacancy creation in two ways, which evidently reduces the chances that the model be identified.

Because we only have independent data information on turnover flows (\( f_j \) and \( s_j \)) and vacancies (\( \nu_t \)) we decided to introduce labor market policies (henceforth LMPs) through only three structural parameters: matching efficiency (\( \phi \)) via Eq. (1), the job destruction rate (\( \delta \)) via Eq. (2), and the cost of posting a vacancy (\( c \)) via Eq. (3). Formally, we let parameters \( \phi, \delta \) and \( c \) in country \( n \) at time \( t \) be log-linear indices of country-specific institutional variables \( X_n^t, \ldots, X_n^k \):

\[
\phi_{nt} = \phi_0 \exp(\sum_i k_i X_n^{nt}), \quad \delta_{nt} = \delta_0 \exp(\sum_i k_i X_n^{nt}), \quad c_{nt} = c_0 \exp(\sum_i k_i X_n^{nt}).
\]

In these equations, the LMP semi-elasticities (\( \phi_k, \delta_k, c_k \)) are common to all countries. However, intercepts (\( \phi_0, \delta_0, c_0 \)) are country-specific. This framework thus identifies institutional effects from policy variations.

Table 5

| Correlation between actual and predicted detrended series. |
|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|
|                 | AUS | FRA | DEU | JAP | PRT | ESP | SWE | GBR | USA |
| Productivity    | 1.00| 1.00| 1.00| 1.00| 1.00| 1.00| 1.00| 1.00| 1.00|
| Unemployment    | 0.83| 0.68| 0.88| 0.87| 0.73| 0.92| 0.77| 0.87| 0.75| 0.81|
| Job finding rate| 0.70| 0.64| 0.70| 0.79| 0.74| 0.77| 0.31| 0.85| 0.82| 0.70|
| Job destruction rate | 0.16| 0.03| 0.32| 0.02| -0.06| 0.20| 0.36| 0.23| 0.34| 0.18|
| Market tightness | 0.71| 0.63| 0.38| 0.51| 0.83| 0.84| 0.43| 0.67| 0.65| 0.63|

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7 That is, with white-noise innovations, \( \ln y_t \sim N(0, \sigma^2_{y_t}) \).
3. The data

We have assembled data on labor market outcomes and institutions for nine OECD countries: Australia, France, Germany, Japan, Portugal, Spain, Sweden, United Kingdom and United States, over the period 1985–2007. These data and their sources are described in detail in the Appendix.

3.1. Unemployment and turnover cycle

Table 1 provides descriptive statistics on the rate of unemployment as well as the probability of entering and exiting unemployment. All series are quarterly. The trend and cyclical components were extracted by HP-filtering the log-transformed series with a smoothing parameter equal to $10^5$, as in Shimer (2005), and re-exponentiating. The volatility of unemployment and of turnover are very different across countries. Japan displays lower and less volatile unemployment, due to lower job destruction rates, than any other country. The US exhibit more turnover and higher exit rates from unemployment. France, and Japan to a lesser extent, display particularly low cyclical volatility in unemployment turnover.

Interesting patterns emerge from trends (Fig. 1). Unemployment culminates in the 1980s in the UK and the US, and in the 1990s in Australia, France, Spain and Sweden. Japan displays a monotonic, increasing trend throughout the 1960–2010 period. Unemployment rebounds in the early 2000s in Portugal and the US. Long-term unemployment trends hide strikingly different trends in turnover rates. Job destruction rates tend to increase in France, Japan, Portugal and Spain and to decrease in Australia, the UK and the US since the mid-1980s. Job-finding rates tend to increase in Australia, France and Spain, and to decrease in Japan, Sweden, the UK and the US. These patterns are potentially associated with important labor market reforms that we now briefly discuss.

3.2. Labor market policies

The set of labor market policy variables used as potential determinants of unemployment stocks and flows in the empirical analysis are the following: i) the replacement rate used to calculate unemployment insurance (UI) benefits at first date of reception; ii) public expenditure on active labor market policies per unemployed worker (ALMPs) normalized by GDP per worker, and broken down into three sub-categories (placement and employment services, employment incentives\(^8\) and training); iii) the OECD index of product market regulation; iv) the OECD index of employment protection for regular contracts; v) the tax wedge (personal income tax plus payroll taxes and social security contributions). We exclude from the analysis LMPs such as the legal minimum wage, union density and other wage bargaining institutions as they mostly affect wages, which are outside the scope of this paper.

Fig. 2 plots the LMP series for all countries between 1985 and 2007 (the period over which we have gathered a balanced sample of labor market outcomes). Some institutions show no change in the period (such as employment protection in the US). The associated policy effects are:

Table 6

<table>
<thead>
<tr>
<th></th>
<th>$\phi$</th>
<th>$\delta$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial replacement rate</td>
<td>-0.028</td>
<td>0.029</td>
</tr>
<tr>
<td>(0.008)</td>
<td>(0.009)</td>
<td></td>
</tr>
<tr>
<td>ALMP placement and services</td>
<td>0.032</td>
<td>-0.101</td>
</tr>
<tr>
<td>(0.006)</td>
<td>(0.007)</td>
<td></td>
</tr>
<tr>
<td>ALMP training</td>
<td>-0.038</td>
<td>-0.097</td>
</tr>
<tr>
<td>(0.016)</td>
<td>(0.019)</td>
<td></td>
</tr>
<tr>
<td>ALMP incentives</td>
<td>0.057</td>
<td>-0.161</td>
</tr>
<tr>
<td>(0.019)</td>
<td>(0.059)</td>
<td></td>
</tr>
<tr>
<td>Product market regulation</td>
<td>-0.025</td>
<td>0.111</td>
</tr>
<tr>
<td>(0.017)</td>
<td>(0.062)</td>
<td></td>
</tr>
<tr>
<td>Employment protection (regular contracts)</td>
<td>-0.043</td>
<td>0.037</td>
</tr>
<tr>
<td>(0.008)</td>
<td>(0.024)</td>
<td></td>
</tr>
<tr>
<td>Tax wedge</td>
<td>0.023</td>
<td>0.037</td>
</tr>
<tr>
<td>(0.008)</td>
<td>(0.023)</td>
<td></td>
</tr>
<tr>
<td>Mean years of higher education</td>
<td>-0.014</td>
<td>-0.051</td>
</tr>
<tr>
<td>(0.008)</td>
<td>(0.009)</td>
<td></td>
</tr>
<tr>
<td>Share 15–24 population</td>
<td>0.016</td>
<td>-0.011</td>
</tr>
<tr>
<td>(0.010)</td>
<td>(0.011)</td>
<td></td>
</tr>
<tr>
<td>Share 55–64 population</td>
<td>-0.017</td>
<td>-0.036</td>
</tr>
<tr>
<td>(0.006)</td>
<td>(0.007)</td>
<td></td>
</tr>
</tbody>
</table>

* These expenditures include incentives to private employment, direct job creation, job sharing and start-up incentives.
cannot be identified in this case. However, in general, LMPs do vary over time and across countries.

France, Portugal, Spain and Sweden offer high support to the unemployed and high employment protection at the same time, whereas the US, the UK, Australia and Canada are on the low side, and Germany and Japan somewhere in-between. Sweden stands alone in its effort to reduce ALMP spendings. It started the period from a very high point, considerably more interventionist than any other country, and converged to a more comparable norm. Japan and Sweden used to spend a lot more than the other countries on placement and labor services. They tend to be overtaken by Great Britain and Australia, and France to a lesser extent; the UK spending more (per unit of labor productivity) in 2007 than Sweden. Product market regulation shows a remarkable convergence toward deregulation in all countries, with Great Britain, Germany, Australia, Spain and Sweden progressively becoming more deregulated than the US. There is some tendency to converge toward a more common model.
of employment protection among European states, with Portugal and Spain (particularly) reducing EPL and the UK and Australia increasing EPL (a bit). There are some variations in labor taxes over time and across countries, but they consistently remain higher in Sweden, France and Germany.

Table 2 displays the correlations between the LMP variables centered around their country-specific means. The three ALMP components are strongly correlated, in particular training and firm incentives. Interestingly, product market deregulation or unemployment insurance reductions are often accompanied by another policy, such as increased expenditure on training or employment incentives or wage subsidies, aiming at reducing social or economic collateral costs. This is much less the case for employment protection which appears much less correlated with other LMPs.

Fig. 6. Job destruction rate.

Fig. 7. Market tightness.
3.3. Intervention mechanisms

As already emphasized, it is important for identification to restrict the channels of policy interventions. Heuristically, in absence of a more formal model of the mechanisms of policy interventions, we ended up restricting the mapping between LMPs and structural parameters in the following way.

A first set of policies affect the search-matching technology. More generous unemployment benefits should reduce unemployed workers’ search intensity. More placement and employment services should help unemployed workers find jobs more easily and improve match quality. Higher quality matches should in turn be more resilient to exogenous destruction shocks. More training provided to unemployed workers should also raise match quality and reduce job destruction. The impact of training on job finding rates is yet ambiguous and possibly negative, as the participation to training programmes may also increase the duration of unemployment. Therefore, we allow the replacement rate, the indices for placement and employment services, and training to determine parameters \( \phi \) and \( \delta \) (matching efficiency and exogenous job destruction).

Employment incentives (like payroll tax discounts), product market regulation, and employment protection to some extent, are another group of policies that operate through similar mechanisms: they primarily affect job creation and job destruction. Employment incentives encourage vacancy creation, but they also make employers less picky and thus facilitate the creation of matches of lower quality, which therefore terminate sooner than later. Less product market regulation fosters competition between firms, which is favorable to employment in a way that can be captured in our model by a reduction in the vacancy cost. At the same time, more competition between firms reduces profit margins and increases the probability of failure, and thus generates more job destruction. Employment protection renders separation more costly; it decreases matching efficiency (i.e. our parameter \( c \)). Consistent with our set of assumptions, they find that: \( i \) more generous unemployment benefits decrease matching efficiency but have no effect on vacancy creation (Table 4 Columns 3 and 4); \( ii \) conversely, tighter employment protection decreases vacancy creation but has no effect on matching efficiency (Table 4 Columns 7 and 8); \( iii \) the tax wedge has a strong negative impact on vacancy creation (Tables 4 and 7). In some cases, the empirical results are more mixed. For instance, Card et al. (2010) conclude in their meta-analysis of active labor market programmes that “training programmes are associated with positive medium-term impacts, although in the short run they often appear ineffective.” This suggests a negative impact of training on the job destruction rate that materializes only in the mid-term once the unemployed has found another job, with little or no short-term effect due to improved matching efficiency.

4. Estimation procedure

The estimation is conducted in two steps. In the first step, we estimate a stationary version of the model that fits the cyclical components of the series of GDP, unemployment, job finding and job destruction rates, and vacancies separately for the nine OECD countries. This will allow us to test the ability of the heterogeneous-worker search-matching model to fit unemployment volatility well in all countries. In the second step, we introduce LMPs into the empirical framework and we estimate their impact on the structural parameters \( \phi \), \( \delta \) and \( c \) by fitting the raw series (non detrended) of unemployment, turnover and vacancies jointly for all nine countries.

4.1. Assessing business-cycle dynamics

The estimation of the parameters controlling the short-term response of the economy to business cycle shocks closely follows the method in Robin (2011). We assume that HP-filtered series follow the model of this paper as in a stationary environment except from any institutional change. Hence, we impose: \( \phi^t = \delta^t = \hat{c}^t = 0 \) to each policy variable (\( k \geq 1 \)) and each country. Ten parameters remain to be estimated: the country-specific vacancy creation cost \( c^t \), the exogenous layoff rate \( \theta^t \), the two parameters of the matching function \( (\psi^t(\cdot)) \), the leisure cost parameter \( z \), the three parameters of the distribution of worker heterogeneity \( (C, \nu, \mu) \), and the two parameters of the latent productivity process \( (\rho, \sigma) \). The number of aggregate states is set to \( N = 150 \), the number of different ability types is taken equal to \( M = 500 \).

The business-cycle (BC) parameters \( \theta_{hc} = (c^t, \theta^t, \nu, z, C, \psi(\nu, \mu, \sigma)) \) are estimated using the Simulated Method of Moments, separately, country by country. In practice, we simulate very long series at quarterly frequency (\( T = 500 \) observations) of aggregate output, unemployment rates, unemployment turnover and vacancies, and we search for the set of parameters \( \theta_{hc} \) that best matches the following 18 country-specific moments: \( i \) the mean, standard deviation and autocorrelation of log-GDP; \( ii \) the mean, standard deviation and kurtosis of log-unemployment; \( iii \) the mean and the standard deviation of logged job finding and job destruction rates, and market tightness; \( iv \) four output elasticities: unemployment, turnover rates and market tightness; \( v \) the elasticities of the job finding rate with respect to market tightness and unemployment rate.

Once these structural parameters are estimated, we filter out the series of aggregate shocks \( y_t \), so as to minimize the sum of squared residuals of log GDP. The parameters and the series of aggregate shocks are then used to simulate the series of unemployment rates.
4.2. Assessing policy effects

In a second step, we introduce LMPs and we estimate all parameters, including the response to LMP shocks, by iterating the following procedure:

1. Given parameters, filter aggregate shocks out by fitting aggregate output series (detrended) by least squares, separately, country by country;
2. Given aggregate shocks, estimate parameters by fitting unemployment turnover and vacancy series (actual, not detrended) by simulating least squares, weighting residual squares by the inverse variance of each series. Contrary to the first estimation, the estimation of policy parameters is done jointly for all countries.

This estimation procedure is considerably easier to implement than any other method, Bayesian or frequentist, for nonlinear state-space models.

The economy is simulated assuming myopic expectations on policy interventions. Whenever a policy variable \( x^k \) is changed, which only happens infrequently, we recalculate the present values of unemployment and of match surplus for all aggregate states, together with the values of job finding and job destruction rate, and keep them set to these levels until the next policy intervention.

We obtain standard errors for the estimates of LMP parameters as follows. Rather than estimating the Jacobian matrix and using the “sandwich” formula, which is numerically cumbersome and not very reliable given the amount of numerical simulations involved, we instead note that Eq. (1) implies that:

\[
\log f_t = \eta \log \theta_t - \log \left( \sum_{u_t} (u_t(m(m) + 0)_{i,t}) \right) - \log \phi^k = \sum_k \phi_k x^k_{nt}.
\]

We then compute standard errors for the parameters \( \phi_k \) using the standard OLS formula for the regression of the left-hand side variable on LMP regressors. This calculation may severely overestimate the precision of the estimation by neglecting estimation errors induced by using parameter estimates instead of true values to predict the left hand side. But it nevertheless provides useful information on how much the simulated series are changed by a small perturbation of the policy parameters. We use a similar approach for the other policy parameters based on Eqs. (2) and (3).

5. The dynamics of cyclical unemployment

5.1. Parameter estimates

The results of the first-stage estimation are reported in Table 3. Productivity is more volatile in European countries than in Australia and the US. Worker ability is less heterogeneous in Portugal and more heterogeneous in Germany and Japan. It follows that the opportunity cost of employment \( z \) is also higher in Portugal and lower in Japan and Germany; otherwise, it does not differ much from 0.7, which is Hall and Milgrom’s (2008) calibration for the US. It is difficult to compare the estimates of the vacancy cost across countries, as they use different ways of measuring vacancies. They are also not comparable with those estimated or calibrated in the other studies (e.g. 0.36 in Pissarides, 2009, 0.43 in Hall and Milgrom, 2008, 0.58 in Hagedorn and Manovskii, 2008), which all use a Mortensen-Pissarides model with a non-zero bargaining power for workers.\(^{12}\) Matching efficiency (\( \phi \)) is higher in Australia and Sweden and lower in France and Germany. The rate of exogenous job destruction (\( \hat{\nu} \)) is higher in the United States, Australia and Spain, and lower in Japan and Portugal. This inference is broadly in line with other micro and macroeconomic evidence on job turnover rates (see Jolivet et al., 2006; Elsby et al., 2012; Murtin et al., 2014).

Note that the elasticity of the matching function was arbitrarily fixed to 0.5 in all country-level estimations. Indeed, we could fit all moments well for any preset value of \( \eta \). We explain this lack of identification as follows. The duration of unemployment is controlled by three components: matching efficiency (\( \phi \)), the meeting elasticity with respect to market tightness (\( \eta \)) and worker employability (the sign of the match surplus). It seems that the latter two components are not separately identified. If one increases the meeting frequency as a function of the number of created vacancies (\( \eta \)), one can cancel that effect by recalibrating the fraction of workers at risk of unemployability (i.e. by putting more mass in the left tail of the ability distribution).

\(^{12}\) If firms have less bargaining power, their ex-ante profits are smaller; the free entry condition then delivers the observed number of vacancies in equilibrium only if the unit cost of vacancy is also smaller. The bargaining power of unemployed workers is assumed equal to zero mainly for analytical simplicity.
5.2. Fitting the cycle

Table 4 shows how the model fits the 18 moments used in estimation, Table 5 reports the correlations between actual and simulated HP-filtered series, and Fig. 3 plots the actual and simulated unemployment cycles.

The fit is generally good (at least for such a simple model). In particular, the model has no problem fitting both the volatility of output and the volatility of unemployment. The mechanism is simple to understand. In good times, unemployment is low and stable and separations follow the process more sluggishly in recovery times. Conversely, in recessions unemployment is high and volatile and separations follow the process more quickly.

Finally, the job destruction rate that is predicted by the model is too uneven or jagged, and its correlation to actual series is poor. This may happen again because the process of endogenous job destruction is too lumpy. Following a negative productivity shock, a mass of workers is instantly laid off, and the job destruction rate is immediately reversed to the frictional rate of exogenous job destruction unless aggregate productivity keeps going further down.

We will see in the next section that this apparent failure at fitting some aspects of turnover and vacancies could be an artifact of detrending (using the Hodrick-Prescott filter). If total output is clearly trended and easily detrended, long-term trends in labor market variables are much more difficult to filter out. This is the reason why Shimer (2005), and his followers, including us, used the HP filter with a smoothing parameter of 100, much greater than the standard value of 1024 recommended for quarterly series. Using 1024 yields a trend of unemployment that undulates like a cycle. In the next section, we will argue that a better way of handling trends in labor market variables is to model them by way of intervention variables (policy or demographics).

Table 10

Share of unemployment variance explained by covariates.

<table>
<thead>
<tr>
<th></th>
<th>AUS</th>
<th>FRA</th>
<th>DEU</th>
<th>JAP</th>
<th>PRT</th>
<th>ESP</th>
<th>SWE</th>
<th>GBR</th>
<th>USA</th>
<th>Mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pseudo-R² of LMPs and business cycle ( = 1 - MSE)</td>
<td>0.78</td>
<td>0.62</td>
<td>0.47</td>
<td>0.78</td>
<td>0.49</td>
<td>0.65</td>
<td>0.88</td>
<td>0.75</td>
<td>0.37</td>
<td>0.61</td>
</tr>
<tr>
<td>Decomposition of pseudo-R²</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Business cycle shocks</td>
<td>0.37</td>
<td>0.35</td>
<td>0.25</td>
<td>0.08</td>
<td>0.42</td>
<td>0.29</td>
<td>0.44</td>
<td>0.29</td>
<td>0.48</td>
<td>0.33</td>
</tr>
<tr>
<td>LMPs</td>
<td>0.42</td>
<td>0.26</td>
<td>0.21</td>
<td>0.70</td>
<td>0.08</td>
<td>0.36</td>
<td>0.44</td>
<td>0.46</td>
<td>-0.10</td>
<td>0.31</td>
</tr>
<tr>
<td>Pseudo-R² of specific LMPs</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Initial replacement rate</td>
<td>0.046</td>
<td>0.019</td>
<td>-0.002</td>
<td>-0.035</td>
<td>0.042</td>
<td>0.028</td>
<td>0.046</td>
<td>0.047</td>
<td>0.031</td>
<td>0.025</td>
</tr>
<tr>
<td>ALMP placement</td>
<td>0.165</td>
<td>-0.024</td>
<td>0.088</td>
<td>0.432</td>
<td>0.022</td>
<td>0.019</td>
<td>0.152</td>
<td>0.195</td>
<td>0.028</td>
<td>0.119</td>
</tr>
<tr>
<td>ALMP training</td>
<td>-0.014</td>
<td>0.014</td>
<td>0.115</td>
<td>-0.004</td>
<td>-0.002</td>
<td>0.008</td>
<td>0.359</td>
<td>0.000</td>
<td>-0.020</td>
<td>0.051</td>
</tr>
<tr>
<td>ALMP incentives</td>
<td>0.004</td>
<td>0.057</td>
<td>0.072</td>
<td>0.001</td>
<td>0.023</td>
<td>0.007</td>
<td>0.549</td>
<td>0.006</td>
<td>0.004</td>
<td>0.080</td>
</tr>
<tr>
<td>Product market regulation</td>
<td>0.052</td>
<td>0.185</td>
<td>0.093</td>
<td>0.088</td>
<td>-0.042</td>
<td>0.086</td>
<td>0.057</td>
<td>0.104</td>
<td>-0.007</td>
<td>0.070</td>
</tr>
<tr>
<td>Employment protection</td>
<td>-0.097</td>
<td>-0.015</td>
<td>-0.028</td>
<td>0.000</td>
<td>0.032</td>
<td>0.205</td>
<td>0.001</td>
<td>-0.004</td>
<td>0.000</td>
<td>0.030</td>
</tr>
<tr>
<td>Tax wedge</td>
<td>0.045</td>
<td>0.033</td>
<td>0.080</td>
<td>-0.038</td>
<td>0.049</td>
<td>0.007</td>
<td>-0.002</td>
<td>0.019</td>
<td>-0.083</td>
<td>0.012</td>
</tr>
</tbody>
</table>

Notes: The simulations are the same as for Table 9. We calculate the mean squared error (MSE) of the benchmark model (i.e. the sum of squared errors for all the series used to estimate the parameters, unemployment, job finding and layoff rates, and tightness) with all LMPs and business cycle shocks. The pseudo-R² is 1 - MSE. We calculate the contribution of business cycle shocks as 1 - MSE(LMP = 0), where MSE(LMP = 0) is the mean square error of the model with LMPs remaining fixed at their country-specific means. The contribution of LMPs is calculated as MSE(LMP = 0) - MSE.
6. The impact of labor market reforms

6.1. Parameter estimates

The estimated policy parameters are reported in Table 6. LMP variables are centered at their country-specific mean and standardized by the cross-country and cross-time standard deviation of the LMP. Policy parameters are thus semi-elasticities that quantify the relative increase in parameters $\phi$, $\delta$, and $c$ when LMPs are increased by one standard deviation around the country-specific mean of the policy variable. All the policy effects have the expected sign (when precisely estimated). Large effects are recorded for ALMP-placement services and training on job destruction rates, which we interpret as the result of improved matching technology. Employment incentives and product market deregulation also have a strong and positive effect on job creation. The replacement rate, employment protection and the tax wedge also have significant effects, although of smaller magnitude (on $\phi$, $\delta$ and $c$ respectively). The bottom part of Table 6 reports the estimated effects of education and demographic variables. Educational achievement moderately reduces the pace of job destruction, as an additional 0.4-year of higher education (one standard deviation) yields a 5.0% reduction in the job destruction rate.\(^{13}\) As expected, older (more experienced) workers tend to remain unemployed longer, but face a lower layoff risk.

6.2. Fitting the trends

Figs. 4–7 show how good the model is at predicting labor market outcomes given productivity shocks and institutional change. Table 7 displays the correlations between actual and predicted series. Actual and simulated unemployment rates are highly correlated for all countries, with an average correlation equal to 0.82. The best fit is obtained for Australia, Japan, Sweden and the UK with correlations close to or above 0.90, while the model performs less well for the US with a correlation of about 0.56.

The fit of job destruction rates is greatly improved by comparison to the cyclical estimation, as the correlation between predicted and observed series jumps from 0.18 in the BC-model to 0.56 in the LMP-model. The fit of job finding rates, which are well predicted except for Germany and Portugal, and the US to a lesser extent, has also improved. Market tightness is well fitted for all countries but the US and Portugal.

The only country for which the model fails the fit test is the US. It may be that by estimating LMP effects jointly we impose to the US labor market a European norm that does not apply to the US. It may also be that simulating the economy at the quarterly frequency does not work well for the US with a correlation of 0.56.

For each individual LMP, it is interesting to look at the cross-country correlation between the average unemployment change and the LMP change. If this correlation were equal to one, this would suggest that the model is linear and that the elasticity of LMPs is identical across countries. As a result, we find that the correlation between unemployment changes and LMP changes is large but not always close to one, which indicates that the model captures some non-linearities and/or heterogeneities that reduced forms tend to miss. We also do not find evidence of much policy complementarity, as the sum of individual effects is similar in value to the DiD effect of the policy mix. This finding contradicts Bassanini and Duval (2009) and other authors.

Note that the correlation with LMP changes is large but not always close to one, which indicates that the model capture some non-linearities that reduced forms tend to miss. We also do not find evidence of much policy complementarity, as the sum of individual effects is similar in value to the DiD effect of the policy mix. This finding contradicts Bassanini and Duval (2009), who report positive interaction effects on the basis of reduced-form regressions. Finally, identical labor market reforms trigger unemployment responses proportional (in magnitude) to the baseline unemployment value — high-unemployment countries such as Spain or France witnessing larger unemployment reductions than the other countries; and more intensive interventions yield proportionally bigger effects (see the correlations in the last column of Table 9).

Next we measure the relative contribution of LMPs and business cycle shocks to the long term variance of unemployment. In general, both

6.3. Assessing the impact of labor market policies

In order to get a sense of the marginal effect of each policy on unemployment, we calculate a “difference-in-differences” (DiD) treatment effect for each LMP separately and all together as follows. First we simulate for the period 1985–2007 the benchmark series of labor market outcomes responding to the estimated series of aggregate productivity shocks and to the observed series of LMP variables, which vary over time. Then we run counterfactual simulations with one specific LMP variable, say $Z$, remaining fixed to its country-specific mean value, while other LMPs are time-varying observed ones, and we re-calculate the average counterfactual unemployment change over the period. Finally, for each country, we calculate DiD policy effects as the benchmark mean unemployment change minus the counterfactual mean change. The latter quantity reflects the effect of the variation in $Z$ over the period. In the last counterfactual simulation corresponding to the line at the bottom of Table 9, all LMPs are frozen, so that the calculated average unemployment change corresponds to the joint effect of all LMPs reforms.

Table 9 reports the results. Placement services, UI initial replacement rate and product market regulation are the main intervention channels by which countries significantly influenced unemployment over the period, these by all means classical policies being accountable for close to one, or more than one percentage point reduction or augmentation of unemployment.\(^{15}\) The other policies yielded, on average, only between 20% and a third of a percentage point.

These average effects hide a variety of interventions across countries, which we summarize as follows. Australia and France increased expenditure on placement services and deregulated product markets. Germany deregulated. Spain massively reduced unemployment benefits, deregulated and reduced employment protection. The UK reduced unemployment benefit, improved placement services and deregulated. The only countries implementing unemployment-augmenting policies are countries with low unemployment rates and hit by a deep and long-lasting recession at the end of the eighties or the beginning of the nineties. Thus Japan and Sweden massively reduced ALMP expenditure. Lastly, Portugal and the US made no noticeable classical policy intervention.
We display below the resulting turnover series for all countries and compare them with comparable series from other studies.

A.3. Resulting series of unemployment turnover

We display below the resulting turnover series for all countries and compare them with comparable series from other studies.

A.2. Other series

OECD (2011) database is used for the quarterly unemployment rate. Quarterly series of job vacancies are borrowed from OECD (2011); Eurostat (2011) and Robin (2011).

References

A.1. Construction of unemployment flow data

We collect data on unemployment flows from various sources, namely Robin (2011); Murtin et al. (2014); Eurostat (2011); OECD Employment Outlook (2010) and Petrongolo and Pissarides (2008). Our constructed series are systematically compared with those by Elsby et al. (2013).

Unemployment flow series are based on unemployment duration data, which exists only on an annual basis for most countries before the mid-1990s, and on a quarterly basis afterwards. We select quarterly data when they are available, otherwise we take annual data assuming constant flows within each year. Next figures show that, within each country, annual and quarterly series are always consistent with each other.

Besides, unemployment duration data generally describe the stock of unemployed workers for several durations of unemployment, namely less than 1 month, less than 3 months, less than 6 months and less than one year. Instantaneous exit and entry rates from/to unemployment can be calculated using any of the latter durations as a benchmark. In some countries, the choice of a given duration matters as outflow rates vary with the time spent in unemployment: There is negative duration dependence or “hysteresis effects”. Following common practice applied in other studies (e.g. Elsby et al., 2013), one selects a benchmark duration of 1 month in countries that display duration dependence. This concerns Australia, Japan, Sweden, the United Kingdom and the United States. Then, quarterly probabilities are recovered from monthly series by using a probabilistic tree. For other countries with stable turnover rates and no duration dependence, quarterly series are used directly to minimize measurement errors.

Finally, unemployment turnover is commonly described by two different types of series: Instantaneous hazard rates arising from a time-continuous framework, and entry and exit probabilities observed at a discrete frequency. We focus on the second type of variable and describe quarterly unemployment entry and exit probabilities. Our sources for flow data are the following:

France: We use annual series from Murtin et al. (2014) until 2003Q1 then Eurostat (2011) quarterly series.
Germany: We use annual series from Murtin et al. (2014) until 2005 then Eurostat (2011) quarterly series.
Japan: We use annual series from Murtin et al. (2014).
Portugal: We use annual series from Murtin et al. (2014) until 1998 then Eurostat (2011) quarterly series.
Sweden: We use annual series from Murtin et al. (2014) until 2004, impose inflow and outflow rates equal to their corresponding 2004 values in 2005, then select Eurostat (2011) quarterly series from 2006Q1 onwards.
United States: We use Robin (2011) quarterly series.

Appendix A. Labour market reforms and unemployment dynamics

By Fabrice Murtin and Jean-Marc Robin

This companion appendix provides further details on data construction and estimations not reported in the main paper.

A.1. Construction of unemployment flow data

We collect data on unemployment flows from various sources, namely Robin (2011); Murtin et al. (2014); Eurostat (2011); OECD Employment Outlook (2010) and Petrongolo and Pissarides (2008). Our constructed series are systematically compared with those by Elsby et al. (2013).

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