Identifying Asymmetric Effects of Labor Market Reforms†

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Abstract

This paper investigates whether and how the effects of labor market reforms depend on the business cycle. Based on search and matching theory, we propose an unobserved components approach with Markov switching in order to disentangle the effects of structural reforms of the matching process and of job creation in distinct phases of the business cycle. Germany serves as a role model because, first, it has experienced large labor market restructuring in recent years and, second, we can exploit very detailed administrative labor market data. Our results show that labor market reforms of the matching process have substantially weaker effects when implemented in recessions. Evidence for Spain confirms that this finding is not only German-specific. From a policy perspective, this result warns against introducing reforms to mitigate the short-run impact of crisis.

Keywords: labor market reforms, search and matching, business cycle asymmetries, Markov switching

JEL Classification: C32, E02, E32, J08

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1 Introduction

The economic and financial crisis in Europe since 2008 has brought the topic of structural labor market reforms on the agenda. Particularly, there is a striking difference in the developments in Germany that conducted labor market reforms before the crisis, and several mostly Southern European countries where reform debates started only as a reaction to worsening labor market conditions. In Germany, the unemployment rate has (almost steadily) been falling since the labor market reforms that were implemented between 2003 and 2005.[1] In Spain and Italy, unemployment rates rose to more than 25 and 12 percent in and after the Great Recession. Both countries implemented large scale reforms to increase labor market flexibility in 2010 and 2012 (Spain) and 2014 (Italy). However, unemployment remains high compared to pre-crisis levels. Accordingly, disagreement about the right implementation and timing of reforms caused heated political debates.

This leads us to the research question whether structural reforms have systematically different effects in good and bad states of the economy. Even though long-term gains of structural reforms are likely to persist irrespective of the timing of the reforms as argued by an extensive theoretical and empirical literature,[2] the short-run impact remains unclear. Our approach disentangles reforms that speed up the matching process (e.g., training programs for the unemployed, lower and shorter unemployment benefit receipt, more intense counseling by the employment agency) and reforms that affect vacancy creation, i.e., labor demand (tax and social security exemptions for low paid or part-time jobs, hiring subsidies, lower employment protection). We provide quantitative evidence that labor market reforms that affect the matching process of unemployed workers and job vacancies indeed have substantially weaker effects in times of crisis. In contrast, reforms in job creation do not depend on the state of the business cycle. Instead, we find a cyclical negative short-run effect of reforms affecting job creation in general. In other words, it takes some time until reforms in job creation materialize their full effect on the economy.

Several lines of reasoning in the theoretical labor market literature suggest that reform effects might be asymmetric over the course of the economy. Michaillat (2012) argues that in case jobs are rationed in recessions, matching frictions and thus also reductions in frictions are less influential in determining labor market outcomes. Kohlbrecher and Merkl (2016) show that with negative aggregate shocks moving the hiring cut-off point in workers' productivity density function, effectiveness of policy interventions impacting the present value of workers becomes time varying.[3] Charpe and Kühn (2012) make the case that especially in a liquidity trap, decreases in workers' bargaining power could reduce employment due to a weakening of aggregate demand. Moreover,

[1] These reforms have become known as the Hartz reforms. Their main aim was to accelerate labor market flows and reduce unemployment duration. See among others Krause and Uhlig (2012) and Launov and Wälde (2016) for a quantitative analysis of the labor market effects of these reforms. Dustmann, Fitzenberger, Schönberg, and Spitz-Oener (2014) are more skeptical that the Hartz reforms alone explain the beneficial development of the German labor market after 2005.

[2] See among others Gomes, Jacquinot, Mohr, and Pisani (2013) and Bernal-Verdugo, Furceri, and Guillaume (2012).

[3] By the same token, compare the argument for asymmetries of minimum-wage effects in Weber (2015).

a downward wage rigidity introduces asymmetry into the labor market (e.g. Abbritti and Fahr, 2013), so that a wage channel of structural reforms may be less effective in recessions when wage growth is low.

In the underlying paper, we put forward a new and general model-based method for the empirical investigation of state-dependent reform effects. This approach simultaneously tackles the two challenges that a researcher faces when analyzing reform effects over the business cycle: 1) we use a time series approach because only long time series data has information on the labor market performance in different recessions and expansions and 2) our econometric model explicitly identifies reforms. For that purpose we construct a Markov-switching unobserved components framework (for other studies using this model class, see Morley and Piger, 2012, Sinclair, 2010) that allows for different effects of the state variables in recessions, both in their own equations and as spillovers (such as in Klinger and Weber, 2016b).[4] The econometric model framework is specified with regard to the established search and matching theory (Diamond, 1982, Mortensen and Pissarides, 1994). In detail, we consider a matching function and a job creation curve. These equations contain fundamental linkages of matching respectively job creation to unemployment, vacancies, productivity, wages and surplus expectations, and isolate components not explained by these linkages. It is these components, i.e., matching efficiency and job creation intensity, which absorb unobserved reform effects. We take two further steps filtering out other potentially relevant influences. First, while the dynamics of our structural reform components are modeled as permanent, we control for transitory components potentially arising from business cycle influences, compare Davis, Faberman, and Haltiwanger (2013), Fujita and Ramey (2009) or Klinger and Weber (2016a). Second, we explicitly filter out potential effects from a changing structural composition of the pool of unemployed, e.g. with regard to qualification or the length of the unemployment spell. Barnichon and Figura (2015) show that a changing decomposition of the unemployment pool may affect matching efficiency in particular in recessions.

A more standard approach to measure reforms would be given by using observed (or at least constructable) indicators such as replacement rates or OECD indexes of employment protection legislation (e.g. Bouis, Causa, Demmou, and Duval, 2012).[5] While this approach has the advantage of clear interpretability, obvious difficulties are connected to measurement, i.e., the strength of reforms, timing/anticipatory effects, and the restriction to parts of the legislation that can be defined in a standardized way. Nevertheless, we compare our unobserved reform components to more directly measured indicators.

We apply our modeling approach to the case of Germany. Germany serves as a role model because, first, it has experienced large labor market restructuring in recent years that was imple-

[4]A similar identification of persistent components is used to estimate potential output and output gaps (e.g., Morley, Nelson, and Zivot, 2003), trend inflation (e.g., Morley, Piger, and Rasche, 2015), the natural rate of unemployment (e.g., Berger and Everaert, 2008, Sinclair, 2010) and hours (e.g., Vierke and Berger, 2016).

[5]Bouis et al. (2012) find that reforms take time to fully materialize and that short-run effects of some labor market reforms might become weaker in bad times.

mented in recessions and expansions, and, second, Germany provides very detailed and high quality labor market data. We find that reforms that affect the matching process have indeed substantially weaker effects in recessions than in expansions. In extreme cases, the positive effects of structural labor market reforms are completely offset in the short-run if implemented in recessions. This finding aligns with the theoretical arguments of Michaillat (2012) who shows that unemployment in recessions is not necessarily search unemployment and thus not amenable to improvements in the matching process. For reforms in job creation, the effect is less pronounced. In fact, for job creation we find that the effect in recessions only is dominated by a general negative correlation of permanent and cyclical effects that holds in and outside of recessions. This finding suggests that reforms in job creation always induce short-run negative cyclical effects. We also apply our model to Spanish data. The results confirm similar asymmetric effects in the Spanish labor market. In fact, in Spain the effect seems to be even more pronounced in terms of the job creation intensity. This finding reassures us that our result is not only German specific, but of general interest.

Our paper is related to a small DSGE literature on time-varying reform effects. Cacciatore, Duval, Fiori, and Ghironi (2016) use a DSGE model with labor market frictions to study product and labor market reforms. They also find that the business cycle conditions at the time of the reform matter for the short-run adjustment. Eggertsson, Ferrero, and Raffo (2014) study markup reductions in product and labor markets at the zero lower bound in a New Keynesian model. They conclude that reforms may have zero or contractionary effects in this case. Our findings are largely complementary as we back these theoretical findings with empirical evidence.

The paper is organized as follows. The subsequent Section 2 introduces our regime-switching unobserved components model. Section 3 describes our data and Section 4 discusses the estimation strategy. Our empirical results and several robustness checks are summarized in Section 5. The final Section 6 concludes.

2 Modeling asymmetric reform effects

In the following, we describe our structural econometric model. It combines principles from search and matching theory and the literature on unobserved components and regime switching. In line with search and matching theory, we model the labor market outcome as the equilibrium of job creation (i.e., the firms' decision on vacancy creation) and the matching process.

2.1 Theoretical background

In a search and matching context, equilibrium (un)employment is the outcome of firms with open vacancies looking for employees and unemployed workers searching for work (see, e.g., Pissarides, 2000). Vacancies and unemployed workers co-exist in equilibrium as they come together randomly via a matching function. The matching function summarizes the costly and time-consuming search behavior of both sides of the market. In Cobb Douglas form it has strong empirical support (see among others Petrongolo and Pissarides, 2001). For this reason, the matching function is the first main building block of our econometric model. We will identify long-run shifts of the matching function, i.e., shifts in matching efficiency, while controlling for cyclical movements (and for the structure of the unemployment pool). We will interpret these shifts as the outcome of structural labor market reforms.[6]

In the standard search and matching model, all unemployed workers look for a job. Firms, however, make an explicit (intertemporal) decision on posting a job vacancy. Given that vacancy posting is costly, they will create vacancies until the expected marginal value of filling the vacancy is equal to the expected marginal costs. Due to the frictions in the market, existing employer-employee matches are of long-run value. For this reason, the decision on vacancy creation is to a large extent forward looking and depends on the prospects of filling the vacancy, the expected surplus of a match, the wage, and possible hiring and firing costs. This job creation decision is the second main building block of our econometric model. As with the matching function, we will identify long-run trends in job creation, i.e., "job creation intensity". Theoretically, these trends can be explained by a decrease in vacancy posting costs, e.g., due to hiring subsidies, a decrease in employment protection such as firing costs, an increase in filling probabilities or moderate wage developments, e.g., due to decreasing unionization. This is what we will refer to as reforms affecting job creation.

We will compare the reforms that we identify as outlined above to well-known indicators that describe the structure of the labor market. Indeed, our reform effects co-move with changes in employment protection or the replacement rate even though they are more broadly defined.

2.2 The econometric model

Equation (1) represents a stochastic matching function (in logs): Transitions from unemployment to employment (M) depend on the lagged numbers of unemployed U and vacancies V. Being in (log) Cobb-Douglas form, the intercept can be interpreted as total factor productivity, i.e., matching efficiency.

$$M_t = \alpha U_{t-1} + \beta V_{t-1} + \phi X_t + \mu_t + \omega_t^M + \alpha^M x_t^M \tag{1}$$

[6]Naturally, aggregate matching efficiency does not only change due to labor market reforms. For instance, Barnichon and Figura (2015) show in a model with worker heterogeneity across search efficiency and market segmentation that the matching efficiency may endogenously change over the business cycle due to cyclical composition and dispersion effects. Our identification is robust towards these effects given that we a) control for cyclical effects in our decomposition and b) explicitly control for potential long run effects of the unemployment composition in a second step.

This term is made time-varying by including a stochastic trend μ_t that evolves as a random walk according to Equation (2).

$$\mu_t = \mu_{t-1} + \epsilon_t^M \qquad \epsilon_t^M \sim N(0, \sigma^2_{\epsilon^M}) \tag{2}$$

Thus, matching efficiency is modeled as a permanent component well suited to stochastically absorb effects of structural reforms addressing frictions in the labor market. This component is obtained after taking into account supply and demand effects via unemployment and vacancies as well as compositional and cyclical effects: Structural impacts from a changing composition of the pool of unemployed are controlled for by a set of variables in X_t.[7] Moreover, the transitory shock ω_t^M to the matching function is allowed to be serially correlated: Following an autoregressive process (with all roots outside the unit circle) according to Equation (3), it can flexibly capture various mean-reverting and cyclical patterns.

$$\omega_t^M = \rho_1^M \omega_{t-1}^M + \rho_2^M \omega_{t-2}^M + \eta_t^M \quad \text{with} \quad |\lambda_1|, |\lambda_2| < 1 \quad \eta_t^M \sim N(0, \sigma^2_{\eta^M}) \tag{3}$$

This transitory components serves to filter any business cycle effects on matching efficiency, compare Davis et al. (2013), Fujita and Ramey (2009), Barnichon and Figura (2015) or Klinger and Weber (2016a).[8] We follow the standard UC approach (e.g. Morley et al., 2003) and specify an AR(2).

Besides matching frictions, reforms can affect incentives for job creation. Therefore, Equation (4) models a job creation curve, where the number of vacancies V_t depends on productivity growth ΔY_t, wage growth ΔW_t and expected future profits $E_t Y_{t+1}$. Here, we label the intercept χ_t "job creation intensity".

$$V_t = \gamma \Delta Y_{t-1} + \iota \Delta W_t + \kappa E_t Y_{t+1} + \chi_t + \omega_t^V + \alpha^V x_t^V + b_0^M \mu_t + b_1 x_t^{VM} \tag{4}$$

Again, in order to capture structural reform effects, time variation is modeled using a stochastic trend.

$$\chi_t = \chi_{t-1} + \epsilon_t^V \qquad \epsilon_t^V \sim N(0, \sigma^2_{\epsilon^V}) \tag{5}$$

By the same token, cyclical impacts are controlled for by an autocorrelated shock.

$$\omega_t^V = \rho_1^V \omega_{t-1}^V + \rho_2^V \omega_{t-2}^V + \eta_t^V \quad \text{with} \quad |\lambda_1|, |\lambda_2| < 1 \quad \eta_t^V \sim N(0, \sigma^2_{\eta^V}) \tag{6}$$

Moreover, we allow a spillover of the matching efficiency trend. This follows the rationale that the

[7] For example, we control for the share of long-term unemployed and unemployed workers with a migration background. See Section 5.3 for details.

[8] Krause, Lopez-Salido, and Lubik (2008) and Christiano, Trabandt, and Walentin (2011) also estimate a time-varying cyclical matching efficiency in a DSGE context.

expected gain from job creation also depends on the probability that the vacancy will be filled. Thus, theoretically better matching can also foster job creation.

Equation (7) models GDP growth ΔY_t as an autoregressive process with state-dependent mean. We implement endogenous regime switching by a two-state first-order Markov process. The state variable Z_t is 0 in the first and 1 in the second regime and $Pr[Z_t = 0|Z_{t-1} = 0] = q$ and $Pr[Z_t = 1|Z_{t-1} = 1] = p$. The equation serves to anchor two regimes, one expansionary and one recessionary. The normalization is given by $c_1^Y < 0$.

$$\Delta Y_t = c_0^Y + c_1^Y Z_t + \omega_t^Y \tag{7}$$

$$\omega_t^Y = \rho_1^Y \omega_{t-1}^Y + \rho_2^Y \omega_{t-2}^Y + \eta_t^Y \quad \text{with} \quad |\lambda_1|, |\lambda_2| < 1 \quad \eta_t^Y \sim N(0, \sigma^2_{\eta^Y}) \tag{8}$$

Based on the regimes and the specified matching and job creation equations, asymmetric reform impacts can be analyzed. For this purpose, in the recessionary regime, we allow the matching efficiency and job creation intensity trends to have different effects in their equations. Particularly, we collect the reform effects of matching efficiency in recessions in variable x_t^M.

$$x_t^M = \beta^M x_{t-1}^M + Z_t(\mu_t - \mu_{t-1}) = \beta^M x_{t-1}^M + Z_t \epsilon_t^M \tag{9}$$

The autoregressive nature of x_t^M captures potential negative long-run effects of reforms in recession. We specify similar processes for the matching spillover on vacancies and the effects of job creation.

$$x_t^V = \beta^V x_{t-1}^V + Z_t(\chi_t - \chi_{t-1}) = \beta^V x_{t-1}^V + Z_t \epsilon_t^V \tag{10}$$

$$x_t^{VM} = \beta^{VM} x_{t-1}^{VM} + Z_t(\mu_t - \mu_{t-1}) = \beta^{VM} x_{t-1}^{VM} + Z_t \epsilon_t^M \tag{11}$$

Thus, $\alpha^M < 0$ respectively $\alpha^V < 0$ would indicate that increases in matching efficiency or job creation intensity have only dampened effects on labor market outcomes during recessions. A negative b_1 would capture a negative spillover of reforms in the matching process on vacancy creation in recessions. We also take into account that these effects can differ for positive and negative changes in the stochastic trends.

Identification can be treated along the lines of the UC literature. By means of Granger's Lemma (Granger and Morris, 1976), the reduced form is an VARIMA-process. In principle, it must provide enough information to uncover the structural parameters. For univariate correlated[9] UC models, Morley et al. (2003) show that identification is given with an AR lag length of at least two. Since our setup is multivariate, we follow Trenkler and Weber (2016) who treat identification of multivariate correlated UC models. A further feature of our model is regime switching. While this introduces additional unknown coefficients in the structural form, the second regime also

[9]Due to the spillover of the matching efficiency trend on the job creation equation, the model can be seen as correlated.

provides a whole new set autocovariance equations of the reduced form (compare Weber, 2011, Klinger and Weber, 2016b), thus ensuring identification.

3 Data

We use data for Germany that begins in 1982Q1 and ends in 2013Q4. We choose Germany for two reasons: i) we have seen important and much discussed labor market reforms in Germany during this period that were implemented in expansions and recessions and ii) Germany has very detailed and long labor market data readily available. Before the German reunification in 1991, our data covers West Germany only. We use the SIAB data set of the Institute for Employment Research (IAB). This data set is a two percent random sample of employment biographies of all individuals in Germany who have been employed subject to social security or who have been registered as unemployed (see Jacobebbinghaus and Seth, 2007 for a detailed data description). As in Klinger and Weber (2016a), we construct monthly series of the number of new matches and the unemployed from these employment biographies. For every person in our data set aged between 15 and 65 years we define the main employment status at the 10th of each month. If the employment status changes from one month to the next, we count this transition as an exit from one status and an entry into another status.

From the same data source, we take the real wage growth of new hires from unemployment.[10] For vacancies, we use the official statistics of the Federal Employment Agency. Real GDP is provided in the national accounts. The business climate as published by the ifo institute in Munich serves as a proxy for expected future job profitability.[11] We take quarterly averages of monthly series, adjust for seasonality and eliminate structural breaks due to German reunification. Figure 1 shows the final time series. Before estimating the econometric model, we demean all series.

The Great Recession is extraordinary with regard to the steepness of the drop in GDP (see Figure 1). Therefore, we add further flexibility to the Markov switching with a dummy in GDP growth during that period, i.e., in the quarters of the most negative GDP growth from 2008Q4 until 2009Q1. Particularly, this ensures that the other recessions in our sample in comparison to this recession also obtain a reasonable recession weight in the estimation.

4 Estimation

We estimate the state-space form of the model in Equations (1), (2), (3), (4), (5), (6), (7), (8), (9), (10), and (11) using a Bayesian framework. Our priors are independent across parameters. We discuss their choice in the following. Table 1 provides an overview.

[10] We thank Thomas Rothe for providing this data. See also Giannelli, Jaenichen, and Rothe (2016).
[11] Before 1991, we use the index for the West German industry.

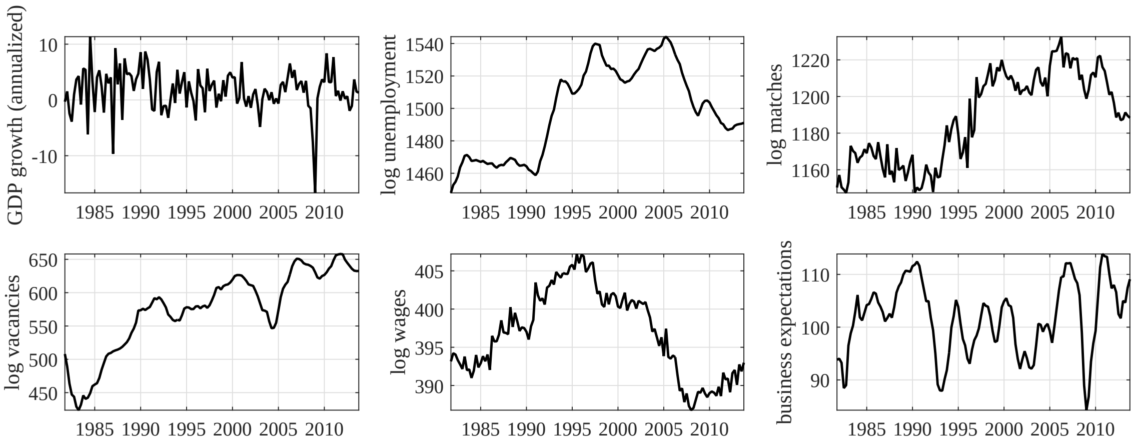

Figure 1: Data plot.

- **Markov switching:** The Markov switching probabilities follow a Beta prior. At the prior mean, the average duration of a recession is 3.33 quarters and the average duration of an expansion is 6.66 quarters. At the prior mean, the economy spends about 33% of the time in recession. Our prior standard deviation is however fairly large.

- **Switching reform parameters:** Our priors for the switching reform parameters are very uninformative. We specify a Normal distribution with mean zero and standard deviation 10.

- **Slope parameters:** We use Normal priors for all slope parameters. See Table 1 for details.

- **Cycle parameters:** For the autoregressive cycle parameters of all equations, ρ_i, our prior is Normal with mean zero and variance $(0.5/i)^2$. This prior shrinks the AR terms toward zero ensuring that the cycle is stationary (Morley et al., 2015). For the variance parameters of the cycle components, we use an inverse Gamma prior. As in Berger, Everaert, and Vierke (2016), we parameterize shape $r_0 = \nu_0 T$ and scale $s_0 = \nu_0 T \sigma_0^2$ of the inverse Gamma in terms of the prior belief σ_0^2 and the prior strength ν_0 relative to sample size T (put differently, the prior belief is constructed from $\nu_0 T$ fictitious observations). We set a prior strength $\nu_0 = 0.1$ and a prior belief $\sigma_{0,\mu} = 5$ for matches and $\sigma_{0,\chi} = 4$ for vacancies. This choice is guided by the fact that the matching series per se is more volatile. For the cycle of output growth, we set a prior belief of $\sigma_{0,y} = 2$.

- **Trend variances:** The trend variances have an inverse Gamma prior. As for the cycle variances, we set a prior strength $\nu_0 = 0.1$ and a prior belief $\sigma_{0,\mu} = 5$ and $\sigma_{0,\chi} = 4$.

We sample from the posterior distribution of the model parameters using the Gibbs algorithm. This algorithm exploits the block structure of the model, i.e., we sample the states, the regimes,

Parameter	Description	Distribution	Mean	Std.
	Markov probabilities			
p	Probability of staying in expansion	Beta	0.8	0.1
q	Probability of staying in recession	Beta	0.75	0.1
	Switching reform parameters			
α^M	Matching reform effect in recessions	Normal	0	10
α^V	Vacancy reform effect in recessions	Normal	0	10
b_1	Matching reform effect in recessions for vacancies	Normal	0	10
β^M	Persistence of matching reforms	Normal	0.5	0.5
β^V	Persistence of vacancy reforms	Normal	0.5	0.5
β^{MV}	Persistence of matching reforms for vacancies	Normal	0.5	0.5
	Parameters of matching equation			
α	Weight on unemployment	Normal	0.9	0.15
β	Weight on vacancies	Normal	0.3	0.2
ρ_1^m	AR(1) of matching cycle	Normal	0	0.5
ρ_2^m	AR(2) of matching cycle	Normal	0	0.25
$\sigma^2_{\eta^M}$	Matching cycle shock variance	Inv. Gamma	27.12	8.25
$\sigma^2_{\epsilon^M}$	Matching trend shock variance	Inv. Gamma	27.12	8.25
	Parameters of vacancy equation			
γ	GDP coefficient	Normal	0.9	0.15
ι	Coefficient on business expectations	Normal	0	5
κ	Coefficient on wage growth	Normal	0	0.1
b_0	Spillover from matching trend	Normal	0	5
ρ_1^v	AR(1) of vacancy cycle	Normal	0	0.5
ρ_2^v	AR(2) of vacancy cycle	Normal	0	0.25
$\sigma^2_{\eta^v}$	Vacancy cycle shock variance	Inv. Gamma	17.36	5.28
$\sigma^2_{\epsilon^v}$	Vacancy trend shock variance	Inv. Gamma	17.36	5.28
	Parameters of GDP growth equation			
c_0	Mean growth in expansions	Normal	4	2
c_1	Shift of mean growth in recessions	Normal	-4.5	2
c_{GR}	Shift of mean growth in Great Recession	Normal	0	5
ρ_1^y	AR(1) of GDP cycle	Normal	0	0.5
ρ_2^y	AR(2) of GDP cycle	Normal	0	0.25
$\sigma^2_{\eta^y}$	GDP cycle variance	Inv. Gamma	4.34	1.32

Table 1: Prior distributions.

and each equations parameters conditional on the remaining parameters and the data. We draw the realizations of the unknown states using the simulation smoother of Durbin and Koopman (2002). Kim and Nelson (1999, Chap. 10) discuss how to sample switching regimes in a state space framework. Our results are based on 30,000 draws after discarding the initial 20,000 draws. To ensure convergence, we analyze CUSUM statistics and trace plots (see Appendix B.

5 Results

5.1 Baseline

First, we discuss the results of our baseline model estimation. In our baseline model, we estimate a standard matching function without controlling for the composition of the pool of unemployed. In Table 2, we summarize the prior and posterior distributions for all estimated parameters. The estimated parameters for the exogenous variables are in line with common intuition. The weight on unemployment in the matching function has a posterior mean of 0.68.[12] Our weight on vacancies is 0.12 at the posterior mean. This number is smaller compared to parameters typically used in the literature. However, the 90% interval of the posterior distributions captures values up to 0.30. Note also that constant returns to scale are not rejected according to our posterior estimates, even though the posterior weight is high on decreasing returns to scale.

For vacancies, we find a positive effect of GDP growth on vacancies (posterior mean of 0.22). Furthermore, surplus expectations have a positive effect on vacancy creation with a posterior mean 0.15 (even though the posterior uncertainty for this parameter is large). In line with theory, real wage growth dampens job creation. The posterior mean of parameter κ is -0.04. However, again estimation uncertainty is large. The spillover from matching efficiency on job creation is unimportant.

Figure 2 shows the trend and the cycle component of matches and vacancies that we obtain from our baseline estimation. The cycle moves around the trend component of both series. For matches and vacancies, both AR lags of the cyclical components are different from zero according to the 90% posterior interval. The decomposition clearly identifies long-run permanent effects and short-run business cycle movement in both series. In matching, there are several up- and downward movements of the permanent trend component. Matching efficiency declines from the mid-80s until the early 1990s. It significantly improves starting in 1992. In fact, this period coincides with the implementation of important labor market reforms in Germany that aimed at fostering active labor market policies. Table 3 summarizes structural labor market reforms in Germany as classified by Bouis et al. (2012). From 2003 to 2005 Germany implemented the largest labor market reforms

[12] Shimer (2005) sets 0.72 for the US. Kohlbrecher, Merkl, and Nordmeier (2016) estimate a weight on unemployment of roughly two thirds based on the same German administrative data (although with an approach that does not account for time varying matching efficiency).

	Prior distribution		Posterior distribution			
	Mean	Std.	Mean	Median	90% HPD interval	Prob(<0)
Markov probabilities						
p	0.85	0.10	0.8283	0.8330	[0.701; 0.939]	
q	0.75	0.10	0.7303	0.7394	[0.584; 0.853]	
Switching reform parameters						
α^M	0.00	10.00	-0.9459	-0.9659	[-1.824; -0.000]	0.950
α^V	0.00	10.00	-0.5206	-0.5199	[-1.161; 0.122]	0.909
b_1	0.00	10.00	-0.0196	-0.0209	[-0.560; 0.513]	0.527
β^M	0.50	0.50	0.7701	0.8510	[0.253; 0.997]	
β^V	0.50	0.50	0.9008	0.9528	[0.620; 0.999]	
β^{MV}	0.50	0.50	0.7991	0.8972	[0.261; 0.999]	
Parameters of matching equation						
α	0.90	0.15	0.6752	0.6831	[0.407; 0.924]	
β	0.30	0.20	0.1175	0.1187	[-0.068; 0.298]	
ρ_1^m	0.00	0.50	0.5821	0.5846	[0.402; 0.760]	
ρ_2^m	0.00	0.25	0.3389	0.3419	[0.167; 0.502]	
$\sigma^2_{\eta^M}$	27.12	8.25	22.7064	21.8290	[14.801; 33.609]	
$\sigma^2_{\epsilon^M}$	27.12	8.25	47.3631	46.6068	[32.609; 64.256]	
Parameters of vacancy equation						
γ	0.15	0.20	0.2191	0.2183	[0.049; 0.394]	
κ	0.00	0.10	-0.0361	-0.0374	[-0.197; 0.125]	
ι	0.00	5.00	0.1488	0.1503	[-0.246; 0.543]	
b_0	0.00	5.00	-0.0196	-0.0126	[-0.370; 0.304]	
ρ_1^v	0.00	0.50	1.2752	1.2735	[1.110; 1.446]	
ρ_2^v	0.00	0.25	-0.3557	-0.3554	[-0.528; -0.189]	
$\sigma^2_{\epsilon^v}$	17.36	5.28	14.4709	13.9874	[9.874; 20.437]	
$\sigma^2_{\eta^v}$	17.36	5.28	19.2259	18.9588	[14.002; 25.378]	
Parameters of GDP growth equation						
c_0	4.00	2.00	3.2995	3.3285	[2.336; 4.133]	
c_1	-4.50	2.00	-3.9115	-3.8829	[-4.859; -2.974]	
c_0+c_1			-0.6120	-0.4128	[-1.836; -0.035]	
c_{GR}	0	5.00	-10.2668	-10.3407	[-13.136; -7.076]	
ρ_1^y	0	0.50	-0.0980	-0.0988	[-0.287; 0.093]	
ρ_2^y	0	0.50	0.0467	0.0446	[-0.130; 0.230]	
$\sigma^2_{\eta^y}$	4.34	1.32	6.9364	6.8257	[5.200; 9.069]	

Table 2: Prior and posterior distributions in baseline model.

known as the Hartz reforms. Using our approach, we identify an increase in matching efficiency in these years. The trend in job creation is less volatile. The major change in the trend occurs after the Hartz reforms where we identify an improvement in job creation intensity.

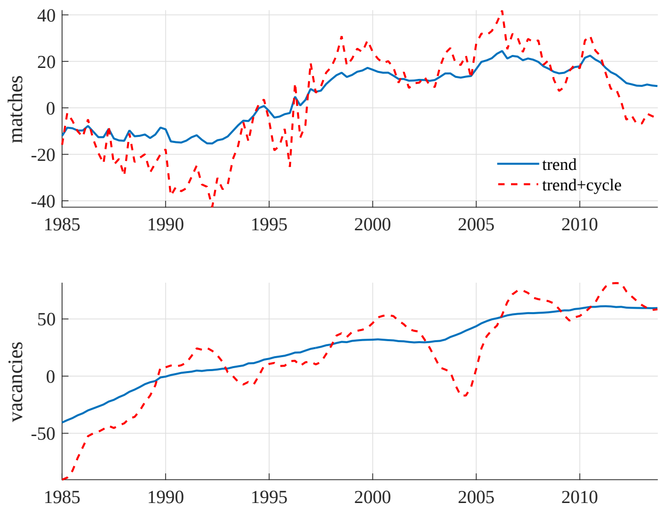

Figure 2: Trend cycle decomposition of matches and vacancies in baseline model.

Year	Reform
1986	Decline in labor tax
1992	Increase in spending on active labor market policies
1997	Decline in job protection on temporary contracts
2000	Decline in union coverage
2005	Decline in unemployment benefit duration and replacement rate

Table 3: Important labor market reforms in Germany (Bouis et al., 2012)

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Given our interest in time varying effects of labor market reforms, we discuss the different regimes that we identify based on GDP growth next. Our estimation clearly disentangles the expansionary and the recessionary regime. Average annualized GDP growth in an expansion is 3.30 percent, whereas it is -0.61 percent in a recession. In Figure 3, we show the probability of recession that we obtain in our estimation. The shaded areas mark periods officially characterized as recessions in Germany by the Economic Cycle Research Institute (ECRI). The probability of a recession is one in the Great Recession, but also other recessions as the one after reunification in 1993 or the one in the early 2000s obtain a high recession weight.

Based on the two regimes and the decomposition of permanent and cyclical component in

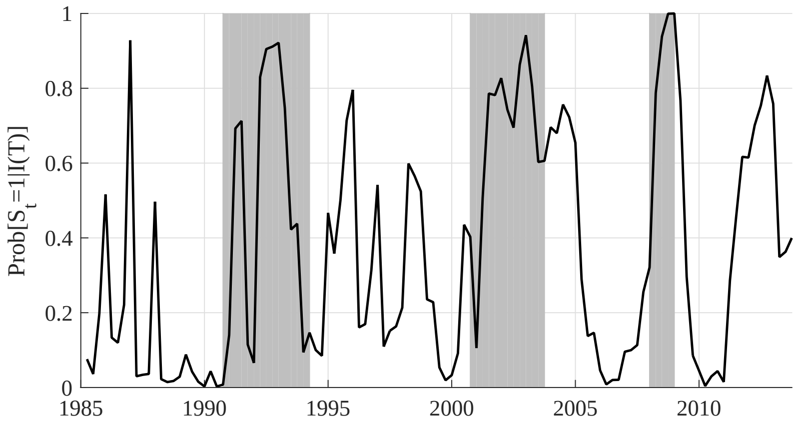

Figure 3: Probability of recession. Shaded regions mark recessions in Germany according to the Economic Cycle Research Institute (ECRI).

matches and vacancies, we can now analyze the reform effects in recessions. At the posterior mean, the reform effects in matches, job creation and the spillover of matches on vacancies are negative (see Table 2). For matching efficiency, the effect is quite substantial with a posterior mean of -0.95. According to the full posterior distribution, the probability of this parameter being smaller than zero is 95 percent. Figure 4 shows the prior and posterior distributions for the switching reform parameters. Compared to the very loose prior, the posterior distribution of α_m is significantly moved to the left. The spillover of matching efficiency on job creation is negligible given the large posterior uncertainty. Interestingly, there is some persistence in the negative reform effects of matching efficiency. The posterior mean of β^M is 0.77. This number implies that after 12 quarters after the reform almost 0.05 of the initial negative effect in recessions remains.

In this specification, we also find a negative reform effect of job creation in recession with a posterior mean of -0.52. The probability of this parameter being negative is 90 percent. However, as we will show in the next subsection this negative parameter only reflects a general negative correlation of trend and cycle in vacancies. For this reason, we do not interpret this finding as a negative reform effect. In contrast, the negative reform effect of matching efficiency is a pure reform effect in recessions as the effect remains is we allow for a general non-zero correlation in matches.

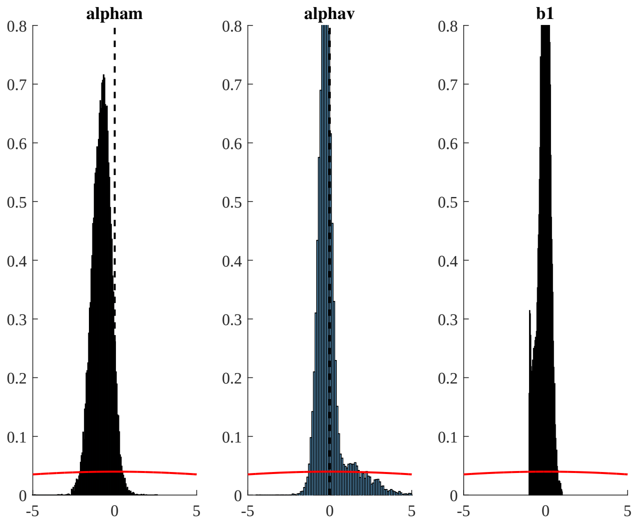

Figure 4: Prior (red) and posterior distribution of regime switching reform parameters.

5.2 Non-zero trend cycle correlation

Our negative reform effect in recession implies a negative correlation of a permanent (reform) component and transitory component in recessions (see Equations (9)-(11)). For example, a positive innovation in the permanent component (i.e., a reform) has negative effects on the transitory component (and thus on the level) in recessions if $\alpha^m, \alpha^v, b_1 < 0$. In the UC literature, it is well known finding that the trend and cycle components of a time series are often negatively correlated. Morley et al. (2003) discuss that the assumption of a zero trend cycle correlation may be crucial for the decomposition results of output. To ensure that we do not falsely interpret a general negative correlation as a negative reform effect, we check whether we still find negative reform effects when we allow for a non-zero trend cycle correlation in our model.

We impose a uniform prior between -1 and 1 on the trend-cycle correlations for matches ψ_m and vacancies ψ_v (Chan and Grant, 2016).[13] It is well-known that a non-zero trend cycle correlation may result in excessive trend volatility and a non-plausible trend-cycle decomposition (Kamber, Morley, and Wong, 2016). To avoid this behavior, we increase the prior strength ν_0 on the variance of the trend component to 0.5 for the vacancy series and set our prior belief for vacancy trend and cycle to $\sigma_{0,\chi} = 3$.[14] Note that this biases our results towards a smaller effect of reforms in vacancy creation given that we increase the prior weight on a smaller trend variance.

Table 4 summarized the posterior distributions in this model specification. Notably, for vacancies, we find a negative correlation of trend and cycle with a posterior mean of -0.38. The trend cycle correlation in matching is slightly positive, but close to zero. Figure 5 shows the decomposition in trend and cycle that we obtain in this specification. The result is very similar to what we observed in the model with a zero correlation. Also, the non-negative trend cycle correlation has only small impacts on the estimated posterior distributions of the parameters for the exogenous variables. But, as suggested above, the assumption of a zero correlation matters for our finding on the negative reform effects in recessions. The posterior distribution of the negative reform effect in job creation is moved towards zero reducing the posterior mean. Under a non-zero trend cycle correlation, the 90% posterior interval includes zero, i.e., there is no clear evidence that the parameter is smaller than zero. In contrast, for the reform effect in matching efficiency the effect remains more clear. The probability of this parameter being smaller than zero is still larger than 90 percent. For this reason, we conclude that only the negative reform effect of reforms targeted at matching efficiency in recessions is a robust finding.

[13] The estimation also follows Chan and Grant (2016) who apply a Griddy Gibbs to sample the correlations.

[14] Kamber et al. (2016) avoid excessive trend volatility by strictly restricting the signal to noise ratio of a Beveridge Nelson decomposition of output. For both of our time series, our prior choice results in a signal to noise ratio at the posterior mean that is less restrictive compared to their restriction.

	Prior distribution		Posterior distribution			
	Mean	Std.	Mean	Median	90% HPD interval	Prob(<0)
Markov probabilities						
p	0.85	0.10	0.8327	0.8382	[0.699; 0.947]	
q	0.70	0.10	0.6939	0.7013	[0.540; 0.824]	
Switching reform parameters						
α^M	0.00	10.00	-0.8628	-0.8480	[-1.818; 0.043]	0.941
α^V	0.00	10.00	-0.2668	-0.2687	[-1.012; 0.481]	0.733
b_1	0.00	10.00	-0.0258	-0.0247	[-0.531; 0.451]	0.538
β^M	0.50	0.50	0.8194	0.9062	[0.345; 0.998]	
β^V	0.50	0.50	0.9238	0.9603	[0.727; 0.998]	
β^{MV}	0.50	0.50	0.8423	0.9289	[0.376; 0.999]	
Parameters of matching equation						
α	0.90	0.15	0.6265	0.6514	[0.216; 0.909]	
β	0.30	0.20	0.0931	0.1048	[-0.156; 0.293]	
ρ_1^m	0.00	0.50	0.5635	0.5765	[0.329; 0.764]	
ρ_2^m	0.00	0.25	0.3279	0.3364	[0.133; 0.495]	
$\sigma^2_{\eta^M}$	27.12	8.25	22.7908	21.7918	[14.943; 33.487]	
$\sigma^2_{\epsilon^M}$	27.12	8.25	46.4772	45.7066	[27.680; 68.285]	
ψ_m	0	0.58	0.0594	0.0519	[-0.338; 0.484]	0.421
Parameters of vacancy equation						
γ	0.15	0.20	0.1730	0.1698	[0.031; 0.322]	
κ	0	0.10	-0.0367	-0.0367	[-0.191; 0.121]	
ι	0	5.00	0.1673	0.1659	[-0.214; 0.545]	
b_0	0	5.00	0.0428	0.0456	[-0.293; 0.350]	
ρ_1^v	0	1.00	1.2573	1.2579	[1.114; 1.418]	
ρ_2^v	0	0.25	-0.3659	-0.3634	[-0.513; -0.225]	
$\sigma^2_{\epsilon^v}$	9.14	1.16	9.7516	9.6361	[7.812; 12.187]	
$\sigma^2_{\eta^v}$	9.76	2.97	25.0965	24.0054	[15.227; 38.655]	
ψ_v	0	0.58	-0.3780	-0.3991	[-0.776; 0.071]	0.923
Parameters of GDP growth equation						
c_0	4.00	2.00	3.1947	3.2213	[2.259; 4.082]	
c_1	-4.50	2.00	-3.9481	-3.8978	[-5.133; -2.887]	
$c_0 + c_1$			-0.7533	-0.5026	[-2.301; -0.043]	
c_{GR}	0	5.00	-10.4017	-10.4684	[-13.256; -7.368]	
ρ_1^y	0.50	1.00	-0.0647	-0.0649	[-0.253; 0.126]	
ρ_2^y	0	0.50	0.0625	0.0626	[-0.120; 0.244]	
$\sigma^2_{\eta^y}$	4.34	1.32	7.1119	6.9887	[5.237; 9.346]	

Table 4: Prior and posterior distributions in model with trend-cycle correlation.

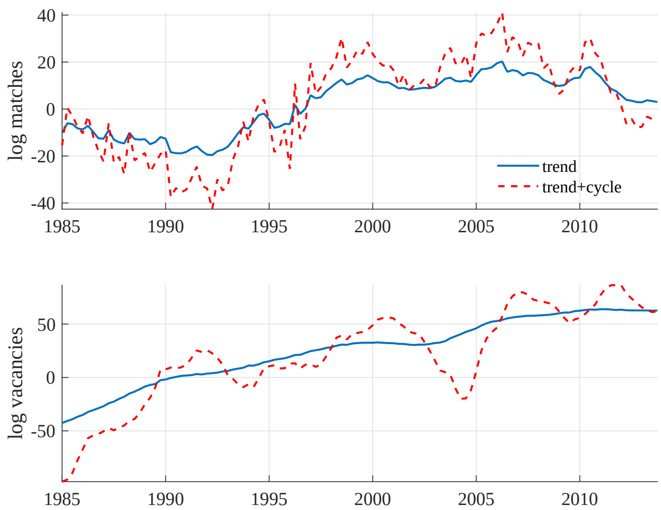

Figure 5: Trend cycle decomposition of matches and vacancies in model with trend cycle correlation.

5.3 Controlling for changes in the decomposition of the unemployment pool

We interpret permanent changes in matching efficiency as reforms of the matching process. Besides the trend-cycle correlation, a potentially important factor that may interfere with our interpretation of reforms is changes in the decomposition of the unemployment pool. For example, in the 40 years that our data period spans, we know that female labor force participation increased. Also, migrants entered the labor force. A different composition of the unemployment pool with respect to different worker characteristics may affect the matching process. To control for such effects, we add several control variables for the composition of the pool of unemployed to our matching function (compare Equation (1); see Kohlbrecher et al., 2016 for a similar approach). To be precise, we control for the share of long-term unemployed (unemployment duration longer than one year), the share of young and old unemployed workers, the share of unemployed with migration background, and the share of female unemployed.[15]

Adding these controls substantially changes the shape of the trend in matching efficiency (see Figure 6). And it affects our reform effects in recessions. In fact, we find that the negative reform effect in recessions becomes much stronger if we control for the composition of the unemployment pool. The posterior mean is now -1.01 suggesting that the recession effect completely offsets the positive reform effects in matching efficiency in recessions. We summarize the important parameters in Table 5. Note that these results are obtained from the general model with a non-zero trend cycle correlation.[16]

In order to shed further light on our measurement concept, we compare the estimated trends in matching efficiency and job creation intensity to official indicators of structural labor market reforms. As the upper panels of Figure 7 show there have been two periods when the OECD employment protection index (EPL) for temporary employment in Germany was substantially lowered due to structural labor market reforms: in 1997, there was a strong decline in the job protection on temporary contracts and in 2003 to 2005 in the wake of the Hartz reforms (see also Table 3). Our measures of reforms mirror these changes, even though we also capture additional up- and downturns. This is unsurprising since a single institutional indicator such as EPL naturally reflects only specific changes. In 1997, we identify a strong improvement in matching efficiency, but also job creation intensity rises. In 2005, we find a large increase in job creation intensity and also of matching efficiency in the Hartz years 2003-2005.

A further indicator of labor market reforms is the replacement rate in case of unemployment

[15] The data is provided by the Federal Employment Agency. For long-term unemployment, we use the same series as in Fuchs and Weber (2015). In early years, some series are only available at annual frequency. Given that we are interested in controlling for long-run trends, we linearly interpolate in these cases.

[16] The estimated parameters of the vacancy and the GDP equation do hardly change compared to the results in Table 5. For brevity, we do not show these results here.

	Prior distribution		Posterior distribution			
	Mean	Std.	Mean	Median	90% HPD interval	Prob(< 0)
Switching reform parameters						
α^M	0.00	10.00	-1.0136	-1.0225	[-1.886; -0.127]	0.966
α^V	0.00	10.00	-0.3051	-0.3077	[-1.058; 0.457]	0.760
b_1	0.00	10.00	0.0282	0.0314	[-0.474; 0.537]	0.455
β^M	0.50	0.50	0.8131	0.9011	[0.322; 0.998]	
β^V	0.50	0.50	0.9261	0.9593	[0.736; 0.998]	
β^{MV}	0.50	0.50	0.8267	0.9166	[0.331; 0.999]	
Parameters of matching equation						
α	0.90	0.15	0.7075	0.7117	[0.431; 0.965]	
β	0.30	0.20	0.3571	0.3543	[0.162; 0.567]	
κ_{female}	0	5.00	-3.1392	-3.1360	[-5.832; -0.374]	0.971
$\kappa_{migrants}$	0	5.00	-2.6989	-2.7045	[-7.078; 1.628]	0.844
κ_{long}	0	5.00	0.3094	0.3155	[-0.690; 1.299]	0.305
κ_{old}	0	5.00	-0.5545	-0.5286	[-2.607; 1.489]	0.673
κ_{young}	0	5.00	0.9983	1.0165	[-2.412; 4.302]	0.309
ρ_1^m	0	0.50	0.6353	0.6345	[0.439; 0.839]	
ρ_2^m	0	0.25	0.2977	0.3022	[0.109; 0.469]	
$\sigma^2_{\eta^M}$	27.12	8.25	24.6569	23.4354	[15.466; 38.172]	
$\sigma^2_{\epsilon^M}$	27.12	8.25	56.5491	54.1093	[36.732; 83.982]	
ψ_m	0	0.58	0.1369	0.1423	[-0.263; 0.520]	0.282

Table 5: Prior and posterior distributions when controlling for the composition of the unemployment pool. We control for the share of female unemployed, unemployed with a migration background, long-term unemployed (more than one year), unemployed older than 55 years, and unemployed workers younger than 25 years (out of total unemployment).

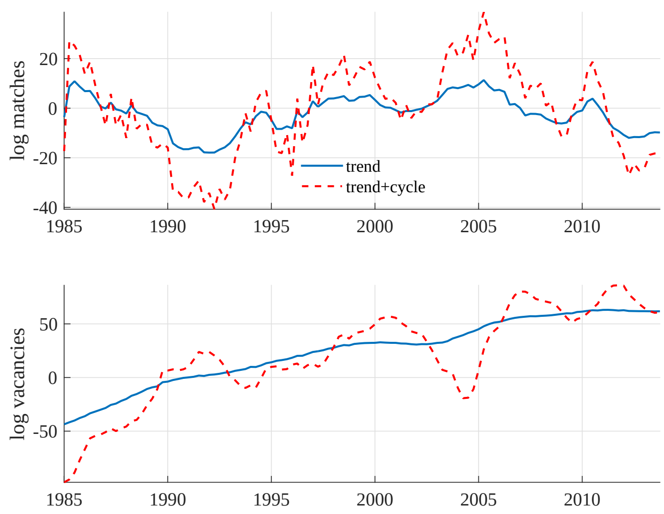

Figure 6: Trend cycle decomposition of matches and vacancies when controlling for changes in the unemployment pool.

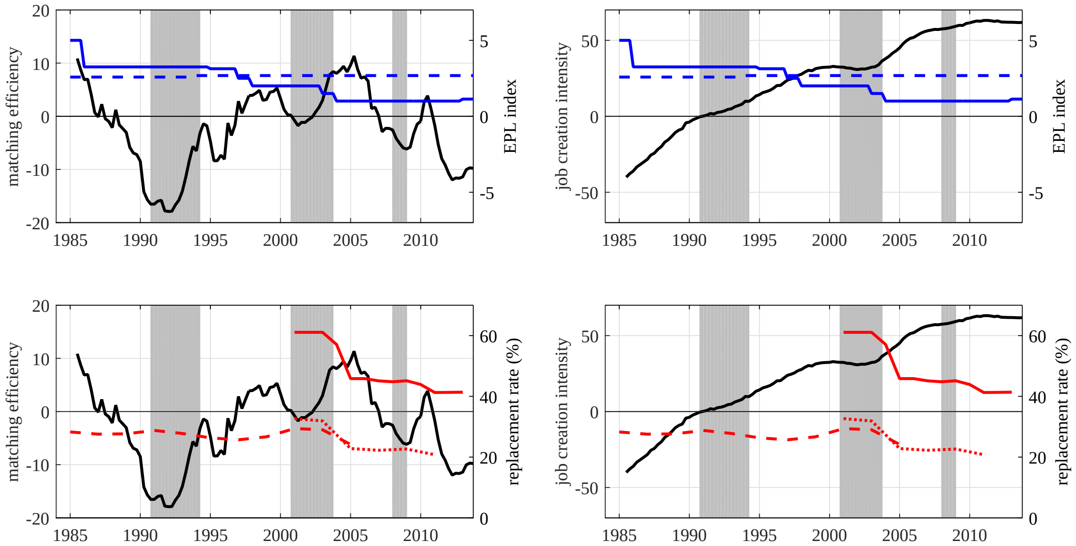

Figure 7: Comparison of trend components vis-à-vis the OECD employment protection indices (upper panels, blue) and the OECD replacement rate (lower panels, red) for Germany. EPL: The dashed line shows the index of regular employment, the solid line shows the index for temporary employment. Replacement rate: The solid line shows the net replacement rate, the dotted (dashed) line shows the gross replacement rates for the average (production) worker.

benefit receipt. The lower panels of Figure 7 show different OECD measures of the replacement rate in Germany over time (net and gross replacement rates).[17] The replacement rate declines modestly in the early 1990s and rises in the early 2000s. Our indicator of matching efficiency also improves in the early 1990s and declines in the early 2000s. In the early 2000s, we also identify a dip in job creation intensity around the time when the replacement rate rises. The most important reduction in the replacement rate was implemented during the Hartz reforms. As discussed already in the context of EPL, these important structural changes in the labor market are clearly reflected in our reform measures. The replacement rate again falls from 2008 to 2010 where matching efficiency and job creation intensity further improve.

5.4 Further robustness checks

5.4.1 Switching cycle variances

We check whether it matters for our results that we assume the shock variances of the cyclical components to be constant across regimes. By doing so, we ensure that our reform effects to not capture changes of the cyclical variances in recessions. Our econometric model and methodology is flexible enough to account for switching cycle variances in addition to the switching GDP growth

[17]Source: OECD Benefits and Wages Statistics. The data on the net replacement rate only starts in 2001. For this reason, we also show the gross replacement rate that is available for a longer period of time.

rate and our reform effects.[18] We indeed find that the cyclical variance of matches is slightly higher in recessions (48.9 to 46.3 at the posterior mean). The cyclical variance of vacancies is nearly identical across the different regimes. Nevertheless, our reform effects are hardly affected by this change. We still find a strong negative effect of implementing reforms in the matching process in recessions in the model without ($\alpha_m = -0.94$ and $Prob(\alpha_m < 0) = 0.95$) and with correlation ($\alpha_m = -0.61$ and $Prob(\alpha_m < 0) = 0.90$).

5.4.2 Differentiating positive and negative "reforms"

Our approach allows to differentiate the impact of reforms that have a positive effect on matching efficiency and job creation and those that have a negative effect. To do so, we modify Equation (1) and (4) and estimate two switching reform parameters for matches and vacancies each: One for positive aggregate reform effects and one for negative ones. Our results do not support the hypothesis that there are different reform effects in recessions conditional on whether the reform is positive or negative. There is a slight tendency for positive reform effects of matching efficiency being affected more if implemented in recessions compared to negative reform effects. For matches, we find a switching reform effect of positive reforms of -0.86 and of -0.50 for negative reforms. For vacancies, we find the opposite pattern with an effect of positive reforms of -0.34 and of negative reforms of -0.69. However, we do not want to over interpret theses findings given that estimation uncertainty is relatively large in these specifications.

5.5 An application to the Spanish labor market

We additionally apply our new model framework to Spain. Thus, we add a perspective on a country that experienced severe damage to the labor market following the Great Recession, in contrast to Germany. By the same token, the Spanish economy performed well in the first half of the 2000s, when the German labor market was slack.

5.5.1 Data

In contrast to Germany, Spain provides no direct data on labor market transitions. We follow the literature and infer the job finding rate out of unemployment from data on the stock of unemployment and short-term unemployment (Shimer, 2012).[19] For vacancies, we use the same series as Murtin and Robin (2016) and update the series with the latest Eurostat data. Wages are aggregate

[18] However, given that we are interested in comparing effects across recession and expansion, we have to guarantee that our two regimes represent recessionary and expansionary phases and not simply breaks in cyclical variances. In order to be comparable to the baseline model, we use the previously estimated probability of recession as an exogenous recession probability in this case.

[19] We update the series as provided by Barnichon and Garda (2016) until 2014Q4.

real wages per employee (from the Spanish national accounts). We measure business expectations with the confidence indicator for manufacturing as published by the OECD.

5.5.2 Results for Spain

Table 6 summarizes the most important parameters for the Spanish model.[20] Note that we directly show the results for a model with a non-zero trend-cycle correlation. As in the German case, we find evidence in favor of dampened reform effects in recession. For matching efficiency, the posterior mean is at -0.75 and for the job creation intensity, the posterior mean is at -1.47. Compared to the German case, these results indicate that the negative reform effect of job creation intensity in recessions is substantially larger in the Spanish labor market. For matching efficiency, a direct comparison is more difficult as we have no data available to control for the decomposition of the unemployment pool. However, in general, these findings back our results from the German case that reform effects are dampened in recessions - even when analyzing a country with a markedly different aggregate performance over time.

	Prior distribution		Posterior distribution			
	Mean	Std.	Mean	Median	90% HPD interval	Prob(< 0)
Switching reform parameters						
α^M	0.00	10.00	-0.7475	-0.7275	[-1.921; 0.312]	0.870
α^V	0.00	10.00	-1.4647	-1.8793	[-3.634; 0.745]	0.752
b_1	0.00	10.00	0.0262	0.0258	[-1.669; 1.712]	
β^M	0.50	0.50	0.8090	0.8932	[0.342; 0.998]	
β^V	0.50	0.50	0.9544	0.9894	[0.768; 1.000]	
β^{MV}	0.50	0.50	0.8428	0.9238	[0.391; 0.998]	
Trend cycle correlations						
ψ_m	0	0.58	-0.0623	-0.0664	[-0.445; 0.336]	0.616
ψ_v	0	0.58	0.1955	0.1849	[-0.305; 0.724]	0.266

Table 6: Prior and posterior distributions in the Spanish application.

[20] Appendix C shows more detailed results on Spain.

6 Conclusions

This paper proposes a Markov switching unobserved components model to analyze state dependent effects of structural labor market reforms. Our econometric model rests upon the established search and matching theory and allows to differentiate structural reforms that i) affect the matching of unemployed workers and firms with job vacancies and ii) foster job creation at the firm level. We estimate the model on German data. The German labor market has experienced many structural reforms in the last decades and at the same time represents a typical example of a European style labor market that is characterized by rather strong employment protections and rigidity. Furthermore, we generate additional evidence in an application to Spanish data.

Our empirical investigation documents a strong interaction of the business cycle and reforms of the matching process. In a recession, the positive effects of an increase in matching efficiency are offset in the short-run. This finding calls for a close monitoring of the business cycle when implementing these kind of labor market reforms. Implementing reforms to alleviate crisis situations turns out to be a costly policy. Even though long-run effects might be beneficial, the short-run costs may erode the public support for such reforms. This finding can be explained by the theoretical arguments of Michaillat (2012) who argues that unemployment in recessions is to a smaller extent explained by search compared to unemployment in expansions. In contrast, reforms that facilitate job creation (e.g., a reduction of vacancy posting costs or lower wages) generally take some time to fully develop their expansionary effects on the economy, but there is no additional dampening effect if these reforms were to be implemented in a recession. Instead, as the example of the German labor market reforms before the Great Recession has shown, implementing reforms outside recession periods promises to be more effective and to avoid adverse effects of reform efforts put forward under pressure of crisis situations.

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A State space form of the baseline model

$$
\begin{aligned}
&Y_t = \Big(H_0(1-Z_t) + H_1 Z_t\Big)\xi_t + \Big(A_0 + A_1 Z_t\Big)X_t + \varepsilon_t, \qquad \varepsilon_t \sim N(0,R) \\
&\xi_t = F\xi_{t-1} + G\psi_t, \qquad \psi_t \sim N(0,Q) \\
&Z_t \in (0,1) \qquad \text{Markov switching} \\
&Pr(Z_t = 1 | Z_{t-1} = 1) = p \\
&Pr(Z_t = 0 | Z_{t-1} = 0) = q
\end{aligned}
$$

with $Y_t = \begin{pmatrix} M_t \\ V_t \\ \Delta Y_t \end{pmatrix}$, $X_t = \begin{pmatrix} 1 \\ U_{t-1} \\ V_{t-1} \\ \Delta Y_{t-1} \\ \Delta W_t \\ E_t Y_{t+1} \end{pmatrix}$, $\xi_t = \begin{pmatrix} \mu_t^M \\ \chi_t^V \\ x_t^M \\ x_t^V \\ x_t^{MV} \\ \omega_t^M \\ \omega_t^V \\ \omega_t^Y \\ \omega_{t-1}^M \\ \omega_{t-1}^V \\ \omega_{t-1}^Y \end{pmatrix}$, $\psi_t = \begin{pmatrix} \epsilon_t^M \\ \epsilon_t^V \\ \eta_t^M \\ \eta_t^V \\ \eta_t^Y \end{pmatrix}$;

and $H_0 = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ b_0 & 1 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \end{bmatrix}$,

$H_1 = \begin{bmatrix} 0 & 0 & \alpha^M & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \alpha^V & b_1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$,

$A_0 = \begin{bmatrix} c^M & \alpha & \beta & 0 & 0 & 0 \\ c^V & 0 & 0 & \gamma & \iota & \kappa \\ c_0^Y & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$, $A_1 = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ c_1^Y & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$,

$$F = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & \beta^M & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & \beta^V & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \beta^{MV} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & \rho^M & 0 & 0 & \rho_2^M & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & \rho^V & 0 & 0 & \rho_2^V & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & \rho^Y & 0 & 0 & \rho_2^Y \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \end{bmatrix}, G = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ Z_t & 0 & 0 & 0 & 0 \\ 0 & Z_t & 0 & 0 & 0 \\ Z_t & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix},$$

$diag(Q) = [\sigma^2_{\epsilon^M}\ \sigma^2_{\epsilon^V}\ \sigma^2_{\epsilon^Y}\ \sigma^2_{\eta^M}\ \sigma^2_{\eta^V}\ \sigma^2_{\eta^Y}]'$, $R = 0_{\{3\times 3\}}$

B Estimation diagnostics

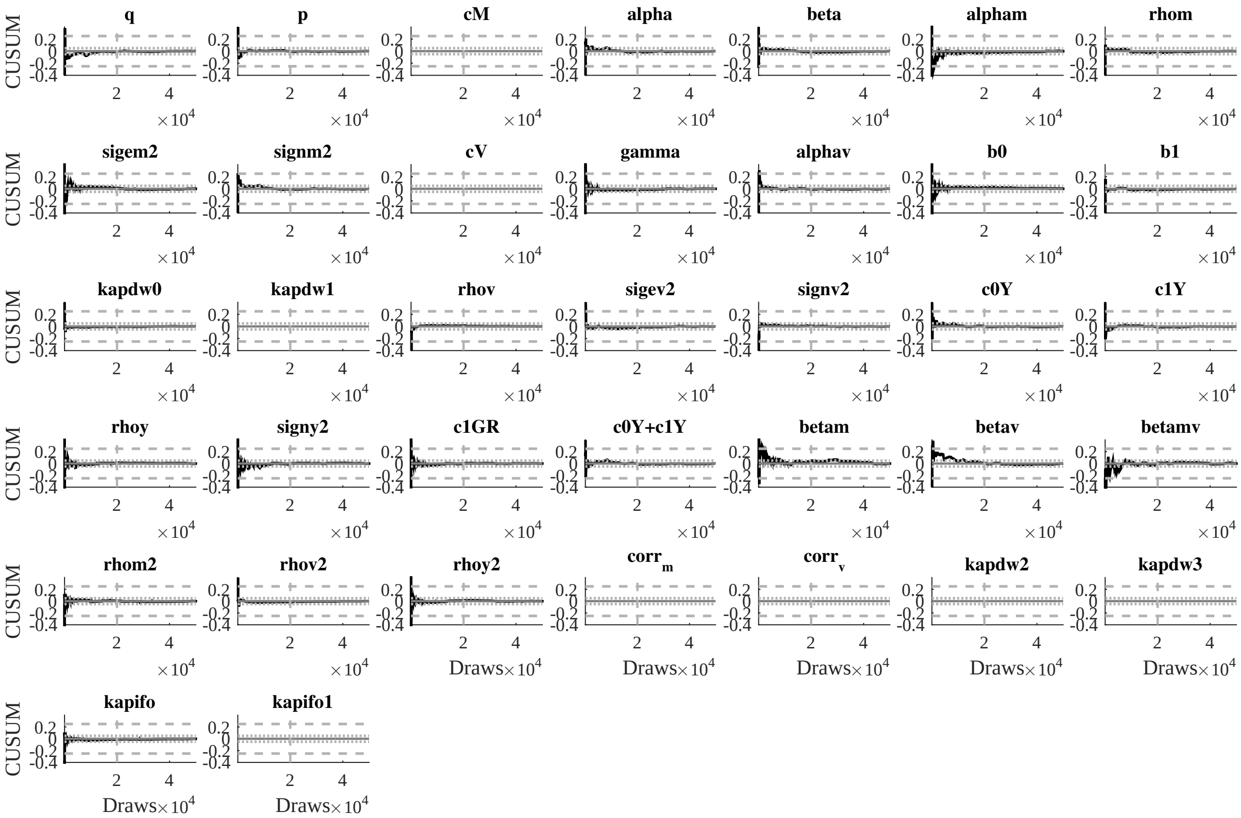

Figure 8: CUSUM convergence plot for baseline estimation.

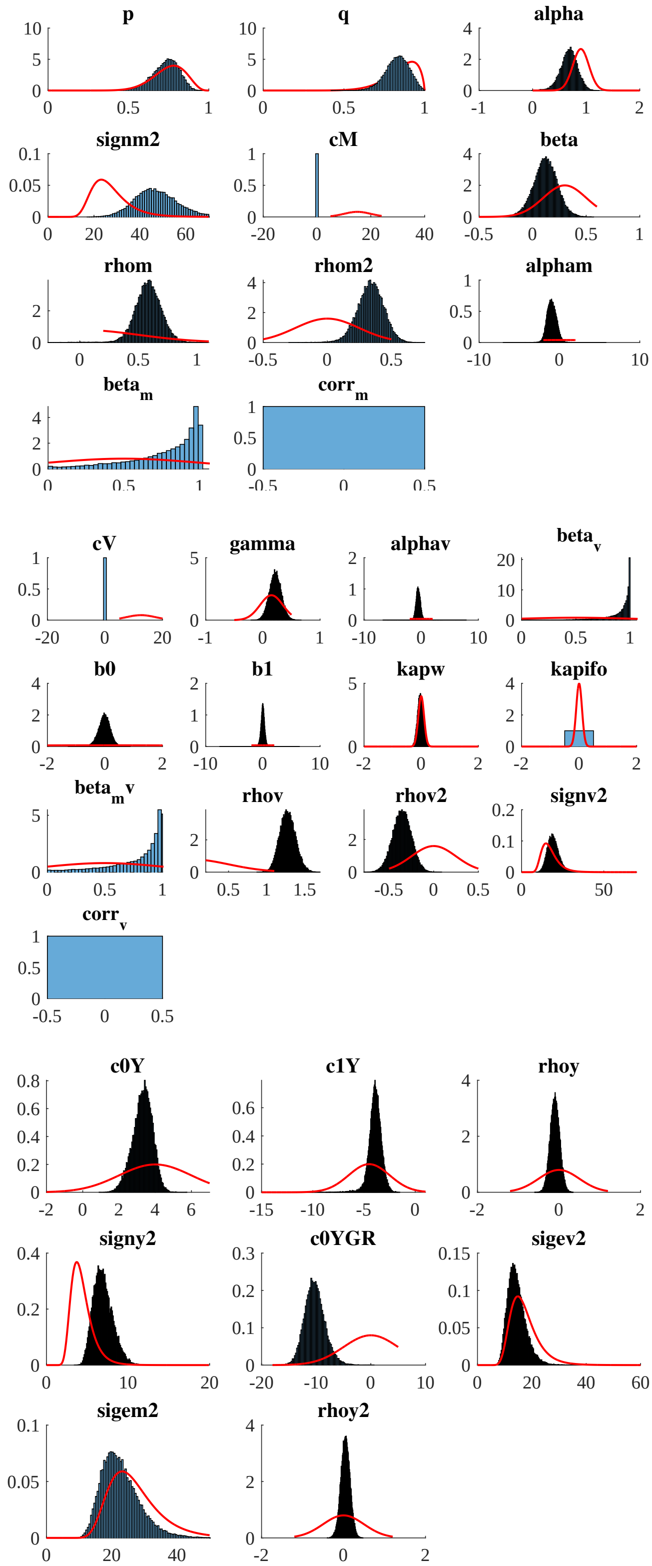

Figure 9: Prior and posterior plots for baseline estimation.

C Details on the estimation with Spanish data

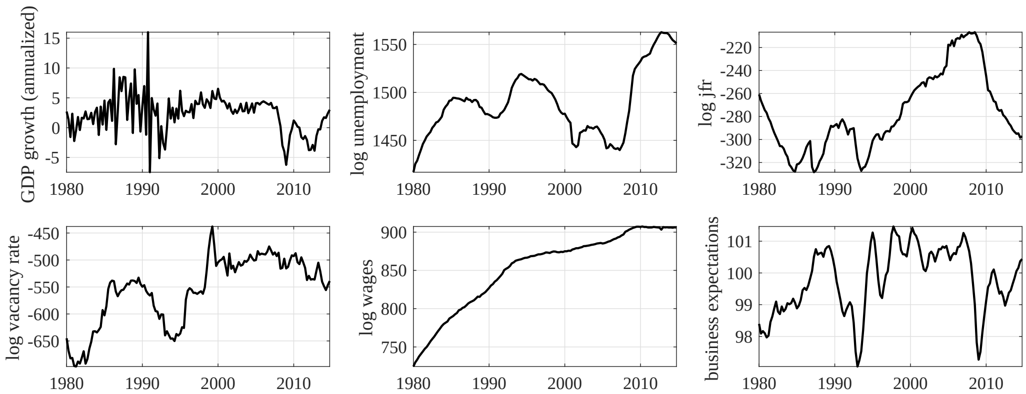

Figure 10: Spanish data used in Section 5.5.

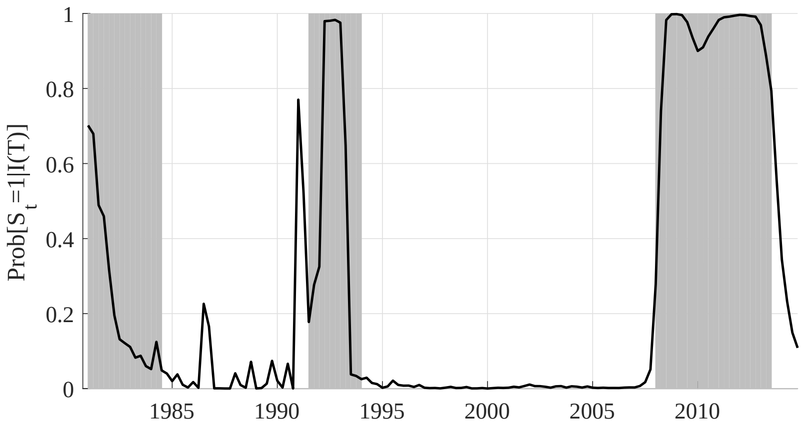

Figure 11: Spanish data: Probability of recession. Shaded regions mark ECRI recessions for Spain.

	Prior distribution		Posterior distribution			
	Mean	Std.	Mean	Median	90% HPD interval	Prob(< 0)
Markov probabilities						
p	0.85	0.10	0.9496	0.9542	[0.902; 0.983]	
q	0.70	0.10	0.8047	0.8105	[0.693; 0.897]	
Switching reform parameters						
α^M	0.00	10.00	-0.7475	-0.7275	[-1.921; 0.312]	0.870
α^V	0.00	10.00	-1.4647	-1.8793	[-3.634; 0.745]	0.752
b_1	0.00	10.00	0.0262	0.0258	[-1.669; 1.712]	
β^M	0.50	0.50	0.8090	0.8932	[0.342; 0.998]	
β^V	0.50	0.50	0.9544	0.9894	[0.768; 1.000]	
β^{MV}	0.50	0.50	0.8428	0.9238	[0.391; 0.998]	
Parameters of matching equation						
α	-0.30	0.30	-0.1980	-0.2015	[-0.386; 0.002]	
β	0.30	0.10	0.0247	0.0241	[-0.021; 0.074]	
ρ_1^m	0.00	2.00	1.2953	1.3114	[1.009; 1.546]	
ρ_2^m	0.00	0.50	-0.3361	-0.3405	[-0.564; -0.094]	
$\sigma^2_{\eta^M}$	9.70	2.81	8.9832	8.4070	[5.677; 14.008]	
$\sigma^2_{\epsilon^M}$	9.70	2.81	13.0371	12.6457	[8.241; 19.191]	
ψ_m	0	0.58	-0.0623	-0.0664	[-0.445; 0.336]	0.616
Parameters of vacancy equation						
γ	0.15	0.20	0.0356	0.0333	[-0.235; 0.312]	
κ	0.00	0.10	-0.0021	-0.0002	[-0.167; 0.160]	
ι	0.00	5.00	0.3862	0.4352	[-4.335; 5.062]	
b_0	0.00	1.00	-0.1891	-0.1470	[-1.356; 0.911]	
ρ_1^v	0.00	2.00	1.0566	1.0712	[0.768; 1.298]	
ρ_2^v	0.00	0.50	-0.1709	-0.1673	[-0.410; 0.059]	
$\sigma^2_{\epsilon^v}$	87.28	25.30	79.7645	76.0155	[50.960; 122.377]	
$\sigma^2_{\eta^v}$	87.28	25.30	88.8984	84.3449	[55.158; 137.894]	
ψ_v	0	0.58	0.1955	0.1849	[-0.305; 0.724]	0.266
Parameters of GDP growth equation						
c_0	4.00	2.00	3.4587	3.4556	[2.911; 4.002]	
c_1	-4.50	2.00	-4.5121	-4.4993	[-5.528; -3.562]	
$c_0 + c_1$			-1.0534	-1.0194	[-2.064; -0.167]	
c_{GR}	0	5.00	-3.2776	-3.2915	[-5.803; -0.670]	
ρ_1^y	0	0.50	-0.0908	-0.0908	[-0.250; 0.069]	
ρ_2^y	0	0.5	0.2982	0.2974	[0.135; 0.466]	
$\sigma^2_{\eta^y}$	4.31	1.25	5.6770	5.6321	[4.741; 6.718]	

Table 7: Prior and posterior distributions in the Spanish application.

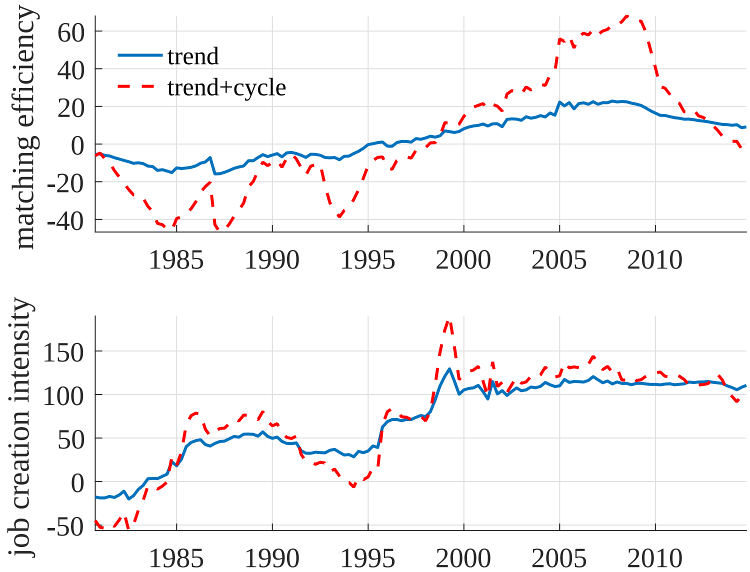

Figure 12: Spanish data: Trend cycle decomposition of matching efficiency and job creation intensity in model with trend cycle correlation.