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Identifying Asymmetric Effects of Labor Market Reforms

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Abstract

This paper investigates whether the effects of structural labor market reforms depend on the business cycle. Based on search and matching theory, we propose an unobserved components approach with Markov switching to distinguish the effects of structural reforms that increase the flexibility of the labor market in recession and expansion. Our results for Germany and Spain show that reforms have substantially weaker expansionary effects in the short-run when implemented in recessions. In consequence, reforms are unlikely to mitigate the impact of crisis in the short-run. From a policy perspective, these results highlight the costs of introducing reforms in recessions.

Zusammenfassung

Dieses Papier untersucht, ob die Effekte von Arbeitsmarktreformen, die die Flexibilität des Arbeitsmarktes erhöhen, mit dem Konjunkturzyklus zusammenhängen. Auf Basis der Such- und Matchingtheorie schlagen wir ein ökonometrisches Modell mit unbeobachtbaren Komponenten und Markov Switching vor, das die Effekte von Reformen in Rezession und Expansion trennt. Unsere Ergebnisse für Deutschland und Spanien zeigen, dass Reformen in Rezessionen kurz- und mittelfristig deutlich geringere positive Effekte auf den Arbeitsmarkt haben. Kurzfristig können die Effekte sogar negativ werden. Dies schränkt das Potential von Reformen kurzfristig die negativen Effekte von Rezessionen abzufedern deutlich ein. Unsere Ergebnisse verdeutlichen die Kosten, die damit verbunden sind Reformen in Rezessionen umzusetzen.

JEL classification: C32, E02, E32, J08

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

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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. The long-term gains of structural reforms that ease market regulation are well-established as argued by an extensive theoretical and empirical literature (see among others Gomes et al., 2013 and Bernal-Verdugo et al., 2012). However, much less is known about the short-run impact of such reforms (Cacciatore and Fiori, 2016). We ask whether structural reforms have systematically different short-run effects when implemented in good and bad states of the economy. In particular, do they entail short-term costs in recessions even though the long-term effects are positive? This question most obviously emerges from the 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.

We address reforms connected to labor supply and demand. As such, our approach measures reforms that speed up the matching process (e.g., training programs for the unemployed, shorter unemployment benefit receipt, better 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). Then, we allow for an asymmetry in the effects of these reforms that depends on whether the economy is in recession or expansion at the time when the reform is implemented. We provide quantitative evidence that labor market reforms indeed have substantially weaker short-term effects in times of crisis.

This paper contributes to a recent and growing literature that focuses on explaining well-established business cycle asymmetries in the labor market (McKay and Reis, 2008, Abbritti and Fahr, 2013, Ferraro, 2016, Kohlbrecher and Merkl, 2016, Pizzinelli and Zanetti, 2017). These theoretical labor market models may give rise to asymmetric effects of policy and hence reforms over the course of the economy. Abbritti and Fahr (2013) introduce a downward wage rigidity to generate asymmetries in the labor market. Then, the wage channel of structural reforms may be less effective in recessions when wage growth is low. Kohlbrecher and Merkl (2016) show that negative aggregate shocks move the hiring cut-off of firms by more in a recession. Then policy interventions that affect the present value of workers become time varying.[2] Michaillat (2012) argues that in case jobs are rationed in

[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), Launov and Wälde (2016), and Klinger and Weber (2016a) for a quantitative analysis of the labor market effects of these reforms. Dustmann et al. (2014) are more skeptical that the Hartz reforms alone explain the beneficial development of the German labor market after 2005.

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

recessions, matching frictions ? and thus also reductions in frictions ? are less influential in determining labor market outcomes. Michaillat (2014) shows that this mechanism triggers countercyclical government multipliers. 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.

In this paper, we contribute to the literature on state dependent reform effects with a new and general model-based method for the empirical investigation of these 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 that exploits the information on the labor market performance in different recessions and expansions that only long time series data provides and 2) our econometric model explicitly identifies components that comprise the reform effects. 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.[3] 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 and job creation to unemployment, vacancies, productivity, wages and surplus expectations, and isolate components not explained by these linkages. We account for the fact that matching also affects job creation. It is these components, i.e., matching efficiency and job creation intensity, which absorb unobserved reform effects. In addition to this theoretical anchoring, we take two further steps in order two obtain an economically interpretable measure of reform components. First, while the dynamics of our structural reform components are modeled as permanent, our unobserved components approach allows to control for transitory components potentially arising from business cycle influences, compare Davis et al. (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, age, 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. Further, we control for sectoral change and mismatch.

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 et al., 2012 and Banerji et al., 2017).[4] While this approach has the advantage of clear interpretability, obvious difficulties are connected to measurement, i.e., the strength of reforms, timing/anticipatory effects (these indicators are only available at annual frequency), and the restriction to the limited parts of the legislation that can be defined in a standardized way.[5] Blanchard and Wolfers (2000) further make

[3] A similar identification of persistent components is used to estimate potential output and output gaps (e.g., Morley et al., 2003), trend inflation (e.g., Morley et al., 2015), the natural rate of unemployment (e.g., Berger and Everaert, 2008, Sinclair, 2010) and hours (e.g., Vierke and Berger, 2017).

[4] 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.

[5] See Duval et al. (ming) and Ciminelli and Furceri (2017) for discussions and approaches on how to improve the measurement of these indicators along at least part of these dimensions.

the point that there is a potential endogenity in indicators that are constructed ex-post by researchers and institutions that observe the actual development of the labor market. In contrast, our concept aims at shedding light on asymmetric effects in terms of a big picture using very comprehensive measures of reforms. These measures are directly derived from search and matching labor theory and therefore have a clear interpretation in the model. The scaling and timing of the reform effects results as an endogenous outcome of our empirical model. In contrast, the size of changes in indexes must be defined based on a priori decisions and may be hard to interpret. Nevertheless, for reasons of transparency, we will compare our unobserved reform components to more directly measured indicators.

We apply our modeling approach to the case of Germany. Germany offers a unique environment for our analysis because, first, it has experienced large labor market restructuring in recent years that was implemented in both 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 a moderate 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 reform effects in the Spanish labor market even though the Spanish economy experienced a very different aggregate performance compared to Germany. In fact, in Spain the dampened reform effect in recessions 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 growing literature that studies time-varying structural reform effects in general equilibrium models. Cacciatore et al. (2016) use a DSGE model with labor market frictions to study product and labor market reforms. In line with our empirical result, they find that the business cycle conditions at the time of the reform matter for the short-run adjustment to the reform. Eggertsson et al. (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 to these theoretical studies 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 for Germany and Spain 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 embeds principles from search and matching theory and the literature on unobserved components and regime switching. We aim to measure effects of reforms that directly affect the performance of the labor market. Particularly, 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 of unemployed workers searching for a job and job vacancies.

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 v_t and unemployed workers u_t 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).

$$m_t = \mu u_t^{\alpha} v_t^{\beta} \tag{1}$$

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 μ and interpret these shifts as reforms of the matching process. Thereby, we control for cyclical movements, for the structure of the unemployment pool, the sectoral structure of the economy and mismatch.[6] We will interpret the shifts in matching efficiency as the outcome of structural labor market reforms.[7] Examples for reforms that affect matching efficiency μ are training programs for the unemployed, shorter unemployment benefit receipt and more intense counseling by the employment agency. Shorter unemployment benefit receipt affects matching efficiency via a higher search intensity of the unemployed.

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 the expected marginal cost of the vacancy is equal to the expected marginal value of filling the vacancy.

$$\frac{\chi}{m_t/v_t} = E_t J_{t+1} \tag{2}$$

[6] For example, we control for the share of long-term unemployed and unemployed workers with a migration background. For mismatch, we construct an index based on occupations. Details follow in Section 3.

[7] 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 and mismatch in a second step. Further, one may argue that matching efficiency or job creation intensity may gradually change due to technological advances. Given the gradual nature of these changes, however, they are not problematic for the switching reform effects in recessions.

The left hand side of this equation captures the expected costs given by the vacancy posting costs χ weighted with the inverse probability of filling the vacancy m_t/v_t, i.e., the expected vacancy duration. The right hand side denotes the expected discounted value of a filled vacancy. 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. The surplus of the match captures aggregate demand effects on the labor market. 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 χ, 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.

As in the standard search and matching model, we do not model endogenous job separations. However, our empirical approach controls for movements in separations via unemployment, i.e., we do not assume a constant separation rate.

We will compare the reforms that we identify 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 (a discussion will follow in Section 5).

2.2 The econometric model

In line with our theoretical considerations, Equation (3) 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 (compare Equation (1)), the intercept can be interpreted as (log) total factor productivity, i.e., matching efficiency.

$$M_t = \mu_t + \omega_t^M + \alpha U_t + \beta V_t + \zeta X_t + \alpha^M x_t^M \tag{3}$$

Matching efficiency is made time-varying by including a stochastic trend μ_t that evolves as a random walk according to Equation (4).

$$\mu_t = \mu_{t-1} + \epsilon_t^M \qquad \epsilon_t^M \sim N(0, \sigma^2_{\epsilon^M}) \tag{4}$$

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, sectoral change and mismatch are controlled for by a set of variables in X_t. 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 (5), it can flexibly capture various mean-reverting and cyclical patterns.

$$\omega_t^M = \rho_1^M \omega_{t-1}^M + \rho_2^M \omega_{t-2}^M + \eta_t^M \text{ with } |\lambda_1|, |\lambda_2| < 1 \quad \eta_t^M \sim N(0, \sigma_{\eta^M}^2) \tag{5}$$

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 unobserved components (UC) approach (e.g., Morley et al., 2003) and specify an AR(2).[9] Note that the permanent nature of reforms does not imply that reforms cannot be reversed, e.g., due to political changes. The random walk specification in (4) is very flexible and also captures negative reforms. Intuitively, the difference to the cyclical component is that the cycle is automatically reversed (i.e., is mean-reverting), whereas the permanent component could only revert due to new stochastic shocks. The x_t^M term captures potential asymmetries of changes in the permanent component of matching efficiency (we define this term in more detail below).

Besides matching frictions, reforms can affect incentives for job creation. Therefore, Equation (6) models a linearized job creation curve in the spirit of Equation (2), where the number of (log) vacancies V_t depends on (log) job creation intensity, (log) matches, and (log) expected profits of a match (details on the measurement follow in Section 3).

$$V_t = \chi_t + \omega_t^V + \gamma E_t J_{t+1} + b^M M_t + \alpha^V x_t^V \tag{6}$$

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

$$\chi_t = \chi_{t-1} + \epsilon_t^V \qquad \epsilon_t^V \sim N(0, \sigma_{\epsilon^V}^2) \tag{7}$$

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

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

Moreover, we allow a spillover of the matching equation via M_t. In line with search and matching theory, this follows the rationale that the expected gain from job creation also depends on the probability that the vacancy will be filled (that also depends on the level of unemployment). Thus, theoretically better matching can also foster job creation. The last term x_t^V comprises the effects of permanent changes in job creation intensity in recessions (details follow below).

Equation (9) 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

8 Krause et al. (2008) and Christiano et al. (2011) also estimate a time-varying cyclical matching efficiency in a DSGE context.

9 The AR(2) cycle allows us to consider a non-zero correlation of trend and cycle in a more general model specification.

regimes, one expansionary and one recessionary. The normalization is given by $c_1^Y < 0$.

$$\Delta Y_t = c_0^Y + c_1^Y Z_t + \omega_t^Y \tag{9}$$

$$\omega_t^Y = \rho_1^Y \omega_{t-1}^Y + \rho_2^Y \omega_{t-2}^Y + \eta_t^Y \quad \text{with} \quad |\lambda_1|, |\lambda_2| < 1 \quad \eta_t^Y \sim N(0, \sigma_{\eta^Y}^2) \tag{10}$$

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 respective equations (3) and (6). Particularly, we collect the reform effects of matching efficiency in recessions in variable x_t^M.

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

The autoregressive nature of x_t^M allows for variable persistence of recession-specific reform effects. We specify similar processes for the reform effects of job creation.

$$x_t^V = \beta^V x_{t-1}^V + Z_t(\chi_t - \chi_{t-1}) = \beta^V x_{t-1}^V + Z_t \epsilon_t^V \tag{12}$$

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. In case of a coefficient taking the value -1, the reform effect would be completely offset in the initial period. Note that as long as the x_t are stationary, the recession-specific effects disappear in the long run. This also rules out selection effects of reforms: e.g., one could argue that under the pressure of economic slump, the reforms being implemented are less effective or generally different compared to reforms in upswings. However, factually we analyze whether reforms with otherwise identical effects on matching efficiency (or job creation intensity) have dampened short-/medium-run effects in recessions. In a robustness check, we will also take into account that these effects can differ for positive and negative changes in the stochastic trends.

Identification of the unobserved permanent and transitory components can be treated along the lines of the UC literature. By means of Granger's Lemma (Granger and Morris, 1976), the reduced form of our econometric model is an VARIMA-process. In principle, it must provide enough information to uncover the structural parameters. For univariate correlated 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 provides a whole new set autocovariance equations of the reduced form (compare Weber, 2011, Klinger and Weber, 2016b), thus ensuring identification. In the robustness checks, we will estimate our econometric model on simulated data from a standard search and matching model in order to ensure that we do not identify spurious switching reform effects.

3 Data

We use data for Germany that begins in 1982Q1 and ends in 2013Q4. We choose Germany as our baseline case 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. For Germany, we can 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). This data has the advantage that it allows a clear definition of matches, i.e., transitions from unemployment to employment, and defines matches and the respective pool of unemployed searching workers in a consistent way. 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 (i.e., employed or unemployed) 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] This follows the search and matching model where only wages of new hires play an allocational role for job creation (Pissarides, 2009, Haefke et al., 2013). For vacancies, we use the official statistics of the Federal Employment Agency. Real GDP is provided in the national accounts. In order to proxy expected profits of a match, we estimate the vacancy equation with a set of relevant observable variables. We use business expectations, GDP and wage growth for wages of new hires.[11] The business climate as published by the ifo institute in Munich serves as a proxy business expectations.[12] 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. This ensures that the recession regime is not exclusively dominated by a quantitatively extraordinary event and are also appropriately defined.

We aim to interpret permanent changes in matching efficiency as reforms of the matching process. 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,

[10] We thank Thomas Rothe for providing this data. See also Giannelli et al. (2016).

[11] Estimations of the reduced form of the model revealed that GDP growth with one lag, contemporaneous business expectations, and wage growth with three lags have the highest explanatory power for vacancies. The coefficients for these variables are denoted by γ_1, γ_2, and γ_3 in the following.

[12] Before 1991, we use the index for the West German industry.

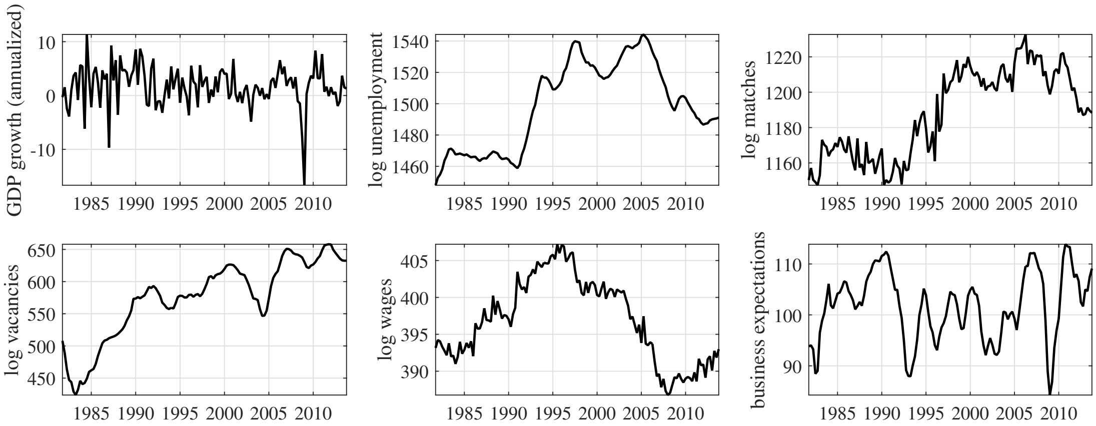

Figure 1: Data plot. See text for data sources.

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 (3); 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. 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.

Next, our measure of changes in the permanent component of matching efficiency may be affected by mismatch across segmented labor markets (Barnichon and Figura, 2015). To control for these influences, we add an index for mismatch across occupations as an additional control variable.[13] Further, we add the share of employees in the service sector as a control variable in the matching and the vacancy equation capturing sectoral change (source: German Quarterly National Accounts).

4 Estimation

We estimate the state-space form of the model in Equations (3), (4), (5), (6), (7), (8), (9), (10), (11), and (12) using a Bayesian framework. Our priors are independent across parameters. We discuss their choice in the following. Table 1 provides an overview.

- **Markov switching:** The Markov switching probabilities follow a Beta prior. At the prior mean, the average duration of a recession is 4 quarters and the average duration of an expansion is 5 quarters. At the prior mean, the economy spends about 44

[13] We use an index measuring the dispersion of relative unemployment rates across 37 occupations (Jackman et al., 2008). See Bauer (2013) for details on how we construct the data on unemployment across occupations based on administrative data on employment and unemployment spells.

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	1	0.1
β	Weight on vacancies	Normal	0.1	0.1
$\zeta's$	Parameter of control variables	Normal	0	5
β	Weight on vacancies	Normal	0.1	0.1
ρ_1^m	AR(1) of matching cycle	Normal	0.75	0.25
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_1	GDP coefficient	Normal	0.9	0.15
γ_2	Coefficient on business expectations	Normal	0	5
γ_3	Coefficient on wage growth	Normal	0	0.1
b_M	Spillover from matching trend	Normal	0	5
ρ_1^v	AR(1) of vacancy cycle	Normal	0.75	0.25
ρ_2^v	AR(2) of vacancy cycle	Normal	0	0.25
$\sigma^2_{\eta^v}$	Vacancy cycle shock variance	Inv. Gamma	9.76	2.97
$\sigma^2_{\epsilon^v}$	Vacancy trend shock variance	Inv. Gamma	9.76	2.97
	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 of parameters to be estimated. See text of a description.

percent 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, ρ_i, of the matching and vacancy equation, our prior is Normal with mean 0.75 for the first lag and mean 0 for the second lag. We specify the prior variance in both cases as $(0.25)^2$. For GDP growth, we use mean zero for both lags. For the variance parameters of the cycle components, we use an inverse Gamma prior. As in Berger et al. (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 $\sigma_{0,\chi} = 3$ 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 $\sigma_{0,\chi} = 3$.

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, 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 Table 3, 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 0.94. Our weight on vacancies is 0.11 at the posterior mean. This number is smaller compared to parameters typically found in studies on US data, but not uncommon for Germany. Further, the 90 percent interval of the posterior distribution captures values up to 0.25. Note also that constant returns to scale are not rejected according to our posterior estimates. Several of our control variables

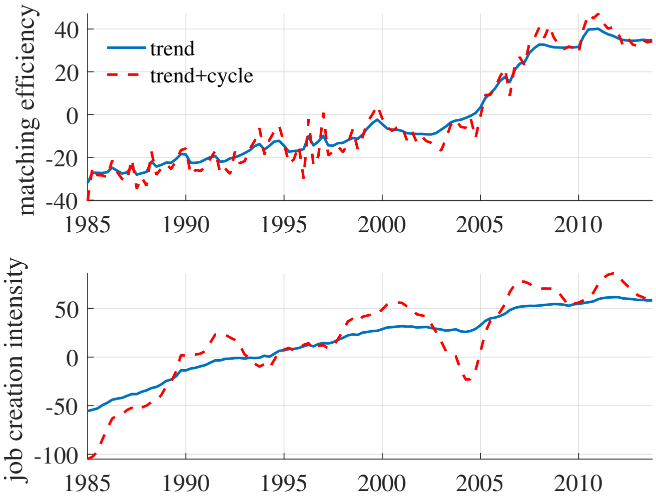

Figure 2: Trend cycle decomposition of matching efficiency and job creation intensity in baseline model (at posterior mean). Source: Own calculation.

affect the number of matches (e.g., the share of migrants and female unemployed workers decrease matching efficiency, the same holds for mismatch).

For vacancies, we find a positive effect of GDP growth on vacancies (posterior mean of $\gamma = 0.20$). Furthermore, surplus expectations have a positive effect on vacancy creation with a posterior mean of $\iota = 0.22$ (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 -0.25. The spillover b_0 from matches on job creation turns out to be unimportant.[14]

Year	Change in legislation
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 2: Important changes in German labor market legislation as identified by Bouis et al. (2012). Source: Bouis et al. (2012).

Figure 2 shows the trend and the cycle component of matching efficiency and job creation intensity that we obtain from our baseline estimation. The cycle moves around the trend component of both series. For vacancies, both AR lags of the cyclical components, ρ_1^v and ρ_2^v, are different from zero according to the 90 percent posterior interval in Table 3. For matches, the AR coefficients, ρ_1^m and ρ_2^m, also suggest some persistence of the cycle in matching efficiency. The decomposition clearly identifies long-run permanent effects and

[14] In order to control for a changing industry composition over time, we further controlled for the share of employees in the service sector in the matching and the vacancy equation. In our estimations, it turned out that the effect of this variable is virtually zero. Thus, we excluded it from our baseline model for efficiency reasons.

	Prior distribution		Posterior distribution			
	Mean	Std.	Mean	Median	90% HPD interval	Prob(<0)
Markov probabilities						
p	0.80	0.10	0.8062	0.8117	[0.681; 0.914]	
q	0.75	0.10	0.7267	0.7360	[0.577; 0.849]	
Switching reform parameters						
α^M	0.00	10.00	-1.0975	-1.0917	[-2.209; -0.022]	0.953
α^V	0.00	10.00	-0.4742	-0.4696	[-1.157; 0.203]	0.886
β^M	0.50	0.50	0.7884	0.8838	[0.264; 0.994]	
β^V	0.50	0.50	0.8955	0.9501	[0.585; 0.998]	
Parameters of matching equation						
α	1.00	0.10	0.9426	0.9432	[0.784; 1.102]	
β	0.10	0.10	0.1199	0.1193	[-0.021; 0.262]	
ζ_{female}	0	5.00	-1.6686	-1.6608	[-2.731; -0.625]	
$\zeta_{migrants}$	0	5.00	-0.6033	-0.6042	[-1.213; -0.014]	
ζ_{long}	0	5.00	0.2977	0.2973	[-0.015; 0.611]	
ζ_{old}	0	5.00	0.0959	0.0988	[-0.239; 0.425]	
ζ_{young}	0	5.00	0.5041	0.4968	[-0.080; 1.118]	
$\zeta_{mismatch}$	0	5.00	-0.0786	-0.0766	[-0.179; 0.020]	
ρ_1^m	0.75	0.25	0.4210	0.4310	[0.116; 0.703]	
ρ_2^m	0.00	0.25	0.1915	0.1976	[-0.039; 0.402]	
$\sigma^2_{\epsilon^M}$	27.12	8.25	23.4550	22.6052	[15.416; 34.491]	
$\sigma^2_{\eta^M}$	27.12	8.25	32.6147	32.0583	[22.153; 45.059]	
Parameters of vacancy equation						
γ_1	0.15	0.20	0.1959	0.1959	[0.042; 0.349]	
γ_2	0.00	5.00	-0.2523	-0.2517	[-0.556; 0.046]	
γ_3	0.00	5.00	0.2164	0.2171	[-0.143; 0.581]	
b_M	0.00	5.00	0.0026	0.0035	[-0.108; 0.108]	
ρ_1^v	0.75	0.20	1.2419	1.2412	[1.104; 1.385]	
ρ_2^v	0.00	0.25	-0.3245	-0.3245	[-0.470; -0.185]	
$\sigma^2_{\epsilon^v}$	9.76	2.97	9.6038	9.5124	[7.742; 11.824]	
$\sigma^2_{\eta^v}$	9.76	2.97	18.7409	18.5032	[13.831; 24.528]	
Parameters of GDP growth equation						
c_0	4.00	2.00	3.3925	3.4205	[2.485; 4.202]	
c_1	-4.50	2.00	-3.9282	-3.9113	[-4.837; -3.038]	
$c_0 + c_1$			-0.5356	-0.3872	[-1.536; -0.033]	
c_{GR}	0	5.00	-10.2881	-10.3546	[-13.101; -7.179]	
ρ_1^y	0	0.50	-0.0856	-0.0858	[-0.272; 0.103]	
ρ_2^y	0	0.25	0.0501	0.0504	[-0.135; 0.234]	
$\sigma^2_{\eta^y}$	4.34	1.32	6.8116	6.6906	[5.098; 8.877]	

Table 3: Prior and posterior distributions of parameters in baseline model. The posterior is obtained from 30,000 Gibbs draws (after discarding a burn-in of 20,000 draws). Source: Own calculation.

short-run business cycle movement in both series. In matching efficiency, there are several up- and downward movements of the permanent trend component. For example, matching efficiency improves around 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 2 summarizes structural labor market reforms in Germany following a broad classification by Bouis et al. (2012).5bg From 2003 to 2005 Germany implemented the largest labor market reforms known as the Hartz reforms. These reforms aimed at increasing the flexibility of the labor market, improving the matching process, and decreasing the unemployment benefit level and duration. Using our approach, we identify an increase in matching efficiency starting in these years. The trend in job creation is less volatile compared to the trend in matching efficiency. The major change in the trend occurs after the Hartz reforms in 2005 where we identify an improvement in job creation intensity.[15] Note that in general also negative effects are caught by our concept of measuring reforms, e.g., as unintended side effects of policy changes. An example is given by the worsening of German labor market institutions until the 1990s, which was accompanied by rising structural unemployment. We observe some periods of falling matching efficiency until 1990. We will provide a more detailed discussion of our reforms versus official reform indicators such as the OECD employment protection index in Section 5.3 for our preferred model specification.

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 3.4 percent, whereas it is -0.5 percent in a recession (at the posterior mean). In Figure 3, we show the posterior probability of being in a recession over time 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. Note, however, that our recession indicator is more informative than the recession periods only. In particular, the recession probability also informs the model about the depth of the recession. Thus, periods with low or negative GDP growth as in 2012 also receive some recessionary weight.

Based on the two regimes and the decomposition of permanent and cyclical component in matches and vacancies, we can finally analyze the reform effects in recessions. At the posterior mean, the additional reform effects in matching efficiency and job creation intensity in recessions are negative (see Table 3). For matching efficiency, the effect is quite substantial with a posterior mean of -1.09. Thus, initial positive reform effects in μ are completely offset in recessions and may even turn negative. According to the full posterior distribution, the probability of this parameter being smaller than zero is 95 percent. The left panel of Figure 4 illustrates the prior and posterior distributions for the switching reform parameter α_m. Compared to the very loose prior, the posterior distribution of α_m is much more centered and moved to the left of zero. Interestingly, there is some persistence in

[15] Germany experienced a period of low real wage growth, known as the wage moderation, starting previously to the reforms. Our approach controls for for wage growth, i.e., our permanent components are unaffected by the wage moderation.

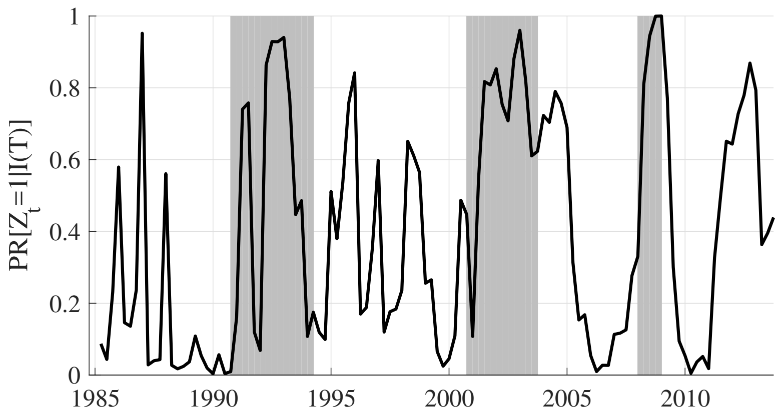

Figure 3: Mean posterior probability of a recession. Source: Own calculation. Shaded regions mark recessions in Germany according to the Economic Cycle Research Institute (ECRI).

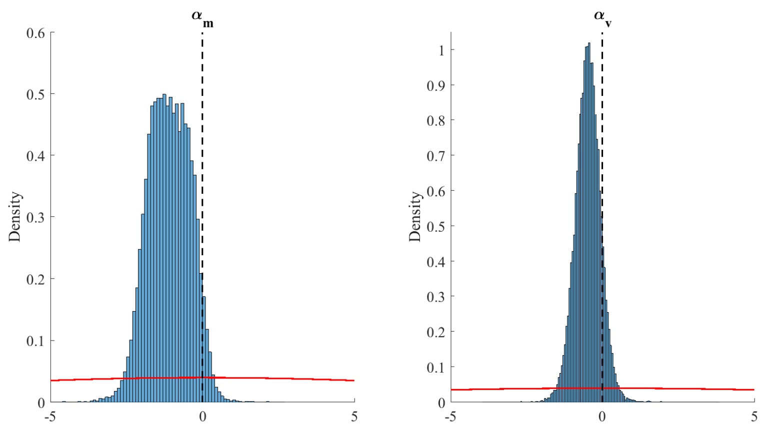

Figure 4: Prior (red line) and histogram of posterior distribution of regime switching reform parameters α_m and α_v. Source: Own calculation.

the negative reform effects of matching efficiency. The posterior mean of β^M is 0.79. This implies that the substantial dampening of reform effects if implemented in recessions lasts for several quarters.

In this baseline specification, we also find a dampening of reform effects of job creation in recessions with a posterior mean of -0.47. The probability of this parameter being negative is 89 percent (see also the right panel of Figure 4 for a comparison of prior and posterior distribution). Again, we identify considerable persistence with $\beta^V = 0.9$. However, as we will show in the next subsection the switching reform effect for job creation becomes less pronounced if we allow for a non-zero trend-cycle correlation of the unobserved components. In contrast, the negative reform effect of matching efficiency is a pure reform effect in recessions as the effect remains if we allow for a general non-zero correlation in matches.

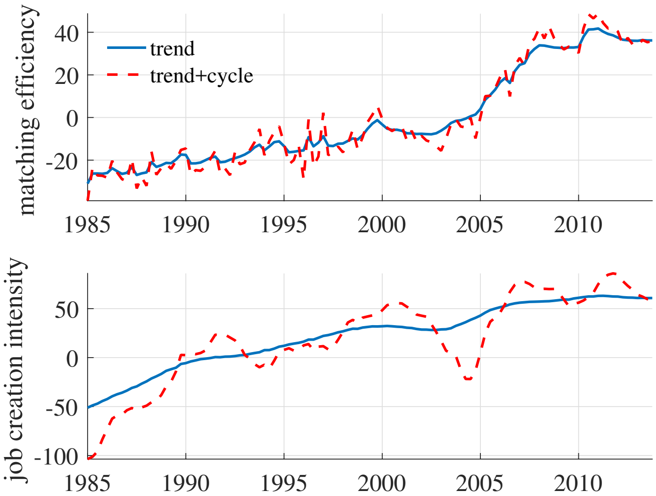

Figure 5: Trend cycle decomposition of matching efficiency and job creation intensity in model with trend cycle correlation (at posterior mean). Source: Own calculations.

5.2 Allowing for a 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 (11)-(12)). 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 $\alpha^m, \alpha^v < 0$. In the UC literature, it is a 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, 2017).[16]

Table 4 summarizes the posterior distributions of the estimated parameters in this model specification. Notably, for vacancies, we find a negative correlation ψ_v of trend and cycle with a posterior mean of -0.32. The trend cycle correlation of matching ψ_m 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. The non-zero trend cycle correlation has only small impacts on the estimated posterior distributions of the parameters for the exogenous variables. However, 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 additional negative reform effect in job creation α_v is moved towards zero reducing the posterior mean. Under a non-zero trend cycle correlation, the 90 percent posterior interval largely includes zero, i.e., there is no clear evidence that the parameter is smaller than zero. In contrast, for the additional reform effect in matching efficiency the effect remains more clear. The probability of this parameter being smaller than zero is still 95 percent. We illustrate a comparison of

[16] The estimation also follows Chan and Grant (2017) who apply a Griddy Gibbs to sample the correlations.

prior and posterior distribution of the switching reform parameters and the correlations in Figure 6.

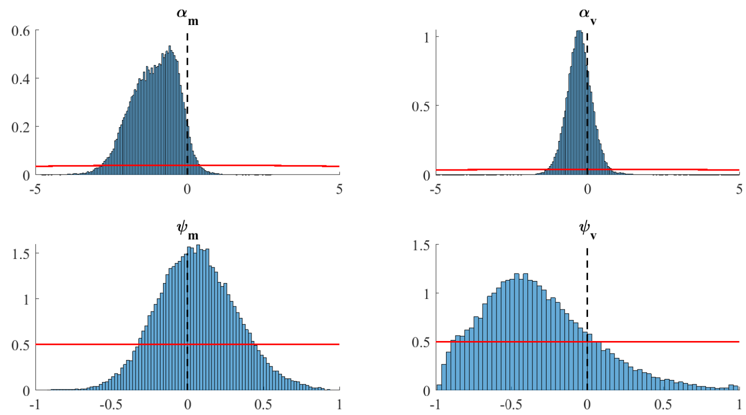

Figure 6: Prior (red line) and histogram of posterior distribution of regime switching reform parameters α_m and α_v and trend-cycle correlations ψ_m and ψ_v. Source: Own calculations.

5.3 Our reforms in comparison to official reform indicators

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 2). 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 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.

[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.

	Prior distribution		Posterior distribution			
	Mean	Std.	Mean	Median	90% HPD interval	Prob(<0)
Markov probabilities						
p	0.80	0.10	0.8059	0.8108	[0.683; 0.914]	
q	0.75	0.10	0.7258	0.7335	[0.578; 0.846]	
Switching reform parameters						
α^M	0.00	10.00	-1.0770	-1.0172	[-2.357; 0.010]	0.947
α^V	0.00	10.00	-0.2568	-0.2616	[-0.925; 0.427]	0.745
β^M	0.50	0.50	0.7966	0.8925	[0.246; 0.995]	
β^V	0.50	0.50	0.9409	0.9674	[0.790; 0.999]	
Parameters of matching equation						
α	1.00	0.10	0.9393	0.9389	[0.786; 1.096]	
β	0.10	0.10	0.1158	0.1166	[-0.026; 0.253]	
ζ_{female}	0	5.00	-1.6286	-1.6198	[-2.719; -0.560]	
$\zeta_{migrants}$	0	5.00	-0.6070	-0.6029	[-1.215; -0.025]	
ζ_{long}	0	5.00	0.2965	0.2964	[-0.021; 0.613]	
ζ_{old}	0	5.00	0.1031	0.1045	[-0.231; 0.434]	
ζ_{young}	0	5.00	0.5213	0.5080	[-0.054; 1.152]	
$\zeta_{mismatch}$	0	5.00	-0.0786	-0.0781	[-0.178; 0.021]	
ρ_1^m	0.75	0.25	0.4121	0.4194	[0.100; 0.699]	
ρ_2^m	0.00	0.25	0.1833	0.1903	[-0.056; 0.400]	
$\sigma^2_{\eta^M}$	27.12	8.25	32.7251	31.9058	[20.802; 47.558]	
$\sigma^2_{\epsilon^M}$	27.12	8.25	23.2198	22.2962	[15.278; 34.334]	
ψ_m	0	0.58	0.0620	0.0566	[-0.349; 0.500]	0.413
Parameters of vacancy equation						
γ	0.15	0.20	0.1887	0.1866	[0.043; 0.342]	
κ	0	5.00	-0.2471	-0.2469	[-0.528; 0.031]	
ι	0	5.00	0.2053	0.2073	[-0.164; 0.564]	
b_0	0	5.00	0.0160	0.0165	[-0.087; 0.121]	
ρ_1^v	0.75	0.25	1.2131	1.2155	[1.062; 1.355]	
ρ_2^v	0.00	0.25	-0.3264	-0.3299	[-0.461; -0.184]	
$\sigma^2_{\epsilon^v}$	9.14	1.16	10.0217	9.8481	[7.941; 12.616]	
$\sigma^2_{\eta^v}$	9.76	2.97	25.4938	23.8585	[14.104; 42.632]	
ψ_v	0	0.58	-0.3254	-0.3705	[-0.849; 0.348]	0.823
Parameters of GDP growth equation						
c_0	4.00	2.00	3.3759	3.3966	[2.491; 4.193]	
c_1	-4.50	2.00	-3.8966	-3.8936	[-4.814; -2.975]	
$c_0 + c_1$			-0.5207	-0.3801	[-1.460; -0.031]	
c_{GR}	0	5.00	-10.3269	-10.3870	[-13.142; -7.314]	
ρ_1^y	0.50	1.00	-0.0849	-0.0844	[-0.276; 0.104]	
ρ_2^y	0	0.50	0.0480	0.0484	[-0.138; 0.230]	
$\sigma^2_{\eta^y}$	4.34	1.32	6.8420	6.7306	[5.108; 8.912]	

Table 4: Prior and posterior distributions of model parameters in model with trend-cycle correlation. The posterior is obtained from 30,000 Gibbs draws (after discarding a burn-in of 20,000 draws). Source: Own calculations.

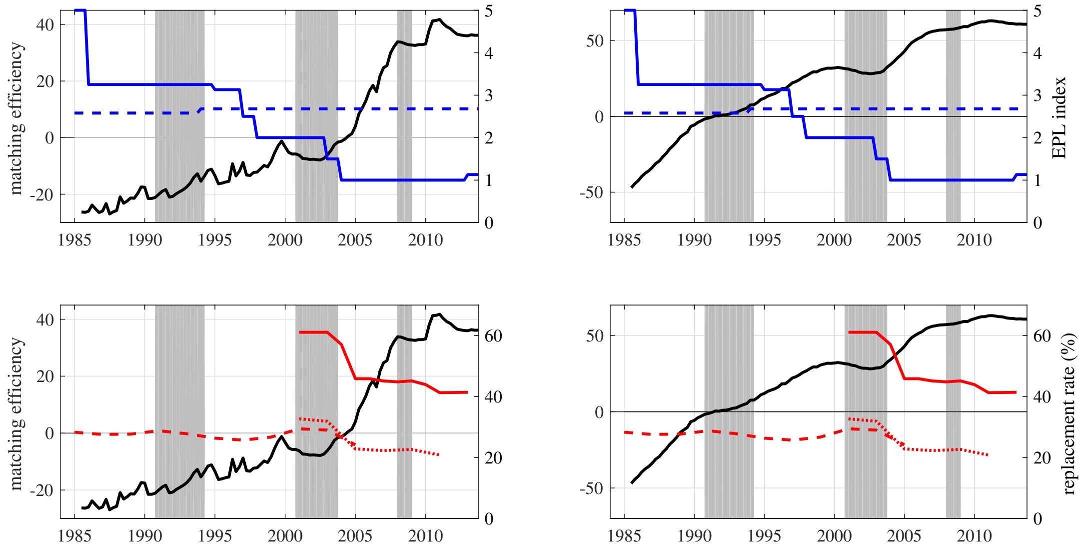

Figure 7: Comparison of trend components vis-à-vis the OECD employment protection indices (upper panels, blue) and the OECD replacement rate (lower panels, red) for Germany. EPL: The dashed line shows the index of regular employment, the solid line shows the index for temporary employment. Replacement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

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 do not capture asymmetric changes of the cycle in recessions. For example, Kohlbrecher and Merkl (2016) argue that US matching functions exhibit non-linearities over the business cycle. Our econometric model and methodology is flexible enough to account for switching cycle variances in addition to the switching GDP growth rate and our reform effects.[18] We indeed find that the cyclical variance of matches is slightly higher in recessions (32.8 to 31.9 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 ($\alpha_m = -1.20$ and $Prob(\alpha_m < 0) = 0.96$) and with correlation ($\alpha_m = -1.28$ and $Prob(\alpha_m < 0) = 0.96$).

[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.

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 (3) and (6) 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 -0.91 and of -0.43 for negative reforms. For vacancies, we find the opposite pattern with an effect of positive reforms of -0.30 and of negative reforms of -0.66 (in the model with trend-cycle correlations). However, we do not want to overinterpret theses findings given that estimation uncertainty is relatively large in these specifications.

5.4.3 A simulation-based check of the econometric model

One way to check the plausibility of the identification of reform asymmetries in our econometric model is to use simulated data. Here, we repeatedly simulate 500 quarterly observations from a standard linearized search and matching model in the spirit of Shimer (2005) and estimate our econometric model on this data. The model is perturbed by a productivity shock generating recessions and expansions, and persistent and transitory shocks to matching efficiency and vacancy posting costs.[19] We simulated the data from a linearized solution of the search and matching model. Our econometric model correctly uncovers the fact that no asymmetries are present. Across repeated simulations, the estimated posterior means of the switching reform parameters α_m and α_v are close to zero and the posterior intervals include zero in more than 90 percent of all repeated estimations. This strengthens our confidence that our measures of switching reform effects are not spurious.

5.5 An application to the Spanish labor market

We additionally apply our new econometric model framework to Spain. We aim to add a perspective on a country that experienced a severe worsening of the labor market conditions in response to 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.

[19] We approximate the random walk shocks with very persistent autoregressive shock with a persistence parameter of 0.9999 to keep a constant steady state. In the search and matching model from which we simulate we use a timing assumption for the matching function as in Equation (3). This timing is in line with the data.

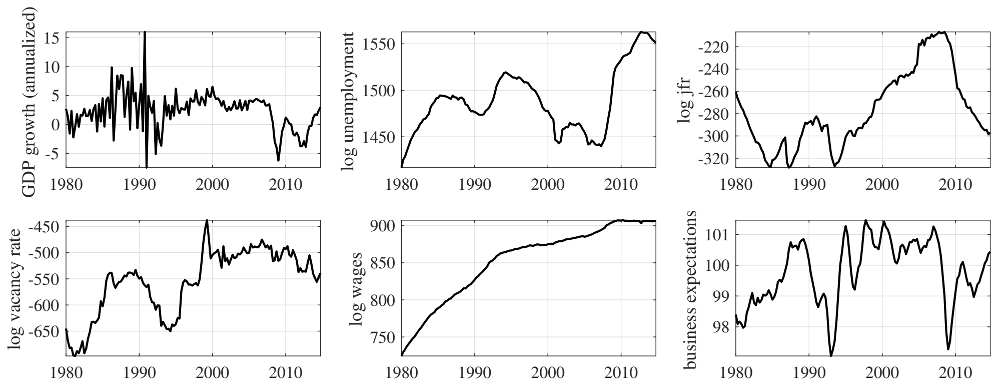

Figure 8: Spanish data. See text for data sources.

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).[20] For vacancies, we use the same series as Murtin and Robin (2016) and update the series with the latest Eurostat data. Wages are aggregate real wages per employee (from the Spanish Quarterly National Accounts). We measure business expectations with the confidence indicator for manufacturing as published by the OECD. Our Spanish series as illustrated in Figure 8 cover the period 1980Q1 to 2014Q4.

5.5.2 Results for Spain

Table 5 summarizes the most important parameters for the Spanish model.[21] 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 -0.20, although estimation uncertainty is large. For job creation intensity, the posterior mean is at -3.25. The probability of this parameter being smaller than zero is higher than 95 percent. Compared to the German case, these results indicate that the additional negative reform effect of job creation intensity in recessions is substantially larger in the Spanish labor market. In fact, the baseline effect of $+1$ is not only dampened but largely overcompensated by the strongly negative additional effect in recessions. This could be interpreted in the sense that in crises (potentially with interest rates near the zero lower bound) reforms increasing competitiveness are contractionary in the short-run (Eggertsson et al., 2014). 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.

[20] We update the series as provided by Barnichon and Garda (2016) until 2014Q4.
[21] Appendix C shows more detailed estimation results on the Spanish data.

	Prior distribution		Posterior distribution			
	Mean	Std.	Mean	Median	90% HPD interval	Prob(< 0)
Switching reform parameters						
α^M	0.00	10.00	-0.2026	0.0027	[-1.927; 0.948]	0.498
α^V	0.00	10.00	-3.2454	-3.2804	[-5.037; -1.601]	0.974
β^M	0.50	0.50	0.8628	0.9213	[0.500; 0.997]	
β^V	0.50	0.50	0.9858	0.9939	[0.946; 1.000]	
Trend cycle correlations						
ψ_m	0	0.58	-0.2708	-0.2710	[-0.807; 0.406]	0.718
ψ_v	0	0.58	0.5073	0.5455	[-0.057; 0.939]	0.073

Table 5: Prior and posterior distributions in the Spanish application. The posterior is obtained from 30,000 Gibbs draws (after discarding a burn-in of 20,000 draws). Source: Own calculations.

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. Within this theoretical setting, we differentiate structural reform components 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 protection 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 more than offset in the short-run. As a result, reforms affecting labor market mechanisms turn out to be less effective in recessions, in contrast to fiscal policy that directly stabilizes demand and that is often found to be more beneficial in the same situation (e.g., Auerbach and Gorodnichenko, 2012, Michaillat, 2014). 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 are 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. 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

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

with $Y_t = \begin{pmatrix} M_t \\ V_t \\ \Delta Y_t \end{pmatrix}$, $X_t = \begin{pmatrix} 1 \\ U_t \\ \Delta Y_{t-1} \\ \Delta W_t \\ E_t Y_{t+1} \end{pmatrix}$,

$\xi_t = (\mu_t^M, \chi_t^V, x_t^M, x_t^V, x_t^{MV}, \omega_t^M, \omega_t^V, \omega_t^Y, \omega_{t-1}^M, \omega_{t-1}^V, \omega_{t-1}^Y)'$, $\psi_t = \begin{pmatrix} \epsilon_t^M \\ \epsilon_t^V \\ \eta_t^M \\ \eta_t^V \\ \eta_t^Y \end{pmatrix}$;

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

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

$$
A_0 = \begin{bmatrix} c^M & \alpha & \beta & \beta & \beta \\ c^V & 0 & \gamma_1 & \gamma_2 & \gamma_3 \\ c_0^Y & 0 & 0 & 0 & 0 \end{bmatrix}, A_1 = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ c_1^Y & 0 & 0 & 0 & 0 \end{bmatrix},
$$

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

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

B Estimation diagnostics

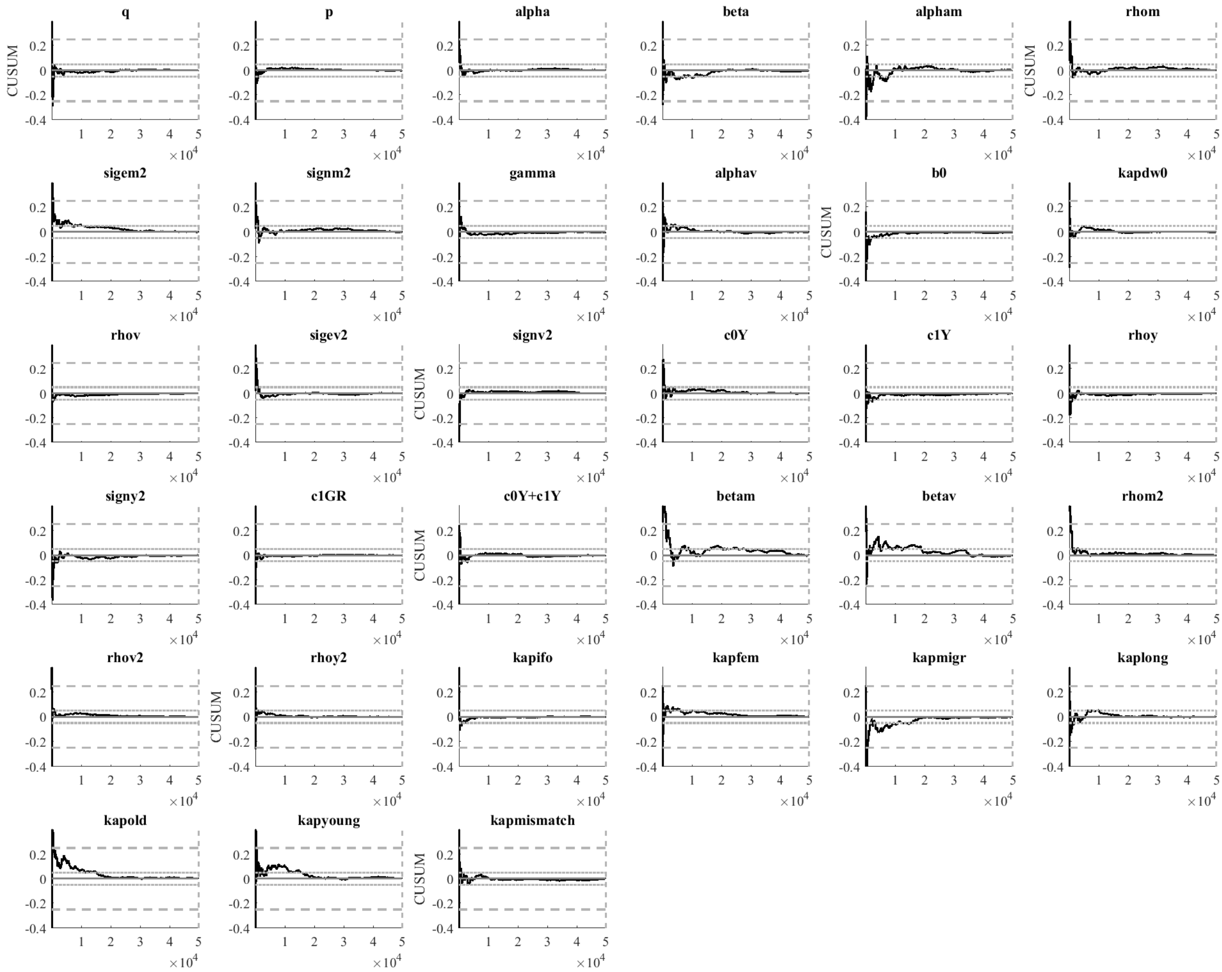

Figure 9: CUSUM convergence plots for baseline estimation. Source: Own calculations.

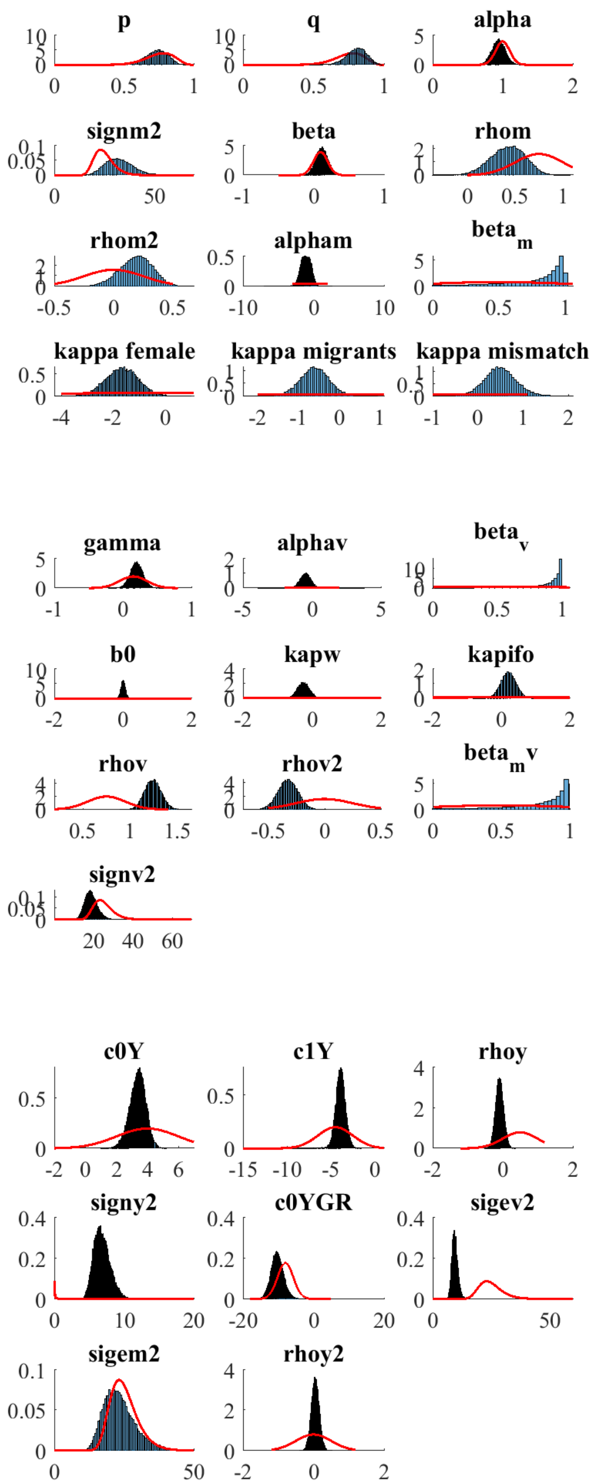

Figure 10: Prior and posterior plots for baseline estimation. Source: Own calculations.

C Details on the estimation for Spain

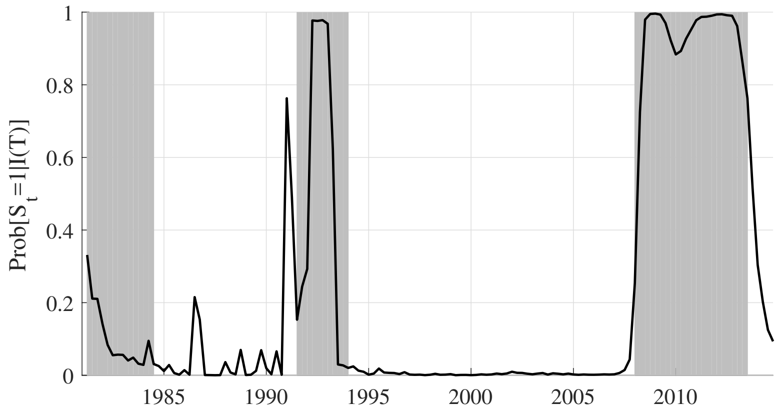

Figure 11: Spanish data: Probability of recession. Shaded regions mark ECRI recessions for Spain.

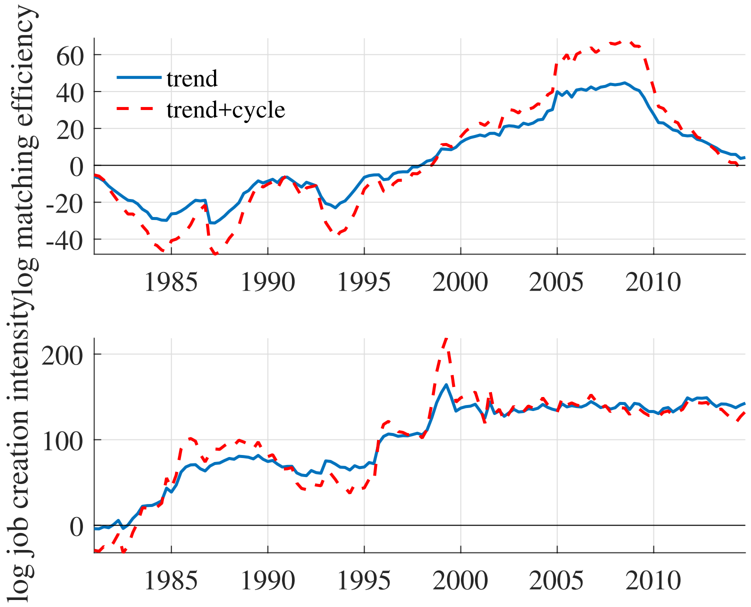

Figure 12: Spanish data: Trend cycle decomposition of matching efficiency and job creation intensity in model with trend cycle correlation.

	Prior distribution		Posterior distribution			
	Mean	Std.	Mean	Median	90% HPD interval	Prob(<0)
Markov probabilities						
p	0.80	0.10	0.9503	0.9543	[0.904; 0.983]	
q	0.75	0.10	0.8034	0.8099	[0.688; 0.899]	
Switching reform parameters						
α^M	0.00	10.00	-0.2026	0.0027	[-1.927; 0.948]	0.498
α^V	0.00	10.00	-3.2454	-3.2804	[-5.037; -1.601]	0.974
β^M	0.50	0.50	0.8628	0.9213	[0.500; 0.997]	
β^V	0.50	0.50	0.9858	0.9939	[0.946; 1.000]	
Parameters of matching equation						
α	0.00	0.10	-0.1307	-0.1306	[-0.260; 0.001]	
β	0.10	0.10	0.0246	0.0238	[-0.022; 0.074]	
ρ_1^m	0.75	0.25	0.9405	1.0436	[0.351; 1.404]	
ρ_2^m	0.00	0.25	-0.2137	-0.2228	[-0.445; 0.052]	
$\sigma^2_{\eta^M}$	9.70	2.81	11.5606	10.9735	[6.715; 18.101]	
$\sigma^2_{\epsilon^M}$	9.70	2.81	14.8053	11.4566	[6.020; 30.907]	
ψ_m	0	0.58	-0.2708	-0.2710	[-0.807; 0.406]	0.718
Parameters of vacancy equation						
γ_1	0.15	0.20	-0.0338	-0.0282	[-0.351; 0.267]	
γ_2	0.00	0.25	-0.1139	-0.1016	[-0.600; 0.333]	
γ_3	0.00	5.00	0.2898	0.3131	[-3.759; 4.326]	
b_M	0.00	1.00	0.1872	0.1901	[-0.221; 0.604]	
ρ_1^v	0.75	0.25	0.9655	0.9699	[0.764; 1.155]	
ρ_2^v	0.00	0.25	-0.0671	-0.0611	[-0.271; 0.120]	
$\sigma^2_{\epsilon^v}$	87.28	25.30	67.6421	64.7087	[43.129; 102.385]	
$\sigma^2_{\eta^v}$	87.28	25.30	78.1717	74.8325	[51.958; 115.295]	
ψ_v	0	0.58	0.5073	0.5455	[-0.057; 0.939]	0.073
Parameters of GDP growth equation						
c_0	4.00	2.00	3.3930	3.4019	[2.854; 3.919]	
c_1	-4.50	2.00	-4.6090	-4.5969	[-5.652; -3.610]	
c_0+c_1			-1.2160	-1.2023	[-2.232; -0.245]	
c_{GR}	0	5.00	-3.0953	-3.1108	[-5.652; -0.428]	
ρ_1^y	0	0.50	-0.0793	-0.0802	[-0.234; 0.083]	
ρ_2^y	0	0.5	0.3033	0.3018	[0.139; 0.467]	
$\sigma^2_{\eta^y}$	4.31	1.25	5.6662	5.6224	[4.742; 6.750]	

Table 6: Prior and posterior distributions in the Spanish application. The posterior is obtained from 30,000 Gibbs draws (after discarding a burn-in of 20,000 draws). Source: Own calculations.

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