# Identifying Asymmetric Effects of Labor Market Reforms[†]

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**Abstract**

This paper investigates whether and how the effects of structural labor market reforms depend on the business cycle. We propose an unobserved components time series 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. From a policy perspective, this result calls for a careful monitoring of the business cycle when implementing labor market reforms and 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 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 as argued by an extensive theoretical and empirical literature,[2] the short-run impact remains unclear. 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, 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 empir-

[1] These reforms have become known as the Hartz reforms. 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).

ical 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.

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 several 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 implemented 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

[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.

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.

Our paper is related to Cacciatore, Duval, Fiori, and Ghironi (2016). These authors use a theoretical 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.

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.

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

This term is made time-varying by including a stochastic trend $\mu_t$ 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 labour 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 $X_t$. Moreover, the shock $\omega_t^M$ 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) or Klinger and Weber (2016a).[6] 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 $\Delta Y_t$, wage growth $w_t$ and expected future profits $E_t Y_{t+1}$. Here, we label the intercept $\chi_t$ "job creation intensity". In a standard search and matching model, this term represents shifts of the job creation curve (e.g., triggered by changes of vacancy posting costs or the wage bargaining).

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

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 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 $\Delta Y_t$ 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

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

recessionary. The normalization is given by $c_1^Y < 0$.

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

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

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 effeciency 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[7] 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.

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

# 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 dataset 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.[8] 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.[9] 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.

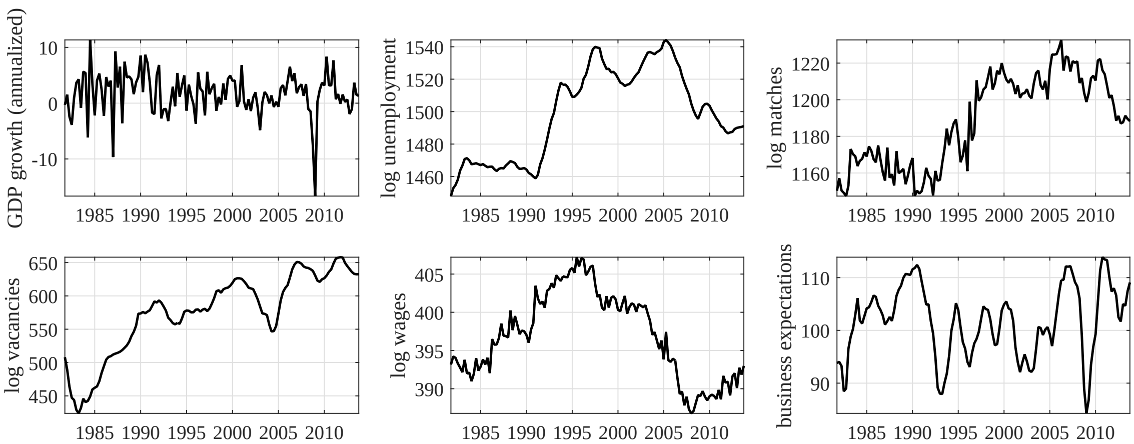


**Figure 1:** Data plot.

The Great Recession is extraordinary with regard to the steepness of the drop in GDP (see

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

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.

- **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, $\rho_i$, 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 $\sigma_0^2$ and the prior strength $\nu_0$ 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, 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

| 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* | | | | |
| $\alpha^M$ | Matching reform effect in recessions | Normal | 0 | 10 |
| $\alpha^V$ | Vacancy reform effect in recessions | Normal | 0 | 10 |
| $b_1$ | Matching reform effect in recessions for vacancies | Normal | 0 | 10 |
| $\beta^M$ | Persistence of matching reforms | Normal | 0.5 | 0.5 |
| $\beta^V$ | Persistence of vacancy reforms | Normal | 0.5 | 0.5 |
| $\beta^{MV}$ | Persistence of matching reforms for vacancies | Normal | 0.5 | 0.5 |
| *Parameters of matching equation* | | | | |
| $\alpha$ | Weight on unemployment | Normal | 0.9 | 0.15 |
| $\beta$ | Weight on vacancies | Normal | 0.3 | 0.2 |
| $\rho_1^m$ | AR(1) of matching cycle | Normal | 0 | 0.5 |
| $\rho_2^m$ | 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* | | | | |
| $\gamma$ | GDP coefficient | Normal | 0.9 | 0.15 |
| $\iota$ | Coefficient on business expectations | Normal | 0 | 5 |
| $\kappa$ | Coefficient on wage growth | Normal | 0 | 0.1 |
| $b_0$ | Spillover from matching trend | Normal | 0 | 5 |
| $\rho_1^v$ | AR(1) of vacancy cycle | Normal | 0 | 0.5 |
| $\rho_2^v$ | 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 |
| $\rho_1^y$ | AR(1) of GDP cycle | Normal | 0 | 0.5 |
| $\rho_2^y$ | 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.

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.

# 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.[10] 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 $\kappa$ 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 labor market reforms in Germany as classified by Bouis et al. (2012). From 2003 to 2005 Germany implemented the largest labor market reforms 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.

[10] 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* | | | | | | |
| $\alpha^M$ | 0.00 | 10.00 | $-0.9459$ | $-0.9659$ | [-1.824; -0.000] | 0.950 |
| $\alpha^V$ | 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 |
| $\beta^M$ | 0.50 | 0.50 | 0.7701 | 0.8510 | [ 0.253; 0.997] | |
| $\beta^V$ | 0.50 | 0.50 | 0.9008 | 0.9528 | [ 0.620; 0.999] | |
| $\beta^{MV}$ | 0.50 | 0.50 | 0.7991 | 0.8972 | [ 0.261; 0.999] | |
| *Parameters of matching equation* | | | | | | |
| $\alpha$ | 0.90 | 0.15 | 0.6752 | 0.6831 | [ 0.407; 0.924] | |
| $\beta$ | 0.30 | 0.20 | 0.1175 | 0.1187 | [-0.068; 0.298] | |
| $\rho_1^m$ | 0.00 | 0.50 | 0.5821 | 0.5846 | [ 0.402; 0.760] | |
| $\rho_2^m$ | 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* | | | | | | |
| $\gamma$ | 0.15 | 0.20 | 0.2191 | 0.2183 | [ 0.049; 0.394] | |
| $\kappa$ | 0.00 | 0.10 | $-0.0361$ | $-0.0374$ | [-0.197; 0.125] | |
| $\iota$ | 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] | |
| $\rho_1^v$ | 0.00 | 0.50 | 1.2752 | 1.2735 | [ 1.110; 1.446] | |
| $\rho_2^v$ | 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] | |
| $\rho_1^y$ | 0 | 0.50 | $-0.0980$ | $-0.0988$ | [-0.287; 0.093] | |
| $\rho_2^y$ | 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.

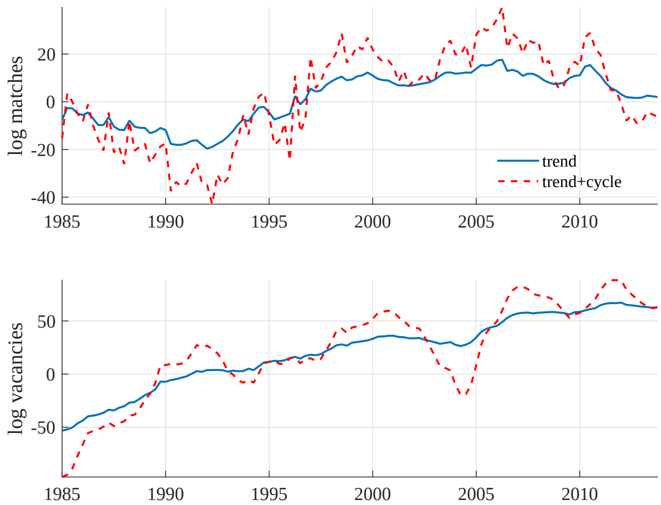


**Figure 2:** Trend cycle decomposition of matches and vacancies in baseline model.

| 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<br>and replacement rate |

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

.

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 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

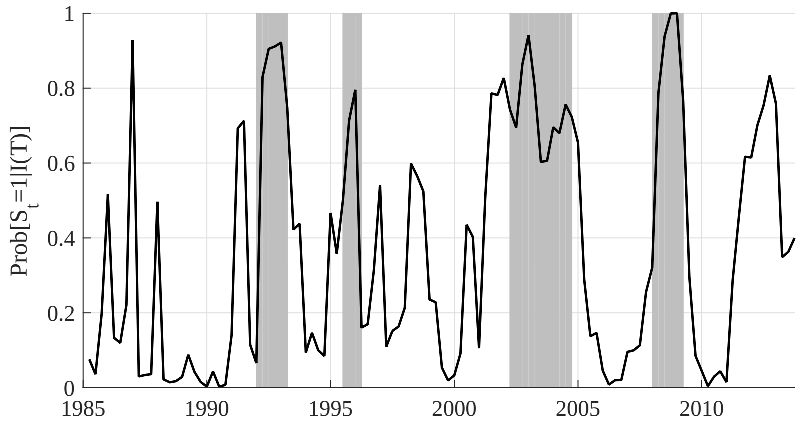


**Figure 3:** Probability of recession. Shaded regions mark recessions in Germany according to the Economic Cycle Research Institute (ECRI).

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 $\alpha_m$ 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 $\beta^M$ 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.

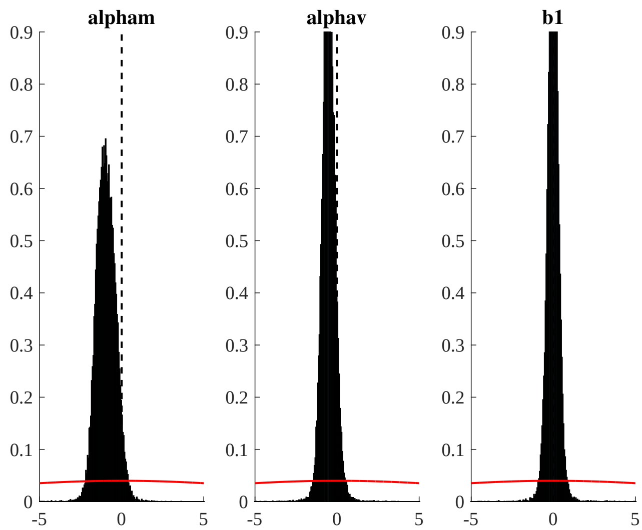


**Figure 4:** Prior (red) and posterior distribution of regime switching reform parameters.

## 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 $\psi_m$ and vacancies $\psi_v$ (Chan and Grant, 2016).[11] 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 $\nu_0$ 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 $\sigma_{0,\chi} = 3$.[12] 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.

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

[12] 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* | | | | | | |
| $\alpha^M$ | 0.00 | 10.00 | $-0.8628$ | $-0.8480$ | [-1.818; 0.043] | 0.941 |
| $\alpha^V$ | 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 |
| $\beta^M$ | 0.50 | 0.50 | 0.8194 | 0.9062 | [ 0.345; 0.998] | |
| $\beta^V$ | 0.50 | 0.50 | 0.9238 | 0.9603 | [ 0.727; 0.998] | |
| $\beta^{MV}$ | 0.50 | 0.50 | 0.8423 | 0.9289 | [ 0.376; 0.999] | |
| *Parameters of matching equation* | | | | | | |
| $\alpha$ | 0.90 | 0.15 | 0.6265 | 0.6514 | [ 0.216; 0.909] | |
| $\beta$ | 0.30 | 0.20 | 0.0931 | 0.1048 | [-0.156; 0.293] | |
| $\rho_1^m$ | 0.00 | 0.50 | 0.5635 | 0.5765 | [ 0.329; 0.764] | |
| $\rho_2^m$ | 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] | |
| $\psi_m$ | 0 | 0.58 | 0.0594 | 0.0519 | [-0.338; 0.484] | 0.421 |
| *Parameters of vacancy equation* | | | | | | |
| $\gamma$ | 0.15 | 0.20 | 0.1730 | 0.1698 | [ 0.031; 0.322] | |
| $\kappa$ | 0 | 0.10 | $-0.0367$ | $-0.0367$ | [-0.191; 0.121] | |
| $\iota$ | 0 | 5.00 | 0.1673 | 0.1659 | [-0.214; 0.545] | |
| $b_0$ | 0 | 5.00 | 0.0428 | 0.0456 | [-0.293; 0.350] | |
| $\rho_1^v$ | 0 | 1.00 | 1.2573 | 1.2579 | [ 1.114; 1.418] | |
| $\rho_2^v$ | 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] | |
| $\psi_v$ | 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] | |
| $\rho_1^y$ | 0.50 | 1.00 | $-0.0647$ | $-0.0649$ | [-0.253; 0.126] | |
| $\rho_2^y$ | 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.

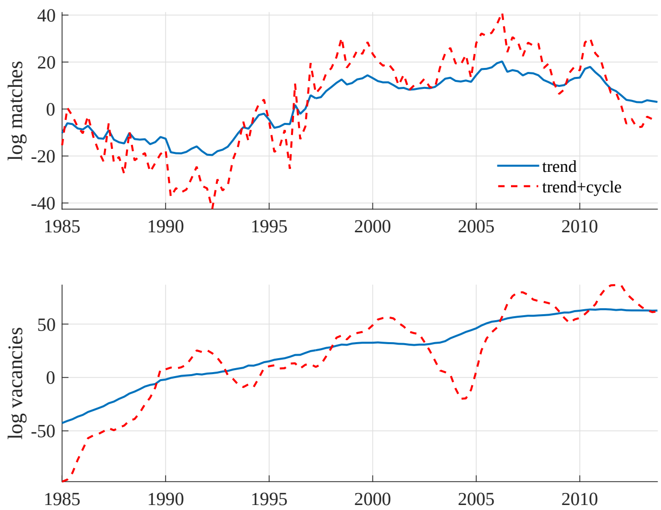


**Figure 5:** Trend cycle decomposition of matches and vacancies in model with trend cycle correlation.

### 5.3 Controlling for changes in the decomposition of the unemployment pool

We interpret permanent changes in matching efficiency as reforms in 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. To control for such effects, we add 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 immigration background, and the share of female unemployed.[13]

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 become 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.[14]

### 5.4 Further robustness checks

[TO BE CONTINUED.]

## 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.

[13] 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.

[14] 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* | | | | | |
| $\alpha^M$ | 0.00 | 10.00 | $-1.0136$ | $-1.0225$ | [-1.886; -0.127] | 0.966 |
| $\alpha^V$ | 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 |
| $\beta^M$ | 0.50 | 0.50 | 0.8131 | 0.9011 | [ 0.322; 0.998] | |
| $\beta^V$ | 0.50 | 0.50 | 0.9261 | 0.9593 | [ 0.736; 0.998] | |
| $\beta^{MV}$ | 0.50 | 0.50 | 0.8267 | 0.9166 | [ 0.331; 0.999] | |
| | *Parameters of matching equation* | | | | | |
| $\alpha$ | 0.90 | 0.15 | 0.7075 | 0.7117 | [ 0.431; 0.965] | |
| $\beta$ | 0.30 | 0.20 | 0.3571 | 0.3543 | [ 0.162; 0.567] | |
| $\rho_1^m$ | 0.00 | 0.50 | 0.6353 | 0.6345 | [ 0.439; 0.839] | |
| $\rho_2^m$ | 0.00 | 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] | |
| $\psi_m$ | 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.

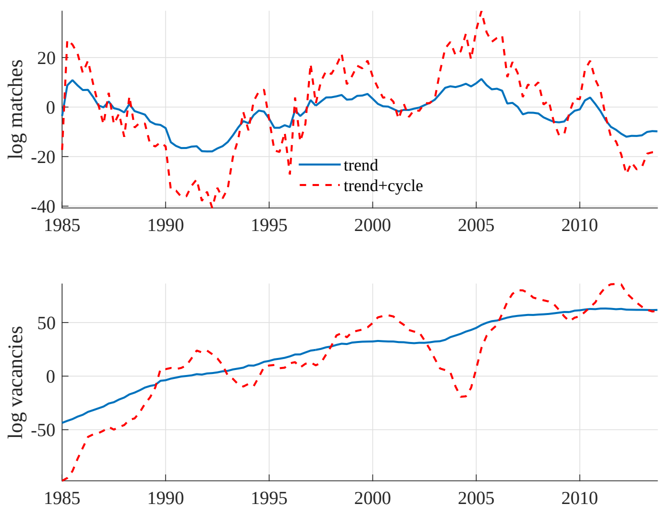


**Figure 6:** Trend cycle decomposition of matches and vacancies when controlling for changes in the unemployment pool.

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 this 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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