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Mismatch unemployment

Evidence from Germany, 2000-2010

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Mismatch Unemployment: Evidence from Germany, 2000-2010

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Contents

Abstract 4

Zusammenfassung 4

1 Introduction 5

2 Defining Mismatch 6

3 Measuring Mismatch 8
3.1 Mismatch Index 8
3.2 Counterfactual Unemployment 9

4 Data Description and Empirical Strategy 9
4.1 Data 9
4.2 Matching Function Estimation 11

5 Results 12
5.1 Mismatch Indices 12
5.2 Counterfactuals 14

6 Robustness 16
6.1 Heterogeneity 16
6.2 Underreporting of Job Vacancies 17

7 Reallocation Processes 17

8 Conclusion 20

References 21

A Appendix: Data 24

B Appendix: Estimation 28

C Appendix: Additional Results 32

Abstract

This paper provides detailed empirical evidence on the scope of mismatch in Germany in the past decade, using a comprehensive administrative data set that allows for disaggregation at the levels of industry, occupation and region. The findings suggest that regional mismatch did not play an important role in explaining movements of aggregate unemployment. Across industries and occupations, there was a decrease in mismatch unemployment from over 5 percent to below 4 percent (on the highest disaggregation level), whereas the share of mismatch unemployment (across industries and occupations) within total unemployment remains almost unchanged between 2000 and 2010. Concluding, mismatch unemployment fell but the Hartz reforms did not reduce mismatch overproportionally compared with search frictions, in line with the fact that reallocation across occupations appears not to have been eased.

Zusammenfassung

In diesem Papier wird das Ausmaß der Mismatch-Arbeitslosigkeit mittels eines umfangreichen administrativen Datensatzes, durch welchen Industrien, Berufe und Regionen in unterschiedlichen Disaggregationsstufen analysiert werden können, quantifiziert. Regionaler Mismatch spielt eine untergeordnete Rolle für die Entwicklung der Arbeitslosenquote in Deutschland. Auf Industrie- und Berufsebene kann festgestellt werden, dass die Mismatch-Arbeitslosenquote von über 5% auf unter 4% fällt (auf der detailliertesten Disaggregationsstufe), aber der Anteil der Mismatch-Arbeitslosigkeit an der aggregierten Arbeitslosenquote in der Beobachtungsperiode von 2000 bis 2010 nahezu unverändert bleibt. Zusammenfassend lässt sich sagen, dass die Mismatch-Arbeitslosigkeit zwar gefallen ist, aber nicht überproportional verglichen mit den Suchfriktionen, da die Reformen u.a. berufliche Reallokationsprozesse nicht beschleunigen konnten.

JEL classification: E24, J6

Keywords: mismatch, unemployment, reallocation, panel data

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1 Introduction

After the launch of the Hartz reforms[1] in Germany the unemployment rate dropped from an all-time high of 14 percent to its current 7 percent, which is the lowest value in 20 years. In many recent papers, economists have attributed this decline to the Hartz reforms (Fahr/Sunde, 2009; Klinger/Rothe, 2012; Hertweck/Sigrist, 2012). Specifically, as matching efficiency has improved, there has been a sharp inward shift of the Beveridge curve. However, what factors were responsible for the improvement of matching efficiency remains an open question. On the one hand, the improvement in matching efficiency may result from reduced labor market frictions. Indeed, the reforms reduced coordination failures, enhanced search intensity and led to more flexibile forms of employment. On the other hand matching efficiency is related to structural factors such as geographical and skill mismatch. The reforms involved a comprehensive set of active labor market measures that might have eased labor market reallocation. Thus, the improvement in matching efficiency may derive from a better fit between the unemployed and vacant positions across regions, industries or occupations (i.e. reduced geographical or skill mismatch).

In this paper, both factors are analyzed to examine their relative contribution to changes in the unemployment rate. First, I provide empirical evidence on the scope of mismatch unemployment in a central European country. I follow the approach of Şahin et al. (2012) and use a sample of German administrative data (with information on the employment status, job search status and unemployment benefit receipt of workers) and vacancy data of the German Federal Employment Agency to compute mismatch indices. These indices describe the behavior of mismatch unemployment in different industries, occupations and regions by capturing the number "of hires lost because of misallocation" (Şahin et al., 2012: p. 10). Because the indices tend to be sensitive to the level of disaggregation, I studied industries and occupations ranging from 3-digit to 1-digit classifications as well as regions at the district and state level. Besides I interacted the 1- and 2-digit occupational codes and the regions on state level. Across industries and occupations, the indices fell until 2005 and followed a hump-shape from 2005 onwards. Across regions, the indices followed a smooth downward trend. When disaggregated into occupation-regions, the indices resembled the ones for occupations. Thus, in Germany, regional mismatch appears to be less important than industrial or occupational mismatch for explaining movements in aggregate unemployment.

Second, a special feature of the research approach is used to contextualize the findings within the movement of the aggregate unemployment rate. A counterfactual unemployment rate which measures the extent of unemployment conditional on search frictions, is computed. Because the gap between the actual (observable) and the counterfactual unemployment rate determines mismatch unemployment, this approach allows me to clarify the extent to which the Hartz reforms reduced labor market frictions and mismatch. The mismatch unemployment rate for industries at the highest level of disaggregation began at 5.2 percent at the beginning of the decade and fell to 3.7 percent toward the end of the decade. At the highest occupational level mismatch unemployment decreased from 5.4 percent to 4.3 percent. Across industries, the percentage of mismatch unemployment in aggregate unemployment decreased from at most 45 percent in the beginning of the decade to 40 percent toward the end of the decade. Across occupations, the percentage of mismatch unemployment in aggregate unemployment remained relatively stable at 45 percent (at most). Compared to the US during the recession, where mismatch accounted for at most 30 percent of the rise in the unemployment rate, mismatch appears to play a more important role in Germany. However, there is no evidence that the Hartz reforms improved the mismatch component overproportionally

[1] In Germany, the Hartz reforms were implemented in three waves from 2003 to 2005. The reforms aimed at reducing unemployment (duration) by accelerating labor market flows and rested on three core elements: first, to improve the efficiency and effectiveness of the placement processes and of the active labor market instruments; second, to set incentives for the unemployed by reorganizing passive labor market policy; and third to increase labor demand by expanding labor market deregulation. For a review, see Jacobi/Kluve (2007).

compared to search frictions, as there was no fundamental change in the composition of aggregate unemployment. To further examine these results, I take an in-depth look at reallocation processes during the decade. The findings show that the switching of workers across occupations accounts for up to 40 percent of the aggregate job finding rate but that there was only a slight increase over time and no change in the time trend after the Hartz reforms. Thus mismatch remained high and relatively constant over time.

The remainder of this paper is organized as follows: Section 2 provides a review of the literature relevant to the present research. In Section 3, I describe the model set-up adopted from Şahin et al. (2012). Section 4 presents the data. The results are illustrated in Section 5 and checked for robustness in Section 6. In Section 7, I discuss the impact of reallocation processes. Section 8 concludes the paper.

2 Defining Mismatch

Mismatch occurs whenever the "qualifications or skills of workers, individually or in the aggregate, are different from the qualifications or skills required for the jobs" (Sattinger, 2012: p. 1). This paper addresses the quantitative side of mismatch.[2] In other words, the focus is on the discrepancy between the number of workers and the number of jobs available in a given market due to incongruence between the skills of workers and the demands of the jobs. To be more precise, quantitative mismatch arises when there is a large number of workers and a small number of vacancies (or vice versa) in a given market. Mismatch results from structural shifts in demand and/or supply that lead to long lasting imbalances in the aggregate economy. To adapt to these shifts and restore balance, firms must restructure (e.g. by using internal labor markets) and workers must change their qualification (occupation or industry, e.g. through training) or relocate across regions. Quantitative mismatch leads to long-run unemployment and hampers firm growth, because workers and jobs would not form a match even if search frictions or imperfect information did not exist. In this sense, mismatch is a structural phenomenon, that is complementary to search frictions and causes the Beveridge curve to shift (Petrongolo/Pissarides, 2001).

Mismatch thus defined was investigated in the 1980's and 1990's to explain the high and persistent unemployment rates in Europe (for a comprehensive study see Padoa-Schioppa (1991)). Abraham (1991) explains why mismatch unemployment was the suspected cause of growing unemployment across Europe. She makes three points. First, the two oil price shocks and technological progress hampered adjustment processes in all labor markets. Second, reallocation processes decelerated, in line with observations of decreased turnover and decreased worker mobility. Third, and most clearly, the Beveridge curve had shifted outward across Europe. The same observations can be made for the US labor market following the Great Recession. As Şahin et al. (2012) note, three observations support the mismatch unemployment hypothesis: First, the construction and manufacturing sector was hit the hardest of any sector during the financial crises yet did not recover. Second, regional mobility was dampened by decreased housing prices (also called house-lock-hypothesis). Third, the Beveridge curve shifted outward.

In the literature of the 1980's and 1990's mismatch unemployment was mainly measured using two approaches. The first approach was to examine measures of dispersion in unemployment rates across sectors, e.g. Jackman/Layard/Savouri (1991). The second approach was to link aggregate

[2] Another strand of the literature concentrates on mismatch at the individual level. In this situation, a qualitative mismatch arises because highly skilled worker match with low-skilled jobs in the short run. Such mismatch thus arises from search frictions or imperfect information. The consequences of qualitative mismatch include wage loss and output reduction. For a thorough review on the two types of mismatch, see Sattinger (2012).

demand and supply to the distribution of vacancies and unemployment at a disaggregated level (Jackman/Roper, 1987) or. Both approaches have been revived in recent work. Similarly to the approach of Jackman/Layard/Savouri (1991), Barnichon/Figura (2011) analyze the dispersion of labor market tightness across labor markets. The job finding rate is decomposed into an overall component, a worker-specific component, a labor-market-specific component and a term representing mismatch. This mismatch term is measured by the dispersion of labor market tightness across labor markets. While related to the older dispersion measures, the decomposition has the advantage of being "directly related to aggregate matching efficiency and thus to equilibrium unemployment" (Barnichon/Figura, 2011: p. 11). Another unique feature of this paper is the consideration of non-separated labor markets. From a quantitative perspective, Barnichon/Figura (2011) show that dispersion explains at least 40 percent of the decline in matching efficiency in the US. However, Barnichon/Figura (2011) focus on the cyclicality of the job finding rate, not on mismatch unemployment. In this paper, I therefore follow the approach of Şahin et al. (2012) in which mismatch unemployment is quantified using indices based on Jackman/Roper (1987). Şahin et al. (2012) thus compare "the actual allocation of unemployed workers across sectors to an ideal allocation" (Şahin et al., 2012, p. 3). The major contribution of Şahin et al. (2012) is the translation of the old indices to a dynamic multi-sectoral search and matching framework. At the same time, this approach captures greater heterogeneity between the sectors by weighting labor market tightness with market-specific matching efficiencies. Quantitatively Şahin et al. (2012)'s findings show that, in the US labor market, mismatch unemployment constitutes up to 30 percent of aggregate unemployment and that it is more pronounced for skills (occupations and education) than for regions. For the British labor market the effects are equal in magnitude (approximately 30 percent) and also most pronounced for skills (Patterson et al., 2013). Herz/van Rens (2011) link the theoretical and empirical literature, developing a model that explicitly addresses the causes of mismatch based on analyses of adjustment costs (i.e. worker and job mobility costs, wage bargaining costs and matching heterogeneities) across labor markets. With estimates for at least three of the four sources, the authors examine the differences in dispersion of the job finding rate. They find no evidence of mismatch unemployment.

In addition to the aforementioned empirical literature, there are also sophisticated theoretical models. Such models capture the sources of mismatch by assuming either non-market-clearing wages (e.g., Lagos (2000)) or constraints on the mobility of workers or vacancies (e.g., Sattinger (2010) or Alvarez/Shimer (2011)). With respect to the business cycle, Carrillo-Tudela/Visschers (2013) propose an approach that examines the interaction between search and reallocation frictions. Shimer (2007) shows that constrained mobility combined with distinct markets has desirable properties in replicating the stylized labor market facts on business cycle frequencies.[3] Parallel to the business cycle perspective, also medium- to long-run perspectives are also present in the literature (e.g. Birchenall (2011)). What these models have in common is that they do not measure mismatch quantitatively but examine in depth the mechanisms (i.e., reallocation processes) and causes (i.e., adjustment costs) underlying mismatch by modeling the behaviour of workers and firms.

[3] In a similar paper by Mortensen (2009), the assumption of constrained worker mobility by Shimer (2007) is dropped. The author shows that equilibrium unemployment arises not only by constraining worker mobility but also through coordination frictions, as the reallocation of workers takes time.

3 Measuring Mismatch

3.1 Mismatch Index

To quantify mismatch unemployment in Germany, I apply the approach of Şahin et al. (2012). The index measures hires that are lost due to a mismatch by comparing the actual (observable) number hires h to an ideal number of hires h^*. The number of hires (actual and ideal) depends on the distribution of unemployed workers and job vacancies over a defined range of distinct labor markets. In each distinct market, hires are governed by a Cobb-Douglas type matching function with constant returns to scale. In the simplest version, the only heterogeneity between the markets is matching efficiency, which captures the amount of search frictions within markets:

$$h_{it} = \Phi_t \phi_i m(u_i, v_i) = \Phi_t \phi_i v_{it}^{\alpha} u_{it}^{1-\alpha} \tag{1}$$

The number of hires h_{it} in submarket i is linked to the number of unemployed workers u_{it} and vacancies v_{it}. The matching efficiency consists of a time-varying component Φ_t and a market-specific component ϕ_i.[4] The matching elasticity α is common across markets. Summarizing across all markets yields the aggregate number of hires:

$$h_t = \Phi_t v_t^{\alpha} u_t^{1-\alpha} \left[\sum_{i=1}^{I} \phi_i \left(\frac{v_{it}}{v_t}\right)^{\alpha} \left(\frac{u_{it}}{u_t}\right)^{1-\alpha} \right] \tag{2}$$

The number hires in the economy depends on the aggregate stocks of unemployment (u_t) and vacancies (v_t) as well as on the vacancy and unemployment shares $(\frac{u_{it}}{u_t}, \frac{v_{it}}{v_t})$. These shares reflect the allocation of unemployment and vacancies across sectors. Thus, to obtain the ideal number of hires, one must first solve for an ideal allocation of unemployment and vacancies. Under this approach, the ideal allocation is a planner's solution. The planner can move unemployed persons costlessly leading to an equalization of matching efficiency weighted market-specific labor market tightness (v-u-ratio) across markets. This ensures "that the planner allocates more job seekers to labor markets with more vacancies and higher matching efficiency" (Şahin et al., 2012, p. 9). More precisely, the ideal allocation fulfills this condition:

$$\phi_i m_i(\frac{v_i}{u_i^*}) = \phi_j m_j(\frac{v_j}{u_j^*}) = ... = \phi_I m_I(\frac{v_I}{u_I^*}) \tag{3}$$

The ideal number of hires follows directly from the social planner's solution with respect to the ideal allocation of workers across sectors:

$$h_t^* = \Phi_t \bar{\phi}_t v_t^{\alpha} u_t^{1-\alpha} \quad \text{where} \quad \bar{\phi}_t = \left[\sum_{i=1}^{I} \phi_i^{\frac{1}{\alpha}} \left(\frac{v_{it}}{v_t}\right) \right]^{\alpha} \tag{4}$$

Search frictions exist in both distributions (the ideal and the actual) but are captured by ϕ_i. By comparing the actual number of hires (h_t) to the optimal number of hires (h_t^*), a mismatch index M_t of is derived[5]:

$$M_t = 1 - \frac{h_t}{h_t^*} = 1 - \sum_{i=1}^{I} \left(\frac{\phi_i}{\bar{\phi}_t}\right) \left(\frac{v_{it}}{v_t}\right)^{\alpha} \left(\frac{u_{it}}{u_t}\right)^{1-\alpha} \tag{5}$$

4 In Sahin et al. (2012), the market-specific component is allowed to vary over time (i.e. ϕ_{it}) because of possible shifts in the specific component during the financial crisis. Nevertheless, in the empirical section, variations over time are shown to be small. Because the introduction of the Hartz reforms is of central interest to the present study, I prove (in Appendix B, Table 7, 8 and 9) that market-specific components do not vary dramatically before and after the reform for occupations, industries and regions.

5 In the absence of heterogeneity the index becomes $M_t = 1 - \sum_{i=1}^{I} \left(\frac{v_{it}}{v_t}\right)^{\alpha} \left(\frac{u_{it}}{u_t}\right)^{1-\alpha}$ which corresponds to the Jackman-Roper-index (Jackman/Roper, 1987).

The mismatch index describes the number of matches that are not realized due to mismatch, or more specifically, misallocation. The index increases with the number of markets considered markets and equals zero when there is no mismatch and one when there is only mismatch. It. The underlying rationale is as follows: in the upper limit of disaggregation, there is only one vacancy or one unemployed worker in a given market, whereas in the lower limit, there is only one market such as in the standard search and matching model. If the number of vacancies and the number of unemployed workers increase in ways that do not affect the vacancy and unemployment shares across sectors, the mismatch index remains the same, i.e., it is invariant to aggregate shocks.

3.2 Counterfactual Unemployment

By defining the job finding rate as the ratio of the number of hires to the number of unemployed, I can calculate an actual and an ideal (or counterfactual) job finding rate. The actual job finding rate f_t is computed as follows:

$$f_t = \frac{h_t}{u_t} = (1 - M_t)\,\bar{\phi}_t \Phi_t \left(\frac{v_t}{u_t}\right)^{\alpha} \tag{6}$$

The counterfactual job finding rate f_t^* is:

$$f_t^* = \bar{\phi}_t \Phi_t \left(\frac{v_t}{u_t^*}\right)^{\alpha} = f_t \cdot \frac{1}{1 - M_t} \left(\frac{u_t}{u_t^*}\right)^{\alpha} \tag{7}$$

The counterfactual job finding rate measures the job finding rate in the absence of mismatch. The higher the degree of mismatch and the closer the actual unemployment rate is to the counterfactual, the higher is the counterfactual job finding rate. Given an initial value for u_t^*, a sequence of counterfactual unemployment rates with the standard law of motion (s_t denotes the separation rate) can be calculated as follows:

$$u_{t+1}^* = s_t + (1 - s_t - f_t^*)\, u_t^* \tag{8}$$

The higher the counterfactual job finding rate is, the lower the counterfactual unemployment rate in the next period, which leads to a future increase in the counterfactual job finding rate. Thus, mismatch not only has a direct effect, measurable by the index, but also an indirect effect, which arises from the difference between counterfactual and actual unemployment, i.e. reduced mismatch relaxes labor market conditions with a time delay. By measuring unemployment in the absence of mismatch, the counterfactual unemployment rate demonstartes the impact of mismatch unemployment when it is compared to the actual unemployment rate.

4 Data Description and Empirical Strategy

4.1 Data

Data on unemployment, job findings and separations were obtained from a random 5 percent sample of the Integrated Employment Biographies (IEB), an administrative data set that tracks the German work force from 1980 onwards. the sample was restricted to observations of employment and job search spells between December 1999 and December 2010 and contains 3 million people with approximately 50 million spells. Workers were considered to be employed if they had a job subject to social insurance contributions and unemployed if they were registered as unemployed and searching for a job.[6] Based on this sample I computed the job finding rates (f_t), separation rates

[6] See Dorner et al. (2010) for a detailed data description and Appendix A for more details on sample selection and descriptive statistics.

(s_t) and the stocks of the unemployed (u_t) at monthly intervals. Job finding rates (and separation rates) are calculated as transitions between unemployment and employment (and vice versa) by a cutoff date.[7] In terms of vacancies, I employed a time series from the Federal Employment Agency that indicates registered vacancies (v_t). Because data on registered vacancies often suffer from underreporting, data from the German Job Vacancy Survey (Kettner et al., 2011) published by the Institute for Employment Research, were also analyzed to check for robustness in Section 6.2.

The main challenge associated to the approach of Şahin et al. (2012) concerns the requirement of highly disaggregated data. The IEB provides industry, occupation and region classification schemes that vary in degree of detail. In this research, labor markets are assumed to be non-overlapping which enables me to divide the sample into subsamples according to the classification schemes. This assumption is subsequently relaxed via clustering the labor markets by both occupations and regions. From these subsamples panel data consisting of time series for unemployment (u_{it}), job finding rates (f_{it}) and separation rates (s_{it}) for the submarkets within a given disaggregation level are generated. These subsamples are then merged with disaggregated vacancy data (v_{it}) from the Federal Employment Agency. Owing to the subsampling, I neglect flows of individuals who switched both, status and submarket simultanously.

In terms of industries, the IEB issues the Classification of Economic Activities 1993, 2003 and 2008, which implies that the industry classification information is subject to changes during the observation period. The partly overlapping nature of the different classifications, enabled the construction of a consistent time series for one of the possible schemes. I followed the approach of Eberle et al. (2011) and used correspondence tables to harmonize the classification in 1993 and 2003 with the base of 2008[8]. Because industry information is exclusively available for employment spells, the information was transcribed to spells of unemployment based on the assumption that unemployed workers would search for jobs in the same sectors their preceding job was in. The Classification of Economic Activities 2008 contains 21 industry sections (1-digit), 88 industry divisions (2-digit) and 272 industry groups (3-digit)[9]. For occupations, I used the official German classification scheme (KldB88), which includes 300 different occupations. This scheme is available at a 1-digit (6 occupation sectors), 2-digit (33 occupation sections) and 3-digit (99 occupation groups) level of accuracy[10]. At the regional level I take the 16 federal states of Germany and 28 administrative districts in West Germany[11]. I also interacted the occupation classification at the 1 and 2-digit level with the 16 federal states (referred to as occupation-regions with 96 sector-states and 528 section-states).

Finally, I refined the data by excluding submarkets for which I did not have enough information, interpolated the series on job finding and separation rates to handle missing values and seasonally adjusted all time series using Census X-12 Arima.[12]

[7] Time aggregation bias in the registered data is approximately 10 percent according to Nordmeier (2012). In addition, I do not incorporate employment to employment flows and flows into and out of non-participation.

[8] The harmonization leads to a loss in quality. Using this assignment mechanism, I captured only 95 percent of the true industry classification from the 2003-2008 assignment and 90 percent from 1993-2008 assignment. This and the transcription of information from employment to unemployment spells led to a larger error in the first half of the decade. In response, I corrected the number of unemployed in each segment before 2005. For details on the correction mechanism see Appendix A.

[9] see https://www.destatis.de/DE/Methoden/Klassifikationen/GueterWirtschaftklassifikationen/Content75/ KlassifikationWZ08.html for details.

[10] see http://statistik.arbeitsagentur.de/Navigation/Statistik/Grundlagen/Klassifikation-der-Berufe/KldB1975-1992/KldB1975-1992-Nav.html for details

[11] These districts are administrative regions, that contain several counties within in a federal state and are constant over time in West Germany (without Berlin) but not in East Germany.

[12] In detail, I exclude markets with fewer than 100 (of 133 possible) observations in time or fewer than 5 transitions (which is equivalent to 100 transitions after projection) on average in and out of unemployment. In other words, if a market has fewer than 5 transitions on average from unemployment to employment but many more transitions from employment to unemployment, this submarket is included because it indicates of a changing allocation across markets. This change in the allocation may be induced by skill-biased technological change or other sources of mismatch. Only in cases where the numbers of transitions from unemployment to employment and from employment to unemployment are very low, were those submarkets excluded for their minor role.

4.2 Matching Function Estimation

Based on the data sets described in the previous section, I derived the time series on v_t and u_t (thus also on labor market tightness $\theta_t = \frac{v_t}{u_t}$) and on job-finding f_t and separation rates s_t (for disaggregated levels u_{it}, v_{it}, θ_{it}, f_{it} and s_{it}). Still missing are the parameters for the matching elasticity α and the market-specific matching efficiency ϕ_i. I derived the parameter α via an OLS estimation of a matching function with aggregate data. My preferred specification is a reduced form matching function that includes a linear (t) and a quadratic (t^2) time trend as well as a dummy (d_{05}) for the period after the Hartz reforms:

$$ln(f_t) = \Phi_0 + \alpha ln(\theta_{t-1}) + t + t^2 + d_{05} + \epsilon_t \tag{9}$$

To account for endogeneity, I included the labor market tightness (θ) with one time lag. The coefficient for α is 0.25, significant at the 1%-level. These results corroborate the observations of Burda/Wyplosz (1994), Gross (1997) and Kohlbrecher/Merkl/Nordmeier (2013). For details on the specification, see Appendix B.

To obtain the market-specific component ϕ_i of the matching efficiency, panel regressions of matching functions were estimated as follows:

$$ln(f_{it}) = \Phi_0 + ln(\phi_i) + d_t + \alpha ln(\theta_{it-1}) + \eta_{it} \tag{10}$$

The group-effects of this panel regression are the logarithmic market-specific components $ln(\phi_i)$. To assess these components accurately, monthly time dummies d_t were included to capture the impact of the Hartz reforms on all markets and seasonal/cyclical variation in the matching efficiency. The use of dummies rather than a specification with trends trends (as in the aggregate estimation) enables greater flexibility. Estimates of group-effects under a specification with trends tend to be very similar to those under a specification with dummies. Based on an F-test of the time dummies the null hypothesis that the effects equal zero is rejected across all panels. Under this specification I ran random effects models[13], which assume that the market-specific component is uncorrelated with lagged labor market tightness. In theory this is reasonable given that movements in labor market tightness are associated with movements along the Beveridge curve, whereas changes in matching efficiency causes the curve to shift. Based on empirical evidence (Klinger/Weber, 2012; Lubik, 2011), shifts of the Beveridge curve and movements along the curve can occur at the same time. In such a case, a fixed effects model would be appropriate. However, the estimates of group-effects do not differ in a fixed effects model. The Hartz reforms could have changed the specific characteristics of a market. Because this would imply a time-varying market-specific component that does not meet the assumption of equation (1), I checked wether the ϕ-estimates differ before and after the reform. Table 7, 8 and 9 (see Appendix B) verify that no strong differences exist across industries, occupations and occupation-regions (at the lowest disaggregation level)[14].

The estimated matching efficiencies in Table 1 for industry sections, for example, show similar patterns to those in Şahin et al. (2012). The highest matching efficiency is observed in the Construction, Agriculture and Mining industries in Germany and in the Mining, Arts and Construction industries in the US. The lowest matching efficiencies are observed in the Household Activities, Electricity/Gas and Financial/Insurance industries in Germany and in the Information, Manufacturing (Durables) and Finance industries in the US. The dispersion of market-specific matching efficiency rises in the degree of disaggregation, implying that the heterogeneity of the markets rises. The estimates of the α-coefficient, i.e., matching elasticities, tend to be smaller at almost every disaggregation level compared with aggregate level (see Table 1). Again, this could have resulted

[13] A simple Hausman test favors a random effects model for nearly all of the panels.
[14] This also holds at more disaggregated levels.

Table 1: Estimates of matching elasticity α and dispersion (standard deviations) of market-specific components ϕ_i

	α estimate	dispersion in ϕ_i
industry level (units)		
sections (20)	0.1811**	0.7381
divisions (74)	0.1108***	0.8507
groups (166)	0.1183***	1.0193
occupation level (units)		
sectors (4)	0.2912***	0.3140
sections (30)	0.1935***	0.6905
groups (61)	0.2228***	0.7822
regional level (units)		
states (16)	0.0447**	0.1729
districts (West, 28)	0.0293***	0.2802
occupation-region level (units)		
sector-states (56)	0.1735***	0.3715
section-states (223)	0.1450***	0.5572

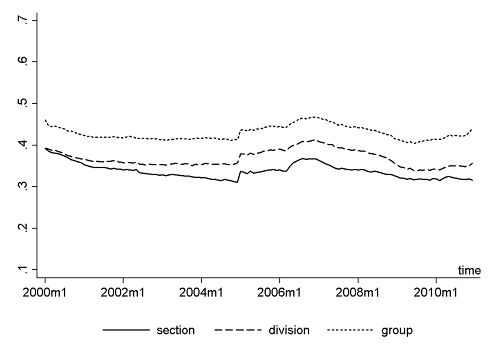
Note: Time series are filtered using Census X-12-Arima. *significant at 10% level. **significant at 5% level. ***significant at 1% level.

from the assumption of distinct markets. In terms of occupations, the elasticities lie within the range proposed by Sunde (2007) who used annual data from West German in a more turbulent period (1980-1995). As Sunde (2007: p. 546) points out, disaggregation by occupation is suitable for capturing "the skill requirements and similarities of tasks as well as the occupation-specific knowledge conveyed in the German apprenticeship system. If they search for a job, individuals usually consider vacancies in their occupational field, and similarly firms target their vacancies to applicants with the specific skills needed for the particular job". This picture is affirmed by the fact that the estimated matching elasticity approximates that obtained with the aggregate data. Across states, the elasticities tend to be very low at the disaggregated levels compared with the aggregate data but remain consistent with the estimates of Lottmann (2012) and Klinger/Rothe (2012). To the best of my knowledge, no prior research has been conducted on empirical matching functions in relation to German industries or clusters of occupations by regions.

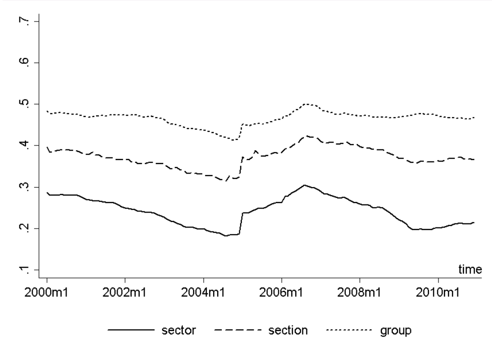
5 Results

5.1 Mismatch Indices

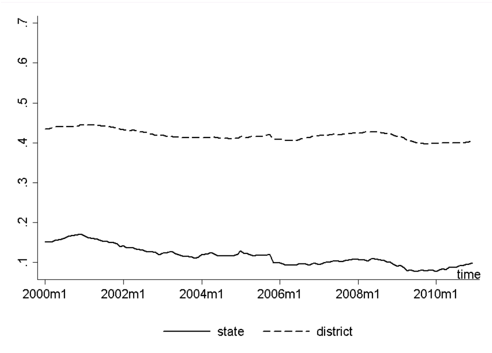
As shown in Figure 1, the mismatch indices reveal a downward trend through 2005, with a jump in December 2004 to January 2005 caused by measurement error resulting from the Hartz reforms and a hump shape from 2005 to 2009. Specifically, the index for industry sections (dotted line, panel a) dropped from 0.45 at the beginning of the decade to 0.40 at the end of the decade. In other words, the number of hires lost due to mismatch declined from 45 to 40 percent. The indices for occupations (panel b) and occupation-regions (panel d) behaved similarly and deceased from 0.50 (0.55) near the beginning of the decade to 0.45 (0.50) toward the end of the decade (at the highest disaggregation level). A hump shape is not observed in regional indices (panel c) in 2005, but the indices fall monotonically throughout the observation period. For more details on the movements of the unemployment and vacancy shares within selected markets and the cyclical properties of the indices, see Appendix C.



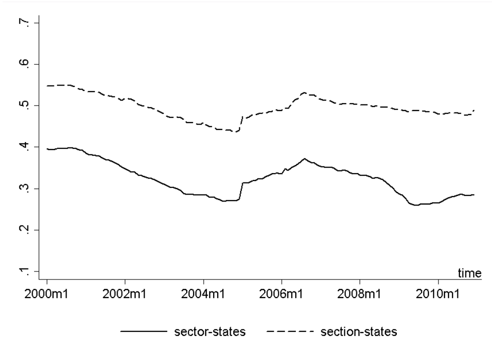
(a) industry



(b) occupation



(c) region



(d) occupation-region

Figure 1: Mismatch indices in relation to different industry, occupation, region and occupation-region levels (with the solid line representing the lowest disaggregation level, the dashed line representing the intermediate level and the dotted line representing the highest disaggregation level)

In general, the situation improved across all labor markets. The hump-shaped patterns at the industry, occupation and occupation-region levels just after the Hartz reforms are a result from redefining the unemployment pool by merging the recipients of unemployment assistance with the recepients of welfare benefits. This consolidation led to a net increase in the size of the unemployed population, which numbered approximately 380,000 people[15]. It is reasonable that these additional unemployed workers were not spread equally across the different submarkets, resulting in changes in unemployment shares and thus increases the indices. Because it takes time to reabsorb these additional workers, mismatch increases in the short run. Across states and districts, the indices fell monotonically across the observation period. At the state level, the mismatch index was the lowest (below 10 percent) in the latter half of the decade. There are two possible reasons for this. First, the sample is not representative with respect to regions. Opting communities (*Optierende Kommunen*) were introduced simultaneously with the Hartz reforms and accommodate unemployed workers independently of the Federal Employment Agency. Therefore, the unemployed and vacancies in the opting communities do not show up in the registries[16]. As opting communities are not spread evenly across regions (geographical focus areas are in Hesse, Lower Saxony and Brandenburg) regional unemployment shares may be unevenly affected. Another problem is spatial dependency as three of the federal states are cities within another federal state (e.g., Berlin is a federal state

[15] Employable recipients of social assistance and welfare benefits entered the unemployment pool. Thus, the records showed a surplus of 580,000 people but an increase of approximately 200,000 people for seasonal reasons.
[16] The data on unemployed workers within the opting communities are available but not representative because of quality problems in the first years. Vacancy data in the opting communities are not provided.

located within Brandenburg). Hence, at the state level, mismatch appears to be low but downward biased from 2006 onwards. As the regional indices show no particular movement over time, I will focus on occupations and industries below.

Although the indices range between one and zero, the level of mismatch is not directly comparable to that of other countries such as the US, due to the dependence of these indices on the number of submarkets, on the one hand, and on the number of hires in the economy, on the other hand. The indices for Germany are much higher than those for the US, even at similar levels of disaggregation[17]. For example, the US indices computed by Şahin et al. (2012) range between 0.03 and 0.09, using a 1-digit industry classification (17 units), whereas the German indices range between 0.31 and 0.37, using a 1-digit industry classification (20 units). In terms of occupation, the US indices peak at 0.14 (2-digit, 21 units) and 0.22 (3-digit, 36 units), whereas the German indices peak at 0.40 (2-digit, 30 units) and 0.50 (3-digit, 60 units). This finding reflects, that the indices measure "hires lost because of misallocation" (Şahin et al., 2012, p: 12). The high indices for Germany do not necessarily translate into a large number number of mismatched people as the number of hires is lower in Germany than in the US.

5.2 Counterfactuals

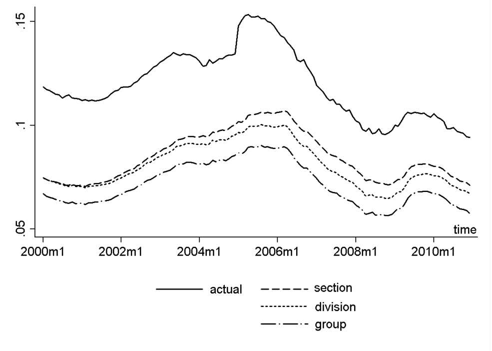
To compare the level of mismatch between Germany and the US, it is more convenient to measure mismatch in terms of unemployment than in terms of hires. Following Şahin et al. (2012), mismatch measured in terms of unemployment can be calculated from the difference between actual and counterfactual unemployment rates as outlined in Section 3.2. For purposes of coherence, I used the unemployment rate from my sample instead of the official unemployment rate in these calculations. The sample unemployment rate is calculated as the ratio of unemployed workers to the sum of unemployed and employed workers[18].

The counterfactual unemployment rates (dashed, dotted and dash-dotted lines) in panels a) and b) in Figure 2 mimic the behavior of the actual unemployment rate (solid line). The difference between the actual and the counterfactual unemployment rates determines mismatch unemployment. Panels c) and d) in Figure 2 illustrate that mismatch decreases throughout the period. The mismatch unemployment rate for industries at the highest disaggregation level started at 5.2 percent at the beginning of the decade and fell to 3.7 percent by the end of the decade. At the highest occupational level, mismatch unemployment decreased from 5.4 percent to 4.3 percent. In relation to the Hartz reforms, a small though remarkable change in the trend was detected in 2003, one that could indicate an improvement in mismatch unemployment caused by the first wave of the reform. However, in 2005 (coinciding with final wave of the Hartz reforms), mismatch unemployment increased in the short run due to the consolidation of unemployment assistance and welfare benefits. After 2005, the downward trend in mismatch unemployment did not accelerate as a result of the reforms, raising the suspicion that the reforms did not substantially decrease mismatch unemployment. This finding is in line with evidence presented by Fahr/Sunde (2009: p. 314), who find positive effects of the Hartz reforms within a search and matching framework, which acts on the frictional margin but "has little to say about the effects of the reform in light of structural unemployment".

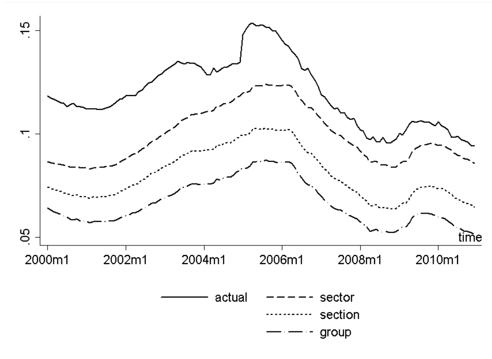
Nevertheless, the reforms could have changed the composition of aggregate unemployment with respect to mismatch. Panels e) and f) in Figure 2 show changes in the percentage of mismatch in

[17] Note, that, despite the similar number of markets, the number of people in these markets differs.

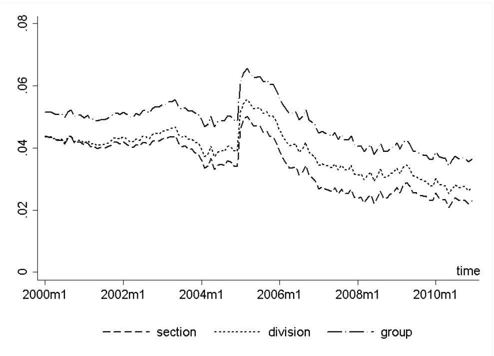
[18] This sample unemployment rate is higher than the official one because in the official one, either self-employed and family workers or (in another version) apprentices, civil servants and marginally paid workers are included. Additionally, the official unemployment rate is determined using a yearly benchmark of the relevant labor force. The difference between both unemployment rates is displayed in Appendix A, Figure 6.



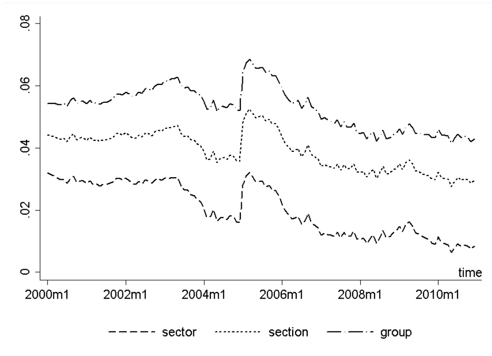
(a) *URs* by industry



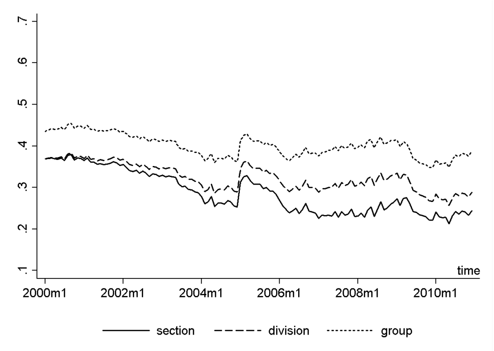
(b) *URs* by occupation



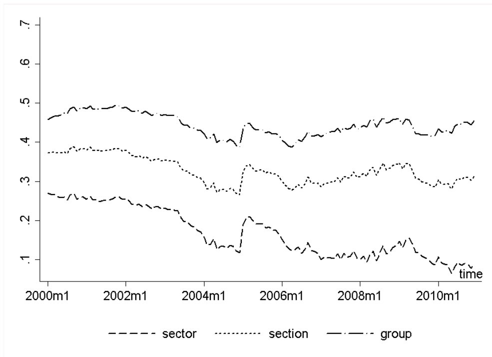
(c) *diff* by industry



(d) *diff* by occupation



(e) *diff %* by industry



(f) *diff %* by occupation

Figure 2: Counterfactual unemployment rates (*UR's*), absolute differences (*diff*) between actual and counterfactual unemployment rates and percentage differences (*diff %*) between the actual unemployment rate at the levels of industry and occupation.

aggregate unemployment. At the industry level, mismatch unemployment accounted for 35 to 45 percent of the actual unemployment rate at the beginning of the decade and 25 to 40 percent at the end of the decade. At the occupation level, mismatch unemployment accounted for 25 to 45 percent of the actual unemployment rate in 2000 and remained relatively constant until 2010.[19] Compared with the US, mismatch appears to have played a much larger role in Germany. In particular, in the observation period between 2005 and 2011, mismatch accounted for only 5 to 10% of aggregate unemployment in the US, using the 1-digit industry classification, 10 to 20 percent using the 2-digit classification and 15 to 30 percent using the 3-digit classification.

[19] Appendix C, Figure 12 shows the corresponding job finding rates.

6 Robustness

6.1 Heterogeneity

The only type of heterogeneity considered thus far is matching efficiency. However, variations in layoff policies or productivity can also influence the distribution of unemployment and vacancies across markets. Without controlling for such effects, differences across markets will not be caused solely by mismatch between workers and jobs in terms of skills or location. Thus, the optimality conditions must equalize labor market tightness, weighted by all factors affecting the equilibrium distribution, while not being subjected to mismatch in the narrow sense. Şahin et al. (2012) show that such effects are easy to implement by defining matching efficiency so that it includes the sector-specific productivity z_i and the probability of maintaining the match $[(1-\Delta)(1-\delta_i)]$ (which consists of two exogenous components, Δ, which is common across sectors, and δ, which is idiosyncratic) weighted by a discount factor β[20]. This overall matching efficiency can be described as follows:

$$x_{it} = \phi_i z_{it} / [1 - \beta(1-\Delta_t)(1-\delta_{it})] \tag{11}$$

Substituting this expression for ϕ_i allows the index to be rewritten as follows:

$$M_{xt} = 1 - \frac{h_t}{h_t^*} = 1 - \sum_{i=1}^{I} \left(\frac{\phi_i}{\bar{\phi}_{xt}}\right) \left(\frac{v_{it}}{v_t}\right)^{\alpha} \left(\frac{u_{it}}{u_t}\right)^{1-\alpha} \tag{12}$$

with

$$\bar{\phi}_{xt} = \sum_{i=1}^{I} \phi_i \left(\frac{x_{it}}{\bar{x}_t}\right)^{\frac{1-\alpha}{\alpha}} \left(\frac{v_{it}}{v_t}\right)$$

and

$$\bar{x}_t = \left[\sum_{i=1}^{I} x_{it}^{\frac{1}{\alpha}} \left(\frac{v_{it}}{v_t}\right)\right]^{\alpha}$$

Again this index captures the amount of misallocation in the economy apart from search frictions. Likewise, search frictions were initially captured by ϕ_i but is now weighted by the overall matching efficiency $\bar{\phi}_{xt}$.

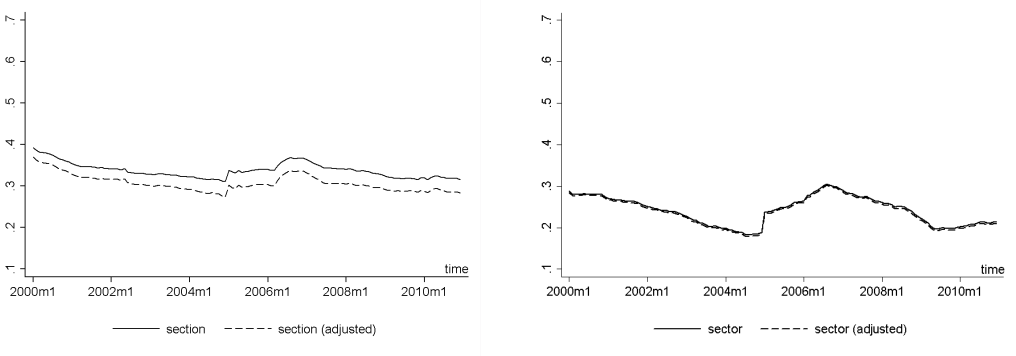
Wages were used as a measure for the productivity z_{it}.[21]. Daily gross wages were observed across spells of employment. Although this measure is right-censored[22] and strongly affected by the institutional setting in Germany (unionization, minimum wages, etc.), it should at least account for some of the movement in productivity. Separation rates are used to measure the probability of maintaining a match $(1-\Delta)(1-\delta_i)$.

As shown in Figure 3, under this specification, the indices become smaller, indicating lower levels of mismatch, a fact that is well-marked for industries (panel a) but not for occupations (panel b). Incorporation of productivity does not alter the movement of the indices as wages move very little, owing to wage moderation in Germany during this period. In a similar way, other measures of aggregate labor productivity hardly moved during this period.

[20] In what follows, I set β=0.98, which corresponds to an interest rate of 2.3 percent.

[21] In my sample I calculate average monthly wages of all employed workers in a given submarket. Because only wages, but not the corresponding hours are observed, movements in this productivity measure can be induced by movements in hours as well. Changes in the composition (the relative proportions of part-time vs. full-time workers) of a market may also induce movements that are unrelated to changes in productivity.

[22] Wages that exceed the upper earnings limit for statutory pension insurance are set to the earnings limit.



(a) industry (sections) (b) occupation (sectors)

Figure 3: Mismatch indices at the lowest disaggregation level with corresponding matching efficiency, productivity and separation rate adjusted indices

6.2 Underreporting of Job Vacancies

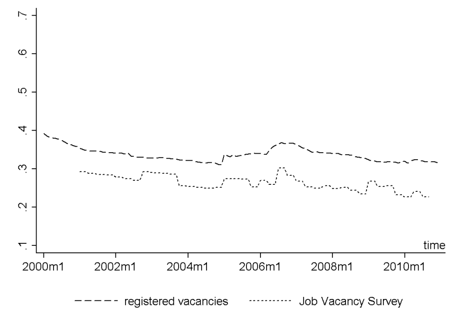
Because it is not mandatory for German firms to report their job vacancies, the data above may be influenced by some degree of underreporting. Underreporting that is equally distributed across the submarkets would cause only a level shift. However,if the number of not reported job vacancies is unequally distributed, vacancy shares could vary across markets, modifying movements of the indices over time. Vacancies for highly skilled persons could be underrepresented whereas vacancies for less skilled workers could be overrepresented in the registered vacancies of the Federal Employment Agency. Although I cannot prove this hypothesis for occupations, possible underreporting pertains to the industry level as well. An intuition regarding the degree of underreporting can be developed, using data of the German Job Vacancy Survey (Kettner et al., 2011) of the Institute for Employment Research. This survey is designed to collect information on the number and structure of job vacancies (registered or not) and staff hiring processes. The Job Vacancy Survey is representative of the broadest level of the industry classification (i.e., industry sections, 1-digit). The data were recorded in the fourth quarter of each year through 2005, after which it was recorded each quarter. The data were extrapolated to obtain quarterly numbers across the whole period. Because the Job Vacancy Survey was provided based on the Classification of Economic Activities 2003, I also compute the unemployment data for this classification scheme[23]. Panel a in Figure 4 displays the index corrected for survey vacancies (dotted line) and the index for registered vacancies (dashed line).[24] Note, however, that the Classification of Economic Activities differs between the two indices (2003 and 2008), which are thus not directly comparable. However, the two indices show similar movements over time (see Figure 4, panel a). The counterfactual unemployment rates (panel b) and mismatch unemployment (panels c and d) move together over time. The underreporting of job vacancies only caused only a level shift.

7 Reallocation Processes

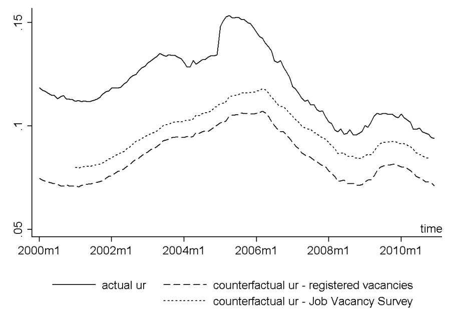
As Şahin et al. (2012: p. 5) conclude, this approach "is robust and easily implementable, even with a high number of labor markets, and multiple sources of heterogeneity, idiosyncratic shocks, and

[23] Again, I harmonized the different schemes using the method in Eberle et al. (2011) and applied the correction proposed in Appendix A.

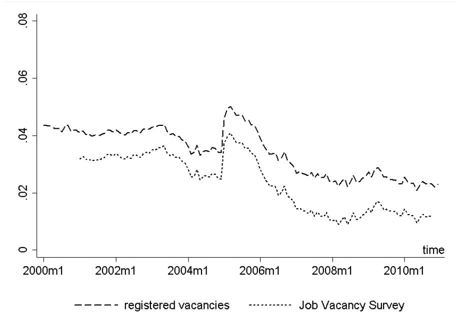
[24] The index derived from the Job Vacancy Survey is based on a yearly data through 2005 and quarterly data subsequently. Using data from the Job Vacancy Survey the estimate on the matching elasticity rose slightly above that for registered vacancies ($\alpha = 0.27$) and is also significant at the 1 percent level. I used $\alpha = 0.25$ to calculate the indices given its coherence with the index computed with registered data and the minimal difference to with the findings of the Job Vacancy Survey.



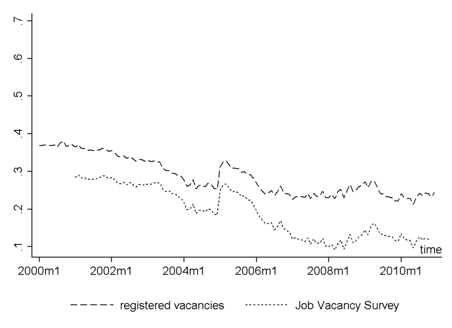
(a) mismatch indices



(b) unemployment rate



(c) difference



(d) difference in %

Figure 4: Job Vacancy Survey vs. registered vacancies.

aggregate fluctuations.[...] The limitation is that one cannot separately quantify the, possibly many, sources of misallocation". Nevertheless, it is possible to examine the mechanisms that determine the (mis)allocation. More precisely, whereas individual reasons for reallocation may be unknown, one can examine wether and to what extent reallocation occurs. The approach of Şahin et al. (2012) does not capture these reallocation processes directly due to the assumption of distinct markets.

This has two consequences. First, it is unclear ex ante wether the reduction in mismatch was caused by workers changing professions or regions (as these flows are neglected) or because they dropped out of the labor force due to retirement or discouragement. For firms, the vacancies could be closed instead of using e.g., restructuring possibilities through internal labor markets.

Second, the assumption of separated markets leads to the exclusion of markets with low observations of flows[25], although the scope of the search process and thus the flows could be much larger the boundaries were defined more flexible. For example, at the level of industry groups, I observed a sufficient amount of transition in only 166 of the 272 markets which could bias the results. For occupations, I observed a sufficient amount of transition in 60 of 99 markets[26]. In addition, the assumption precluded consideration of the transition of people who switched their status as well as their industry, occupation or region (or occupation-region combination). Thus, the job finding rate across markets is downward biased. Table 3 shows that the job finding rate is only half as high as the rate at the aggregate level. This effect increases if more markets are considered because, as markets increasingly resemble each other, the likelihood of switching to another occupation, industry or region rises. This pattern influences the estimation results by altering the relationship between the job finding rate and labor market tightness. Stops (2012) demonstrates using an estimation of a matching function, that matching workers to vacancies across submarkets significantly

[25] Note, that submarkets that had fewer than 100 transitions (from unemployment to employment and vice versa) on average per month after projections were excluded.

[26] For the US, Şahin et al. (2012) also observe only 60 percent of the markets, using a 3-digit occupational code. However, in the US, the 60 percent represents only 15.6 percent of the unemployed in the CPS whereas my 60 percent of the markets reflects approximately 70 percent of all unemployed workers in the sample

affects the hirings. Even market-specific matching efficiencies may be affected. Specifically, a more diffusible submarket could have a higher matching efficiency, an effect that may not be captured in the panel estimation of the selection of (partly) downward biased flows. As illustrated in Figure 2 at the occupation level, the percentage of mismatch unemployment in aggregate unemployment remains unchanged. Thus, there is little reallocation despite changes in collaborative duties of workers triggered by the Hartz reforms. Workers were encouraged to search and even take jobs that were outside their field of occupation. This affects the mobility decisions of the unemployed that determine the reallocation process in the labor markets. As Aldashev (2012) has shown with German data, patterns of occupational and regional mobility patterns have a large positive impact on the job finding rate[27]. Aldashev (2012: p. 122) concludes that, without occupational mobility, matches would have decreased by approximately 3 to 6 percent. To analyze reallocation, I examined the job findings of people who switched both their labor market status and occupation[28]. If the Hartz reforms did improve occupational mismatch in ways that were undetected by the indices, a difference in reallocation across occupations should be observable. Where the individuals came from and went to is not of interest in this analysis. Then I related these job findings to the pool of unemployed in the preceding period and compared it to the aggregate job finding rate. This procedure provides an intuition regarding the percentage of labor market flows neglected due to the assumption of distinct markets.

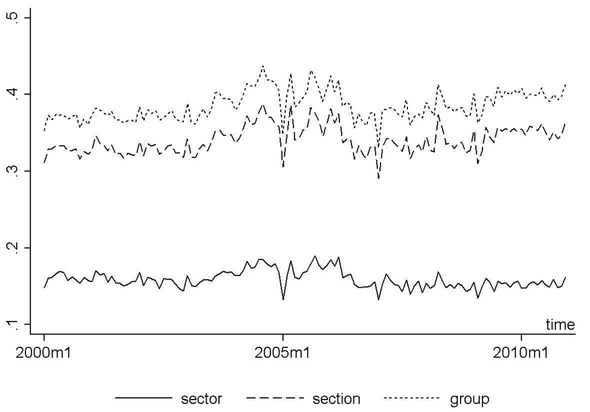


Figure 5: Job finding rate of movers as percentage of the aggregate job-finding rate at different occupation disaggregation levels (with the solid line representing the lowest, the dashed line representing the intermediate level and the dotted line representing the highest disaggregation level).

Figure 5 shows that the percentage of the unemployed who changed occupation and simultaneously took up employment, rose slightly over time. For example, at the highest disaggregation level (occupation groups, dotted line) movers' job finding rate as percentage of the aggregate job finding rate rose from 35 percent at the beginning up to 41 percent by the end of the decade.[29] However, no change in the time trend after the Hartz reforms is observed. Thus, the Hartz reforms do not appear to have eased reallocation in ways that would have influence the unemployment caused by mismatch decisively. Thus, the findings that there was no change in the composition of mismatch unemployment at the occupation level are reasonable.

[27] This problem may be even more pronounced in the US. In Germany, only 3 to 4 percent (Longhi/Brynin, 2010) of workers switch occupations, whereas in the US, approximately 13 percent switch occupations (Kambourov/Manovskii, 2008).

[28] For unemployment spells, occupational information refers to a person's preceding job. For employment spells, it refers to the occupation in which a person is currently employed.

[29] On average, over the whole period, approximately 7 to 10 percent of the data on the aggregate job finding rate were lost due to my refinements or missing values in the occupation data. Approximately 54 to 74 percent were captured through the assumption of distinct markets.

8 Conclusion

In this paper, I have shown that mismatch unemployment plays an important role in the German labor market. Mismatch indices, based on to Şahin et al. (2012), depict a downward trend at various levels (industry, occupation, region and occupation-regions). Geographical mismatch, by contrast appears to play no important role in explaining movements of aggregate unemployment. At the levels of industry and occupation, a downward trend is observed during the first half of the decade. In the latter half of the decade, the indices remained stable (except for the hump-shape due to the Hartz reforms).

Mismatch was measured in terms of total unemployment by calculating counterfactual unemployment rates. This approach allows one not only to disentangle the contributions of labor market frictions and mismatch to aggregate unemployment but also to compare Germany with the US in this regard. The mismatch unemployment rate for industries at the highest disaggregation level started at 5.2 percent in the beginning of the decade and dropped to 3.7 percent by the end of the decade. At the highest occupational level, mismatch unemployment decreased from 5.4 percent to 4.3 percent. In the aftermath of the reforms, a hump-shaped pattern, but no strong effect in the downward trend, is observed. The percentage of mismatch unemployment across industries in aggregate unemployment decreased from 45 percent at the beginning of the decade to 40 percent by the end of the decade. The percentage of mismatch unemployment across occupations in aggregate unemployment remained relatively stable at a level of approximately 45 percent. Compared with the US data, these numbers are large. In the US, mismatch accounted for at most 30 percent of aggregate unemployment during the recession.

On the one hand, these numbers are high because the mismatch indices represent upper limits. They suffer from an upward bias, owing to the assumption of distinct markets. On the other hand, the findings suggest that the Hartz reforms did not change the composition of aggregate unemployment in terms of mismatch. This approach does not explain why the reforms had no substantial impact on the mismatch component. Nonetheless, as shown in the last section, there was no change in occupational reallocation trends after the Hartz reforms, suggesting that the reforms did not alter the mechanism underlying mismatch unemployment. To conclude, there is still potential to reduce skill mismatch by easing reallocation processes across German labor markets.

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A Appendix: Data

Data structure and selection

The data set I use for the analysis is a 5% random sample of the Integrated Employment Biographies (IEB). The IEB merges four different registers and contains spell data for registered job search (reliable since 2000), unemployment benefit receipt, training measures (provided by the Federal Employment Agency as part of active labor market policy) and employment for every worker.

The data set includes parallel notifications if e.g. workers receive unemployment benefits while working in spare-time (so-called *Hinzuverdiener*) or they receive unemployment benefits while searching for a job. To handle parallel notifications, I exclude all spells of unemployment benefit receipt and training measures. From the remaining spells on registered job search I exclude notifications of on-the job search, sickness up to 6 weeks and advice seeking. From the remaining employment spells I drop notifications not subject to social security (marginally employed) and of apprentices, trainees, family assistants, artists, mariners and individuals receiving partial and early retirement pensions. Civil servants and self-employed are not included inherently. Left over are employment spells subject to social security (part and full time) and unemployment spells of people who are available and actively searching for a job. After this procedure 3,080,025 persons and 49,126,247 spells remain in the sample.

The unemployment spells are not representative geographically because of opting communities (so-called *Optionskommunen*). Opting communities were introduced together with the Hartz reforms and maintain unemployed persons independently from the Federal Employment Agency. Although the opting communities transfer their data to the Federal Employment Agency, I don't use it because of quality issues. But with respect to occupations and industries these data are representative.

As illustrated in Figure 6, on the aggregate level the data mimic the behaviour of official data provided by the Federal Employment Agency. However, the number of unemployed persons in the sample is understated compared to official data (left panel) because unemployed persons in the opting communities are not incorporated. The unemployment rate in the sample is overstated compared to official data (right panel) because I use a narrower definition of employment.

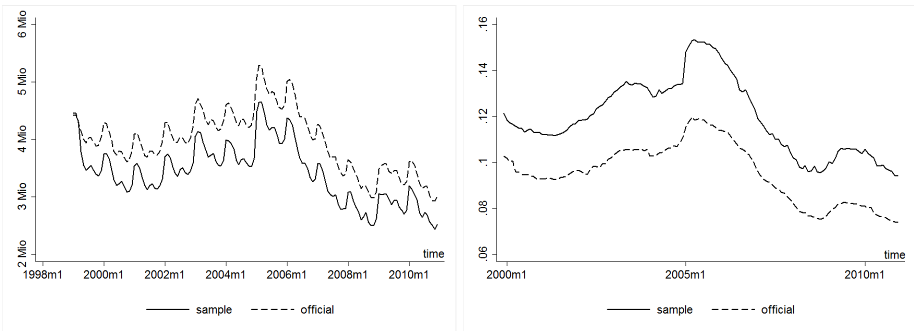
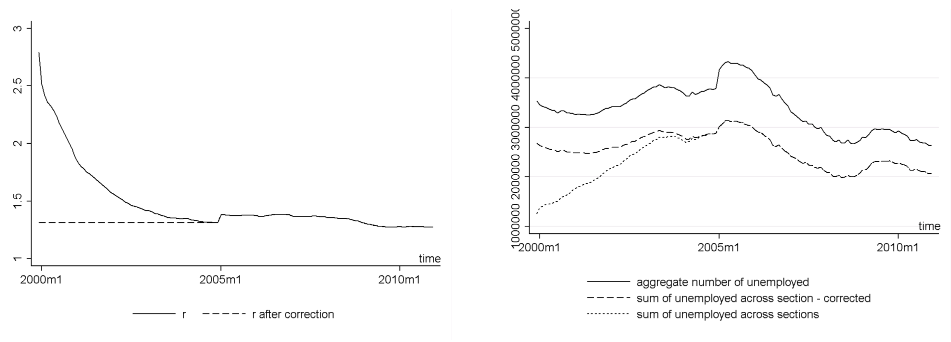


Figure 6: Comparison of sample (solid line) to official data (dashed line)

Correction mechanism on unemployment for industries

Because the industry classification information is subject to changes over time (Classification of Economic Activities 1993, 2003 and 2008), I use the method of Eberle et al. (2011) to harmonize the (partly overlapping) classifications. As base I choose the Classification of Economic Activities 2008 because registered vacancies are available for that classification. This method generates long time series, but has the shortcoming that only 95% of the true industry classification from 2003 to 2008 and 90% from 1993 to 2008 is captured by the assignment mechanism. Besides the industry information is available for spells of employment. I transcribe the information over to spells of unemployment by assuming that unemployed workers search for a job in the sector of their last employment. This is only possible, if a persons worked at least once during the observation period, otherwise I don't have information on the industry. However, these measurement errors bias the number of unemployed and thus labor market tightness. If I aggregate the number of unemployed over all segments of a certain disaggregation level and compare it to the stock of unemployed on an aggregate level, it turns out that the gap between these two is not constant over time. As the left panel of figure 7 shows, the gap (measured as the ratio (r) of aggregate unemployed to the sum of unemployed across sectors) is wider in the beginning than in the end of the observation period. This means, that the gap is not solely determined by the segments I exclude from my data (then the gap would be constant over time), but also by a downward bias through measurement error. To correct for this measurement error I set the ratio of aggregate unemployed to the sum of unemployed across sectors constant to the value in December 2004. Afterwards I back out the number of unemployed which are understated and redistribute them equally over the segments. If I again sum this new measure of unemployment across sectors and compare it to the aggregate number of unemployed the gap is constant as the right panel of 7 illustrates.



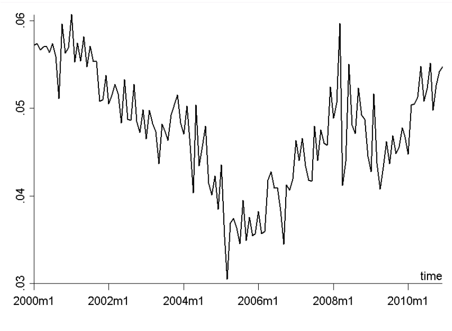
(a) ratio by industry section

(b) number of unemployed

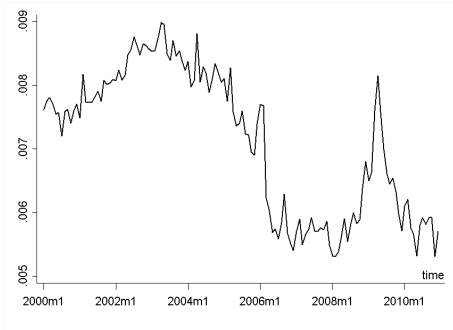
Figure 7: Left panel depicts ratio of aggregate number of unemployed and sum of number of unemployed across sections (r, solid line) and ratio r after correction (dashed line); right panel depicts aggregate number of unemployed (solid line), sum of number of unemployed across sections (dotted line) and sum of unemployed across sections after correction (dashed line)

Descriptive statistics

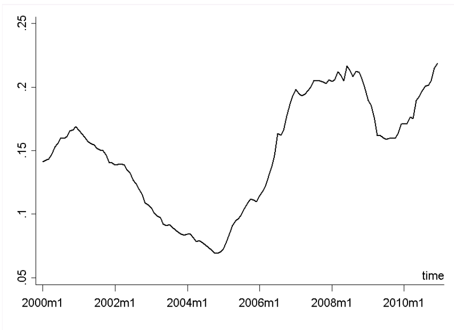
Figure 8 shows seasonally adjusted (Census X-12 ARIMA) time series for the job finding rate (f_t), separation rate (s_t) and labor market tightness (v-u ratio, θ_t) on an aggregate level. The job finding rate (panel 1) amounts to averagely 4.8 percent per month over the sample period and is procyclical. The separation rate (panel 2) averages 0.7 percent and is countercyclical. Both findings are in line with the observations of Nordmeier (2012). The labor market tightness (panel 3) falls remarkably until 2005 and rises steadily after that with a slight slump during the financial/euro crisis. The sample yields an average labor market tightness of 0.15 which is procyclical.



1 f_t



2 s_t



3 θ_t

Figure 8: seasonally adjusted (Census X-12 Arima) time series of the aggregate job finding rate (f_t), separation rate (s_t) and labor market tightness (θ_t)

Table 2: variable means, standard deviations and correlations of cyclical components

	mean	std	correlation with GDP
f	0.0475	0.0066	0.5030
s	0.0071	0.0011	-0.6893
θ	0.1474	0.0448	0.7846
θ_{corr}	0.3114	0.0744	0.7632

Notes: The time series are filtered with Census X-12-Arima. Cyclical components are filtered with HP-filter with smoothing parameter 14400.

Table 3: means and standard deviations of job finding rates (f_{it}), separation rates (s_{it}) and labor market tightness (θ_{it})

	f_{it}			s_{it}			θ_{it}		
	mean	between	within	mean	between	within	mean	between	within
industry level (units)									
sections (20)	0.0240	0.0138	0.0088	0.0082	0.0057	0.0021	0.1260	0.0800	0.0551
divisions (74)	0.0215	0.0142	0.0105	0.0082	0.0065	0.0035	0.1109	0.0833	0.0606
groups (166)	0.0206	0.0157	0.0124	0.0083	0.0071	0.0038	0.1030	0.0828	0.0642
occupation level (units)									
sectors (4)	0.0354	0.0122	0.0061	0.0076	0.0059	0.0021	0.1632	0.0910	0.0839
sections (30)	0.0257	0.0151	0.0101	0.0058	0.0051	0.0021	0.1647	0.1142	0.1044
groups (60)	0.0260	0.0171	0.0107	0.0059	0.0054	0.0028	0.1916	0.1373	0.1316
regional level (units)									
states (16)	0.0464	0.0091	0.0072	0.0077	0.0030	0.0012	0.1496	0.0632	0.0592
districts (West, 28)	0.0516	0.0142	0.0093	0.0064	0.0016	0.0013	0.1887	0.0548	0.0724
occupation-region level (units)									
sector-states (56)	0.0368	0.0136	0.0126	0.0085	0.0061	0.0036	0.1626	0.1209	0.1203
sections-states (223)	0.0317	0.0162	0.0147	0.0078	0.0072	0.0042	0.1813	0.1648	0.1372

Notes: The time series are filtered with Census X-12-Arima. The number of observations is changing between the levels of disaggregation due to missing values.

Job Vacancy Survey

Because it is not mandatory for the firms to report their vacancies, the data may be influenced by some degree of underreporting. To get an intuition about the underreporting, I additionally used data of the German Job Vacancy Survey (Kettner et al., 2011) from the Institute for Employment Research. This survey is designed to collect information on the number and structure of job vacancies (registered or not) and on staff hiring processes.

1 absolute values 2 by labor market tightness

Figure 9: comparison registered vacancies (solid line) to Job Vacancy Survey (dashed line) in absolute values (left panel) and by labor market tightness (right panel)

Using the survey data instead of the registered data, the market tightness doubled to 0.31 and is still procyclical. The time series on job vacancies from the Job Vacancy Survey and from the Federal Employment Agency are highly correlated (>0.9). The Job Vacancy Survey is representative at a 1-digit industry classification level (Classification of Economic Activities 2003, until the third quarter 2010).

B Appendix: Estimation

Aggregate level

At an aggregate level, I first estimate a simple matching function with OLS of the following form:

$$h_t = \Phi_t + u_{t-1} + v_{t-1} + [...] + \epsilon \tag{13}$$

I include lagged values for the stock of unemployed and vacancies to account for endogeneity. However, when I use the current values instead of the lagged ones, the elasticity of the matching function α is always lower (last column 0.1659 instead of 0.2189). Besides, a Ramsey (RESET) test on the functional form (which is equivalent to test on the linear (translog) approximation of the CES function) is performed. The preferred specification includes a linear and quadratic time trend as well as a dummy which takes on the value one for periods after the Hartz reforms. The dummy captures the structural break (which also shifted the Beveridge Curve) induced by the Hartz reforms and is common in the German literature (e.g.Kohlbrecher/Merkl/Nordmeier (2013)). Although the Ramsey test cannot be rejected even without the dummy (see model 3), the coefficient on vacancies is negative. By including the dummy, the elasticity on vacancies turns out to be significantly positive, the adjusted R^2 rises, the Ramsey test jumps up, the Durbin-Watson statistic is close to 2 and a test on constant returns to scale cannot be rejected (see Table 4).

Table 4: estimates for matching function aggregate level 2000-2010 (monthly)

	(1)	(2)	(3)	(4)
Φ	4.3260	11.8474^{***}	16.7499^{***}	5.4381^{***}
u_{t-1}	0.4387^{***}	-0.0287	0.2148^{***}	0.6813^{***}
v_{t-1}	-0.0478	-0.0587	-0.0611^{**}	0.2189^{***}
t		-0.0031^{***}	-0.0349^{***}	-0.0354^{***}
t^2			0.0000^{***}	0.0000^{***}
D_{Hartz}				-0.2585^{***}
R^2	0.2134	0.7023	0.7349	0.7886
Ramsey	0.0000	0.0000	0.1664	0.8966
Durbin-Watson	0.5236	01.4758	1.6176	1.8980
constant returns				✓

Note: All timeseries are filtered by Census X-12-ARIMA. Variables are in logarithms.

Based on these results, the estimation of a reduced form matching function appears to be reasonable. Again a linear time trend, a quadratic time trend and a dummy indicating periods after the Hartz reform are included.

$$f_t = \Phi_t + \theta_{t-1} + [...] + \epsilon_t \tag{14}$$

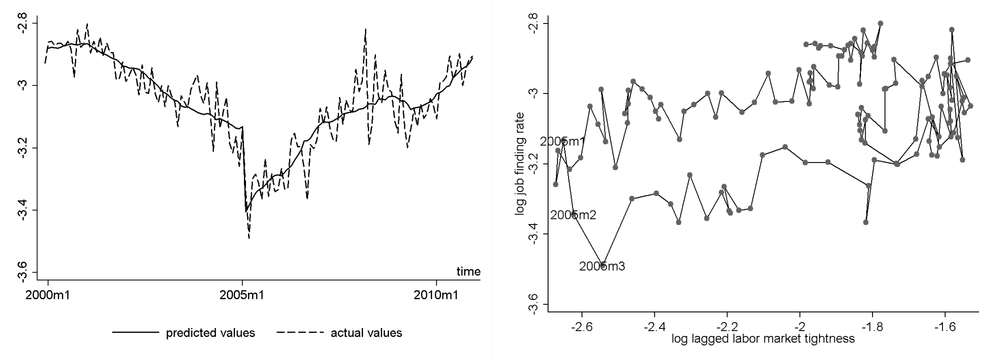
This estimation yields a coefficient on the vacancy share of 0.25, which is similar to the estimate of the simple matching function (0.22). The estimation shows an adjusted R^2 of 80 percent, the Ramsey test rejects misspecification and the Durbin-Watson statistic is again close to 2.

Table 5: estimates for reduced form matching function aggregate level 2000-2010 (monthly)

	(1)	(2)	(3)	(4)
Φ	-2.7437^{***}	-1.3361^{***}	16.5362^{***}	7.2955^{***}
θ_{t-1}	0.1590^{***}	0.2677^{***}	0.1106^{***}	0.2506^{***}
t		-0.0022^{***}	-0.0700^{***}	-0.0368^{***}
t^2			0.0001^{***}	0.0000^{***}
D_{Hartz}				-0.2813^{***}
R^2	0.1281	0.4002	0.6133	0.7955
Ramsey	0.0634	0.0639	0.0000	0.8282
Durbin-Watson	0.4420	0.6582	1.0036	1.8780

Note: All time series are filtered by Census X-12-ARIMA. Variables are in logarithms.

As can be seen in panel a in Figure 10, the model fit is good under the preferred specification. Although the dummy variable for the Hartz reforms captures the structural break, it could be possible that the coefficient of labor market tightness differs before and after the reforms or that there is only a temporary effect of the reforms due to the merger of employable recipients of social assistance and welfare benefits. However, panel b in Figure 10 shows, that the relationship between the job finding rate and labor market tightness (both in logarithms) is similar in periods before and after the reforms. The reforms led only to a level shift.



1 actual job finding rate vs. predicted job finding rate

2 job finding rate vs. labor market tightness

Figure 10: scatter plot of job finding rate vs. labor market tightness (both in logarithms) and model fit by comparing actual and predicted job finding rate.

To see to what extent the estimates are downward biased by the underreporting in registered vacancies, I run the same estimation with vacancies from the Job Vacancy Survey.

Table 6: estimates for reduced form matching function with vacancies of Job Vacancy Survey aggregate level 2000-2010 (monthly)

	(1)	(2)	(3)	(4)
Φ	-2.7388^{***}	-1.955^{***}	20.2870^{***}	9.6925^{***}
θ_{t-1}	0.2798^{***}	0.3330^{***}	0.1757^{***}	0.2767^{***}
t		-0.0013^{***}	-0.0834^{***}	-0.0465^{***}
t^2			0.0001^{***}	0.0000^{***}
D_{Hartz}				-0.2311^{***}
R^2	0.2451	0.3409	0.6202	0.7583
Ramsey	0.1002	0.0148	0.0000	0.7770
Durbin-Watson	0.5557	0.6403	1.1298	1.8657

Note: All time series are filtered using Census X-12-ARIMA. Variables are in logarithms. Vacancies from the Job Vacancy Survey are reported every fourth quarter of each year through 2005 and each quarter afterwards. The time series is therefore interpolated to reach a monthly frequency.

The coefficient on the vacancy share is slightly higher ($\alpha = 0.27$) than the coefficient with registered data. The estimation still shows a good model fit. The Ramsey test rejects misspecification and the Durbin-Watson statistic is close to 2.

Disaggregate level

The estimates of group-effects (i.e. market- specific matching efficiency) across industries, occupations and regions are extracted from a panel regression. The panel regressions on a reduced form matching function include time dummies to capture cyclical effects and to account for the fact, that the Hartz-reforms also changed the institutional setting. As this could induce a change in the market-specific component, the sample was split into two periods, before 2005 and after 2005. Although the Hartz reforms were launched between 2003 and 2005, the end of 2005 is taken as cutting point, because the reforms needed some time to reveal their full effects.

Tables 7, 8 and 9 show that the differences between the matching efficiencies before and after the reform are relatively small. At the lowest disaggregation level of industry (1-digit, industry section), the market-specific matching efficiency are on average higher after the reforms. The largest difference appears in the Mining and Quarrying section. Nonetheless, only 7 of 20 industry sections improved. At the occupation level, no improvement is recognized and only one sector (Technics) shows a higher matching efficiency than before the reforms. At the regional level, there is a general improvement as 8 of 16 states reveal a higher matching efficiency after the reforms. It is salient that these 8 states are located in the south and middle of Germany. Most pronounced is the increase in Bavaria.

However, the estimates have to be taken cautiously. Even though some industry sections reveal a quite big improvement, like Mining and Quarrying, the vacancy share of Mining and Quarrying is small. This implies that the effect on the mismatch indices is also rather small according to equation (4).

Table 7: estimates for matching efficiencies – industries: sections (1-digit)

	industry section	$\phi_i^{\text{00-10}}$	ϕ_i^{before05}	ϕ_i^{after05}
A	Agriculture, Forestry and Fishing	2.1244	2.0929	2.2313
B	Mining and Quarrying	2.7516	1.8656	2.8106
C	Manufacturing	1.2507	1.3488	1.2270
D	Electricity, Gas, Steam and Air Conditioning Supply	0.2938	0.1786	0.3465
E	Water Supply, Sewerage, Waste Management and Remediation Activities	0.6772	0.6339	0.5786
F	Construction	3.0259	2.8440	2.9941
G	Wholesale and Retail Trade, Repair of Motor Vehicles and Motorcycles	1.1665	1.2196	1.1561
H	Transportation and Storage	1.5340	1.5137	1.5509
I	Accommodation and Food Service Activities	1.6069	1.9427	1.5324
J	Information and Communication	0.6625	0.7297	0.7186
K	Financial and Insurance Activities	0.4927	0.5833	0.4937
L	Real Estate Activities	0.4614	0.4378	0.4302
M	Professional, Scientific and Technical Activities	0.8543	0.9289	0.8915
N	Administrative and Support Service Activities	1.4321	1.5290	1.6141
O	Public Administration and Defense, Compulsory Social Security	0.8755	0.8850	0.8531
P	Education	0.7708	0.7895	0.7095
Q	Human Health and Social Work Activities	1.7357	1.9422	1.8276
R	Arts, Entertainment and Recreation	1.1865	1.2032	1.1046
S	Other Service Activities	1.0923	1.3040	1.07719
T	Activities of Households as Employers, Undifferentiated Goods and Services-producing Activities of Households for Own Use	0.2825	0.2948	0.2726
	mean	1.2133	1.2133	1.2200

Table 8: estimates for matching efficiencies – occupations: sectors (1-digit)

	occupation sector	$\phi_i^{\text{00-10}}$	ϕ_i^{before05}	ϕ_i^{after05}
I	Agriculture	0.8954	0.8029	0.9999
III	Manufacturing	1.4597	1.6061	1.3420
IV	Technics	0.6312	0.6127	0.6342
V	Services	1.2131	1.2658	1.1753
	mean	1.0496	1.0719	1.0378

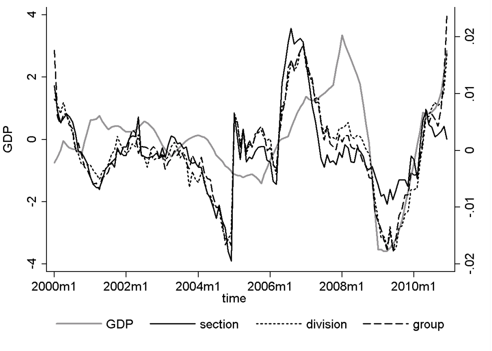
Table 9: estimates for matching efficiencies – regions: states

	state	$\phi_i^{\text{00-10}}$	ϕ_i^{before05}	ϕ_i^{after05}
1	Schleswig-Holstein	1.0391	1.0767	0.9843
2	Hamburg	0.9578	0.9957	0.8773
3	Lower Saxony	1.0265	1.0223	1.0149
4	Bremen	0.7722	0.7983	0.7356
5	North Rhine Westphalia	0.8400	0.8513	0.8219
6	Hesse	0.9858	0.9612	0.9709
7	Rhineland Palatinate	1.1157	1.0442	1.1134
8	Baden-Wuerttemberg	1.1996	1.0951	1.1965
9	Bavaria	1.5030	1.3481	1.5455
10	Saarland	0.8898	0.8752	0.8764
11	Berlin	0.7794	0.8458	0.7828
12	Brandenburg	0.9628	1.0157	0.9999
13	Mecklenburg-Vorpommern	0.9865	1.0328	1.0038
14	Saxony	1.0000	1.0169	1.0485
15	Saxony-Anhalt	0.9838	0.9830	1.0608
16	Thuringia	1.1739	1.1673	1.2220
	mean	1.0135	1.0081	1.0164

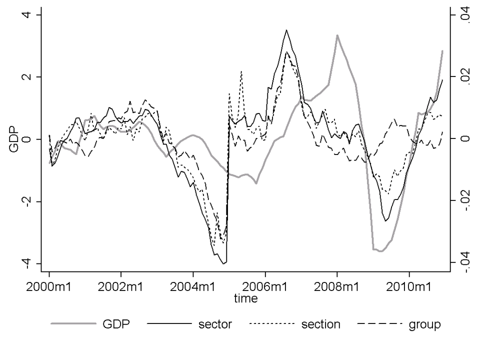
C Appendix: Additional Results

Cyclicality

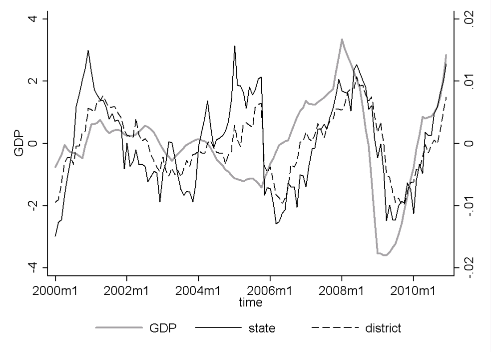
An interesting feature of the indices is their cyclicality. The US indices reveal a counter-cyclical pattern (Şahin et al. (2012), p. 25), whereas in Germany the cyclical components (extracted using HP-filter with smoothing parameter $\lambda = 14400$ (Hodrick/Prescott, 1997)) of the indices showed a very low positive correlation that is always below 0.5 (also cross correlations) to the cyclical components of GDP. Except at the regional levels, the indices appeared to lead the business cycle. The positive correlation and the lead property may be induced by the vacancy share. As Stock/Watson (1999)[p.41] observes, vacancies tend to lead the cycle, which is also the case in Germany during the observation period (correlation of 0.7 at a lead of one quarter). However, the variation over time is relatively small (see right hand scale). Besides, the cyclical components of the indices do not correlate with the cyclical components of the unemployment rate. Also the trend components of the indices and the unemployment rate are not correlated.



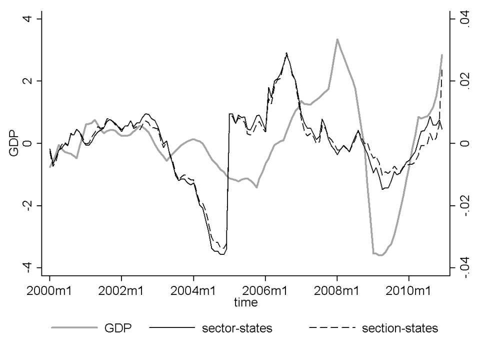
1 industry



2 occupation



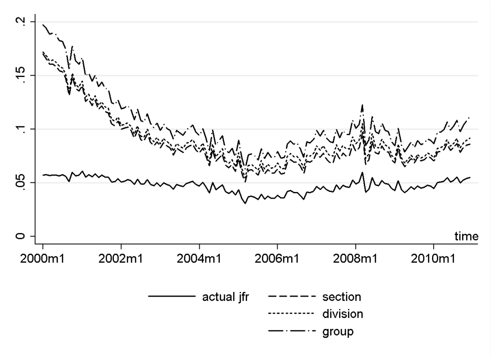
3 region



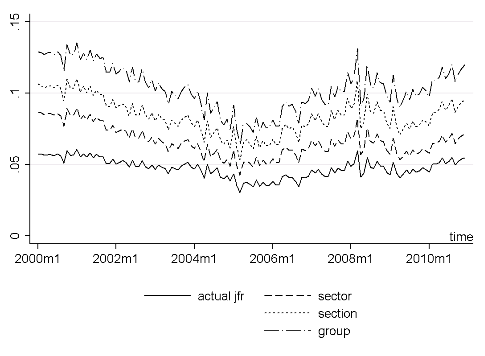
4 occupation-region

Figure 11: cyclical components of GDP and mismatch indices at different disaggregation levels (with solid line representing lowest disaggregation level, dashed line representing intermediate and dotted line representing highest disaggregation level; solid grey line corresponds to GDP; cyclical components filtered using HP-filter, $\lambda = 14400$, quarterly GDP is extrapolated to be monthly. Left scale shows GDP, right scale shows indices.)

job finding rates



1 industry



2 occupation

Figure 12: actual (solid line) and counterfactual (dashed, dotted and dashed-dotted lines) job finding rates for different industry and occupation levels

selected unemployment and vacancy shares

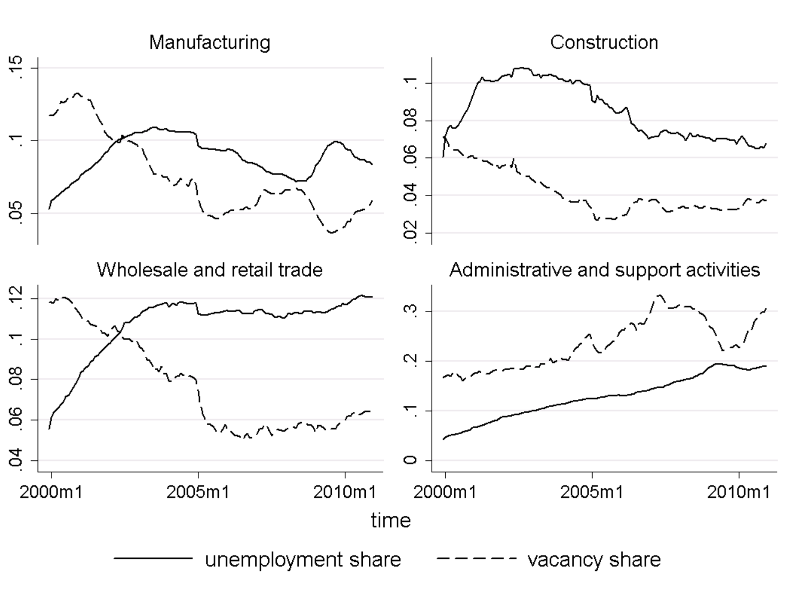


Figure 13: unemployment (solid line) and vacancy shares (dashed line) for industry sections (1-digit)

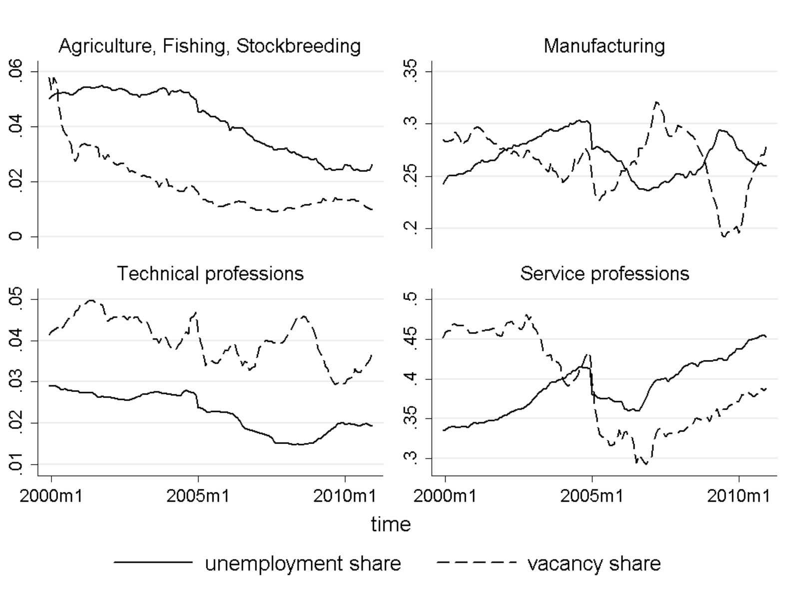


Figure 14: unemployment (solid line) and vacancy shares (dashed line) for occupation sectors (1-digit)

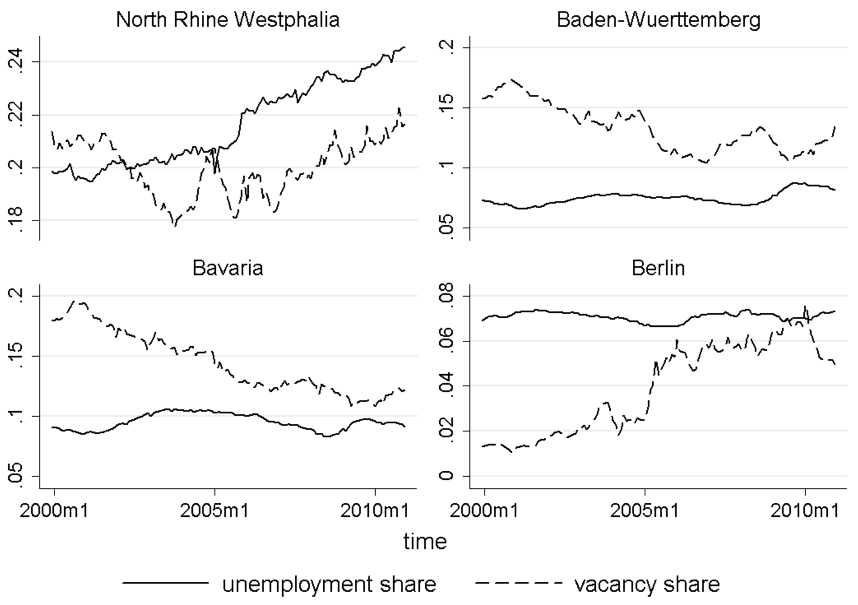


Figure 15: unemployment (solid line) and vacancy shares (dashed line) at state level

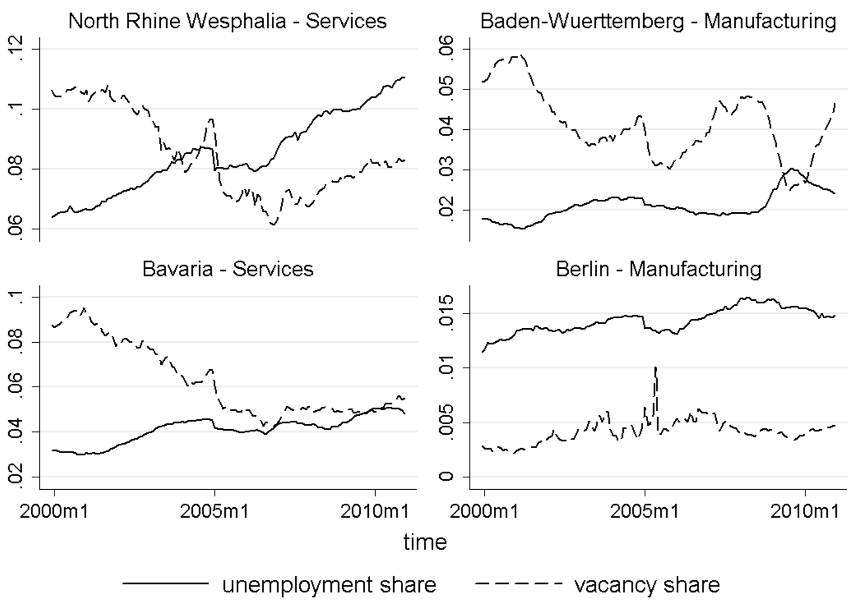


Figure 16: unemployment (solid line) and vacancy shares (dashed line) for occupation-regions (1-digit x states)

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