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Optimal Regional Labor Market Policies

Philip Jung
Philipp Korfmann
Edgar Preugschat

Philip Jung
TU Dortmund and IZA

Philipp Korfmann
TU Dortmund

Edgar Preugschat
TU Dortmund

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ABSTRACT

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We document large and persistent spatial dispersion in unemployment rates, vacancies, labor market tightness, labor market flows, and wages for Germany on a granular regional level. We show that in the 1990s differences in inflows from employment to unemployment were the key driver of regional dispersion in unemployment rates while in the 2000s outflows became more important. To account for the documented regional dispersion we develop a spatial search and matching model with risk-averse agents, endogenous separations and unobservable search effort that leads to moral hazard and quantify the relative importance of 4 potential structural driving forces: dispersion in productivity, in the bargaining strength of workers, in idiosyncratic risk components and in regional matching efficiency. Based on region-specific estimates of these factors we then study the resulting policy trade-off between insurance, regional redistribution and efficiency. We design (optimal) region-specific labor market policies that can be implemented using hiring subsidies, layoff taxes, unemployment insurance benefits and transfers financed by social insurance contributions. We find that a move towards an optimal tax system that explicitly conditions on regional characteristics could lead to sizable welfare and employment gains.

Corresponding author:
Philip Jung
Faculty of Business, Economics and Social Sciences
Technical University of Dortmund
Vogelpothsweg 87
44227 Dortmund
Germany

E-mail: philip.jung@tu-dortmund.de

1 Introduction

Regional earnings and unemployment disparities are large and persistent in Germany. East German workers for example earned 30% less on average during the period 1994-2004 and faced unemployment rates of 20%, twice as high as West German workers. These differences are not a permanent fate though. A decade later, in 2014, the striking divide between the East and the West is still visible in unemployment rates, but it became much less pronounced. Unemployment rates have almost halved to 10% on average in the East and were only 60% larger than in the West. However, the catch-up of the East masks substantial variation across regions when looking at a more granular scale. Many employment districts in the West fell behind and the gap between booming southern districts and the rest of the country has widened over time.

In this paper we address three interdependent questions: are flows into or out of unemployment the key drivers of regional dispersion in unemployment rates in Germany? What are the underlying structural causes for regional dispersion in these flows? Is regional dispersion inefficient and - if so - what region-specific instruments can be used to improve employment and welfare?

We answer these questions by studying regional dispersion and its consequences for regional policy based on German employment agency district data for the years 1994-2014.[1] We empirically document spatial dispersion and time trends for key labor market variables like in- and outflow rates, vacancies, market tightness, and wages utilizing administrative micro data and a newly digitized data series of job openings. We show that inflows have been the key driver of regional unemployment dispersion for the nineties, as emphasized by Bilal (2019) for France, but outflows dominate the picture after the so-called Hartz reforms of the unemployment insurance system in 2005. To explain the cross-sectional dispersion and the trends over time we develop a multi-region variant of a structural search and matching model based on Jung and Kuester (2015) that includes risk-averse agents, endogenous separations and unobservable search effort. The model features a trade-off between insurance, redistribution and efficiency considerations and implies a rich set of *region-specific* instruments to counteract frictions above and beyond the classical search externalities (Kline and Moretti, 2014). We use the model to estimate the relative importance of potential underlying causes for regional dispersion that have been suggested in the literature: dispersion in productivity, matching efficiency, bargaining strength and idiosyncratic firm risk. We then quantify the relative importance of each of these channels in explaining regional dispersion for Germany. Taking the estimated structural labor market differences as policy-invariant (at least in the shorter run), we then use the model to ask how an optimal labor market policy could look like in Germany. We offer a quantitative exploration of the regional-specific differences in

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[1]Part of the paper is based on a dissertation chapter of Korfmann (2020).

key tax instruments necessary to decentralize a constrained efficient allocation and study the resulting employment and welfare gains. We describe these steps and our findings in more detail next.

We use data from the employment panel of integrated employment biographies (SIAB) and monthly vacancy stocks obtained from the federal employment agency (BA) to ask whether inflows into unemployment account for the bulk of the regional dispersions or whether outflows from unemployment are more important in Germany.[2] An examination of the evolution of the underlying worker flows can help to discriminate between various potential explanations for regional dispersion: In the decade 1994-2004 (before the German Hartz IV reform) inflows into unemployment account for 70% of the regional dispersion in unemployment rates, in line with findings for France (Bilal, 2019). However, in the aftermath of the Hartz reforms (see Hartung et al., 2018) the picture changes. Regional variation in inflows rates have declined substantially, which coincides with a sharp decrease in the level of these rates throughout all districts. At the same time differences in outflow rates across regions have increased, while the average increase in outflow rates over time is small. In the decade following the Hartz reforms (2005-2014) - largely driven by the booming southern states - outflows become substantially more important and account for 60% of the regional dispersion.[3] A story to tell is a tale of two regions: East Germany and North Rhine-Westphalia (NRW), the former coal area and most densely populated region in the Western part of Germany. Districts located in these two regions exhibited the highest unemployment rates already in 1994 but due to different reasons. In NRW, unemployment was high because outflow rates were low, while East German districts exhibited above-average inflow rates. Throughout our observation period, unemployment rates in East Germany approached West German levels and this catch up was driven by a substantial decrease in inflow rates. Districts in NRW, however, fell behind as outflow rates did not rise, as they did in the southern districts, and the declines in inflows were the lowest in the country.

Can the above stylized facts inform us about structural differences across regions? To answer this question we develop a multi-region variant of a structural search and matching model based on Jung and Kuester (2015) that features immobile risk-averse agents, endogenous separation and moral hazard leading to a trade-off between regional insurance, redistribution and efficiency. We treat a district as a closed labor market by assuming away labor

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[2]Our research is related to the literature on the ins and outs of labor markets flows (e.g. Elsby et al., 2011). Although differences in regional unemployment rates in Germany are well documented (Patuelli et al., 2012), an analysis of the underlying labor market flows is still missing from the literature.

[3]The new evidence we provide on the importance of inflows vs. outflows rates for unemployment differentials echoes findings of the research on the importance of worker flows for the development of the aggregate unemployment rate in Germany, see Hertweck and Sigrist (2015), Jung and Kuhn (2014), Hartung et al. (2018) for Germany. Concerning other countries, our results for the nineties are in line with those of Bilal (2019), who finds that inflows explain the majority of the variations in regional unemployment rates in the U.S. and France. We add that the explanatory power of inflow rates is time-varying.

mobility across these markets.[4] We estimate the model with a uniform tax and unemployment insurance (UI) benefit system on the federal level that capture stylized aspects of the German system. The purpose of the model is twofold: First, we use the model to estimate regional differences in key parameters that might capture underlying structural differences across regions. Second, given these estimates on regional heterogeneity, we ask how a policy maker could design a tax and transfer scheme that optimally addresses regional disparities.

To this end we allow regions to differ along 4 dimensions that have been suggested in the literature to account for regional dispersions over space: (1) A *wage channel* capturing the idea that East German wages had been set 'too high' relative to productivity after reunification forcing workers into unemployment or migration to the West (Burda and Hunt, 2001), which gives wage setting by (Western) unions a key role in explaining regional dispersions; (2) A *matching efficiency* channel that allows for regional differences in matching particular skill requirement of jobs to unemployed workers (Fahr and Sunde, 2006); (3) A *productivity channel*, that - due to sorting decisions by firms or agglomeration forces (Bilal, 2019) - lead to regional differences in labor market outcomes; (4) An *idiosyncratic risk channel* in which differences in firm characteristics across space (Eeckhout et al., 2014) translate into larger idiosyncratic uncertainty of the profit path of a given match. We look at regional data averaged over two time periods, 1994-2005 and 2006-2014, before and after the Hartz reforms and back out the respective structural parameters sets based on a steady state approximation of the model in both periods. We allow the benefit system to change over time to potentially capture a fundamental break in German labor market institutions due to the Hartz 4 reforms that has affected in particular the inflow rates over time as shown in Hartung et al. (2018).[5] The model allows us to quantify the relative importance of these channels based on regional variations in wages, in- and outflows and market tightness.

When viewed through the lens of a search and matching model the large differences in wages during the nineties need to be explained by large differences in productivity in the East. Over time however, a catch-up process has let to a relative increase in productivity in the eastern districts by over 20%. Productivity increases (at least relative to vacancy creation cost) would tend to increase outflow rates in most models that follow Mortensen and Pissarides (1994). However, the probability of finding a job has barely changed between 1994 and 2014 in the East. To account for these facts wage setting is a key driver in the East. To rationalize observed outflow rates the model demands a strong bargaining position of workers in the East during the nineties pushing wages up *relative* to productivity compared

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[4]Inter-regional migration in Germany is not negligible, but as we show in a companion paper (Jung et al., 2021) it is limited and heavily concentrated in young age cohorts. We provide an upper bound on the gains from mobility using the mismatch index developed by Sahin et al. (2014), see appendix (D.0.1).

[5]The literature investigating the Hartz reforms is extensive. See, for example, Hertweck and Sigrist (2015), Launov and Wälde (2016), Klinger and Rothe (2012), Krause and Uhlig (2012), Klinger and Weber (2016).

to other western regions in line with some narratives pointing towards unions from the West that aimed at keeping East German wages close to western standards (see Burda and Hunt, 2001). Over time, however, the bargaining strength of unions declined. Tightness data and outflow rates together identify the underlying matching efficiency by region. Interestingly, we find that in the nineties the East and the South, home to the districts with the lowest and the highest productivity, face similar high levels of matching efficiency. The West and the North, in contrast, were less efficient in matching worker to firms. Over time, the matching efficiency in the East declined somewhat, but remained through out the 2000s larger than in the North or the West. Finally, to explain the regional dispersion in inflow rates we find that idiosyncratic productivity risk is a bit higher both in the former coal area in NRW as well as in the East. The Hartz reforms lead to an increase in the match surplus in all districts that has lowered inflow rates substantially.

The estimated structural disparities might call for region-specific policies (Glaeser and Gottlieb, 2008 and Kline and Moretti, 2013).[6] The design of these policies will depend crucially on the determinants of local unemployment and possible underlying inefficiencies: for example, a measure designed to increase hirings in eastern Germany might not be well suited when unemployment is high because employment relationships are terminated more often. Once we have an estimate on regional differences in primitive parameters in place we can ask how an optimal regional labor market policy mix would look like. With the optimal policy mix, the planner implements the constrained-efficient allocation, given the unobservable search effort of workers. Our model provides simple formulas for the design of optimal hiring subsidies in a region, optimal firing taxes as well as optimal net replacement rates of the UI benefit system both for a world without redistribution across regions, i.e. in a setup where we require the tax-code to be self-financing within a region, and with redistribution, where we allow for transfers across districts. We find only a small role for variations of the unemployment insurance replacement rate by region, being lowest in the East *and* in the South reflecting relatively high matching efficiency levels. The planner's optimal hiring subsidies and layoff taxes, however, vary substantially across districts, though in a way that again comes at a surprise if one only looks at heterogeneity across unemployment rates. In both periods, East German districts are subject to policies at a rather average level, while the layoff taxes and hiring subsidies are particularly high in NRW and lowest in Bavaria. The

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[6]While Kline and Moretti (2013) abstract from the layoff margin and studies the relations ship between outflows and hirings subsidies based on deviations of the Hosios condition, there is little work that accounts for the importance of both layoffs and hirings. The present article is closest to the study of Bilal (2019), who rationalizes regional variations in job losses and hirings in a model with worker and firm mobility. In his model, spatial unemployment rate differentials are due to pooling externalities that drive the location choice of firms: High productive firms co-locate in slack labor markets, while low productive firms locate in tight labor markets. The co-location of the latter leads to high unemployment that is driven by high separation rates in tight labor markets. Our empirical results point to a more complex mechanism, as we do not observe that higher layoff rates coincide with tighter labor markets.

social planner would subsidize job openings in NRW by twice as much as in the South and by around 30% more compared to the East. Moreover, it would prevent separations by large firing taxes also twice as high relative to average wages as in the South. This result is due to the estimated large idiosyncratic risk component that explains the NRW data. The optimal labor market policy mix leads - in the absence of any redistribution across districts - to gains in employment of around 2% in the South and up to 8% in the East during the 2000s, in the nineties potential employment gains were even larger. The corresponding welfare gains are more homogenous across regions and sizable (around 23%). These gains are achieved by ensuring that worker and firms, when making hiring and firing decisions, internalize the cost and gains on the social inurance system properly. If one were willing to impose a utalitarian planner and would allow for regional transfers an optimal policy would then equalize average consumption across regional districts which implies substantial transfers to the East but would not equalize employment opportunities. In fact the optimal policy mix with respect to labor market institutions would hardly change.

This paper is organized as follows. Section 2 describes the data, discusses the sample selection and provides a detailed overview on the development of local labor markets in Germany. In section 3, we present the model. Section 4 estimates the model, relates regional variations to structural model parameters and quantitatively evaluates the optimal policy mix. Section 5 concludes.

2   Regional labor market development

This section briefly introduces the microdata we utilize to construct local unemployment rates and workers flows. More details are provided in appendix A. We then provide a comprehensive overview of the development of regional labor markets in Germany.

2.1   Data and sample selection

Our primary data source is the employment panel of integrated employment biographies (SIAB), an administrative data set provided by the Institute for Employment Research (IAB).[7] The SIAB is a two-percent representative sample of all individuals who are unemployed or subject to social insurance contributions and covers the years $1975 - 2014$. The panel represents approximately 80% of the labor force, as self-employed and civil servants are excluded. We focus our analysis on the period $1994 - 2014$ to include East German

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[7]This study uses the weakly anonymized version of the SIABSample of Integrated Labour Market Biographies (Years 1975 - 2014). Data access was provided via on-site use at the Research Data Centre (FDZ) of the German Federal Employment Agency (BA) at the Institute for Employment Research (IAB) and subsequently remote data access.

workers, but occasionally report results for West-Germany for the years 1980-1994.[8]. The individual employment histories are used to construct monthly unemployment, inflow rates, and outflow rates. This data is merged with monthly vacancy data. We obtain data on the vacancy stock for $2000 - 2014$ from the federal employment agency and combine them with newly digitized data from their official historical reports. The construction of monthly worker histories follows Jung and Kuhn (2014). In particular, we aggregate the daily employment histories to a monthly frequency using predefined reference weeks. Labor market states are assigned to a worker based on a hierarchical ordering, see appendix A for the details.

The regional level of analysis is the employment agency district. The territory of each EAD is based on the geographical division of 2014. There are 154 districts. We treat the three EADs covering Berlin as a single one because the territorial borders were subject to many changes during the observation period. Each district includes approximately three municipalities (*Kreise*, NUTS3). The SIAB data contains information on the municipality in which the workplace is located for every employed worker. In contrast, information on the place of residence for employed and unemployed workers is only available from 1999 onwards. To obtain consistent data on regional transitions covering the whole observation period, we assign the district of the last employment spell as the current place of residence when an individual becomes unemployed. We impute the location information of unemployed workers entering from non-employment by setting it to the location of their next employer if the employment is consecutive.

We obtain data on registered vacancies from the federal employment agency for the years 2000 to 2014. Earlier data is digitized using the official monthly as well as annual reports (*Amtliche Nachrichten der Bundesagentur für Arbeit*) of the employment agency. We observe the number of vacancies that are reported to the FEA, which cover approximately $40 - 50\%$ of all vacancies (Brenzel et al. (2016)). However, other sources are not representative at this highly disaggregated regional level. Moreover, the reported vacancies before 2000 include job offers for seasonal workers or promoted vacancies, while the vacancies received from the FEA are based on a modified concept, where seasonal jobs and promoted jobs are excluded. We re-scale vacancies before 2000 by a constant factor to account for the level shift.[9] The geographical area corresponding to an EAD stayed roughly constant until the year 2012, after which a significant reorganization of the territory took place. As the regional level of the SIAB data is based on the division of territory in 2014, we adjust the vacancy data correspondingly. Specifically, we use overlapping data for old and new territorial classifications to modify the vacancy counts to be representative of the 2014 allocation of territory. The modifications of the vacancy data are discussed in detail in appendix A.3. Overall, we assemble a regional

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[8]Information on workers in East Germany in 1992 and 1993 is used to impute the location variable.

[9]We re-weight vacancies before 2000 by a factor of 0.7 to account for job offers for seasonal workers or promoted vacancies. The adjustment factor is based on overlapping aggregate vacancy data from Hartmann and Reimer (2010) for the period $2001 - 2009$.

data set spanning the years $1980-2014$ for West and $1994-2014$ for West and East Germany.

2.2 Regional labor market disparities

This section provides a comprehensive overview of the development of disparities in regional labor markets over time. To better visualize the spatial variations, we group the unemployment agency districts according to their cardinal directions. However, to highlight the specific labor market characteristics of the former coal and steel region situated in the federal state North Rhine-Westphalia we subdivide the western districts into "NRW" and "South-West" (or "S-W") so that we obtain 5 main regions (see the map in Fig. 1).[10]

Figure 1: Map of employment agency districts and regions
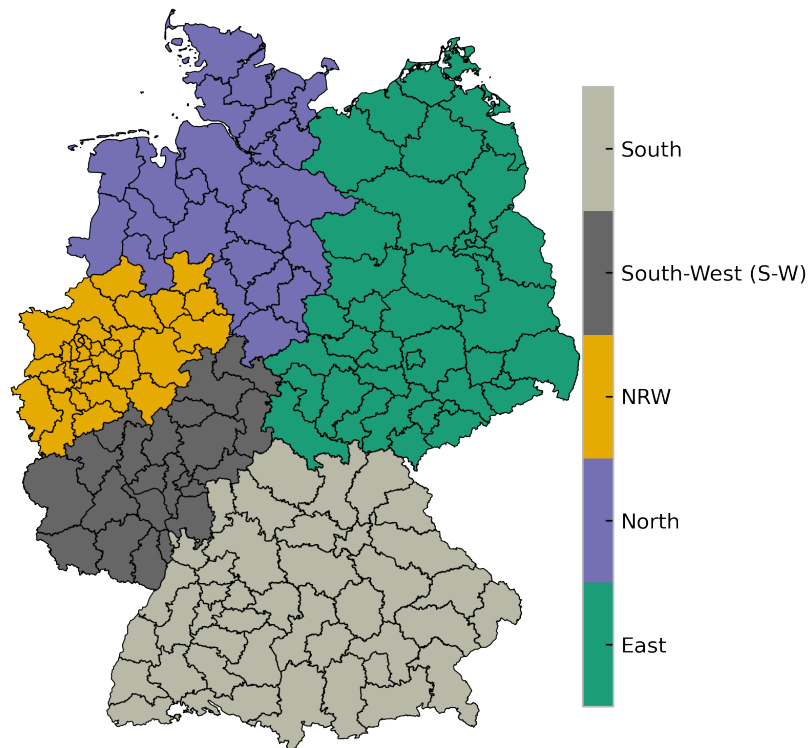
Notes: The black grid lines indicate EAD borders, the colored regions indicate the five regions.

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[10]South: Bavaria and Baden-Wuerttemberg; NRW: North Rhine-Westphalia; South-West (S-W): Hesse, Saarland, and Rhineland Palatinate (dark green); North: Schleswig-Holstein, Hamburg, Bremen, and Lower-Saxony; East: Berlin, Saxony, Saxony-Anhalt, Thuringia, and Mecklenburg-West Pomerania. Note, we summarize the regions South, South-West, West and North by "West Germany" and East we also call "East Germany".

Figure 2 shows the development of unemployment rates during 1994-2014. In 1994, eastern EADs were decoupled from the others as they exhibit unemployment rates almost twice as high. While the average difference to West German EADs had declined up to 2004, unemployment had increased to even higher levels across all districts. During the subsequent ten years, unemployment rates decreased significantly, but dispersion, measured as squared deviation from the average started to increase around the year 2004 as documented in appendix C.

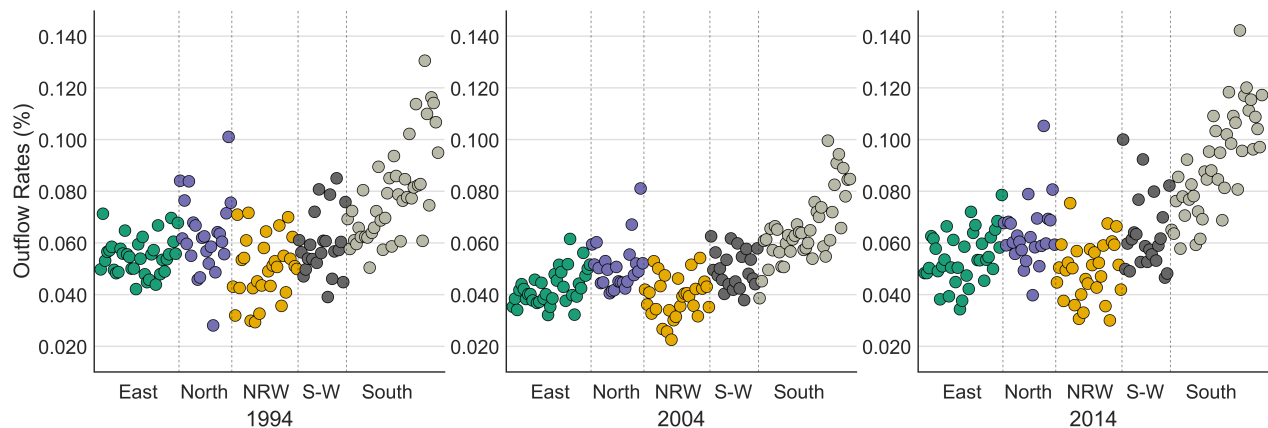Figure 2: Unemployment rates by employment agency district
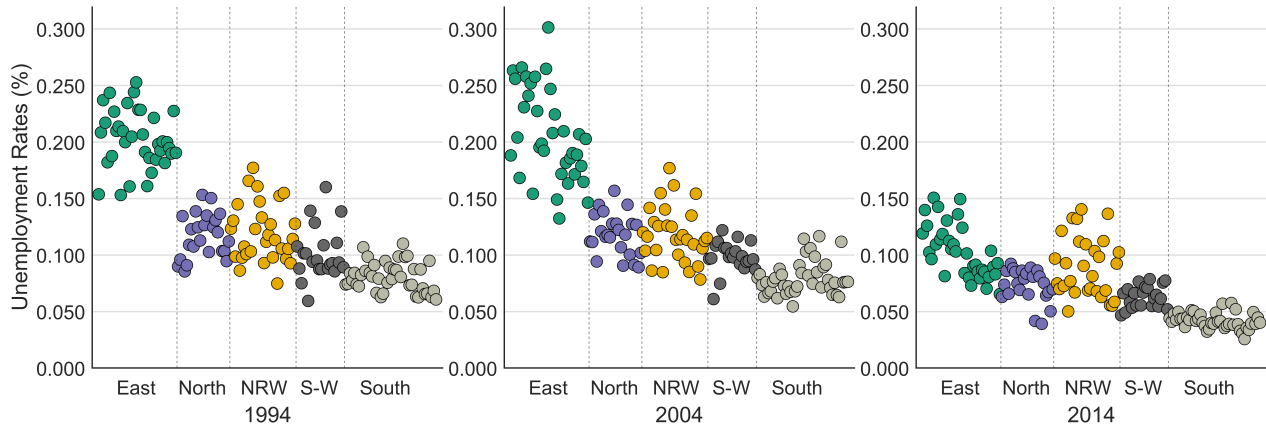
Notes: The figure displays the average monthly unemployment rate in 154 employment agency districts for the years 1994, 2004 and 2014.

The development also provides suggestive evidence about which districts are responsible for the increase in the dispersion of the unemployment rates in West Germany and the stagnating dispersion in Germany. We find that it is predominantly districts located in North-Rhine Westphalia that exhibit high unemployment rates in 2014, while eastern EADs unemployment rates have almost converged to West German levels. Overall, while the dispersion across EADs increased, regional unemployment rates decreased by 54% on average, from 1994 to 2014.

In the following paragraphs, we link the observed differences in unemployment rates to the underlying variations in worker flows. As can be seen from Figure 3, the high unemployment rates in East Germany are not the result of lower transitions out of unemployment. The outflow rates are similar across all but the southern EADs, where we observe approximately 50% above-average rates for all points in time. The rates are stable over the observation period. In fact, the average change between 1994 and 2014 was 5.0%. This small change indicates that outflow rates are not the major driver of the between-district or over-time variation in unemployment rates. The distribution of inflow rates, which is shown in Figure 4, paints a different picture of regional disparities. Foremost, it is remarkably similar to the distribution of unemployment rates: Inflow rates in East German districts are more than

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Figure 3: Outflow rates by employment agency district

Notes: The figure displays the average monthly unemployment inflow rate in 154 employment agency districts for the years 1994, 2004 and 2014.

twice as high in 1994 and 2004, compared to all other regions. In 2014, the differences had almost completely vanished, which is reminiscent of the low dispersion. Overall, we observe an average decrease in the inflow rates of 63% throughout the sample period.

Figure 4: Inflow rates by employment agency district
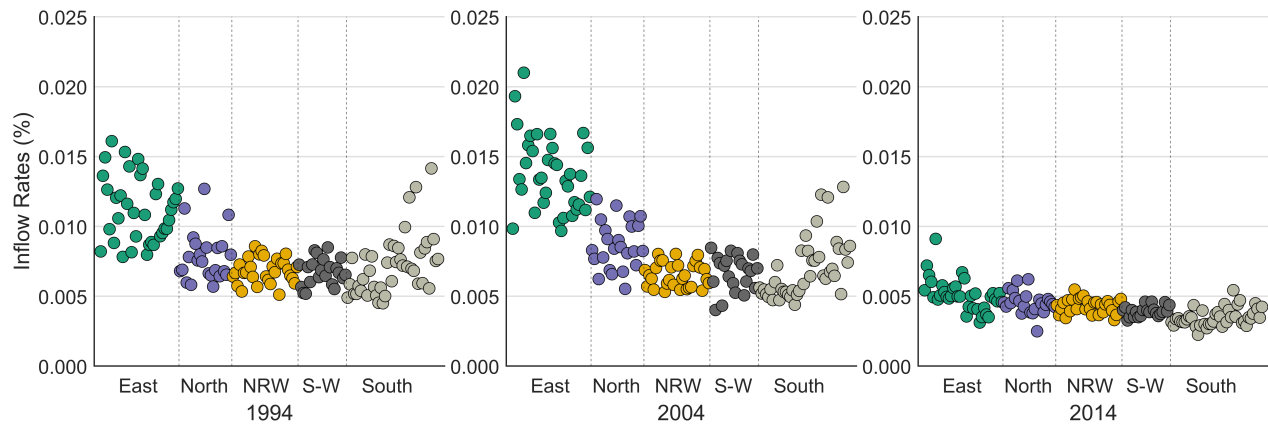
Notes: The figure displays the average monthly unemployment inflow rate in 154 employment agency districts for the years 1994, 2004 and 2014.

Unemployment rate decomposition We employ a two-state stock-flow model to quantify the importance of the transitions in and out of unemployment for the variation in unemployment rates across districts. Specifically, we exploit the steady state relationship of the unemployment rate where $u_j^* = \frac{\xi_{jt}}{\xi_j + f_j}$ approximately holds (Fujita and Ramey, 2009). We decompose the volatility around the average unemployment rate in each year

$$ln(u_j^*/\bar{u}) = (1 - \bar{u}) \ln(\xi_j/\bar{\xi}) - (1 - \bar{u}) \ln(f_j/\bar{f}) + \epsilon_j, \tag{1}$$

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where a bar denotes the average rate across districts and ϵ denotes the error term. We write this expression in abbreviated form as $du = d\xi + df + \epsilon$. Fujita and Ramey (2009) show that $ln(u_j/\bar{u})$ can be decomposed into

$$1 = \frac{Cov(du, d\xi)}{Var(du)} + \frac{Cov(du, df)}{Var(du)} + \frac{Cov(du, \epsilon)}{Var(du)}, \tag{2}$$

where, e.g., $\frac{Cov(du,d\xi)}{Var(du)}$ measures the contribution of the inflow rate to the variation of the unemployment rate across districts. Table 1 presents the results.[11]

They mirror the observed changes of the distribution of outflow and inflow rates, as displayed in Figures 3 and 4. Over the sample period, inflow rates account for, on average, 59% of the unemployment rate variation across EADs. However, their contribution decreases from 70% in 1994-2004 to 43% in 2005-2014. Variations in outflow rates account for, on average, 42% and their importance increases from 31 in 1994-2004 to 58% in 2005-2014.

Table 1: Decomposition of regional unemployment rate disparities

	1994 - 2014	1994 - 2004	2005 - 2014
Outflows	0.42	0.31	0.58
Inflows	0.59	0.70	0.43

Notes: The table presents the results of a variance decomposition of the unemployment rates across districts for different time intervals. "Outflow" ("Inflow") indicates the contribution of the rate to the variation of unemployment rates across districts.

Our descriptive evidence shows that differences in inflow rates are the main reason for the variation in unemployment rates during 1994-2004. Bilal (2019) also finds that variations in job losses explain a significant part of regional unemployment rate differentials in the U.S. and France. However, inflow rates have become much more similar across EADs after the Hartz reforms, while the differences in outflow rates have increased. As a result, the latter have become more critical in the determination of regional differences in unemployment rates.

Wages and vacancies Figure 5 displays the deviations of the wage from the average wage across districts in each year. Wages exhibit a substantial dispersion across EADs and this dispersion is very persistent as the correlation between 1994 and 2014 is above 0.9. They are lowest in East German EADs. However, eastern districts catch up to the average wage as the gap is reduced from -30% in 1994 to -20% in 2014.

While unemployment rates are one of the most important labor market indicators, labor market tightness is also informative with respect to the state of the economy. Figure 6 displays

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[11]Note, in the table and in the following we have ignored the contribution $Cov(du, \epsilon)/Var(du)$, which is negative but very small. Therefore, the contributions of the main components do not sum exactly to 100%.
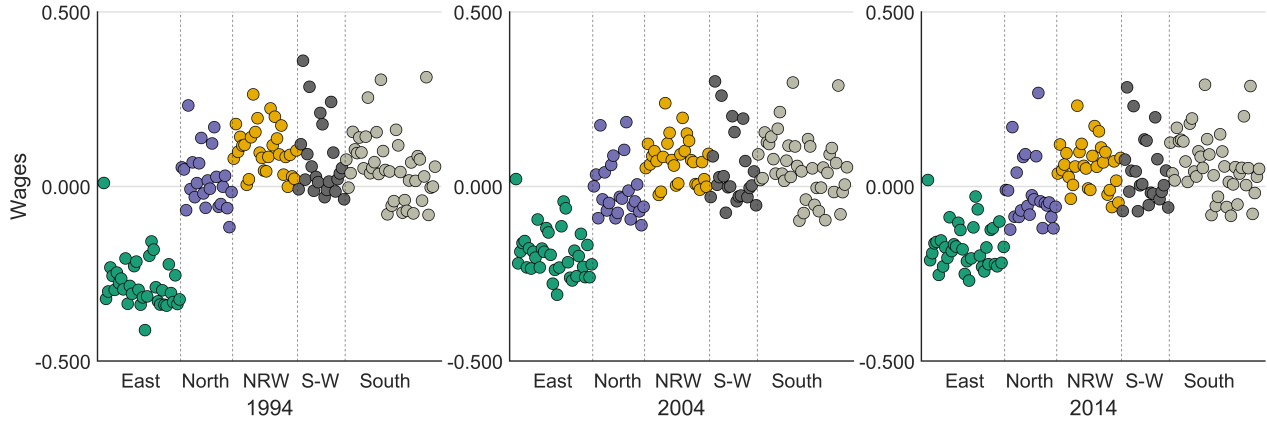
Figure 5: Wages by employment agency district

Notes: The figure displays the average (log) deviation of the wage from the average wage in each year in 154 employment agency districts for the years 1994, 2004 and 2014.

labor market tightness −the ratio of vacancies over unemployed− across EADs. From 1994 to 2004, tightness has decreased across all districts mirroring the increase in unemployment rates. In the next 10 years, markets have become substantially tighter. This is generally favorable for job-seekers because they compete for relatively more open vacancies.

Figure 6: Labor market tightness by employment agency district
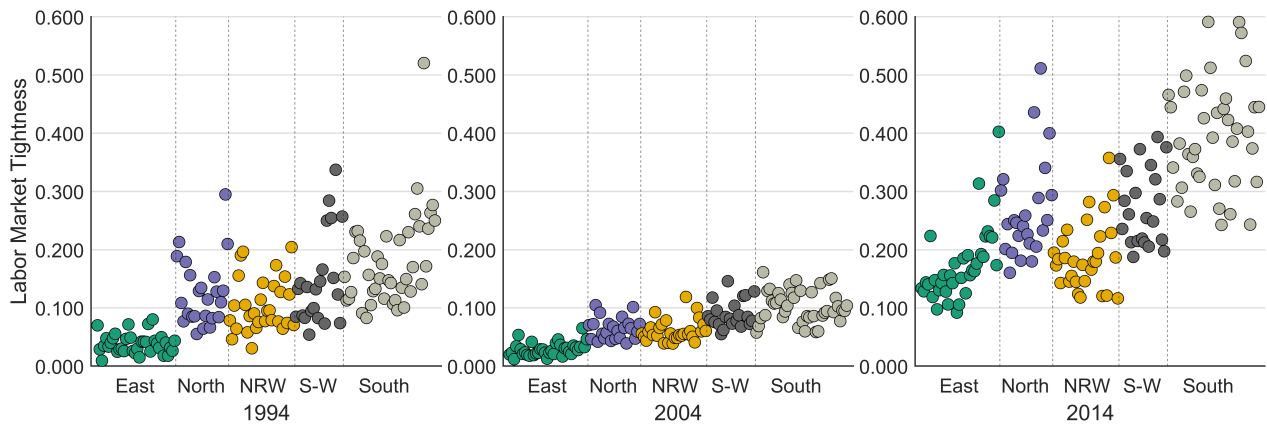
Notes: The figure displays the average labor market tightness (the ratio of vacancies over unemployed) in 154 employment agency districts for the years 1994, 2004 and 2014.

We also inspected job-to-job transitions as displayed in figure 7. With the exception of Eastern districts in 1994 we find no substantial variation of job-to-job transitions rates across EADs. Therefore, these transitions seem to have little impact on the regional variation in employment rate differentials. We will therefore abstract from job-to-job transitions when modeling the German labor market.

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Figure 7: Job-to-job Transitions
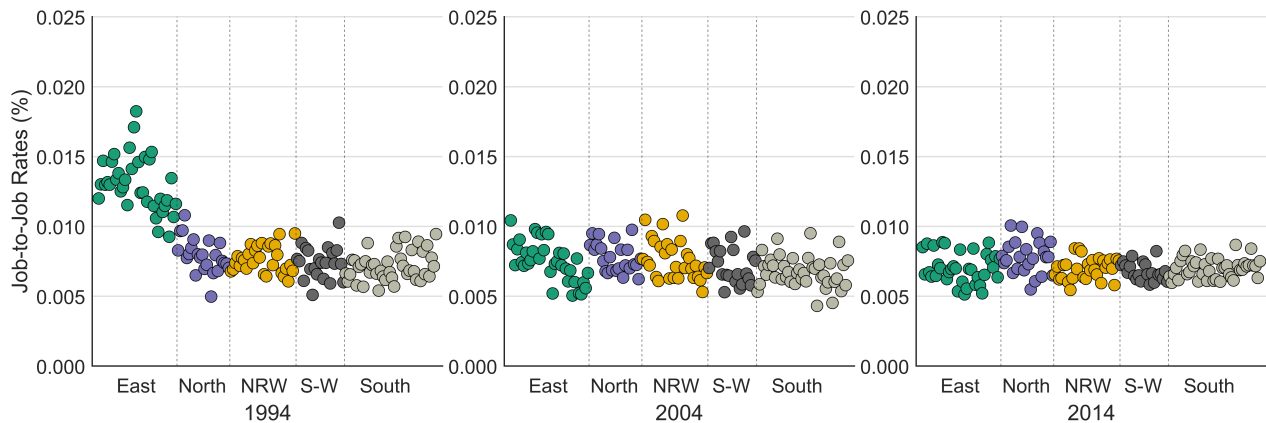
3   The model

This section develops a spatial model of the economy in which risk-averse workers are immobile across regions and face labor market frictions in the tradition of Diamond (1982), Mortensen and Pissarides (1994). The model features heterogeneity to capture regional differences in the matching process, in the bargaining position, in productivity and in firm risk. The moral hazard friction due to unobserved search effort calls for a rich set of labor market instruments including hiring subsidies, a positive role for job protection via taxes on separations and unemployment insurance by region to decentralize a constrained efficient allocation. The model abstracts from agglomeration forces that would induce a particular distribution of workers over regions over time and takes population size per region as given and fixed. Our model builds on a steady state version of Jung and Kuester (2015) and Ignaszak et al. (2020), where we introduce regional heterogeneity.[12]

Time is discrete and continues forever. In the following we focus on the steady state of the model. There are I regions populated by infinitely-lived workers of mass one on each region. A fraction e_i of these workers is employed and the remainder is unemployed $u_i = 1 - e_i$ at the beginning of the period. Workers can not move from one region to another. Workers and firms take the unemployment insurance (UI) benefit system, layoff taxes, hiring subsidies, and production taxes as given. There are no bond markets to self-insurance for workers but workers on each region i own an equal share of all firms currently in that region.[13] Each region produces a freely tradable homogeneous good with a price normalized to 1.

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[12]Our presentation focuses on the regional features of the model and we refer the reader to Jung and Kuester (2015) for further details.

[13]An elegant way to justify this no-bond trade assumption is by following the ideas of Ravn and Sterk (2016) who generate it endogenously.

3.1 Workers

A worker living in region i and discounting the future with $\beta \in (0, 1)$ has lifetime utility of

$$E_0 \left\{ \sum_{t=0}^{\infty} \beta^t [U(c_t^i) - \overline{h} \cdot \mathbb{I}(\text{not working}_t^i) - \iota \cdot \mathbb{I}(\text{search}_t^i)] \right\}. \tag{3}$$

E_0 denotes the expectation operator conditional on the first period. The worker enjoys utility from consumption, c_t^i with a standard felicity function $U(c) : \mathbf{R}^+ \to \mathbf{R}$. $\mathbb{I}$ is the binary indicator function. Workers differ by a utility cost of search, ι. They incur these costs only if they search for a new job. The cost $\iota \sim F_\iota(0, \sigma_\iota^2)$ is assumed to be *i.i.d.* both across worker, region and time, where $F_\iota(\cdot, \cdot)$ is the logistic distribution with mean 0 and variance $\sigma_\iota^2 = \pi \frac{\psi_s^2}{3}$, with $\psi_s > 0$ and π being the mathematical constant. We denote with $\overline{h}$ the average search cost in utility units.

Workers cannot self-insure against income fluctuations through saving or borrowing but might receive dividend income Π^i (described below) from owning the firms in their region. Ownership rights are distributed equally across inhabitants of the region.

Let w_t^i be the wage that an employed worker earns. Consumption of the worker is given by

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\begin{aligned}
c_{u,t}^i &:= b_t^i + \Pi_t^i && \text{if unemployed at the beginning of } t, \\
c_{e,t}^i &:= w_t^i + \Pi_t^i && \text{if employed at the beginning of } t.
\end{aligned} \tag{4}
$$

If the worker enters the period being unemployed, the worker receives an amount b_t^i of unemployment benefits. The government, by assumption, conditions payment only on the worker's current employment status. A worker who enters the period being employed receives wage income or, if separated, a severance payment equal to the period's wage. We will describe the value functions and profit equations recursively and denote future values with primes.

Value of an employed worker Let ξ^i be the separation rate of existing matches in region i. Before separations occur, the value of an employed worker is

$$V_e^i = \quad U(c_e^i) + [1 - \xi^i]\beta V_e^{i\prime} + \xi^i[V_u^{i\prime} - U(c_u^i)]. \tag{5}$$

A worker who is employed at the beginning of the period consumes c_e^i irrespective of the separation decision (due to severance payments). With probability $1 - \xi^i$ the match continues. With probability ξ^i, instead, the match separates and the worker immediately start to searching for new employment. V_u^i is the value of a worker who starts the period unemployed.

Value of an unemployed worker and search   An unemployed worker chooses a cut-off strategy balancing her search costs ι with the expected discounted gain from search:

$$\iota^{s,i} = f^i \beta \Delta^{i\prime} \tag{6}$$

Here $\Delta^i \equiv V_{e,t}^i - V_{u,t}^i$ denotes the gain from employment relative to unemployment and f^i marks the job-finding rate. Using the properties of the logistic distribution, the probability that the worker searches is given by

$$s^i = Prob(\iota \leq \iota^{s,i}) = 1/[1 + \exp\{-\iota^{s,i}/\psi_s\}]. \tag{7}$$

and the conditional expectation can be shown to be

$$\int_{-\infty}^{\iota_t^{s,i}} \iota dF_\iota(\iota) \equiv \Psi(s^i) = -\psi_s[(1 - s^i)\log(1 - s^i) + s^i \log s^i] \tag{8}$$

which can be interpreted as the option value of having a choice to search.

Hence, the discounted present value of unemployment at the beginning of the period is

$$
\begin{aligned}
V_u^i &= U(c_u^i) - \overline{h} + \Psi(s^i) + s^i f^i \beta \Delta^{i\prime} + \beta V_u^{i\prime} \tag{9} \\
&= U(c_u^i) - \overline{h} - \psi_s \log(1 - s^i) + \beta V_u^{i\prime} \tag{10}
\end{aligned}
$$

The worker consumes c_u^i when unemployed, has an average search cost of $\overline{h}$ and an option value of searching due to the idiosyncratic cost distribution. With probability s^i the worker decides to search and obtains a job offer with probability f^i, so the product is the transition probability of moving to employment if unemployed today. The second line follows by substituting in the optimal choice s^i into the option value $\Psi(s^i)$. If the worker does not search or does not receive an offer, she remains unemployed receiving a discounted value of unemployed $\beta V_u^{i\prime}$. For later reference we can derive

$$\Delta^i = U(c_e^i) - U(c_u^i) + [1 - \xi^i][\overline{h} + \psi_s \log(1 - s^i)] + [1 - \xi^i]\beta \Delta^{i\prime} \tag{11}$$

3.2   Firms

Firms can freely enter and are owned in an equal amount by the inhabitants of the region. Firms discount future profits with a given discount factor R^i that we allow to be region specific (derived below). Firms build a match with one worker to produce output. A firm that enters the period matched to a worker can either produce or separate from the worker. Production entails a firm-specific resource cost, ϵ_j each period. This fixed cost is independently and identically distributed across firms and time with distribution function $F_\epsilon(x; 0, \psi_{\epsilon,i})$. $F_\epsilon(\cdot, \cdot)$

is the logistic distribution with mean zero and regional-specific variance $\sigma_{\epsilon,i}^2 = \pi \frac{\psi_{\epsilon,i}^2}{3}$. The firm separates from the worker whenever the idiosyncratic cost shock, ϵ_j, is larger than threshold $\epsilon_t^{\xi,i}$, which is determined by bargaining described below. Using again the properties of the logistic distribution, conditional on the threshold, the separation rate can be expressed as

$$\xi^i = Prob(\epsilon_j \geq \epsilon^{\xi,i}) = 1/[1 + \exp\{(\epsilon^{\xi,i})/(\psi_{\epsilon,i})\}]. \tag{12}$$

and the option value of having a choice can be denoted by $\Psi^i(\xi^i) = -\psi_{\epsilon,i}[(1-\xi^i)\log(1-\xi^i) + \xi^i \log \xi^i]$.

The value of a firm at the beginning of the period, before the realization of idiosyncratic cost shocks, is given by

$$J^i = \begin{array}{c} (1-\xi^i)\left[\exp\{a^i\} - \tau_J^i - w^i + \frac{J^{i\prime}}{R^i}\right] \\ -\xi^i\left[\tau_\xi^i + w^i\right] + \Psi^i(\xi^i) \end{array} \tag{13}$$

if workers and firms separate, the firm might pay a layoff tax τ_ξ^i. Severance payments are equal to the current wage, so the firm statically insures the worker against unemployment risk but not over time. If the match survives it will produce output with the regional specific productivity $\exp\{a^i\}$, pays the worker a wage w^i and faces a social insurance contribution or a production tax τ_J^i proportional to output (or wages in equilibrium). A match that produces this period continues into the next. To create a vacancy in region i firms have to pay a cost κ_v^i. If the firm finds a worker, the worker is hired this period and can start producing from the next period onward. If the firm hires a worker the firm might receive a hiring subsidy τ_q^i that pays out at the end of this period after matching took place. Firms post vacancies in each region as long as the gains cover the cost of a vacancy. In the free-entry equilibrium the following condition holds:

$$\kappa_v^i = q^i \frac{J^{i\prime}}{R^i} + q^i \tau_q^i, \tag{14}$$

where q^i is the probability of filling a vacancy. Let v^i be the number of vacancies posted. The number of matches m^i and the separation rate determine the evolution of employment

$$e^{i\prime} = [1 - \xi^i] \cdot e^i + m^i.$$

and we assume a constant-returns matching function:

$$m^i = \chi^i \cdot \left[v^i\right]^\gamma \cdot \left[[\xi^i e^i + 1 - e^i]s^i\right]^{1-\gamma}, \quad \gamma \in (0,1). \tag{15}$$

Here, $\chi^i > 0$ is matching efficiency which we allow to differ across regions. $\theta^i := v^i/([\xi^i e^i + 1 - e^i]s^i)$ is the market tightness. The job-finding rate is $f^i := m^i/([\xi^i e^i + 1 - e^i]s^i) = \chi^i[\theta^i]^\gamma$,

and the job-filling rate is $q^i := m^i/v^i = \chi^i[\theta^i]^{\gamma-1}$. The mass of workers who potentially search is $\xi^i e^i + 1 - e^i$, with $\xi^i e^i$ being workers separated at the beginning of the period and $u^i = 1 - e^i$ the number of unemployed at the beginning of the period. s^i is the fraction of those who actually search.

Total production of output in region i is given by

$$y_t^i = e^i(1 - \xi^i)\exp\{a^i\} \tag{16}$$

where $e^i(1 - \xi^i)$ is the mass of existing matches that are not separated at the beginning of the period.

Dividends Dividends accruing in region i arise from firm profits, namely,

$$
\begin{aligned}
\Pi^i &= e^i\Psi(\xi^i) + e^i(1 - \xi^i)\left[\exp\{a^i\} - \tau_J^i - w^i\right] - e^i\xi^i\left[w^i + \tau_\xi^i\right] \\
&\quad - \kappa_v v^i + v^i q^i \tau_q^i.
\end{aligned}
\tag{17}
$$

and are distributed back lump sum within the region.

3.3   Bargaining between firm and worker

At the beginning of the period, workers and firm bargain over the wage and the severance payment as well as over a state-contingent plan for separation using a standard Nash-bargaining protocol

$$\{w^i, \epsilon^{\xi,i}\} = \arg\max_{w^i, \epsilon^{\xi,i}}(\Delta^i)^{1-\eta^i}(J^i)^{\eta^i}, \tag{18}$$

where η measures the bargaining power of the firm. The first-order condition for the wage is as follows

$$(1 - \eta^i)J^i = \eta^i\frac{\Delta^i}{U'(c_e^i)}. \tag{19}$$

The first-order condition for the separation cutoff yields

$$\epsilon^{\xi,i} = \left[\exp\{a^i\} - \tau_J^i + \tau_\xi^i + \frac{J^{i\prime}}{R^i}\right] + \frac{\beta\Delta_{u,}^{i\prime} + \psi_s\log(1 - s^i) + \overline{h}}{U'(c_e^i)}.$$

Note that we allow the bargaining strength to differ across regions reflecting heterogeneity in union coverage.

3.4   Government

The government of the region finances its spending by imposing a tax on firm τ_J^i and possibly on separation τ_ξ^i. It runs an UI benefit scheme to finance the unemployment payments $u^i b_t^i$

and possibly offers hiring subsidies. The government balances

$$[e^i(1-\xi^i)\tau^i_J + e^i\xi^i\,\tau^i_\xi] + \Delta B^i = u^i b^i_t + q^i v^i \tau^i_q \tag{20}$$

where ΔB is a financing item the region receives/pays from the general country-wide government that mechanically balances the local budget for a given policy instruments.

3.5 The local planner

To determine the optimal labor market policy instruments, we will focus on a constrained efficient allocation for a given region where the local government respects the constraint that all unemployed and all employed workers have to be treated equally, i.e., we do not allow the government to condition on the duration of unemployment.

Let Δ^i be the promised utility difference between the employment state and unemployment. The government starting with a particular promise and employment level e^i then solves the following maximization problem

$$
\begin{aligned}
W(\Delta^i, e^i) &= \max_{\xi^i,\theta^i,c^i_e,c^i_u,\Delta^{i\prime}} e_i U(c^i_e) + (1-e^{i\prime})U(c^i_u) \\
&\quad + (e^i\xi^i + (1-e^{i\prime}))(\Psi_s(s_i) - \overline{h}) + \beta W(\Delta^{i\prime}, e^{i\prime}) \\
&\quad s.t. \\
e^{i\prime} &= e^i(1-\xi^i) + (e^i\xi^i + 1 - e^{i\prime})s^i\chi^i(\theta^i)^\gamma \\
s^i &= 1/[1 + \exp\{-s^i\chi^i(\theta^i)^\gamma\beta\Delta^{i\prime}/\psi_s\}] \\
\Delta^i &= U(c^i_e) - U(c^i_u) + (1-\xi^i)[\overline{h} + \psi_s\log(1-s^i)] + [1-\xi^i]\beta\Delta^{i\prime} \\
e^i(1-\xi^i)\exp\{a^i\} + \Delta B^i &= e^i c^i_e + u^i c^i_u - e^i\Psi(\xi^i) + (e^i\xi^i + 1 - e^{i\prime})s^i\theta^i\kappa^i_v
\end{aligned}
$$

The objective function of the local government is utilitarian welfare maximization with equal weighting of employed and unemployed workers. It takes promised utility differences as given, i.e., respects the moral hazard constraint that idiosyncratic search cost are unobservable to the government, hence it takes the privately optimal search decision as given. The final constraint imposes a local balanced budget rule, i.e., it rules out any redistribution across regions. This assumption avoids the political economy involved in regional redistribution and focuses instead on welfare improvements within a world of balanced budgets.

3.6 The global planner

For our welfare analysis we consider two scenarios. In the first case we rule out interregional transfers and require $\Delta B^i = 0 \ \forall i$. In the second scenario we allow for an optimal transfer scheme in steady-state, where a global planner maximizes $\sum_i \omega^i \hat{W}^i(\Delta B^i)$ subject to

17

$\sum_i \omega^i \Delta B^i = 0$ with employment weights ω^i and $\hat{W}^i(\Delta B^i)$ defined as the optimal steady state value of the local planner conditional on ΔB^i. It turns out that the optimal transfer choices equate the Lagrange multipliers on the local budget constraints across regions. This can be shown to imply an equalization of aggregate consumption across regions in the logarithmic case, i.e. $\omega^i(e^i c_e^i + u^i c_u^i) = \omega^{i'}(e^{i'} c_e^{i'} + u^{i'} c_u^{i'})$ for any two regions i, i'.

3.7 The optimal policy mix

With these assumptions in place, it follows from arguments in Jung and Kuester (2015) and Ignaszak et al. (2020) that an optimal set of instruments that decentralizes the constrained-efficient allocation of the local planner's solution can be characterized by the following proposition:

Proposition 1. *Let* $\Omega := \frac{\eta}{\gamma}\frac{1-\gamma}{1-\eta}$ *be the Hosios measure of search externalities and* $\zeta = \frac{\psi_s}{f(1-s)}\frac{1-e}{[\xi e + (1-e)]}\frac{U'(c_u)-U'(c_e)}{U'(c_u)U'(c_e)}$ *be a measure of tension between moral hazard and insurance of the unemployed. The following tax rules then implement the constrained-efficient allocation in steady state:*

$$
\begin{aligned}
\tau_q^i &= \frac{\kappa_v^i}{q^i}\left[1-\Omega^i\right] + \frac{\eta^i}{1-\eta^i}\zeta^i \\
\tau_\xi^i &= \tau_J^i + \tau_q^i + (1-s^i f^i)\zeta^i \\
b^i &= \tau_q^i\frac{(1-\beta)}{\beta}e^i + \frac{e^i}{\beta}[1-\beta(1-s^i f^i)(1-\xi^i)]\zeta^i + \Delta B^i \\
\tau_J^i &= \frac{1-e^i}{e^i}b^i - \xi^i(1-s^i f^i)\zeta^i - \frac{\Delta B^i}{e^i}
\end{aligned}
$$

Proof. The proof is a straightforward adoption of proposition 1 in Jung and Kuester (2015).
□

To see the main trade-offs more easily it is helpful to focus on a particular case with logarithmic utility evaluated at the Hosios-condition where we allow the discount factor to go to $\beta \to 1$.

Corollary 1. *Under the same conditions as in Proposition 1, assume furthermore that* $\beta \to 1$,. *Define* $D_2 = D-1$ *as the adjusted duration* $D = \frac{1}{sf}$ *over which the government on average pays unemployment benefits to an unemployed worker, let* $\epsilon_{D_2} := \frac{D}{D_2}\frac{f}{\psi_s}(1-s)c_u U'(c_u)$ *be the elasticity of duration* D_2 *with respect to an increase in consumption of an unemployed worker in the next period. Assume logarithmic utility* $U(c)=log(c)$,*then* $\zeta = \frac{(c_e - c_u)}{\epsilon_{D_2}}$ *and we get in*

steady state

$$\frac{\tau_q^i}{w^i} = \left[1 - \Omega^i\right] \frac{e^{a^i} \kappa_v^i}{w^i q^i} + \frac{\eta^i}{1 - \eta^i} \frac{D^i}{1 + D^i \epsilon_{D_2, b}^i} - \frac{\eta^i}{1 - \eta^i} \frac{D^i}{1 + D^i \epsilon_{D_2, b}^i} \frac{\Delta B^i}{w^i}, \tag{21}$$

$$\frac{\tau_\xi^i}{w^i} = \frac{\tau_q^i}{w_i} + \frac{\tau_J^i}{w_i} + \frac{(D^i - 1)}{1 + D^i \epsilon_{D_2, b}^i} - \frac{(D^i - 1)}{1 + D^i \epsilon_{D_2, b}^i} \frac{\Delta B^i}{w^i}, \tag{22}$$

$$\frac{b^i}{w^i} = \frac{1}{1 + D^i \epsilon_{D_2, b}^i} + \frac{D^i \epsilon_{D_2, b}^i}{1 + D^i \epsilon_{D_2, b}^i} \frac{\Delta B^i}{w^i} \tag{23}$$

$$\frac{\tau_J^i}{w^i} = -\frac{\Delta B^i}{w^i e^i} \tag{24}$$

Proof. The corollary is a straightforward extension of corollary 3 in Jung and Kuester (2015). □

Focus first on a world where the state government does not provide transfers, so $\Delta B = 0$. Equation (24) tells us to set the net-replacement rate according to the standard Bailey-Chetty formula (Baily, 1978, and Chetty, 2006); the lower the micro-elasticity of search is, the larger the government can grant consumption insurance. If there is no moral hazard, so $\epsilon_{D_2, b}^i \to 0$ the planner can offer full insurance to the worker. Equation (22) shows that the government grants hiring subsidies above and beyond the Hosios condition (the case when $\Omega = 1$). When making a hiring decision of an unemployed, firms do not take into account the relaxation of the financing constraint of the social insurance system that arises from their private action. To align private and social incentives, it is optimal to subsidize hirings proportionally to the duration weighted net benefit payments. The term $\frac{D^i}{1 + D^i \epsilon_{D_2, b}}$ is the net replacement rate time the expected duration D of an unemployment spell weighted by the relative bargaining strength of the firm. Moreover, the planner ensures that the match takes the cost of the UI benefit payments for the duration of the unemployment spell and the fiscal cost of newly re-hiring the worker τ_q, into account when separating, as equation (23) shows. Given that the match already insures the first month of unemployment via severance payment, one month has to be subtracted from the average unemployment duration $\frac{D^i - 1}{1 + D^i \epsilon_{D_2, b}}$. The profit tax goes to zero in the limit, for $\beta < 1$ this is no longer true and social insurance contributions are used to balance the system.

How do governmental transfers across regions, ΔB, optimally change the local labor market instruments? As equation (24) shows social insurance contributions are reduced one for one with an increase in transfers, in other words consumption of the employed are increased proportionally. The net replacement rate increases because the local government trades of insurance and moral hazard and the unconditional transfer allows to tilt the system towards more insurance. Given that the extra Euro is a redistribution, the match does not need to internalize these costs, so both the hiring subsidy as well as the firing tax are reduced accordingly.

Finally, we turn to the role of regional heterogeneity in key parameters, abstracting from redistribution, $\Delta B = 0$, and evaluated at the optimal tax system.

Proposition 2. *If the labor market transfer system is locally optimal as shown in proposition 1, utility is logarithmic and there are no regional transfers $\Delta B^i = 0$, then the endogenous choices are implicitly given by the following system of equations:*

$$c_e^i = \frac{[1 - \psi_\epsilon^i \log(1 - \xi^i)]}{1 - [\log(D^i \epsilon_{D_2,b}^i + 1) + \psi_s \log(1 - s^i) + \overline{h}]} e^{a^i}$$

$$\frac{c_u^i}{c_e^i} = \frac{1}{D^i \epsilon_{D_2,b}^i + 1}$$

$$\theta^i = c_e^i \frac{\beta\gamma}{(1 - \beta\gamma)\kappa_v^i} \left[\frac{f^i}{(\epsilon_{D_2,b}^i + s^i f^i)} - \psi_s \log \frac{(1 - s^i)}{s^i} \right]$$

$$\xi^i = \frac{1}{1 + \exp\left\{ e^{a^i} \frac{1 + \frac{\kappa_v^i}{e^{a^i}\gamma} \frac{\theta^i}{f^i} + \frac{s^i \psi_s}{(1-s)}(1 - s^i f^i)\left(\frac{c_e^i - c_u^i}{\exp\{a^i\}}\right) + \frac{c_e^i}{\exp\{a^i\}}(\overline{h} + \psi_s \log(1 - s^i))}{\psi_\epsilon^i} \right\}}$$

$$s^i = \frac{1}{1 + e^{-\frac{f^i}{\psi_s} \frac{\log(D^i \epsilon_{D_2,b}^i + 1) + \overline{h}(1 - \xi^i) + (1 - \xi^i)\psi_s \log(1 - s^i)}{1 - \beta(1 - \xi^i)}}}$$

If moreover $\psi_\epsilon^i = \widetilde{\psi_\epsilon^i} e^{a_i}$ and $\kappa_v^i = \widetilde{\kappa_v^i} e^{a_i}$ are proportional then the relative consumption choice $\frac{c_u^i}{c_e^i}$, market tightness θ^i, separation probability ξ^i and the search probability s^i are independent of productivity, and consumption c_e^i scales linearly in productivity.

Proof. The proof is a straightforward extension from Ignaszak et al. (2020). $\qquad\square$

Proposition 2 shows that under the stated assumptions local productivity only scales consumption without affecting search, hiring or separations. To the extent that hiring cost and idiosyncratic risk scales proportionally in productivity, it is straightforward to see that productivity differences can not account for regional dispersion at all. The assumption of idiosyncratic risk scaling with productivity implies that shocks hit multiplicative or as a fraction of the size of the project. Given that we still allow $\widetilde{\psi_\epsilon^i}$ to vary across markets this assumption is purely for convenience and has no bearing on the results other than a re-scaling. Scaling vacancy posting cost by productivity is equivalent to assuming that the hiring cost are paid in units of local wages. Hence, hiring cost are expressed in units of local managerial time that is needed to create a hiring. We checked robustness of our results to the alternative assumption that hiring cost are expressed in unit of the final output good. Proposition 2 already indicates that this choice would affect the estimate of the matching efficiency but would leave all other parameters unaffected. We now turn to our quantitative analysis.

4 Quantitative evaluation

The purpose of this section is twofold: First, we utilize the model to translate observed regional labor market disparities into regional heterogeneity of structural parameters. Based on a benchmark calibration that approximates the German tax and UI system we use region-specific wages, vacancies, job-finding and separation rates to identify four structural parameters for each district. We relate the recovered structural changes to existing theories brought forward to explain the labor market development in Germany: matching efficiency, productivity, idiosyncratic risk, and bargaining strength. We look at two time-intervals, one before the Hartz-reforms 1994 to 2004 and one after the Hartz reforms 2005 to 2014. The Hartz reform has been identified by Hartung et al. (2018) as a potential causal factor in explaining the subsequent large decline in flows from employment to unemployment. We implement this reform in the model by targeting different replacement rates before and after the reform while keeping the other parameters constant for the whole sample period.

In the second part of this section we assume that the structural parameters are invariant to labor market policy instruments and evaluate the welfare and employment effects of an optimal policy mix for each region based on proposition (1). We start by focussing on welfare gains that are achievable for region dependent policy instruments without redistribution. This exercise allows us to provide an important insight on local labor market disparities as we determine to what degree these disparities are driven by local inefficiencies. We end by allowing for transfers across regions based on a utilitarian planner to study the size of transfers and how an optimal policy mix with transfers across regions affects unemployment and inequality.

4.1 Calibration

One period represents a month and we assume log utility throughout. We treat preferences on consumption, search cost and discounting as homogenous across employment districts and calibrate them initially such that the model resembles a fictional average agency district. This baseline calibration serves as our benchmark for the subsequent quantitative exercise where we allow certain parameters to vary across region. The fictional economy is formed based on average worker flows, vacancies, and wages in all EADs in Germany between 1994 and 2005. Annual averages of monthly job-finding and separation rates are taken directly from the data. Labor market tightness and wages are the employment weighted average of the vacancy to unemployment ratio and the average wage in each district.[14]

Table 2 summarizes the calibrated parameters. The time-discount factor is calibrated to

---

[14]We re-weight vacancies before 2000 by a factor of 0.7 to account for job offers for seasonal workers or promoted vacancies. The adjustment factor is based on overlapping aggregate vacancy data from Hartmann and Reimer (2010) for the period $2001 - 2009$.

$\beta = 0.996$ to match a monthly real interest rate of 0.04. We set the disutility from searching to $h = 0.56$ to target an unemployment rate of 0.105. In the model, not all of the unemployed search, so this calibration implies that in the steady-state the share of non-searching worker amounts to 19%, matching the proportion of unemployed workers that do not search actively but are available on short notice in 2014.[15] We set $\psi_s = 0.5$ to match an elasticity of the average duration of unemployment concerning benefits of 0.5. This value is well in the range of the estimates of the literature (Schmieder and Von Wachter, 2016).

Table 2: Calibrated parameters

Parameter		Value
Preferences		
β	discount factor	0.996
$\bar{h}$	disutility of work	0.56
ψ_s	scaling par. utility of search costs	0.50
Vacancies, matching and bargaining		
κ_v	vacancy posting costs	2.5
γ	match. func. elast. w.r.t vacancies	0.250
χ	matching efficiency	0.14
η	bargaining power	0.18
Production and layoffs		
A	Productivity	0.94
ψ_ϵ	disp. of idiosyncratic costs	4.27
Labor Market Policy		
b_{pre}	Replacement rate pre reform	0.670
b_{post}	Replacement rate post reform	0.603
τ_q	Vacancy posting subsidy	0
τ_J	UI contribution tax	0.04
τ_ξ	Layoff tax	6

Notes: The table presents the calibrated parameter values. We calibrate the model to resemble the average unemployment agency district during $1994 - 2004$.

We calibrate vacancy posting costs to $\kappa_v = 2.5$ monthly wages. This value is based on the estimated vacancy posting costs of Muehlemann and Pfeifer (2016). The elasticity of the matching function with respect to vacancies is calibrated to $\gamma = 0.25$, based on an estimation described in appendix C.1.1. To determine the bargaining parameter, we target the average

---

[15]We obtain the number of individuals participating in employment agency measures on unemployment in 2014 from Fuchs et al. (2014).

monthly labor market tightness in the fictional economy. This leads to $\eta = 0.18$. The matching efficiency parameter in the benchmark economy is determined within the model and set to $\chi = 0.14$. This value leads to an average population weighted average job-finding rate of 0.057, as in the data.

Concerning productivity, we target in our benchmark the average wage normalized to 1 and obtain a productivity parameter of $A = 0.94$, where $A \equiv \exp\{a\}$. All regional wage variation is always specified relative to this average. Recall that realized productivity is endogenous due to the idiosyncratic cost shocks and depends on the cut-off value that determines the point at which a destruction of the match occurs. The dispersion parameter for the cost shock is calibrated to $\psi_\epsilon = 4.27$, to match the average population weighted separation rate of 0.0088.

Last, we set the policy variables. These variables are expressed in terms of local wages when we allow for regional dispersion. We set the replacement rate, $b = c_u/c_e$, such that in the steady-state benefit payments replace 67% of wages before the Hartz reforms. This value corresponds to the official replacement rate for a worker with one or more children in the first year of unemployment. We assume that the Hartz reforms lead to a decline in the outside option of 10%, which is a catch-all for the duration and age dependent changes discussed in detail by Hartung et al. (2018). We set vacancy subsidies to $\tau_q = 0$. Layoff taxes are set to a constant value, in terms of wages, $\tau_\xi = 6$. This assumption is a compromise, as there are no layoff taxes, per se, but the government protects workers through a statutory notice period of around three months as well as a firing protection scheme, severance payments and red tape cost, which are partly paid to the worker.[16] The government balances its budget through social insurance contributions of the match τ_J of around 4%.

4.2 Structural disparities

We look next at two time-periods: before the Hartz reforms (1994-2004) and afterwards (2005-2014). We treat each period as a steady state of the model (ignoring changes in expectation, anticipation effects or transition dynamics) and ask, what structural differences might be able to explain the regional dispersion documented above in each of the time periods. We allow four parameters to differ across employment districts capturing variation in productivity, matching efficiency, bargaining power and idiosyncratic cost risk. We control for the time change due to the Hartz reforms that took place between 2003-2005 and impose a change in the net replacement rate of 6 age points in the year 2005 following Hartung et al. (2018).

Given these assumptions, the four parameters are jointly identified based on observed regional variations in wages, labor market tightness, job-finding and separation rates. The

---

[16]This choice mainly affects our findings on optimal policy. A lower separation tax makes the initial steady state more inefficient, so the employment gains tend to be a bit larger. All relative statements across region are unaffected though.

productivity parameter A_i and wages are strongly (positively) correlated, though not one-to-one across regions because the idiosyncratic cost shocks make productivity endogenous. For example, a higher cut-off value can lead to selection effects. More matches are destroyed, but the remaining ones are overall more productive. The idiosyncratic cost shocks are shaped by the observed inflow rates. A larger variance leads - ceteris paribus - to more separations and higher productivity ex-post. Outflow rates, in turn, combined with labor market tightness data, determine the matching efficiency via functional form assumptions on the matching process, and the bargaining power. Both rates have a feedback effect on the cut-off value that determines inflows. Intuitively, a higher probability of finding a match, makes existing matches less valuable. Competitive pressure is higher, so there will be *more* separations, ceteris paribus.

Figure 8 displays the obtained structural disparities in 1994-2004. As expected, we find that productivity in eastern districts is well below the West German levels. Besides this vast difference, the variations across districts in the North, West, or South are substantial. The districts with the highest productivity in their respective region are Berlin (East), Hamburg (North), Dusseldorf (NRW) and Frankfurt (S-West) and Munich (South). They are all major centers of economic activity. Overall, the productivity distribution resembles the wage distribution (Figure 5) though the mapping is not fully monotone.

Figure 8: Structural labor market disparities $(1994 - 2004)$
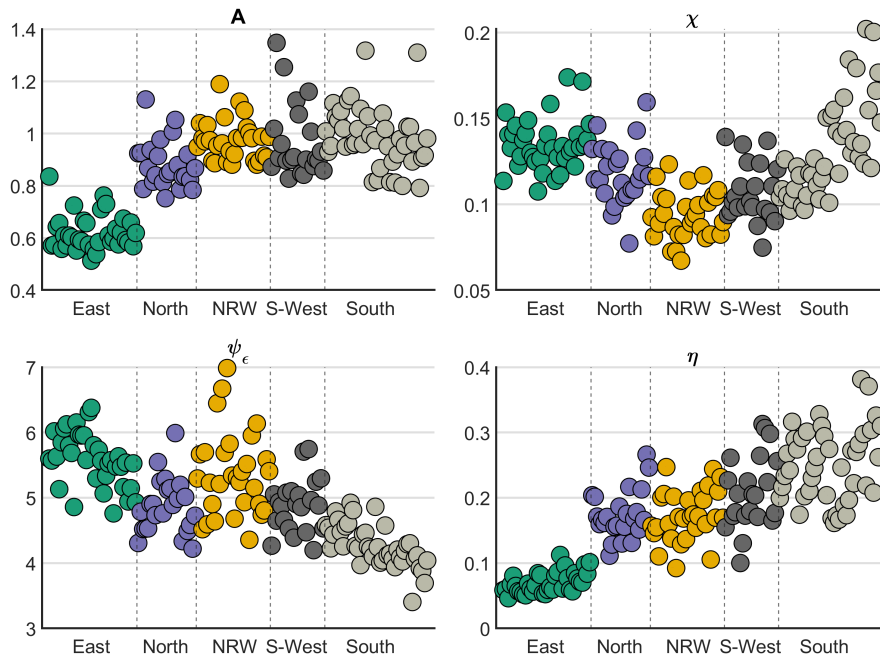
Notes: The figure displays the identified values of the four region-specific structural parameters: Productivity (A), matching efficiency (χ), match uncertainty (ψ_ϵ), and bargaining power (η). We determine the parameters within the model given the observed variation in wages, labor market tightness, separation, and job-finding rates. We target the averages of these four variables within $1994 - 2004$.

Regarding matching efficiency we find that eastern and southern districts exhibit the

highest values (upper right). Hence, high unemployment in East Germany is likely not attributable to low efficiency in the matching market, indeed EADs located in NRW exhibit the lowest efficiency, which mirrors their low job-finding rates. Similarly, the high frequency of flows into employment, in combination with a tight labor market, in the South identifies an above-average efficiency of the matching market.

The uncertainty of continuing a match (ψ_ϵ) captures the variations in inflow rates (lower left). Consequently, we find a high uncertainty in the East and in NRW. As shown in the empirical section, separation rates do not vary much across the other regions. The structural parameter, however, does exhibit significant variation. This variation is due to differences in the surplus of a match, which additionally shapes the identified distribution. The match surplus depends on the job-finding rate: A higher job-finding rate increases the value of unemployment and, thus, leads to a smaller surplus and lower match uncertainty, given constant separation rates. This second effect determines the higher and lower parameter values of ψ_ϵ in NRW and the South, respectively.

Concerning the bargaining power of firms, we uncover an increasing pattern from East to South (lower right). The variation of the identified parameters across districts matches the distribution of labor market tightness closely. While eastern workers are paid wages that are high relative to productivity, most of the southern workers receive wages that are low relative to productivity in their respective region. This finding is consistent with explanations that emphasized that wages in the East were bargained up by West German labor unions immediately after the reunification (see Burda and Hunt, 2001).

Next we look at changes over time. Figure 9 displays the structural disparities in 2005-2014. The figure suggests that the qualitative profile of the parameters changes only slightly when looking at variations over employment districts. Productivity and the bargaining power of firms are still lowest in the East and highest in parts of the South, however both productivity as well as the bargaining power has increased in the East relative to all other districts.[17] While the matching market is still most efficient in the South, matching efficiency has decreased in the East substantially. Also, districts located in East and NRW exhibit the highest job-match uncertainty, similar to the previous period. While uncertainty is high in the East due to higher separation rates, it is high in NRW because of the low efficiency of the matching market.

The key driver of the change in inflow (or EU) rates between the two periods are the Hartz labor market reforms and the associated substantial decline in benefits in particular for older employed workers.[18] Figure 10 reports the relative change in EU and and outflow

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[17]Note that we measure wages in relative terms ($\hat{w}_i \equiv w_i \sum_j e_j / \sum_j w_j e_j$) and do not capture wage growth, but rather the distance to the average wage.

[18]The importance of the link between unemployment benefits and separation rates has been investigated by Hartung et al. (2018). They show that the reform induced decrease of the replacement rate for long-term and older employed workers is responsible for a large portion of the decline of the aggregate separation rate.

Figure 9: Structural labor market disparities $(2005 - 2014)$
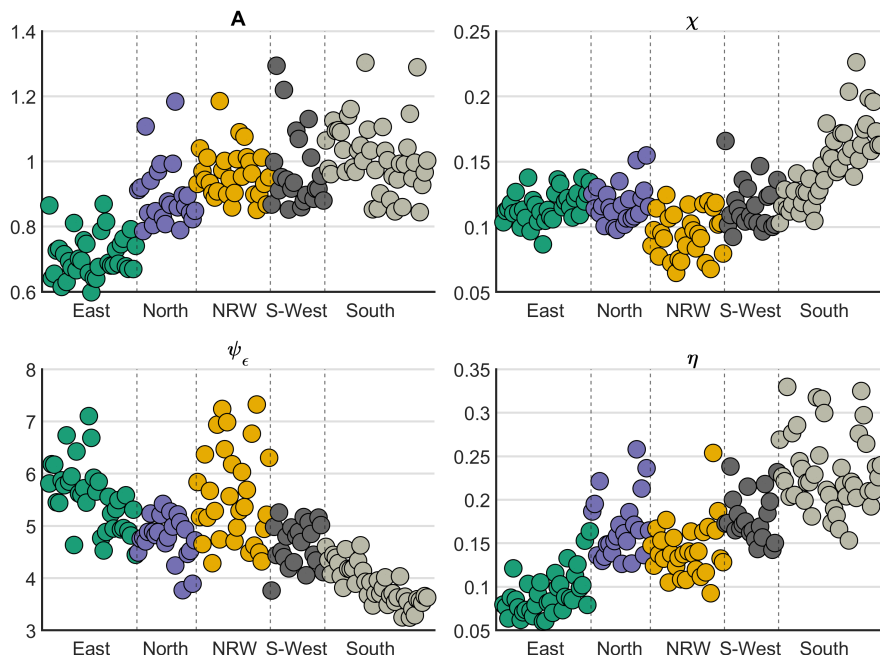
Notes: The figure displays the identified values of the four region-specific structural parameters: Productivity (A), matching efficiency (χ), match uncertainty (ψ_ϵ), and bargaining power (η). We determine the parameters within the model given the observed variation in wages, labor market tightness, separation, and job-finding rates. We target the averages of these four variables within $2005 - 2014$.

(or UE) rates, if we evaluate the model at the structural estimates of the post-Hartz decade but assume the same level of UI benefits as in the pre-Hartz decade. EU rates would be 47% higher, while UE rates would be 5% lower on average in the data. The counterfactual predictions of the model are very similar on average. However, as the figure makes clear, there is substantial cross-sectional variation even within a narrow defined region like the East, which is not captured by the average UI change. This heterogeneity needs to be captured in the model by variation in the four structural dimensions.

Three main changes over time are visible when we compare the structural parameter estimates: First, productivity in the East caught up over time but remains substantially below the rest. Second, the bargaining power of firms increased by around 40% in the East but is still substantially below the rest while it declined in NRW and the South. Third, the matching efficiency declined in the East and increased in the South.

As discussed above, productivity increases do affect wage inequality but do not directly translate into changes in labor market flows in our model. The variance of idiosyncratic risk did not change systematically over time, in contrast to matching efficiency and bargaining strength. The increase in firms' bargaining power over time in the East might be the result of more flexible collective bargaining agreements. This argument was put forward by Dustmann et al. (2014) who find that the share of workers covered by an industry-wide bargaining agreement decreased by almost 20 age points to 56% from 1995 to 2008. They argue that more

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Figure 10: Impact of the Hartz reforms on EU and UE rates $(2005 - 2014)$
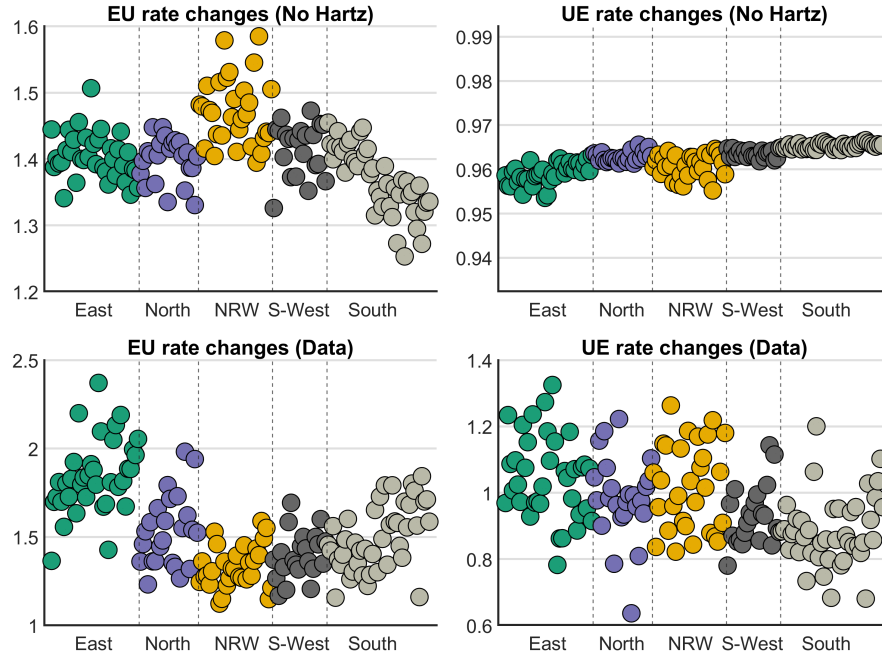
Notes: The upper part displays, how EU and UE rates would change (relative to their $2005 - 2014$ value), if we use the structural estimates from the period $2005 - 2014$ but allow the UI benefit system to remain at their pre-Hartz values. The lower part displays the ratio of EU rates and UE rates for the period 1994-2004 relative to 2005-2014.

flexible agreements led to an increase in competitiveness through lower wages and increased labor demand in Germany. Boeri et al. (2019) provide evidence that this decline was stronger in the East than in rest of Germany within 1996 and 2013: While the share of workers subject to an industry-wide agreement decreased by 38% in East Germany, the decrease in West Germany amounts to 25%.[19] The more substantial decrease in East Germany mirrors the evolution of the bargaining power uncovered here. In our model, an increase in bargaining power alone has an ambiguous implication for separation and unemployment rates: The higher bargaining power of firms leads to two counteracting effects with respect to job-finding. First, lower wages decrease the workers' search incentives; second, more vacancies lead to higher job-finding rate. With respect to separations, the impact on the surplus of the match is ambiguous and depends, among other things, on how the economy deviates from the Hosios condition. On the one hand if the worker's bargaining position is strengthened, the surplus of existing matches goes down because the value of alternative offers the worker might get when leaving the match goes up. On the other hand the likelihood of receiving new jobs goes down, because profits and therefore job-finding rates tend to go down. Which of these effects dominate tend to be a function of the size of the inefficiency of the market, that is it is a function of the deviation from the Hosios condition (see Jung and Kuhn (2014) for a formal derivation of these effects in a more standard search and matching model).

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[19]cf., Boeri et al. (2019), Table 3

The decline in matching efficiency mainly in the East conflicts with the view that the Hartz reforms might have improved the efficiency of the matching market, which subsequently led to the favorable development in Germany.[20] While we document increases in job-finding rates for some regions, matching efficiency decreases in most districts as labor market tightness exhibits substantial increases.[21] Overall, the decreases in matching efficiency imply that gains in efficiency were not responsible for a significant share of the unemployment decreases up to the year 2014.

Recovering the structural parameters allows us to discuss the mechanism proposed by Bilal (2019) to account for regional differences in separation rates for France. In his model, more productive firms sort into locations where the contact rate ($\chi\theta^{-\alpha}$) is higher, which is inversely related to labor market tightness. He argues that more productive firms forego relatively higher profits the longer they do not employ a worker. Therefore, they are willing to pay higher wages in less tight labor markets. He infers that productive (or unproductive) firms co-locate. This co-location leads to an equilibrium where unemployment is high in low productive regions, which also exhibit tight labor markets. In these regions, unemployment is high due to more frequent job-losses. High productive regions exhibit slack labor markets, high wages, and low rates of job loss. Empirically, our findings concerning the relationship between worker flows and productivity are similar: separation rates decrease in local productivity; the job-finding rate is slightly negatively correlated with the separation rate; and the contact rate is positively correlated with the separation rate. However, we find almost no supporting evidence that productivity is higher in slack labor markets.[22] In contrast, productivity slightly increases with labor market tightness.

Having an estimate in place on structural variation across regions we might ask how policy makers should react to these regional differences under the assumption that the structural parameters are indeed invariant to changes in labor market policy variables. We discuss the implication for optimal policy next.

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[20] For example, see Klinger and Weber (2016) and Launov and Wälde (2016).

[21] We find no increase in aggregate matching efficiency after the mid-2000s, while Klinger and Weber (2016) document an increasing efficiency. Compared to Klinger and Weber (2016), the development of our aggregate job-finding rate differs substantially. These differences might be due to a different control of worker states, in particular the large definitorial changes of non-employed spouses that became officially unemployed in the years 2003-2005. Our methodology does account for these changes. We provide further details in the appendix (Section C.2). Note that our estimated changes of region-specific matching efficiency are comparable to Bauer (2013) for West Germany. We confirm the heterogeneous changes at the federal-state level using linear-least-squares regression models, to mitigate concerns that not accounting for local spillovers might bias our results (Stops and Fedorets, 2019). The estimates are provided in the appendix (Table C.3).

[22] Note that for some districts in Bavaria where separation rates are relatively high, productivities (wages) are relatively low and these regions exhibit high tightness.
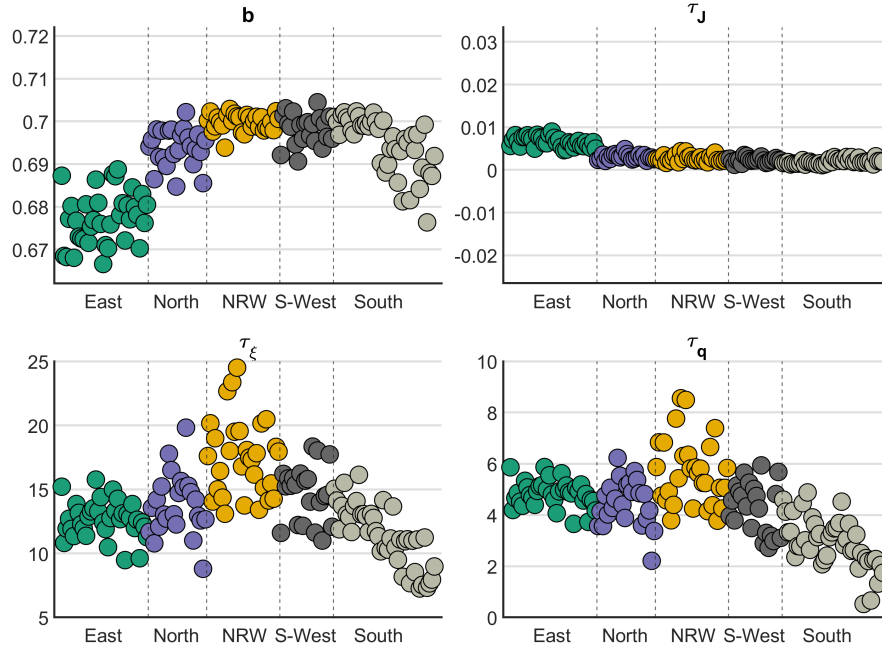
4.3 The optimal policy mix

In this section, we quantitatively evaluate the optimal labor market policy mix that achieves the constrained-efficient solution in each employment agency district. We assume that the region-specific values of A, χ, ψ_ϵ and η are invariant to policy changes in both time intervals. We start by assuming that each region has to ensure a balanced budget, so we abstract initially from redistribution issues across regions both via taxes and via the social security systems. Two mechanism will drive our findings: the optimal choice of policy instruments allows for a more efficient use of resources; however, the imposition of a balanced budget puts pressure on districts with high levels of unemployment, who currently receive implicit transfers via the social security system. This effect almost exclusively effects consumption, rather then employment outcomes. Hence, the welfare gains for these regions will be smaller than expected when looking at the employment gains alone.

Figure 11 displays the regional variation of the policy instruments for the period 1994-2004. To compare the hiring subsidy and the separation tax we express them in units of the local monthly wage. We find that the planner does not fully insure the unemployed (upper left), as their search effort is unobservable. However, unemployment benefits increase compared to the steady-state value of 0.67. Without the layoff taxes and hiring subsidies (lower left and lower right), the higher benefits would lead to a lower search effort. The hiring subsidies counteract this effect since they reward firms if they relieve the social insurance system by employing a worker. With higher subsidies, firms are more ly to post a vacancy, which increases the job-finding rate and workers' search incentives. Similarly, the layoff taxes ensure that firms internalize the social costs of their separation decision, i.e., the benefit payments for the duration of the unemployment spell and the subsidies paid to reemploy the worker.

The observed benefit structure is in line with the intuition provided in Corollary 1. In East Germany and parts of the South, an increase of unemployment insurance benefits has a more substantial impact on search effort. In general, our findings highlight that unemployment benefits do not need to vary a lot across districts when the other tax instruments are utilized optimally. Also, the production tax is small and does not show much variations across regions.

The planner instead uses hiring subsidies and layoff taxes. The planner still subsidizes hirings in the South despite that, according to the classic Hosios condition, the firms' bargaining power ($\eta > \alpha$) is too high compared to the matching elasticity. Due to low wages (relative to productivity), there is excessive vacancy creation, and the posted vacancies crowd each other out. In the absence of the moral-hazard insurance motive, the planner would therefore levy a hiring tax. However, the planner grants subsidies because of the positive effect of hiring a worker on the social insurance system that is not fully internalized by private vacancy creation. Moreover, the large separation taxes needed to render the separation de-

Figure 11: The optimal policy mix $(1994 - 2004)$

Notes: The figure displays the optimal policy mix in the planner's economy $(1994 - 2002)$. b represents the replacement rate $\left(\frac{c_u}{c_e}\right)$ and τ_J the optimal production tax. τ_ξ and τ_q are the layoff taxes and hiring subsidies, respectively. Taxes are expressed in multiples of local wages.

cision optimal leads to large costs to the firm. A hiring subsidy reduces the tax burden. Separations are taxed to make firms internalize the additional costs for the social system incurred by separating from a worker. The resulting cost for society depends on the duration of the average unemployment spell. Thus, it is more beneficial to keep the marginal worker in NRW in employment because her average unemployment duration is longer, compared to workers in southern districts. Indeed it is somewhat surprising that the optimal tax code will heavily subsidize the western parts of Germany (NRW) via hiring subsidies and protect employment via separation taxes to ensure an optimal outcome rather than the East, which receive an average treatment. In the south both hiring subsidies and employment protection are lowest.

Figure 12 displays the resulting unemployment rate changes by district. We see that the western parts of Germany (NRW) would benefit the most with respect to changes in unemployment, while some Bavarian districts would actually increase their unemployment rate.

Table 3 displays the policy-induced changes in employment, job-finding rates, search effort, separation rates, and welfare. We compare the allocation in the steady-state to the planner's constrained-efficient allocation. Again, it is important to keep in mind that the imposition of a balanced budget implies that the employment gains due to the optimal policies do not lead to a proportional increase in consumption. Employment rises in all

Figure 12: Change in unemployment rates with locally optimal policies

(a) Change in unemployment 1994-2004

(b) Change in unemployment 2005-2014
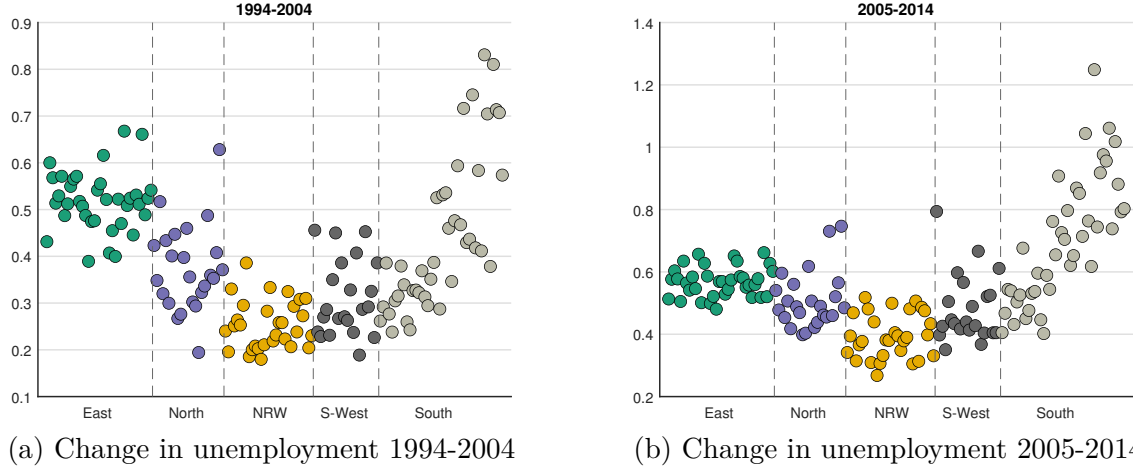
Notes: The figures display the ratio of the locally optimal unemployment rate to the actual unemployment rate for the years 1994-2004 (left) and 2005-2014 (right).

regions. These employment increases are achieved through fewer separations and more hires, as firms internalize the respective social costs or benefits through the layoff tax and hiring subsidy. Moreover, the workers' search effort increases, despite the higher benefit level. The decreases of the separation rates go through changes in the surplus of a match. The surplus increases in layoff taxes but also depends on all labor market decisions of the workers, which in turn are affected by the replacement rate. For example, layoffs in eastern districts fall the least compared to the other regions, despite high match uncertainty. This outcome indicates that the change of the match-surplus was small. Overall, the optimal policy mix induces a welfare increase between 2% and 3%, while the employment gains with up to 15% are largest for the East and with 5% smallest for the South.

Table 3: Steady-state compared to the planner economy $(1994 - 2004)$

	Employment	ξ	s	f	Welfare
East	0.158	-0.2	0.045	0.588	0.027
North	0.105	-0.788	0.02	0.305	0.021
NRW	0.126	-1.187	0.023	0.306	0.021
S-West	0.095	-1.029	0.015	0.249	0.024
South	0.057	-0.737	0.006	0.184	0.029

Notes: The table presents the (log) change in employment, separation rates (ξ), search effort (s), job-finding rates (f) and welfare under the optimal regional labor market policy mix. The change is measured relative to the individual steady state.

The regional variation of the optimal policy mix in 2005-2014, which is displayed in Figure 13, closely resembles the one during the earlier period. The planner utilizes all tax

instruments: benefits increase, layoffs are taxed and hires subsidized. Moreover, the production tax and the replacement rate show little regional variation. We observe small changes for districts located in the North or South. The most pronounced difference can be observed for the EADs in eastern Germany and NRW. Eastern districts now receive an increase in benefits that is comparable to the other EADs, which is due to the decrease in matching efficiency. When efficiency declines, UI benefits have a smaller impact on the unemployed's search effort. Also, the decrease in the efficiency of the matching market leads to higher layoff taxes and hiring subsidies as the average duration of an unemployment spell is prolonged. In NRW, the planner grants even more substantial hiring subsidies compared to the previous period due to lower matching efficiency. In general, layoff taxes and hiring subsidies decrease with the firms' bargaining power, i.e., decrease as the districts' unemployment level approaches the socially optimal level. When unemployment is above its efficient level, as in some northern and southern regions, the planner grants hiring subsidies because of the moral hazard insurance motive.

Figure 13: The optimal policy mix $(2005 - 2014)$
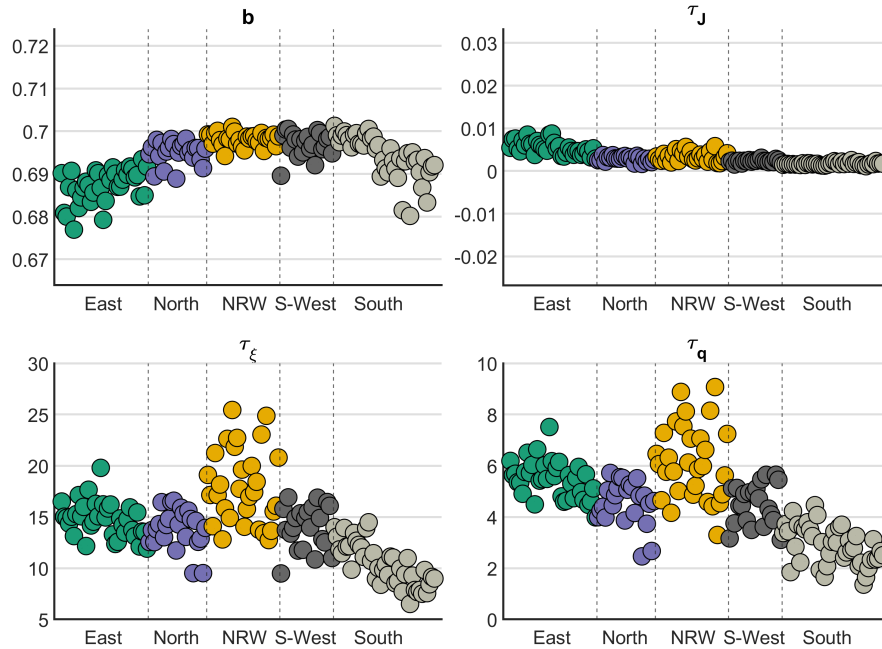
Notes: The figure displays the optimal policy mix in the planner's economy $(2008 - 2014)$. b represents the replacement rate $(\frac{c_u}{c_e})$ and τ_J the optimal production tax. τ_ξ and τ_q are the layoff taxes and hiring subsidies, respectively. Taxes are expressed in multiples of local wages.

Table 4 displays again the policy-induced changes for the period 2005-2014. Compared to the steady-state, employment rises in all regions; however, by a more modest amount of 2% to 8%. Again, these increases are the result of the lower separation and higher job-finding rates. Workers' search effort shows only minor changes compared to the steady-state. Reductions in layoffs are more substantial as the uncertainty of a match is lower compared

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to the earlier period, which strengthens the reaction of separation rates to match-surplus changes. Welfare increases in all regions by around 3%. The welfare effects are larger in recent years compared to the nineties despite lower employment gains because output losses are smaller. In the nineties the dramatic cut in separation rates due to the increase in separation taxes implies that less productive matches are sustained, reducing output per person employed substantially. This option value effect dominates the positive effects from the employment gains.

Table 4: Steady-state compared to the planner economy $(2005 - 2014)$

	Employment	ξ	s	f	Welfare
East	0.076	-0.17	-0.018	0.464	0.035
North	0.051	-0.456	-0.03	0.278	0.032
NRW	0.078	-0.686	-0.024	0.327	0.03
S-West	0.045	-0.537	-0.033	0.254	0.033
South	0.017	-0.24	-0.039	0.171	0.038

Notes: The table presents the (log) change in employment, separation rates (ξ), search effort (s), job-finding rates (f) and welfare under the optimal regional labor market policy mix. The change is measured relative to the individual steady state.

Overall, the planner's allocation leads to heterogeneous changes across districts, while welfare and employment increase substantially. While our results do not change with respect to the displayed regional variation, our findings are quantitatively sensitive to the initial policy values. If we lower the layoff taxes in the benchmark calibration, making the benchmark calibration more inefficient, then the average employment and welfare gains become larger.[23] We now ask, how a globally optimal scheme would look like in the long run if a utilitarian social planer who equally weights all inhabitants is allowed to set transfers and the social insurance system jointly.

4.4 Optimal policy with transfers

This section briefly looks at the globally optimal labor market policy and transfer scheme. We now do not insist that there is no redistribution across employment district but allow for transfers across regions. We focus on steady state welfare and abstract from transition dynamics. We use the employment shares during the decade 1994-2004 as weights and only demand that total (employment weighted) transfers across districts sum to zero. Figure 14

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[23]In the previous analysis, vacancy posting costs depend on local productivity as we treat them as district-specific. As another sensitivity check we also looked how results changed if we assumed fixed posting costs (in terms of the numeraire good). Again, the shape of the identified parameters is qualitatively similar, only the bargaining power is rescaled in terms of productivity without changing the interpretation.

plots the transfer scheme that is implied by the uniform social security system in the decentralized benchmark calibration (that can run a deficit). Note that the large direct transfers to the East that have been administered in particular in the nineties are not included. We see that the social security system implicitly transfers money to districts in the West and the East while the South is a contributor region.

Figure 14: Implied transfers of the calibrated model

(a) Local transfers 1994-2004   (b) Local transfers 2005-2014
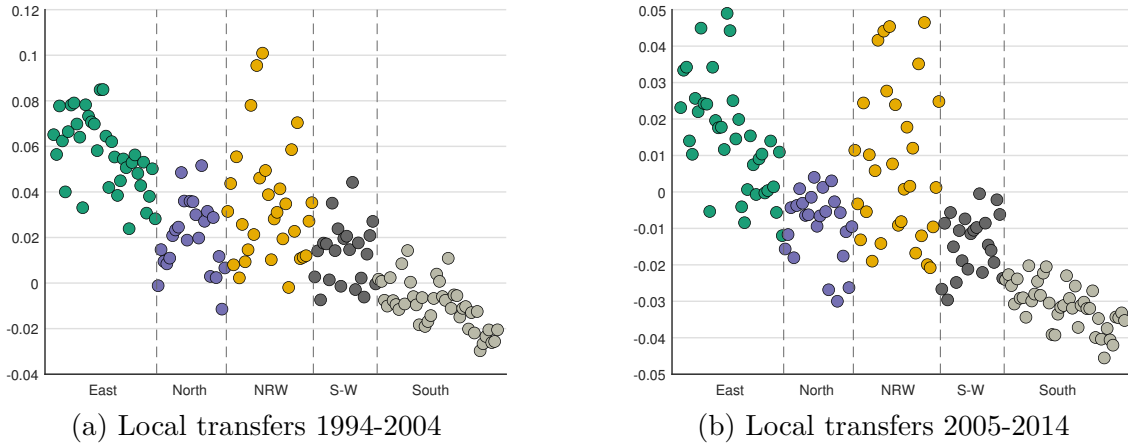
Notes: Part (a) and (b) display the local transfer scheme implied by the social insurance system for the decade 1994-2004 and 2004-2015, respectively.

In figure 15 we contrast this scheme with the globally optimal transfer scheme, which equalizes marginal utilities across employment districts. The transfer levels to the East get larger because the utilitarian planner would equalize the large consumption differences. Interestingly, once an optimal policy is in place, many districts in NRW would become net payers, North would receive more transfers and part of South-West would have to pay more.

Figure 15: Global Transfers

(a) Globally optimal transfers 1994-2004   (b) Globally optimal transfers 2005-2014
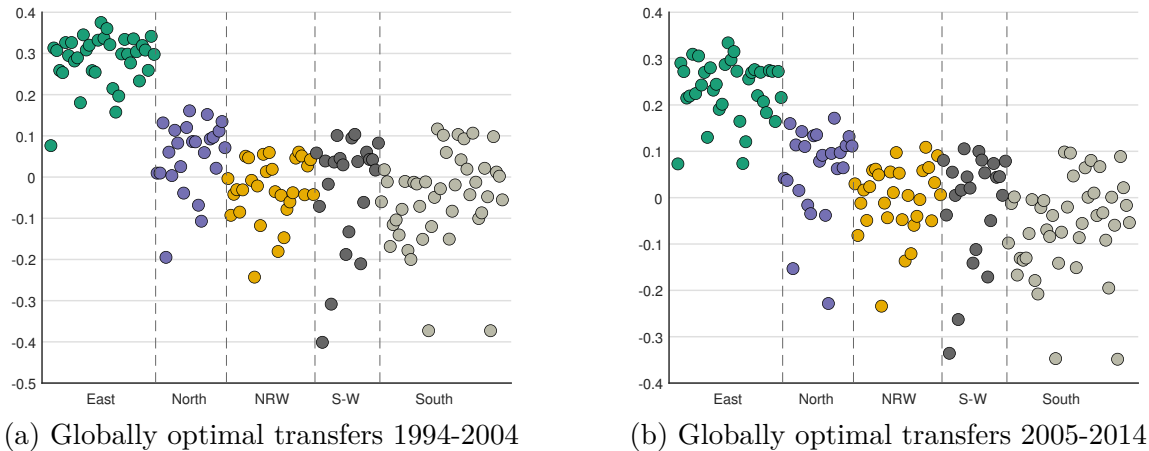
Notes: Part (a) and (b) display the optimal transfer scheme for the decade 1994-2004 and 2004-2015, respectively.

Figure 16 shows how employment across districts change relative to the employment

scheme obtained without redistribution. Unsurprisingly, the social planner redistributes towards the East and in part to the North while all other regions have to pay on average. However, there is substantial heterogeneity across districts. Many districts even in the South would be net recipient while a few super-rich districts would be heavily taxed.

Figure 16: Change in unemployment rates with globally optimal policies
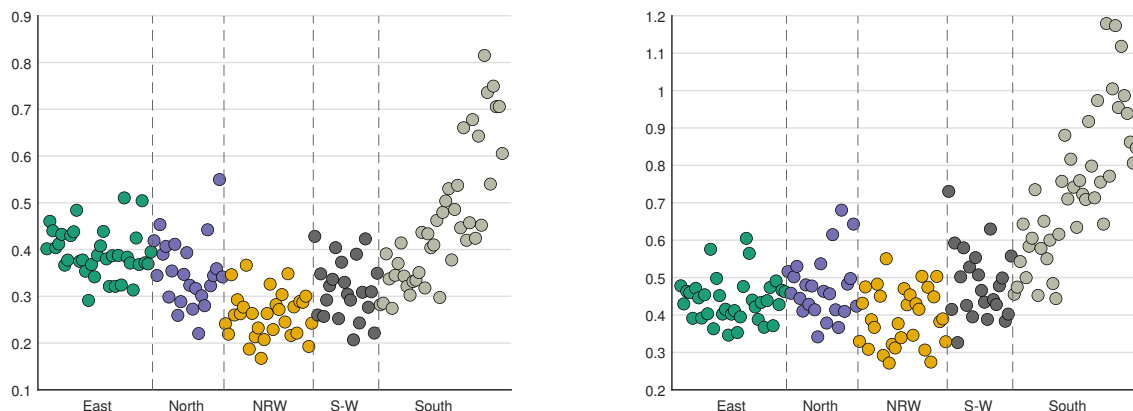
(a) Ratio of optimal to actual unemployment 1994-2005

(b) Ratio of optimal to actual unemployment 2005-2014

Notes: Part (a) and (b) display the ratio of globally optimal unemployment to actual unemployment 1994-2004 and 2005-2014, respectively.

Eastern districts use the transfers to subsidize employment such that unemployment rates are lower or employment rates are higher compared to the solution without redistribution across districts. The pattern of optimal instruments is otherwise very similar.

5 Conclusion

In this paper, we analyze regional disparities in unemployment rates and the underlying labor market flows in Germany. Our analysis is based on administrative unemployment insurance records and newly compiled vacancy data on the employment agency district level. We present new evidence on the importance of worker flows for regional unemployment differentials. A decomposition of the unemployment rate variation across districts shows that separation rates explain 70% of the regional differences during 1994-2004. Over time, however, their importance in the determination of unemployment rate differentials diminished, leaving job-finding rates responsible for 58% of the variation in 2005-2014. This finding suggests that when designing policies to mitigate local unemployment, the government should take into account both margins because the transmission of policies goes through the flow rates (Jung and Kuhn, 2014, and Hartung et al., 2018).

We then utilize a multi-region model with search and matching frictions to identify structural differences between regions. Given these structural disparities, we evaluate how an optimal policy mix that jointly balances local search externalities and externalities caused by the

provision of unemployment insurance benefits affects welfare and unemployment disparities. The optimal region-specific policy mix leads to significant increases in welfare and employment compared to the steady-state. This result suggests that local labor market policies are an effective means to increase overall welfare.

Throughout we made the simplifying assumption that labor is immobile between employment districts. Allowing labor to be mobile would affect the size of the transfer across regions as population size changes and transfers feed back into migration decisions. Inter-regional migration in Germany is clearly not negligible, but as we show in a companion paper (Jung et al. (2021)) it is limited and heavily concentrated in young age cohorts. An integrated framework featuring both the frictions of our model and accounting labor mobility is beyond the scope of this paper. However, we believe that there is room for the region-specific policies along the lines we have outlined to deliver significant gains even if labor is mobile. In particular, these gains can be obtained without regional transfers, so the classical question of redistribution across regions can be largely separated from the question how to design regional instruments.

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A Data

The SIAB is a two-percent representative sample of all individuals who are unemployed or subject to social insurance contributions and covers the years $1975 - 2014$. The panel covers approximately 80% of the labor force, as self-employed and civil servants are excluded. We focus our analysis on the period $1994 - 2014$ to include East German workers, but occasionally report results for West-Germany for the years 1980-1994.[24] The construction of monthly worker histories follows Jung and Kuhn (2014). In particular, we aggregate the daily employment histories to a monthly frequency using predefined reference weeks. Labor market states are assigned to a worker based on a hierarchical ordering. In general, parallel notifications are treated as follows: an employment notification replaces an unemployment notification, which in turn replaces non-participation. We exclude individuals with no information on their employment status or geographic location. Inactive employment relationships (e.g., maternity leave) are excluded as are marginally employed workers if they do not have a parallel unemployment spell. An individual is defined as employed if we observe a full-, part-time, or apprentice employment notification. A worker is marked as unemployed if she registered as unemployed at the federal employment agency. The registration-based measure is not consistently recorded for the years before 2000. Therefore, we use information on the unemployment benefit recipient status to construct prior histories. The flow data based on the benefit recipient definition is adjusted following Hartung et al. (2018). We remove the differences in levels between registered unemployed and benefit recipients and extend the registration-based flow rates backward using the growth rates of the benefit-recipient rates.[25] We control for inflows from nonemployment to unemployment in early 2005 that are due to regulatory changes. We follow Hartung et al. (2018) and exclude individuals that entered unemployment from nonemployment in the first six months of 2005 and did not transition to employment up to 2007.

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[24]Information on workers in East Germany in 1992 and 1993 is used to impute the location variable if applicable.

[25]The adjustment preserves the cyclical variation of each rate but adjusts for the level difference. As worker flow rates are highly volatile, we set the level difference to the average monthly difference in the first six months of 2000. Note that the mismatch index is invariant to aggregate changes in unemployment or vacancies. The relative distribution determines the size of mismatch.

Figure A.1: Aggregate unemployment rates (East and West Germany)
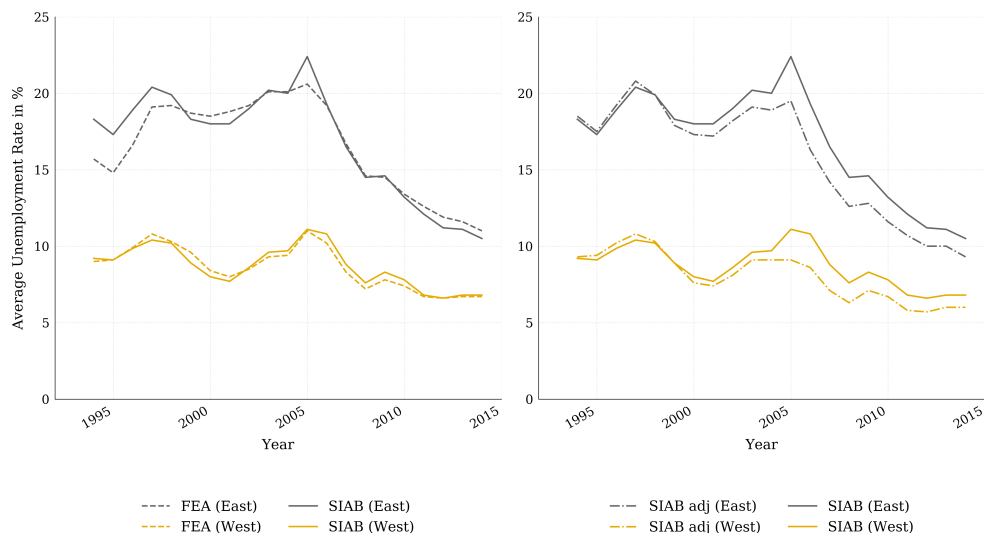
Notes: The figure displays the average monthly unemployment rates in East and West Germany. The left panel displays the official unemployment rates (FEA) as well as the unadjusted unemployment rates from SIAB. The right panel displays the SIAB unemployment rate with and without the inflow correction (SIAB adj). The official unemployment rates are measured in terms of the dependent civilian labor force. The constructed unemployment rates from SIAB data take into account the average annual number of civil servants in East and West Germany.

Figure A.1 shows the resulting aggregate unemployment rates for East and West Germany as well as the corresponding official rates. The left panel shows the unadjusted time series, while the right panel displays the effect of the inflow adjustment. The constructed series closely resembles the official rate in level and cyclicality. The modification of the inflows from nonemployment mainly affects the unemployment rates after 2005.[26]

A.1   Individual employment histories

A contribution limit to the social security system leads to top coding of wages. Following Gartner (2005), we impute all censored wages at the social security threshold in each year.

We provide additional evidence on the regional development across occupations in the appendix. Our data covers 25 occupations for the years $1980 - 2013$. Information on the occupation in which a person is working is available for every employment spell. Occupations are classified based on the "Klassifikation der Berufe 1988", which was not subject to changes during the observation period.[27]   If a worker becomes unemployed, we assume that she is

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[26]The official unemployment rates are measured in terms of the dependent civilian labor force, which we obtain from "Arbeitslosigkeit im Zeitverlauf: Entwicklung der Arbeitslosenquote (Strukturmerkmale)", 2019, Statistik der Bundesagentur für Arbeit. The constructed unemployment rates from SIAB data take into account the average annual number of civil servants in East and West Germany. We obtain the number of civil servants from the Statistical Offices of the Federation and the Länder ("74111-01-04-4-B" and "74111-01-05-4", Statistical Offices of the Federation and the Länder, Germany, 2019.).

[27]The first version was developed in the 1960s. It was modified in 1975, as well as in 1988. Importantly,

searching for a job in the occupation of her last employment. To estimate sector-specific matching efficiencies, we need detailed data on monthly unemployment in and outflows for each sector. Therefore, we drop occupations where we either have to many missing data points or observe only a low number of monthly transitions. In total, we drop 8 of 33 occupations from the sample. In the empirical analysis, we drop occupations with less than 100 monthly transitions out of unemployment or more than five missing observations of unemployment flow or stock variables. Specifically, we exclude the following occupations: Agriculture and fishery (1-6) miners (7-9), ceramists (12), paper manufacturer (16), printer (17), wood conditioner (18) and leather manufacturers (37). The occupation unskilled labour (53) is disregarded due to missing observations for East Germany.

A.2   Vacancies

This section describes the frequencies of the vacancy data and the regional adjustment procedure. We digitize monthly or quarterly data on vacancy stocks for employment agency districts and occupational classifications from official (archived) publications of the federal employment agency. From 2000 onward, we obtain the vacancy data directly from the FEA. Table A.1 shows the frequencies and sources of the vacancy data. In addition to registered vacancies, we data on unemployment (rates and stocks) when possible. The data on unemployment is utilized to demonstrate the comparability of SIAB to official data when computing the mismatch index. In general, we interpolate quarterly data to a monthly frequency. Moreover, we linearly interpolate missing values.

Vacancy data for employment agency districts are digitized from monthly ANBA publications for the years $1976 - 2000$. Data for East Germany is available from 1991 onward. To obtain regional data comparable to the SIAB data, we correct the vacancy stocks for territorial changes. Specifically, we adjust for changes in district territory within the years 2012 and 2013. We provide a discussion of the adjustment procedure discussed in a subsequent section.

the 2-digit level was not subject to any change during the observation period; only 4-digit and lower categories were modified. The KldB 88 was replaced in 2011 by the KldB 2010, adjusting the classification scheme to international standards. Employment notifications after 30.11.2011 follow the new classification of 2010 but are recoded, and inaccuracies may occur.

Table A.1: Vacancy data: Sources and frequencies

Sector	Time	Frequency	Source	Other data
West Germany				
Occupation	$1972 - 1981$	m	ANBA$_a$	U
	$1982 - 1997$	q	ANBA$_a$	U
	$1998 - 2000$	m	ANBA$_m$	
	$2000 - 2013$	m	FEA	
EAD	$1976 - 1999$	m	ANBA$_m$	U, u
	$2000 - 2014$	m	FEA	
East Germany				
Occupation	$1992 - 1997$	q	ANBA$_a$	
	$1998 - 2000$	m	ANBA$_m$	
	$2000 - 2013$	m	FEA	
EAD	$1991 - 1999$	m	ANBA$_m$	U, u
	$2000 - 2014$	m	FEA	

Notes: ANBA$_a$ (ANBA$_m$) indicates that the report was published annually (monthly). We list the total time period but use data from 1980 onward. "Other data indicates the other time series digitized: U number of unemployed; u unemployment rate.

For occupations, we obtain a monthly vacancy series from annual ANBA publications for the years $1972 - 1981$. Within $1982 - 1996$, we interpolate the quarterly data collected from annual ANBA publications to a monthly frequency. For the period from 1997 to 2000, we digitize registered vacancies from monthly ANBA publications. East German vacancy data by occupation are available from 1992 onward. For occupations, the vacancies include seasonal jobs up to 2005. These seasonal jobs are predominantly in agricultural occupations. Here, we observe a drop in the average number of vacancies from almost 50000 in 2004 to 4000 in 2005. Therefore, we exclude the agricultural sector from our sample. The occupational classification scheme corresponds to one of the SIAB data. The vacancy data digitized from the ANBA is reported for 33, 2-digit occupational codes, which were not subject to changes during the observational period. During some years, the data is only available at a quarterly frequency. Vacancy data received from the FEA covers the years $2000 - 2013$ and is aggregated

in accordance to the classification of the ANBA data.

A.3 Re-confinement of the employment agency districts

The SIAB data utilized in this article is based on territorial borders of 2014. Between 2012 and 2013, the territory of the employment agency districts was partially re-confined. In particular, the total number of EADs reduces from 176 to 156.[28]

Our vacancy data before 2000 comes from historical annual reports and employment agency districts are based on non-fictional territorial borders in each year. Thus, we cannot recalculate the districts' vacancy stocks. Also, vacancy data received from the FEA for the years $2000 - 2007$ is based on territorial borders before the re-confinement.

To match the regional unit of the individual employment histories, we approximate the vacancy distribution for all years before 2007. The approximation is based on overlapping vacancy data for old and new territorial classifications. Specifically, we obtain vacancy data for the old and new territorial borders for each employment agency district. This data covers the period from January 2007 to June 2012. Hence, we can infer the number of vacancies gained (lost) due to re-confinement.

Our adjustment procedure is as follows: Assume there are two districts X and Y, where X received parts of the territory of Y during the re-confinement in 2012. Let the districts based on the new territory be denoted by X' and Y'. The FEA provides us with non-fictional (X, Y) and fictional (X', Y') EAD vacancy data for the period 2007 to 2012, where fictional data is based on the territorial borders after 2012. We use this overlapping period to identify the average share of vacancies lost in Y ($\bar{\alpha} = \frac{1}{T} \sum_t^T \alpha_t$) solving the system of equations for each t:

$$
\begin{aligned}
V_{X',t} &= V_{X,t} + \alpha_t V_{Y,t} \\
V_{Y',t} &= V_{Y,t} - \alpha_t V_{Y,t}.
\end{aligned}
$$

The average shares are then used to adjust the number of vacancies in both districts for all months before 2007 (e.g., $V_{Y',t} = V_{Y,t} - \bar{\alpha} V_{Y,t}$). If an exchange of territory happened between only two districts, we can infer the exact number of vacancies lost (gained) for the giving (receiving) district. However, in a situation where multiple districts exchange territory, we estimate the mean share.

Concerning East Germany, we digitize ANBA publications from January 1991 up to December 1999 and append them with data from the FEA. Again, we have to correct for territorial changes using data for the territorial borders in 2014 available for the period 2007 to 2014 and vacancy data for the old territorial boundaries spanning 2000 to 2012. Three

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[28]The reassignment happened in three steps on 1.7.2012, 1.10.2012, and 1.1.2013.

employment agency districts are newly formed: Greifswald, Freiberg, and Bernburg. Two EADs are discontinued because of a merger (Wittenberg and Gera). Overall, all average shares of vacancies lost (gained) can be calculated. Nine districts were not subject to any territorial changes.

The number of vacancies of 68 out of the 156 districts does not need to be approximated because the district's borders do not change, or a new district is an exact combination of two or more old EADs. The following subsection lists the EADs where the number of vacancies was approximated and describes the identification of the average shares. We compare our corrected time series to the official vacancy series during the overlapping period 2007 to 2012 in Section A.3.2. The mean percentage derivation from the correct number of vacancies is 3% in West and 6% in East Germany.

A.3.1 Territorial changes

North Rhine-Westphalia   In North Rhine-Westphalia, all shares of vacancies lost (gained) can be calculated. The following districts were subject to territorial changes: On the 1.7.12, Hamm receives territory from Dortmund, and Recklinghausen receives territory from Gelsenkirchen. On the 1.10.12, Aachen-Düren is newly formed out of Aachen and Düren. Meschede-Soest is formed out of Meschede and Soest, and Ahlen-Münster is formed out of Ahlen and Münster. On the 1.1.13, Mettmann is newly formed out of parts of the districts Düsseldorf and Wuppertal. Solingen-Wuppertal is formed out of Solingen as well as parts of Wuppertal.

Baden-Wuerttemberg   In Baden-Wuerttemberg, all shares of vacancies lost (gained) can be calculated. The following districts were subject to territorial changes: On the 1.7.12, Heidelberg receives territory from Mannheim. On the 1.10.12 Ulm receives territory from Ravensburg. Karlsruhe-Rastatt is formed out of Karlsruhe and Rastatt. Konstanz-Ravensburg is formed out of Konstanz and parts of Ravensburg. Nagold-Porfzheim is formed out of Nagold and Pforzheim. Schwaebisch Hall – Tauberbischofsheim is created out of Schwaebisch Hall and Tauberbischofsheim. Rottweil – Villingen-Schwenningen is formed out of Rottweil and Villingen-Schwenningen.

Hesse   In Hesse, all shares of vacancies lost (gained) can be calculated. The following districts were subject to territorial changes: On the 1.10.12, Bad Hersfeld-Fulda is newly formed out of the complete territory of Fulda as well as parts of Bad-Hersfeld. Kassel receives territory from Bad-Hersfeld. Korbach receives territory from Marburg and Kassel. Marburg receives territory from Wetzlar. Limburg-Wetzlar is newly formed out of Wetzlar and parts of Marburg. On the 1.1.13 Offenbach receives territory from Frankfurt. Gießen

receives territory from Frankfurt. Bad Homburg is newly formed out of parts of Frankfurt and Darmstadt.

Rhineland-Palatinate and Saarland In Rhineland-Palatinate and Saarland, all shares of vacancies lost (gained) can be calculated. The following districts were subject to territorial changes: On the 1.10.12, Saarland is newly formed out of Saarlouis, Saarbruecken, and Neunkirchen. Bad-Kreuznach receives territory from Koblenz. Trier receives territory from Mayen. Koblenz-Mayen is newly formed out of parts of Koblenz and Mayen. Landau receives territory from Ludwigshafen.

Schleswig-Holstein and Hamburg On the 1.10.12, Bad Oldesloe receives parts from Elmshorn and Lübeck. Elmshorn receives parts from Luebeck and Neumuenster. Flensburg receives parts from Heide and Neumuenster. Heide receives parts from Elmshorn. Kiel receives parts from Neumünster. Neumünster receives parts from Kiel and Flensburg. Hamburg does not change.

Due to multiple territorial trades, we estimate the mean share. Since Luebeck does not receive any additional territory and, on average, 99% of vacancies stay in Lübeck we assume, that flows to Elmshorn and Bad-Oldesloe are zero. This assumption enables us to identify the flow from Elmshorn to Bad-Oldesloe.

We estimate the following system of equations for districts: Kiel (K,K'), Flensburg (F,F'), Neumuenster (N,N'), Heide (H,H') and Elmshorn (E,E').

$$
\begin{aligned}
V_{K'} &= (1-\alpha)V_K + \beta V_N \\
V_{E'} &= (1-\tau)V_E + \psi V_N \\
V_{H'} &= (1-\phi)V_H + \zeta V_N + \tau V_E \\
V_{F'} &= (1-\delta)V_F + \gamma V_N + \phi V_H \\
V_{N'} &= (1-\beta-\gamma-\zeta-\psi)V_N + \alpha V_K + \delta V_F
\end{aligned}
$$

The coefficients are estimated using a seemingly unrelated regression with the following restrictions: $\tau = 0, \delta = 0, \gamma = 0, \beta = 0$.

Lower Saxony and Bremen

1. Nordhorn and Emden-Leer

   Nordhorn only receives territory. Emden is merged with parts of Leer to form Emden-Leer. Leer is discontinued, and the area is divided between the districts of Nordhorn and Emden-Leer. Hence, the inflow from Leer to Nordhorn as well es Emden-Leer can be calculated.

2. Lueneburg-Uelzen and Celle

   Lueneburg is merged with parts of Uelzen to form Lueneburg-Uelzen. Uelzen is discontinued, and the area is divided between the districts of Lueneburg-Uelzen and Celle. Celle receives territory from Uelzen and loses territory to Hannover. The shares of territory lost (gained) can be calculated

3. Bremen-Bremerhaven, Stade and Nienburg-Verden

   Bremen is merged with parts of Bremerhaven to form Bremen-Bremerhaven. Hence, the share of vacancies lost from Bremerhaven to Bremen-Bremerhaven can be calculated. As Bremerhafen is split up and the area is divided between Bremen-Bremerhaven and Stade, the latter share can be calculated. Stade receives parts of Bremerhaven and Verden. The share of Verden to Stade can be calculated using prior results. Verden is discontinued and merged with parts of Nienburg to Nienburg-Verden. The share of vacancies lost from Nienburg to Nienburg-Verden and Nienburg to Hannover can be calculated.

4. Helmstedt, Hannover, and Hameln

   Helmstedt receives parts of Braunschweig and to Helmstedt. Hence, the share of vacancies transferred from Braunschweig to Helmstedt can be calculated. Hannover receives territory from Celle, Nienburg, and Hameln. As the shares of Celle and Nienburg to Hannover have been calculated, the share of Hameln to Hannover follows as residual. Using the last calculated share number of vacancies transferred from Hildesheim to Hameln follows as a residual.

5. Goettingen, Braunschweig-Goslar and Hildesheim

   (a) Braunschweig-Goslar (BSG) is newly formed out of parts of Braunschweig (BS), without territory given to Helmstedt and Goslar (G).

   (b) Goettingen (GOE') consists of Göttingen and parts of Goslar and Hildesheim (H), without territory given to Hameln and Goettingen.

   (c) Hildesheim (H') consists of parts of Braunschweig and parts of Hildesheim.

   The shares of vacancies lost (gained) cannot be calculated directly. Hence, we need to solve the following system of equations:

   $$
   \begin{aligned}
   V_{H'} &= (1-\alpha)V_{BS} + (1-\gamma)V_H \\
   V_{BSG} &= \alpha V_{BS} + \beta V_G \\
   V_{GOE'} &= V_{GOE} + (1-\beta)V_G + \gamma V_H
   \end{aligned}
   $$

We apply the restriction $\gamma = 0$ because Hildesheim loses only parts of the small municipality Northeim (29000 inhabitants) to Göttingen. This restriction enables us to calculate the other shares each month.

Bavaria   On the 1.10.12, Bamberg-Coburg is newly formed out of Bamberg and Coburg. Bayreuth-Hof is newly formed out of Bayreuth and parts of Hof. Regensburg receives parts of Landshut. Weiden receives parts of Hof. Donauwörth receives parts of Memmingen. Freising receives parts of München. Kempten-Memmingen is newly formed out of Kempten and parts of Memmingen. Landshut-Pfarrkichen is newly formed out of parts of Landshut and Pfarrkirchen. München loses parts of its territory to Freising and Weilheim. Traunstein receives parts of Pfarrkirchen. Weilheim receives parts of München.

On the 1.1.13, Ansbach-Weißenburg is newly formed out of Weißenburg and parts of Ansbach and Nürnberg. Fürth is newly formed out of parts of Nürnberg and Ansbach.

All shares from reassignment on 1.10.12 can be calculated. Due to multiple territorial trades on 1.1.2013, we apply a restriction to identify the flows. Nürnberg gives only parts of the municipality Roth (24000 inhabitants) to Ansbach-Weißenburg. Hence, we assume this flow to be zero.

Brandenburg   On the 1.10.12, Cottbus receives territory from Potsdam. The mean share of lost territory, measured in percent of vacancies lost to Cottbus, can be calculated.

Mecklenburg-West Pomerania   On the 1.1.13, Greifswald is formed out of parts of Neubrandenburg and Stralsund. Rostock loses parts to Stralsund. The mean share of vacancies lost can be calculated.

Saxony   On the 1.7.12, Bautzen and Riesa receive parts of Dresden. On the 1.1.13, Freiberg is newly formed out of parts of Chemnitz, Leipzig, and Ostschatz. On an unknown date, Annaberg-Buchholz receives parts of Zwickau. Vacancy flows can be identified, and the mean share of vacancies lost can be calculated for every district.

Saxony-Anhalt   On the 1.7.12, Dessau-Roßlau-Wittenberg is formed out of Wittenberg and parts of Halle and Dessau-Roßlau. Halle receives parts of Weißenberg. On the 1.1.13, Bernburg is newly formed out of parts of Madgeburg, Sangerhausen, and Dessau-Roßlau. Vacancy flows can be identified, and the mean share of vacancies lost can be calculated for every district.

Thuringia   On the 1.7.12, Altenburg-Gera is formed out of Altenburg, Gera, and parts of Jena. Erfurt receives parts of Suhl. Gotha loses parts to Suhl. Vacancy flows can be

Figure A.2: Impact of the adjustment for territorial changes on the vacancy data

(a) West EADs

(b) East EADs
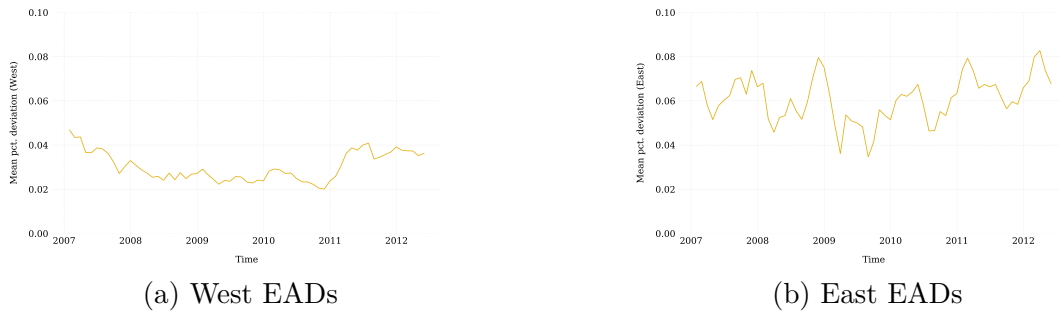
Notes: This figure shows the average deviation of the adjusted from the official number of vacancies in all UADs subject to territorial changes.

identified, and the mean share of vacancies lost (gained) can be calculated for every district.

Berlin   We treat Berlin as one employment agency district and do not correct for territorial changes between the single districts.

A.3.2   The adjusted vacancy data

After the adjustment, we compare the adjusted time series to the true distribution of vacancies across districts. In particular, we compute the average percentage deviation from the official series. Figure A.2 shows the average - non zero - deviation during the overlapping period. The average deviation of our adjusted series is around 3% in West and 6% in East Germany.

Figure A.3 shows the official as well as our constructed series for vacancies in Germany. The digitized data is aggregated from the adjusted district level. Our territorial adjustment procedure does not affect the aggregate number of vacancies. The deviations of the digitized from the official series in the mid-1990s are the result of differences in printed and official data.

Figure A.3: Comparison of official and digitized vacancy data
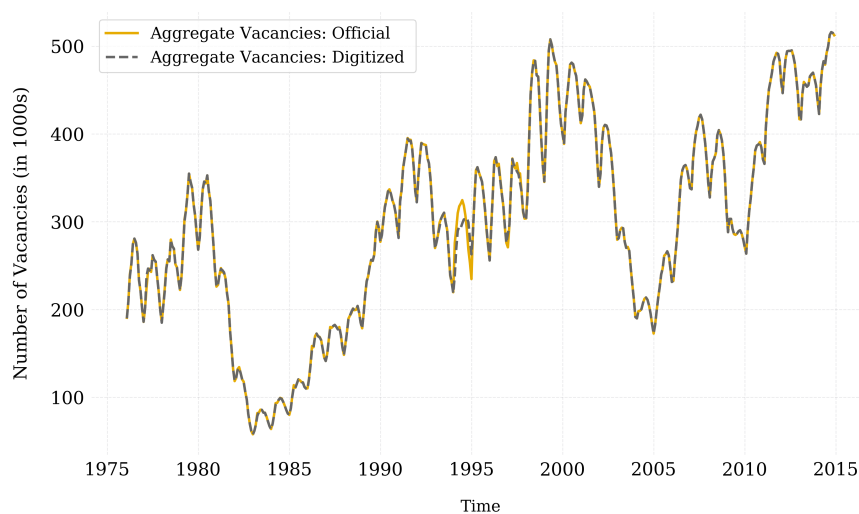
Notes: This figures displays the official as well as the adjusted series for registered vacancies in Germany (West Germany until 1992). The adjusted series is based on (1) adjusted digitized data up to 2000, (2) the FEA vacancy data adjusted for territorial changes and (3) the FEA data for new territorial borders.

B   Classification

Table B.1: District Classification

Code District	Code District	Code District
030 AA Greifswald	373 AA Paderborn	729 AA Fürth
031 AA Neubrandenburg	375 AA Recklinghausen	735 AA Nürnberg
032 AA Rostock	377 AA Rheine	739 AA Regensburg
033 AA Schwerin	381 AA Siegen	743 AA Schwandorf
034 AA Stralsund	383 AA Meschede – Soest	747 AA Schweinfurt
111 AA Bad Oldesloe	387 AA Wesel	751 AA Weiden
115 AA Elmshorn	391 AA Solingen – Wuppertal	759 AA Würzburg
119 AA Flensburg	411 AA Bad Hersfeld – Fulda	811 AA Augsburg
123 AA Hamburg	415 AA Darmstadt	815 AA Deggendorf
127 AA Heide	419 AA Frankfurt	819 AA Donauwörth
131 AA Kiel	427 AA Gießen	823 AA Freising
135 AA Lübeck	431 AA Hanau	827 AA Ingolstadt
139 AA Neumünster	433 AA Bad Homburg	831 AA Kempten – Memmingen
211 AA Braunschweig – Goslar	435 AA Kassel	835 AA Landshut – Pfarrkirchen
214 AA Bremen – Bremerhaven	439 AA Korbach	843 AA München
221 AA Celle	443 AA Limburg – Wetzlar	847 AA Passau
224 AA Emden – Leer	447 AA Marburg	855 AA Rosenheim
231 AA Göttingen	451 AA Offenbach	859 AA Traunstein
234 AA Hameln	459 AA Wiesbaden	863 AA Weilheim
237 AA Hannover	511 AA Bad Kreuznach	035 AA Cottbus
241 AA Helmstedt	515 AA Kaiserslautern – Pirmasens	036 AA Eberswalde
244 AA Hildesheim	519 AA Koblenz – Mayen	037 AA Frankfurt (Oder)
251 AA Lüneburg – Uelzen	523 AA Ludwigshafen	038 AA Neuruppin
257 AA Nordhorn	527 AA Mainz	039 AA Potsdam
261 AA Oldenburg – Wilhelmshaven	535 AA Montabaur	AA Berlin Süd
264 AA Osnabrück	543 AA Landau	955 AA Berlin Nord
267 AA Stade	547 AA Neuwied	AA Berlin Mitte
274 AA Vechta	555 AA Saarland	041 AA Bernburg
277 AA Nienburg – Verden	563 AA Trier	042 AA Dessau-Roßlau – Wittenberg
311 AA Aachen – Düren	611 AA Aalen	043 AA Halberstadt
315 AA Bergisch Gladbach	614 AA Balingen	044 AA Halle
317 AA Bielefeld	617 AA Freiburg	045 AA Magdeburg
321 AA Bochum	621 AA Göppingen	046 AA Weißenfels
323 AA Bonn	624 AA Heidelberg	047 AA Sangerhausen
325 AA Brühl	627 AA Heilbronn	048 AA Stendal
327 AA Coesfeld	631 AA Karlsruhe – Rastatt	093 AA Erfurt
331 AA Detmold	634 AA Konstanz – Ravensburg	094 AA Altenburg – Gera
333 AA Dortmund	637 AA Lörrach	095 AA Gotha
337 AA Düsseldorf	641 AA Ludwigsburg	096 AA Jena
341 AA Duisburg	644 AA Mannheim	097 AA Nordhausen
343 AA Essen	647 AA Nagold – Pforzheim	098 AA Suhl
345 AA Gelsenkirchen	651 AA Offenburg	071 AA Annaberg-Buchholz
347 AA Hagen	664 AA Reutlingen	072 AA Bautzen
351 AA Hamm	671 AA Waiblingen	073 AA Chemnitz
353 AA Herford	674 AA Schwäb. Hall – Tauberb.	074 AA Dresden
355 AA Iserlohn	677 AA Stuttgart	075 AA Leipzig
357 AA Köln	684 AA Ulm	076 AA Oschatz
361 AA Krefeld	687 AA Rottweil – Villingen-Schw.	077 AA Pirna
364 AA Mettmann	711 AA Ansbach – Weißenburg	078 AA Plauen
365 AA Mönchengladbach	715 AA Aschaffenburg	079 AA Riesa
367 AA Ahlen – Münster	723 AA Bayreuth – Hof	080 AA Freiberg
371 AA Oberhausen	727 AA Bamberg – Coburg	092 AA Zwickau

Employment agency districts according to territorial status in 2014.

Online Appendix

C   Dispersion over time

We briefly discuss what the documented differences mean for aggregate dispersion measures: we focus on three key labor market variables across time and districts: unemployment rates and in- and outflow rates. These three indicators give a good overview of how equal local labor markets in Germany are and which flow rate most likely is the dominant source of the evolution of the unemployment rate dispersion. The dispersion (D_t) is defined as the squared deviation of the respective variable from its average across districts

$$D_{m,t} = \frac{1}{I} \sum_{i=1}^{I} \left(\frac{m_{it} - \bar{m}_t}{\bar{m}_t} \right)^2 \quad \text{for m} \in \{\xi, f, u\}, \tag{25}$$

where $\bar{m}_t$ represents the average at time t. ξ is the separationinflow rate, f the outflow and u the unemployment rate. An increase in dispersion is associated with a more unequal distribution across markets.

Figure C.1 displays the results for West and united Germany (East and West Germany). Germany and West Germany show a large level difference in the dispersion of the unemployment rate, which indicates that the rates across districts located East and West differ substantially (left panel). We find that, despite the decrease in aggregate unemployment (Figure 1), the regional dispersion for both regions is higher in 2014, compared to 1994. Hence, the changes in unemployment rates were heterogeneous. Furthermore, the declining dispersion in united Germany during the 2000s, in combination with the increasing dispersion in West Germany starting in 2005, suggests that East German labor markets converge toward the average unemployment rate while West German EADs fall behind.

Figure C.1: Regional dispersion of labor market variables
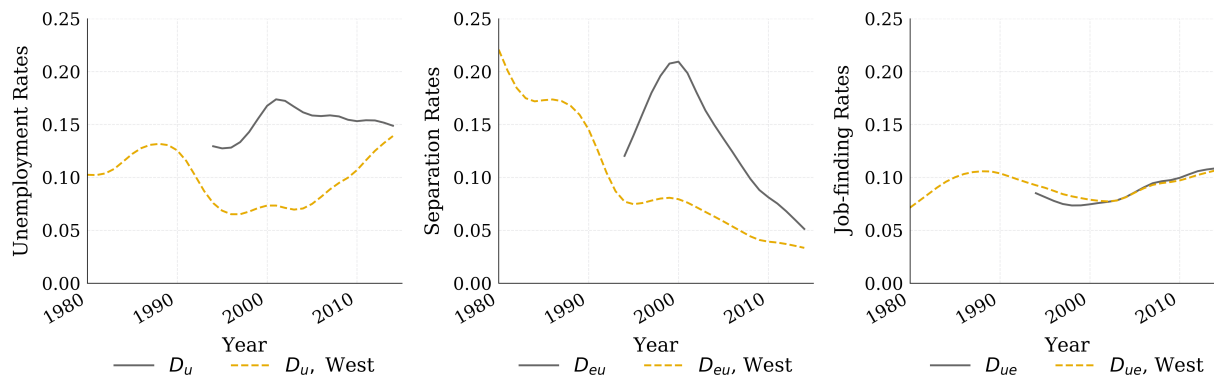
Notes: The figure displays the annual dispersion of unemployment rates, in- and outflow rates across employment agency districts. All series display the HP-filtered trend ($\lambda = 6.25$).

Concerning inflow rates (center panel), we find that the addition of East Germany leads to

a substantial increase in the dispersion, compared to West Germany, which suggests that eastern EADs exhibit considerably different inflow rates. However, inflow rates have become much more similar throughout the sample period. In West Germany, we observe a substantial decrease in dispersion from 25% to below 5%. The average squared deviation from the mean inflow rate in Germany increases up to the year 2000. Afterward, we observe a decrease from 20% to 5%. The dispersion of job finding rates is similar in level and trend between West and united Germany (right panel). Hence, outflow rates in eastern districts are similar to those in western districts. Concerning the development over time, West Germany exhibits a decline from 1990 to 2004, after which the dispersion increases. Across all districts, the increase in dispersion commences already in 1997.

To summarize, the dispersion of local unemployment rates, in West and united Germany, has increased over the last two decades—despite a decrease in aggregate unemployment.

Variations in inflow rates did not cause this development since their dispersion across districts decreased substantially. It will most likely be related to the development of outflow rates in West Germany because western districts are the primary driver of the dispersion of the outflow rate over time.

C.1 Estimates of the matching efficiencies

This subsection presents the estimated vacancy shares and sector-specific matching efficiencies.

C.1.1 Estimates of the matching parameters

To derive the mismatch indices, we need an estimate of the vacancy share of the matching function (γ) as well as the regional matching efficiency parameter (χ_i). The matching process in each market can be described by a reduced-form Cobb-Douglas matching function with constant returns to scale. We estimate model equation ((26))using linear least squares at the aggregate level to recover the vacancy share of the matching function (γ):[29]

$$\ln(f_t) = \ln(\Phi_0) + D_t + D_m + \gamma \ln(\theta_t) + \epsilon_t \tag{26}$$

Labor market tightness is denoted by $\theta_t = \frac{v_t}{u_t}$ and f_t is the job-finding rate. To account for the endogeneity problem of the matching function, we model the time-varying component of the aggregate matching efficiency using time trends and structural break dummies similar to Borowczyk-Martins et al. (2013) and Sedláček (2016). In the baseline

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[29]We chose the following functional form $m_t = \Phi_t V_t^\gamma U_t^{1-\gamma}$, where Φ_t represents aggregate matching efficiency (Barnichon and Figura, 2015). The function relates total hires (m_t) to the stock of vacancies (V_t) and unemployed (U_t). Model ((26)) is a transformation where divide by the stock of unemployed, take logs, and model aggregate matching efficiency using a time trend.

specification, D_t includes a quartic time trend. In a sensitivity analysis, we include dummies for the implementation of the Hartz reforms, the dot-com bubble, the great recession as well as the reunification of Germany in 1991. Moreover, we include monthly time dummy variables (D_m) to account for seasonal fluctuations. The results are presented in Table C.1 of the appendix. Our estimates are in line with prior results (e.g., Burda and Wyplosz, 1994 and Hertweck and Sigrist, 2015). Our preferred estimate is $\gamma = 0.25$, which we use to calculate our mismatch indices in the subsequent sections.[30]

On more disaggregated sectoral levels, we estimate panel regressions of the form

$$\ln(f_{it}) = D_t + D_m + \ln(\chi_i) + \gamma \ln(\theta_{it}) + \epsilon_{it}, \tag{27}$$

where χ_i is the time-invariant district-specific matching efficiency. While we treat matching efficiency as time-invariant in our benchmark analysis, we provide evidence on the time variation of χ_i in the appendix (Table C.3).

C.1.2 Matching efficiencies - results

Table C.1 presents the estimates of model ((26)) for different time intervals and specifications. Our preferred estimate is shown in Column (1).

Table C.1: Estimates of the vacancy elasticity in Germany

| Parameter | Time Frame | | | |
	(1)	(2)	(3)	(4)
	1994 to 2014	2000 to 2014	1994 to 2014	2000 to 2014
α	0.25***	0.26***	0.24***	0.29***
D_{05}		$\checkmark$	$\checkmark$	$\checkmark$
$D_{00,09}$			$\checkmark$	$\checkmark$
D_m	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$
$R2$	0.78	0.78	0.78	0.79

Notes: The table presents estimates of model (26). Regressions include a qEadratic time trend as well as structural break dummies. "***" indicates significance at the 99 percent level. Values are rounded.

Individual matching efficiency parameter ϕ_i are estimated using model ((27)). The estimated vacancy share, the standard deviation as well as minimum and maximum

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[30]Note that, based on the construction of the data, hires in period t are workers who transition from unemployment to employment in between the months t and $t+1$.

matching efficiency are presented in Table C.2, i.e., χ_{min} (χ_{max}) is the minimum (maximum) matching efficiencies across sectors.

Table C.2: Vacancy shares and sectoral matching efficiencies

Sector	α	$std(\chi)$	χ_{min}, χ_{max}	Time Frame
(1) States (16)	0.19^{***}	0.13	0.81, 1.34	$1994 - 2014$
(2) UA Districts (156)	0.16^{***}	0.24	0.55, 1.80	$1994 - 2014$
(3) UA Districts (36, E)	0.13^{***}	0.11	0.81, 1.31	$1994 - 2014$
(4) UA Districts (118, W)	0.19^{***}	0.27	0.57, 1.80	$1980 - 2014$

Notes: Regressions include a quartic time trend, monthly dummy variables to control for seasonal fluctuations and structural break dummies. "***" indicates significance at the 99 percent level.

To determine time-varying matching efficiency we estimate

$$\ln(f_{it}) = D_t + D_m + I_{t<2005}\ln(\chi_i) + I_{t>2004}\ln(\chi_i) + \alpha\ln(\theta_{it}) + \epsilon_{it}, \tag{28}$$

where $I_{t<2005}$ is an indicator for the months prior to 2005.

Table C.3 presents estimates of the occupation (groups) and state specific matching efficiencies. Estimates across occupational groups are comparable to the estimates of Bauer (2013). The relative ranking of state-specific matching efficiencies is as well similar, with Bremen (Bavaria) exhibiting the lowest (highest) efficiency. Furthermore, she documents comparable changes in state-specific matching efficiencies in West Germany. However, she finds increasing efficiency in East German states. Our results might be the result from the longer time period, as the analyses the period 2000 to 2009.

Table C.3: Estimates of occupation- and state-specific matching efficiencies (χ_i)

Sector	$1994 - 2014$	$1994 - 2004$	$2005 - 2014$
	Occupations		
III Manufacturing	1.50	1.51	1.50
IV Technical professions	0.58	0.55	0.63
V Service professions	1.14	1.09	1.21
	States		
Schleswig-Holstein	1.07	1.13	1.00
Hamburg	0.94	0.98	0.89
Lower Saxony	1.01	1.02	0.99
Bremen	0.84	0.87	0.81
North Rhine-Westphalia	0.82	0.84	0.78
Hesse	0.95	0.95	0.94
Rhineland Palatinate	1.01	0.97	1.02
Baden-Wuerttemberg	1.06	1.01	1.07
Bavaria	1.34	1.26	1.39
Saarland	0.84	0.82	0.86
Berlin	0.92	1.01	0.86
Brandenburg	1.05	1.16	0.97
Mecklenburg-West Pomerania	1.08	1.22	0.97
Saxony	1.06	1.13	1.00
Saxony-Anhalt	1.00	1.10	0.94
Thuringia	1.15	1.25	1.07

Notes: The table presents estimates obtained using model ((27)). Estimations include a qEadratic time trend, monthly dummy variables to control for seasonal fluctuations as well as structural break dummies (when applicable). Efficiencies for $1994 - 2004$ and $2005 - 2014$ (Column 3, and 4, respectively) are estimated using model ((28)).

C.2 Aggregate changes in job-finding rates and the relation to changes in matching efficiencies

The development of local labor markets suggests a decline in matching efficiency in some states between $1994 - 2002$ and $2008 - 2014$. We argue that the differences from our results compared to Klinger and Weber (2016), who observe a large increase in the trend of matching efficiency from 2006 to 2011, are due to a different treatment of marginal employment and mini-jobs. While we treat marginally employed as unemployed if they have a parallel unemployment spell and as out of the labor force otherwise, Klinger and Weber (2016) treat them as employment in the case of no parallel unemployment notification. The inclusion of marginal employment leads to a higher job-finding rate and potentially induces a break in 1999, as marginal jobs are fully recorded from this point onward (cf., Hartung et al. (2018), Figure 17). Table C.4 presents our observed increases of the aggregate job-finding rates between $1994 - 2002$ and $2008 - 2014$. While Klinger and Weber (2016) document an increase of the aggregate job-finding rate from (approximately) 7% to 9% (i.e., of 29%) we find that the rates have increased by 8% to 11%.[31]

Table C.4: Aggregate changes in job-finding and separation rates

	1994 - 2002	2008 - 2014	2010 - 2014	$\Delta 2008 - 2014$	$\Delta 2010 - 2014$
Job-find.	5.36%	5.80%	6.00%	8%	11%
Separat.	0.79%	0.52%	0.49%	-34%	-38%

Notes: The table presents the average monthly aggregate job-finding and separation rate for different time intervals. $\Delta 2008 - 2014$ denotes the percentage change between $1994 - 2002$ and $2008 - 2014$. $\Delta 2010 - 2014$ denotes the percentage change between $1994 - 2002$ and $2010 - 2014$

A difference in treatment of the vacancy series will most likely not cause the different results. While we adjust our vacancy series (downwards) before 2000 to account for the change in composition as seasonal jobs were excluded from the measure from this point onwards, Klinger and Weber (2016) level up the vacancies series after 2000.[32] This adjustment should not affect the differences in results as the market tightness exhibits only a level-shift.

Moreover, the decrease in matching efficiency in some regions cannot be the result of our inflow-correction. This adjustment lowers the number of unemployed after 2005 while leaving the number of hires mostly unaffected as the excluded unemployed are detached from the labor market. Thus, the job-finding rate increases.

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[31]Our results deviate from Hartung et al. (2018) as we consider both, West and East Germany

[32]" *The official definition of vacancies changed in 2000 and does no longer include vacancies for so-called minijobs and other marginal jobs. As we consider all types of dependent employment, however, an analogue definition is preferable – we corrected the break by additional statistics and the multiplier gained from the overlapping year.*", Klinger and Weber (2016) (Online appendix, page 2).

C.3 Fit of the unemployment distribution across regions

This section provides evidence that the regional variations of SIAB unemployment rates closely resemble the actual distribution of unemployment rates across EADs.[33] Figure C.2 shows the annual dispersion of unemployment rates across EADs for unemployment data obtained from our sample (SIAB) as well as from the federal employment agency (FEA). The annual dispersion of the SIAB data matches the dispersion of the FEA data in level and trend for West and united Germany.

Figure C.2: Dispersion of unemployment rates (Robustness)
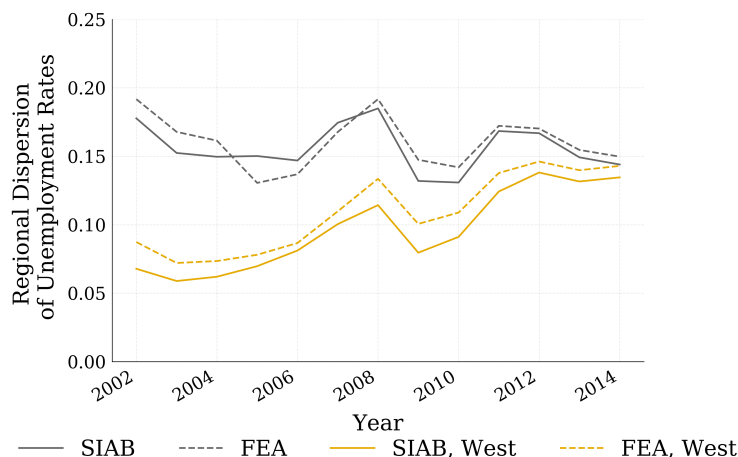
Notes: The figure displays the annual dispersion of unemployment rates for unemployment data obtained from our sample (SIAB) as well as from the federal employment agency (FEA). Data on employment is taken from SIAB.

To compute the mismatch indices presented in section **??**, sectoral matching efficiencies need to be estimated using outflow rates for highly disaggregated sectors. A mismatch index abstracting from heterogeneity in matching-efficiency relies solely on the distribution of unemployment and vacancies

$$M_t = 1 - \sum_{i=1}^{I} \left(\frac{v_{it}}{\bar{v}_t} \right)^{\alpha} \left(\frac{u_{it}}{\bar{u}_t} \right)^{1-\alpha}.$$

We utilize this specific index to facilitate a comparison between data sources. Concerning geographical mismatch, we highlight the comparability of the unemployment data sourced from SIAB and official unemployment data. The vacancy share is set to 0.25.[34] We

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[33]We use different data sources for official regional unemployment rates. Rates from 1994 to 1999 are taken from the ANBA publications; Rates from 2001 onward are obtained from "Arbeitsmarktstatistik der Bundesagentur für Arbeit" from Statistische Ämter des Bundes und der Länder, Deutschland, 2017 (13211-02-05-4).

[34]This index is similar to the one developed by Jackman and Roper (1987) if one sets $\alpha = 0.5$.

conclude that the SIAB data is a good representation for the true distribution of unemployment across districts and occupations.

Figure C.3 shows the annual average benchmark mismatch index constructed using SIAB data (M, SIAB) and using different data sources for West Germany. We additionally compute the M index using official unemployment data from the FEA (M, BA) and using monthly vacancy and unemployment data from ANBA (M, ANBA). For the latter, we do not correct for territorial changes between employment agency districts. The comparison of the M index across different data sources shows almost no differences in cyclicality. Indices computed using the official data for unemployment are only slightly higher, compared to the index based on SIAB data. At the same time, the absolute difference is quite stable. Hence, the sample from SIAB used in this paper is a good approximation of the actual distribution of unemployment across districts. Furthermore, the territorial correction of the vacancy series does not lead to differences in the cyclicality of the indices.

Figure C.3: Mismatch index, Districts (West Germany)

Notes: The figure presents baseline mismatch indices computed for West German employment agency districts using three different data sources. The mismatch index M, SIAB is the yearly average of the mismatch index without district specific matching-efficiency computed using SIAB micro-data as well as the adjusted vacancy series. M, ANBA is computed using unadjusted unemployment as well as vacancy data sourced from the ANBA publications. M, BA is computed using the adjusted vacancy data as well as official unemployment data from the FEA.

Figure C.4 plots the index for East Germany. We compute the M index using official unemployment data from the FEA (M, BA, and M, ANBA) and using annual average unemployment data based on SIAB data (M, SIAB). The indices are comparable in level

and cyclicality. Overall, mismatch driven by heterogeneity in the distribution of unemployment and vacancies is low. The unemployment data sourced from SIAB is a good representation of the actual distribution of unemployed across EADs.

Figure C.4: Mismatch index, Districts (East Germany)

Notes: The figure presents baseline mismatch indices computed for East German employment agency districts using three different data sources. The mismatch index M, SIAB is the yearly average of the mismatch index without district specific matching-efficiency computed using SIAB micro-data as well as the adjusted vacancy series. M, ANBA is computed using unadjusted unemployment as well as vacancy data sourced from the ANBA publications. M, BA is computed using the adjusted vacancy data as well as official unemployment data from the FEA.

C.4 Regional mismatch: Additional evidence

In this subsection, we provide evidence on mismatch across employment agency districts in West and East Germany and across federal states. Furthermore, we account for heterogeneity in separation rates, productivity, and allow for time-varying matching-efficiency.

Mismatch across East German EADs is low (Figure C.5, left panel): The optimal allocation of the planner would increase hires by below 5% for both measures of mismatch.

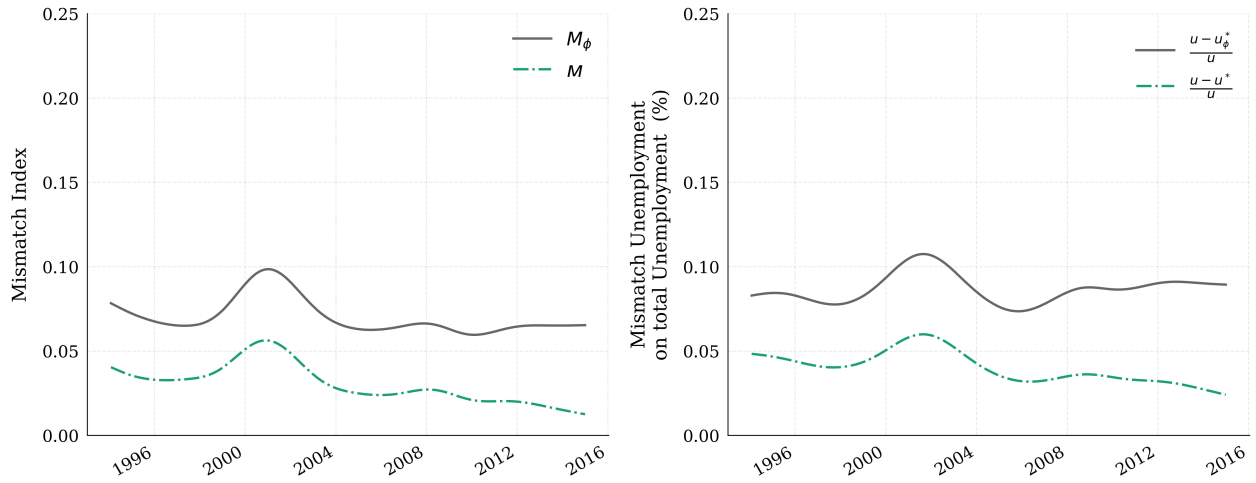Figure C.5: Regional mismatch across East German EADs
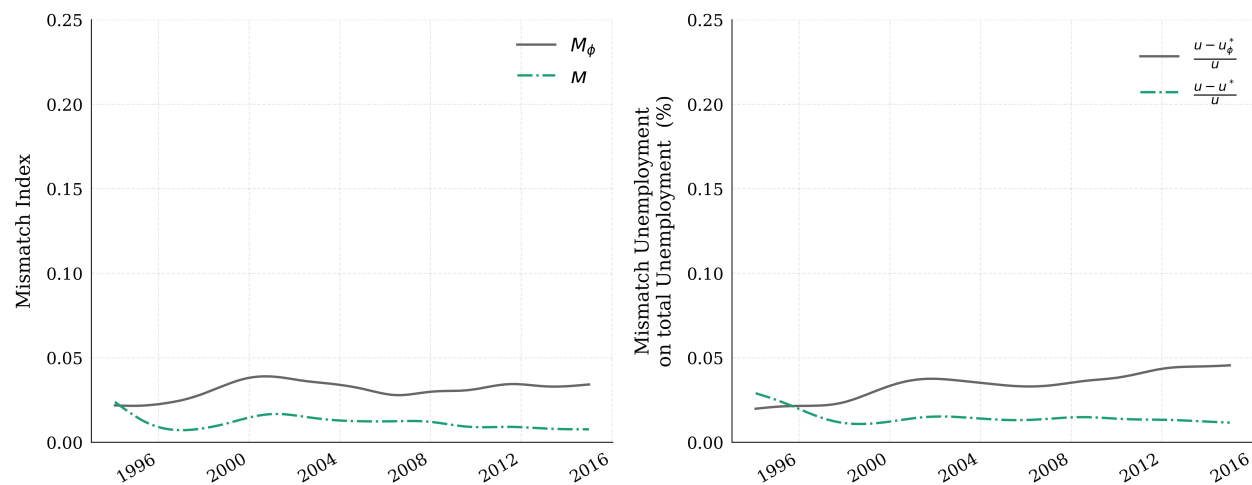
Notes: The figure presents the mismatch indices M and M_ϕ as well as the corresponding mismatch unemployment rates. The indices are HP-filtered with a smoothing parameter $\lambda = 100{,}000$.

The optimal allocation of the planner would increase aggregate hires by below 10% for both measures of mismatch by eliminating mismatch across federal states (Figure C.6).

Time variation in matching efficiency leads a level change in mismatch, while heterogeneity in separations and productivity (wages) decreases mismatch (Figure C.7; left and right panel, respectively). The index M_{x_t} is derived in section D.1. We approximate productivity by the wage.

Figure C.6: Regional mismatch across federal states

Notes: The figure presents the mismatch indices M and M_ϕ as well as the corresponding mismatch unemployment rates. The indices are HP-filtered with a smoothing parameter $\lambda = 100,000$.

Figure C.7: Regional mismatch across employment agency districts: Sensitivity
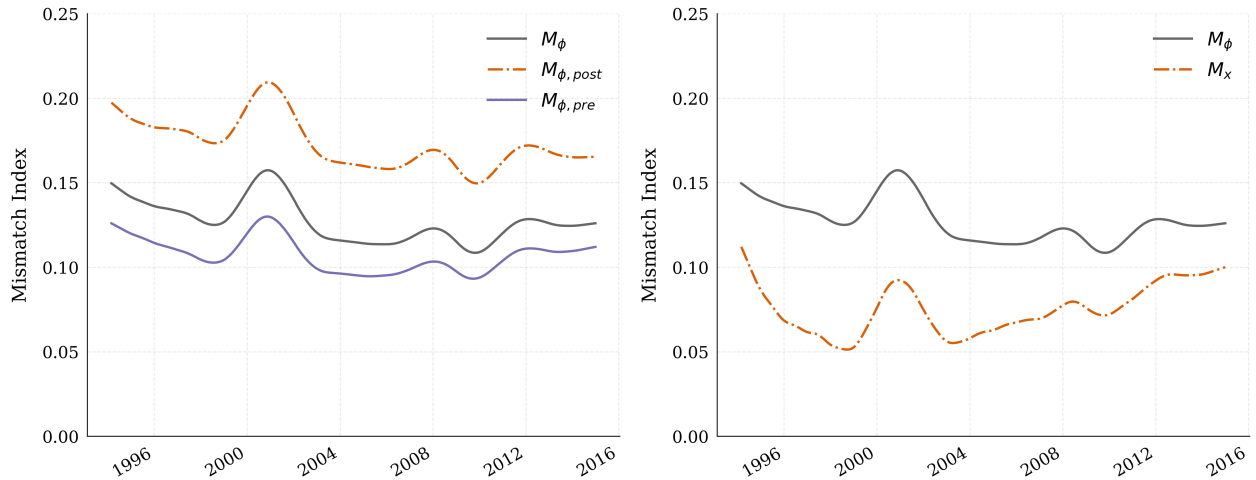
Notes: The figure presents the mismatch indices M_{θ_t}, M_{x_t} and M_{ϕ_t}. The indices are HP-filtered with a smoothing parameter $\lambda = 100,000$. M_{θ_t} represents the estimates presented in the main text. M_{ϕ_t} is estimated using the region-specific matching efficiencies provided in Table C.3. Post indicates the use of the matching efficiencies valid for the period after 2005 and pre for the period before 2006. M_{x_t} is estimated based on the measure derived in Section D.1.

Regional mismatch in West Germany   For West Germany, we extend the index backward to 1980. The fraction of hires lost due to misallocation of unemployment across West German EADs and the corresponding contribution to the aggregate unemployment rate during $1980 - 2014$ are displayed in Figure C.8. The index unadjusted for heterogeneity (M_t) decreases throughout the period and lies below 5%. Accounting for differences in matching efficiency $(M_{\chi,t})$ leads to a considerable rise in the level of mismatch: Redistributing unemployed based on the planner's rule leads to an average increase in hires of 15%. In general, mismatch in West Germany is similar in level and cyclicality during $1994 - 2014$ compared to Germany.[35] Moreover, the right panel shows

Figure C.8: Regional mismatch across West German EADs
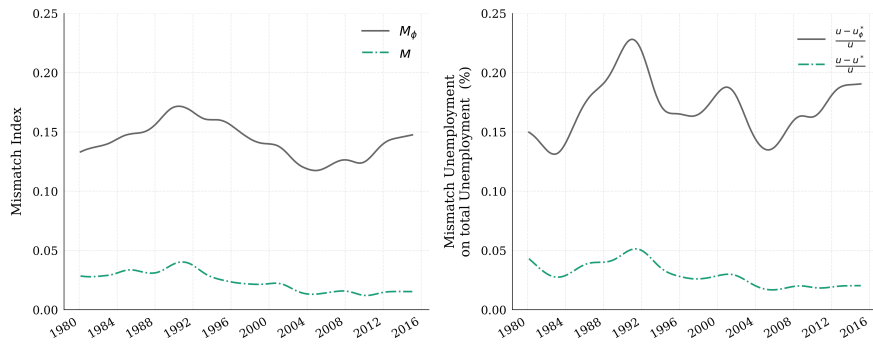
Notes: The figure presents the mismatch indices M and M_χ as well as the corresponding contribution of mismatch to aggregate unemployment. The unit of analysis are 118 employment agency districts. All series display the HP-filtered trend $(\lambda = 100{,}000)$.

that regional mismatch is not the leading cause of high unemployment during the 1990s and early 2000s. The declining contribution of mismatch in 1992 and 2001 coincides with a high and long-lasting increase in separations (Hartung et al. (2016)). A change in separations generally leads to a more substantial change in the counterfactual rate. This is due to lower (higher) optimal compared to actual unemployment (employment). Therefore, the contribution to aggregate unemployment behaves countercyclical to the actual unemployment rate.

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[35]The size of the indices is not comparable across different these regional classifications as the number of segments, vacancies and unemployed differ (cf., Sahin et al., 2014). However, the mismatch unemployment rate $(u_t - u_t^*)$ can be used compare the severity of mismatch: When accounting for heterogeneity in matching efficiency, the mismatch unemployment rate is 16% higher in Germany than in West Germany.

D Mismatch unemployment

Our analysis abstracted from mobility between regions. In this appendix, we provide an upper bound estimate for the potential increase in aggregate employment when mobility frictions are absent. We employ a measure developed by Sahin, Song, Topa, and Violante (2014) capturing the impact of misallocation between markets on unemployment. It is based on a comparison of an optimal and the actual distribution of the unemployed for a given number of vacancies. The optimal allocation is derived from a dynamic search and matching model, where a planner redistributes unemployed at no cost to maximize employment. We find that geographical mismatch in Germany in $1994 - 2014$ at the district level is non-negligible as eliminating mismatch can increase aggregate hires by $10 - 15\%$. The increase in hires corresponds to a decline in aggregate unemployment of approximately the same magnitude. As with our structural model we indeed find an increasing importance of mismatch unemployment at the end of the sample, which is closely related to the decrease of inflow rates. Furthermore, a large share of the unemployed has to be reallocated to achieve the reduction $(30 - 38\%)$. In the first decade, the primary relocation flow goes from East Germany to West Germany, particularly to Bavaria. In the second decade, unemployed workers especially from NRW are relocated, again, to Bavaria. The changes in the reallocation pattern mirror the changes in the distribution of the unemployment rate: While the eastern districts have caught up substantially, in terms of distance to the average unemployment rate, unemployment in West German regions is stagnating. Our results concerning mismatch unemployment contribute to the studies that focus on the efficiency of the spatial unemployment distribution (Sahin et al., 2014, and Marinescu and Rathelot, 2014). Our contribution, relative to the existing research on mismatch in Germany, is the extension of the mismatch measure by more than 20 years and the analysis at a much more disaggregated regional level. While Bauer (2013) analyses mismatch during $2000 - 2010$ in West Germany with a special focus on the effect of the Hartz reforms; we describe the development of regional mismatch in Germany over three decades. Hutter and Weber (2017) explore the role of mismatch for accuracy of matching function forecasts. They use official vacancy and unemployment data from the federal employment agency and compute a mismatch measure for 21 occupations and 50 regions. Other studies are, for example, Erken et al. (2015) (Netherlands); Patterson et al. (2016) and Turrell et al. (2018) (both U.K.), who analyze mismatch and quantify the associated output loss. Our findings will be reflected in estimates on the heterogeneity of matching efficiency parameters across employment districts discussed next.

Mismatch might arise if many unemployed seek jobs in markets with low vacancies and frictions to mobility impede an adjustment. This misallocation then leads to an inefficient level of aggregate unemployment. While we do not analyze the possible sources of

mismatch, the measure can be interpreted as an upper bound for the importance of frictional worker mobility across sectors for aggregate unemployment.[36]

We document mismatch during two periods: 1980-2014 as well as 1994-2014. The analysis of the more extended period focuses on the development in West Germany. For 1994-2014, we investigate mismatch in East and West Germany. The subsequent sections introduce and discuss the measurement approach and present the results.

D.0.1 Measuring mismatch

This section attempts to obtain an upper bound on the gains from mobility. To that end we estimate a model of regional mismatch a la Sahin et al. (2014) where a planner can reallocate unemployed workers across regions given matching frictions. Quantitatively, we find that if a planner could reallocate the unemployed across EADs this would lower unemployment by, on average, 15%.

Recall from Sahin et al. (2014) that the mismatch index measure the effect of mismatch across local labor markets on aggregate unemployment by comparing an optimal to the actual distribution of the unemployed. Based on the planner's optimal allocation rule, the index estimate the fraction of hires lost due to mismatch and recover counterfactual unemployment rates. The optimal allocation is derived within a dynamic search and matching model, where a planner redistributes unemployed at no cost to maximize employment.

Model The economy consists of distinct regional labor markets $i \in I$, and each market is subject to frictions captured by a matching function. Assume that these frictions are captured by a Cobb-Douglas matching function of the form: $h_{it} = \Phi_t \chi_{it} v_{it}^\gamma u_{it}^{1-\gamma}$. Hires, unemployment and vacancies at time t in sector i are given by h_{it}, u_{it} and v_{it}, respectively. Unemployed workers can only search in one region. The vacancy elasticity of the matching function γ is assumed to be constant across time and regions. Φ_t represents aggregate and χ_{it} region specific matching efficiency. Individuals are risk neutral and are either employed or unemployed ($\sum_{i=1}^{I} e_{it} + u_{it} = 1$). There is no on the job search, matches are destroyed at the exogenously give rate ξ_t and vacancies arise exogenously.[37]

In the benchmark environment, the planner minimizes unemployment, given sector-specific matching efficiencies and vacancy shares. Moreover, there are no reallocation costs. The

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[36]Herz and van Rens (2019) estimate the underlying frictions of mismatch. Their results point to wage frictions as the main cause of mismatch. Marinescu and Rathelot (2018) present evidence on mismatch for the U.S. taking into account the geography of job search. They find that the departure from the assumption of distinct markets does not lead to a large increase in mismatch.

[37]An extension of the model, where the planner takes into to account differences in separation rates and productivity, is presented in appendix (Section D.1).

planner's optimal allocation rule across sectors can be written as

$$\chi_{1t}\left(\frac{v_{1t}}{u_{1t}^*}\right)^\gamma = \cdots = \chi_{It}\left(\frac{v_{It}}{u_{It}^*}\right)^\gamma, \tag{29}$$

where u_i^* represents the optimal number of unemployed that should be searching in sector i. The allocation rule implies that ((30)) has to hold for each sector pair j and k.

$$\frac{v_j}{u_j^*} = \left(\frac{\chi_k}{\chi_j}\right)^{\frac{1}{\gamma}}\frac{v_k}{u_k^*} \tag{30}$$

In short, the optimal allocation equalizes matching efficiency weighted vacancy to unemployment ratios across sectors. The planner re-allocates unemployed to sectors with higher matching efficiencies and labor market tightness.

Mismatch Index We utilize this optimality condition to construct a measure for hires lost due to mismatch. Specifically, we measure the impact of the misallocation of unemployed on hires by comparing the planner's optimal hires to the number of actual hires. The mismatch index ((31)) then captures the fraction of hires lost due to misallocation.

$$M_{\chi,t} = 1 - \frac{h_t}{h_t^*}, \tag{31}$$

The aggregate number of hirings h_t in period t can be recovered by summing h_{it} across all sectors. The corresponding expression is

$$h_t = \Phi_t v_t^\gamma u_t^{1-\gamma}\left[\sum_{i=1}^I \chi_{it}\left(\frac{v_{it}}{v_t}\right)^\gamma\left(\frac{u_{it}}{u_t}\right)^{1-\gamma}\right].$$

Optimal hirings h_t^* are based on the planner's allocation of unemployed across sectors (u_{it}^*), taking vacancies and sectoral matching efficiencies as given

$$h_t^* = \Phi_t v_t^\gamma u_t^{1-\gamma}\left[\sum_{i=1}^I \chi_{it}\left(\frac{v_{it}}{v_t}\right)^\gamma\left(\frac{u_{it}^*}{u_t}\right)^{1-\gamma}\right]$$

Substituting for the planner's allocation rule for each district pair ((30)) the equation simplifies to $h_t^* = \bar{\chi}_t\Phi_t v_t^\gamma u_t^{1-\gamma}$. Here, sector specific matching efficiencies are weighted by the respective vacancy shares and aggregated to a scaling factor $\bar{\chi}_t = [\sum_i^I \chi_{it}^{\frac{1}{\gamma}}\left(\frac{v_{it}}{v_t}\right)]^\gamma$, which is constant across sectors. The mismatch index then simplifies to

$$M_{\chi,t} = 1 - \sum_{i=1}^I \left(\frac{\chi_{it}}{\bar{\chi}_t}\right)\left(\frac{v_{it}}{v_t}\right)^\gamma\left(\frac{u_{it}}{u_t}\right)^{1-\gamma}. \tag{32}$$

As demonstrated by Sahin et al. (2014), the index is invariant to aggregate shocks and lies within zero and one. In addition, it is increasing in the level of disaggregation − i.e., indices with a different disaggregation level are not directly comparable. Moreover, the index can be calculated solely on the basis of the empirical distribution of unemployed, vacancies and matching efficiencies.

Counterfactual unemployment The fraction of hires lost has direct implications for aggregate unemployment. We derive the planner's optimal job-finding rate and subsequently construct a counterfactual unemployment rate − absent any mismatch. The actual job-finding (f_t) is given by:

$$f_t = \frac{h_t}{u_t} = (1 - \mathcal{M}_{\chi,t})\bar{\chi}_t \Phi_t \left(\frac{v_t}{u_t}\right)^\gamma,$$

where we exploit that equation ((32)) is equivalent to $h_t = (1 - M_{\chi,t})h_t^*$. Mismatch lowers the job-finding rate as the planner's distribution is more efficient. Based on the planner's allocation of unemployment across sectors, the optimal job-finding rate is

$$f_t^* = \chi_t \Phi_t \left(\frac{v_t}{u_t^*}\right)^\gamma = f_t \frac{1}{1 - \mathcal{M}_{\chi,t}} \left(\frac{u_t}{u_t^*}\right)^\gamma.$$

Hence, we can recover the optimal rate using the actual rate and the mismatch index. Note that the optimal job-finding rate is higher than the actual rate because of the efficient allocation of unemployed and because the optimal aggregate unemployment rate is most likely lower ($u_t^* < u_t$). We then derive the sequence for the counterfactual unemployment rate using the flow equation ((33)), f_t^* and an initial value u_0^*.

$$u_{t+1}^* = \xi_t + (1 - \xi_t - f_t^*)u_t^* \tag{33}$$

The separation rate is taken as exogenous, similar to the model. We select $u_0^* = \frac{\xi_0}{\xi_0 + f_0^*}$, where $f_0^* = f_t \frac{1}{1 - \mathcal{M}_{\chi,t}}$.

The share of unemployment that is caused by mismatch is measured as the difference between actual and optimal unemployment rate. Note that mismatch not only directly affects unemployment through lower hires but also through lower unemployment u_t^*, which leads to an even higher job-finding rate.

D.0.2 Regional mismatch in Germany

We estimate regional mismatch at the EAD level and present two mismatch measures: The M index, which is driven by the distribution of unemployment and vacancies, and the M_χ

index, which additionally accounts for the constant heterogeneity in matching efficiency.[38] To derive the mismatch indices, we need an estimate of the vacancy share of the matching function (γ), which in our preferred estimation following Borowczyk-Martins et al. (2013) and Sedláček (2016) is ($\gamma = .25$). We delegate the details of our estimation and various sensitivity checks to appendix C.1.1.

The mismatch indices and the contribution of mismatch to aggregate unemployment in 1994-2014 are presented in Figure D.1. The M_t index shows a declining trend from 2001 onward. Moreover, the estimated degree of mismatch is low as the fraction of hires lost due to misallocation is below 6%. The $M_{\chi,t}$ index indicates that local labor market frictions − captured by matching efficiency − are an important source of heterogeneity. Aggregate hires can be increased by, on average, 12% more, when the planner takes differences in matching efficiency into account. The contribution to aggregate unemployment (right panel) shows a u-shaped pattern over the period 2000-2005 but stabilizes at around 15% from 2012 onward. This development suggests no role for geographical mismatch in the increase in unemployment during the mid-2000s. The increase of the contribution to

Figure D.1: Regional mismatch across employment agency districts
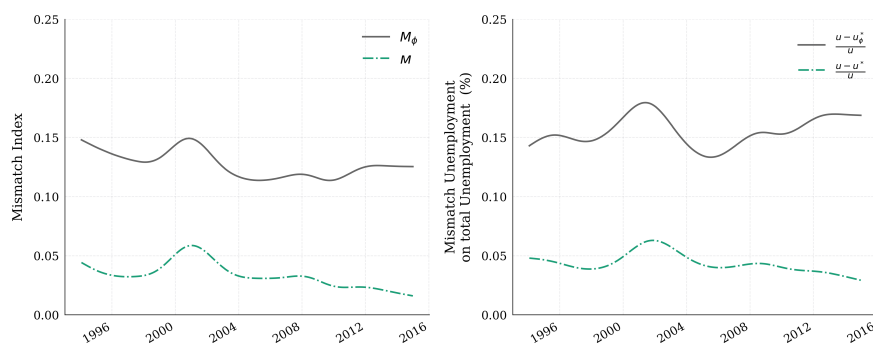
Notes: The figure presents the mismatch indices M and M_χ as well as the corresponding contribution of mismatch to aggregate unemployment. The unit of analysis are 154 employment agency districts. All series display the HP-filtered trend ($\lambda =100,000$).

aggregate unemployment from 2005 onward is attributable to the increase of mismatch (left panel) and to the overall decrease of separations, which was documented in a previous section. More formally, the flow equation of unemployment can be rearranged to

$$\Delta u_{t+1} - \Delta u_{t+1}^* = -s_t(u_t - u_t^*) + f_t^* u_t^* - f_t u_t. \tag{34}$$

Hence, the change in differences between actual and counterfactual unemployment rate depends negatively on the separation rate if $u_t > u_t^*$. Therefore, the decrease in separation rates has increased the importance of mismatch.

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[38]Without heterogeneity in matching efficiency the index reduces to $M = 1 - \sum_{i=1}^{I} \left(\frac{v_{it}}{v_t}\right)^\gamma \left(\frac{u_{it}}{u_t}\right)^{1-\gamma}$ (c.f. Sahin et al., 2014).

Visualizing the share of unemployed, which has to be reallocated to eliminate mismatch unemployment, is instructive to understand the direction and size of the changes the planner undertakes to eliminate mismatch. We chose federal states to illustrate regional differences. Mismatch at the federal state level is lower but exhibits similar movements over time compared to mismatch across employment agency districts (Figure C.6). Figure D.2 displays the fraction of misallocated unemployed by state

$$\frac{u_{jt}^M}{u_t} = \frac{u_{it}}{u_t} - \left(\frac{\chi_i}{\bar{\chi}}\right)^{\frac{1}{\gamma}} \frac{v_{it}}{v_t}. \tag{35}$$

A negative (positive) value indicates that actual unemployment is below (above) its optimal value. In 1994 (left panel), the planner reallocates a total of 37% of the unemployed to a different state. One-third of this fraction lives in NRW, while two-thirds come from the six East German states. Almost all (81%) are relocated to Bavaria. In 2014 (right panel), the planner moves 30% of the unemployed to a different state. Of this 30%, 60% (25%) are from NRW (eastern states) and 80% are moved to Bavaria. These results are congruent with the change in the unemployment distribution presented in prior sections. During the first years of our sample, unemployment rates are highest in East Germany, while during the later years, districts in North-Rhine Westphalia (NRW) exhibit similar unemployment but substantially lower job-finding rates compared to the eastern states.

Figure D.2: The deviation of actual from optimal unemployment at the federal state level

(a) 1994 (b) 2014
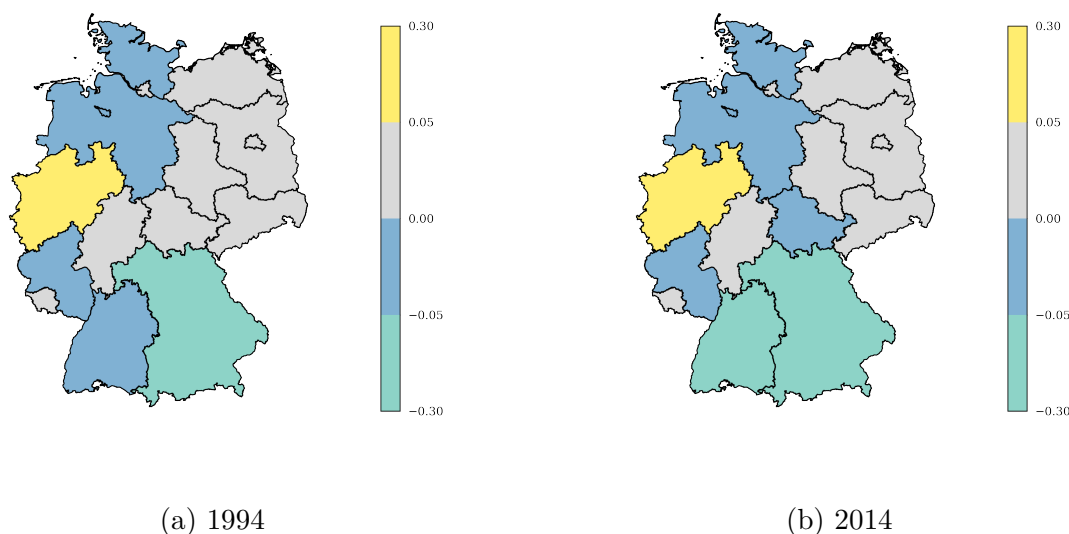
Notes: This figure displays the redistribution of unemployed across federal states based on the allocation rule ((35)). The planner takes the heterogeneity in matching efficiency into account.

Bavaria is the central receiving region due to its above-average job-finding rates. Hence, to equalize matching efficiency weighted unemployment-vacancy ratios, the number of

unemployed residing in the south has to rise.

Mismatch across East German EADs is low: The optimal allocation of the planner would increase hires by below 5%. Here, mismatch is low as unemployment rates are high in all districts and decrease homogeneously up to 2014. Moreover, labor market tightness does not vary a lot. Similar unemployment rates and labor market tightness leave no room for the planner to minimize aggregate unemployment in East Germany (Figure C.5).

For West Germany, we extend the index backward to 1980. The index unadjusted for heterogeneity (M_t) decreases throughout the period and lies below 5%. Accounting for differences in matching efficiency ($M_{\chi,t}$) leads to a considerable rise in the level of mismatch: Redistributing unemployed based on the planner's rule leads to an average increase in hires of 15%. Moreover, mismatch in West Germany is similar in level and cyclicality during 1994-2014 compared to Germany (Figure C.8).

We provide a sensitivity analysis in the appendix. We compare versions of the mismatch indices estimated using SIAB data to indices based on official unemployment data (Section C.3). We conclude that the SIAB data provides a good approximation of the actual distribution of unemployment across regions. Section C.4 of the appendix offers a supplementary analysis where differences in separation rates and productivity, as well as time variation in matching efficiency, are taken into account. Time variation in matching efficiency leads to minor level changes, while heterogeneity in separations and productivity decreases mismatch (Figure C.7).

Note that the results should be interpreted as an upper bound, as the planner reallocates the unemployed at no cost. The presence of regional preferences or moving costs, for example, might substantially change the implied reallocation pattern as both are essential frictions of inter-regional migration (e.g., Heise and Porzio (2019) and Schmutz and Sidibé (2019)). Since at the lowest spatial level mismatch accounts for only 15% of aggregate unemployment, which implies that removing mismatch leads to a two percentage point decrease of the unemployment rate. Tough of course these numbers are sizable, if the relocation cost are large as suggest for example by Kennan and Walker (2011), reducing unemployment through local policies seems to be another promising approach, which we turn to next.

D.1 The model (Mismatch)

This section briefly describes the framework developed by Sahin et al. (2014) and derives the optimal allocation rule.

Benchmark The economy is populated by risk-neutral individuals who can either be employed or unemployed. Unemployed workers search for a job. Labor markets are distinct: an individual can only search in one market (district) i. Hence, $\sum_i^I (e_{it} + u_{it}) = 1$ Vacancies arise exogenously. There is no on-the-job search. Let next period's values be denoted by " ' ".

New matches in each district are determined by a Cobb-Douglas matching function $m_{it} = \Phi_t \chi_{it} v_{it}^\gamma u_{it}^{1-\gamma}$, where $\Phi_t \chi_{it}$ is the matching efficiency and γ the vacancy share. Each employed worker produces Z units of output. All existing matches are destroyed at the exogenous rate ξ_t. Aggregate shocks, Z_t, ξ_t, Φ_t are drawn from the conditional distribution $\Lambda_{Z,\xi,\Phi}(Z', \xi', \Phi'; Z, \xi, \Phi)$, i.e., the realization of next period's parameters depend only on their current state. The vector of vacancies is drawn from the conditional distribution function $\Lambda_v(v'; v, Z', \xi', \Phi')$, i.e., they depend on their current state and next period's realization of aggregate productivity, separation rate, and matching efficiency. The sector-specific matching efficiencies are independent across sectors and are drawn from the independent distribution function $\Lambda_\chi(\chi'; \chi)$, where χ is the vector of matching efficiencies. Each period consists of three stages. In the first stage, the distribution of employment and the vector of vacancies, matching efficiencies, and the aggregate shocks ($\{v, \phi, \xi, Z, \Phi\}$) are observed. The planner then decides how to allocate unemployment across districts. In the second stage, new hires are formed based on the matching-function, and production takes place. At the last stage, a fraction of job-matches separates exogenously, and the employment distribution in the next period is determined. The planner's problem is the following

$$V(e; v; \phi, Z, \xi, \Phi) = \max_{0 \leq u_i} \sum_i^I Z(e_i + h_i) + \beta \mathbb{E}[V(e'; v', \phi', Z'\xi', \Phi')] \tag{36}$$

$$s.t. \quad : \tag{37}$$

$$\sum_i^I u_i \leq u \tag{38}$$

$$\sum_i^I (e_i + u_i) = 1 \tag{39}$$

$$h_i = \Phi \chi_i v_i^\gamma u_i^{1-\gamma} \tag{40}$$

$$e_i' = (1 - \xi)(e_i + h_i) \tag{41}$$

$$\Lambda_{Z,\xi,\Phi}(Z', \xi', \Phi'; Z, \xi, \Phi), \Lambda_v(v'; v, Z', \xi', \Phi'), \Lambda_\chi(\chi'; \chi) \tag{42}$$

Th Lagrangian for the planner's problem is

$$\max_{u_i} \mathcal{L} = \sum_i^I Z(e_i + h_i) + \beta \mathbb{E}[V(e'; v', \chi', Z', \xi', \Phi')] - \mu(u_i - u)$$

Taking the first derivative with respect to u_i and rearranging yields

$$Z(1-\gamma)\Phi\chi_i v_i^\gamma u_i^{-\gamma} + \beta\mathbb{E}\left[\frac{\partial V'}{\partial e_i'}\right](1-\xi)(1-\gamma)\Phi\chi_i v_i^\gamma u_i^{-\gamma} = \mu,$$

where we use $\frac{\partial V'}{\partial u_i} = \frac{\partial V'}{\partial e_i'}\frac{\partial e_i'}{\partial u_i}$. Using the envelope theorem gives

$$\frac{\partial V}{\partial e_i} = \frac{\partial \mathcal{L}}{\partial e_i} = Z + \beta(1-\xi)\mathbb{E}\left[\frac{\partial V'}{\partial e_i'}\right].$$

Iterating this equation forwards yields: $\mathbb{E}\left[\frac{\partial V'}{\partial e_i'}\right] = \frac{Z}{1-\beta(1-\xi)}$.

Substituting the latter result into the first order condition and rearranging gives

$$(1-\gamma)\chi_i\left(\frac{v_i}{u_i}\right)^\gamma = \frac{\mu}{\Phi(Z + \beta\frac{Z}{1-\beta(1-\xi)}(1-\xi))}.$$

Note that all right hand side variables are independent of the sector. Hence, the planner's optimal allocation rule then follows directly, denoting the planner's allocation with "*":

$$\chi_1\left(\frac{v_1}{u_1^*}\right)^\gamma = ... = \chi_I\left(\frac{v_I}{u_I^*}\right)^\gamma. \tag{43}$$

Heterogeneity in productivity and separation rates   Allowing productivity and separation rates to differ between districts leads to a modified optimality condition. We approximate productivity by wages. The planner now re-allocates the unemployed taking into account regional differences in matching-efficiency, number of vacancies, separation rates as well as productivity.[39]

The benchmark index is driven by two sources of heterogeneity: the distribution of vacancies and differences in matching efficiencies. Two other relevant sources of heterogeneity are productivity and separation rates. The model can be extended to account for these additional factors. A key difference is that the planner now maximizes employment. Allowing productivity (z_{it}) and separation rates (ξ_{it}) to differ between districts leads to a modified optimality condition. The modified planner's allocation rule

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[39]For a detailed derivation the reader is referred to Sahin et al. (2014).

$$\frac{v_{jt}}{u_{jt}^*} = \left(\frac{x_{kt}}{x_{jt}}\right)^{\frac{1}{\gamma}} \frac{v_{kt}}{u_{kt}^*} \tag{44}$$

must hold in equilibrium for each district pair j and k. To ease notation z_i denotes district specific matching efficiency weighted by productivity and separation rate $x_{it} = \frac{z_{it}\chi_{it}}{1-\beta(1-\xi_{it})}$.

The planner now reassigns the unemployed taking into account sectoral differences in matching efficiency, vacancies, separation rates and productivity. Going through the same steps as for the benchmark index, the fraction of hires lost due to mismatch is capture by

$$M_{x,t} = 1 - \sum_{i=1}^{I} \left(\frac{\chi_{it}}{\bar{\chi}_{xt}}\right)\left(\frac{v_{it}}{v_t}\right)^{\gamma}\left(\frac{u_{it}}{u_t}\right)^{1-\gamma}, \tag{45}$$

where

$$\bar{\chi}_{xt} = \sum_{i=1}^{I} \chi_{it}\left(\frac{x_{it}}{\bar{x}_t}\right)^{\frac{1-\gamma}{\gamma}}\left(\frac{v_{it}}{v_t}\right) \quad \text{and} \quad \bar{x}_t = \left[\sum_{i=1}^{I} x_{it}^{\frac{1}{\gamma}}\left(\frac{v_{it}}{v_t}\right)\right]^{\gamma}.$$

The counterfactual unemployment rate can be constructed in the same way as for the M_χ index.